Hope Speech in Social Media Texts using Transformer

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Abstract

Systems to regulate and remove hateful, abusive, and offensive content from the internet have been developed in the last several years. But occasionally, those in positions of authority abuse this type of censorship to thwart the democratic right to free speech. Consequently, studies must address online content that is uplifting, encouraging, and supporting from a positive reinforcement perspective. In this regard, HOPE_ IberLEF 2024 created a dataset to recognize positivity in social media comments to encourage those who need mindset treatments. It consisted of two tasks with main two aims. Task-1 is about hope speech for equality, diversity,and inclusion, and task-2 is about hope for an expectation for future desire. Then we have been involved in two tasks and propose the tasks with three algorithms, including Logistic regression, Word2Vec, and Transformer-base. Among these three algorithms, the model with Transformer-based outperformed all others. For task-1, our model achieved a 0.55 macro F1-score. For Polyhope binary data, the model achieved 0.75 and 0.82 macro F1- scores for Spanish and English respectively. Similarly, for polyhope multiclass data, our model achieved 0.48 macro F1-score and 0.55 F1-score in Spanish and English datasets respectively.

Keywords

Hope speech, social media, machine learning, NLP, transformer

1. Introduction

Social integration increases the importance of knowing and being known through social networking platforms. It is essential for everyone's overall well-being, especially those more susceptible to social isolation [1]. One of the most important aspects of social media messages is positive ideas, encouragements, thankfulness, appreciation, and acknowledgments provided to participants by their peers in times of illness, stress, and isolation [2]. These elements significantly impact people's mental, physical, and psychological well-being [3]. Despite these benefits, social media content also contains a significant number of spiteful or unpleasant posts like hate and offensive [4, 5], abusive comments [6] fake news [7], etc. In this regard, there has a significant number of studies have been taking place to tackle these and cyber-bullying in general. However, in a real scenario, some people heal the heartbreak of people and extend their sense of living. These people always speak or wish positivity for themselves and others as optimists. Any concepts associated with positive ideas, encouragements, aspirations, support, and wishes that might refresh the mind of the victim are known as hope speech.

As noted by Palakodety et al [1], hope speech is a kind of speech that can help people feel less worried in an unfriendly setting. In this paper, hope speech can be seen in two ways. a) in terms of Equality, diversity, and inclusion [1], b) in terms of expectation [8]. The aim of the former is to ensure hope in the aspect of equality, diversity, and inclusion whereas the later concerns hope as an expectation in a future [8, 9]. People who have high hopes do not respond to obstacles the same way as people who have low hopes; rather, they see obstacles as challenges to be overcome and use their pathway ideas to map out a different course to their objectives [8]. Moreover, it has been discovered that a lot of positive factors, like academic success and reduced despair, are correlated with high hope. Low hope, on the other hand, is linked to unfavorable consequences like diminished well-being [10, 11, 12]. The

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greater hope is consistently related to better academic, athletic, physical health [13], psychological adjustment, and psychotherapy outcomes. Hope speech identification is the process of identifying whether a comment is Hope Speech or Non-Hope Speech.

The advancements in natural language processing (NLP) techniques and machine learning algorithms have opened a golden opportunity to leverage this desirability [14, 15]. They enable us to build a language model in these two dimensions by using valuable social media opinions [16]. We use negative opinions to moderate social media content and positive opinions to boost equality, diversity, inclusion, and expectations. As part of the (HOPE@IberLEF 2024) shared task, this paper discusses whether those social opinions are hope speeches or not [17]. In this regard, gold-standard Spanish and English datasets are provided by the competition organizers [9].

2. Related works

It's important to refer to the universal feelings that result from the collection of beliefs about the caliber of our lives as well-being, thriving, happiness, and life satisfaction [18]. Generally, favorable life outcomes can multiply personal achievement and performance by extending from one stage of life to another [19]. To uplift and boost those merits, a significant number of research works are being developed [1, 2, 3, 8, 17]. Since 2021, for instance, Hope Speech Detection for Equality, Diversity, and Inclusion(EDI) is taking place for various languages including English, Tamil, Malayalam, Kannada, Spanish, and so on [1, 8, 15].

Roy et al. [20] presented a dataset of multilingual hope speeches in English, Tamil, Malayalam, and Kannada that encourage EDI. It was gathered to guarantee EDI in language technology and to spread optimism. Since it includes information from the LGBTQIA+ community, people with disabilities, and women working in science, engineering, technology, and management (STEM) have been participated [4]. To develop benchmark systems, they tested the Hope Speech dataset for Equality, Diversity, and Inclusion (HopeEDI) using various cutting-edge deep learning and machine learning models.

Puranik et al. [21] have attempted to find and promote good and supportive information on various sites. They employed different transformer-based models to categorize social media remarks as hope speech or not hope speech in English, Malayalam, and Tamil dialects. They have traversed through transfer learning of several state-of-the-art transformer models for languages such as English, Tamil, and Malayalam. From their experimentation, ULMFiT achieved an F1-score of 0.9356 on English data. On the other hand, mBERT achieved a 0.8545 F1-score on the Malayalam test dataset and distilmBERT achieved a 0.5926 weighted F1-score on Tamil test dataset.

A hope-speech identification work such as [22, 23] was introduced to automatically identify online content that could help to temper hate on social media. Pre-processing and transfer-learning models have been utilized during an experiment. According to the result, Convolution neural networks in the pre-trained multilingual-BERT model produced the greatest results, 0.54 macro-F1 over other benchmarks.

Junaida and Ajees [24] demonstrated deep learning methods for word representation using context-aware string embedding and text representation utilizing pooled document embedding and recurrent neural networks (RNN). It has assessed and contrasted the three models using various methodologies for every language. Based on the observation, the suggested method performed better than the baselines and operated as intended. The languages with the greatest weighted average F-scores are Malayalam, Tamil, and English, with values of 0.84, 0.93, and 0.58, respectively.

3. System Description

In this section, we offer thorough information regarding the dataset and details of the experiments carried out in our study. Moreover, it dives into the dataset statistics, preprocessing, algorithm selection, and the workflow of the proposed model.

3.1. Datasets

For any machine learning task, the dataset is crucial and mandatory. The real world has various data types like text, video, audio, time series, etc. Preparing datasets for a specific task is labor-intensive and time-consuming, especially in the NLP domain. Opportunely, for this study, we have been given a gold-standard dataset by (HOPE@IberLEF 2024) workshop [9, 25, 26]. It consisted of two datasets for two tasks. The first dataset is a dataset in the Spanish language aiming to identify hope speech in terms of quality, diversity, and inclusion [25]. This dataset was collected between 2020 and 2023. It is an improved and extended version of the previous Spanish_HopeEDI dataset [9]. The corpus consisted of training, development, and test datasets. The training and development datasets are from tweets and a test set from tweets related to the LGTBI collective and other topics. The data of the first task is annotated the datasets as Hope Speech(HS) [27] if the text of the tweet:

- explicitly supports the social integration of minorities.
- it's a positive inspiration.
- explicitly encourages people who might find themselves in a situation.
- unconditionally promotes tolerance.

On the contrary, it is marked as Not Hope Speech(NHS) [27] if the text of the tweet:

- expresses a negative sentiment towards a community.
- explicitly seeks violence or
- uses gender-based insults.

On the other hand, the second task's data aims to hope speech in terms of expectations [8, 27]. In this case, the most recent tweets were retrieved in the period from January 2022 to June 2022 [8]. The dataset consisted of both English and Spanish tweets in binary and multiclass labels. The following table 1 shows the data statistics of both tasks.

Table 1
Data statistics of both tasks.

Task	Lang	Train data	Deve	Test	Total
1	Spanish	1400	200	400	2,000
2	English	6192	1032	1032	8,256
	Spanish	6904	1150	1152	9,206

Training Data: The portion of the data that our model is trained on [3]. This is the real data both input and output that our model sees and gains knowledge from.

Validation Data: The portion of data used to fit the model on the training dataset, perform regular evaluations of the model, and make necessary adjustments to the hyperparameters (first set parameters before the model starts learning). When the model is training, this data is useful. Moreover, this dataset gives you insight into how your model would perform in a test dataset. If your model performs better in the development dataset, it's some sort of clue that your model would work on the test datasets too, even if it's not completely guaranteed [28].

Testing Data: Testing data offers an objective assessment once the model has been fully trained and developed [29]. In our case, the model forecasts or classifies some values when we supply the testing data inputs (that were unseen and not labeled). We assess our model by contrasting its output with the manually transcripted real output present on the organizer's side. The following table 2 shows sample instances of data. In table 2 second column, the abbreviations in the brackets 'G', 'R', and'UR' represent generalized, realistic, and unrealistic hope respectively.

Table 2
Instances of data on few samples.

Text	Label	Sample type	Lang	Task
Como el LeBron James original es un poco capullo con los lgbt el LeBron de aquÃ pues tambiÃ©n	NHS	Train	Spanish	1
Si eres neutral en situaciones de injusticia estÃ¡s eligiendo el lado del opresor ðŸŒˆ #LGTBI	HS			
basta iara, no quiero ser lesbianaðŸ’”	NHS	Dev		
#EsUnError La violencia contra las mujeres, los niÃ±os, las personas mayores y la comunidad LGBT.	HS			
Wtf por que dicen que kenma es trans???	—	Test		
The final project was approved. We will work on digital library system development and imlementation for SZU. (InShaAllah).âœŒ #URL#	Hope Speech(G)	Train	Eng	2
"Her, Who I Yearn For" is an absolutely perfect comic! It's living rent free in my head!	Not Hope Speech			
#USER# Sorry youâ€™re a good coach but you coaching united and Ronaldo so I hope you fail. Sincerely	Hope Speech(R)			
I wish Twitter would automatically turn off retweets when you follow someone, Iâ€™m tired of doing it manually	Hope Speech(UR)			
I don't know for sure. I hope I'm wrong. I would LOVE for you and I to revisit this tweet and me to be wrong.	Hope Speech(G)	Dev		
Can't believe I am saying this but Mr. Fluffman has gotta make folks yearn for the days of Laura Hill!	Not Hope			
I donâ€™t ask for much but I pray I meet someone that loves just as hard as I do.	Hope Speech(R)			
wish I could tell someone I'm gonna break all their fingers one by one without getting a chat-ban	Hope Speech(UR)			
I pray for the day they let you be an announcer for an entire game	—	Test		
no dormi pero es por q no tengo sueÃ±o fkkdiwjd	Not Hope	Train	Spanish	
OjalÃ¡ no la vaya a cascar, como eso es lo Ãºnico que sabe ðŸ«¢	Hope Speech(G)			
ojala encuentre alguien como yo alguna vez en mi vida â™¥	Hope Speech(R)			
Y ojalÃ¡ el querer siempre pudiera mÃ¡s q el no moverse.	Hope Speech(UR)			
obvio me baje y voy a esperar el 600 yo no te camino ni en pedo hasta casa	Not Hope	Dev		
Uy cualquier cosa puse JAJAJAJA ojalÃ¡ quÃ© hoy ningÃºn Gil,las apaguÃ©.	Hope Speech(G)			
ojalÃ¡ no hubiera existido esa noche de septiembre, ni de junio, ni de mayo, ni de abril, ni todo 2022	Hope Speech(UR)			
Anhelo que llegue el dÃa en el que ya no sufra por tu ausencia	Hope speech(R)			
te desearÃa lo mejor, pero ya me tuviste	—-	Test		

3.2. Preprocessing

Preprocessing is preparing raw data for machine learning algorithms by cleaning, converting text into numeric mode, and organizing it(annotating) [30]. It is the vital stage that fills in the gaps between raw data and useful insights because raw data is rarely in an ideal state [31, 32]. During the data preparation phase of machine learning tasks, there are typical or standard activities that we should use. The following are some among others.

Handling Missing Data: In real-world datasets, handling missing data is a difficult task because some users did not fill out the required fields [33]. The pre-processing methods like imputation, removal of missing data, and removing null values ensure that the model is fed accurate and comprehensive data [34]. It must be handled to prevent the model from performing worse [35]. In addition, we used "raw['category'].fillna(0, inplace=True)" to handle empty strings of class labels. Where 'raw' is the data-frame object variable and 'category' is the column name of class variable.

Data Cleaning: Finding and fixing inaccuracies or flaws in the data is known as data cleaning [36]. In this regard, we explored our datasets and corrected the inaccuracies encountered.

Data Encoding: Since machine learning algorithms usually operate on numerical data, it is necessary to properly encode categorical or text data variables into numerical [36]. based on the algorithm we have been implementing, two types of techniques are employed. For traditional machine learning algorithms, we have employed the 'TF-IDF' text vectorization approach. Because it understands the context using the instance positions. In addition, the 'class label' attributes are converted by using the function known as to_numeric(). In the case of deep learning algorithms, they have their vectorizer known as "keras Tokenizer". After the tokenization process, again 'keras Embedding' function is used to convert the text into numeric form.

Apart from these built-in preprocessing tasks, we have also used user-defined way of methods to remove unwanted characters like numbers, special symbols, extra white spaces, and so on from the texts. In the case of English language texts, there is a chance of throwing the stop word because their presence in the text did not bear any further relevance rather consuming the computational cost. This also helps to increase the relevance of the datasets and then the performance of the model too [37].

3.3. Model selection

To train the model, we picked and used the algorithms from three levels: machine learning, deep learning, and transformer-based. From machine learning, we picked up logistic regression. Logistic regression is most commonly used for classification problems. In logistic regression, the logistic function (sigmoid) plays a vital role in modeling the relationship between the input features and the probability of outputs. The model trains by using maximum likelihood estimation to optimize the parameters [15].

We have used Word2Vec with the LSTM algorithm from deep learning. In deep learning, Neural Networks (ANNs) are used and it's a relatively new class of machine learning techniques to address complicated problems. ANN is made up of two or more layers of processing units called neurons that are intended to resemble the human nervous system. Layers and activation factors enable these models to acquire hierarchical non-linear characteristics for class distinction. Neural network type, the number of layers, the number of neurons, and activation functions at each layer are all specified by this architecture [38].

The novel deep learning (DL) architecture that has gained popularity and enabled recent advances in the field of natural language processing is known as Transformer. It was first introduced in the paper, Vaswani et al. [39] to improve the caliber of DL and NLP research tasks. It has shown remarkable efficiency and has a lot of potential for general usage in artificial intelligence applications. It mainly uses the self-attention process to extract inherent properties. The table 3 shows three algorithms from common state-of-the-arts.

Table 3
The summary of selected algorithms.

No	Algorithm	Vectorization method
1	Logistic regression	TF-IDF
2	Word2Vec+LSTM	Word2vec embedding
3	Transformer-based	Transformer embedding

The parameters details for the table 3 are as follows. In the case of logistic regression, we accepted all default parameters except employing the TF-IDF vectorization approach.

For deep learning algorithms, we chose 'Word2Vec & LSTM' algorithms to make a comparison between traditional machine learning and transformer-based. Actually, Word2Vec came from gensim models and LSTM from the Keras framework. The Word2Vec algorithm is parameterized as (vector_size=100, window=5, min_count=1). These are some of the most common parameters among others. The 'window' here is the size of the token before and after the target token to grasp the sense of semantics from the context. In the case of LSTM, it used a sequential mode of learning with a sequence size of 128. The activation function is set to the sigmoid and loss is 'binary_crossentropy'. Particularly, we set the batch size to 32 and epochs to 10.

In the case of the transformer, Input_layer is Input of max_length, whereas embedding_layers are the embedding of input_dimension in Word2Vec embedding. The attention layers are the embedding layer of self-attention, and finally, it utilizes the 'sigmoid' activation function for the binary classification. However, in the case of multiclass classification, it utilized 'softmax' as an activation function because it takes the maximum values to determine the outputs. The model tries to optimize the error using the 'adam' optimizer and the loss function set to the 'binary_crossentropy' value. Likewise, the model has trained in 5 epochs for 32 sample batch-size.

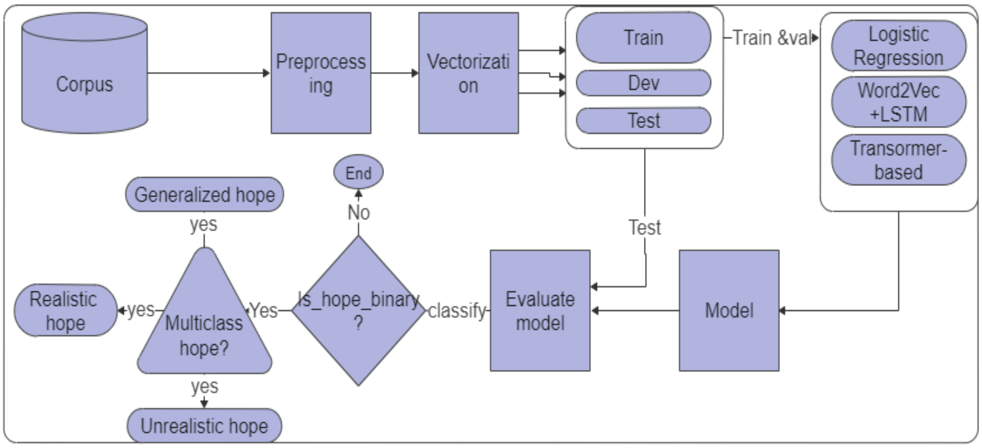

Figure 1: The workflow of proposed solution

4. Result and Discussion

The developed models were based on the Logistic regression(LR), Word2Vec with LSTM, and Transformer-base classifier and they have been evaluated in terms of precision, recall,macro-F1, and accuracy scores. However, the macro-F1 mainly determines the model's performance because it evaluates the model by harmonizing the class labels. According to the result published by the task organizer, the transformer-based classifier outperformed logistic regression and Word2Vec + LSTM.

The models classify social media posts in test datasets into hope speech or not hope speech in binary classification, and generalized hope, realistic hope, and unrealistic hope in case of multiclass classification as expected. We mentioned the results in terms of macro and weighted metrics of model evaluations: macro-precision (P), macro-recall (R), macro F1-score, and weighted average precision, recall, F1, and accuracy. The table 4 shows the detail.

Table 4
Task-1 result summary in Spanish language only.

Algorithm	M_Pr	M_R	M_F1	W_Pr	W_R	W_F1	Acc
Logistic Reg	0.56	0.50	0.45	0.50	0.50	0.52	0.52
Word2Vec+LSTM	0.58	0.54	0.50	0.50	0.54	0.54	0.56
Transformer	0.59	0.57	**0.55**	0.59	0.57	0.55	0.57

Where M_Pr,M_R,M_F1,W_Pr,W_R,W_F1, and Acc represent average macro-precision,recall,F1-score,average weighted-precision,recall,F1-score and accuracy respectively.

Similarly, the result of task 2 is mentioned in terms of evaluation metrics: Precision (P), Recall (R), F1-score, and the average macro F1-scores in the table 5 below.

Table 5
Task-2 result summary on both binary and multiclass classification

Lang	Classification	Algorithm	M_Pr	M_R	M_F1	W_Pr	W_R	W_F1	Acc
Spanish	Binary	LR	0.71	0.72	0.71	0.75	0.74	0.74	0.74
		Word2Vec	0.73	0.73	0.73	0.76	0.76	0.76	0.76
		Transformer	0.80	0.73	**0.75**	0.80	0.80	0.79	0.80
	Multiclass	LR	0.47	0.30	0.30	0.60	0.66	0.59	0.66
		Word2Vec	0.47	0.51	0.32	0.70	0.67	0.68	0.67
		Transformer	0.49	0.39	**0.48**	0.62	0.68	0.61	0.68
English	Binary class	LR	0.79	0.79	0.79	0.79	0.79	0.79	0.79
		Word2Vec	0.81	0.81	0.81	0.81	0.81	0.81	0.81
		Transformer	0.82	0.82	**0.82**	0.82	0.82	0.82	0.82
	Multiclass	LR	0.46	0.43	0.42	0.56	0.62	0.58	0.62
		Word2Vec	0.54	0.44	0.45	0.58	0.59	0.56	0.59
		Transformer	0.59	0.53	**0.55**	0.64	0.66	0.65	0.66

According to the result that was published by the organizers of shared tasks, our models have revealed a comparative performance. In task 1, our model achieved a 0.55 macro-F1 score on the transformer-based algorithm.

Similarly, in task 2 (binary classification), the better result was recorded as a 0.82 F1 score in the English dataset and a 0.75 F1 score in the Spanish dataset whereas in the case of multiclass classification, the better result was recorded as 0.48 F1 score in Spanish data and 0.55 F1-score in English dataset.

In both tasks, task-1 and task-2 the transformer-based algorithm outperformed other baseline algorithms and the model in the English dataset outperformed over Spanish datasets. This shows that the selected models well experienced English data than Spanish. More importantly, the pre-processing task has a positive impact on enhancing the model quality that utilizes English datasets than non-English datasets. All the details are mentioned in the table 4 & 5.

5. Conclusion and Future Work

Hope is a positive frame of mind that is both present- and future-focused. It is founded on the desire for favorable results in one's life or the world as a whole and may also be found in motivational speeches about those who have faced hardship. The paper addresses the development of systems to identify and promote positive, uplifting content on social media, in contrast to the usual focus on detecting and removing negative content. Specifically, it evaluates the HOPE_IberLEF 2024 dataset designed to recognize positivity in social media comments with two main tasks: one focusing on hope speech related to equality, diversity, and inclusion, and the other on future-oriented hope. It also compares three algorithms—Logistic Regression, Word2Vec, and Transformer-based models—finding that the Transformer-based approach outperforms the others. On the other side, we realized that the performance of the model highly depends on the size and quality of the data sets.

Finally, since the NLP task can identify hope speech on social media posts and uphold human mindsets, the jobs ought to be transferred to other languages. Furthermore, by offering additional algorithms for the languages utilized here and expanding the number of dataset sizes, the performance of the suggested model in this study should be enhanced.

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