quality is crucial for improving the upper TBSA task and our OE component can serve as a simple but effective solution. Besides, we find that maintaining sentiment consistency within the same target mention, especially for whose with several words (e.g., "*portobello and asparagus mole*" in the last input), is difficult for the "Base model" and "Base model+**BG**", while our "Full model" alleviates this issue by employing the SC component to make predictions based on the features from the current and the previous time step.

Impact of ϵ and s Here, we investigate the impacts of the maximum proportion ϵ of the boundary-based scores and the window size s on the prediction performance. Specifically, the experiments are conducted on the development set of $\mathbb{D}_{\mathrm{R}}$, the largest benchmark dataset. We vary ϵ from 0.3 to 0.7, increased by 0.1, and two extreme values 0.0 and 1.0 are also included. The range of the window size s is 1 to 5. According to the results given in Figure 2, we observe that the best results are obtained at ϵ=0.5. The ϵ value basically affects the importance of the sentiment scores from the BG component in the final tagging decision and 0.5 is a good trade-off between absorbing boundary information and eliminating noises. We also observe that a moderate value of s (i.e., s = 3) is the best for the TBSA task, probably because too large s may enforce the model to attend the larger context and increase the possibility of associating with irrelevant opinion words, on the other hand, too small s is likely not sufficient to involve the potential opinion words.

Related Works

As mentioned in Introduction, Target-based Sentiment Analysis are usually divided into two sub-tasks, namely, the Opinion Target Extraction task (OTE) and the Target Sentiment Classification (TSC) task. Although these two subtasks are treated as separate tasks and solved individually in most cases, for more practical applications, they should be solved in one framework. Given an input sentence, the output of a method should contain not only the extracted opinion targets, but also the sentiment predictions towards them. Some previous works attempted to discover the relationship between these two sub-tasks and gave a more integrated solution for solving the complete TBSA task. Concretely, (**?**) employed Conditional Random Fields (CRF) together with hand-crafted linguistic features to detect the boundary of the target mention and predict the sentiment polarity. (**?**) further improved the performance of the CRF based method by introducing a fully connected layer to consolidate the linguistic features and word embeddings. However, they found that a pipeline method can beat both of the model with joint training and the unified model. In this paper, we reexamine the task, and proposed a new unified solution which outperforms all previous reported methods.

Conclusions

We investigate the complete task of Target-Based Sentiment Analysis (TBSA), which is formulated as a sequence tagging problem with a unified tagging scheme in this paper. The basic architecture of our framework involves two stacked LSTMs for performing the auxiliary target boundary detection and the complete TBSA task respectively. On top of the base model, we designed two components to take the advantage of the target boundary information from the auxiliary task and maintain the sentiment consistency of the words within the same target. To ensure the quality of the boundary information, we employ an auxiliary opinion-based target word detection component to refine the predicted target boundaries. Experimental results and case studies well illustrate the effectiveness of our proposed framework, and a new state-of-the-art result of this task is achieved. We publicly release our implementation at `https://github.com/lixin4ever/E2E-TBSA`.

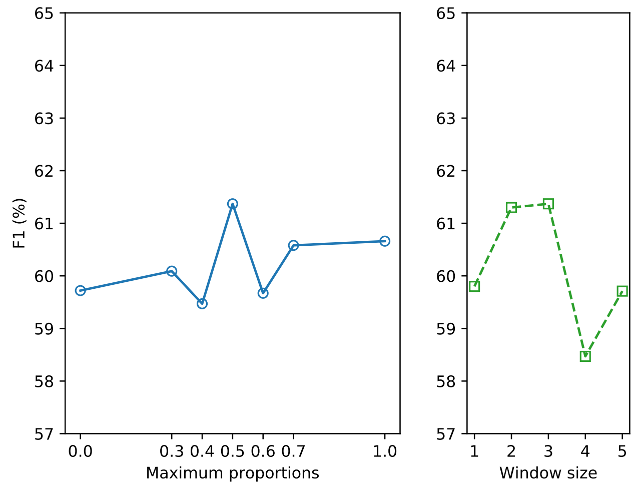

Figure 2: F1 scores (%) on the development set of $\mathbb{D}_{\mathrm{R}}$ with different ϵ and s values.

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