Detecting Unassimilated Borrowings in Spanish

An Annotated Corpus and Approaches to Modeling

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Table of Contents

Table of Contents

What is lexical borrowing?

Lexical borrowing is the incorporation of words form one language into another language.

For ex., using in Spanish words that come from English:
podcast, app, online, crowdfunding, spin-off, big data, fake news...

- Lexical borrowing is a type of linguistic borrowing.
  - Linguistic borrowing is the process of reproducing in one language the patterns of other languages Haugen (1950)
- Borrowing and code-switching are related and have frequently been described as a continuum Clyne et al. (2003)
  - Code-switching = mixing two languages in one sentence.
    Ex: *You start a sentence in English y la acabas en español*
    Poplack (1980); Poplack et al. (1988)

Lexical borrowing vs Code switching

	Code Switching	**Lexical Borrowing**
Speaker	bilinguals	monolinguals
Grammar compliance	both languages	recipient language
Level of integration	not integrated	can be integrated
NLP approach	one tag per token (*à la POS-tagging*)[1]	extraction of spans of interest (*à la NER*)

[1] see Computational Approaches to Linguistic Code-Switching workshops (CALCS) Solorio et al. (2014); Diab et al. (2016); Aguilar et al. (2018); Solorio et al. (2020, 2021)

Why is borrowing an interesting phenomenon?

Borrowing in Linguistics:

- Borrowing is a manifestation of how languages change and interact (diachronic linguistics and contact linguistics) Weinreich (1963)

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Borrowing in NLP:

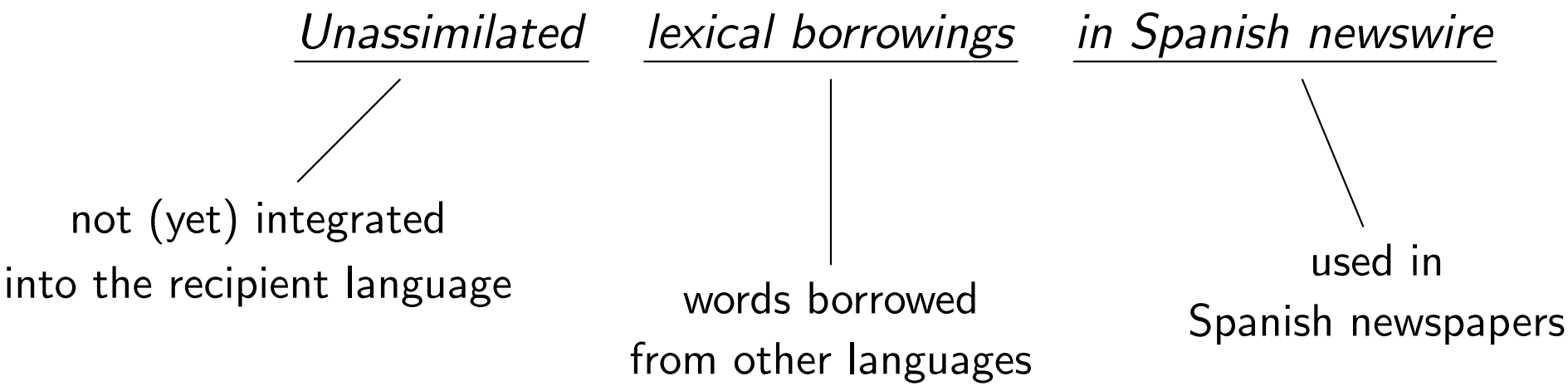
- Borrowings are a common source of out-of-vocabulary words Gerding Salas et al. (2018).
- Automatically detecting lexical borrowings from text has proven to be relevant for NLP downstream tasks:
  - Parsing Alex (2008)
  - Text-to-speech synthesis Leidig et al. (2014)
  - Machine translation Tsvetkov and Dyer (2016)

Previous work on English borrowing detection

- Growing interest in the influence of English in other languages Görlach (2002).
- With a focus on English lexical borrowings (a.k.a *anglicisms*)
- Previous work on automatic detection of borrowings in different European languages: German, French, Italian, Norwegian, Finnish, Spanish Andersen (2012); Chesley (2010); Furiassi and Hofland (2007); Garley and Hockenmaier (2012); Losnegaard and Lyse (2012); Mansikkaniemi and Kurimo (2012); Serigos (2017); Álvarez Mellado (2020)

Table of Contents

The task



Words from other languages (mainly English) that have recently been imported into Spanish and that are being used in Spanish newspapers

Ex: *Las prendas bestsellers se estampan con motivos florales, 'animal print' o a retales tipo patchwork*

Best-seller clothes show flower print, animal print or patchwork style

Limitations in previous work on anglicism detection

Previous work introduced a CRF model for anglicism detection on Spanish newswire (F1=86) (Álvarez Mellado, 2020). However, both the dataset and modeling approach had significant limitations:

- The dataset consisted only of headlines.
- The dataset focused exclusively on a single source of news
- The number and variety of borrowings were limited
- There was a significant overlap in borrowings between the training set and the test set (which prevented assessment of whether the modeling approach was actually capable of generalizing to previously unseen borrowings)
- The best results were obtained by a CRF model, and more sophisticated approaches were not explored.

Table of Contents

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  92% of the borrowings in the test set are OOV

The corpus

The corpus was:

- Composed of a collection of texts from Spanish newspapers
- Annotated with lexical borrowings with 2 tags:
  - `ENG`: for English borrowings
  - `OTHER`: for borrowings from other languages
- In CoNLL format
- With BIO encoding
  Because borrowings can be single token (*app*) or multitoken (*machine learning*)

The corpus: counts

Set	Tokens	ENG	OTHER	Unique
Training	231,126	1,493	28	380
Development	82,578	306	49	316
Test	58,997	1,239	46	987
Total	372,701	3,038	123	1,683

Table: Corpus splits with counts

The corpus: example

```
En  O
este  O
mes  O
especialmente  O
puede  O
ser  O
de  O
utilidad  O
apuntarnos  O
al  O
batch  B-ENG
cooking  I-ENG
Benching  B-ENG
,  O
estar  O
en  O
el  O
banquillo  O
de  O
tu  O
crush  B-ENG
mientras  O
otro  O
juega  O
de  O
titular  O
```

Table of Contents

Conditional Random Fields model

A CRF model with handcrafted features. The following set of binary features from (Álvarez Mellado, 2020) were used:

– Bias
– Token
– Uppercase
– Titlecase
– Character trigram
– Quotation marks
– Suffix
– POS tag (provided by `spaCy`)
– Word shape (provided by `spaCy`)
– Word embedding (Spanish word2vec by Cardellino (2019))
– URL (provided by `spaCy`)
– Email (provided by `spaCy`)
– Twitter (`#hashtag` or `@username`)

CRF results

Previous work with a similar CRF on a different dataset had reported and F1 score of 86.41 (Álvarez Mellado, 2020). We got F1=55.44.

Set	Precision	Recall	F1
Development			
ALL	74.13	59.72	66.15
ENG	74.20	68.63	71.31
OTHER	66.67	4.08	7.69
Test			
ALL	77.89	43.04	55.44
ENG	78.09	44.31	56.54
OTHER	57.14	8.70	15.09

Table: CRF performance on the development and test sets

Transformer-based models

We evaluated two Transformer-based models:

- BETO base cased model: a monolingual BERT model trained for Spanish (Cañete et al., 2020)
- mBERT: multilingual BERT, trained on Wikipedia in 104 languages (Devlin et al., 2019)

Both models were run using the `Transformers` library by HuggingFace (Wolf et al., 2020).

Transformer-based models results

	Development			Test		
	Precision	Recall	F1	Precision	Recall	F1
BETO						
ALL	73.36	73.46	73.35	86.76	75.50	80.71
ENG	74.30	84.05	78.81	87.33	77.99	82.36
OTHER	47.24	7.34	11.93	36.12	8.48	13.23
mBERT						
ALL	**79.96**	**73.86**	**76.76**	**88.89**	**76.16**	**82.02**
ENG	80.25	84.31	82.21	89.25	78.85	83.64
OTHER	66.18	8.6	14.41	45.30	7.61	12.84

BiLSTM-CRF model with different types of embeddings

Can a BiLSTM-CRF model fed with different embeddings that encode different linguistic information outperform the results obtained by the Transformer-based models?

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This is what we found out:

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- English BERT $+$ Spanish BETO embeddings $>$ mBERT embeddings
- BPE embeddings $\Longrightarrow$ better F1
- Character embeddings $\Longrightarrow$ better recall

Best BiLSTM-CRF results

Embeddings	**Development**			**Test**		
	Precision	Recall	F1	Precision	Recall	F1
BETO+BERT and BPE						
ALL	**85.84**	77.07	**81.21**	**90.00**	76.89	82.92
ENG	86.15	88.00	87.05	90.20	79.36	84.42
OTHER	72.81	8.8	15.60	62.68	10.43	17.83
BETO+BERT, BPE, and char						
ALL	84.29	**78.06**	81.05	89.71	**78.34**	**83.63**
ENG	84.54	89.05	86.73	89.90	80.88	85.14
OTHER	73.50	9.38	16.44	61.14	9.78	16.81

(Best results with mBERT obtained F1=76 on the dev set and F1=82 on the test set. So yes, it seems that a BiLSTM-CRF fed with different embeddings could outperform mBERT)

BiLSTM-CRF model with codeswitch embeddings

Can lexical borrowing detection be framed as transfer learning from language identification in codeswitching?

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Codeswitch embeddings (Sarker, 2020) = Fine-tuned Transformer-based embeddings pretrained for language identification on the Spanish-English section of the LinCE codeswitching dataset (Aguilar et al., 2020)

BiLSTM-CRF with codeswitching embeddings

Embeddings	**Development**			**Test**		
	Precision	Recall	F1	Precision	Recall	F1
Codeswitch						
`ALL`	80.21	74.42	77.18	90.05	76.76	82.83
`ENG`	80.19	85.59	82.78	90.05	79.37	84.33
`OTHER`	85.83	4.70	8.78	90.00	6.52	12.14
Codeswitch + char						
`ALL`	81.02	74.56	77.62	89.92	77.34	83.13
`ENG`	81.00	85.91	83.34	89.95	80.00	84.67
`OTHER`	73.00	3.67	6.91	68.50	5.43	9.97
Codeswitch + BPE						
`ALL`	**83.62**	**75.91**	**79.57**	90.43	78.55	84.06
`ENG`	83.54	86.86	85.16	90.57	81.14	85.59
`OTHER`	94.28	7.55	13.84	67.17	8.70	15.30
Codeswitch + BPE + char						
`ALL`	82.88	75.70	79.10	**90.60**	**78.72**	**84.22**
`ENG`	82.90	86.57	84.66	90.76	81.32	85.76
`OTHER`	87.23	7.75	14.03	66.50	8.70	15.13

(Best results with the BiLSTM-CRF fed with unadapted embeddings obtained F1=81 on the dev set and F1=83 on the test set)

Table of Contents

Discussion and wrap-up

- A new dataset of Spanish newswire annotated with unassimilated lexical borrowings (more borrowing-dense, OOV-rich)
- 4 types of models for lexical borrowing detection:
  - CRF model with handcrafted features (F1=55)
  - Transformer-based models (BETO: F1=80, mBERT: F1=82)
  - BiLSTM with Transformer-based word embeddings (BERT+BETO) and subword embeddings (BPE, char) (F1=83.6)
  - BiLSTM with embeddings pretrained on codeswitched data (F1=84.2)
- Error analysis: Recall was a weak point for all models. Most frequent false negatives:
  - upper-case borrowings (such as *Big Data*)
  - borrowings in sentence-initial position (in titlecase)
  - words that exist both in English and Spanish (like *primer* or *red*)
- BPE embeddings seem to improve F1 score.
- Character embeddings seem to improve recall

Resources

- Corpus

  `https://github.com/lirondos/coalas`

- HuggingFace models

  `https://huggingface.co/models?arxiv=arxiv:2203.16169`

- Paper

  `https://arxiv.org/abs/2203.16169`

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