Double Policy Network for Aspect Sentiment Triplet Extraction (Student Abstract)

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Abstract

Aspect Sentiment Triplet Extraction (ASTE) is the task to extract aspects, opinions and associated sentiments from sentences. Previous studies do not adequately consider the complicated interactions between aspect and opinion terms in both extraction logic and strategy. We present a novel Double Policy Network with Multi-Tag based Reward model (DPN-MTR), which adopts two networks ATE, TSOTE and a Trigger Mechanism to execute ASTE task following a more logical framework. A Multi-Tag based reward is also proposed to solve the limitations of existing studies for identifying aspect/opinion terms with multiple tokens (one term may consist of two or more tokens) to a certain extent. Extensive experiments are conducted on four widely-used benchmark datasets, and demonstrate the effectiveness of our model in generally improving the performance on ASTE significantly.

Introduction

ASTE was a task of extracting aspect terms, corresponding opinions and sentiment polarity, which was proposed in 2020(Peng et al. 2020). Earlier studies have achieved great progress, but most of the adopted methods are similar to relation extraction, treating aspect and opinion as two parallel entities and extracting them simultaneously (Peng et al. 2020; Xu et al. 2020; Wu et al. 2020; Mukherjee et al. 2021; Yu Bai Jian et al. 2021; Xu, Chia, and Bing 2021). BMRC (Chen et al. 2021) is the most recent research to take aspect and opinion extraction as two separate sub-tasks. However, the limitation is that it could not extract timely aspect-based context embedding for detecting opinions. This many cause error cases that wrong interactions are detected between irrelevant aspects and opinions.

In this paper, we propose a novel Double Policy Network with Multi-Tag based Reward model (DPN-MTR) to address the challenges. An upper-level policy network is designed as the main task to realize Aspect Term Extraction (ATE), a lower-level policy network is taken as a subordinate task for Target State oriented Opinion Term Extraction (TSOTE). A trigger mechanism is designed between upper and lower-level to extract and transfer immediate context based evidence. A novel Multi-Tag based Reward are designed to overcome the limitation for identifying aspect/opinion with multiple tokens. The code of this work is publicly available at https://github.com/lixt47/DPN-SR.

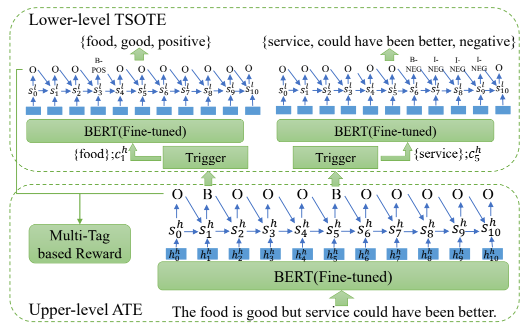

Figure 1: An Example of Double Policy Network

Method

In Figure 1, the DPN-MTR model decomposes the ASTE task into two level policy networks: an upper-level ATE and a lower-level TSOTE. For the ith sentence $x_i = \{w_{i,1}, ..., w_{i,n}\}$, where $w_{i,j}$ is the jth token in the sentence, x_i is encoded into a hidden vector h_i by a pre-trained BERT. h_i is then fed into upper (h_i^h) and lower (h_i^l) level networks separately. The output are the sentiment triplets $y = \{(t, o, p)\}$ extracted from x_i. t is the aspect, o is the opinion and p is the sentiment polarity $\{+1, 0, -1\}$.

ATE Main Task in Upper-level: ATE can extract all aspects in a sentence, which is regarded as a sequence labeling task. We employ a BIO tagging scheme for locating aspects. For token $w_{i,j}$ at position j in sentence x_i, the state s_j^h in the main task is determined by: the current hidden vector h_j^h; the action embedding $\hat{a}_j^h$; the learnable embedding p_j^h of the part-of-speech (POS) tag of token $w_{i,j}$ getting from spaCy (https://spacy.io/); and the previous state s_{j-1}^h.

$$s_j^h = \tanh(W_s^h[h_j^h; \hat{a}_j^h; p_j^h; s_{j-1}^h]) \tag{1}$$

A labeling layer μ^h is proposed to calculate distribution of action a_j^h:

$$\mu^h(a_j^h|s_j^h) = softmax(W_\mu^h s_j^h) \tag{2}$$

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	14lap			14res			15res			16es		
Model	P	R	F1	P	R	F1	P	R	F1	P	R	F1
WhatHowWhy(Peng et al. 2020)	37.38	50.38	42.87	43.24	63.66	51.46	48.07	57.51	52.32	46.96	64.24	54.21
JET(Xu et al. 2020)	55.39	47.33	51.04	70.56	55.94	62.40	64.45	51.96	57.53	**70.42**	58.37	63.83
GTS(Wu et al. 2020)	57.12	53.42	55.21	71.76	59.09	64.81	54.71	55.05	54.88	65.89	66.27	66.08
PASTE(Mukherjee et al. 2021)	59.7	55.3	57.4	66.7	66.5	66.6	63.6	59.8	61.6	66.1	69.8	67.9
BMRC(Chen et al. 2021)	**65.91**	52.15	58.18	72.17	65.43	68.64	62.48	55.55	58.79	69.87	65.68	67.35
ASTE-RL(Yu Bai Jian et al. 2021)	64.80	54.99	59.50	70.60	68.65	69.61	**65.45**	60.29	62.72	67.21	69.69	68.41
Span-ASTE(Xu, Chia, and Bing 2021)	63.44	55.84	59.38	**72.89**	70.89	71.85	62.18	64.45	63.27	69.45	71.17	70.26
Ours	61.45	**59.30**	**60.36**	69.60	**77.16**	**73.19**	61.84	**70.52**	**65.90**	64.66	**79.38**	**71.27**

Table 1: Results on the development and test set of the ASTE task

Trigger Mechanism Once the main task has successfully extracted an aspect, it will invoke a trigger mechanism to extract context vector c_j^h of the extracted aspect, and transfer it to the lower-level subordinate task.

$$c_j^h = tanh(W_g^l s_{\hat{j}}^h) \quad (3)$$

TSOTE in Lower-level: When the TSOTE subordinate task has received the context vector c_j^h, it will extract all the corresponding opinions and classify an immediate sentiment polarity. We use a unified tagging scheme TSO to locate opinion terms. For a new token $w_{i,k}$ at position k in sentence x_i, state s_k^l in subordinate task is determined by: the current hidden state h_k^l; the action vector $\hat{a}_k^l$; the learnable embedding p_k^l of current POS tag; the previous state s_{k-1}^l. A labeling layer π^l is proposed to calculate action a_j^h:

$$s_k^l = \tanh(W_s^l[h_k^l; \hat{a}_k^l; p_k^l; s_{k-1}^l; c_j^h]) \quad (4)$$

$$\pi^l(a_k^l|s_k^l) = softmax(W_\pi^l s_k^l) \quad (5)$$

Multi-Tag based Reward (MTR): We designed a Multi-Tag based Reward mechanism that provides a reward after the whole sentence has been labeled, defined as follows:

$$rmt^h = \sum_{i^a}^{A} sgn(for\ k\ in\ K : a_{i^a-k}^h = t_{i^a-k}^h) + N \times F1_{ATE} \quad (6)$$

$$rmt^l = \sum_{i^o}^{O} sgn(for\ k\ in\ K : a_{i^o-k}^l = o_{i^o-k}^l) + N \times F1_{ASTE} \quad (7)$$

where i^a/i^o is the end position of an aspect/opinion term, A/O indicates the sets of aspect/ opinion terms. K is the true length of the extracted aspect or opinion terms. $F1_{ATE}$ and $F1_{ASTE}$ are the F1 score metric of ATE and ASTE tasks. This method can make an average 3% improvement compared with traditional aspect/opinion detection strategies.

Experiments

We compare our model with seven baselines in Table 1 on ASTE-Data-V2 dataset(Xu et al. 2020) and 14res, 15res, 16res are the data of the restaurant domains and 14lap is of the laptop domain. Elements in bold are the best results and those with underlines are second-best. Experimental results show that the proposed model outperforms the state-of-the-art baselines significantly. Each component can make significant positive contributions towards model performances.The running efficiency is also very competitive.

Conclusion

The research proposes a novel DPN-MTR model to address the main limitation of existing studies, which don't adequately consider the complicated interactions between aspect and opinion extraction. DPN-MTR adopts Double Policy Networks with Trigger Mechanism to extract aspects and opinions from sentences following a more logical framework. Experimental results exhibit the advantages of the proposed model. In the future, we will focus on further improving the generalization ability and robustness of the model.

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