A Hybrid Approach for Aspect-Based Sentiment Analysis Using Hierarchical Attention

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Sentiment analysis is a solution proposed to deal with the overwhelming number of opinionated texts available online by extracting opinions or sentiments at a level of documents, sentences, or aspects. Among all the level of granularities, aspect-based sentiment analysis (ABSA) is the most complex task and the focus of our work. The proposed solution relies on the hybrid approach introduced by Wallaart and Frasincar (2019) that combines a domain ontology and a neural network. In our work, we aim to increase the flexibility and performance of the baseline method in modeling the input data by including the rotatory attention of the neural network into a hierarchical architecture.

The employed domain ontology is manually created based on a set of hierarchical structured concepts that assigns either negative or positive sentiments to the aspects. If the domain ontology is inconclusive (no sentiment or conflicting sentiment prediction), the neural network is used as backup.

The baseline model used as backup is a Left-Center-Right Separated Neural Network with Multiple Rotatory Attention. Given an aspect at the sentence level, the model reduces the dimensionality of the sentence with n word embeddings to only four vector representations associated with the left and right contexts of the aspect, and the aspect itself (with respect to the left and right contexts). The main disadvantage of the baseline model is that the four vector representations are computed using only local information. Our solution for this shortcoming is to create a hierarchical architecture with extra attention layers that update each of the four vectors with an importance score computed at the sentence level. The newly obtained vectors are used as input for the final sentiment prediction.

We define the hierarchical attention by means of four methods. The first two methods introduce the attention weighting either on the final or on the iteration-level four vectors of the rotatory attention. The third method is similar to the first method but separately applies the attention weighting on the final two context vectors and two aspect vectors. The fourth combines the second and the third method and separately applies the attention weighting on the context and aspect vectors of each iteration of the rotatory attention.

Given the SemEval 2015 and 2016 restaurants datasets, we notice that the fourth method is the best option to tackle hierarchical attention, boosting the testing accuracy of the baseline model with 0.6 and 0.3 percentage points, respectively, when using BERT word embeddings. To explain why the hierarchical attention is able to provide better results, we randomly select a sentence within a restaurant review with two aspects with different sentiments (Fig. 1). We consider the aspect “atmosphere” as the sentiment target, and the intensity of the blue colour as a relevance indicator based on the attention weights. Given that the simple rotatory attention of the baseline model considers that words like “cozy”, “horrible”, and also “service” (the second aspect of the sentence) are relevant, the model assigns a wrong sentiment prediction to the target “atmosphere”. On the other hand, the hierarchical attention does not assign a high attention score to the aspect “service” and helps the model to provide the correct prediction.

Figure 1: Context vectors with and without hierarchical attention.

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