Cross-lingual Aspect-Based Sentiment Analysis

Jakub Šmíd[1]

1 Introduction

Aspect-based sentiment analysis is a natural language processing task that aims to identify the sentiment of each aspect of a product or service. Multiple sentiment elements are involved in ABSA, as shown in Figure 1.

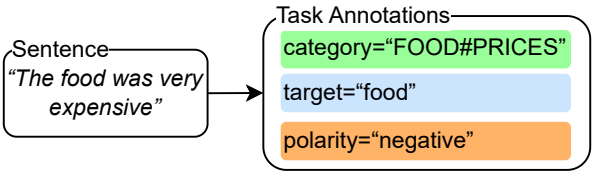

Figure 1: Example of the elements in ABSA.

Cross-lingual ABSA aims to transfer knowledge from one language to another. This work addresses zero-shot cross-lingual settings, where the model is fine-tuned only on the data from the source language and does not have access to any data from the target language.

2 Proposed Solution

This work proposes a sequence-to-sequence method that addresses multiple ABSA tasks simultaneously: target-aspect-sentiment detection (TASD), aspect term extraction (ATE), aspect category detection (ACD), and identifying (aspect category, aspect term) tuples (ACTE). ATE identifies aspect terms, ACD detects aspect categories, and TASD identifies all (aspect term, aspect category, sentiment polarity) triplets. The method transforms each sentiment triplet (c, a, p) into a natural language phrase "$P_c(c)$ is $P_p(p)$, given the expression: $P_a(a)$", where $P_z(\cdot)$ is a projection function that maps the sentiment element z from its original format to a natural language form. Figure 2 shows an example of the input and target construction.

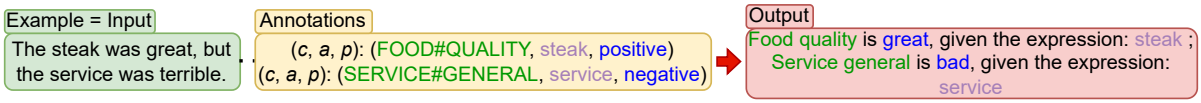

Figure 2: Example of the output construction from the input and annotations.

This work also introduces a method for classifying the sentiment polarity of aspect terms and categories. Both proposed methods can be used with prompting and traditional fine-tuning. Prompting encourages a pre-trained model to make specific predictions by providing a prompt specifying the task to be done.

[1] student of the master degree program Software Engineering, field of study Computer Science and Engineering, specialization Natural Language Processing, e-mail: biba10@students.zcu.cz

3 Achieved Results

The proposed methods were evaluated using multiple Transformer-based models, outperforming previous state-of-the-art results on benchmark datasets in multiple languages. Table 1 shows the best results achieved.

Lang	ACD	ATE	ACTE	TASD	Polarity
cs-en	79.46 (87.20)	73.80 (86.85)	63.34 (79.12)	58.22 (73.59)	91.06 (95.01)
es-en	80.76 (87.20)	72.50 (86.85)	62.70 (79.12)	58.60 (73.59)	93.08 (95.01)
fr-en	84.73 (87.20)	77.70 (86.85)	70.02 (79.12)	64.95 (73.59)	93.91 (95.01)
nl-en	79.67 (87.20)	67.14 (86.85)	59.28 (79.12)	53.86 (73.59)	92.77 (95.01)
ru-en	81.00 (87.20)	76.40 (86.85)	67.10 (79.12)	62.50 (73.59)	93.60 (95.01)
tr-en	77.33 (87.20)	64.46 (86.85)	52.87 (79.12)	52.87 (73.59)	92.30 (95.01)
en-cs	80.21 (85.45)	69.20 (84.80)	59.32 (74.99)	52.57 (67.30)	89.99 (88.59)
en-es	78.60 (85.53)	71.95 (80.66)	60.65 (72.38)	56.61 (68.03)	93.00 (94.29)
en-fr	78.19 (80.77)	74.44 (80.38)	61.52 (67.70)	53.21 (60.56)	86.67 (90.31)
en-nl	78.37 (81.43)	64.94 (81.16)	59.13 (70.33)	54.70 (64.17)	91.32 (91.55)
en-ru	83.26 (86.79)	66.98 (81.88)	61.16 (75.00)	55.22 (68.61)	90.44 (91.30)
en-tr	82.15 (83.31)	57.50 (71.95)	46.38 (60.92)	42.86 (54.40)	93.43 (93.78)

Table 1: The best achieved micro F1 scores in percentages for each task and language combination, with the monolingual results for a given target language in parentheses.

In the sequence-to-sequence method, the mT5 model (Xue et al., 2021) achieves the best overall results when used with prompting, significantly improving the performance. The cross-lingual results are promising, often within 5 to 15% of the monolingual results, depending on the specific task and the combination of source and target languages. The cross-lingual results for sentiment polarity classification are excellent, often within 2% of the monolingual results.

4 Conclusion

This work proposes methods for solving ABSA tasks that can be used with prompting and traditional fine-tuning. The sequence-to-sequence method can address multiple ABSA tasks simultaneously. Our proposed methods achieve new state-of-the-art results on benchmark datasets in multiple languages. Prompting is especially effective for the sequence-to-sequence method when used with the mT5 model. The cross-lingual results are promising, often within a few per cent of monolingual results. Overall, this work significantly contributes to the cross-lingual ABSA field.

5 Acknowledgment

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References

Xue, L., Constant, N., Roberts, A., Kale, M., Al-Rfou, R., Siddhant, A., Barua, A., & Raffel, C. (2021). MT5: A massively multilingual pre-trained text-to-text transformer. *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 483–498.