Cross-lingual hate speech detection based on multilingual domain-specific word embeddings

Aymé Arango, Jorge Pérez and Barbara Poblete

ABSTRACT
Automatic hate speech detection in online social networks is an important open problem in Natural Language Processing (NLP). Hate speech is a multidimensional issue, strongly dependant on language and cultural factors. Despite its relevance, research on this topic has been almost exclusively devoted to English, with limited coverage of other languages. Most supervised learning resources, such as labeled datasets and NLP tools, have been created for this same language. Considering that a large portion of users worldwide speak in languages other than English, there is an important need for creating efficient approaches for multilingual hate speech detection. In this work we propose to address the problem of multilingual hate speech detection from the perspective of transfer learning. Our goal is to determine if knowledge from one particular language can be used to classify other language, and to determine effective ways to achieve this. We propose a hate specific data representation (i.e., hate speech word embeddings) and evaluate its effectiveness against general-purpose universal representations most of which, unlike our proposed model, have been trained on massive amounts of data. We focus on a cross-lingual setting, in which one needs to classify hate speech in one language without having access to any labeled data for that language. We show that the use of our simple yet specific multilingual hate representations improves classification results compared to other data representations. We explain this with a qualitative analysis showing that our specific representation is able to capture some common patterns in how hate speech presents itself in different languages. We expect that our proposal and results can be a first step towards identifying cross-lingual hate patterns specially in low-resource languages.

Our proposal constitutes, to the best of our knowledge, the first attempt for constructing multilingual specific-task representations. Despite its simplicity, our model outperformed the previous approaches for most of the experimental setups. The best path to take for solving the problem of cross-lingual hate-speech detection is still unknown, and our findings can orient future solutions toward the use of domain-specific representations.

CCS CONCEPTS
• Computer systems organization → Embedded systems; Redundancy; Robotics; • Networks → Network reliability.

KEYWORDS
hate speech classification, experimental evaluation, social media,

1 INTRODUCTION
Online social media platforms have become an important means of interaction among millions of users worldwide. Timely information, including news and opinions, as well as political campaigns and other organized communications take place in this online environment. However, along with many useful exchanges, there is also the manifestation of certain communication disorders such as fake news and hate speech which can produce harmful side-effects. Hate speech, which is our focus in this paper, is usually understood as abusive or threatening speech or writing that expresses prejudice against particular groups. It is a phenomenon related to human behaviour that spans across different cultures and languages, which can seriously limit the use of social platforms for groups like women, minorities and other vulnerable segments. Furthermore, virtual-world hateful expressions can have the aggravated effect of sometimes translating into actual hate crimes in the physical world.\(^1\)

Automatic detection of hate speech messages in online social media platforms is an open and challenging multidimensional problem. Despite the worldwide extent of this problem, limitations of existing solutions are even more profound when we consider that most of the research in this area has been centered in text written in English \(^2\). This is also evidenced by the scarcity of models and learning resources (specific datasets, lexicons or word representations) for hate speech detection in languages other than English. There have been some recent efforts towards systematically addressing the multilingual aspects of hate speech detection \[^3, 4, 14, 47\]. Most of these works rely on emerging multilingual tools developed by the NLP community, in particular general-purpose multilingual text representations \[^17, 21, 45\]. These are representations for words or short texts that map input text data from several different languages into a single feature space. However, as an emergent topic, there is still no consensus on how to satisfactorily undertake multilingual hate speech. Hence, it becomes imperative to find and compare approaches that are language-agnostic or that can take advantage of resources from more represented languages and apply them to languages with little to no resources.

We are particularly interested in cross-lingual settings in which we have target language for which it is assumed that there are no available resources (e.g., specific labeled data) for hate speech and one needs to leverage resources from a different language. This setting is sometimes called zero-shot multilingual learning, as one usually trains a model using data from one language, and then test it for a different target language without providing any labeled data for the target language. Cross-lingual and language-independent approaches would facilitate transfer learning from English (and other languages) to low-resource languages.

We specifically analyzed in this paper which are the most effective alternatives for cross-lingual hate speech classification. We first consider approaches based on general-purpose multilingual text representations, in particular multilingual word embeddings \[^17, 21, 45\]. We hypothesize that general-purpose multilingual word embeddings may not effectively capture some patterns that naturally arise.

\(^{1}\)https://time.com/5436809/twitter-apologizes-threat-mail-bomb-suspect/
\(^{2}\)https://www.cbc.ca/news/canada/toronto/mosque-stabbing-suspect-1.5732078
when words are used in a hateful context, instead of a general context. For instance, while some words related to nationality, religion, and race can be used in neutral contexts in general text, they can appear in very different contexts when used in hate speech, acquiring harmful meanings [22].

Motivated by the previous observation, we propose a set of multilingual word embeddings specifically created for hate speech. To achieve this we adopted the method proposed by Faruqui and Dyer [23], which finds embedding projections that maximize the correlation between word embeddings from different feature spaces. We use this method to align several monolingual hate speech embeddings independently created for each language in an unsupervised way. We evaluate the effectiveness of our approach in relation to other general-purpose representations by using them as input features for several machine learning models and on three different languages: English, Spanish and Italian.

Our findings show that in general, the use of our hate specific representations improved cross-lingual models performance in comparison to general-purpose representations and pre-trained models. This suggests that besides the information provided by translating the general meaning of words to different languages, there are more specific cross-cutting patterns in how hate speech is displayed in those languages. These patterns allow us to transfer knowledge from one language to another when detecting hate speech. Along this line, we provide a qualitative analysis of our domain-specific multilingual embeddings by exploring word contexts in the three languages that we consider. Our preliminary analysis show that hate specific embeddings are able to capture non-traditional translations of words from one language to other. For instance, if for a general purpose multilingual embedding the natural context-based translation (see Section 4.3 for details) of the Italian word “migranti” is “migrants” in English, and “migrantes” in Spanish, in our hate embedding the translations are “illegals” and “palestinos”, respectively. We show several other classes of translations and discuss how they can be used not only for classification but also for better understanding of hate speech as a multicultural problem.

Contributions:
1. We introduce the first domain-specific multilingual word representation (word embeddings) for hate speech classification.
2. We present a comprehensive evaluation of different approaches for cross-lingual hate speech detection.
3. We qualitatively show cross-lingual relations between terms in the context of hate speech derived from our domain-specific embeddings.

Warning: Because of the topic that we consider, some example words mentioned in the paper may be considered offensive.

Reproducibility: All of our code, experiments, and datasets, as well as our proposed word embeddings for hate speech will be publicly available in a centralized repository.

In the rest of the paper we first describe the related work on hate speech detection in monolingual and multilingual settings in Section 2. In Section 3 we present our methodology including the standard models and input representations that we consider, introducing also our hate-specific word embeddings representations. Our main quantitative and qualitative results are presented in Section 4.

2 RELATED WORK
In this section we review works related to hate speech detection in monolingual and multilingual scenarios, as well as methods for word embedding projections.

2.1 Monolingual Hate Speech Detection
Although the field of automatic hate speech detection has gained popularity in the past years, most of the existing approaches have been constructed for monolingual English scenarios. Several of them have approach the problem using traditional machine-learning strategies [16, 19, 51] and different types of representations mixing text representations with handcrafted features extracted from messages meta-information [36, 48]. The English hate speech detection has also been addressed with deep-learning methods and word embedding representations [25, 27, 37, 52]. In addition, critical analysis of English systems and datasets have been conducted, helping to understand better the problem in English scenarios[6, 20, 44].

Other languages such as Spanish [38], Italian [43], and Portuguese [24], have been addressed using similar techniques as in the English approximations, though in a fewer amount of works which might be in part due to the lack of available resources.

2.2 Cross-lingual Hate Speech Detection.
As it has been shown for other tasks [17, 18], a multilingual approximation to the hate speech problem would help to advance the state of the art for under-represented languages. For languages with little to no results, one would need approaches in which no information about the target language (the one over which one wants to detect hate) is used during the training process. We refer to this constrained scenario as cross-lingual. In spite of several approaches designed for dealing with hate speech in different languages [3, 14, 40], there are only a few reports on strict cross-lingual evaluation on the recent related literature [4, 33, 47].

Translating all the data to a common language as strategy is one of the strategies that have been applied. Pamungkas and Patti [35], explored this strategy using English, Spanish, Italian and Deutsch datasets. Once all data is in the same language, a monolingual strategy is applied.

Meta-information from the network dynamics of the message and the message authors could be considered “multilingual” features as they are not directly related to the language in which the text is written. This type of features is used by Arango et al. [7] where they are combined with traditional machine-learning models in cross-lingual evaluation for English and Spanish datasets.

Aluru et al. [4] experimented in a cross-lingual (zero-shot and few-shot learning) manner over nine different languages. They tested different combinations of different machine learning models and vector representations such as MUSE3 and LASER4 embeddings. The combination of LASER and a Logistic Regression (LR) model turned out to be the best combination in most of the experimental setups. This show that traditional machine learning models still have to be considered for this task.

Extracting features from pre-trained models is the strategy followed by Stappen et al. [47]. The authors proposed an architecture

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3https://github.com/facebookresearch/MUSE
4https://github.com/facebookresearch/LASER
where initially the tokenized text is propagated through a pre-trained model, extracting vector representations. These representations are fed into a classification model. Fine-tuning pre-trained multilingual models like BERT\(^5\) over the training data as an end-to-end classification model is another strategy that have been used also in the related literature [39, 47].

The best performance reported by each of them was achieved using different representations and different models. There are not categorical conclusions about which model perform better for this scenario. The cross-lingual evaluation of hate speech is still a new research area, and the results are just a few. The different approximations usually rely on general-purpose representations and models. We did not find works reporting efforts to construct specialized representations (word embeddings) for this problem as is one of the focus of our paper.

2.3 Monolingual Specific Domain Word Embeddings.

In the related literature can be found some works describing the construction of specific-domain word embeddings for hate speech detection, but only in monolingual scenarios. As far as we know, there are not reported efforts for constructing multi-lingual specific domain word embeddings.

Kamble and Joshi [31] constructed word embeddings using a Word2Vec model Hindi-English code-mixed tweets from the hate speech domain. To show their effectiveness they trained different deep-learning hate speech classifiers. Alatawi et al. [2] also describe the construction of Word2Vec word-embeddings in the domain of English white supremacist hate speech. The authors perform qualitative and quantitative comparison of these embeddings with other from general domain. In both cases the specific-domain corpus is obtained using previously known hateful terms as queries. Badjatiya et al. [10] propose the construction of English word embeddings for the specific domain of hate speech using a labeled dataset and an LSTM-based model. However, their validation strategy was considered wrong since the same dataset was used for constructing embeddings and validation purposes [6].

2.4 Projection-Based Multilingual Word Embeddings

Although some specific techniques can be applied for constructing multilingual embedding for specific-tasks, the projection technique represents an attractive option as it requires resources relatively easy to obtain for most of the tasks [26]. The general idea is to linearly project two vector spaces into a common one by optimizing the relationship between dictionary-paired vectors obtained from bilingual dictionaries. The bilingual dictionaries can be induced from the data (unsupervised methods) [8, 17, 32] or provided beforehand (supervised methods) [23, 30, 34, 41]. Different projection techniques have been proposed in the related literature defining different optimization problems such as minimizing distances between equivalent vectors [34], minimizing cosine distance modifications [30], maximizing correlations between equivalent terms [23] among others. Ruder et al. [42] presented a complete survey about different types of alignments. As far as we know, none of these techniques have been applied for creating multilingual embeddings for the hate speech domain.

3 METHODOLOGY

With the goal of analyzing which are the most effective alternatives for multilingual hate speech classification, we evaluate different settings by combining diverse input representations (language independent features, word and sentence embeddings) and several models (traditional machine learning and deep learning models) that use those representations to solve a cross-lingual task. These experiments allow us to evaluate how our hate speech word representations (that we will introduce in Section 3.3) perform in comparison with the general-purpose ones. As we are interested in the cross-lingual scenario, we conducted our experiments over three datasets in different languages: English, Spanish and Italian.

3.1 Datasets

For the purpose of validating our results we needed annotated datasets. The availability of annotated datasets (specially for non-English languages) is very poor and we are aware of this limitation. With our proposal we intend to make the best of very poor sources.

For the English language we mixed two different datasets. The first one was constructed by Arango et al. [6]. For constructing this dataset, the authors combined two previously published datasets [19, 50]. The types of hateful content addressed in this dataset are racism, sexism and xenophobia. We consider these three classes as hateful, thus having a final dataset with only two labels: hateful, with 2,920 texts, and non-hateful with 5,576.

The tweets on this dataset were originated in the context of hate in the United States of America. Therefore the targets of hate, as well as specific terms, are framed on that particular cultural context.

We also considered the English Twitter dataset proposed by Basile et al. [12] for hate speech against immigrants and women, therefore the targets of hate are similar to the one in the Arango et al. [6] dataset. Each tweet is tagged as either hate (5,390) speech or normal (7,415).

For the Italian language we consider the dataset described by Sanguinetti et al. [43], which is part of a hate speech Italian monitoring program. This dataset includes 1,291 tweets expressing hate against immigrants and other 5,637 negative examples.

The Spanish dataset constructed by Pereira-Kohatsu et al. [38] is composed of tweets addressing topics of racism, sexism and xenophobia. We use it as a binary dataset where 1,576 of the tweets are labeled as hateful and 4,434 as non hateful. The authors of the dataset recovered tweets specifically originated in Spain. In order of collecting more labeled examples we also considered the Spanish Twitter dataset proposed by Basile et al. [12] composed by 2,228 addressing hate speech against immigrant and women; and 3,137 non-hateful tweets.

A summary of the datasets statistics can be found in Table 1.

3.2 General-Purpose Multilingual Representations

Recall that our input is composed of short texts from social media (tweets). The metadata information present in those tweets could
be considered as features, but unfortunately is only available in very few of the available datasets. Therefore we considered only text representations that we describe next.

We consider three types of multilingual embeddings: MUSE [17], BERT [21] and LASER [45]. MUSE is a set of general embeddings aligned for multilingual contexts. BERT is a general purpose pretrained model for NLP that can be used to produce embeddings for sentences (sequences of words). BERT can be trained in an unsupervised way from big corpora, and the authors of the original model provided a BERT version trained over a corpus containing text from 104 languages [21]. From now on we call it multilingual BERT (or mBERT for short). In some of the monolingual results, we also consider the monolingual versions of BERT and fine tune it for the specific task (we refer the reader to [21] for details on fine tuning BERT). LASER [45] is a recently proposed model to produce multilingual embeddings for sentences. As opposed to mBERT, LASER was constructed specifically for the multilingual context. Although the three models has recently been used on multilingual hate speech detection [4, 15], there is still no consensus about which of these representations perform better for this task. We evaluate the usefulness of these three representations using them to construct input features for several classification models.

3.3 Hate-Speech-Specific Word Embeddings

Besides the standard representations described in the previous sections and since the phenomenon of hate speech has its own characteristics, we also consider a domain-specific representation. Thus, we constructed specific word representations using a projection embedding technique with the following general steps: (1) constructing monolingual vector spaces for each language separately in an unsupervised way, (2) preparing a bilingual dictionary for each pair of languages, and (3) aligning the monolingual spaces into a single embedding space. This method has the advantages of being independent of the algorithm used for constructing the monolingual embeddings, and only requiring a bilingual dictionary instead of a big amount of parallel or labelled data [9, 42].

We next describe every one of the above mentioned steps in more detail.

3.3.1 Monolingual vector spaces. Using the Twitter API⁶, we recovered tweets for every language by simply using some general hateful terms as queries. The seeds would guarantee the existence of hateful terms in the resulting word embedding vocabulary and a higher probability for hateful tweets to appear in the corpora compared with recovering them randomly. The sizes of the corpora are: 30M English, 10M Spanish and Italian each.

In our specific context, the hateful terms were obtained from the multilingual Hurtlex lexicon [13]⁷ and an English lexicon constructed by Davidson et al. [19]⁸. With the recovered data, we trained Word2Vec models for each individual language (English, Spanish, and Italian).

We emphasize that the process described here is a simple process that can essentially be replicated for any language by only having a set of hateful words, without the need of any data specifically labelled for hate speech. This is a necessary condition to be applicable in low resource contexts.

3.3.2 Bilingual dictionary. As bilingual dictionary we used word-aligned pairs from Hurtlex [13]. The Hurtlex multilingual lexicon helped us to match hateful terms between different languages. According to Shakurova et al. [46] better results are obtained when the bilingual lexicon is from the specific domain of the task. The particularity of Hurtlex is that it includes terms that have different colloquial equivalents that are not usually included in generic dictionaries, as well as words that could appear usually in hateful content. As an example we show in Table 2 the bilingual equivalences of the English word “pussy”.

3.3.3 Aligning the monolingual spaces. As alignment algorithm, we adopted the framework proposed by Faruqui and Dyer [23]⁹ since it has been applied to different domain-specific tasks such as: sequence labelling for Curriculum Vitae parsing [46], text categorization [5], cross-lingual information retrieval, and document classification [26]. In this process, a pair of monolingual word vectors are projected into a common space by learning two projection matrices $V$ and $W$ that maximize the correlation between the dictionary-paired projected vectors.

3.4 Models for Hate Speech Classification

In the current research on the cross-lingual detection subject, different methods have been used with similar results. Since the best model for approaching the problem is still not clear, we perform experiments with several methods including traditional machine

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### Table 1: Description of the datasets we used for hate speech evaluation. For each dataset we show the number of tweets per class.

| Language | Dataset          | Hate  | Non-Hate | Total |
|----------|------------------|-------|----------|-------|
| English  | Arango et al. [6] | 1,490 | 5,576    | 7,066 |
|          | Basile et al. [12]| 5,390 | 7,415    | 12,805|
| Spanish  | Pereira et al. [38]| 2,228 | 3,137    | 5,365 |
| Italian  | Sanguinetti et al. [43]| 1,291 | 5,637    | 6,928 |
| Total    |                  | 11,975| 26,199   | 38,174|

### Table 2: Equivalences of the word “pussy” in the specific hateful lexicon Hurtlex, and the generic dictionary MUSE.

| Hurtlex         | MUSE Dictionary       |
|-----------------|-----------------------|
| conejo, concha, chuca, | coño, chocho          |
| coño, chuca, almeja, |                        |
| punta, vagina, chocha, |                        |
| chocho, chica, raja  |                        |
| figa, figara, tartaruga, |                        |
| gnocca, mona, sorca, |                        |
| patonza, ciciotta, passera, |                        |
| fica, cono, paffia, pincia |               |

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⁶https://github.com/tweepy/tweepy
⁷https://github.com/mfaruqui/crosslingualcca
⁸https://github.com/t-davidson/hate-speech-and-offensive-language/blob/master/lexicons/refined_ngram_dict.csv
⁹https://github.com/valeriobasile/hurtlex

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Figure 1: Constructing process of the Hate-Speech-Specific Word Embeddings.

learning methods and deep learning models. As traditional machine learning models we used Logistic Regression, XGBoost (XGB), Support Vector Machines, Random Forest (RF), Decision Trees (DT), and Naïve Bayes classifiers.

Regarding the deep learning models that we considered, we tested: Convolutional Neural Networks (CNN), Feedforward Neural Networks (FNN), Long Short-Term Memory networks (LSTM). In addition, we combined LSTM and CNN layers (LSTMCNN), as well as LSTM with Attention (LSTMATTN). All these models were tuned in order to find the best possible values for the different hyperparameter combinations. We also performed fine-tuning of the corresponding monolingual BERT models for Italian, Spanish, and English for conducted some monolingual experiments as reference for the cross-lingual ones.

4 EVALUATION AND RESULTS

We tested several combinations of models and input representations for hate speech detection. We evaluated the different combinations in both, monolingual (Section 4.1) and cross-lingual (Section 4.2) scenarios. The available data in the three different languages-datasets (Section 3.1) were portioned into training, development and testing sets. These partitions remained the same for all the experiments.

The traditional machine learning models were combined with LASER sentence embeddings. On the other hand, DNN architectures were combined with word embeddings extracted from pre-trained monolingual and multilingual BERT (mBERT), MUSE multilingual word embeddings and our hateful multilingual word embeddings (HateEmb).

4.1 Monolingual Evaluation

Despite the fact that our main goal is the cross-lingual evaluation of hate speech detection, we considered important to perform comparisons of cross-lingual results with their monolingual counterparts. Intuitively, the closer the cross-lingual results are to the monolingual ones, the better they were able to transfer knowledge satisfactorily from one language to another.

In Table 3, we show the results (in terms of F-score) obtained in a monolingual evaluation using different word (and sentence) embeddings representations combined with different DNN models. At each column header we show how input features are computed (BERT, MUSE, HateEmb, etc.). An exception is the “Fine-tuned BERT” column in which the task was solved end to end by adapting the parameters of a pre-trained BERT model to the hate speech specific task. We only report the best result over all models that we tested, and over each result we depict the model used to obtain that result (for instance, the best result for the English language using BERT input features was obtained by using an LSTM network with Attention).

In this monolingual case we can observe that, as expected, using multilingual input representations (mBERT, MUSE and HateEmb) did not improve classification results. Moreover, for the three datasets that we consider, the BERT-based models show the best performances. Another important observation is that the use of our hate-speech-specific word embeddings (HateEmb), although did not present the best results, they show results similar to other multilingual input representations. Actually, if we only compare the results of the multilingual input representations, HateEmb surpass MUSE in the three languages and also mBERT for the Italian language.

4.2 Cross-Lingual Evaluation

Table 4 shows the results of cross-lingual experiments using several different input representations. In these experiments we first picked an input representation (shown in column headers as mBERT, MUSE, LASER and HateEmb in Table 4), then train a classifier using a source language (second column), and finally test it over a different target language (first column). As we have mentioned, this setting is sometimes referred as zero-shot multilingual transfer learning, as no data of the target language is presented during training. This is, arguably, the most challenging multilingual transfer task. We tested several different models over the input representations, and we report the one that gave the best result for every combination.

As we expected, the results in the cross-lingual setting are lower than the ones obtained in the monolingual evaluation. The use of our proposed HateEmb embeddings show promising results, obtaining the best results in four of the six configurations with a considerable margin in several of them. We show the difference between the results of our embeddings compared with the best alternative method in the last column of Table 4. Our HateEmb is surpassed only by configurations in which the multilingual BERT model is used to obtain input features. In that cases our proposal is the second best. It should be noticed that BERT is a huge model with millions of parameters and needing specialized hardware to be trained. In contrast, our embeddings are really lightweight and can be trained in general purpose machines.

The models that worked better in combination with the HateEmb embeddings are the ones based on LSTM architectures. From all the traditional machine learning models used, the best performances were obtained by using an XGBoost classifiers for the cases

18https://github.com/marcopoli/ALBERTo-it
19https://github.com/dccuchile/beto
20https://github.com/huggingface/transformers
Table 3: Monolingual hate speech evaluation using F-score. The "Fine-Tuned-Bert" column shows the F-score obtained by fine-tuning monolingual pre-trained Bert. Each of the other columns represents a different word-embedding representations. The best performing models are annotated in the corresponding cell. The numbers on bold letters represent the best performance per training-testing setup.

| Testing     | Training     | Input Representations | Fine-tuned BERT | BERT | mBERT | MUSE | HateEmb |
|-------------|--------------|-----------------------|-----------------|------|-------|------|---------|
| English_test| English_train|                       |                 |      |       |      |         |
|             |              | Fine-tuned BERT       | 73.45           | 74.51| 74.40 | 70.26| 73.59   |
| Spanish_test| Spanish_train|                       |                 |      |       |      |         |
|             |              | mBert                 | 73.45           | 70.74| 70.15 | 67.57| 69.82   |
| Italian_test| Italian_train|                       |                 |      |       |      |         |
|             |              |                      | 69.37           | 69.74| 68.98 | 63.95| 69.38   |

Table 4: Cross-lingual hate speech evaluation using F-score. The representations considered were: representations from multilingual Bert (mBert), MUSE, LASER and our specific hate representations (HateEmb). The numbers on bold letters represent the best performance per training-testing setup.

| Testing     | Training     | Input Representations | mBERT | MUSE | LASER | HateEmb (diff) |
|-------------|--------------|-----------------------|-------|------|-------|----------------|
| Spanish_test| English_train|                       |       |      |       |                |
|             |              | mBert                 | 56.80 | 50.73| 52.25 | 60.64          |
|             |              |                      |       |      |       | +0.34          |
| Italian_train|               |                       |       |      |       |                |
|             |              | ATTN                  | 55.21 | 46.22| 54.70 | 54.82          |
|             |              |                      |       |      |       | +0.20          |
| Italian_test| English_train|                       |       |      |       |                |
|             |              | FNN                   | 60.73 | 55.40| 54.87 | 61.82          |
|             |              |                      |       |      |       | +0.09          |
| Spanish_train|               |                       |       |      |       |                |
|             |              | ATTN                  | 62.24 | 53.81| 55.09 | 58.38          |
|             |              |                      |       |      |       | -3.86          |
| English_test| Spanish_train|                       |       |      |       |                |
|             |              | LSTM                  | 61.64 | 48.19| 53.76 | 63.91          |
|             |              |                      |       |      |       | +1.27          |

of LASER input representations. The best DNN model varies depending on the experiment, therefore conclusions about the best performing DNN for this task can not be taken.

Several hyper-parameters were tested in an exhaustive hyperparameter tuning process. The best hyper-parameters were different depending on the cross-lingual setup and model. Since they are many, for the sake of space, we describe all in the code repository (to be publicly available).

The fact that our hateful embeddings were competitive with the more sophisticated but general ones, lead us to the hypothesis that we were able to capture important semantic information about hate-speech when training and aligning our embeddings for different languages. We qualitatively assess a related hypothesis in the following section.

4.3 Qualitative Evaluation of Hate Embeddings

The intrinsic quality of multilingual word embeddings is usually evaluated on the Bilingual Lexicon Induction (BLI) task [42, 49]. This task measures how well the vectors representing translations in different languages are close to each other in the common embedding space. BLI relies on nearest neighbor search in the multilingual embedding space identifying the most similar word in the target language given a word in a source language. The target and source words are expected to be translations for each other according to a validation dictionary [26].

We have several difficulties for using a BLI-like quantitative method to assess the intrinsic quality of our embeddings. The main difficulty is that, as we have argued before, we consider that hate speech is a problem where word meanings could go well beyond literal translations. Thus, having a low BLI score for general terms would not necessarily mean a low quality for hate speech detection. Moreover, we already used the translation of some specific hate speech terms as bilingual dictionary when constructing our embeddings (see Section 3.3). Thus, using that same bilingual dictionary as a validation set for our embeddings would be meaningless. One possible option would be to manually construct new hate speech
specific bilingual dictionaries for evaluation which would be a highly time-consuming process. Moreover, being the hate speech problem a cultural phenomenon, to go beyond standard trivial translations of words, one would need experts in the cultural use of complicated terms in different languages.

Therefore, we decided not to measure the quality of our embedding based on quantitative tasks, but instead we present more specific qualitative analysis along the same idea of BLI-like tests. The analysis gives some evidence that our created embeddings have the potential to map terms that are similarly used for hate speech in different languages.

4.3.1 Cross-lingual relations in vectors spaces. Our first qualitative evaluation is inspired by BLI and consists in, giving a seed term, observing the most related terms across-languages. In Table 5, we show a sample of the relations between the terms comparing our embeddings (HateEmb) with general purpose multilingual embeddings (MUSE). These terms were manually selected trying to represent some groups that might be the focus of a hate, and ensuring their equivalences were not present in the bilingual dictionary that we use for aligning our embeddings (thus showing a new relation).

For each selected source term, we show the nearest neighbor (NN) embedding in the common space corresponding to a word in a language different to the source language. In most cases the nearest neighbors in the MUSE space are terms which standard meanings are the same in both languages. For example, for the Italian word “migranti”, we found that the nearest terms on the MUSE space is “migrants” in English and “migrantes” in Spanish. On the other hand, the nearest neighbors on the HateEmb space are “illegals” and “palestinos” words in English and Spanish, respectively, whose standard (neutral) translations do not match with the source word. Although not direct translations of each other, we argue that these words are likely to appear in similar context in hateful scenarios in the languages that we considered.

We consider that evaluating the hate speech specific embeddings considering literal translations such as “migranti” and “migrante” it is not suitable, since in the hateful content the word “migranti” could acquire different meanings. The right equivalence to expect is not known, due to the complexity of the hate speech problem. Moreover, expecting same relations in different languages (e.g. “migrants” - “terrorist” = “migrantes” - “terroristas”) would be also wrong. The targets of hate in different languages are different depending on the socio-cultural scenario. We prefer to extract information from vector spaces and datasets, and qualitatively evaluate the observed relations.

In most of the cases we were able to observed non-trivial translations when exploring our hateful embeddings, though in some others we could observe that the equivalences are the same as in MUSE (e.g. “negros” in Spanish, as “blacks” and “neri” in English and Italian, respectively).

More experimentation is definitely needed to derive a more robust conclusion, but we think that the qualitative results presented here are a positive evidence on how our domain-specific embeddings are capturing non-trivial meanings and translations.

4.3.2 Cross-lingual relations in labeled datasets. In this section we qualitatively explore the ability of our embeddings to capture equivalences between hateful concepts in different languages over a labeled dataset. In the previous section we use similarity measures (nearest neighbors) over the general embedding space and for all the vocabulary used to construct those embeddings (unlabeled data). In contrast, in this section we focus on texts from the positive class of the hate speech labeled datasets in different languages. That is, we focus on multilingual data that we know that contains hateful information. We use our domain-specific hate embeddings plus association rules to devise a similarity measure among terms in different languages as a way to obtaining new and more specific translations for complicated hate concepts. The motivation for this experiment is twofold. On the one hand this would serve as an intrinsic qualitative evaluation as we can asses how good are the translations obtained for simple hateful terms. On the other hand we expect that this experiment allows us to preliminary obtain a more rich set of equivalences regarding hate in different languages.

We next explain in more detail the method we devised to obtain the equivalences. For the first step, let $x$ be a word and $U$ a set of words all from one of the labeled datasets. From each dataset, we extract association rules of the form $\{x\} \Rightarrow U$ with the following semantics: if $x$ occurs in a text $T$ (tweet in our case), then $U \subseteq T$ with certain confidence [28]. In that way we can find words that usually occur together in the same text. We extracted rules for the top most frequent terms $x$ in each dataset and we measure the strength of the rules using the standard support and confidence metrics. All the rules extracted were refined by imposing lower bounds in confidence and support [29].

We note that in each dataset and for each frequent term $x$, one can obtain many different association rules. Using all the rules with the form $\{x\} \Rightarrow U_j$ we computed the context of the word $x$ as $C(x) = \bigcup U_j$. Finally, our similarity measure for two words is based on the similarity of contexts for those words. We still need to introduce an additional notation before presenting our similarity measure. For every word $u \in C(x)$ we denote by $supp_u(x)$ and $conf_u(x)$ the support and confidence of term $u$ in the association rule of the form $\{x\} \Rightarrow U$ it appears. Given words $u$ and $v$, appearing in contexts, say $C(x)$ and $C(y)$, respectively, we define the following expression that essentially compares their support and confidence metrics in their respective contexts:

$$1 - \frac{|supp_u(x) - supp_v(y)|}{2} + \frac{|conf_u(x) - conf_v(y)|}{2}$$

We denote this expression simply by $met-sim(u,v)$. Finally, we can combine the above similarity for context words with an usual embedding similarity based on cosine similarity by averaging both:

$$sim(u,v) = (cos-sim(u,v) + met-sim(u,v))/2$$

That is, we give the same importance to how the vectors are similar across the multilingual vector spaces (cosine similarity), but also how they have similarly importance in the association rules they appear in.

We have all the necessary ingredients to define the context similarity of words. Let $x$ and $y$ be words (possibly from datasets in different languages) with contexts $A = C(x)$ and $B = C(y)$. Then their context similarity, denoted by $cont-sim(x,y)$ is defined as

$$\frac{1}{2} \left( \max_{u \in A} \left( \max_{v \in B} \left( \text{mean}_{v \in B} \left( \max_{u \in A} \left( \text{mean}_{v \in B} \left( \text{max}_{u \in A} \left( \text{sim}(u,v) \right) \right) \right) \right) \right) \right)$$
Table 5: Terms extracted from the datasets and their Nearest Neighbors in vector spaces of different languages.

| Italian Source Term | NN in HateEmb space | NN in Muse space |
|---------------------|---------------------|-----------------|
| migranti           | illegals palestinos | migrants mигранты |
| gitanos             | portuguese negro    | gypsy gитано    |
| English Source Term | Spanish             | Italian         |
| muslums             | musulmanes musulmani | musulmani     |

Table 6: For some seed terms we found the top most similar terms in the different datasets. The similarities were calculated separately for Hateful and Non-Hateful classes so we can observe different relations depending on the nature of the expressions. The numbers represent the similarity achieved on each case. As vector representations were use HateEmb.

| English Seed Term | Spanish | Italian | Spanish | Italian |
|-------------------|---------|---------|---------|---------|
| girls             | perra   | immigrati | cosas   | dire    |
|                   | 0.73    | 0.73    | 0.69    | 0.68    |
| muslums           | putos   | fascismas | subnormal | arriva |
|                   | 0.72    | 0.71    | 0.68    | 0.68    |
| Spanish Seed Term | English | Italian | Spanish | Italian |
|                   | invaders | vivere | fingers | caccia |
|                   | 0.66    | 0.74    | 0.61    | 0.74    |
| palestinos        | disaster | cancro | iraqi   | 'l'accordo' |
|                   | 0.64    | 0.79    | 0.64    | 0.73    |
| Italian Seed Term | English | Spanish | English | Spanish |
|                   | living  | sudacas | actually | cosas   |
|                   | 0.74    | 0.82    | 0.72    | 0.82    |
| terroristi        | refugees | podemos | something | subnormal |
|                   | 0.72    | 0.82    | 0.71    | 0.81    |
|                   | welcome | fascistas | actually  | ridiculo |
|                   | 0.69    | 0.80    | 0.72    | 0.82    |

That is, for every word in x’s context (A) we compute its maximum similarity with words in y’s context (B) and take the mean over all those similarities, and the other way around (mean over B of the maximum similarities with words in A), and the results of both directions are averaged.

We use our embeddings and the above defined context-based similarity to perform the following experiment over the labeled datasets. For each dataset of every language, we first selected some frequent words appearing in the hateful-labeled texts. We call them seed terms. Then for each seed term we selected the words that are more (context-) similar over all the words appearing in hateful labeled texts in a different language. Table 6 shows examples of seed terms and the top three most similar words (with their respective similarity score). As a comparison the table also shows the experiment for the same seed terms but considering the most similar word over the non-hate texts.

Despite of the fact that the labeled datasets are relatively small and from specific types of hate, we still find interesting cross-lingual relations. As expected these relations are different depending on the nature of text, that is hateful or non-hateful. For example, for the Spanish word “terroristi”, we found the words “muslums” and “fascistas” as the most similar words in the hateful texts in English and Spanish, respectively.

That means that, according to our similarity function, the word “muslums” appears in similar contexts in English as “terroristi” in Italian. (e.g. muslims race, idiot, cult murder terrorism.)

These relations can be interpreted as a cross-cultural similarity in the way this two concepts are, in a similar way, part of the hate speech phenomenon.

We emphasize that these relationships although only qualitative, cannot be so clearly found when one perform the same experiment using other general purpose multilingual embeddings (see Table 7 in the Appendix).

5 DISCUSSION AND CONCLUDING REMARKS

We have presented a detailed analysis of cross-lingual hate speech approaches, with the goal of transferring knowledge from one (or more) languages to another.

Our results indicate that there indeed are cross-cutting patterns in hate speech that span different languages. In particular, in our cross-lingual evaluation setup our domain specific HateEmb embeddings show the best overall results.
Table 7: Results for an experiment similar to the one presented in Table 6 but considering the general purpose MUSE multilingual embeddings instead of our hate-specific embeddings.

| English Seed Term | Hateful Data | No-Hateful Data |
|-------------------|--------------|-----------------|
|                   | Spanish      | Italian         | Spanish      | Italian         |
| girls             | gusta — 0.75 | islamico — 0.71 | mamion — 0.70 | vedere — 0.69  |
|                   | mujeres — 0.74 | estranieri — 0.71 | bene — 0.68  |                 |
|                   | españa — 0.76 | ecco — 0.76     | guerra — 0.73 | pero — 0.76    |
|                   | musulmanes — 0.72 | italia — 0.75   | ilegno — 0.71 | europe — 0.76  |

| Spanish Seed Term | English | Italian | English | Italian |
|-------------------|---------|---------|---------|---------|
| gitanos           | hopefully — 0.70 | credo — 0.68 | cock — 0.68 | cambiare — 0.66 |
|                   | complete — 0.70 | pensa — 0.68 | gotta — 0.67 | straniero — 0.66 |
| palestinos        | beaners — 0.61 | duce — 0.68  | return — 0.69 | largo — 0.69   |
|                   | disaster — 0.61 | bestie — 0.67 | syrian — 0.68 | corridio — 0.69 |

| Italian Seed Term | English | Spanish | English | Spanish |
|-------------------|---------|---------|---------|---------|
| migranti          | refugees — 0.73 | refugiados — 0.72 | migrants — 0.74 | mamion — 0.74 |
|                   | living — 0.72   | quere — 0.70  | take — 0.71  | catalan — 0.71 |
| terroristi        | religion — 0.75 | maltitos — 0.73 | migrants — 0.73 | vienio — 0.72  |
|                   | quaran — 0.75   | mienstras — 0.724 | ready — 0.72 | mamion — 0.72  |

Their competitiveness with other more sophisticated general-purpose representations is a sign that they are able to capture important specific domain information.

We also performed a qualitative exploratory analysis, which showed cross-lingual relations in our vector spaces and within datasets, supporting the observation that the context of words in a hateful scenario is very different from the context of the same words in a general scenario. This validates the importance of specific-domain representations for the hate-speech detection problem. As our results show, the construction of domain-specific hate-speech word embeddings can be a key tool to further explore in cross-lingual scenarios. We expect that transferring knowledge from one language to another in hate speech detection, will contribute to the development of better models for this task from a multilingual perspective. Thus, improving the diversity of application scenarios to other languages spoken worldwide without requiring massive amounts of labeled data.

For future work, we are interested in exploring other algorithms for constructing specific representations for this task, since it seems a promising way to improve classification results.

A APPENDIX

A.1 Similarities across datasets using MUSE embeddings.

Table 7 shows results for an experiment similar to the one presented in Table 6 but considering the general purpose MUSE multilingual embeddings instead of our hate-specific embeddings.

REFERENCES

[1] Sweta Agrawal and Amit Awekar. Deep learning for detecting cyberbullying across multiple social media platforms. In Advances in Information Retrieval - 40th European Conference on IR Research, ECIR 2018, Grenoble, France, March 26-29, 2018. Proceedings, pages 141–153, 2018. doi: 10.1007/978-3-319-76941-7_11.

[2] Hind Saleh Alatawi, Areej Maatog Alhothali, and Kawthar Mustafa Moria. Detecting wht supremacism hate speech using domain specific word embedding with deep learning and BERT. CoRR, abs/2010.00357, 2020. URL https://arxiv.org/abs/2010.00357.

[3] Sattam Almatarerh, Pablo Gamallo, and Francisco J. Ribadas-Pena. Citius-cole at semeval-2019 task 5: Combining linguistic features to identify hate speech against immigrants and women on multilingual tweets. In Proceedings of the 13th International Workshop on Semantic Evaluation, SemEval@NAACL-HLT 2019, Minneapolis, MN, USA, June 6-7, 2019. pages 387–390, 2019.

[4] Sai Sakerth Ahuru, Binoy Mathew, Punyajoy Saha, and Animesh Mukherjee. Deep learning models for multilingual hate speech detection. CoRR, abs/2004.06465, 2020.

[5] Waleed Ammar, George Mulcaire, Yulia Tsvetkov, Guillaume Lample, Chris Dyer, and Noah A. Smith. Massively multilingual word embeddings. CoRR, abs/1602.01925, 2016.

[6] Aymé Arango, Jorge Pérez, and Barbara Poblete. Hate speech detection is not as easy as you may think: A closer look at model validation. In Benjamin Pfrommer, Max Chevalier, Eric Gaussier, Yoelle Maarek, Jian-Yun Nie, and Falk Scholer, editors, Proceedings of the 2nd International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2019, Paris, France, July 21-25, 2019. pages 45–54, ACM, 2019. doi: 10.1145/3331184.3331262.

[7] Aymé Arango, Jorge Pérez, and Barbara Poblete. Hate speech detection is not as easy as you may think: A closer look at model validation (extended version). Information Systems, page 101584, 2020.

[8] Mikel Artetxe, Gorka Labaka, and Eneko Agirre. Unsupervised statistical machine translation. In Ellen Rislof, David Chiang, Julia Hockenmaier, and Jun Ichi Tsujii, editors, Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018, pages 3632–3638, Association for Computational Linguistics, 2018. doi: 10.18653/v1/d18-1399.

[9] Mikel Artetxe, Tobias Riecke, and Dani Yogatama. On the cross-lingual transferability of monolingual representations. In Dan Jurafsky, Joyce Chai, Natalie Schlüter, and Joel R. Tetreault, editors, Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020, pages 4623–4637, Association for Computational Linguistics, 2020.

[10] Pinkesh Badiana, Shashank Gupta, Manish Gupta, and Vasudeva Varma. Deep learning for hate speech detection in tweets. In Proceedings of the 26th International Conference on World Wide Web-Companion, pages 759–760. International World Wide Web Conferences Steering Committee, 2017.

[11] Dimitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. CoRR, abs/1409.0473, 2014.

[12] Valerio Basile, Cristina Bosco, Viviana Patti, Manuela Sanguinetti, Elisabetta Fersini, Debra Nozza, Francisco Rangel, and Paolo Rosso. Shared task on multilingual detection of hate. SemEval 2019, Task 5, https://competitions.codalab.org/competitions/19935.

[13] Elisa Bassignana, Valerio Basile, and Viviana Patti. Hurtleics: A multilingual lexicon of words to hurt. In Elena Cabrio, Alessandro Mazzei, and Fabio Tamburini, editors, Proceedings of the Fifth Italian Conference on Computational Linguistics (CLiC-IT 2018), Torino, Italy, December 10-12, 2018, volume 2253 of CEUR Workshop Proceedings, CEUR-WS.org, 2018.

[14] Diego Benito, Oscar Araque, and Carlos Angel Iglesias. GSI-UPM at semeval-2019 task 5: Combining linguistic features to identify hate speech against immigrants and women on multilingual tweets. In Proceedings of the 13th International Workshop on Semantic Evaluation, SemEval@NAACL-HLT 2019, Minneapolis, MN, USA, June 6-7, 2019. pages 396–403, 2019.
Cross-lingual hate speech detection
based on multilingual domain-specific word embeddings

3-7, 2018, Proceedings, pages 745–760, 2018.