

Hybrid deep neural network model for aspect and opinion extraction with multi-head attention-driven sentiment analysis

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ABSTRACT

Finding and extracting significant features from review sentences is known as aspect triplet extraction, and it provides succinct information on the elements that users have addressed. This method makes sentiment analysis and opinion mining easier, which helps to provide an adequate understanding of user opinions in reviews. This research presents a novel approach to achieve aspect-sentiment triplet-extraction (ASTE) using a deep neural network and transformer-based multi-head attention model. The proposed hybrid model adopts a pipeline methodology, concurrently extracting opinions and aspects while performing sentiment classification. The study addresses the intricate challenge of identifying triplets that capture nuanced relationships between terms and sentences, employing a deep neural network for joint extraction of aspects and opinions using a sequential tagging method. Sentiment classification is seamlessly integrated into the pipeline, treating sentiment recognition as a classification task, and aspect and opinion extraction as text-extraction challenges. Evaluations was out experimentally on the SemEval 2016 restaurant dataset demonstrate the effectiveness of the model, despite issues with unequal distribution of data.

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1. INTRODUCTION

Aspect-sentiment triplet-extraction (ASTE) involves the separation of mentions of a target entity, associated sentiment, and an opinion range providing context for the sentiment. Current research commonly employs pipeline methods or a combined approach utilizing sequential tagging to address this issue. Identifying triplets that convey rich interconnections between terms and sentences is a challenging research problem. In the realm of aspect-based sentiment analysis (ABSA), recent research efforts have explored various techniques to enhance the extraction of aspect-sentiment triplets, aiming for more accurate and comprehensive sentiment understanding. Notably, a study by [1] introduced a multi-turn machine-reading-comprehension (MTMRC) task and a bi-directional MRC (BMRC) architecture. This work focused on constructing links between components using non-restrictive, restrictive, and sentiment-classifying queries.

This research seeks to improve the precision and effectiveness of ASTE within sentiment analysis by designing a transformer-based multi-head attention network. The proposed method integrates a hybrid model within a pipeline structure that concurrently extracts opinions, aspects, and performs sentiment classification. To achieve this, we utilize a deep neural network tailored for the simultaneous extraction of aspects and opinions through a sequential tagging technique. Sentiment classification is treated as a distinct task within the pipeline, while aspect and opinion extraction are managed as text-extraction challenges. The key contribution of this work is its ability to capture and classify intricate relationships between terms and sentences, addressing imbalanced data challenges, as evidenced by experiments on the SemEval 2016 restaurant dataset. This method significantly advances ASTE and offers a reliable solution for more accurate sentiment analysis in complex review datasets.

Dai and Song [2], proposed a method for mining extraction patterns from pre-existing training instances using the output of a dependency parser. This approach, incorporating both annotation and rule-labeled supplementary information, demonstrated improved accuracy compared to existing state-of-the-art methods. The introduction of bidirectional-encoder-representations from transformers (BERT) in [3] marked a significant leap in linguistic representation. Pre-training deep bidirectional representations using textual data resulted in state-of-the-art performance on various natural language processing (NLP) tasks, including sentiment-related benchmarks. Addressing the challenge of improving correlations among targets and opinions, [4] proposed a two-stage approach involving sequence tagging and the insertion of artificial tags called perceivable pairs. Their model outperformed state-of-the-art approaches across different datasets.

A unified model for end-to-end target-based sentiment analysis was introduced in [5], utilizing a unified tagging method. Experimental evaluations on benchmark datasets demonstrated the superiority of their system over competitors. To enhance entity-relation extraction, [6] presented a novel paradigm, recasting the problem as a set of related questions. Provided a two-step process, using a unified model to forecast the what, how, and why, and pairing the results to produce triplets [7]. Poria *et al.* [8], challenged existing views, highlighting gaps and unexplored territory essential for complete sentiment comprehension. They proposed a trajectory for further study, addressing ignored and unsolved topics. The work in [9] proposed a comprehensive model, offering state-of-the-art outcomes without the need for parsers or additional language resources. Comparative analyses with various baselines and SemEval Challenge results confirmed the model's efficacy. Introducing the grid tagging scheme (GTS) in [10], the authors tackled the aspect-focused opinion extraction (AFOE) task with a unified grid tagging operation. GTS models, based on CNN, BiLSTM, and BERT, outperformed strong baselines in aspect-oriented opinion pair extraction and opinion triplet extraction datasets. End-to-end triplet extraction was explored by [11], utilizing a position-aware tagging technique. Experimental findings demonstrated superior performance compared to state-of-the-art methods. Reframing ABSA as an opinion triplet extraction task, proposed a multi-task learning framework for simultaneous aspect and opinion term extraction, achieving superior performance on SemEval benchmarks [12]. Li *et al.* [13], the authors introduced an innovative method for aspect-term extraction (ATE), leveraging summaries of opinions and aspect detection history to outperform existing state-of-the-art methods. A unique deep multi-task learning architecture based on long short-term memory (LSTM) was presented in [14], showcasing efficiency in aspect phrase extraction across two industry-standard datasets.

The dual cross-shared RNN framework (DOER) was introduced in [15], demonstrating superior performance in generating aspect term-polarity pairings across three benchmark datasets. Proposed a new technique for aspect term extraction using unsupervised learning of distributed representations of words and dependency paths [16]. A paradigm shift was presented in [17] with ASTE-RL, treating aspect and opinion words as reasons for communicated emotion within a hierarchical RL framework. Experimental results demonstrated superiority over current best practices in computer and restaurant industry datasets. These studies collectively contribute to the evolving landscape of ABSA, showcasing advancements in triplet extraction techniques and providing valuable insights for future research directions.

2. RESEARCH METHOD

Proposed hybrid method designed for the extraction of triplets in aspect-based sentiment analysis (ABSA). Figure 1 illustrates the architecture of the proposed hybrid method, which consists of two crucial steps.

2.1. Aspect and opinion extraction

The first step involves the extraction of opinions and aspects from a given review sentence. A deep neural network text extraction method is employed to accomplish this task. The input to this step is a review sentence, and the output comprises the extracted aspects and opinions. This subsection discusses the joint extraction of opinions and aspects from review sentences using the pre-trained and fine-tuned BERT method via Hugging-Face-Transformers. The fine-tuning process encompasses several tasks, starting with the

representation of a review sentence as, $X = \{x^1, x^2, x^3, \dots, x^N\}$, having N tokens. Using this review sentence, the Aspect-Sentiment Term Extraction method first tries to identify all the triplets. $T = \{(a_i, o_i, s_i)\} |T|$, where $i = 1$. The a_i is used to define the aspect, o_i is used to define the opinion, s_i is used for defining the sentiment and $|T|$, is used to define the magnitude of the triplets. Further, this hybrid method uses a position-tagging method. The position-tagging method A_s is used for defining the aspect at the starting point and A_e is used for defining the aspect at the ending point. Also, O_s is used for defining the opinion at the starting point and O_e is used for defining the opinion at the ending point. Moreover, as the review texts are already embedded, the position encoding method has been used for embedding the position of the opinion and aspect tokens. The tokens which have been contextualized, $CR_e = \{r_{e1}, r_{e1}, \dots, r_{el}\}$, are then represented using the BERT method. For the classification of the tokens, the Softmax method has been used which is represented using $Y = Softmax(CR_{e1}W_{e1} + b_{e1})$. When the classification tokens are classified, then the results are separated using the target which is set using the opinion set $Y_o = \{o_1, o_2, \dots, o_m\}$ and aspect set $Y_A = \{a_1, a_2, \dots, a_m\}$.

Figure 2 shows a model that takes multiple inputs from a review sentence and processes them using a BERT-based language model. The model then splits into two parallel paths to predict the start and end positions of aspects and opinions in the text. Each path uses dense and flatten layers followed by activation to generate final outputs. It helps identify and extract important opinion words and aspect terms from the sentence efficiently.

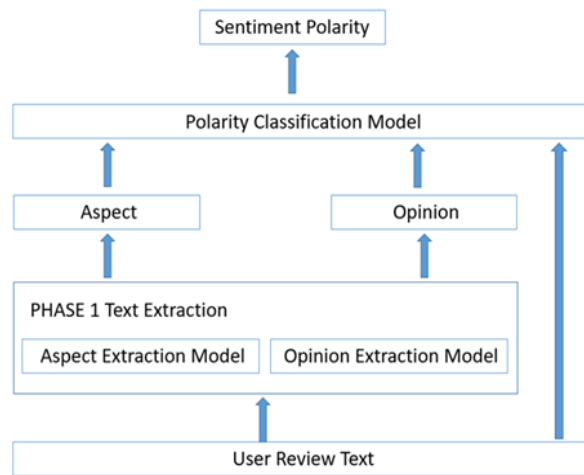


Figure 1. Hybrid method for the extraction of triplets

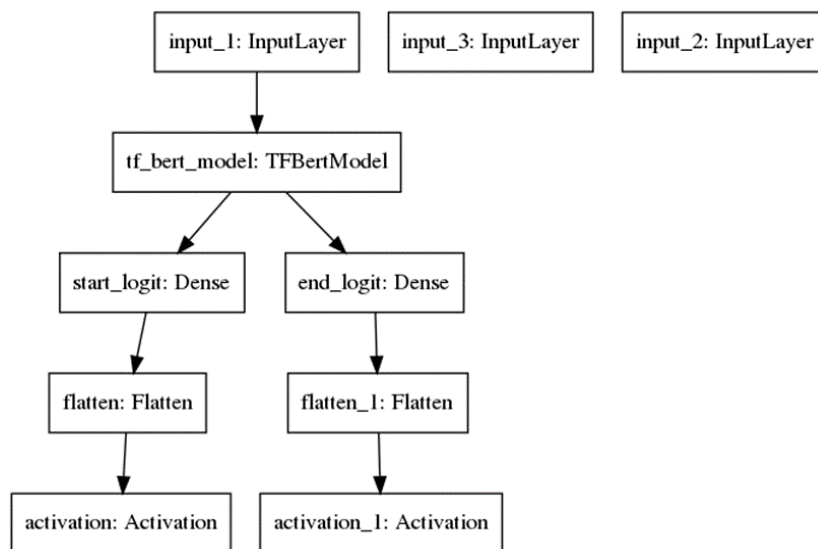


Figure 2. A proposed method for opinions and aspects text extraction from using the review sentence

2.2. Polarity classification

The proposed TFBERT method, pre-trained and optimized with token and position-embedded layers along with transformer blocks, forms the backbone of this classification approach. The input to this method is a review sentence represented as $S = \{s_1, s_2, s_3... s_l\}$. In this process, both the encoded opinion set $Y_O = \{o_1, o_2... o_m\}$ and aspect set $Y_A = \{a_1, a_2... a_m\}$ are passed through an encoder. The resulting encoded sets, along with the input sentence S, collectively contribute to the classification of polarity. This method ensures a comprehensive evaluation of sentiment polarity by considering both the opinions and aspects extracted from the input review sentence, thus enhancing the overall robustness of our proposed framework.

The fundamental transformer-encoder comprises two integral components: the multi-head-attention (MHA) method and a fully connected layer. Within the transformer-encoder framework, the MHA plays a pivotal role in capturing various states of the input, employing a self-attention approach for constructing both input and output representations. The Context-Aspect-Word-Interaction is achieved through the MHA, where the inputs for the MHA function consist of a value-pair, a query 'q,' and a set of keys 'k' defined as $k = \{k_1, k_2, k_3, ..., k_n\}$. The calculation of scaled dot product attention involves determining weights through the dot product of keys and query 'q,' with the distribution of attention computed using (1).

$$Attention(k, q) = Softmax(s(k, q)) \quad (1)$$

2.2.1. Attention mechanism and head integration

In (2), the semantic-gain's' is employed to calculate semantic relevance between the aspect-word and context, constituting the scoring mechanism in (2):

$$s = ktanh([k_i, q_j].W_a) \quad (2)$$

This scoring mechanism is vital in the multi-head attention mechanism (MHA) computation, where eight heads are utilized for learning information across different batches. The heads, represented as $head_i$, are calculated using the attention function in (3), (4).

$$head_i = Attention(k, q) \quad (3)$$

$$MHA = (head_1 \oplus head_2 \oplus head_3 \dots \oplus head_h).W_o \quad (4)$$

The MHA function mitigates the vanishing-gradient issue by offering a more straightforward path to the inputs. Augmentation of hidden and output states with a context vector C_i , computed through (5), addresses this concern using (5).

$$C_i = \sum_{j=1}^{T_x} a_{ij} h_j \quad (5)$$

2.2.2. Attention calculation and alignment method

In (6), the attention a_{ij} for the i^{th} output, which is determined by softmax (e_{ij}). The e_{ij} values are obtained using (7), where 'f' represents the alignment method, scoring inputs surrounded by the j^{th} output at the i^{th} position. The hidden state $S_{(i-1)}$, derived from the previous time step, influences the alignment method, which can be additive, multiplicative, or a dot product, offering flexibility in computation.

$$a_{ij} = softmax(e_{ij}) = \frac{exp(e_{ij})}{\sum_{k=1}^{T_x} exp(e_{ik})} \quad (6)$$

$$e_{ij} = f(S_{i-1}, h_i) \quad (7)$$

This comprehensive transformer-encoder mechanism integrates attention, multi-head functionality, and context augmentation to effectively capture and process sequential information within various NLP tasks.

3. RESULTS AND DISCUSSION

The implementation of the presented hybrid method has been carried out in Python, utilizing the Keras deep neural-network approach for both training and testing across two phases. The evaluation of the method is performed on the SemEval 2016 restaurant dataset, and a concise overview of this dataset is provided in the subsequent section.

3.1. Dataset

This section delves into a brief explanation of the SemEval dataset, originating from five distinct challenges [18]-[20]. Opinions are classified for each term and sentence as presented in [21], serving as the foundation for training and testing of opinion terms and sentences [22]. Figure 3 provides an overview of the class distribution within the validation, testing, and training datasets.

In SemEval, the customer reviews for the restaurant dataset are categorized into three classes: neutral (NEU), positive (POS), and negative (NEG). The analysis from Figure 3 reveals an imbalance in the dataset, characterized by a substantial number of positive reviews, a smaller quantity of neutral reviews, and a moderate number of negative reviews during the training phase. This distribution pattern persists consistently in both the validation and testing datasets [23].

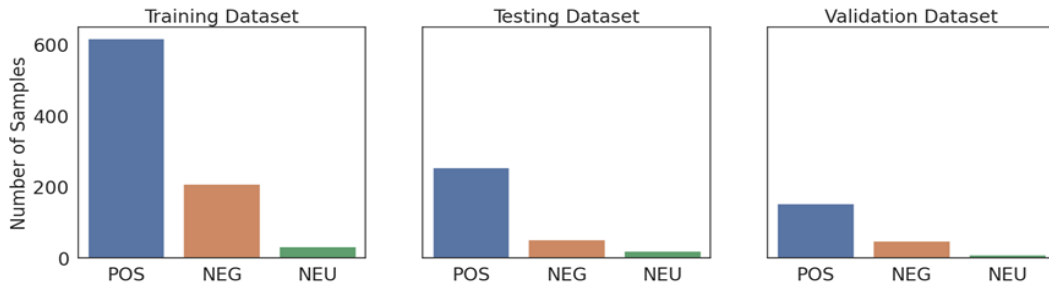


Figure 3. Sentiment class distribution in training, testing, and validation datasets

3.2. Opinion and aspect extraction: methodology for evaluation

To assess the performance of the opinion and aspect extraction, a parameter known as "exact match" is introduced. This parameter gauges the precision of the method by aligning with the specific location of opinion terms and aspects. The extraction process is conceptualized as a text extraction challenge, where the logit of the initial and ending locations of opinions and aspects serves as the output. The model is trained for 20 iterations, optimizing four cross-category entropy-loss functions. Each function corresponds to one opinion and one perspective state, focusing on the initial and ending locations within the training set. Figure 4 presents a line graph illustrating the precise match score, loss, and validation loss across the 20 iterations during both the training and validation phases.

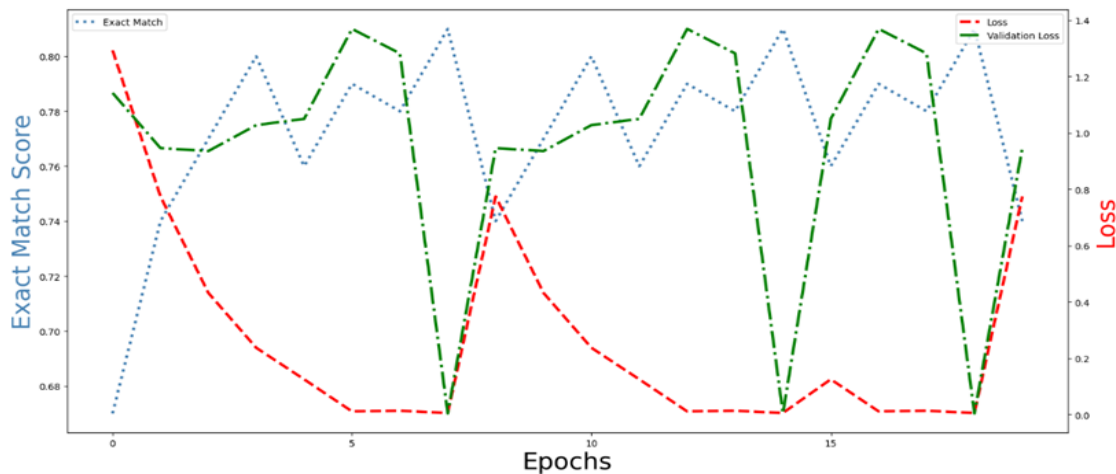


Figure 4. Exact match score, loss, and validation loss during the training phase

A comprehensive overview of the training, validation, and testing results for the four loss functions and an exact match is provided in Table 1. This evaluation framework ensures a thorough understanding of the model's performance in extracting aspects and opinions over the course of training iterations.

Table 1. Aspect and opinion extraction results for training, validation, and testing

Phase	Aspect start loss	Aspect end loss	Opinion start loss	Opinion end loss	Exact match score
Training	0.0134	0.0033	0.0142	0.0041	81%
Validation	0.0912	0.1012	0.0902	0.0972	76%
Testing	-	-	-	-	75%

3.3. Polarity classification model

Utilizing an enhanced TFBERT pre-trained method, which incorporates location and token embeddings for each opinion and aspect, along with customer review sentences or text, transformation blocks, and attention-heads, a deep neural-network has been designed for polarity classification. The model, trained with an Adam optimizer, undergoes 30 iterations to classify polarity data. The objective is to optimize accuracy while minimizing the Sparse-Categorical Cross-Entropy Loss-Function.

Upon closer examination of individual classes during testing phase, the positive review class exhibited a recall of 95%, precision of 77%, and an f-measure of 85%. In contrast, the neutral and negative review classes displayed less favorable metrics, with accuracy, recall, f-measure, and precision all falling below 50%. This highlights a significant imbalance in the dataset, comprising 210 samples for the positive class, 96 samples for the negative class, and a mere 16 samples for the neutral class in Table 2. Figure 5 provides a visual representation of the classification results for each stage. Notably, during training, most of the samples were accurately identified, resulting in a 99% precision rate. However, validating and testing the neutral class samples exhibited a 50% success rate, underscoring the challenges posed by imbalanced data.

Table 3 presents a comparative analysis between the proposed system and existing models, evaluating key metrics such as accuracy, precision, recall, and F1-score. Oudalov *et al.*, [24], the model achieved a precision of 46.96, recall of 64.24, and an F1-score of 54.21. Reported a precision of 65.65, recall of 54.28, and an F1-score of 59.42 [12]. Demonstrated a precision of 70.17, recall of 55.95, and an F1-score of 62.26 [10]. Reported an accuracy of 70.91, precision of 69.87, recall of 65.68, and an F1-score of 67.35 [25]. Additionally, [17] achieved an accuracy of 72.11, precision of 67.21, recall of 69.69, and an F1-score of 68.41. In comparison, the proposed model exhibited superior performance with an accuracy of 76, precision of 74, recall of 76, and an F1-score of 73.

Table 2. Precision, recall and f1-score metrics for testing phase

	Testing phase			
	Precision	Recall	F1-score	Support
Positive	0.77	0.95	0.85	210
Negative	0.76	0.46	0.57	96
Neutral	0.25	0.06	0.10	16
accuracy			0.76	322
macro avg	0.59	0.49	0.51	322
weighted avg	0.74	0.76	0.73	322

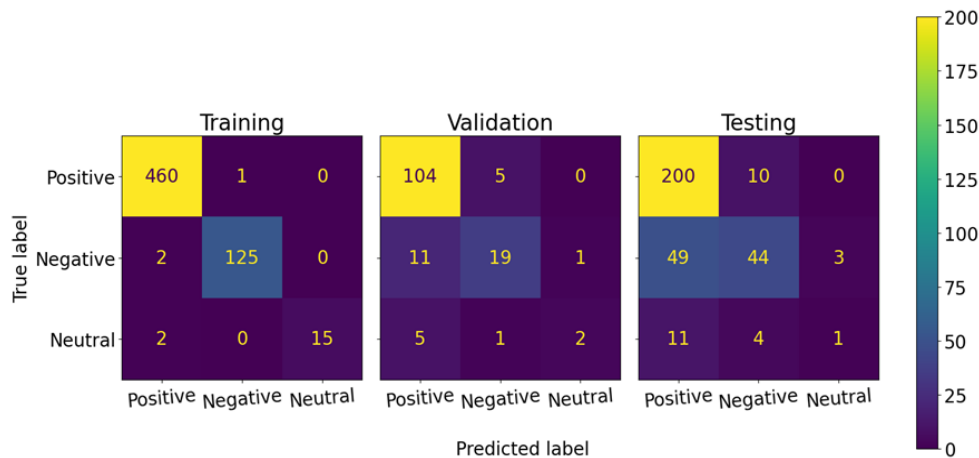


Figure 5. Confusion matrix for training, validation and testing phases

Table 3. Comparison of the existing system with proposed system

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
WhatHowWhy [23]	-	46.96	64.24	54.21
OTE-MTL [12]	-	65.65	54.28	59.42
GTS (BiLSTM) [10]	-	70.17	55.95	62.26
JET ^a (BiLSTM) [24]	58.45	63.59	50.97	56.59
JET ^o (BiLSTM) [25]	60.90	70.94	57.00	63.21
GTS (BERT) [10]	-	65.89	66.27	66.08
JET ^a (BERT) [23]	63.75	70.42	58.37	63.83
JET ^o (BERT) [23]	-	63.57	71.98	67.52
TOP [25]	70.91	69.87	65.68	67.35
ASTE-RL [17]	72.11	67.21	69.69	68.41
Proposed Model	76	74	76	73

4. CONCLUSION

This paper introduced a hybrid method for joint extraction of aspect and opinion, coupled with sentiment classification using a pipeline approach. Leveraging a Transformer-based Multi-Head Attention Network, the proposed model demonstrated promising results in extracting nuanced relationships between terms and sentences. The pipeline approach allowed for the simultaneous extraction of aspect and opinion, as well as sentiment classification, addressing the challenges posed by Aspect-Sentiment triplet extraction (ASTE). The experimental evaluations on the SemEval 2016 restaurant dataset showcased the effectiveness of the proposed method, achieving high accuracy during training. However, challenges emerged during the validation and testing phases, particularly in handling imbalanced data distribution across sentiment classes. The insights gained from this study not only contribute to the advancement of sentiment analysis methodologies but also underscore the importance of addressing data imbalances in real-world scenarios. Further research could delve into the refinement of the proposed hybrid model, exploring variations in network architectures, hyperparameter tuning, and alternative deep learning frameworks. Investigating the application of transfer learning techniques, such as leveraging pre-trained language models, could also contribute to improved performance on sentiment analysis tasks.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Vijay Rajpurohit	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sanjeev Kaulgud	✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mrutyunjaya Mathad	✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Shivamurthaiah														

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest




DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.




REFERENCES

- [1] S. Chen, Y. Wang, J. Liu, and Y. Wang, "Bidirectional machine reading comprehension for aspect sentiment triplet extraction," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 35, no. 14, pp. 12666–12674, May 2021, doi: 10.1609/aaai.v35i14.17500.
- [2] H. Dai and Y. Song, "Neural aspect and opinion term extraction with mined rules as weak supervision," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 2019, pp. 5268–5277, doi: 10.18653/v1/p19-1520.
- [3] U. Kamath, K. L. Graham, and W. Emara, "Bidirectional encoder representations from transformers (BERT)," in *Transformers for Machine Learning*, Chapman and Hall/CRC, 2022, pp. 43–70.
- [4] L. Huang *et al.*, "First target and opinion then polarity: Enhancing target-opinion correlation for aspect sentiment triplet extraction," *arXiv preprint arXiv:2102.08549*, 2021.
- [5] X. Li, L. Bing, P. Li, and W. Lam, "A unified model for opinion target extraction and target sentiment prediction," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, no. 01, pp. 6714–6721, Jul. 2019, doi: 10.1609/aaai.v33i01.33016714.
- [6] X. Li *et al.*, "Entity-relation extraction as multi-turn question answering," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 2019, pp. 1340–1350, doi: 10.18653/v1/p19-1129.
- [7] H. Peng, L. Xu, L. Bing, F. Huang, W. Lu, and L. Si, "Knowing what, how and why: a near complete solution for aspect-based sentiment analysis," *Proceedings of the AAAI Conference on Artificial Intelligence*, Apr. 2020, doi: 10.1609/aaai.v34i05.6383.
- [8] S. Poria, D. Hazarika, N. Majumder, and R. Mihalcea, "Beneath the tip of the iceberg: current challenges and new directions in sentiment analysis research," *IEEE Transactions on Affective Computing*, vol. 14, no. 1, pp. 108–132, Jan. 2023, doi: 10.1109/taffc.2020.3038167.
- [9] W. Wang, S. J. Pan, D. Dahlmeier, and X. Xiao, "Coupled multi-layer attentions for co-extraction of aspect and opinion terms," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 31, no. 1, Feb. 2017, doi: 10.1609/aaai.v31i1.10974.
- [10] Z. Wu, C. Ying, F. Zhao, Z. Fan, X. Dai, and R. Xia, "Grid tagging scheme for aspect-oriented fine-grained opinion extraction," in *Findings of the Association for Computational Linguistics: EMNLP 2020*, 2020, pp. 2576–2585, doi: 10.18653/v1/2020.findings-emnlp.234.
- [11] L. Xu, H. Li, W. Lu, and L. Bing, "Position-aware tagging for aspect sentiment triplet extraction," in *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2020, pp. 2339–2349, doi: 10.18653/v1/2020.emnlp-main.183.
- [12] C. Zhang, Q. Li, D. Song, and B. Wang, "A multi-task learning framework for opinion triplet extraction," in *Findings of the Association for Computational Linguistics: EMNLP 2020*, 2020, pp. 819–828, doi: 10.18653/v1/2020.findings-emnlp.72.
- [13] X. Li, L. Bing, P. Li, W. Lam, and Z. Yang, "Aspect term extraction with history attention and selective transformation," in *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence*, Jul. 2018, pp. 4194–4200, doi: 10.24963/ijcai.2018/583.
- [14] X. Li and W. Lam, "Deep multi-task learning for aspect term extraction with memory interaction," 2017, doi: 10.18653/v1/d17-1310.
- [15] H. Luo, T. Li, B. Liu, and J. Zhang, "DOER: dual cross-shared RNN for aspect term-polarity co-extraction," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 2019, pp. 591–601, doi: 10.18653/v1/p19-1056.
- [16] Y. Yin, F. Wei, L. Dong, K. Xu, M. Zhang, and M. Zhou, "Unsupervised word and dependency path embeddings for aspect term extraction," *arXiv preprint arXiv:1605.07843*, 2016.
- [17] S. Yu Bai Jian, T. Nayak, N. Majumder, and S. Poria, "Aspect sentiment triplet extraction using reinforcement learning," in *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, Oct. 2021, pp. 3603–3607, doi: 10.1145/3459637.3482058.
- [18] M. Pontiki, D. Galanis, J. Pavlopoulos, H. Papageorgiou, I. Androutsopoulos, and S. Manandhar, "SemEval-2014 task 4: aspect based sentiment analysis," in *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)*, 2014, pp. 27–35, doi: 10.3115/v1/s14-2004.
- [19] M. Pontiki *et al.*, "Semeval-2016 task 5: Aspect based sentiment analysis," in *Proceedings of the 10th international workshop on semantic evaluation (SemEval-2016)*, pp. 19–30, 2016.
- [20] T. Hercig, "UWB at SemEval-2018 Task 3: irony detection in english tweets," in *Proceedings of The 12th International Workshop on Semantic Evaluation*, 2018, pp. 520–524, doi: 10.18653/v1/s18-1084.
- [21] S. Chaitusaney and A. Yokoyama, "An appropriate distributed generation sizing considering recloser-fuse coordination," in *2005 IEEE/PES Transmission & Distribution Conference & Exposition: Asia and Pacific*, pp. 1–6, doi: 10.1109/tdc.2005.1546838.
- [22] Z. M. Z. Madhoushi, A. R. Hamdan, S. Zainudin, "Aspect-based sentiment analysis methods in recent years," *Asia-Pacific Journal of Information Technology & Multimedia*, vol. 8, no. 1, 79–96, 2019, doi: 10.17576/apjitm-2019-0801-07.
- [23] K. Scaria, H. Gupta, S. Goyal, S. Sawant, S. Mishra, and C. Baral, "InstructABSA: instruction learning for aspect based sentiment analysis," in *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 2: Short Papers)*, 2024, pp. 720–736, doi: 10.18653/v1/2024.naacl-short.63.
- [24] J. Z. Maitama, N. Idris, A. Abdi, L. Shuib, and R. Fauzi, "A systematic review on implicit and explicit aspect extraction in sentiment analysis," *IEEE Access*, vol. 8, pp. 194166–194191, 2020, doi: 10.1109/access.2020.3031217.
- [25] A. Oudalov *et al.*, "Novel protection systems for microgrids," 2009. <http://www.microgrids.eu/documents/688.pds>.




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