Guest Editorial: Sentiment Analysis as a Multidisciplinary Research Area

I. Prologue

THE last two decades have witnessed an enormous amount of research works on sentiment analysis and significant progress has been made. In terms of depth, finer-grained semantic schemas are defined, such as aspect [1], target [2], and category [3]. In terms of broadness, multimodal sentiment analysis [4] touches audio and video channels. Conversational sentiment analysis [5] considers contextual and time-dependent relations and domain-specific sentiment analysis settings tackles real-life challenges, including but not limited to user profiling [6], financial prediction [7], abusive language detection [8], and mental health [9].

Despite this very active landscape, there is a declining trend in linking sentiment analysis with theories from other disciplines. Sentiment analysis seemed to become more "self-sustainable." Dialogue with other disciplines, from a scientific perspective, means considering contributions from linguistics, psychology, and cognitive science, and from a practical perspective means producing task-aware results for downstream applications instead of hacking performance metrics on standard benchmarks (when testing a large population of models, we will be doing "accuracy-hacking," similar to P-hacking [10]). In contrast, an obsession with several established evaluation environments risks a research area into "involution," an anthropological concept used to describe cultural forms that reached a definitive form, but only continued to develop their internal complexity [11].

Sentiment analysis is hardly single origin. The term evolved from at least two threads of research, i.e., lexical semantics and web data mining. In the former, sentiment information for adjectives was called "polarity" or "semantic orientation" [12]; in the latter, sentiment information for a whole piece of web text was called "opinion" [13]. Today, these classical definitions of sentiment analysis (i.e., at word or sentence level) are more or less solved problems in closed-form evaluation (e.g., 91.5% on LJ-5k [14] and 97.5% on SST-2 Binary classification [15]).

This is good, but does further progress on models advance us one step toward AI, or less ambitiously, natural language understanding? Our central question being how could sentiment analysis stay relevant to the larger AI community and escape the involution trap, we reiterate three ideas. The *first* idea is that sentiment analysis may draw new methods from other reference disciplines, including statistics, semiotics, and psychological and behavioral studies. One such example is sentic computing, which combines neural networks, knowledge base, and syntactic patterns to engineer the pipeline for sentence-level sentiment analysis. The *second* idea is to consider its interrelated, peer tasks. In a 2017 article [16], sentiment analysis is described as a suitcase problem that requires simultaneously solving many other NLP tasks, including subjectivity detection, anaphora resolution, word sense disambiguation, sarcasm detection, and aspect extraction.

Today, we have the multitask learning [17] framework that enables information sharing among those tasks to improve performance. There are still opportunities to further understand what has been shared, why that is useful for sentiment analysis, and discover new coupling tasks. The *third* idea is to adapt sentiment analysis to the theories and data structures of its applying field. In many scenarios, sentence-level sentiment is not the endpoint data format, instead, the aggregated time series or statistical information, such as sentiment intensity matter more. In the context of social media analytics, sentiment may be personalized and bounded by a graphical structure. In the context of financial prediction, target variables [18], [19] may have complicated confounding relations. It is nontrivial to introduce sentiment information to the theory or via surrogate variables while keeping the original assumptions unchanged. Recently, the interest in applying NLP for online portfolio theories is rising, e.g., [20] and [21]. Very likely in the near future, we will know more financial theories where performing sentiment analysis may yield unexpected results or new insights [22].

II. Contents of This Special Issue

This Special Issue focuses on bringing multidisciplinary knowledge into sentiment analysis. For this reason, we favor research that introduces theories that are not usually part of the standard sentiment analysis framework or interpret the meaning of sentiment analysis in a different task or context. We hope these studies potentially attract researchers to read more on the literature that they usually will not. Therefore, we accepted a large percentage of review papers, and had to exclude incremental works, e.g., a new neural network architecture that changes performance on popular benchmarks but lacks a rationale, and applications of the same method on a different language domain or data set. Out of all the submissions received, six were selected to appear in this Special Issue. Three of the accepted papers review certain research scopes and the rest three feature original research.

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In [A1], Chen et al. discover the increasing popularity of applications of soft computing methods in sentiment analysis. Soft computing is an umbrella term for fuzzy logic, neural networks, evolutionary computing, and other algorithms that tolerate imprecise or approximate results. Recommender systems and sentiment analysis are two of the important applications for such algorithms, and there is a recent article collection from *Applied Soft Computing* dedicated to it [23]. According to the authors' bibliometric analysis of research articles using structural topic modeling, soft computing shifts research foci from recommender systems to sentiment analysis in the past two decades. We expect to see more research on this trend, e.g., using fuzzy logic for aspect-based sentiment analysis or sentiment knowledge base reasoning.

In [A2], Toshevska and Gievska present different deep learning methods for the two key style transfer steps, i.e., the representation learning of style and the generation of the sentence in a new style, are respectively surveyed. Being the more concise and engineering-perspective twin of another recent survey [24], this article investigates the modification and control of sentiment in generated texts. In the style transfer task, sentiment can be understood within a broader range of interrelated pragmatic attributes, such as politeness, emotion, humor, sarcasm, and many more.

Next, in [A3], Abonizio et al. compared a taxonomy of text data augmentation methods under the usual real-life situations of imbalanced and label-lacking data for sentiment analysis. They discover that in most cases back-translation is a more favorable augmentation method, whereas the choice of classifier and dataset features both have a significant impact on the most suitable augmentation method. This provides a useful guideline for data-dependent real-life applications and showcases the relative complexity of model deployment.

The fourth article in this Special Issue is [A4]'. Sentiment signal, of course, cannot be fully preserved in the textual format without paralanguage, such as acoustic pitch, speed, and facial expressions. In [A4], Hussain et al. proposed a novel attention mechanism for acoustic data and enhanced the signal at challenging noise levels. This research can be potentially useful for many multimodal sentiment analysis tasks.

Next, in [A5], Najar and Bouguila focus on the sparsity problem of high-dimensional count data. It is a fairly common problem for many bag-of-words like models, TF-IDF, and topic modeling. Empirical results show that the smoothed generalized Dirichlet model improves emotion detection efficiency and robustness not only for text data, but also for videos and images. We hope this research article can draw attention to advances in computational statistics and high-dimensional statistics as a source of inspiration for natural language processing.

Finally, in [A6], Tu et al. explore adding commonsense knowledge to conversation modeling using graph attention and transformer models. Commonsense is an important foundation for intelligence and may be the final source of sentiment or valence activation.

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Appendix
Related Articles

[A1] X. Chen et al., "A bibliometric review of soft computing for recommender systems and sentiment analysis," *IEEE Trans. Artif. Intell.*, to be published, doi: 10.1109/TAI.2021.3116551.

[A2] M. Toshevska and S. Gievska, "A review of text style transfer using deep learning," *IEEE Trans. Artif. Intell.*, to be published, doi: 10.1109/TAI.2021.3115992.

[A3] H. Q. Abonizio, E. C. Paraiso, and S. Barbon Junior, "Toward text data augmentation for sentiment analysis," *IEEE Trans. Artif. Intell.*, to be published, doi: 10.1109/TAI.2021.3114390.

[A4] T. Hussain et al., "A novel temporal attentive-pooling based convolutional recurrent architecture for acoustic signal enhancement," *IEEE Trans. Artif. Intell.*, to be published, doi: 10.1109/TAI.2022.3169995.

[A5] F. Najar and N. Bouguila, "Smoothed generalized Dirichlet: A novel count data model for detecting emotional states," *IEEE Trans. Artif. Intell.*, to be published, doi: 10.1109/TAI.2021.3120043.

[A6] G. Tu, J. Wen, C. Liu, D. Jiang, and E. Cambria, "Context- and sentiment-aware networks for emotion recognition in conversation," *IEEE Trans. Artif. Intell.*, to be published, doi: 10.1109/TAI.2022.3149234.

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[9] S. Ji, S. Pan, X. Li, E. Cambria, G. Long, and Z. Huang, "Suicidal ideation detection: A review of machine learning methods and applications," *IEEE Trans. Comput. Social Syst.*, vol. 8, no. 1, pp. 214–226, Feb. 2021.

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