Aspect-Based Sentiment Analysis

Kartikeya Sharma*
Indian Institute of Technology, Delhi
2015CS10234
`cs1150234@iitd.ac.in`

Navreet Kaur*
Indian Institute of Technology, Delhi
2015TT10917
`tt1150917@iitd.ac.in`

Abstract

Recently, there has been an increase in the number of review websites for various products and services. Often, these reviews are accompanied by a subjective score given by the reviewer. However, this score is often not sufficient to understand the review completely. Mining opinions from reviews about specific entities and their aspects can help consumers decide what to purchase and businesses to better monitor their reputation and understand the needs of the market. Our work aims to provide a framework to decompose the review score into various aspects and assign them individual scores, for which we aim to use a simple CNN model followed by clustering and sentiment analysis.

1 Introduction

Reviews on products on various internet websites usually take the form of a review text accompanied by a review score. One major problem with such reviews is that the score often takes into account many factors the review is based on, and the overall review score fails to highlight these factors individually. To illustrate, reviews for a restaurant on a listing site such as Zomato often take into account various elements (from here on referred to as 'aspects') such as food, service, ambience and so on, however they list a single review score. For example, in the sentence *"The food at this restaurant is incredible but the ambience is terrible"*,'food' and 'ambience' are aspects. Our work aims to decompose a review into its constituent aspects, and provides a framework for decomposing the score into individual scores for these aspects.

Aspect extraction is an important task in Natural Language Processing and has been studied by several earlier works. Any approach for aspect extraction and sentiment analysis needs to keep into consideration two factors: simplicity of the model, so that it may be used on resource-limited devices without much processing power and automatic feature extraction, which is always preferred in NLP.

To address these concerns, we plan on using a shallow convolutional neural network model (DE-CNN) as proposed in Hu Xu et al., 2018 to get the potential aspect words in a review. We would then use a clustering algorithm to cluster these aspects into a few global categories. For example, "service", "staff" and "hospitality" could all fall in the same cluster. We refer this as 'Aspect Categorization'. We then plan on assigning a sentiment score to these aspect categories such that the combination of scores of all aspect categories is consistent with the total review score. In the next section, we describe our model in a more detailed manner and list down the contributions we propose to make.

2 Model

Our model is implemented in two stages: **(1) Aspect Extraction, (2) Aspect Categorization and Sentiment Analysis**. Given a review, we summarize it by outputting polarities of particular fixed aspects. For example, for this review: *'It's a nice place to relax and have conversation..But the food was okay, nothing great'*, the model should output {AMBIENCE: *Positive*, FOOD: *Negative*, SERVICE: *Neutral*}.

2.1 Proposed Contributions

We propose to make the following contributions:

- Reproduce the results of DE-CNN [Hu Xu et al.,2018] and improve the existing model for Aspect Extraction. For this, we use the code provided by the authors on github and datasets mentioned in Section 3.1.

*equal contribution

Figure 1: Aspect Sentiment Table for 'Apple Mac Mini' as Target of Interest [source]

- Explore the effect of different pooling aggregation functions in DE-CNN on aspect extraction task.
- Clustering the extracted aspects into a few number of aspect categories that describe the overall review.
- For each review, summarize the review by assigning sentiment polarity to each aspect category.
- Scrape Zomato reviews and demonstrate the working of our model which, when given a restaurant, outputs an aspect sentiment table for the same, as in Figure 1 which shows the results on the laptop domain.

For Aspect Extraction, we use a double embedding and CNN-based neural network as used by Hu Xu et al., 2018, as shown in Figure 2. Here, the first two layers are embedding layers, one for general purpose embeddings and one for domain specific embeddings. The next part of the network consists of convolution layers followed by an MLP which gives the desired aspects as output. It does so by tagging each input word as start/end of an aspect or as a non-aspect word. Next, we plan to use the embeddings of the extracted aspect words to cluster them into more coarse level categories. For each target of interest, for example, a particular restaurant or laptop, we plan to combine all the reviews to produce an aspect sentiment table.

2.2 Baseline

For comparing our results on the aspect extraction task, we use the following baselines:

- CRF (Pennington et. al., 2014)
- IHS RD (Chernyshevich, 2014)
- NLANGP (Toh and Su, 2016)

For the task of sentiment analysis, we use the baseline provided by *SemEval-2016 Task 5* for subtask 1 (Sentence-level Aspect-Based Sentiment Analysis), slot 3 (Sentiment Polarity).

3 Experiments

3.1 Datasets

For the task of reproducing the results of Hu Xu et al., 2018, we use the laptop domain dataset from subtask 1 of *SemEval-2014 Task 4* and restaurant domain dataset from subtask 1, slot 2 of *SemEval-2016 Task 5*, same as used for original DE-CNN evaluation.

For the purpose of extending the model, we plan to conduct our experiments on two benchmark datasets: one from laptop domain and other from restaurant domain on subtask-1, slot-2 and 3 (Opinion Target Expression and Sentiment Polarity) of *SemEval-2016 Task 5*. These datasets contain review sentences annotated with the aspect terms and their polarities. We follow the same pre-processing pipeline followed by Hu Xu et al., 2018. We use GloVE (Pennington et. al., 2014) pre-trained embedding for the general-purpose embedding and train the domain-specific emebedding using fastText (Bojanowski et al., 2016).

3.2 Evaluation Metrics

For the Aspect Extraction task, we use F1-score as the evaluation metric. Since the clustering is unsupervised, we measure clustering quality as follows: we compare the annotated data, which maps each aspect term to an aspect category (for example, 'decor' aspect term belongs to 'ambience' cat-

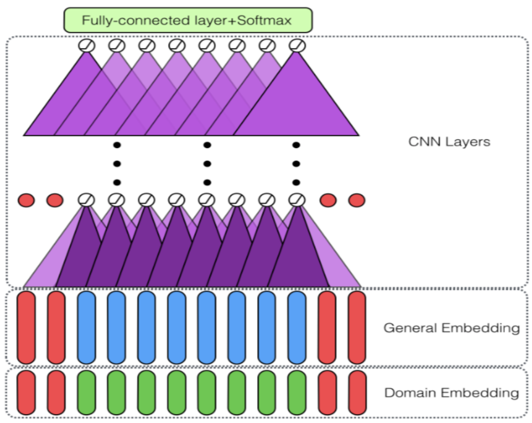

Figure 2: DE-CNN model [Hu Xu et al.,2018]

egory) to the clustering output and count the number of aspect pairs which are in the same cluster in the annotated data but are in different clusters in the output of the clustering algorithm and use this as our error metric. We use accuracy and mean-squared-error to evaluate the aspect sentiment polarity table.

References

Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation , volume 1.In *Proceedings of the 2014 confer- ence on empirical methods in natural language processing (EMNLP)*, pages 1532 - 1543.

Maryna Chernyshevich. 2014. Ihs r&d belarus: Cross-domain extraction of product features using crf. In *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)*, pages 309 - 313.

Zhiqiang Toh and Jian Su. 2016. Nlangp at semeval-2016 task 5: Improving aspect based sentiment analysis using neural network features. In *Proceedings of the 10th international workshop on semantic evaluation (SemEval-2016)*, pages 282 - 288.

Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2016. Enriching word vectors with subword information. *arXiv preprint arXiv:1607.04606.*

Hu Xu, Bing Liu, Lei Shu and Philip S. Yu. 2018. Double Embeddings and CNN-based Sequence Labeling for Aspect Extraction. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics*, pages 592 - 598.