Back to Reality: Leveraging Pattern-driven Modeling to Enable Affordable Sentiment Dependency Learning

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Abstract
Aspect-based Sentiment Classification (ABSC) is a challenging sub-task of traditional sentiment analysis. Due to the difficulty of handling potential correlations among sentiment polarities of multiple aspects, i.e., sentiment dependency, recent popular works tend to exploit syntactic information guiding sentiment dependency parsing. However, syntax information (e.g., syntactic dependency trees) usually occupies expensive computational resources in terms of the operation of the adjacent matrix. Instead, we define the consecutive aspects with the same sentiment as the sentiment cluster in the case that we find that most sentiment dependency occurs between adjacent aspects. Motivated by this finding, we propose the sentiment patterns (SP) to guide the model dependency learning. Thereafter, we introduce the local sentiment aggregating (LSA) mechanism to focus on learning the sentiment dependency in the sentiment cluster. The LSA is more efficient than existing dependency tree-based models due to the absence of additional dependency matrix constructing and modeling. Furthermore, we propose differential weighting for aggregation window building to measure the importance of sentiment dependency. Experiments on four public datasets show that our models achieve state-of-the-art performance with especially improvement on learning sentiment cluster.

Introduction
In order to solve the absence of explicit sentiment information of some aspects in the context, recent studies on ABSC (Pontiki et al. 2014) began to focus on the parsing of sentiment dependency among aspects. For example, The laptop’s storage is large, so does the battery capacity, the customer praised both storage and battery capacity, while no direct sentiment description of battery capacity is available in the review. The methods capable of dependency learning can be approximately categorized into the topological structure-based dependency parsing methods (Zhang, Li, and Song 2019a; Huang and Carley 2019), and syntax tree distance-dependent methods (Phan and Ogunbona 2020). Meanwhile, some works adopt hybrid dependency modeling strategies to enhance the model’s ability to learn sentiment dependency. However, due to the additional startup time and expensive resources occupation of dependency tree learning, they are not the ideal solutions for dependency learning in long texts, especially texts with multi-aspects. Fig 1 shows the brief comparisons between the dependency-tree based models and non-dependency-tree based model†.

Those dependency tree-based methods generally employ the graph convolution network (GCN) and attention mechanism (Bahdanau, Cho, and Bengio 2014) to model the sentiment dependency. There are diversities of attention mechanisms proposed in the previous research (Wang et al. 2016; Ma et al. 2017), e.g., multi-grained attention (Zhang, Li, and Song 2019a) and multi-head attention (Vaswani et al. 2017). These works ignore the efficiency drawback of syntax tree handling. With the development of pre-trained models (PTMs), researchers began to propose methods based on PTM (e.g., BERT). Those methods based on PTMs achieve promising performance, indicating that PTMs may learn the potential sentiment dependencies. Scholars have recognized that the sentiment polarity of the target aspect is highly related to its local context, and considerable improvements have been obtained by integrated modeling between the local context and the global context (Yang et al. 2021; Phan and Ogunbona 2020). Moreover, the local context feature can be easily adapted to enhance various models.

Table 1: The average resources occupation of popular ABSC models. “P.T.”, “T.T.” and “A.S.” indicate the data processing time, training time in 10 epochs and additional storage requirement. * indicates the non-dependency based models, and † indicates our models.

| Models            | Laptop14 | Restaurant14 |
|-------------------|----------|--------------|
|                   | P.T. (sec) | T.T. (sec) | A.S. (kb) | P.T. (sec) | T.T. (sec) | A.S. (kb) |
| BERT-BASE  *      | 1.62     | 221.24      | 0         | 3.17       | 351.52     | 0         |
| LCF-BERT  *       | 2.89     | 612.72      | 0         | 3.81       | 1513.62    | 0         |
| ASGCN-BERT        | 13.29    | 273.12      | 7054      | 19.52      | 413.86     | 9457      |
| RGAT-BERTX        | 35421.51 | 212.41      | 157444    | 40094.46   | 335.56     | 188340    |
| LSA-T  †          | 3.16     | 233.56      | 0         | 4.32       | 391.83     | 0         |
| LSA-S  †          | 20.56    | 259.52      | 0         | 30.23      | 414.25     | 0         |

Our study shows that sentiment dependency usually exists in the sentiment cluster, which implies the possibility of fast modeling of sentiment dependency. We exploit

†The experiments are performed on RTX 2080 GPU, AMD R5-3600 CPU with PyTorch 1.9.0. The original size of the Laptop14 and Restaurant14 datasets are 336kb and 492kb, respectively.
this finding by introducing sentiment patterns (SP) to improve ABSC. Meanwhile, we propose a sentiment dependency learning framework based on the local sentiment aggregating mechanism. The LSA handles the sentiment dependency within the aggregation window (AW), avoiding the participation of tree and graph structures. The AW is composed of aspect-emphasized context features, e.g., the features learned using the BERT-SPC input format. But we propose the embedding-based local context focus (ELCF) to build the aggregation window due to its effectiveness. There are different implementation of the ELCF feature extraction, i.e., token-distance based method (Zeng et al. 2019) and syntax-based distance (Phan and Ogunbona 2020). Besides, we propose differential weighting for window components to enhance our models. The experimental results show the proposed model outperforms previous models. There are other methods based on diversities of attention mechanisms (Tang et al. 2016, Chen et al. 2017, Tay, Tuan, and Hui 2018, Lin, Yang, and Lai 2019) and syntactic dependency trees. Phan and Ogunbona (2020) propose the ATAE-LSTM which employs the attention mechanism to emphasize the key context features. The ELCF outperforms the LCF and is more stable.

2 The embedding-based local context focus is proposed to enhance the LCF mechanism. The ELCF avoids calculating and dumping context weights and embeds the distances between aspect and context words to extract local context features. The ELCF outperforms the LCF and is more stable.

3 The differential weighting strategy for AW building is proposed to enhance LSA. And the experimental results show that the influence of sentiment information from different directions in the AW is different.

4 We study the effectiveness of simplified AW and conduct ablation experiments to evaluate the performance of simplified AW. Besides, we discuss the pros and cons of LSA and the dependency tree-based models.

Related Works

Existing popular ABSC methods can be divided into methods based on classic attention mechanisms, methods based on dependence, and methods based on pre-trained models. And some works could be classified into multiple categories.

Attention-based Methods

Wang et al. (2016) propose the ATAE-LSTM which employs the attention mechanism to emphasize the key context containing important sentiment information. In order to explore the relatedness between aspects and context, Ma et al. (2017) propose an LSTM-based model based on a novel interactive attention mechanism and achieves hopeful performance. Instead of only using the classical coarse-grained attention, Fan, Feng, and Zhao (2018) propose pairs of fine-grained attention mechanisms accompanied with coarse-grained attention, and the proposed model significantly outperforms the previous models. There are other methods based on diversities of attention mechanisms (Tang et al. 2016, Chen et al. 2017, Tay, Tuan, and Hui 2018, Lin, Yang, and Lai 2019) and syntactic dependency trees. Phan and Ogunbona (2020) propose the BERT-based models and exploit dependency trees to learn sentiment information. Instead of directly modeling dependency tree, the GCN is able to model topological relation and obtains promising performance. Meanwhile, some methods (He et al. 2018, Zhang, Li, and Song 2019b) exploit the dependency tree to measure the distance between aspect and context words, those methods avoid modeling the dependency tree directly and have better efficiency.

PTM-based Methods

The pre-trained models prompt the development of ABSC. BERT is one of the first pre-trained models to be applied in ABSC, which achieves exciting performance by fine-tuning without any model modification (Xu et al. 2019). Rietzler et al. (2019) argue that besides fine-tuning, domain adaption of BERT on target corpus could make a great improvement for ABSC. Zhao, Hou, and Wu (2020) and Wang et al. (2020) propose the BERT-based models and exploit dependency trees to learn sentiment information. Instead of directly modeling dependency tree, the GCN equipped with an attention mechanism to learn dependency trees, because the GCN is able to model topological relation and obtains promising performance. Meanwhile, some methods (He et al. 2018, Zhang, Li, and Song 2019b) exploit the dependency tree to measure the distance using syntactical information to guide the model to learn the ELCF feature and obtain considerable results.

Methodology

Fig. 3 shows the main architecture of the LSA framework. The LSA-based model uses BERT to learn the ELCF features of all provided aspects, and the aggregation window travels upon the ELCF features of adjacent aspects. We concatenate the global context feature and aggregation window feature to predict aspect polarity in case of potential loss of sentiment information outside the aggregation window.

Preliminaries

Fig. 1 shows an example of aspect-based sentiment classification, where “atmosphere”, “food” and “service” contain positive sentiment, while “dinner” and “drink” contain neutral sentiment. In ABSC, there are not only multiple aspects with different sentiment polarities, but also the polarity between each aspects may be dependent or even contradictory.
Figure 1: Dependency-based context example parsed from a real restaurant review. The colored words are tokens from aspect terms, and the arrowed lines indicate the dependency relations.

Figure 2: Visualization of sentiment cluster and sentiment coherency.

Sentiment Pattern
Inspired by existing works (Zhang, Li, and Song 2019a; Zhao, Hou, and Wu 2020) which proved sentiment polarity between aspects is not always independent, we introduce sentiment pattern (SP), i.e., the underlying empirical principles of organization of sentiment polarities, to help the model to learning sentiment dependency. Precisely modeling for sentiment patterns may be difficult, we can develop our model under the guidance of SP. We propose two sentiment patterns in this paper and prove our arguments by experiment analysis.

Sentiment Cluster  The aspects containing similar sentiment polarity tend to cluster as shown in Fig 2. As users generally organize the opinions of aspects before giving the review, it is intuitive to realize that users tend to cluster the aspects according to the polarity category. i.e., SP1. Table 2 show the number of sentiment clusters with different sizes in the four public datasets.

Table 2: The number of sentiment clusters with different sizes.

| Datasets    | Cluster Size | 1  | 2  | 3  | 4  | ≥ 5 | All |
|-------------|--------------|----|----|----|----|-----|-----|
| Laptop14    |              | 1616| 400| 112| 34 | 12  | 2174|
| Restaurant14|              | 2121| 681| 258| 71 | 33  | 3164|
| Restaurant15|              | 1056| 203| 56 | 23 | 3   | 1341|
| Restaurant16|              | 1415| 281| 74 | 32 | 6   | 1808|

Sentiment Coherency  Sentiment polarities of multiple aspects are possible to subject to the sentiment coherency as shown in Fig 2. In the case of heuristic thinking, users are probably to bring up an aspect that has the same polarity as pre-commented aspects for any thinking pause. The pattern of sentiment coherency can be classified into global and local coherency. We design our model referring to the local sentiment coherency. i.e., SP2.

Local Sentiment Information Aggregation
The local sentiment aggregating mechanism is based on SP1 and SP2. The implementation of LSA depends on the aspect-oriented context feature, e.g., ELCF features or other aspect emphasized features. We construct the aggregation window using ELCF features of adjacent aspects, i.e., the k-th (k = 1 is used in this paper) left- and right-adjacent aspects are adopted to build the aggregation window. The calculation of local context can be classified into the token distance-based method and syntax distance-based method. In this paper, we adopt both methods to extract ELCF features and construct the aggregation window. i.e., LSA-T (token distance-based ELCF features) and LSA-S (syntax distance-based ELCF features), respectively.

Token Distance-based Local Context
Token distance-based local context is calculated using the distance of token-aspect pairs. Assume $W^c = \{w^c_1, w^c_2, \ldots, w^c_n\}$ is the token set after tokenization. The distance $D_t$ of a token-aspect pairs is calculated as follow:

$$D_t = \frac{\sum_{i=1}^{m} (p_i - p^c_i)}{m}$$

where $p_i (i \in [1, m])$ and $p^c_i$ are the positions of i-th token within the aspect and the position of any context token, respectively. $m$ is the length of an aspect. Then LSA uses the
embedded distance to learn ELCF features. The LSA-T contains two implementations: LSA with Masking Embedding (ME), i.e., LSA-T-ME and LSA with Distance Embedding (DE), i.e., LSA-T-DE. The former convert the distance vector into 0,1 mask vector (Zeng et al. 2019) to obtain the ELCF feature, while the latter forward the distance into embedding without converting.

Besides, we determine the local context and assign the local context tags according to $D_t$:

$$T_t = \begin{cases} 0, & D_t > \alpha \\ 1, & \text{other} \end{cases}$$

where $n$ is the length of the tokenized context; $\alpha (\alpha = 3)$ is a fixed threshold to measure local context. This implementation is called LSA with Distance Embedding, i.e., LSA-T-DE.

**Syntax Distance-based Local Context** Although directly learning syntax structure is inefficient, we can employ the distance calculated from the syntax structure to measure local context and model the local context. Fig. 1 shows a syntax-based tree from a sample with multi-aspects. The distance $D_t$ can be calculated according to the shortest distance between a token node and aspect nodes in the syntax-based tree. Consistent with the token-based local context calculation method, the syntactic structure-based method also calculates the average distance between the aspect-token and context token:

$$D_t = \frac{\sum_{i=1}^{m} \min\text{dist}(t, t_i^{aspect})}{m}$$

where $\min\text{dist}$ indicates the shortest distance between $i$-th token within the aspect and context token $t$ from the non-local context. Similar to the LSA-T, the LSA-S also contains two implementations: LSA with Masking Embedding (ME), i.e., LSA-S-ME and LSA with Distance Embedding (DE), i.e., LSA-S-DE.

**Aggregation Window** We use BERT as the base model to encode input text. Assume that $H^c$ is the context feature learned from BERT:

$$H^T_i = W^T_i H^c$$
$$H^L_i = W^L_i H^c$$
$$H^R_i = W^R_i H^c$$

where $H^T_i$, $H^L_i$, and $H^R_i$ are the ELCF feature of the target aspect, the feature of left- and right-adjacent aspect. $W^T_i \in \mathbb{R}^{n \times d_h}$, $W^L_i \in \mathbb{R}^{n \times d_h}$ and $W^R_i \in \mathbb{R}^{n \times d_h}$ are the local context weight vectors of aspects. We apply the self-attention for ELCF feature of each aspect:

$$H^{lsa}_{SA} = [H^L_{SA}, H^T_{SA}, H^R_{SA}]$$
$$H^{lsa} = W^{lsa} H^{lsa}_{SA} + b^{lsa}$$

$H^L_{SA}, H^T_{SA}, H^R_{SA}$ are ELCF features learned by self attention. $d_h$ is the dimension of the hidden size and $H^{lsa}_{SA}$ is the window composed of the ELCF features of multiple adjacent aspects. $H^{lsa}$ is the output representation of LSA, $W^{lsa}$ and $b^{lsa}$ are the trainable weight and bias parameters.

**Aggregation Window Padding** We need to pad the aggregation window using the aspect-based features. Here are three padding cases shown in Fig. 4. It is worthy noting that padding sentiment aggregation window does not degenerate model because the padded components are duplicated and the same as edge adjacent aspects. Besides, the padded components have the same sentiment information which maintain SP1 and SP2 while modeling the sentiment clusters.

**Differential Weighted Aggregation Window** The LSA treats the sentiment information of adjacent aspects on both left and right sides equally. However, According to SP2, it is natural for us to realize that the importance of sentiment information of the left- and right-adjacent aspects are probably different. Thereafter, we propose differential weighting to differential adjust the contribution of sentiment information from the left-adjacent (previous) aspect and the sentiment information of the right-adjacent (following) aspect. Assume $\eta$ is the adjustable weight of the ELCF feature of left and right aspects:

$$H^{dwa}_{alsa} = [\eta H^L_{SA}, H^T_{SA}, (1 - \eta) H^R_{SA}]$$

where $H^{dwa}_{alsa}$ is the ELCF feature learned through differential weighting Strategy.

**Output Layer**

For the purpose of compensating the loss of context feature caused by ELCF calculation, we combine the global context feature and feature learned from the local sentiment aggregating to predict sentiment polarities as following:

$$O_{fusion} = W^f [H^{lsa}, H^c] + b^f$$
$$O_{dense} = W^d O_{fusion} + b^d$$
$$\hat{y} = \frac{\exp(O_{dense})}{\sum_1 \exp(O_{dense})}$$

where $O_{fusion}$ and $\hat{y}$ are the feature of first token and predicted sentiment polarity, respectively. $C$ indicates the number of polarity categories. $W^f \in \mathbb{R}^{n \times 2d_h}$, $b^f \in \mathbb{R}^{2d_h}$ and $W^d \in \mathbb{R}^{1 \times C}$, $b^d \in \mathbb{R}^{C}$ are the trainable weight and bias vectors.
Model Training

We use the BERT-BASE \(^4\) as the underlying model, and optimize our model using Adam. The objective function is cross-entropy as follows:

\[
L = - \sum_{i} y_i \log y_i + \lambda \| \Theta \|_2
\]  

(13)

where \(\lambda\) and \(\Theta\) are the \(L_2\) regularization and parameter set of the model.

Experiments

Datasets and Hyper-parameters

To comprehensively evaluate the performance of the local sentiment aggregating mechanism, we conducted experiments on four datasets \(^5\) (containing multiple aspects): the Laptop14 and Restaurant14 datasets from SemEval-2014 Task4 \((\text{Pontiki et al. 2014})\), the Restaurant15, Restaurant16 datasets from SemEval-2015 task12 \((\text{Pontiki et al. 2015})\) and SemEval-2016 task5 \((\text{Pontiki et al. 2016})\), respectively.

Table 3: The statistics of four datasets with multiple aspects.

| Datasets | Positive Train | Positive Test | Negative Train | Negative Test | Neutral Train | Neutral Test |
|----------|----------------|--------------|----------------|---------------|--------------|--------------|
| Laptop14 | 994            | 341          | 870            | 128           | 464          | 169          |
| Rest14   | 2164           | 728          | 807            | 196           | 637          | 196          |
| Rest15   | 909            | 326          | 256            | 180           | 36           | 34           |
| Rest16   | 1240           | 468          | 437            | 117           | 69           | 30           |

For fair comparisons with other BERT-based state-of-the-art models, we adopt the commonly used hyperparameter settings. The learning rate of LSA models are 2e-5. The batch size and maximum text length are 16 and 80, respectively. The \(L_2\) regularization parameter \(\lambda\) is 1e-5, and the local context threshold \(\alpha\) is 3 for both LSA-T and LSA-S. Each model trained for five rounds and the average performance is presented.

Compared Models

We compare the performance of LSA-T and LSA-S with following state-of-the-art models (most of them are dependency learning based models):

- **BERT-BASE** \((\text{Devlin et al. 2019})\) is the baseline of BERT-based models.
- **RGAT-BERT** \((\text{Wang et al. 2020})\) is a relational graph attention network based on refined dependency parse tree.
- **SDGCN-BERT** \((\text{Zhao, Hou, and Wu 2020})\) is a GCN-based model that can capture the sentiment dependencies between aspects.
- **DGEDT-BERT** \((\text{Tang et al. 2020})\) is a dual-transformer based network enhanced by dependency graph.
- **SK-GCN-BERT** \((\text{Zhou et al. 2020})\) is a GCN-based model which exploit the syntax and commonsense to learn sentiment information.

- **LCF-BERT** \((\text{Zeng et al. 2019})\) employs the local context focus mechanism based on token distance to emphasize the local context feature.
- **LCFS-BERT** \((\text{Phan and Ogunbona 2020})\) adopts the syntax-based distance to enhance model in extracting local context feature.
- **ASGCN-BERT** \((\text{Zhang, Li, and Song 2019a})\) ASGCN-BERT is a dependency learning model we develop based on the ASGCN. We deploy a pretrained BERT which works as the embedding layer to enhance the ASGCN.

Figure 5: Visualization of performance under differential weighting on the Restaurant15 dataset.

Analysis of Overall Performance

Table \(^6\) shows the main experimental results. Overall, the LSA-based models obtain substantial improvements over most of the BERT-based models on four datasets. In particular, the LSA-S-ME achieves better accuracy than LSA-S-DE on the Restaurant14 dataset. LSA-S and LSA-T variants obtain impressive performance on the Restaurant15, Restau-

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\(^4\) Implemented by huggingface, available at: https://github.com/huggingface/transformers

\(^5\) The processed datasets are available with the code in supplementary materials.

\(^6\) Table
Table 4: The overall performance of LSA variants on four datasets. † and ‡ indicate the performance of our implementation and the results retrieved from the published papers, respectively. The best experimental results are heightened in bold.

| Models                  | Laptop14 Acc | Laptop14 F1 | Restaurant14 Acc | Restaurant14 F1 | Restaurant15 Acc | Restaurant15 F1 | Restaurant16 Acc | Restaurant16 F1 |
|-------------------------|--------------|-------------|-----------------|-----------------|-----------------|----------------|-----------------|----------------|
| BERT-BASE†             | 79.73        | 75.5        | 82.74           | 73.73           | 82.16           | 64.96          | 89.43           | 74.2           |
| BERT-PT‡                | 78.89        | 75.89       | 85.92           | 79.12           | -               | -              | -               | -              |
| RGAT-BERT†             | 80.94        | 78.2        | 86.68           | 80.92           | -               | -              | -               | -              |
| SDGCN-BERT†            | 81.35        | 78.34       | 83.57           | 76.47           | -               | -              | -               | -              |
| SK-GCN-BERT‡           | 79.0         | 75.57       | 83.48           | 75.19           | 83.2            | 66.78          | 87.19           | 72.02          |
| DGEDT-BERT‡            | 79.8         | 75.6        | 86.3            | 80.0            | 84.0            | 71.0           | 91.9            | 79.0           |
| LCF-BERT-CDM†          | 80.3         | 76.85       | 86.28           | 80.24           | 83.83           | 69.97          | 90.62           | 76.93          |
| LCF-BERT-CDW†          | 79.73        | 76.07       | 86.16           | 80.12           | 83.77           | 69.03          | 91.0            | 77.1           |
| LCFs-BERT-CDM†         | 79.99        | 76.51       | 86.31           | 80.32           | 83.4            | 68.81          | 90.81           | 75.86          |
| LCFs-BERT-CDW†         | 80.25        | 76.72       | 86.43           | 80.84           | 84.07           | 69.67          | 90.35           | 76.28          |
| ASGCN-BERT‡            | 79.83        | 75.89       | 84.76           | 77.94           | 84.22           | 72.9           | 91.05           | 77.05          |
| LSA-T-ME               | 81.09        | 77.31       | 86.40           | 80.77           | 84.69           | 71.97          | 91.0            | 77.44          |
| LSA-T-DE               | 80.88        | 77.27       | 86.25           | 80.14           | 84.69           | 71.55          | 91.92           | 77.50          |
| LSA-S-ME               | 81.04        | 78.16       | 86.70           | 80.86           | 85.25           | 72.22          | 91.22           | 77.81          |
| LSA-S-DE               | **81.35**    | **78.35**   | **87.14**       | **81.04**       | 84.81           | 72.21          | **92.20**       | **79.50**      |

Discussion

Our model outperforms BERT-BASE by approximately 2% accuracy on all four datasets. Compared with GCN-based SDGCN and SK-GCN-BERT, LSA-based models significantly improve the classification accuracy and F1 on the Restaurant14 dataset. The comparisons suggest that the local sentiment aggregating is competent to handle the sentiment dependency without any GCN architecture.

Differential Weighting on Aggregation Window

Differential weighting is used to model the aspect order in the text. Because when users comment on an aspect, they tend to comment based on the polarity of the pre-commented aspects. We use differential weighting to model this effect. We use \( \eta \) (where \( \eta \in [0, 1] \)) to adjust the contribution of the previous aspect's ELCF feature. A greater \( \eta \) means more contribution of the previous aspect's ELCF feature.

The difference between simplified AW (SAW) and differential weighting AW (DAW) with \( \eta = 0 \) or \( \eta = 1 \) is the network structure, as the DAW employs a full-connected layer with \( 3 \times d_h \) input size (2 \( \times d_h \) in SAW learning the window features). Figures 5 and 6 show the performance of the model under different \( \eta \). It is clear to observe the significance of the aspects on both sides are different. However, because the datasets are small and contain error data, our experiment shows different optimal \( \eta \) for LSA variants on different datasets. On the other hand, the fixed hyperparameter \( \eta \) is hard to precisely model the significance of the sentiment information of side aspects. We will consider adaptive \( \eta \) calculation methods in the future.

Aggregation Window Decomposition

We study the effectiveness of simplified LSA, i.e., only the local context feature of the aspect on the left or right side are adopted to construct LSA. Table 5 shows the experimental results. Compared with the full LSA, although the simplification process might lose some contextual information, in certain cases, it can still achieve promising results.
We also tried to construct \([CLS] + \text{Context} + [SEP] + \text{Aspect} + [SEP]\) to build sentiment AW, and also achieved promising performance. We are exploring other possibilities and expect LSA to supersede the dependent learning approach based on auxiliary data, e.g., graph structure data.

**RQ3: What are the difference between convolution and window-based aggregation?** Convolution and AW are different from AW in concept and implementation. The main differences are as follows:

- **Modeling target.** Convolution is usually used for the basic network to learn text features, e.g., learning embedded text features. However, the sentiment AW aims at learning aspect-specific context features, e.g., ELCF feature, and the AW only works in sentiment cluster.

- **Processing granularity.** Convolution is an ideal operation to learn semantic connections between tokens. However, the purpose of AW learns the coarse-grained context feature, i.e., global context feature weighted according to the target aspect. Since the AW contains few components, convolution has no advantage in modeling AWs.

**The threatening of aggregation window building** The parsing of the syntax tree greatly affects the extraction of ELCF features. We use spaCy to obtain the syntax tree as previous works. Although LSA achieves impressive performance improvement, due to the problem of compatibility between spaCy and BERT, e.g., tokenization strategy, there are considerable samples among four datasets (including train and test datasets) are tokenized into different token set usage between spaCy and BERT. In that case, there is a non-negligible error rate in calculating aspect-token pair distance and extracting ELCF feature. We believe that using the syntax tree induced by pre-trained model will alleviate this problem and bring about substantive performance improvement.

**Conclusion**

We introduce sentiment patterns, which guides the proposal of the efficient local sentiment aggregating mechanism to learn the sentiment dependency between aspects. Compared with the dependency tree-based models, the LSA only exploits the distance information of the aspect-token pair to improve modeling for the sake of saving computational resources. Moreover, the LSA-based models outperform the BERT/GCN-based models on four commonly used datasets. We also propose differential weighting to measure the importance of sentiment information of different aspects.
which provides a new clue for sentiment dependency modeling. In the future, we plan to work on other window construction methods and propose a self-adaptive differential weighting method to improve the performance of LSA.

Acknowledgment

Thanks to the anonymous reviewers to help us improve this work. This research is funded by the National Natural Science Foundation of China, project approval number: 61876067; The Guangdong General Colleges and Universities Special Projects in Key Areas of Artificial Intelligence of China, project number: 2019KZDZX1033. And this research is supported by the Innovation Project of Graduate School of South China Normal University, project number: 2019LKKXM038.

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