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Beyond the Single Post

Unraveling Sentiment in Social Conversations

Simran Udhani[1], Khechraay Arkaay[2], Manish Bhardwaj[3*]
Department of Computer Science & Engineering
Swami Keshvanand Institute of Technology, Management and Gramothan Jaipur, India
[1]simranudhani08@gmail.com, [2]khechraayarkaay2517@gmail.com, [3]Assistant Professor, manish.bhardwaj@skit.ac.in
[*]Corresponding Author

Abstract—This paper provides a comprehensive review of the advancing field of sentiment analysis, with a specific focus on social post-reply pairs. Understanding sentiment within the context of dialogues is crucial, as replies often reflect or are influenced by the sentiment expressed in preceding posts. The review explores how researchers have progressed from analyzing isolated posts to examining the interactive nature of social media conversations. Key areas covered include techniques for contextual sentiment analysis, leveraging user relationships (e.g., pseudo-friendships), modeling sentiment evolution, and diverse real-world applications like spam detection. Key challenges, such as the limited availability of specialized datasets and the intricacies of interpreting nuanced sentiments in online communications, are critically analyzed. By addressing these complexities, this paper underscores the significance of capturing the dynamics of social media interactions and provides an extensive overview of state-of-the-art methodologies for sentiment analysis in post-reply contexts.

Index Terms—Sentiment Analysis, Social Media, Post-Reply Interaction, Natural Language Processing (NLP), Machine learning (ML)

Introduction

The exponential growth of social media has dramatically altered how people communicate and share information, creating dynamic online spaces where discussions, debates, and personal expressions flourish. Understanding the sentiment dynamics within these interactions is crucial for a variety of applications, ranging from gauging public opinion to informing marketing strategies. Sentiment analysis, the automated process of determining the underlying sentiment or emotion within text, is instrumental in uncovering these insights. Traditionally, sentiment analysis has often focused on individual units of text, treating each post or comment as an isolated expression. However, this approach neglects a fundamental aspect of online communication: context. Social media interactions are intrinsically dialogical, meaning the sentiment expressed in a reply is often intertwined with the sentiment and content of the preceding post [1].

Consider the comment, ”That’s awful.” Out of context, this statement appears undeniably negative. However, imagine this comment as a reply to a post about a person’s favorite sports team suffering a crushing defeat. In this context, ”That’s awful” takes on a different meaning, expressing shared disappointment rather than negativity directed towards the original poster. This simple instance emphasizes the critical need to analyze sentiment within the broader context of the conversation.

Post-reply pairs offer a valuable lens through which to understand the nuances of sentiment in online dialogue. By examining the relationship between a post and its replies, we can unearth patterns that reveal the true sentiment being imparted. This approach is akin to teaching AI to decipher the often unspoken rules of online communication, recognizing the subtle cues and contextual dependencies that shape meaning. The importance of this research extends beyond simply improving sentiment classification accuracy. It has profound implications for how we understand online communities as a whole. Every comment or interaction contributes to a larger ”web” of interconnected meanings. Comments influence each other, shaping shared understanding and the overall sentiment of the community [2].

The key areas underpinning this research include foundational concepts such as sentiment analysis, emotion analysis, natural language processing (NLP), and machine learning (ML), as well as contextual analysis, user relationships, and sentiment evolution. This review paper will explore the methodologies, datasets, and applications driving advancements in sentiment analysis of social post-reply pairs. It will also address the challenges that will further enhance our ability to unravel the intricate tapestry of sentiment and dialogue in online social interactions.

Background

This section introduces the foundational concepts and techniques that underpin sentiment analysis of social post-reply pairs.

A. Sentiment Analysis and Emotion Analysis

A computational process of identifying and categorizing opinions expressed in a piece of text, to determine whether the writer’s attitude towards the topic is positive, negative, or neutral [3]. Extending beyond basic sentiment classification, emotion analysis delves into the spectrum of human emotions conveyed through text. Emotion analysis focuses on recognizing and categorizing specific emotions, such as joy, anger, sadness, or fear, providing deeper insights into the emotional context of communication.

B. Natural Language Processing (NLP)

Natural Language Processing (NLP), as described in the LinkedIn Learning course [4], comprises the following components :

- Natural refers to human language used in everyday communication, rather than computer programming languages.
- Language, a system of communication which includes speech, text, and grammar rules.
- Processing is the act of manipulating and analyzing data using computer algorithms and techniques.

Natural language processing (NLP) is a branch of artificial intelligence (AI) that enables computers to understand and process human language. NLP is a multidisciplinary field that combines knowledge from the following areas [4]:

- Linguistics, the scientific study of language, including its structure, meaning, and history. NLP leverages linguistic knowledge to understand the rules and patterns of human language.
- Computer Sciences, which provides the algorithms, programming languages, and techniques for processing language data on computers.
- Mathematics and Statistics offers tools for analyzing and model language data statistically to identify patterns and make predictions.
- Psychology and Cognitive Sciences help understand how humans process and use language, which is valuable in developing systems that are useful.

C. Text Cleaning and Processing Techniques

Text data is heavy and the lighter we make it earlier, the better it gets for resource consumption in the later stages [5]. Thus, text cleaning and processing are essential preparatory steps in Natural Language Processing (NLP) to ensure the input data is structured and meaningful for computational models.

1) *Text Tokenization:* Tokenization is the process of breaking down stream of textual content into its parts, words, terms, symbols or other meaningful elements [5]. These tokens serve as the foundational building blocks for further analysis and processing.

2) *Cleansing Text:* Text data undergo a series of cleansing steps before it's ready for analytics and machine learning. Key steps include [5]:

- Formatting and standardization of text
- Remove Punctuation
- Remove abbreviations or convert them to their full form.
- Case conversion to standardize text.
- Remove elements like hashtags, mentions, and URLs.

3) *Stopword Removal:* Stopwords are a group of words that carry no meaning by themselves, such as ”in”, ”and”, ”the” and ”which” [5]. Removing them helps to focus on the more insightful words in the text.

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4) *Stemming:* A stem is the base part of a word to which affixes can be attached to form derivatives (e.g., 'combin' is the stem for 'combine,' 'combining,' and 'combined'). Stemming is the process of converting a word into its stem. It retains the base form of the word, thereby reducing the total number of unique words and grouping together words with similar meanings [5].

5) *Lemmatization:* Similar to stemming, lemmatization produces a proper root word that belongs to the language. For instance, 'combine' is the lemmatized version of 'combine,' 'combined,' and 'combining.' As opposed to stemming, which often produces incomplete words, lemmatization ensures that 'combine' is a proper English word [5]. *6) Advanced Text Processing:*

- N-grams: N-grams is a sequence of *n*-items in a sample of text (e.g., bigrams for two-word combinations), capturing context and relationships between words [5].
- Part-of-Speech (POS) Tagging: Assigns grammatical tags (e.g., noun, verb) to words, aiding in syntactic and semantic analysis. It is also utilized in tasks such as entity recognition, data filtering, and sentiment analysis [5].
- TF-IDF (Term Frequency-Inverse Document Frequency): A number of machine learning algorithms do not process textual data directly; they require numeric features. Therefore, text must be transformed into an equivalent numeric representation to enable the application of machine learning techniques.

TF-IDF is a technique used for converting text into a numeric table representation. The output of TF-IDF is a

table where rows represent documents in a corpus, and columns correspond to words within the corpus. Each cell contains a value indicating the relevant strength of the word to a particular document. Higher values denote a stronger correlation between the word and the document

[5].

Literature Review

A. Emotion Analysis for the Upcoming Response in OpenDomain Human-Computer Conversation

Li and Zhang [1] addressed the task of predicting the emotion of an upcoming response in open-domain humancomputer conversations. This research deviates from traditional sentiment analysis, which typically focuses on classifying the sentiment of existing texts. Instead, it aims to proactively anticipate the emotional tone of a yet-to-be-generated response, making it particularly relevant to the development of emotionally intelligent dialogue systems. The study emphasizes the challenges posed by the non-existence of the response at the time of prediction and the need to incorporate contextual information for accurate emotion classification.

This study utilizes a multi-faceted dataset approach:

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- Conversation Dataset: A massive dataset of nearly 10 million post-reply pairs collected from various Chinese forums, microblog websites, and community Question and Answer platforms forms the basis for the retrieval structure.
- NLPCC Datasets: Datasets from NLPCC2013 [6] and NLPCC2014 [7], focused on emotion classification tasks, were used to train a traditional Bidirectional LSTM model to label the replies in the training dataset.
- Training Dataset: This dataset comprises over 1.3 million post-reply pairs, mirroring the structure of the Conversation Dataset. The replies in this dataset were labeled with emotion categories using the pre-trained Bidirectional LSTM model.
- Test Dataset: A human-annotated test dataset of 1996 post-reply pairs serves as the ground truth for evaluating the model's performance. Each data point was annotated by three individuals, achieving a moderate inter-rater agreement with a Kappa score of 0.427. This dataset covers eight emotion categories: like, surprise, disgust, fear, sadness, happiness, anger, and none.

This dataset construction process underscores the complexities of obtaining large-scale, annotated data for emotion analysis in dialogue systems.

The authors propose a novel deep learning architecture that jointly represents the current utterance and its retrieved candidate responses for emotion prediction. The model employs:

- Bidirectional LSTMs (Bi-LSTMs): These networks encode the current utterance and each retrieved candidate response into contextualized embeddings, capturing sequential information in both directions. Bi-LSTMs have demonstrated strong performance in various NLP tasks.
- Representation Jointing: The sentence embeddings from the Bi-LSTMs, representing the current utterance and retrieval results, are concatenated. This joint representation captures the semantic relationship between the conversation context and potential responses.
- Retrieval Structure: A two-step retrieval process selects relevant candidate responses from a corpus of 10 million post-reply pairs. The first step uses a keyword-based retrieval system akin to Lucene and Solr, while the second step re-ranks these candidates using a model trained on features like textual similarity and word embedding measures.

The key innovation lies in integrating retrieval-based information. This enriches the limited context of the current utterance and aims to provide a more comprehensive representation of the potential emotional direction of the upcoming response.

Experimental results, as shown in Table 1, indicate that the model surpasses baseline approaches such as SVM, CNN, LSTM, and Bi-LSTM across evaluation metrics like precision(P), recall(R), and F-measure(F).

The inclusion of retrieval results significantly elevates these metrics, particularly precision, recall, and F-measure, demonstrating the model's effectiveness in leveraging the added context for improved emotion prediction. However, recall scores, although improved, remain lower than precision,

Method	Accuracy	Macro Average			Micro Average		
		P	R	F	P	R	F
SVM	0.4118	0.1669	0.0283	0.0484	0.2222	0.0335	0.0581
CNN	0.4284	0.1571	0.0021	0.0041	0.1667	0.0026	0.0052
LSTM	0.4238	0.2413	0.0165	0.0309	0.2639	0.0167	0.0314
Bi-LSTM	0.4279	0.3231	0.0183	0.0346	0.2658	0.0185	0.0346
Li and Zhang Method	0.4259	0.3892	0.0786	0.1308	0.4026	0.0819	0.1361

TABLE I: Performance comparison of emotion classification methods.

suggesting areas for further refinement to capture the full spectrum of emotional nuances in responses.

Despite its strengths, the study has limitations. The model relies on the current utterance and retrieved responses, neglecting broader conversation history and user-specific context. Additionally, emotion prediction operates independently from the response generation process, hindering its direct applicability in real-time dialogue systems. Finally, the model's evaluation is confined to a specific dataset, which may limit its generalizability to different conversational domains or languages.

In this study they proposed extending their work aligned with the overarching goals of sentiment analysis in social media conversations by incorporating broader conversational context, user profiles, and external knowledge. They also advocate for integrating emotion prediction with response generation in unified frameworks. These directions underscore the need for models capable of capturing the intricate interplay between sentiment, language, and context in dynamic social interactions.

B. Exploring and Inferring User-User Pseudo-Friendship for Sentiment Analysis with Heterogeneous Networks

Another crucial aspect of sentiment analysis in social media conversations involves understanding the complex interplay between user relationships and sentiment expression. Deng et al. [8] introduced an approach to analyze sentiment in social post-reply pairs by leveraging the concept of "user-user pseudo-friendship" inferred from heterogeneous networks.

The study employs two real-world forum datasets:

- PF1901 (Political Forum): This dataset consists of 1,901 labeled posts from 232 unique users discussing three US presidential candidates. Notably, the dataset includes explicit user-user friendship information, with an average of 3.37 friends per user. Human annotators labeled posts as positive, negative, neutral, or ”not sure,” enabling the calculation of sentiment polarity for each post.

- MF1560 (Military Forum): This dataset comprises 1,560 labeled posts from 320 unique users discussing five controversial topics. Unlike PF1901, this dataset lacks explicit friendship information, making it suitable for evaluating the effectiveness of pseudo-friendship inference. Human annotation follows the same procedure as in PF1901.

Deng et al. constructed a heterogeneous information network encompassing users, posts, topics, and sentiment labels. The core of their approach lies in inferring pseudo-friendship between users based on the similarity and dissimilarity of their opinions on different topics. This inference relies on a novel meta path-based similarity measure that captures both the sentimental context and the network structure. Key methodological steps include:

- Meta Path-Based Similarity: This measure quantifies the degree of similarity or dissimilarity between users based on the consistency or conflict of their opinions on shared topics, leveraging meta paths like ”user-post-topic-postuser”.
- User Regularization: A regularization term incorporates the inferred pseudo-friendship into a semi-supervised learning framework, encouraging consistent sentiment scores among pseudo-friends and dissimilar scores among pseudo-foes.
- Post-Post Relations: The model incorporates various postpost relations, including content similarity, ”reply-to” relationships, and user consistency (multiple posts from the same user on a topic).
- Sentiment Propagation: The model utilizes a graph-based approach to propagate sentiment scores from labeled to unlabeled posts, guided by both inferred user-user relationships and post-post relations.

The study compares the proposed graph-based method (UserReg) against several baseline models, including:

- SentiWordNet [9]: An unsupervised lexicon-based approach that assigns sentiment scores based on the average sentiment of words in a post.
- SVM [10]: A supervised machine learning model trained on labeled data.
- SSL+WV [11]: A semi-supervised approach that leverages word-level similarity between posts.
- SSL+Dissim [12]: An extension of SSL+WV incorporating post dissimilarity based on ”reply-to” relations.
- LP/LP+ [13]: Unsupervised/semi-supervised methods that utilize post-post relations without considering useruser relationships

In this study, they demonstrated the superior performance of their proposed UserReg model, which significantly outperforms all baseline approaches across various metrics. For instance, on the PF1901 dataset with 100 labeled samples (10.5% of the data), UserReg achieves an accuracy of 69.03%, compared to 61.24% for SVM and 66.07% for LP+. This improvement highlights the effectiveness of incorporating inferred user-user pseudo-friendship into sentiment analysis. These results strongly suggest that leveraging social network information, particularly inferred pseudo-friendship, can significantly enhance the accuracy of sentiment analysis in social media conversations.

Despite its notable contributions, there are certain limitations. One significant challenge is computational scalability, as constructing and analyzing large-scale heterogeneous networks can be computationally expensive, making it difficult to apply in real-time scenarios or to process massive datasets effectively. Additionally, the noise inherent in social media data, such as slang, sarcasm, and inconsistencies, can impact the accuracy of both sentiment analysis and the inference of pseudo-friendship. The model's dataset dependency is another limitation, as its performance may vary across different social media platforms or datasets due to platform-specific communication styles and network structures.

In conclusion, the study by Deng et al. presents a significant advancement in sentiment analysis by effectively integrating social network information and sentiment propagation. The proposed methodology holds considerable potential for developing more sophisticated and accurate sentiment analysis tools for social media conversations. Further research addressing the identified challenges and exploring new avenues, such as incorporating temporal dynamics and multilingual capabilities, will pave the way for a deeper understanding of sentiment in complex social interactions.

C. Modeling Post-level Sentiment Evolution in Online Forum Threads

While the integration of social network information enhances sentiment analysis, understanding the dynamic nature of sentiment within conversations is equally crucial. Cercel and Trausan-Matu [14] address this challenge by proposing a novel approach for modeling post-level sentiment evolution in online forum threads. This study is particularly relevant to analyzing social post-reply pairs as it delves into how sentiment propagates and transforms within threaded conversations, offering valuable insights into the intricate dynamics of sentiment flow in social interactions.

The study focuses on analyzing real-world forum threads sourced from the Internet Argument Corpus (IAC) [15]. IAC is a well-known repository of online discussions, indicating the study's reliance on a substantial corpus of real-world conversations. This paper underscores the use of a forum thread titled ”What is God?” comprising 43 posts for illustrating the proposed methodology.

The chosen dataset is particularly relevant to the task of modeling sentiment evolution as forum threads inherently possess a temporal structure with posts appearing sequentially over time. Additionally, the reply structure within these threads provides crucial context for understanding how sentiment influences subsequent posts and shapes the overall sentiment trajectory of the conversation.

In this study, they introduced a five-step method for modeling post-level sentiment evolution, combining opinion mining, graph theory, and sentiment analysis techniques. The core of their approach lies in representing forum threads as post-reply graphs and progressively refining these graphs to capture the essence of sentiment evolution. The five steps are as follows:

- Preprocessing: This step involves applying natural language processing techniques like tokenization and syntactic parsing to each post in the initial post-reply graph.
- Fact Removal: Posts containing only factual information without expressing opinions are identified and removed from the graph. This step ensures that the analysis focuses solely on sentiment-bearing posts.
- Sentiment Identification: The sentiment of each remaining post is determined by analyzing the sentiment strength of opinion words within the post, leveraging resources like SentiWordNet [9].
- Neutral Sentiment Removal: Posts identified as having neutral sentiment are removed, further refining the graph to represent only posts expressing positive or negative sentiment.
- Vertex Aggregation: This step involves two subprocesses:

1) Parent-child vertex aggregation merges vertices with the same sentiment if they have a direct parent-child relationship in the graph.
2) Sibling vertex aggregation merges vertices with the same sentiment that share a common parent in the graph. This aggregation process simplifies the graph, highlighting key sentiment shifts and dominant sentiment clusters within the thread.

The resulting aggregated multipost-reply graph provides a visually intuitive and simplified representation of the postlevel sentiment evolution within the thread. The methodology effectively leverages the temporal and reply structure of forum threads to model sentiment dynamics, demonstrating the potential of graph-based approaches for analyzing sentiment evolution in social conversations.

The study presents a visual demonstration of the proposed methodology applied to forum thread. The series of graphs generated through these processes effectively illustrates how the initial post-reply graph is progressively refined to reveal the core sentiment trends and relationships within the conversation. These visual analysis provides evidence of the methodology's ability to capture and represent sentiment evolution patterns in forum threads.

The study primarily focuses on visual analysis and lacks a comprehensive quantitative evaluation framework, making it challenging to objectively benchmark its performance against other sentiment analysis techniques. This limitation is likely due to the exploratory nature of the research, which emphasizes introducing a novel approach for visualizing and understanding sentiment dynamics. Future research could address this gap by employing standard metrics for quantitative evaluation and comparative analysis.

Moreover, the study is constrained to online forum threads, raising questions about its applicability to other social media platforms with differing conversational structures. The computational complexity of constructing and analyzing large-scale post-reply graphs further poses challenges for realtime applications or processing massive datasets. Developing scalable graph processing techniques or approximation algorithms could enhance the methodology's efficiency.

Despite these limitations, this study makes a notable contribution by introducing an innovative graph-based approach to modeling post-level sentiment evolution, offering valuable insights for advancing sentiment analysis research.

D. Extracting useful reply-posts for text forum threads summarisation using quality features and classification methods

Equally important to understanding sentiment dynamics is the ability to identify replies that contribute significantly to the overall sentiment and information flow within social conversations. Osman and Salim [16] tackled this challenge by exploring methods for extracting useful reply-posts for text forum threads summarization using quality features and classification methods. This study, though not directly focused on sentiment analysis, holds significant relevance to the topic of ”sentiment analysis of social post-reply pairs.” The ability to identify high-quality replies that encapsulate the essence of a conversation can enhance sentiment analysis by focusing on the most informative and sentiment-rich segments within a thread.

The study employs two datasets specifically curated for analyzing forum thread dynamics:

- TripAdvisor forum for New York City (NYC) [17]: This dataset consists of 100 text-based discussion threads encompassing a total of 816 reply-posts.
- Ubuntu Linux distribution forum [18]: This dataset also includes 100 threads comprising 773 reply-posts.

Both datasets are inherently structured for analyzing sentiment evolution due to the following characteristics:

- Temporal Structure and Metadata: Forum threads inherently possess a temporal order with posts appearing sequentially over time.
- Reply Structure: The nested reply structure within threads provides context for understanding how sentiment propagates and influences subsequent posts [19], [20].

In this study, they presented a two-part methodology for identifying high-quality reply-posts:

1) Quality Feature (QF) Extraction and Scoring: This stage involves defining and extracting 12 QFs that capture various aspects of reply quality, including:

- Similarity Features: Cosine similarity between reply and initial post, word overlap, centroid similarity with other replies, and reply-to-reply similarity.
- User Activity Features: Whether the reply is from the initial post author and the number of replies by the user in the thread.
- Timeliness Features: Position of the reply within the thread.
- Sentiment Features: Presence of positive and negative comment words.
- Amount of Data Features: Number of words in the reply.
- Question Types Features: Presence of 5W-1H question words and question marks.

2) Each reply-post is assigned a weight based on the scores of these 12 QFs.

3) Classification using Machine Learning (ML): Five ML algorithms are employed to classify replies into three categories: High-Quality (HQ), Low-Quality (LQ), and Non-Quality (NQ). The algorithms used are:

- Support Vector Machine (SVM)
- Naive Bayes (NB)
- Logistic Regression (LR)
- Random Forest (RF)
- Decision Tree (DT)

The classifiers utilize the 12 QF scores and human judgments to learn patterns that distinguish high-quality replies from others. The best performing classifier for each dataset is then used to rank replies and select the top-ranked ones for summarization.

The classification approach, by learning patterns from humanannotated data, indirectly accounts for thread interactions and how replies contribute to the overall information flow.

The study demonstrates promising results for identifying high-quality replies using the proposed methodology. The Decision Tree (DT) algorithm achieved the best performance for the NYC dataset with an F1-score of 0.806, while the Support Vector Machine (SVM) performed best for the Ubuntu dataset with an F1-score of 0.855.

Furthermore, the authors compare their classification model with two baseline methods from Bhatia et al. [21]. The proposed model with 12 QFs and three reply categories significantly outperforms both baselines, indicating the effectiveness of incorporating a comprehensive set of quality features for reply selection.

The summarization results based on the selected high-quality replies also show promising performance. The QFCThS method, which combines QF scores with classification, outperforms the QFThS method, which relies solely on QF scores. This highlights the benefit of using ML classifiers to refine the selection process and identify the most relevant replies for summarization.

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Although the study demonstrates the effectiveness of quality features and classification for reply selection, it has some limitations:

- Lack of Explicit Sentiment Analysis: The study primarily focuses on identifying informative and relevant replies for summarization rather than directly analyzing sentiment.
- Limited Generalizability: The study's focus on forum threads raises questions about the generalizability of the approach to other social media platforms with different conversational structures and dynamics.

The study presents a valuable framework for identifying highquality replies in forum threads using quality features and classification methods. Although not directly focused on sentiment analysis, the ability to select the most informative replies can significantly enhance sentiment analysis by focusing on the most relevant segments within a conversation. Future research could explore integrating sentiment features more explicitly into the QF framework and adapting the methodology for broader applicability across diverse social media platforms.

E. Enhancing Spam Comment Detection on Social Media With Emoji Feature and Post-Comment Pairs Approach Using Ensemble Methods of Machine Learning

Understanding sentiment evolution hinges on identifying high-quality replies, though addressing the pervasive issue of spam comments is equally vital for upholding the accuracy of sentiment analysis. Sajja et al. [2] delve into this critical aspect by exploring methods for enhancing spam comment detection on social media with emoji feature and post-comment pairs approach using ensemble methods of machine learning. This study, while not directly focused on sentiment analysis, holds significant relevance to the topic of ”sentiment analysis of social post-reply pairs” as spam comments can severely distort sentiment analysis results, leading to inaccurate interpretations of online conversations. Effective spam detection can help create cleaner datasets for sentiment analysis, leading to more reliable and meaningful insights. // The study uses the SpamID-Pair data set, sourced from Medley Data Repository, which is specifically designed to identify spam content in Indonesian. This dataset stands out due to its focus on:

- Indonesian Language: It addresses the scarcity of publicly available datasets for spam detection in languages other than English.
- Rich Emoji Usage: It includes a large volume of emojis, reflecting the prevalent use of emojis in social media communication, which often carries significant sentimental value.
- Post-Comment Pairs: The dataset is structured as pairs of posts and comments labeled as spam or not-spam. This pairing allows for analyzing the context of comments in relation to the original post, which can be valuable for understanding sentiment evolution within a thread.

The dataset is derived from the Instagram accounts of 12 Indonesian celebrities with over 15 million followers, suggesting a substantial volume of data and likely includes temporal information given its origin from a social media platform. Sajja et al. employ a multifaceted approach to enhance spam comment detection:

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1) Emoji Feature Incorporation: The study recognizes the potential of emojis as carriers of sentiment and intent and integrates them as features in the spam detection process. This innovative approach goes beyond traditional text-based methods to capture the nuanced emotional cues often conveyed through emojis.

2) Post-Comment Pairs Approach: Instead of analyzing comments in isolation, the study utilizes a stacked postcomment pair as input to the machine learning models. This approach enables the models to consider the context of the original post when evaluating the sentiment and intent of a comment, potentially leading to more accurate spam detection.

3) Ensemble Methods of Machine Learning: The study explores the effectiveness of various machine learning algorithms, including Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Extreme Gradient Boosting (XG Boost), and others. To further improve performance, the researchers utilize ensemble voting techniques, combining the predictions of multiple models to achieve higher accuracy and robustness.

The study demonstrates significant improvements in spam comment detection by incorporating emoji features and utilizing a post-comment pairs approach.

- The inclusion of emoji features led to an average increase in performance (accuracy and F1-score) of 4% to 6% across various machine learning models. This highlights the value of considering emojis as sentiment-bearing elements in social media communication.
- The post-comment pairs data further enhanced detection performance by an average of 0.7% to 2.11%. This emphasizes the importance of contextual analysis in understanding the sentiment and intent behind comments.

The SVM with an RBF kernel emerged as the best-performing stand-alone method, while the ensemble soft voting technique achieved the highest average performance in terms of accuracy and F1-score.

The authors also compare their approach with previous studies [22], [23] on spam detection, mainly focusing on Indonesianlanguage content on Instagram. Their approach, particularly the incorporation of emojis and post-comment pairs, demonstrates a significant advancement in the field. The study acknowledges certain limitations, despite the promising results:

- Limited Contextual Understanding: While the postcomment pairs approach captures some context, it may not fully grasp the intricate semantic relationships between posts and comments. Future research could explore deeper semantic analysis using techniques like deep learning or graph-based methods to improve contextual understanding.
- Focus on Spam Detection: The study's primary focus on spam detection leaves open the question of how these methods can be directly applied to sentiment analysis tasks. Further investigation is needed to adapt and refine these techniques for sentiment classification, especially considering the nuances of Indonesian language and emoji usage.

The study demonstrates the effectiveness of incorporating emoji features and a post-comment pairs approach for improved spam detection, paving the way for cleaner and more reliable datasets for sentiment analysis.

The findings highlight the need for deeper contextual understanding in both spam detection and sentiment analysis, encouraging future research to explore advanced techniques for semantic relationship analysis.

This study contributes to a more robust and nuanced understanding of sentiment dynamics in social media conversations by addressing the challenge of spam comments and pushing the boundaries of contextual analysis.

CHALLENGES

The analysis of sentiment within social media post-reply pairs faces numerous intertwined challenges:

1) Contextual Complexity and Data Scarcity: Accurately gauging sentiment requires grasping the intricate contextual interplay between posts and replies. This includes understanding subtle linguistic cues such as sarcasm, irony, and figurative language, as well as the impact of emojis. The lack of sufficiently large annotated datasets that capture this complexity is a major obstacle. Many existing datasets are limited in scope and often focus on specific domains or languages. Furthermore, the presence of spam and low-quality content further contaminates datasets.
2) Dynamic Sentiment Evolution: Sentiment isn't static; it shifts and evolves across conversations. Models must capture this temporal dynamic, understanding how initial sentiments are modified by subsequent replies. Predicting the sentiment of an upcoming response, before it is even posted, presents a unique challenge. The absence of widely accepted evaluation metrics for sentiment evolution hinders comparative analysis and progress assessment.
3) User Relationships and Influence: Social connections affect sentiment expression. Friends may share similar opinions while adversaries may hold opposing views. Inferring these "pseudo-friendships" and "pseudo-enmities" from complex social networks is computationally demanding and adds to the problem's complexity. The lack of readily available explicit friendship data necessitates the development of methods to infer these relationships.
4) Algorithmic Limitations: Current algorithms often fail to capture the full contextual richness and dynamic nature of social interactions. While deep learning and ensemble methods show promise, more sophisticated models are needed to fully understand the nuances of social communication.

CONCLUSION

The analysis of sentiment within social media post-reply pairs is important for understanding online interactions, necessitating a move beyond the analysis of isolated posts. This review has examined key contributions from recent studies, revealing advancements in the field and highlighting the importance of context, user relationships, and dynamic shifts in sentiment. The reviewed sources—Sajja et al. [2], Li and Zhang [1], Osman and Salim [16], Cercel and Trausan-

Matu [14], and Deng et al. [8]—collectively provide a comprehensive view of the challenges and opportunities in this domain.

Recent studies have contributed significantly to advancing sentiment analysis in social media. Sajja et al. [2] illustrate how incorporating multimodal features, such as emojis, enhances spam detection models, showcasing the importance of moving beyond simple text-based analysis to include sentiment-rich elements. Similarly, Li and Zhang [1] highlight the value of context in sentiment modeling by developing methods to predict emotions in upcoming conversational responses, thereby pushing the boundaries of emotion analysis within human-computer interactions.

Osman and Salim [16] emphasize the need to identify high-quality replies within social media threads, introducing quality features such as relevance, user activity, and sentiment. Their work demonstrates how prioritizing meaningful replies can improve information retrieval and thread summarization. Cercel and Trausan-Matu [14] address the dynamic nature of sentiment, proposing methods to trace how sentiment evolves over time within online discussions. Finally, Deng et al. [8] underscore the role of social relationships in sentiment expression, revealing how inferred connections, such as ”pseudofriendships” and ”pseudo-foes,” influence sentiment dynamics and interactions.

To further advance sentiment analysis, future research must prioritize the development of diverse datasets that encompass multiple social media platforms, languages, cultural contexts and demographics. The application of advanced deep learning architectures that understands user relationships, sentiment evolution, and contextual factors which will be crucial for capturing the complexities of social interactions. Additionally, a deeper understanding of cultural nuances, sarcasm, and irony is necessary to avoid misinterpretation in post-reply pairs.

Exploring multimodal analysis, such as integrating text, emojis, and images, is vital for building comprehensive sentiment models. The interplay between these modalities can provide richer insights into emotional expressions. Furthermore, future approaches should incorporate broader contextual factors, such as temporal dynamics, relational influences, and external events, to create more robust and nuanced sentiment analysis systems.

The field of sentiment analysis for social media post-reply pairs is steadily advancing toward more sophisticated models capable of addressing the complexities of online interactions. By embracing multimodal analysis, dynamic sentiment modeling, and the integration of user relationships, future research can significantly enhance sentiment analysis capabilities, contributing to a deeper understanding of human interactions in digital spaces.

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