BERT-ASC: Implicit Aspect Representation Learning through Auxiliary-Sentence Construction for Sentiment Analysis

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Abstract
Aspect-based sentiment analysis (ABSA) task aim at associating a piece of text with a set of aspects and meanwhile infer their respective sentimental polarities. The state-of-the-art approaches are built upon fine-tuning of various pre-trained language models. They commonly attempt to learn aspect-specific representation from the corpus. Unfortunately, the aspect is often expressed implicitly through a set of representatives and thus renders implicit mapping process unattainable unless sufficient labeled examples are available. However, high-quality labeled examples may not be readily available in real-world scenarios. In this paper, we propose to jointly address aspect categorization and aspect-based sentiment subtasks in a unified framework. Specifically, we first introduce a simple but effective mechanism to construct an auxiliary-sentence for the implicit aspect based on the semantic information in the corpus. Then, we encourage BERT to learn the aspect-specific representation in response to the automatically constructed auxiliary-sentence instead of the aspect itself. Finally, we empirically evaluate the performance of the proposed solution by a comparative study on real benchmark datasets for both ABSA and Targeted-ABSA tasks. Our extensive experiments show that it consistently achieves state-of-the-art performance in terms of aspect categorization and aspect-based sentiment across all datasets and the improvement margins are considerable. The code of BERT-ASC is available in Github1.

1 Introduction
The information provided by individuals on the Web is usually considered more trustworthy than those provided by the vendor (Bickart and Schindler, 2001). Therefore, understanding online reviews can create value for businesses and public service to improve the quality. Aspect-Based Sentiment Analysis (ABSA) is a fine-grained task that requires detecting the aspects and their respective polarities in a piece of text (Pontiki et al., 2014; Saeidi et al., 2016a). In the literature, we distinguish two types of aspects. An aspect-term, also called target, is explicitly expressed in the sentence and an aspect-category that barely appears in the text and instead is mentioned implicitly through a set of indicators (Wu et al., 2021). For instance, consider the running example shown in Table 1, the sentence \(s_1\) expresses implicitly a positive opinion towards the aspect category Food through the aspect-term coffee and the opinion-word outstanding. Note that the statistics of benchmark datasets, Table 2, show that the majority of sentences express opinions in response to various aspects implicitly (e.g., use the term coffee to evaluate food). Therefore, the effective addressing of these sentences would largely determine the performance of ABSA.

The implicit aspect is still a challenging NLP task in practical, but it has not received sufficient attention from the research community. The earlier solutions were traditional machine learning-based classifiers SVM (e.g., SVM) (Kiritchenko et al., 2014; Brun et al., 2014), which employed feature extraction based on various types of syntactic information parser, n-grams, and the sentiment lexicon. However, the aspect category is mostly mentioned implicitly in the text and thus renders feature extraction unattainable. The state-of-the-art solutions have been built upon various Deep Neural Network (DNN). The traditional DNN-based models (Ma et al., 2018; Liu et al., 2018) commonly attempted to learn the aspect-specific representation through various mechanisms (e.g., attention and deep memory). Recently, a considerable shift towards fine-tuning the pre-trained language models (Sun et al., 2019; Wu and Ong, 2021) has been experienced

1The code of BERT-ASC: https://github.com/amurtadha/BERT-ASC.
to jointly address aspect categorization and aspect-based sentiment subtasks. Specifically, ABSA is reformulated to a question answering task as follows. The text is considered as sentence A in setting of the original BERT (Devlin et al., 2018), while a query (e.g., this sentence describes an opinion towards food ?) is regarded as sentence B. Despite of the impressive performance of this approach on the aspect-term that appears explicitly in the sentence A (Karimi et al., 2020), the implicit aspect requires mapping each aspect to its indicators and thus relies on sufficient labeled examples, which might not be readily available in the real scenario.

In this paper, we propose a novel solution to jointly address aspect categorization and aspect-based sentiment subtasks in a unified framework, namely BERT-based Auxiliary Sentence Constructing (BERT-ASC). First, we leverage the labeled (L-LDA) to associate each aspect with a set of seed words in a given corpus. Intuitively, the pre-trained language models (Devlin et al., 2018) are trained to map the features that often occur in the same context into close points in the embedding space (Ahmed et al., 2021). For instance, “meal” and “bread” that describe food are located very close in the latent space. Inspired by this intuition, we exploit the semantic distribution of the seed in the embedding space to capture more coherent indicators. Specifically, we construct the auxiliary-sentence that relies on the semantic distance between the aspect’s seed and the sentence on-target. Finally, we fine-tune the pre-trained language model (e.g., BERT) to learn the aspect-specific representation in response to the automatically constructed auxiliary-sentence instead of the aspect itself (i.e., adopted in (Sun et al., 2019)). In such a scenario, the process of mapping between the indicators and their implicit aspects becomes easier and thus can reduce the learning cost.

In brief, the main contributions are three-fold:

1. We present a simple but effective mechanism to construct an auxiliary-sentence of the implicit aspect based on its seed semantic distribution in the embedding space;

2. We introduce a BERT-based fine-tuning approach that jointly addresses the aspect categorization and the aspect-based sentiment in a unified framework. The model is trained to learn the aspect-specific representation in response to the automatically constructed auxiliary-sentence instead of the aspect itself.

3. We evaluate the proposed solution on benchmark datasets for TABSA and ABSA tasks. Our extensive experiments show that it consistently achieves state-of-the-art performance in terms of aspect categorization and aspect-based sentiment subtasks across all the test datasets and the improvement margins are considerable.

The remaining of the paper is organized as follows. Section 2 reviews related work. Section 3 describes the propose solution. Section 4 presents the experimental settings and empirically evaluates the performance of the proposed solution. Finally, we conclude this paper with Section 5.
2 Related work

Aspect-based sentiment analysis is a fine-grained classification problem (Pontiki et al., 2014; Saeidi et al., 2016a). Unlike the explicit aspect-term, the aspect-category is mostly described implicitly, and thus renders learning its representation a more challenging task. Th implicit aspect is a challenging NLP task in practical, but has not received sufficient attention from the research community.

The unsupervised techniques commonly tackled the task as a sequence labeling based on prior knowledge (e.g., Wordnet and manually category’s seed). Co-occurrence association rule mining approach (Schouten et al., 2017) attempted to enable activation value spreading between tokens in the same sentence. However, these approaches heavily depend on handcrafted features and unfortunately some categories, e.g., general and miscellaneous, are very abstract. The supervised approaches addressed the task as a multi-class classification problem. SVM-based models (Castellucci et al., 2014; Kiritchenko et al., 2014) introduced a set of features, including n-grams, syntax information, and lexicon features. However, these techniques cannot capture semantic context of different aspects accurately.

Various approaches were proposed to learn the aspect-specific representation in the corpus. A hybrid method (Zhou et al., 2015) introduced modeling the semantic relations based on domain-specific embeddings as hybrid features for a logistic regression classifier. A Convolutional neural network-based features model (Toh and Su, 2016) incorporated the automatically learnable features and the n-grams and POS tags to train one-vs-all linear classifiers. An LSTM equipped with a CNN layer model (Xue et al., 2017) addressed jointly aspect categorization and sentiment subtasks simultaneously. A gated recurrent units equipped with a topic attention mechanism (Movahedi et al., 2019) proposed to filter the aspect-irrelevant information away. Recently, BERT-based fine-tuning models (Sun et al., 2019) was proposed to address the task as a question answering. A context-guided BERT-based fine-tuning approach (Wu and Ong, 2021), which adopted a context-aware self-attention network. It introduced to learn distributing the attention under different contexts. Graph neural network (Li et al., 2021; Dai et al., 2021) introduced to integrate the syntax information into the learning process to enhance aspect-context capturing. However, these approaches (at least in the current settings) cannot perform well on the implicit aspect.

It is noteworthy that a related task, namely Target-Aspect-Sentiment detection (TASD), aims at detecting target-aspect-sentiment triples from a sentence. Joint detection approaches (Wu et al., 2021; Wan et al., 2020) separated the task into two subproblems, namely binary text classification sequence labeling. A single neural model was built upon BERT that minimizes a combined loss function of the two subproblems. Recently, a new task, namely Aspect-Category-Opinion-Sentiment (ACOS) Quadruple Extraction, was introduced (Cai et al., 2021) through two datasets Restaurant-ACOS and Laptop-ACOS. Th Goal is to extract all aspect-category-opinion-sentiment quadruples in a review sentence, which of great value to ABSA by providing the implicit aspects and their respective opinions.

3 The proposed solution

We begin by defining both TABSA and ABSA tasks, then present the technical details of the proposed solution shown in Figure 1. Particularity, it first leverages the supervised LDA to extract a set of seeds for each aspect. Then, it generates an auxiliary sentence for the aspect on-target by modeling the semantic relations to its seed. Note that auxiliary sentence construction is carried out off-line and before the training process begins. Finally, it fine-tunes BERT to learn the aspect-specific representation in response to the automatically auxiliary sentence. We next describe this process in detail.

3.1 Task Description

1. TABSA Task. We formulate the SentiHood dataset (Saeidi et al., 2016b) as a TABSA task. Given a sentence review \( s \) that consists of a sequence of words \( \{w_1, w_2, ..., w_n\} \) in which \( m \) words \( \{w_1, ..., w_m\} \) are from a set \( T \) of \( k \) pre-identified targets \( \{t_1, ..., t_k\} \), the goal is to predict the sentiment for each aspect category associated with each unique target explicitly mentioned in the sentence. Given a sentence review \( s \) and a predefined target list \( T \) and a list of aspect categories \( C = \{price, transit-location, safety, general\} \), the model is required to label each pair \( \{(t, c) : (t \in T, c \in C)\} \) with \( y \in \{negative, positive, none\} \). Note that the model predicts a single sentiment label for
Consider the sentence $s_2$ of the running example in response to service, the generated auxiliary-sentence consists of the semantic candidate waiters and its syntactical modifier friendly. Aspect categorization layer takes the aspect sentiment layer’s output and then applies a binary classification (i.e., whether the aspect on-target is discussed in the input sentence?), whereas none label denotes 0 and 1 otherwise.

Table 3: An example of top-5 seed for SemEval 2014 task 4 dataset.

| Aspect     | Seed                      |
|------------|---------------------------|
| Food       | delicious, chicken, menu, beef, sushi |
| Price      | charge, cheap, reasonable, bill, inexpensive |
| Service    | waiters, attentive, rude, reservations, staff |
| Ambience   | crowded, decor, loud, atmosphere, scene |

3.2 Aspect Seed Extraction

A significant proportion of the text is tagged with different aspects. In other words, the implicit aspect exists in the corpus as a set of explicit indicators, also called seed. Previous work manually built a list of seed for each category, which grows up based on prior knowledge (e.g., WordNet) (Schouten and Frasincar, 2016; Ahmed et al., 2020). To keep the work without additional human efforts, we take advantage of the labeled corpora to extract the aspect’s seed. To this end, we adopt Labeled LDA (L-LDA) (Ramage et al., 2009a). Specifically, for each document $d \in D$, the traditional LDA basically assigns a multinomial mixture distribution $\theta^{(d)}$ over all $K$ topics from a Dirichlet prior $\alpha$. In contrast, L-LDA leverages the labeled corpus to restrict $\theta^{(d)}$ to be defined only over the topics (i.e., the aspects in this scenario) that correspond to its labels $\Lambda^{(d)}$. The technical details are well-explained in (Ramage et al., 2009a). An example of top-5 extracted seed for SemEval 2014 task 4 dataset is illustrated in the Table 3.

3.3 Auxiliary-Sentence Construction

As the ultimate goal is to jointly address aspect categorization and aspect-based sentiment subtasks simultaneously, we thus incorporate the semantic context and syntax information to construct the auxiliary-sentence as shown in Figure 1. In other words, aspect categorization relies on the semantic relations between sequences in response to a given aspect, while aspect-based sentiment focus on the aspect-opinion words, also called modifiers (Liu, 2012; Hu and Liu, 2004; Li et al., 2021). Consider the sentence $s_1$ of the running example Table 1, Food is semantically indicated through the semantic term coffee, while the opinion-word outstanding
sentimentally expresses its polarity. To this end, we first capture the semantic candidates, then syntactically generate their opinion-words as follows.

3.3.1 Semantic candidates

The pre-trained language models (Mikolov et al., 2013; Devlin et al., 2018) are trained to map the features that often occur in the same context into close points in the latent space (He et al., 2017; Ahmed et al., 2020). Figure 2 depicts the distribution of food-opinion words in the latent space. As can be seen, the words are located very closely, which enables leveraging the semantic distance. Therefore, we apply the semantic distance between the seed of the aspect on-target and the input sentence. Then, the words that meet a pre-specified threshold (e.g., 0.8) are considered as semantic candidates. Note that the threshold can be specified using the validation set. Consider sentence \( s_1 \) of the running example Table 1, given the aspect food, the term coffee is semantically very close to the seed menu in the embedding space. Thus, we consider coffee as a semantic candidate for the aspect food. Next, we exploit the syntactic information to extract the opinion words.

3.3.2 Syntactic information

Now that we obtain the semantic candidates, we leverage the dependency tree to extract target-opinion words, which has been widely adapted in many NLP tasks (Davison et al., 2019; Peters et al., 2019). As BERT was trained on a large corpus in order to learn the semantic context, a fine-tuning phase is thus needed to adapt modeling (i.e., understanding) in a specific domain (Xu et al., 2019; Du et al., 2020). Our goal is to learn the representation in response to a given aspect, i.e., the query in the BERT’s notation (Devlin et al., 2018). In our implementation, we concatenate the automatically generated auxiliary-sentence \( a \) of the aspect on-target with the sentence review \( s \).

Let \( x = ([CLS], a_1, ..., a_m, [SEP], s_1, ..., s_n, [SEP]) \), where \( a_1, ..., a_m \) is the auxiliary-sentence (with \( m \) tokens) and \( s_1, ..., s_n \) is a review sentence, [CLS] and [SEP] are the special token. We feed \( x \) to BERT:

\[
Z = BERT(x),
\]

where \( Z \) denotes the hidden layers. The BERT-based models mostly consider \( h_{CLS} \) token as the sentence representation. However, the authors of (Jawahar et al., 2019) have investigated the language structure learned by BERT and have found that the semantic features can be extracted from the top layers. Inspired by the Feature Pyramid Networks (FPNs) (Lin et al., 2017), we follow (Karimi et al., 2020) by exploiting the top four layers of BERT. Specifically, one more BERT layer is added that takes the previous and the current layers as input and meanwhile performs predictions for each layer separately. The intuition behind this architecture is that the deeper layers contain the most semantic information in response to the category on-target (Lin et al., 2017). Note that BERT-ASC

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2https://github.com/google-research/bert
Did I mention that the coffee is outstanding

Figure 3: An example of the dependency parser for sentence $s_3$ of the running example.

| Dataset     | Train (sentence) | Test (sentence) | # Aspects | MA Prop (%) |
|-------------|------------------|-----------------|-----------|-------------|
| SemEval     | 3,041            | 800             | 5         | 23.65 %     |
| SentiHood   | 3,724            | 1,491           | 4         | 31.0 %      |

Table 4: The statistics of datasets. MA Prob indicates the percentage of sentences labeled with more than one category.

requires $|C|$ (i.e., number of aspects) forward passes during inference time, while standard fine-tuning only requires one forward pass to get the prediction of all the aspects. Actually, the inference speed can be easily improved if we reuse the siamese transformer networks (Reimers and Gurevych, 2019).

4 Empirical Evaluation

4.1 Datasets

We evaluate our solution with benchmark datasets in English for both TABSA and ABSA tasks. For the TABSA task, we used the SentiHood dataset\(^3\) (Saeidi et al., 2016b), which was built from Question Answering Yahoo corpus with location names of London and UK. The dataset consists of sentence reviews that evaluate at least one aspect category $c$ in response to the target $t$. For each sentence, our solution predicts the label $y$ for each target-aspect pair $(t, c)$. For the ABSA task, we used the benchmark dataset introduced by SemEval 2014 Task 4\(^4\) (Pontiki et al., 2014), which consists of restaurant reviews collected from Citysearch New York corpus. Each sentence review is annotated with a set of aspect categories and their respective polarities. Each dataset is partitioned to train, validation and test sets as in its original paper. The statistics of the datasets are shown in Table 4.

4.2 Experimental Settings

We follow the settings of the original BERT-base model (Devlin et al., 2018), our model consists of 12 heads and 12 layers with hidden layer size 768, and the total number of parameters for our model is 138M. When fine-tuning, we keep the dropout probability at 0.1 and set the number of epochs to 3. The initial learning rate is $3 \times 10^{-5}$ for all layers with a batch size of 32. For the seed extraction, we used the open-source code of L-LDA\(^5\) (Ramage et al., 2009b) and select the top-10 representatives for each aspect. We used the Stanford CoreNLP as the dependency parser. For the auxiliary sentence construction, we initialize the feature vectors with word vectors trained by word2vec with negative sampling on each dataset, setting the embedding size to 200, window size to 10, and negative sample size to 5. The semantic distance threshold is set to value 0.3 and 0.4 for SemEval and SentiHood datasets, respectively. Note that these values are set based on the validation set.

We follow the experimental settings of the tasks definition (Pontiki et al., 2014; Saeidi et al., 2016b), which were widely adapted in the comparative methods (Sun et al., 2019; Wu and Ong, 2021), we define two subtasks for each dataset as follows. Aspect categorization subtask aims to detect the aspect described in a given sentence. Note that the label none represents the absence of a given aspect in the sentence. Aspect-based sentiment classification subtask aims to associate each detected aspect (i.e., ignore none label) with its respective polarity (i.e., negative and positive for SentiHood, and negative, neutral, positive, conflicting for SemEval).

4.3 Exp-I: ABSA

During the evaluation with ABSA task, we follow the task’s description (Pontiki et al., 2014) and the comparative methods (Sun et al., 2019; Wu and Ong, 2021). For aspect categorization, we report Precision, Recall, and F1 scores. For aspect-based sentiment classification, we report the accuracy metrics for three different evaluations: binary classification (i.e., negative or positive), 3-class classification.

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3SentHood: https://github.com/uclnlp/jack/tree/master.
4SemEval-2014 Task 4: https://alt.qcri.org/semeval2014/task4/.
5L-LDA: https://github.com/JoeZJH/Labeled-LDA-Python
### Table 5: Model performance on the SemEval-2014 Task 4 ABSA dataset, with best performances in bold.

| Model                        | Aspect Categorization | Aspect Sentiment |
|-----------------------------|-----------------------|------------------|
|                             | Precision  | Recall  | F1 score | Binary  | 3-Class  | 4-Class  |
| XRCE (Brun et al., 2014)    | 83.23      | 81.37   | 82.29    | -       | -        | 78.1     |
| NRC-Canada (Kiritchenko et al., 2014) | 91.04      | 86.24   | 88.58    | -       | -        | 82.9     |
| BERT-single (Devlin et al., 2018) | 92.78      | 89.07   | 90.89    | 93.3    | 86.9     | 83.7     |
| BERT-NLI-M (Sun et al., 2019) | 93.15      | 90.24   | 91.67    | 94.4    | 88.7     | 85.1     |
| CG-BERT (Wu and Ong, 2021)  | 93.02      | 90.00   | 91.49    | 94.3    | 89.9     | 85.6     |
| BERT-NLI-B (Sun et al., 2019) | 93.57      | 90.83   | 92.18    | 95.6    | 89.9     | 85.9     |
| QACG-BERT (Wu and Ong, 2021) | 94.38      | 90.97   | 92.64    | 95.6    | 90.1     | 86.8     |
| BERT-ASC (ours)             | **96.17 (.32)** | **92.04 (.26)** | **94.05 (-)** | **95.8 (.27)** | **91.7 (.38)** | **87.5 (.46)** |

Aspect categorization and sentiment classification corresponds to Subtask 3 and Subtask 4, respectively. Mean and standard deviation of 5 runs with different seeds. The comparative results are retrieved from the original papers.

4.3.1 Comparative Baselines

We compare our solution to the systems that achieved the best performance in the SemEval competition and the BERT-based state-of-the-art solutions:

- **XRCE** (Brun et al., 2014). An SVM-based approach relied on features extracted from syntactic information parser and BOW. For aspect categorization subtask, it trained a logistic regression-based model to compute the probability of belonging to a given aspect.

- **NRC-Canada** (Kiritchenko et al., 2014). NRC-Canada reported the best performance in SemEval 2014 competition task 4. It is an SVM-based approach that relied on feature extraction, including ngrams, non-contiguous ngrams, and lexicon features, etc.

- **BERT-single** (Devlin et al., 2018). A BERT-based baseline that takes the sentence as input and addresses the task as a multi-label classification problem.

- **BERT-NLI-M** (Sun et al., 2019). A sentence-pair BERT-based fine-tuning model, which was trained to learn the aspect-specific representation as a pseudo-sentence natural language inference.

- **CG-BERT** (Wu and Ong, 2021). It is a context-guided BERT-based fine-tuning model, which adopted a context-aware self-attention network. It thus introduced to learn distributing the attention under different contexts.

- **BERT-NLI-B** (Sun et al., 2019). It is a variant of BERT-pair-NLI that concatenated the aspect category with each sentimental valance as an auxiliary sentence and then addressed the task as a binary classification problem (i.e., \( y \in \{\text{yes, no}\} \)) to obtain the probability distribution.

- **QACG-BERT** (Wu and Ong, 2021). QACG-BERT is an improved variant of CG-BERT model that introduced learning quasi-attention weights in a compositional manner to enable subtractive attention lacking in softmax-attention.

4.3.2 Results

We use the dev set to select the best model and average 5 run performances with different seeds and report the detailed evaluation results in Table 5 from which we have made the following observations. (1) The traditional machine learning-based approaches XRCE and NRC-Canada report the lowest performance due to the limited ability in context understanding of these models; (2) The baseline BERT-single cannot perform accurately compared to the other BERT-based approaches due to the absence of the auxiliary-sentence, which boosts BERT to capture the context of the aspect; (3) For the aspect categorization task, our solution consistently achieves the state-of-the-art performance in terms of Precision, Recall and F1 scores. Besides, our solution gives the best recall score with 1.07% improvement over the previous state-of-the-art model, and thus demonstrates the ability of the proposed solution to accurately detect the correct category; (4) For aspect-based sentiment task, our solution outperforms the state-of-the-art model in terms of binary and multi-class performance. As can be seen, we report the best performance on 3-
| Model                        | Aspect Categorization | Aspect Sentiment |
|-----------------------------|-----------------------|------------------|
|                            | Strict Accuracy       | Macro-F1  | AUC | Accuracy | AUC |
| LSTM-Loc (Saeidi et al., 2016b) | -                     | 69.3  | 89.7 | 81.9     | 83.9 |
| SenticLSTM (Ma et al., 2018)       | 67.4                  | 78.2  | -   | 89.3     | -   |
| Dmu-Entnet (Liu et al., 2018)       | 73.5                  | 78.5  | 94.4 | 91.0     | 94.8 |
| BERT-single (Devlin et al., 2018)  | 73.7                  | 81.0  | 96.4 | 85.5     | 84.2 |
| BERT-NLI-M (Sun et al., 2019)      | 78.3                  | 87.0  | 97.5 | 92.1     | 96.5 |
| CG-BERT (Wu and Ong, 2021)         | 79.7                  | 87.1  | 97.5 | 93.7     | 97.2 |
| BERT-NLI-B (Sun et al., 2019)      | 79.8                  | 87.5  | 96.6 | 92.8     | 96.9 |
| QACG-BERT (Wu and Ong, 2021)       | 80.9                  | 89.7  | 97.8 | 93.8     | **97.8** |
| BERT-ASC (Ours)                 | **81.2 (.24)**        | **91.1 (.27)** | **98.2 (.31)** | **94.0 (.25)** | **97.4 (.23)** |

Table 6: Model performance on SentiHood TABSA dataset with best performances are highlighted in bold. Mean and standard deviation of 5 runs with different seed. The comparative results are retrieved from the original papers. The symbol “-” indicates not reported in the original paper.

class (i.e., negative, neutral or positive), which are the most dominant labels in sentiment analysis with 1.6% improvement. Due to the widely recognized challenge of sentiment analysis, the achieved improvements can be deemed very considerable. The experimental results suggest that a well-designed auxiliary-sentence can boost BERT to accurately perform on ABSA task.

### 4.4 Exp-II: TABSA

We validate the effectiveness of the proposed solution with TABSA task on SentiHood dataset. For fair comparison, we follow the experimental settings of the comparative methods (Saeidi et al., 2016b; Ma et al., 2018; Sun et al., 2019; Wu and Ong, 2021). Only four aspect categories (i.e., most frequently appear in the corpus) are considered (i.e., price, transit-location, safety and general). For aspect categorization subtask, we report the results of strict accuracy metric, Macro-F1 score and AUC. Strict accuracy requires the model to correctly detect all aspect categories to a given target, while Macro-F1 is the harmonic mean of the Macro-precision and Macro-recall of all targets. For sentiment classification subtask, we report accuracy and AUC metrics.

#### 4.4.1 Comparative Baselines

In addition to the comparative methods of ABSA, including BERT-pair-NLI-B, BERT-pair-NLI-M, CG-BERT and QACG-BERT (Sun et al., 2019; Wu and Ong, 2021), we also compare our solution to the following models:

- **LSTM-Final** (Saeidi et al., 2016b). It used a bidirectional LSTM to learn a classifier for each category. It regraded the final state as the aspect-specific representation in response to the target;
- **LSTM-Location** (Saeidi et al., 2016b). It is a variant of LSTM-Final, which considered the representation of the target index as the aspect-specific representation;
- **SenticLSTM** (Ma et al., 2018). An attentive biLSTM introduced leveraging the external information as commonsense knowledge from SenticNet (Cambria et al., 2016);
- **Dmu-Entnet** (Liu et al., 2018). A bidirectional EntNet (Henaff et al., 2016) that exploited the external memory chains with a delayed memory update mechanism to track entities.

#### 4.4.2 Results

Consistent with Exp-I, we use the dev set to select the best model and average 5 run performances with different seeds and report the detailed evaluation results the SentiHood dataset in Table 6 from which we have made the following observations. Compared to the traditional DNN-based approaches, our solution achieves the best performance with large margins in terms of strict accuracy, Macro-F1 sentiment accuracy with 7.7%, 12.6% and 3% improvements, respectively. Compared to the previous Bert-based state-of-the-art models, our solution consistently achieves the state-of-the-art performance for aspect categorization and aspect-based sentiment subtasks in terms of strict Accuracy, Macro-F1 and sentiment accuracy with 81.2%, 91.1% and 94.0%, respectively. Due to the widely recognized challenge of sentiment analysis, the achieved improvements can be deemed very considerable.
considerable. This clearly suggests that a carefully-designed collaboration between prior knowledge and DNN can effectively perform better than a pure DNN on TABSA task.

4.5 Case study

To better illustrate the effectiveness of BERT-ASC in terms of mapping the implicit aspects to their indicators, we perform a case study shown in Table 7. Particularly, we use the baseline BERT-NLI (Sun et al., 2019) as the comparative baseline. The reason behind this choice is that BERT-NLI employed the concept of sentence B in the setting of BERT (Devlin et al., 2018), which is very related to BERT-ASC. It is noteworthy that QACG-BERT (Wu and Ong, 2021) eliminated sentence B and introduced an attention mechanism to learn aspect-specific representation. Table 7 depicts some examples that BERT-NLI fails to accurately predict. As can be seen in $s_1$, the presence of the word “air” leads BERT-NLI to wrongly associate the sentence with the aspect ambience, while BERT-ASC does not construct an auxiliary-sentence to ambience. Similarly, BERT-NLI assigned an extra aspect ambience to the sentence $s_2$ due to the word “loud”, which is often used to describe the environment. As mentioned in Section 1, mapping the implicit aspect to its indicators heavily relies on sufficient labeled examples, which may not readily available in the real scenario. $s_3$ is an illustrative example to a such scenario, the word “saag”, which indicates food, may barely occur in the reviews and thus leads BERT-NLI to wrong prediction. However, the collaboration between food’s seed and its semantic distribution in the embedding space encourages BERT-ASC to capture the token “saag” and its syntactic modifier “good”. All this examples suggest that a well-designed auxiliary sentence construction can boost the performance of BERT to significantly learn the implicit-aspect representation.

4.6 Error Analysis

For further improvement of our solution in the future, it is important to scrutinize the failure cases, which could be best classified into three major categories:

1. **Inaccurate syntactic relations.** This type of error is unhappily produced by the dependency parser, which is slightly tolerant to the informal expressions and complexity of online reviews (Li et al., 2021). Consider the illustrative example of error analysis Table 8, the atmosphere in the sentence $s_1$ is modified by nice and dark, but only nice is detected by the parse and thus leads to wrongly polarity predicting.

2. **Inaccurate semantic candidates.** This type of error basically occurs when a token is semantically close to the seed of an irrelevant aspect. For example, sushi in the sentence $s_2$ is a candidate of irrelevant aspect (i.e., food).

3. **Incomplete coverage.** This category of errors occurs when no semantic candidate is detected. For example, the service in sentence $s_3$ is left without any candidates.

5 Conclusion

In this paper, we have proposed a novel solution to address jointly the implicit aspect categorization and sentiment subtasks in a unified framework. It first introduces a simple but effective mechanism to construct an auxiliary-sentence for the implicit aspect based on the semantic relatedness of the seed words of the aspect on-target in the embedding space. Then, it encourages BERT to learn the aspect-specific representation in response to the automatically generated auxiliary-sentence instead.
of the implicit aspect itself. Our extensive experiments have shown that the proposed approach consistently achieves state-of-the-art performance on both ABSA and TABSA task. For future work, it is interesting to note incorporating prior knowledge with the pre-trained language models. e.g., BERT, is potentially applicable to other classification tasks; technical solutions however need further investigation.

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| $s_i$ | Sentence | Annotated aspect | Auxiliary-sentence |
|-------|----------|-----------------|--------------------|
| $s_1$ | The **atmosphere** was **nice** but it was a little too **dark**. | $\{(\text{ambience}, \text{conflict})\}$ | $\{(\text{atmosphere}, \text{nice})\}$ |
| $s_2$ | I trust the people at go sushi it never **disappoint**. | $\{(\text{anecdotes}, \text{positive})\}$ | $\{(\text{sushi}, \text{disappoint})\}$ |
| $s_3$ | It shouldn’t take **ten minutes** to get your drinks. | $\{(\text{service}, \text{negative})\}$ | $\{(\text{service, -})\}$ |

Table 8: An illustrative example of the error analysis.
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