HOPE2024@IberLEF: A Cross-Linguistic Exploration of Hope Speech Detection in Social Media

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Abstract

This paper presents a comprehensive investigation into the detection of hope speech across English and Spanish languages on social media platforms, aiming to understand and promote positive discourse. Hope, an extraordinary human capacity enabling flexible anticipation of future events and potential outcomes, is crucial for fostering equality, diversity, and inclusion in online communities. The study, part of the broader HOPE task at IberLEF 2024 [1], encompasses two complementary subtasks: "Hope for Equality, Diversity, and Inclusion" and "Hope as Expectations". Advanced Natural Language Processing (NLP) techniques, including BERT and transformers, were employed to develop robust methodologies for detecting hope speech in both binary and multiclass contexts. The research explores the impact of hope speech on mental well-being and resilience while discussing the challenges and ethical aspects of analyzing hope in social networks. The findings confirm the promising ability to accurately identify expressions of hope across different languages, underscoring NLP's potential to promote positive communication dynamics in the online environment.

Keywords

Natural Language Processing, Machine Learning, Deep Learning, Transformer models, Hope speech, Social media, Analyzing,

1. Introduction

Nowadays, social networks are an integral part of our lives. People often express their thoughts there. The growth of social networks such as Instagram and Twitter has been driven by their key characteristics: they are quickly adopted, cost-effective, easily accessible, and provide a certain degree of anonymity [2]. These platforms have become an integral part of people's lives, serving not only as spaces for social interaction but also as rich sources of data for various scientific studies, especially in the field of NLP [3].

Hate speech [4, 5, 6], sentiment analysis, fake news [7] detection, and hope speech identification are decisive tasks in NLP [8], aimed at discerning the nuanced aspects of human communication. They are addressed through various models, including traditional machine learning, deep learning [9], and transformer-based approaches. Traditional machine learning methods employ algorithms like Support Vector Machine (SVMs), Naive Bayes, and Logistic Regression, often relying on handcrafted features. Deep learning techniques, such as Recur-

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rent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks, excel at capturing intricate patterns in text data. Transformer-based models, such as Bidirectional Encoder Representations from Transformers (BERT), have revolutionized natural language processing tasks by utilizing attention mechanisms and contextual embeddings. These models have achieved outstanding results in many fields. The study [10] demonstrates their effectiveness in both detecting hopeful speech and identifying hate speech on social media. BERT and its variants, in particular, show high performance and adaptability across various tasks and languages.

Social networks, with their extensive user base and diverse content, provide researchers with unprecedented opportunities to study human behavior and communication models [11]. By analyzing the language used in posts, comments, and messages, researchers can gain insight into various aspects of human psychology, including emotions, relationships, and beliefs [12]. Moreover, social media data allows for real-time insights into social trends, cultural shifts, and public sentiments, making them valuable resources for sociological and psychological research [13].

One area of particular interest in social media analysis is the study of hope. Hope, defined as the expectation of positive outcomes in the future, plays a crucial role in shaping human thoughts, feelings, and actions [8]. On social networks, people often openly express their hopes, dreams, and aspirations, providing researchers with a wealth of data to study.

Hope is when we can anticipate what might happen in the future and what outcomes we expect. It affects our feelings and behavior, even if what we expect may be unlikely. Hope [1] is a positively colored emotion that arises from tense anticipation of the fulfillment of a desired outcome and anticipates the possibility of its achievement; a philosophical, religious, and cultural concept related to understanding the state of a person experiencing this emotional process.

Understanding how hope is expressed and perceived on social networks can provide valuable information about people's well-being and resilience. By studying the language and content of hopeful messages, researchers can identify patterns related to goal setting, mechanisms for overcoming difficulties, and reactions to adversity. Additionally, examining the dynamics of hope in online communities can shed light on factors that contribute to people's ability to cope with setbacks and life challenges.

Furthermore, analyzing hope in social networks can have practical implications for various fields, including psychology, sociology, and public health. For example, identifying linguistic markers of hopelessness or despair in online discourse can help in the early detection of mental health problems and facilitate targeted interventions [14]. Similarly, understanding the factors that instill hope and optimism in virtual communities can aid in developing strategies to enhance resilience and well-being in offline settings.

Despite the potential benefits of studying hope in social networks, there are also challenges and limitations to consider. For example, the enormous volume of data generated on these platforms poses challenges in terms of data processing and analysis. Moreover, the public nature of interaction on social networks raises ethical concerns regarding confidentiality, consent, and data usage. Researchers must carefully address these issues to ensure that their studies are

[1] https://en.wikipedia.org/wiki/Hope

conducted by ethical norms such as fear, joy, and depression, and how they communicate with each other, including hostile language.

Over the past few years, several researchers have studied psychological traits and other tasks in social media analysis, such as emotion analysis (fear, anger, happiness, depression), hate speech language, identifying offensive languages, and detecting misogyny using NLP techniques [15]. However, hope speech in social networks is yet to be studied as an NLP task. As far as we know, there are only two available corpora for detecting hope speech: the Hope Speech for Equality, Diversity, and Inclusion (HopeEDI) dataset [16] and the corpus presented by Palakodety, KhudaBukhsh, and Carbonell [17], both of which include multilingual examples in English.

2. Related work

The related work [18] in the field of hope speech detection on social media platforms has seen significant contributions, with various methodologies and approaches being employed to address this task. Studies have been conducted on the classification of textual data into hope and non-hope categories, utilizing machine learning algorithms such as SVM and K-Nearest Neighbour (KNN). Research has emphasized the challenges of cross-lingual classification due to linguistic differences between languages, highlighting the importance of selecting appropriate algorithms for different linguistic contexts. Furthermore, extensive experimentation has been undertaken to optimize performance through the meticulous selection of hyperparameters, resulting in enhanced classification accuracy. These studies contribute to the ongoing research on cross-lingual text classification and offer valuable insights for future endeavors in this area.

The paper [8] introduces a novel dataset for hope speech detection in English tweets, marking a significant contribution to the field, as hope has been relatively understudied in social media analysis tasks. The dataset classifies tweets into "Hope" and "Not Hope" categories, further categorizing hope tweets into three fine-grained classes: "Generalized Hope", "Realistic Hope", and "Unrealistic Hope". The annotation process employed a rigorous selection of annotators and detailed guidelines, resulting in high inter-annotator agreement scores. Baseline experiments using various learning approaches, including traditional machine learning and deep learning models, highlighted the challenge of multiclass hope speech detection. While simpler machine learning models performed well in binary classification, neural network models, particularly transformers, showed superior performance in multiclass classification. The paper underscores the potential of hope speech detection in various NLP applications and proposes future directions for research, including expanding the dataset size and exploring different languages and social media platforms.

In the paper [19], a Convolutional Neural Network (CNN) model is proposed for the detection of hope speech in short texts, addressing the HOPE 2023 shared task at IberLEF 2023. The study emphasizes the importance of automatically detecting hope speech to mitigate hostile environments and alleviate illnesses like depression. The approach utilizes lexical features and a preprocessing step to handle special characters and tokenization. By training a 5-layered CNN using Keras, the model aims to learn relevant lexical features related to hope in both Spanish tweets and English YouTube comments. However, the study identifies opportunities for improvement in the datasets, particularly regarding the presence of certain lexical features contradicting the definition of hope speech and issues with incorrect labeling in the English dataset, which contributed to dataset imbalance. The paper contributes to the field by presenting a method capable of learning features associated with hope in short texts, despite the challenges encountered with dataset quality and imbalance.

The article [20] investigates how hope manifests in various forms of speech on social media. The authors use natural language processing (NLP) tools such as LIWC, NRC-emotion-lexicon, and vaderSentiment to analyze the psycholinguistic, emotional, and sentimental features of posts. The study identifies unique cognitive, emotional, and communicative characteristics associated with different types of hope and proposes a method to classify these types using machine learning. Models such as LightGBM and CatBoost demonstrate high effectiveness, outperforming traditional methods and competing with deep neural networks.

The article [21] provides an overview of the IberLEF 2024 workshop, including the tasks, evaluation metrics, and results. The tasks address a wide range of NLP challenges, including named entity recognition, sentiment analysis, and machine translation. The evaluation metrics are carefully designed to measure the performance of the systems on the tasks. The results show that the IberLEF 2024 workshop is a valuable resource for the NLP community, and that the tasks and evaluation metrics can be used to benchmark the performance of NLP systems for Iberian languages.

This paper examines an approach using a pretrained BERT model for sequence classification tasks aimed at detecting hope in English and Spanish texts.

3. Methodology

The methodology for detecting hopeful speech in the HOPE datasets in English and Spanish using a pre-trained BERT model for sequence classification is as follows (Figure 1). The model is based on the BERT model, which includes multiple transformer layers, allowing it to effectively capture contextual information from input sequences. The model is configured for sequence classification by adding a classification layer on top of the base BERT model. During training, the model is fine-tuned for a specific classification task using a labeled dataset. In the script, the input data is preprocessed by tokenizing text sequences, encoding them into input IDs, and creating attention masks to distinguish real words from padding tokens. The training process involves optimizing model parameters using the AdamW optimizer and a linear learning rate scheduler. The trained model is then evaluated on a separate test dataset, and its performance is assessed using metrics such as accuracy and a classification report. Finally, the predicted labels are mapped back to their original categories and saved to a file for further analysis. The goal of the model is to explore relevant lexical features related to hope in both Spanish tweets and English YouTube comments. However, opportunities for improving the datasets were identified during the study, particularly regarding the presence of certain lexical features contradicting the definition of hopeful speech and issues with incorrect labeling in the English dataset, contributing to dataset imbalance. The work contributes to the field by presenting a method capable of exploring features associated with hope in short texts, despite challenges with data quality and imbalance.

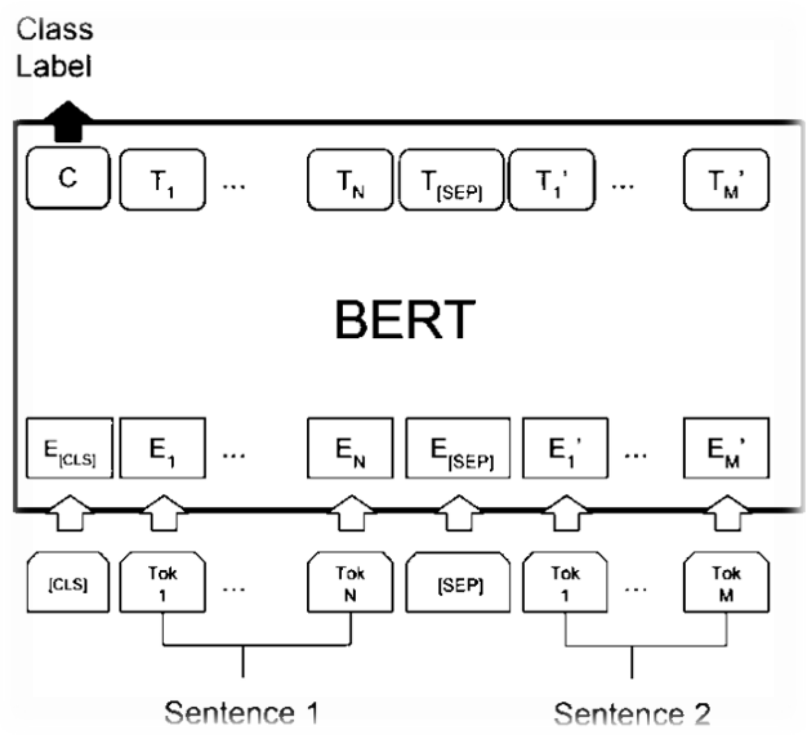

Figure 1: Example of pre-trained BERT model for sequence classification tasks.

3.1. Core methodology

The methodology encompasses two primary tasks: binary classification (hope vs. non-hope) and multiclass classification (Generalized Hope, Unrealistic Hope, Realistic Hope). The following steps outline the proposed approach:

Data Preparation: - The dataset comprising English and Spanish tweets is preprocessed to handle text normalization, including tasks such as removing special characters, punctuation, and tokenization. - The dataset is divided into training, validation, and test sets for both binary and multiclass classification tasks, ensuring language-wise stratification to maintain data integrity.

Model Selection and Fine-Tuning: - BERT and transformer-based models are chosen for their effectiveness in capturing contextual information in text. - Pre-trained BERT models, such as bert-base-multilingual-cased, are fine-tuned on the hope speech detection task using transfer learning. The models are initialized with weights pretrained on large-scale language modeling tasks to leverage their contextual understanding capabilities. - For binary classification, the final layer of the BERT model is adapted to a binary classification output, whereas for multiclass classification, modifications are made to accommodate the multiple classes.

Training and Evaluation: - The fine-tuned BERT models are trained on the training data for both binary and multiclass classification tasks, employing appropriate loss functions (e.g., binary cross-entropy for binary classification and categorical cross-entropy for multiclass classification) and optimization techniques (e.g., Adam optimizer). - Model performance is evaluated on the validation set using evaluation metrics such as accuracy, precision, recall, and F1-score. Hyperparameter tuning may be performed to optimize model performance. - The best-performing models are selected based on validation set performance and further evaluated on the test set to assess their generalization capabilities.

3.2. Extended Methodology

In addition to the core methodology outlined above, several extensions and enhancements can be incorporated to further improve the hope speech detection task:

Language-specific Fine-Tuning: - Given the linguistic nuances between English and Spanish, separate fine-tuning of BERT models can be performed for each language to better capture language-specific contextual information. This involves training language-specific BERT models on the respective datasets to enhance classification performance.

Ensemble Learning: - Ensemble learning techniques, such as model averaging or stacking, can be employed to combine predictions from multiple BERT and transformer-based models trained with different architectures or pretrained embeddings. This ensemble approach can mitigate the risk of overfitting and improve classification accuracy by leveraging diverse model representations.

Data Augmentation and Balancing: - Techniques such as data augmentation, including back translation and synonym replacement, can be utilized to augment the training data and address class imbalances, particularly in the multiclass classification task where certain classes may be underrepresented. Additionally, oversampling or undersampling strategies can be employed to balance class distributions and improve model robustness.

3.3. Task overview

The first task [22] centers on fostering Equality, Diversity, and Inclusion by identifying hope speech within Spanish tweets. It addresses the crucial role of hope speech in mitigating hostility and providing inspiration, particularly for vulnerable groups such as the LGTBI community, racial minorities, and individuals with disabilities. Social media interactions significantly shape individuals' perceptions and attitudes towards society, making the detection of hope speech essential for promoting inclusion and support. This task includes two subtasks: 1.a focuses on detecting hope speech within the LGTBI domain, while 1.b extends the analysis to identify hope speech in unknown domains.

The second task [23] delves into the concept of hope as expectations and aspirations, exploring its impact on individuals' mental states and behaviors within English and Spanish texts. It acknowledges the significance of social media platforms in shaping individuals' expressions and provides insights into well-being and goal-directed behaviors. This task involves binary and multiclass hope speech detection, aiming to distinguish between expressions of hope and non-hope across various domains. Subtask 2.a focuses on binary hope speech detection, while Subtask 2.b expands the classification to include multiple categories of hope speech.

3.4. Datasets

The dataset consists of two collections of data, one in Spanish and the other in English, which were collected from 2019 to 2022 [22].

The Spanish dataset is an expanded version of the Spanish HopeEDI dataset utilized in the ACL LT-EDI-2022 Spanish task [16], whereas the English dataset is a segment of the HopeEDI dataset. Both datasets include tweets and YouTube comments covering diverse social topics, with comments categorized as either Hope Speech (HS) or Non-Hope Speech (NHS). In the Spanish corpus, HS refers to tweets promoting social integration, supporting the LGTBI community, encouraging LGTBI individuals, or advocating for tolerance. Conversely, NHS encompasses tweets expressing negativity, advocating violence, or using gender-based insults. Chakravarthi et al. [24] reported that the dataset comprises around 2,550 Spanish tweets and 28,424 English YouTube comments [25, 26].

The table 1 provides an overview of the dataset used in the study, categorized into train and test sets for binary and multiclass hope speech detection tasks in both Spanish and English. The train sets include counts of samples labeled as "Hope" and "Not Hope" for binary classification and further divided into "Generalized Hope", "Realistic Hope", and "Unrealistic Hope" for multiclass classification. Similarly, the test sets display the distribution of samples across the same categories for evaluation. For instance, the binary test set contains a total of 2,553 "Hope" samples and 5,500 "Not Hope" samples in Spanish, and 3,634 "Hope" samples and 3,590 "Not Hope" samples in English. Likewise, the multiclass test sets show the counts for each subclass within the "Hope" category for both languages.

Train sets			
Data sets	**Category of data**	**Spanish**	**English**
Binary-Test	Hope	379	541
	Not Hope	773	491
Multiclass-Test	Generalized Hope	206	309
	Realistic Hope	77	124
	Unrealistic Hope	96	108
Test sets			
Binary-Test	Hope	2,553	3,634
	Not Hope	5,500	3,590
Multiclass-Test	Generalized Hope	1,337	2,026
	Realistic Hope	579	585
	Unrealistic Hope	637	750

Table 1
Data set in English and Spanish languages

4. Results

Table 2 illustrates the performance assessment outcomes of the proposed model across diverse tasks and languages, demonstrating its application on datasets in both English and Spanish.

Tasks	M_Pr	M_Re	M_F1	W_Pr	W_Re	W_F1	Acc
PolyHope Binary (English)	0.848	0.844	0.845	0.848	0.846	0.846	0.846
PolyHope Multiclass (English)	0.642	0.668	0.652	0.732	0.718	0.723	0.718
PolyHope Binary (Spanish)	0.802	0.814	0.807	0.831	0.826	0.828	0.826
PolyHope Multiclass (Spanish)	0.642	0.645	0.640	0.793	0.788	0.789	0.788

Table 2
Application results proposed model

Metrics such as Macro Precision (M_Pr), where precision for each class is calculated independently and then averaged to obtain macro-precision, Macro Recall (M_Re), where recall for each class is calculated independently and then averaged to obtain macro-recall, and Macro F1-score (M_F1), where F1-score for each class is calculated independently and then averaged to obtain macro-F1-score, were used to evaluate the results. Additionally, Weighted Precision (W_Pr), Weighted Recall (W_Re), and Weighted F1-score (W_F1) were employed. In this context, precision, recall, and F1-score are calculated independently for each class and then weighted by the number of examples of each class to obtain the respective weighted metrics. These metrics were used for both binary and multiclass classification tasks, allowing assessment of the model's accuracy, recall, and balance across different classes.

In the English binary hope speech detection task, the model achieved precision, recall, and F1-score of 0.848, 0.844, and 0.845 respectively. The weighted precision also stands at 0.848, with recall and F1-score at 0.846, indicating a well-balanced performance across classes. The model achieved high precision, recall, F1-score, and accuracy values, indicating its strong ability to accurately classify and make correct overall predictions.

Similarly, in the English multiclass hope speech detection task, the model attained precision, recall, and F1-score of 0.642, 0.668, and 0.652. The weighted precision, recall, and F1-score were 0.732, 0.718, and 0.723 respectively. In this case, precision, recall, and F1-score for the M class (macro-averaged values) are lower compared to binary classification, suggesting a more challenging task in this scenario.

Transitioning to the Spanish dataset, the binary hope speech detection model exhibited precision, recall, and F1-score of 0.802, 0.814, and 0.807. The weighted precision, recall, and F1-score were also 0.831, 0.826, and 0.828 respectively. The model also demonstrates high precision, recall, F1-score, and accuracy values, highlighting its effective adaptation to tasks across different languages.

For the multiclass hope speech detection in Spanish, the precision, recall, and F1-score were 0.642, 0.645, and 0.640. The weighted precision, recall, and F1-score stood at 0.793, 0.788, and 0.789 respectively. Similarly, as observed in the English multiclass task, the macro-averaged metrics (M) are lower compared to binary classification, which may indicate the complexity of recognizing multiple classes.

Analysis of these results leads to the conclusion that the model performs well in binary classification tasks in both languages. However, multiclass classification requires additional effort, especially for tasks in the Spanish language.

4.1. Analysis of the use of similar methods

Table 3 presents a comparison of the results of applying competitive models (PolyHope Binary and PolyHope Multiclass) on English and Spanish datasets.

The results of Method 1 and Method 2 showed identical results across all metrics for both binary and multiclass classification tasks, demonstrating high accuracy (Acc) of 0.846 and 0.736, respectively. The proposed method exhibited a slight improvement in binary classification, increasing M_Pr and W_Pr accuracy to 0.848. However, in multiclass classification, its results were lower than those of Methods 1 and 2, with an accuracy of 0.718. Method 3 showed the worst results across all metrics in both classification tasks, particularly standing out with a low accuracy of 0.736 in binary classification and 0.586 in multiclass classification.

The results of the model chosen by the author stand out with high performance in both binary and multiclass classifications. In binary classification, the model's scores for English were slightly better than those of Participants 1 and 2, and the scores for Spanish were comparable. In multiclass classification, the chosen model's results were significantly better, especially in Spanish, where metrics such as weighted precision and recall reached 0.793 and 0.788, respectively.

Overall, the analysis highlights the stable high performance of Participants 1 and 2 in binary classification, the lower performance of Participant 3, and the excellent results in both tasks when using the model chosen by the author.

A detailed study of the performance of the pretrained BERT model for sequence classification in various tasks and languages underscores the importance of reliable model training and evaluation. The stable high performance in both binary and multiclass classifications, especially on the Spanish dataset, illustrates the model's effectiveness in handling diverse linguistic contexts. These results not only demonstrate the model's capability but also provide insights into areas for further improvement, particularly in multiclass scenarios where precision and recall can be enhanced.

Methods	PolyHope Binary							PolyHope Multiclass						
	M_Pr	M_Re	M_F1	W_Pr	W_Re	W_F1	Acc	M_Pr	M_Re	M_F1	W_Pr	W_Re	W_F1	Acc
Method 1	**0.846**	**0.845**	**0.846**	**0.846**	**0.846**	**0.846**	**0.846**	**0.665**	**0.678**	**0.671**	**0.743**	**0.736**	**0.739**	**0.736**
Method 2	0.846	0.845	0.846	0.846	0.846	0.846	0.846	0.665	0.678	0.671	0.743	0.736	0.739	0.736
Proposed method	0.848	0.844	0.845	0.848	0.846	0.846	0.846	0.642	0.668	0.652	0.732	0.718	0.723	0.718
Method 3	0.736	0.737	0.736	0.737	0.736	0.737	0.736	0.543	0.442	0.453	0.575	0.586	0.560	0.586

Table 3
Comparison of the results of applying competitive methods (on English dataset)

5. Conclusion

In conclusion, this study contributes to the growing body of research on hope speech detection in social media contexts, particularly in English and Spanish languages. By leveraging advanced NLP techniques, including BERT and transformer models, we have developed robust methodologies for binary and multiclass classification tasks, achieving promising results in accurately identifying expressions of hope. Our findings underscore the importance of understanding and

Methods	PolyHope Binary							PolyHope Multiclass						
	M_Pr	M_Re	M_F1	W_Pr	W_Re	W_F1	Acc	M_Pr	M_Re	M_F1	W_Pr	W_Re	W_F1	Acc
Proposed method	**0.802**	**0.814**	**0.807**	**0.831**	**0.826**	**0.828**	**0.826**	**0.642**	**0.645**	**0.640**	**0.793**	**0.788**	**0.789**	**0.788**
Method 1	0.820	0.774	0.790	0.825	0.826	0.820	0.826	0.507	0.437	0.441	0.670	0.689	0.669	0.689
Method 2	0.820	0.774	0.790	0.825	0.826	0.820	0.826	0.507	0.437	0.441	0.670	0.689	0.669	0.689
Method 3	0.707	0.715	0.710	0.745	0.738	0.741	0.738	0.467	0.301	0.297	0.599	0.657	0.594	0.657

Table 4
Comparison of the results of applying competitive methods (on Spanish dataset)

promoting positive communication dynamics on social media platforms, especially in fostering equality, diversity, and inclusion, and enhancing individuals' well-being and resilience.

Despite the challenges associated with data processing, linguistic nuances, and ethical considerations, our research highlights the potential of NLP approaches in uncovering valuable insights into human behavior and communication patterns. Moving forward, further research is warranted to explore additional languages, domains, and social media platforms, as well as to address ongoing challenges in dataset quality, model generalization, and ethical data usage. By continuing to advance our understanding of hope speech and its impact on society, we can better support individuals and communities in navigating the complexities of modern communication landscapes.

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