LIDOMA at HOPE2023@IberLEF: Hope Speech Detection Using Lexical Features and Convolutional Neural Networks

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Abstract

Hope speech can help to reduce hostile environments and alleviate illnesses and depression, which makes it important to detect it automatically. In this paper, we present our submission for the HOPE: Multilingual Hope Speech Detection shared task at IberLEF 2023, which includes two sub-tasks: detecting hope speech in Spanish tweets and English YouTube comments. We proposed a word-based tokenization approach to train a Convolutional Neural Network (CNN). Our decision to use CNNs was inspired by previous works in hope speech detection that achieved good results using this method. Our approach achieved the fourth place in both sub-tasks. The source code to reproduce our results can be found at https://github.com/moeintash72

Keywords

Convolutional Neural Networks, Hope Speech Detection, Natural Language Processing, CEUR-WS

1. Introduction

Hope speech is useful in several situations: it can relax hostile environments and can ease illness and depression. Automatically detecting it is important for mental health, combating discrimination, and fostering peaceful environments. The HOPE: Multilingual Hope Speech Detection shared task [1] at IberLEF 2023 [2], consists of the following two subtasks: to detect hope speech in Spanish tweets and in English YouTube comments, respectively.

Hope speech detection is a challenging task due to the rich mixture of positive and negative feelings involved in it [3]. Hence, it is highly challenging to select features for training a model for detecting hope speech. Fortunately, Convolutional Neural Networks (CNN) [4, 5] provide a way to resolve this challenge by automatically detecting relevant features associated with

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every class (in this case, hope speech vs non-hope speech), reducing the problem to choosing a relevant embedding. Furthermore, CNNs have already proven to be useful in hope speech detection as demonstrated in [6, 7, 8].

From an embedded text, CNNs can identify local patterns or motifs in the following way: the convolutional layer can learn the essential features related to word embedding. Subsequently, further layers can relate these features to the golden labels while also adjusting parameters to prevent overfitting and other undesired events. For hope speech detection, we designed a 5-layered CNN. The first layer generates an embedding from a bag of words representation. The second layer is convolutional and extracts relevant lexical features related to hope. The third and fourth layers are designed to fine-tune the lexical feature extraction process by utilizing techniques such as max pooling [9] to prevent overfitting and reduce the dimension of the output. Lastly, the fifth layer relates the lexical features to the binary golden label to make a prediction.

The structure of this paper is as follows: in Section 2, we describe some state-of-the-art works on hope speech detection and comment on the complexity of defining hope. In Section 3, we detail our methodology. In Section 4, we provide a description of both datasets. Additionally, we outline our experimental workflow. In Section 5, we discuss the results of our experiments. Finally, in Section 6, we conclude the paper.

2. Related Work

There have been various approaches to studying hope, including psychological [10, 11], philosophical [12, 13], and medical [14, 15]. All these perspectives share the idea that hope relates to future expectations, which aligns with the definition of hope in the Oxford Learner's dictionary [16]: "*hope is a belief that something you want will happen*". However, in [17, 18], the authors presented a different perspective on hope, slightly twisted from the previous ones, by considering it as a type of *peace speech.* Although seeking peace is an important aspect of hope (for example, as in hoping for peace between Pakistan and India), the definition presented in [17, 18] certainly deviates from the other approaches mentioned above by considering *expectancy towards the future* as an implicit feature of hope.

Building upon that line, Chakravarthi [20] changes the definition of hope even more by orienting it towards equality, diversity, and inclusion (EDI). This led to the organization of two shared tasks: one at the First Workshop on Language Technology for Equality, Diversity, and Inclusion (LT-EDI-EACL) in 2021 [21] and the second at the next edition of the same workshop in 2022 [22]. In the first workshop, participants detected hope speech in English and Dravidian languages, such as Tamil and Malayaman, and the teams who used CNNs were EDIOne [7], IIITT [23], IIIT_DWD [24], Amrita [25], cs_english [26], KU_NLP [27], NLP-CUET [28], TEAM HUB [29], and MUCS [30].

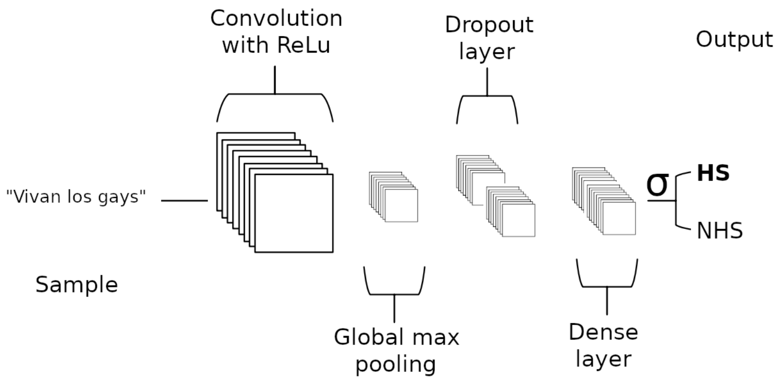

Figure 1: Example of our CNN model.

3. Methodology

Our main goal was to develop a method capable of learning features related with hope in short texts. To achieve this, we preprocessed all samples by removing special characters, tokenized them and generated the vocabulary. As described in the introduction, we used a 5-layered CNN to embed the samples from a Bag of words representation and retrieve relevant lexical features.

The initial step of our method was to preprocess the samples from both datasets. This involved removing emoticons, special characters and pictographs flags (iOS), transport and map symbols, as well as URL patterns. Additionally, we lowercase all text.

The next step was to use a label encoder to convert the golden label into a numerical representation, with $NHS = 1$ (non-hope speech) and $HS = 0$ (hope speech).

The final step was to train our 5-layered CNN using Keras (Figure 1). In the first layer, an upper bound on the accepted features needed to be specified, which was then embedded in the second layer with a fixed dimension. Next, in the convolutional layer, the size and number of kernels were specified, as well as the activation function. We chose ReLU, one of the most popular, fastest, and optimal activation functions [31], which maps a value x to the maximum value between 0 and x. For the output layer, the sigmoid function was chosen [32, 33], which maps a value x to the probability of belonging to a class. Finally, an L_2 penalty on the kernels was added to prevent overfitting.

4. Experimental Setup

4.1. Data

The task involves analyzing two datasets, one in Spanish and the other in English. The Spanish dataset contains approximately $2,550$ tweets, while the English dataset contains around $28,424$

YouTube comments.

Language	Split	Hope Speech	Not Hope Speech	Total
HopeEDI (English)	Train data	2229	23221	25450
	Test data	21	4784	4805
SpanishHopeEDI (Spanish)	Train data	791	821	1612
	Test data	150	300	450

Table 1
Statistics of the datasets

The Spanish dataset [34] is an extension of the SpanishHopeEDI dataset [35], which was collected during 2021 and 2022. It consists of tweets related to LGBT issues that have been annotated as either HS (hope speech) or NHS (non-hope speech). In Table 2 shows six examples from the dataset along with their English translations (trigger warning). Regarding the definition of hope employed in this dataset, [35] provides the following definition:

A tweet is considered as HS if it:

- Explicitly supports the social integration of minorities.
- Is a positive inspiration for the LGTBI community.
- Explicitly encourages LGTBI people who might find themselves in a situation.
- Unconditionally promotes tolerance.

On the contrary, a tweet is marked as NHS if it:

- Expresses negative sentiment towards the LGTBI community.
- Explicitly seeks violence.
- Uses gender-based insults.

The English dataset, referred to as HopeEDI [20], was collected from November 2019 to June 2020 and comprises comments posted on YouTube videos related to socially relevant topics such as equality, diversity, inclusion, COVID-19, women in STEM, Black Lives Matter, among others. Table 3 displays six examples from the dataset (trigger warning). Regarding the definition of hope employed in this dataset, [20] provides a definition of hope that is distinct from the one used for the Spanish dataset:

A YouTube comment/posts is considered as HS if it: *offers support, reassurance, suggestions, inspiration and insight.* We assume that a comment is NHS otherwise.

This definition is more general than the one presented for the Spanish dataset, and prevents us from using techniques from code-mixing tasks as in [36, 37, 38, 39].

4.2. Experimental workflow

We split both datasets into a 90:10 ratio, resulting in 20,385 samples in the training set and 2,266 samples in the validation set. Our 5-layered CNN (Figure 2) was trained using the following specifications:

Tweet	Golden Label	English Traduction
Cuando una pinche fea no soporta la belleza de mi sinaloca y la acusa de ser un "asqueros trans", lo triste es que siendo "maestra" se atreve a decir eso. No pertenezco a la comunidad LGBT+ pero mucha gente que adoro sí, y esta clase de comentarios me envergan! CHINGA TU MADRE!	HS	When a fucking (pinche) ugly woman can't stand the beauty of my *Sinaloca* and accuses her of being a "disgusting trans"... The sad thing is that, although she is a "teacher", she dares to say such a thing. I don't belong to the LGBT+ community but a lot of people I adore do, so these kinds of comments makes me feel very furious! (me envergan!) GO FUCK YOURSELF! (CHINGA TU MADRE!)
DEUDA DE LA DEMOCRACIA. La población trans-trava de la provincia de Santa Fe va por la Ley Integral Trans, una norma que busca dar respuesta integral a las vulneraciones que padecen desde siempre. Escribe .	HS	DEBT OF DEMOCRACY. The trans-trava (*trava* is a very pejorative slur from South America against transvestites and drags, with a similar story than the N word) population of the province of Santa Fe fights for the Comprehensive Trans Law, a regulation that seeks to provide a comprehensive response to the violations they have always suffered. Writes .
Hoy se subió un compañere trans a vender sus caramelos y dijo sentirse orgullose de los jóvenes que salieron a marchar sobre todo de Inti y Bryan. Además está harta de este congreso machista y homofóbico! Que no se vaya la rabia!	HS	Today a trans mate got on a bus (*se subió a vender* implies the existence of a bus or similar) to sell his candies and said they was proud of the young people who came out to march, especially Inti and Bryan. They (T.N. I correct this from the original tweet, where the author used female instead of non-binary) is also fed up with this *macho* and *homophobic* congress! Let the rage not go away!
la homofobia es algo tan mmm medio gay que te moleste que un tipo se coma una pinga	NHS	Homophoby is something so... very gay: the fact that you are upset about a guy sucking (coma) a cock (pinga).
Pero tu crees que si la chupo un poco mas crecera?: Mi último paciente del día y la co...	NHS	But, do you think that if I suck that cock (T.N. by the hashtags, we can conclude that this guy wants to *chupar* a cock) a little more it will grow? My last patient of the day and the as...
NOOOOO MARICA PERO-	NHS	The correct translation of this tweet is *NO WAY! BUT-* instead of *NO! SISSY/FAGGOT!, BUT-*. In Colombia, Venezuela and some parts of Ecuador and Panama, they use *Marica* in this kind of contexts, in a non-homophobic way.

Table 2
Six examples from the Spanish dataset

- The first layer inputs a maximum of 20,000 features and generates an embedding with 49 dimensions.
- The second layer is a Conv1D with 128 filters, a kernel size of 3, and a ReLU activation function. It is regularized with an L2 penalty on the kernel and bias weights.
- The third layer is a Global Max Pooling layer, which takes the maximum value over the time dimension and reduces the previous layer's output to a fixed-length vector.
- The fourth layer is a Dropout layer with a rate of 0.6, which helps to prevent overfitting.
- The fifth and final layer is a Dense layer with 2 units and a sigmoid activation function, who determines the final class: HS or NHS.

The model is compiled with the categorical cross-entropy loss function, the Nadam optimizer, and the categorical accuracy metric. We trained it through 40 epochs. Figure 3 depicts the

Tweet	Golden Label
LGBTQ+ means Lets Get Biden To Quit plus Kamala, which is an agenda I fully support!	HS
Once you accepted the degenerate gay lifestyle you opened the flood gates to other degeneracy. Stop complaining you allowed it to happen to your society.	HS
I love and respect you Hadar but I dont agree with this. Gender ideology is a disgusting thing that pollutes the minds of children who are indoctrinated in schools from a very early age as a future mother I cant support this thing.	HS
oh not ,dont tell me your lesbian because you start to like me.. lol	NHS
Thank you so much for sharing this video and letting us know about LBGTQ+, happy pride month.	NHS
I loved that video	NHS

Table 3
Six examples from the English dataset

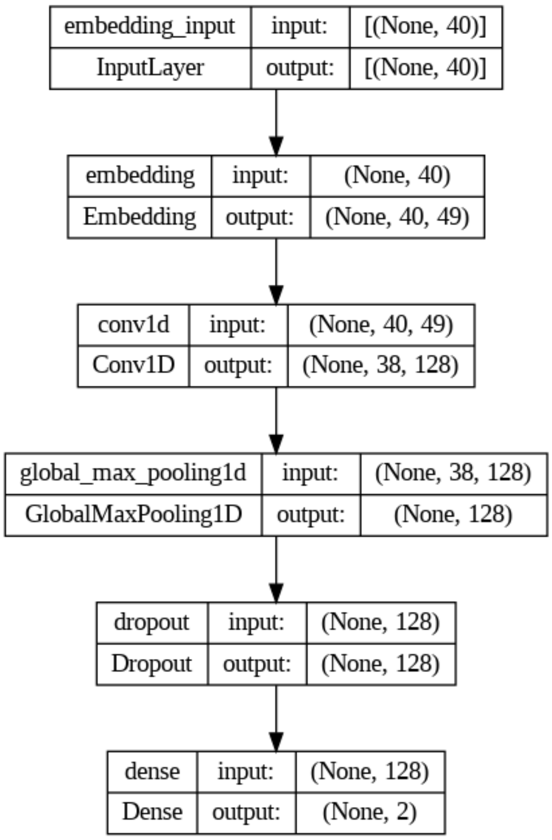

Figure 2: Our CNN model.

evolution of the performance through the epochs.

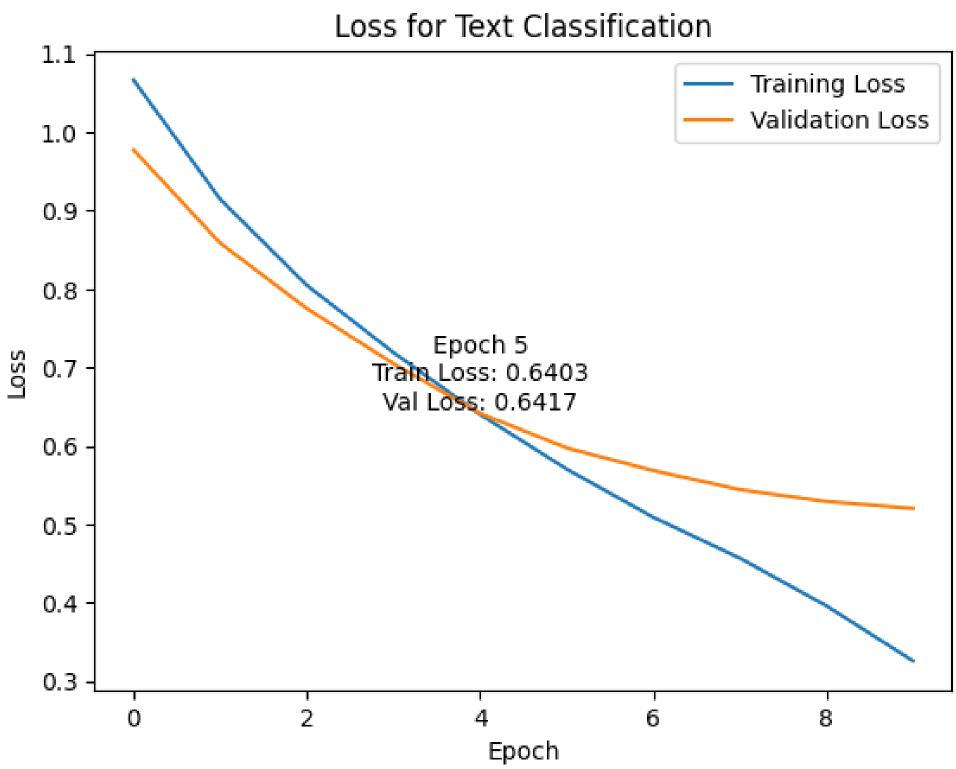

Figure 3: Evolution of our model through the 40 epochs.

5. Results and Discussion

In the Spanish dataset, our recall was 0.7467 for HS and 0.8533 for NHS. Our precision was 0.5864 for HS and 0.8533 for NHS. We believe that the low precision in HS was due to several hope speech samples that, although supportive of LGBT+ issues, also included violent language or offensive slurs such as “CHINGA TU MADRE” (a Mexican slur equivalent to “fuck yourself”) or “trava” (a South American slur against tranvestites and drags). These lexical features are often found in homophobic speech, which may have led to the low performance of our model. The full leaderboard can be consulted in Table 4

The English dataset, on the other hand, was extremely unbalanced, as can be seen in Table 4.1, with only 8.76% HS samples and 91.24% NHS samples. This has led each team to obtain a generally high precision in NHS samples but a very low precision in HS samples. Additionally, the golden labeling had little relation to the definition from [20]. For instance, the YouTube comment “I loved that video” was labeled as NHS, even though it offers support and inspiration. It could be possible that this comment is from an anti-LGBT+ video, but that information is not included in the dataset, making it impossible for the model to learn it. Another example is the sample “Thank you so much for sharing this video and letting us know about LBGTQ+, happy pride month." which was labeled as NHS, although it clearly offers support, reassurance, and inspiration to the LGBTQ+ community. In the HS labeling case, we found that some anti-LGBT+ comments were labeled as HS, such as "Once you accepted the degenerate gay lifestyle you opened the flood gates to other degeneracy. Stop complaining you allowed it to happen to your society". The full leaderboard can be consulted in Table 5.

Pos.	Team	Average Macro F1	Precision HS	Recall HS	F1 HS	Precision NHS	Recall NHS	F1 NHS
1	haanh764	0.9161	0.8671	0.9133	0.8896	0.9555	0.9300	0.9426
2	JL_DomOlmedo	0.7437	0.9091	0.4667	0.6167	0.7855	0.9767	0.8707
3	zahraahani	0.7430	0.6215	0.7333	0.6728	0.8535	0.7767	0.8133
4	**moeintash**	**0.7238**	**0.5864**	**0.7467**	**0.6569**	**0.8533**	**0.7367**	**0.7907**
5	ronghao	0.7103	0.5699	0.7333	0.6414	0.8444	0.7233	0.7792
6	honghanhh	0.7034	0.7765	0.4400	0.5617	0.7699	0.9367	0.8451
7	juanmanuel.calvo	0.6626	0.8361	0.3400	0.4834	0.7455	0.9667	0.8418
8	varsha2010399	0.5913	0.8293	0.2267	0.3560	0.7164	0.9767	0.8265
9	aswathyprem	0.4864	0.7368	0.0933	0.1657	0.6845	0.9833	0.8071
10	Mesay	0.4815	0.3333	0.1667	0.2222	0.6667	0.8333	0.7407
11	mgraffg	0.4198	0.2500	0.0333	0.0588	0.6628	0.9500	0.7808

Table 4
Evaluation results for the Spanish dataset. LIDOMA team is stated as *moeintash*.

Pos.	Team	Average Macro F1	Precision HS	Recall HS	F1 HS	Precision NHS	Recall NHS	F1 NHS
1	JL_DomOlmedo	0.5012	0.0163	0.1905	0.0301	0.9963	0.9496	0.9724
2	juanmanuel.calvo	0.4989	0.0000	0.0000	0.0000	0.9956	1.0000	0.9978
3	zahraahani	0.4975	0.0000	0.0000	0.0000	0.9956	0.9944	0.9950
4	**moeintash**	**0.4974**	**0.0000**	**0.0000**	**0.0000**	**0.9956**	**0.9941**	**0.9949**
5	varsha2010399	0.4937	0.0000	0.0000	0.0000	0.9955	0.9795	0.9875
6	honghanhh	0.4862	0.0128	0.2857	0.0246	0.9965	0.9036	0.9478
7	ronghao	0.4822	0.0116	0.2857	0.0223	0.9965	0.8934	0.9421
8	mgraffg	0.4651	0.0150	0.6190	0.0292	0.9980	0.8211	0.9009
9	haanh764	0.4429	0.0065	0.3333	0.0128	0.9962	0.7770	0.8730

Table 5
Evaluation results for the English dataset. LIDOMA team is stated as *moeintash*.

6. Conclusions

In this paper, we proposed a convolutional neural network model based on lexical features to tackle the Hope Speech detection task, for the HOPE 2023 shared task at IberLEF 2023. We based our work on the particular definition of Hope proposed for this task, which differs from other definitions in the field mentioned in Section 2, and obtained fourth place in both subtasks: Spanish tweets and English YouTube comments.

We identified and brought to light some opportunities to improve these datasets. For example, in the Spanish dataset we found that certain lexical features, such as slurs, were present in both types of samples, which could contradict their definition of hope speech as "not seeking violence". In the English dataset we faced a highly unbalanced dataset with incorrect labeling for both hope speech and non-hope speech samples.

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