Overcoming Challenges in Sentiment Analysis: A Comprehensive Literature Review

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Abstract—This survey of the literature addresses several methods and approaches for sentiment analysis and opinion-driven information systems. It provides a new technique for phrase-level sentiment analysis that distinguishes contextual polarity and outperforms the standard approach. The survey covers techniques for dealing with issues including privacy, manipulation, and economic impact as well as difficulties with sentiment-aware applications. Also included is Semantic Orientation (SO), which captures the evaluative element and potency of text and serves as a measure of subjectivity and opinion. The review also covers a multi-level learning strategy for extracting aspects from statistical, pattern-based, and rule-based methods, using probabilistic graphical algorithms and lexicons to retrieve associated opinion words. To deal with explicit and implicit polarity shift, a hybrid strategy combining rule-based methods and a graph-theoretic model is proposed, increasing the performance of the machine learning classification algorithm in ABSA. In addition, this survey will also describe how sentiment analysis is useful for analyzing people's emotions, opinions, and feedback expressed on social media platforms like Twitter and Facebook and challenges of identifying sarcasm in sentiment analysis. It also addresses the challenge of identifying sarcasm in sentiment analysis, which can lead to inaccurate analysis of emotions. Overall, this survey of the literature provides a comprehensive overview of various methods and techniques used in sentiment analysis, their limitations, and potential applications in analyzing emotional and subjective aspects of literature and social media.

Index Terms—Sentiment Analysis, Sarcasm, Natural Language Processing, Semantic Orientation, Metaphor detection.

1 Introduction

Sentiment analysis is a computational technique that aids in locating and extracting the subjective and personal information from a given text, including emotions, opinions, and attitude. Sentiment analysis is subjective because emotions are not always clear-cut and ignores sarcasm, negation, grammar mistakes, misspellings, Emoji's or irony which leads to inaccurate analysis. Sentiment analysis can be used in a literature review to extract and examine the text's subjective material, such as the author's feelings, opinions, and attitudes, as well as those of the characters. Sentimental analysis can be used in the discipline like - literary studies, psychology, and sociology to understand the aspects of emotion of written work.

Sentiment analysis can aid in a literature review by helping to detect and examine the tone and sentiment of the texts under consideration. It is especially helpful in analyzing the themes and motifs of a particular work and identifying patterns and trends across multiple texts. Moreover, sentiment analysis can be utilized to investigate how cultural and historical contexts shape the emotional content of literary works.

One challenge with sentiment analysis in literature is the need for contextual understanding. As literary works often use metaphor, symbolism, and other literary devices, it can be difficult for sentiment analysis tools to accurately identify the intended emotion. Additionally, literary works often include multiple perspectives and emotions, making it challenging to accurately classify the overall sentiment of the text.Notwithstanding the aforementioned challenges, sentiment analysis can still offer valuable insights into the emotional aspects of literary works. When used in conjunction with human interpretation and analysis, sentiment analysis tools can enable researchers to gain a more profound understanding of the emotional and subjective elements present in literature.

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2 Problem Statement

Sentiment Analysis is popular in extracting subjective information from the text, although it fails or do not accurately capture the emotions and ignores sarcasm, negation, grammar mistakes, misspellings, Emoji's or irony which leads to inaccurate analysis. Therefore, this literature review will focus to address the problem to identify different methods and approaches for sentimental analysis that can accurately capture subjective information from text, including sarcasm, negation, grammar mistakes, misspellings, Emoji's or irony, which can be applicable in the field of sociology, literary studies and psychology. Additionally, the literature review will explore the challenges faced by existing sentiment analysis techniques and discuss how they could be improved. The review will also investigate the current state-of-the-art techniques in sentiment analysis and their effectiveness in capturing sentiment accurately. Furthermore, it will examine the potential applications of sentiment analysis in fields such as marketing, politics, and customer service. The ultimate goal of this literature review is to provide insights into the advancements and limitations of current sentiment analysis methods and highlight potential areas for future research.

3 Literature Survey Comparison

Sr. No.	Paper Name	Discussed Algorithm	Dataset Used	Input	Output	Pros	Cons
1	Improving sentiment analysis with learning concepts from concept, patterns lexicons and negations.	PLSA, LDA, SVM, Naive Bayes, Hybrid Approach of rule-based approach and SimRank algorithms.	SemEval 2014 Restaurant (3041), SemEval 2014 Laptop (3045).	Aspect_opinion (AO), Possible Opinion (PO), SenticNet4, predefined aspect group AG(Food)	**Accuracy** of 84.73% with F1 value of 81.28%. **Laptop data: Accuracy** of 82.06% with F1 value of 80.71%.	Using a mix of rules and SimRank algorithms improves sentence interpretation accuracy..	Doesn't search more keywords that reverse the polarity of opinionated words, doesn't refine more complex pattern rules.
2	Improving Sentiment Analysis by Emotion Lexicon Approach on Vietnamese Texts.	Combined emotion lexicon with the classification model, transformers models, text classification, Text-CNN, Bi-GRU.	UIT-VSMEC, UIT-VSFC, and ViHSD.	**UIT-SMEC:** Fear 5.73, Surprise 4.36, Anger 7.04 **UIT-VSFC:** +ve 49.38, -ve 4.02, NEUTRAL 46.60	**UIT-VSMEC:** Accuracy of 67.03% **UIT-VSFC:** Accuracy of 83.40% by macro F1-score.	VnEmoLex lexicon improves the performance of classification. Boosts the classification model and text pre-processing.	Social media texts pose an ambiguity problem. Abbreviation, emoticons confuse the classifier which hinders actual emotion detection from the text.
3	Lexicon Based Methods for Sentiment Analysis.	Lexicons are extracted and SOCAL, which uses word polarity and strength to assign positive or negative labels.	Amazon's Mechanical Turk service and few other dictionaries are used.	Dictionary of adjectives, Trucker's ratings, individual payments.	The distribution of responses by SO value and average pairwise agreement Turkers.	Intensifiers improve classification and SO-CAL is a robust sentiment analysis method that outperforms others.	No discussion on machine learning-based approaches, does not address the performance of SO-CAL on text types other than reviews, such as social media posts or articles.
4	Multilingual Sentiment Analysis: A Systematic Literature Review.	**Preprocessing Techniques:** Tokenization, Negation. **Machine Learning:** SVM, Naive Bayesian. **Evaluation and Hybrid Methods** discussed.	SemEval-2013, SentiMix, SentiCoref, SentiArt, MultiLing-SET, and SemEval-2016. It consists text data in multiple languages.	Various articles multiple languages: **IEEE Explore** - 64, **Science Direct** - 57, **Springer Link** - 66, **ACM Digital Library** - 18, **Google Scholar** - 131	Identified 45 topics: **Two Languages:** 31%, **English mixed sentences:** 91%, **Machine Learning Techniques:** 51% articles.	Various applications like opinion mining, social media analysis, brand monitoring, and customer feedback analysis.	Lack of labeled data, language-specific nuances, code-switching. Do not focus on range of languages.
5	Multilingual Sentiment Analysis: A Deep Learning Approach.	Deep learning models: CNN, RNN, LSTM, GRU. Used Pre-processing techniques and Word embedding.	Used existing datasets of English, Arabic, and Portuguese multilingual tweets.	14,400 (80%) tweets from our dataset and testing them on 3,600 (20%) tweets.	Accuracy- **CNN:** 85.91, **Bi-LSTM:** 84.35, **Bi-GRU:** 83.78, **F1-score:** 85.08%, **AUC:** 94.33%.	Ability to handle multiple languages, automatically learn from the data and capture complex patterns in the text.	Require large amounts of labeled training data, can face problem if applied to a language that is not trained on model.

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TABLE 1

Sr. No.	Paper Name	Discussed Algorithm	Dataset Used	Input	Output	Pros	Cons
6	Arabic Dialect Identification Using Different Machine Learning Methods.	MFCC, KNN, Random Forest, Multi-Layer Perceptron methods.	Acoustic Arabizi Dialect Corpus, collected from YouTube.	The punctuation dictionary, the acoustic model as input and audio recording of speaker.	**Recognition rate: Overall-** 93.16%.	The system can identify speaker's dialect - useful in speech recognition and language translation.	No comparison between approaches to other existing's for Arabic dialect identification. The lack of standardization, and the presence of code-switching and mixed dialects.
7	Presence of informal language, such as emoticons, hashtags, and slang, impact the performance of sentiment analysis models on social media text	Methodology used: CNN, machine learning techniques, Emotion detection, Deep learning, informal language.	**Dataset used:** Sarcasm, Sentiment and Emoticon dataset.	All 3 dataset are taken as input for model, model was **trained** on 80% of the data and **tested** on 20%.	**Achieved Accuracy:** Sarcasm dataset - 96.47%, Sentiment dataset - 95.28%, Combination of both - 95.1%	Overcome challenges like informal language on social media platforms which helped improve the accuracy till 96%	The major **drawback** found is: model cannot segregate new forms of informal slangs, such as new emojis and hashtags on the analysis models.
8	Sentiment Analysis and Sarcasm Detection using Deep Multi-Task Learning.	**Techniques Used:** Sarcasm detection, multitask learning-based framework, Deep neural network, Bi-LSTM	**Dataset used:** Sarcasm and Sentiment dataset	**227,599 Tweets:** Labeled as: neutral, negative, positive sentiment. **28,619 Tweets:** Labeled as: not sarcastic and sarcastic.	This method out performs the existing methods by a **margin** of 3%, with an **F1-score** of 94%	Inaccurate sentiment analysis caused by the use of sarcasm is handled successfully.	Heavily depends on the provided dataset. Will fail in case of unseen datasets as neutral sentiments have led to poor recall score
9	Opinion mining and sentiment analysis	Naive Bayes, SVM, and maximum-entropy-based classification, supervised and semi-supervised learning.	Congressional floor-debate transcripts, Cornell movie-review datasets, Customer review, French.	The input is text data: reviews, tweets, blog posts, and articles. May be in multiple languages.	Gives score or label that indicates the polarity of the text. The score is scaled on binary label positive or negative.	Covers techniques that promise opinion-oriented information to face new challenges.	Facing difficulty in handling sarcasm, irony, and ambiguity in text, the need for domain-specific lexicons and training data.
10	Opinion mining for national security: techniques, domain applications, challenges and research opportunities	**Methodology used:** Opinion Mining, Kansei Approach.	ACM, IEEE, SCIENCE DIRECT, Springer-Link, and SCOPUS.	**Labelled dataset:** positive, negative reviews, polarity labels	Polarity of the group of words in terms of positive or negative, feelings and emotions.	Hybrid approach enhanced emotion in dataset, Kansei is capable of measuring people's emotional states.	Improvement in hybrid approach is required by including few more techniques, in order to increase the accuracy.

4 Discussed Future Work

4.1 Improving sentiment analysis with learning concepts from concept, patterns lexicons and negations:

In Future, the proposed model will refine its method to retrieve aspect terms and opinion words using complex pattern rules, search for polarity-reversing keywords, and expand its domain.

4.2 Improving Sentiment Analysis by Emotion Lexicon Approach on Vietnamese Texts:

To address ambiguity in social media texts, will enhance the model's performance by utilizing semantic labels and grammatical rules for sentiment analysis

4.3 Lexicon Based Methods for Sentiment Analysis:

The paper outlines future research directions, such as improving the SO-CAL method for sentiment analysis by integrating contextual information and developing discourse parsing methods. It also highlights the robustness of lexicon-based approaches and their applicability across different domains and languages.

4.4 Multilingual Sentiment Analysis: A Systematic Literature Review:

The paper suggests future work in sentiment analysis, including the development of resources for less commonly used languages, the ability to handle informal multilingual texts, the identification of appropriate preprocessing techniques for various languages, and the use of a combination of evaluation models to more accurately assess sentiment analysis performance.

4.5 Multilingual Sentiment Analysis: A Deep Learning Approach:

The future work discussed in this paper says that it may explore the ability of transformer-based models to successfully tackle the sentiment analysis problem for corpora containing documents in multiple Arabic dialects.

4.6 Arabic Dialect Identification Using Different Machine Learning Methods:

Future work involves using medium and short-duration acoustic waves, applying new techniques such as Gaussian Mixture and different features like LPC, LPCC, or LSF to improve accuracy, increasing the dataset size, and applying the same approach to detect sub-regional dialects in specific Arab regions.

4.7 Presence of informal language, such as emoticons, hashtags, and slang, impact the performance of sentiment analysis models on social media text?:

Future studies can look into how additional informal language styles, including emoticons and hashtags, affect the effectiveness of sentiment analysis models. To further enhance the performance of sentiment analysis models, various model architectures and machine learning approaches, such as recurrent neural networks (RNNs) and transformer networks, should be investigated.

4.8 Sentiment Analysis and Sarcasm Detection using Deep Multi-Task Learning:

To enhance the performance of sentiment analysis models, the author recommends future studies to investigate multi-task learning frameworks that consider sarcasm as well as appropriate pre-processing techniques to remove stop words without undermining the importance of neutral statements in the dataset.

4.9 Opinion mining and sentiment analysis:

The paper suggests future work in sentiment analysis, such as improving algorithms, addressing multilingual challenges, and exploring new applications like sentiment analysis in visual media or social networks.

4.10 Opinion mining for national security: techniques, domain applications, challenges and research opportunities:

The study suggests that future research should use the theoretical findings of the opinion mining method and literature review. Opinion mining has been successful in various popular domains, but domain-specific emotion words limit its effectiveness. The study proposes exploring advanced techniques for opinion mining in national security.

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