A Comprehensive Review of Sentiment Analysis: From Rule-Based Methods to Deep Learning and Future Directions

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Abstract: ***The following paper provides a systematic review of Sentiment Analysis in Natural Language Processing from the preliminary rule of thumb to modern deep learning methods. The background, main milestones, and significant techniques are discussed: lexicon-based strategies, machine learning, and recent deep learning applications based on BERT and BERT-like models are described. The paper also identifies and elaborates on existing issues in Sentiment Analysis such as the handling of sarcastic remarks, sentiment that is context-sensitive, and problems related to some specific domains. We also look at the uses of Sentiment Analysis in various industries such as social networks analysis, protection of brand image, and stock market prediction. In addition, the paper also elucidates certain areas of contemporary development and the direction of the further development of sentiment analysis including multimodal sentiment analysis, explainable AI and integration of common-sense reasoning. This review summarizes the current state of the issues relating to Sentiment Analysis present and possible future developments in the field.***

Keywords: Sentiment Analysis, NLP, Machine Learning, Deep Learning, BERT, Aspect- based Sentiment Analysis, Multimodal Sentiment Analysis

1. Introduction

One of the subfields of Natural Language Processing, known as Sentiment Analysis has become a powerful tool to effectively get subjective information from the textual data. Sentiment Analysis also incorporates computational methods to determine positive or negative sentiments present in the text and other forms of subjective data [1]. Sentiment analysis has become deemed as crucial more than ever before due to the drastic increase in user-generated content on social media, reviews, and other forms of online interaction. As a result, this paper attempts to present the state and evolution of Sentiment Analysis with the usage of various AI approaches starting from rule-based and finishing with modern approaches based on deep learning. This paper try analyze the approaches used for the implementation of Sentiment Analysis, describe the existing issues, and consider possible advancements of this rapidly growing subject.

2. Background of Sentiment Analysis

Sentiment Analysis is another term originating from the context of the two related fields, which are text mining and opinion mining. Previous studies conducted in the earlier years of the millennium were targeting the detection of subjective as well as the classifier set of words in text [2]. Nevertheless, Sentiment Analysis came to be a specific field of research only in mid 2000s.

Pang and Lee ‘s survey paper was path breaking that survey in which they have primarily collected earlier works and made Sentiment Analysis as a sub-branch of NLP [3]. They described the many uses of automated sentiment classification in different fields and thus attracted bigger attention of both academic and commercial circles.

The importance of Sentiment Analysis quickly became apparent across multiple sectors:

- **Business:** Organizations understood the importance of monitoring customer feedback, reviews, and mentions from the social media which would help them to know the perception that people have about the products they are offering [4].
- **Politics:** The stakeholders in political campaigns and analysis understood that Sentiment Analysis would help in monitoring the view of the public in political causes and candidates [5].
- **Social media:** Due to the publicity of social networking sites, there was a significant development in Sentiment analysis to measure the public mood and larger trends [6].
- **Finance:** Follows 2009, Sentiment Analysis adopted became the financial sector to potentially use the flow of the market with the news articles and social media sentiments [7].

These early applications laid down the theoretical and practical versatility of Sentiment Analysis.

3. Evolution of Sentiment Analysis Techniques

The evolution of Sentiment Analysis techniques is categorized into 3 main approaches: It has broadly three types namely lexicon, machine learning, and deep learning-based respectively. The approaches delivered new capabilities and enhanced performance.

3.1 Lexicon-based approaches:

Based on this context, Lexicon-based methods were among the initial models applied to Sentiment Analysis. These methods are based on precompiled lists of nouns that are indicated in regard to the positive, negative or neutral

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sentiment. Key developments in lexicon-based approaches include:

SentiWordNet: An opinion mining lexical resource [8].

VADER (Valence Aware Dictionary and sentiment Reasoner): A rule-based SA tool designed for sentiments Analysis in Social Networking Service with specific focus on the sentiments expressed in twitter [9].

Despite their ease of interpretability and effectiveness, lexicon-based approaches fail to capture contextual sentiments and a specific domain's words.

3.2 Machine Learning approaches:

Machine Learning (ML) methods in Sentiment Analysis also became widespread because of their ability to work with greater patterns given by the data.

- **Supervised Learning methods:** Naive Bayes, Support Vector Machines, and Maximum Entropy classifiers were found useful for sentiment classification [10]. Usually they exploit bag-of-words or n-gram features to express text, thus enabling the methods to learn more intricate features than the lexicon-based methods.
- **Unsupervised Learning methods:** The nature of the content was further studied using Latent Dirichlet Allocation (LDA) and other topic modeling techniques to understand the latent topic and their respective sentiments [11]. These methods enable the identification of patterns in the sentiment of huge text data without the need for prior training of the algorithms, which can help in understanding the structure of sentiment.

3.3 Deep Learning approaches:

Deep learning in sentiment Analysis witnessed improved performance of the applications.

Recurrent Neural Networks (RNNs): LSTM networks and Gated Recurrent Units (GRUs) became popular because of their richness in the long-distance dependencies of the text [12]. They work well for sentiment analysis because these architectures can capture the dependency between the words and keep vital information over long sequences in the text.

Convolutional Neural Networks (CNNs): Originally, created for image processing, CNNs are applied to textual analysis and demonstrated good results in capturing spatial dependencies in text [13]. In sentiment analysis, CNNs are able to learn relevant n-grams or phrases arising out of sentiments and irrespective of the position of the n-grams or phrases in the text.

Transformer-based models: The novel structure of the Transformers [14], and the successive models such as BERT [15] and GPT [16] acted as a cornerstone in the evolution of SA, NLP. These models are trained generally on massive amount of text data and can then be trained well to fit on Sentiment Analysis jobs and outperform other models due to their ability to model contextual dependencies in text.

Every one of the mentioned stages has contributed to much improvement in the success and complexity of trying to perform Sentiment Analysis on text, and going from very basic methods of just using words to complex models of trying to examine the actual capability of the human language.

4. Current State-of-the-Art in SA

Specifically, this paper focuses on the following as the current state-of-the-art in sentiment analysis:

So far as architectures and solutions proposed are concerned, the current state of the art in SA remains predominantly devoted to the transformers and their derivatives.

4.1 Transformer based models and their impact

In the recent past, transformer models are the current go-to in many NLP tasks including but not limited to Sentiment Analysis. Key developments include:

- **BERT (Bidirectional Encoder Representations from Transformers):** It has been found successful in various NLP problems like Sentiment classification [15]. BERT poses more advantages in kindling better sentiment examination in acknowledgment of multifaceted linguistic landmarks.
- **RoBERTa(A Robustly Optimized BERT Pretraining Approach):** An improvement of BERT that actually performs even better in terms of evaluation of sentiments of a text [17]. This model demonstrates that it possible to further optimize transformer-based architectures for a sentiment analysis.
- **XLNet:** Proposed an autoregressive pretraining technique, which is a better approach than BERT for many tasks comprising sentiment analysis [18]. As to the advantages of XLNet over BERT, this technique slightly removes some weaknesses of the latter and might provide a more elaborate understanding of the sentiments.

These models have led to a great improvement; realizing much more than eighty percent on better sentiment classification. For example, Sun et al. have introduced the policing for the SentiHood and SemEval2014 Task 4 datasets. with the introduced BERT-based model [19].

4.2 Multilingual and cross lingual Sentiment Analysis

Since the materials are accessible on the Internet, it is becoming important to blog in several languages, and therefore, MULTILINGUAL sentiment analysis has become rather relevant. Notable work includes:

- **Multilingual BERT (mBERT):** As stated in [20], Pires et al. achieved zero shot cross-lingual sentiment classification. This is critical to the creation of a sentiment analysis model that is multilingual and does not require language-specific training data.
- **XLM-RoBERTa:** Conneau et al proposed it which they claimed to be a multilingual model that was better than the previous approaches in the cross-lingual benchmarks [21]. This model may prove useful in enhancing sentiment analysis for multiple languages,

Culture dependent analysis, and so on, which makes this model a futuristic advancement for multi-lingual sentiment analysis.

4.3 Aspect-based sentiment analysis

At the aspect level, aspect-based sentiment analysis (ABSA) aims at the estimation of a given population's stance regarding specific aspects or topic of the given entity thereby offering a more refined evaluation than sentiment categorization. Recent advancements include:

- **BERT-ADA (Aspect-based Domain Adaptation):** Rietzler et al. [22] introduced a domain adaptation method for ABSA using BERT. This approach combines BERT's pre-training with a fine-tuning of the model to certain domains, which helped improve the aspect level sentiment tasks in various domains.
- **RACL (Relation-Aware Collaborative Learning)-BERT:** Chen and Qian [23] proposed the new strategy for ABSA of using a multi-task learning network. In this way, this approach is training a number of the subtasks associated with ABSA and thusly enhancing the efficiency of aspect-based sentiment analysis.

4.4 Emotion detection and further breaking it down to sentiment analysis

Research has expanded beyond basic positive/negative classification to more nuanced emotion detection: There are not only simple positive or negative classification of the given text but also being more specific in identifying the emotions included there.

- **GoEmotions:** Demszky et al., [24]. later presented a vast, high-level emotion dataset with seventy-two subcategories of emotion and these include joy, sadness, anger, disgust, approval, and surprise among others. Because of this dataset, it becomes possible to train much better emotion detection models that can recognize even more types of human feelings expressed in the text.
- **EmoNet:** More large-scale work in this area was suggested by Abdul-Mageed and Un- gar [25]. For the given characteristics of the appraisal in the texts of social networks and blogs, EmoNet is intended to work in conditions of low-formality, context-sensitivity, and lexico-grammatical non-standardity of the emotion expressions.

5. Challenges in Sentiment Analysis

Despite significant progress, several challenges remain in Sentiment Analysis:

5.1 Sarcasm and Irony Detection

Sarcasm and irony are still difficult to identify when it comes to sentiment analysis because they are examples of the subtlety of language. Modern techniques, for example, contextual sarcasm detection with convolutional networks and LSTM, self-attention networks for irony detection laid down by Ghosh and Veale [26] and Tay et al. [27] attempt to embrace contextual information to detect these forms of expressions.

5.2 Context-dependent sentiments

The technique of sentiment analysis essentially requires a proper understanding of context. Static approaches are more rigid and do not comprehend the hidden consequences of the words that occurs in a given piece of text. Context is very important while analyzing the sentiment of the piece of text as the same words may have different connotations to them. The BERT-pair model described by Sun et al. [19] avoids this by training the model on the interaction between the two sentences, making the sentiment more context sensitive.

5.3 Domain adaptation

The second problem that was identified is that of poor portability where sentiment classifiers tend to do poorly on new domains of text that they have not being trained on. This method of sentiment classifiers is a problem when moving to a new domain where the features used are different from those the classifier has been trained on.

Currently, there is a trend in techniques such as VADER Hutto and Gilbert [9] and Adversarial Domain Adaptation Du et al. [28] that are trying to develop models that will remain relevant in learning regardless of the domain.

5.4 Handling multimodal data

The advanced usage of multimedia content in more and more communication channels requires the SA methods that address the multiple data modality. Multimodal Transformers Rahman et al. [29] also brought a shift in this regard and allowed working with text, image, and audio data in sentiment analysis.

6. Applications of Sentiment Analysis

Sentiment Analysis finds applications in various domains:

- **Social media monitoring:** Hootsuite tools use sentiment analysis for real-time social media monitoring allowing organizations to constantly track sentiments on different social sites and adjust to new trends or problematic topics [30].
- **Brand reputation management:** RepTrak uses sentiment analysis to measure corporate reputation which can support the improvement of reputation management by tracking people's attitudes in the available channels [31].
- **Customer feedback analysis:** Companies like Amazon and Airbnb use sentiment analysis to automatically categorize large batches of customer feedback and respond to customer reviews more efficiently. [32].
- **Political opinion tracking:** These include using sentiment analysis in the voting prediction where people's sentiments on social media and other interactive platforms are identified. Several studies have used sentiment analysis to predict election outcomes [5][33].
- **Financial market prediction:** In corporate world context, sentiment analysis is applied where the social media sentiment is used to predict the financial markets. Bollen et al. demonstrated that Twitter sentiment can predict stock market trends [7].

7. Future Directions in Sentiment Analysis

Several promising directions are emerging in Sentiment Analysis research:

- **Integration with common sense reasoning:** By embedding common sense knowledge into sentiment analysis models, it attempts to give contextual understanding and nuanced interpretation of text. Ma et al. (2018) suggests integrating ways to perform common sense reasoning in order to gain more human like perception of sentiment in high inferential contexts [34].
- **Explainable AI in sentiment analysis:** It is important to build AI systems that not only predict sentiment but also explain why they did so for purposes of creating trust and understanding with AI systems. Work of Ribeiro et al. (2016) on making sentiment analysis models more interpretable so that users can understand which factors affect the predictions of sentiment [35].
- **Real-time sentiment analysis in streaming data:** Sentiment analysis on high volume, high velocity data streams is becoming an increasingly critical need for techniques in the age of big data. Such applications require the real time development of sentiment analysis methods.
- **Multimodal sentiment analysis:** More generally, it is an emerging area of research on integrating text, audio, and visual cues for the purpose of more accurate sentiment prediction. As the world dives deeper into video content and multimedia communications, Poria et al. (2017) suggested it would be useful to combine several modalities to not only obtain a more comprehensive perspective on sentiment, but also one which better fits a discussion [36].
- **Ethical considerations and bias mitigation:** More importantly, working to correct for the biases of demographics and culture in sentiment analysis models is necessary to guarantee that people, regardless of their demographic or cultural backgrounds, are analyzed honestly. In this direction, attempts at enhancing the existing models and datasets to reduce bias in sentiment analysis systems can be designed.

8. Conclusions

Consequently, it is worth discussing that the ways and means of performing Sentiment Analysis has changed from simple rule-based classifications towards state-of-the art Deep Learning methods. Today, there are still many difficulties, regarding, for example, the context, irony, and domain adaptation, but the development of the field is fast. Other next-generation successors of these research areas encompass multimodal analysis, explainable AI, and bias reduction, which will enable the improvement of Sentiment Analysis in the future.

With daily growth of social media and consumption of augmented content, the role of Sentiment Analysis in capturing the sentiments of populations, enhancing customers' satisfaction, and optimization of decisions in different fields will be more imperative. The combination of Sentiment Analysis with other advanced AI tools is quite promising for the development of a more accurate way of understanding feelings and opinions of people reflected in the texts.

References

[1] Bing Liu. Sentiment analysis: Mining opinions, sentiments, and emotions. *Cambridge University Press*, 2020.

[2] Janyce M. Wiebe, Rebecca F. Bruce, and Thomas P. O'Hara. Development and use of a gold-standard data set for subjectivity classifications. *Proceedings of the 37th annual meeting of the Association for Computational Linguistics*, pages 246–253, 1999.

[3] Bo Pang and Lillian Lee. Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, 2(1-2):1–135, 2008.

[4] Ronen Feldman. Techniques and applications for sentiment analysis. *Communications of the ACM*, 56(4):82–89, 2013.

[5] Andranik Tumasjan, Timm O. Sprenger, Philipp G. Sandner, and Isabell M. Welpe. Predicting elections with twitter: What 140 characters reveal about political sentiment. In *Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media*, pages 178–185, 2010.

[6] Alexander Pak and Patrick Paroubek. Twitter as a corpus for sentiment analysis and opinion mining. In *Proceedings of the Seventh International Conference on Language Resources and Evaluation (LREC'10)*, 2010.

[7] Johan Bollen, Huina Mao, and Xiaojun Zeng. Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1):1–8, 2011.

[8] Andrea Esuli and Fabrizio Sebastiani. Sentiwordnet: A publicly available lexical re- source for opinion mining. In *Proceedings of the Fifth International Conference on Language Resources and Evaluation (LREC'06)*, pages 417–422, 2006.

[9] C.J. Hutto and Eric Gilbert. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Eighth International AAAI Conference on Weblogs and Social Media*, 2014.

[10] Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. Thumbs up? sentiment classification using machine learning techniques. In *Proceedings of the 2002 Conference on Empirical Methods in Natural Language Processing (EMNLP 2002)*, pages 79–86, 2002.

[11] Chenghua Lin and Yulan He. Joint sentiment/topic model for sentiment analysis. In *Proceedings of the 18th ACM conference on Information and knowledge management*, pages 375–384, 2009.

[12] Duyu Tang, Bing Qin, and Ting Liu. Document modeling with gated recurrent neural network for sentiment classification. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1422–1432, 2015.

[13] Yoon Kim. Convolutional neural networks for sentence classification. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1746–1751, 2014.

[14] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, L- ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems*, pages 5998–6008, 2017.

[15] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre- training of deep bidirectional transformers for language understanding. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 1:4171–4186, 2019.

[16] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33, 2020.

[17] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.

[18] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, and Quoc V. Le. Xlnet: Generalized autoregressive pretraining for language understanding. In *Advances in Neural Information Processing Systems*, pages 5753–5763, 2019.

[19] Chi Sun, Luyao Huang, and Xipeng Qiu. Utilizing bert for aspect-based sentiment analysis via constructing auxiliary sentence. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, volume 1, pages 380–385, 2019.

[20] Telmo Pires, Eva Schlinger, and Dan Garrette. How multilingual is multilingual bert? *arXiv preprint arXiv:1906.01502*, 2019.

[21] Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzm´an, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. Unsupervised cross-lingual representation learning at scale. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8440–8451, 2020.

[22] Alexander Rietzler, Sebastian Stabinger, Paul Opitz, and Stefan Engl. Adapt or get left behind: Domain adaptation through bert language model finetuning for aspect-target sentiment classification. In *Proceedings of The 12th Language Resources and Evaluation Conference*, pages 4933–4941, 2020.

[23] Zhuang Chen and Tieyun Qian. Relation-aware collaborative learning for unified aspect- based sentiment analysis. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 3685–3694, 2020.

[24] Dorottya Demszky, Dana Movshovitz-Attias, Jeongwoo Ko, Alan Cowen, Gaurav Ne- made, and Sujith Ravi. Goemotions: A dataset of fine-grained emotions. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4040–4054, 2020.

[25] Muhammad Abdul-Mageed and Lyle Ungar. Emonet: Fine-grained emotion detection with gated recurrent neural networks. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*, volume 1, pages 718–728, 2017.

[26] Aniruddha Ghosh and Tony Veale. Magnets for sarcasm: Making sarcasm detection timely, contextual and very personal. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 482–491, 2017.

[27] Yi Tay, Anh Tuan Luu, Siu Cheung Hui, and Jian Su. Reasoning with sarcasm by reading in-between. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics*, volume 1, pages 1010–1020, 2018.

[28] Chunning Du, Haifeng Sun, Jingyu Wang, Qi Qi, and Jianxin Liao. Adversarial and domain-aware bert for cross-domain sentiment analysis. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4019–4028, 2020.

[29] Wasifur Rahman, Md Kazi Hasan, Sangwu Lee, AmirAli Bagher Zadeh, Chengfeng Mao, Louis-Philippe Morency, and Ehsan Hoque. Integrating multimodal information in large pretrained transformers. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2359–2369, 2020.

[30] Bogdan Batrinca and Philip C. Treleaven. Social media analytics: a survey of techniques, tools and platforms. *AI Society*, 30(1):89–116, 2015.

[31] Charles J. Fombrun, Leonard J. Ponzi, and William Newburry. Stakeholder tracking and analysis: The reptrak® system for measuring corporate reputation. *Corporate Reputation Review*, 18(1):3–24, 2015.

[32] Svetlana Kiritchenko, Xiaodan Zhu, and Saif M. Mohammad. Sentiment analysis of short informal texts. In *Journal of Artificial Intelligence Research*, volume 50, pages 723–762, 2014.

[33] Hao Wang, Dogan Can, Abe Kazemzadeh, Fran¸cois Bar, and Shrikanth Narayanan. A system for real-time twitter sentiment analysis of 2012 u.s. presidential election cycle. *Proceedings of the ACL 2012 System Demonstrations*, pages 115–120, 2012.

[34] Yukun Ma, Haiyun Peng, and Erik Cambria. Targeted aspect-based sentiment analysis via embedding commonsense knowledge into an attentive lstm. In *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.

[35] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. ”why should i trust you?”: Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1135–1144, 2016.

[36] Soujanya Poria, Erik Cambria, Devamanyu Hazarika, Navonil Majumder, Amir Zadeh, and Louis-Philippe Morency. Context-dependent sentiment analysis in user-generated videos. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 873–883, Vancouver, Canada, 2017. Association for Computational Linguistics.

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