Abstract

Aspect-based sentiment analysis (ABSA) aims to associate a text with a set of aspects and infer their respective sentimental polarities. State-of-the-art approaches are built on fine-tuning pre-trained language models, focusing on learning aspect-specific representations from the corpus. However, aspects are often expressed implicitly, making implicit mapping challenging without sufficient labeled examples, which may be scarce in real-world scenarios. This paper proposes a unified framework to address aspect categorization and aspect-based sentiment subtasks. We introduce a mechanism to construct an auxiliary-sentence for the implicit aspect using the corpus’s semantic information. We then encourage BERT to learn aspect-specific representation in response to this auxiliary-sentence, not the aspect itself. We evaluate our approach on real benchmark datasets for both ABSA and Targeted-ABSA tasks. Our experiments show that it consistently achieves state-of-the-art performance in aspect categorization and aspect-based sentiment across all datasets, with considerable improvement margins. The BERT-ASC code is available at https://github.com/amurtadha/BERT-ASC.

1 Introduction

The information provided by individuals on the Web is usually considered more trustworthy than that provided by vendors (Bickart and Schindler, 2001). Aspect-based sentiment analysis (ABSA) entails identifying and analyzing sentiment expressed towards specific aspects or features within text, such as products or services. This approach is essential in applications like customer reviews analysis, where it allows for a nuanced understanding of sentiment towards individual aspects (e.g., service quality, price), enabling businesses to assess overall satisfaction and areas for improvement effectively (Pontiki et al., 2014; Saeidi et al., 2016a). There are two types of aspects: aspect-terms, which are explicitly mentioned in the sentence, and aspect-categories, which are rarely explicit and are inferred through indicators (Wu et al., 2021). Aspect-terms are specific words or phrases directly denoting the object being reviewed, while aspect-categories are broader themes inferred from context and opinion words (Pontiki et al., 2014). For example, in the sentence $s_i$ from Table 1, ‘coffee’ is an aspect-term expressing a positive opinion towards the implicit aspect-category ‘Food’ through the word ‘outstanding’. Identifying aspect-terms involves locating specific mentions, whereas identifying aspect-categories requires understanding implicit cues in the text. 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., using 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 practice, but it has not received sufficient attention from the research community. The earlier solutions were traditional machine learning-based classifiers such as SVM (Kiritchenko et al., 2014; Brun et al., 2014), which employed feature extraction based on various types of syntactic information such as parser, n-grams, and the sentiment lexicon. However, the aspect category is mostly mentioned implicitly in the text and thus makes feature extraction unattainable. The state-of-the-art solutions have been built upon various Deep Neural Networks (DNNs). 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 pre-trained language models (Sun et al., 2019; Wu and Ong, 2021) has been experienced to jointly address aspect categorization and aspect-based sentiment subtasks. Specifically,
ABSA is reformulated into a question-answering task as follows: The text is considered as sentence A in the setting of the original BERT (Devlin et al., 2019), while a query (e.g., “Does this sentence describe an opinion towards food?”) is regarded as sentence B. Despite the impressive performance of this approach on the aspect-term that appears explicitly in sentence A (Karimi et al., 2021), the implicit aspect requires mapping each aspect to its indicators and thus relies on sufficient labeled examples, which may not be readily available in real-world scenarios.

In this paper, we propose a novel solution to jointly address aspect categorization and aspect-based sentiment subtasks in a unified framework, namely the BERT-based Auxiliary Sentence Constructing (BERT-ASC). First, we leverage Labeled Latent Dirichlet Allocation (L-LDA) to associate each aspect with a set of seed words in a given corpus. Intuitively, the pre-trained language models (PLMs) (Devlin et al., 2019) are trained to map features that often occur in the same context into close points in the embedding space (Ahmed et al., 2021). For instance, “meal” and “bread”, which describe food, are located very close in the latent space. Inspired by this intuition, we exploit the semantic distribution of the seeds in the embedding space to capture more coherent indicators. Specifically, we construct an auxiliary sentence that relies on the semantic distance between the aspect’s seed and the sentence on-target. Finally, we fine-tune the PLM (e.g., BERT) to learn aspect-specific representations based on automatically constructed auxiliary sentences, rather than the aspect itself (as adopted in (Sun et al., 2019)). Given $s_1$ in Table 1, BERT-NLI trains with the auxiliary sentence “What is the sentiment of food?”, while our BERT-ASC uses the generated auxiliary sentence “What is the sentiment of coffee?”. This approach simplifies the mapping process between indicators and their implicit aspects, thereby reducing the learning cost.

In brief, the main contributions are three-fold:

1. We present a simple but effective mechanism to construct an auxiliary sentence for 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 aspect categorization and aspect-based sentiment analysis 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 analysis subtasks across all test datasets, and the improvement margins are considerable.

The remainder of the paper is organized as follows. Section 2 reviews related work. Section 3 describes the proposed 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; Saedi et al., 2016a). Unlike the explicit aspect-term, the aspect-category is mostly described implicitly, making learning its representation a more challenging task. The implicit aspect is a challenging NLP task in practice but has not received sufficient attention from the research community. It is noteworthy that there exists a closely related task known as Target-Aspect-Sentiment Detection (TASD), which focuses on identifying target-aspect-sentiment triples within a given sentence. Previous approaches to TASD, such as those presented in (Wu et al., 2021) and (Wan et al., 2020), have typically divided the problem into two distinct subtasks: binary text classification and sequence labeling. These methods employed a single neural model built upon BERT, aiming to minimize a combined loss function that addresses both subproblems. Recently, a novel task has emerged in the field, termed Aspect-Category-Opinion-Sentiment (ACOS) Quadruple Extraction, as introduced in (Cai et al., 2021). This task is supported by two datasets: Restaurant-ACOS and Laptop-ACOS. The primary objective of ACOS Quadruple Extraction is to identify and extract all aspect-category-opinion-sentiment quadruples present within a review sentence. This task holds significant value for Aspect-Based Sentiment Analysis (ABSA) as it provides insights into implicit aspects and their associated opinions.
Did I mention that the coffee is outstanding? *(Food, Pos) {F} Food {F} coffee

Waiters are very friendly and the pasta is out of this world. *(Service, Pos), (Food, Pos) {F} service {F} Waiters friendly

I hear that under LOC1 is quite cheap *(LOC1, Price, Pos) {F} price in LOC1 {F} cheap in LOC1

Table 1: Running example with sentences $s_1$ and $s_2$ from SemEval and $s_3$ from SentiHood. For instance, $s_2$ expresses positive opinions on Service (waiters) and Food (pasta), while $s_3$ describes a positive opinion on the Price of LOC1 (cheap). Words in bold indicate aspect candidates. Comparison of auxiliary sentences for BERT-NLI and BERT-ASC. {F} represents "What is the sentiment of ".

Table 2: The percentage of sentences that express opinions towards various aspects implicitly in the SemEval and Sentihood datasets is notable. A category is considered an implicit aspect if it is not explicitly mentioned in the text. For example, in the sentence "the sushi is yummy", the aspect of food is implied but not directly stated.

| Dataset   | Implicit Aspect Percentage |
|-----------|---------------------------|
|           | Train | Test  |
| SemEval   | 77.6% | 73.8% |
| SentiHood  | 96.8% | 97.9% |

The unsupervised techniques commonly tackle the task as sequence labeling based on prior knowledge (e.g., WordNet and manually constructed category’s seeds). Co-occurrence association rule mining approaches (Schouten et al., 2018) attempt 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 address the task as a multi-class classification problem. SVM-based models (Castellucci et al., 2014; Kiritchenko et al., 2014) introduce a set of features, including n-grams, syntax information, and lexicon features. However, these techniques cannot accurately capture the semantic context of different aspects.

Last decade, various approaches have been proposed to learn aspect-specific representations in a corpus. A hybrid method (Zhou et al., 2015) introduced modeling 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 automatically learnable features with 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 aspect categorization and sentiment subtasks simultaneously. A Gated Recurrent Units model equipped with a topic attention mechanism (Movahedi et al., 2019) proposed filtering aspect-irrelevant information away. A BERT-based fine-tuning model (Sun et al., 2019) was proposed to address the task as question answering. A context-guided BERT-based fine-tuning approach (Wu and Ong, 2021), which adopted a context-aware self-attention network, was introduced to learn distributing attention under different contexts. (Venugopalan and Gupta, 2022) introduced an unsupervised approach for aspect term extraction using guided LDA with manually aspect seed words and enhanced by linguistic rule-based regular expressions. Graph Neural Networks (GCNs) (Li et al., 2021; Dai et al., 2021; Zhao et al., 2022) were introduced to integrate syntax information into the learning process to enhance aspect-context capturing. Incorporating implicit sentiment and explicit syntax knowledge via self-supervised pre-training (Li et al., 2022). A domain adaptation method that retrieves and edits prototypes from unlabeled target data to enhance word transferability, enabling cross-domain aspect term extraction and sentiment classification (Chen and Qian, 2022). A hierarchical dual GCNs model with two GCNs for extracting syntactic and semantic information. It uses a self-attention matrix for semantic extraction and a dependency feature-aware GCN for syntactic mapping, with multiple layers to capture various linguistic features (Zhou et al., 2023). However, these approaches, at least in their current settings, struggle with implicit aspect detection. While they have shown impressive performance in identifying explicitly mentioned aspect-terms within sentences, handling implicit aspects remains challenging. Detecting implicit aspects requires mapping each aspect to its indicators, a process that depends heavily on having a sufficient number of labeled examples. Unfortunately, such labeled examples are often scarce in real-world scenarios (Ahmed et al., 2021).

In-Context Learning (ICL) allows Large Language Models (LLMs) to perform tasks efficiently by using in-context examples without fine-tuning...
This approach has influenced sentiment analysis through dense demonstration retrieval and context-based extension. Dense retrieval uses vectors for semantic matching to enhance LLM performance by retrieving relevant examples (Reimers and Gurevych, 2019; Wang et al., 2022). LLM-R introduced iterative training with a reward model and knowledge distillation for a bi-encoder-based dense retriever. However, task-specific retrievers may require lengthy training. Recent advancements like structured prompting by Hao et al. (2022) and novel position embeddings by Ratner et al. (2023) aim to improve integration of examples into LLMs. Su et al. (2024) proposed context splitting and a voting mechanism for relevant context selection. However, handling aspect detection and aspect sentiment simultaneously remains challenging, as both tasks typically rely on the same input data and are interdependent.

To overcome this limitation, BERT-ASC introduces the concept of constructing an auxiliary sentence, which encourages the model to encode sentences in response to generated auxiliary sentences. This strategy enhances the model’s ability to capture aspect-specific representations, even when the aspects are not explicitly mentioned in the text. Most similar to our work in incorporating auxiliary sentences is BERT-NLI (Sun et al., 2019). However, in BERT-NLI, the auxiliary sentence is constructed by questioning about the category on target. For example, consider sentence s1 "Did I mention that the coffee is outstanding?" from the running example in Table 1; their auxiliary sentence might be, "What do you think of the food?". We believe this approach is more suitable for aspect-terms where the aspect is explicitly expressed. In contrast, we first extract representative words for the aspect category, such as 'coffee' for 'food' in s1, and then construct the auxiliary sentence as: "What do you think of the coffee?". This approach alleviates the need for BERT to map the category to its related terms, thereby potentially boosting performance.

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. To provide a clearer understanding of the proposed approach, the workload is illustrated in pseudo-code format in Algo 1. In particular, it first leverages supervised

| 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 |

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

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 constructed auxiliary sentence. We will now proceed to describe this process in greater detail.

3.1 Task Definition

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 \( \{w_1, w_2, \ldots, w_m\} \) in which m words \( \{w_1, w_2, w_n\} \) are from a set \( T \) of k pre-identified targets \( \{t_1, \ldots, t_k\} \), 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 each unique target-aspect pair in a sentence.

2. ABSA Task. We formulate the SemEval-2014 Task 4 dataset (Pontiki et al., 2014) as an ABSA task. The target-aspect pairs \( \{t, c\} \) of TABSA become only an aspect category \( c \). Given a review sentence s, the model attempts to predict a sentiment label \( y \in \{negative, neutral, positive, conflict, none\} \) for each aspect category \( c : (c \in C) \) with a predefined category list \( C = \{food, price, service, ambience, anecdotes\} \).

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 through a set of explicit
indicators, also referred to as seeds. Previous work manually built a list of seeds for each category, which was expanded based on prior knowledge (e.g., WordNet) (Schouten and Frasincar, 2016; Murtadha et al., 2020). To minimize additional human effort, we leverage the labeled corpora to extract the aspect’s seeds. For this purpose, we adopt Labeled LDA (L-LDA) (Ramage et al., 2009a). Specifically, for each document $d \in D$, traditional LDA typically assigns a multinomial mixture distribution $\theta(d)$ over all $K$ topics from a Dirichlet prior $\alpha$. However, L-LDA uses the labeled corpus to constrain $\theta(d)$ to be defined only over the topics (i.e., the aspects in this context) that correspond to its labels $\Lambda(d)$. The technical details are well-explained in (Ramage et al., 2009a). An example of the top-5 extracted seeds for the SemEval 2014 Task 4 dataset is illustrated in 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 focuses 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 in 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

Language models (Mikolov et al., 2013; Devlin et al., 2019) are trained to map the features that often occur in the same context into close points in the latent space (He et al., 2017; Murtadha 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 us to leverage 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 in 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 previous work (Hu and Liu, 2004; Popescu and Etzioni, 2005; Bloom et al., 2007; Qiu et al., 2011; Zeng et al., 2019). Figure 3 depicts the dependency relations of sentence $s_1$ in the running example. We designed three rules to capture the syntactic information of the semantic candidates as follows:

- We consider the opinions that share the grammatical relation *amod* (adjectival modifier) (de Marneffe and Manning, 2008). For example, in the phrase “very delicious sushi,” we extract delicious as a syntactic modifier.

- We include the opinions satisfying the relation *nsubj* (nominal subject). Note that *nsubj* may appear between various POS (e.g., nouns, adverbs, or adjectives), we only include adjectives that modify nouns. For example, in the sentence “The sushi is yummy,” we can extract yummy as a modifier.

- We also include the outlier modifiers that satisfy the grammatical relation *advmod* (adverb modifier). For example, “Genetically modified food,” we extract Genetically as an outlier modifier of the opinion word modified.

In brief, the automatically constructed auxiliary sentence given the aspect food is “coffee is outstanding”. It is noteworthy that the auxiliary-sentence is initialized to the aspect itself in case no candidate is detected. Finally, we encourage the BERT model to learn implicitly the aspect-specific representation in response to the constructed auxiliary-sentence instead of the aspect itself, as in (Sun et al., 2019).

### 3.4 BERT-based classifier

Recently, BERT\(^1\) (Devlin et al., 2019) achieved state-of-the-art performance in the ABSA task and has been widely utilized in many NLP tasks (Davison et al., 2019; Peters et al., 2019; Ahmed et al., 2023). As BERT was trained on a large corpus to learn the semantic context, a fine-tuning phase is thus needed to adapt the modeling (i.e., understanding) to 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 BERT’s notation (Devlin et al., 2019). In our implementation, we concatenate the automatically generated auxiliary-sentence $a$ of the aspect on-target with the sentence review $s$. Let

$$ x = ([CLS], a_1, \ldots, a_m, [SEP], s_1, \ldots, s_n, [SEP]) $$

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

$$ Z = BERT(x), \quad (1) $$

where $Z$ denotes the hidden layers. BERT-based models mostly consider the $h_{CLS}$ 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 semantic features can be extracted from the top layers. Inspired by Feature Pyramid Networks (FPNs) (Lin et al., 2017), we follow (Karimi et al., 2021) by exploiting the top four layers of BERT. Specifically, one more BERT layer is added that takes both the previous and the current layers as input and performs predictions for each layer separately. The intuition behind this architecture is that the deeper layers contain more semantic information in response to the category on-target (Lin et al., 2017). Note that BERT-ASC requires $|C|$ (i.e., the

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\(^1\)https://github.com/google-research/BERT
Algorithm 1 Training Procedure

1: **Input:** Corpus $C$, Aspects $A$, Pre-trained BERT model
2: **Output:** Fine-tuned BERT model for aspect-specific representation
3: **procedure** EXTRACT SEEDS($C$, $A$)
4:  
5:  
6:  
7:  
8:  
9: **procedure** CONSTRUCT AUXILIARY SENTENCES(Seed sets)
10:  
11:  
12:  
13:  
14: **procedure** FINE TUNE BERT
15:  
16:  
17:  
18:  
19:  
20:  
21:  
22: **end procedure**

Time Complexity: LDA typically has a complexity of $O(KDN)$, where $K$ represents the number of topics (or aspects), $D$ is the count of documents, and $N$ signifies the average number of words in each document. Adding a labeling step in supervised LDA does not substantially alter the overall complexity order. For the construction of auxiliary sentences, the time complexity is mainly influenced by the number of words in the input sentence and the number of seed words associated with the aspect. Assuming there are $W$ words in the sentence and $S$ seed words, and given that the calculation of semantic distance is constant in time, this phase would have a time complexity of $O(WS)$. Space Complexity: The primary space demands are attributed to storing the document-word matrix and the topic-word distributions, generally amounting to $O(DN + KV)$, where $V$ is the size of the vocabulary. In the case of supervised LDA, additional space is needed for label-topic distributions; however, this typically constitutes a marginal increase compared to the document-word matrix’s size. The space required for constructing auxiliary sentences mainly involves storing the seed words and the words in the input sentence, which is $O(W + S)$.

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$^2$ (Saeidi et al., 2016b), which was built from the Question Answering Yahoo corpus with location names from London and the 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$^3$ (Pontiki et al., 2014), which consists of restaurant reviews collected from the Citysearch New York corpus. Each sentence review is annotated with a set of aspect categories and their respective polarities. Each dataset is partitioned into train, validation, and test sets as described in its original paper. The statistics of the datasets are shown in Table 4.

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

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

We use BERT as our baseline, which has been widely employed by the comparative baselines. It is important to note that other language models, such as RoBERTa (Liu et al., 2019) or Sentence-BERT (Reimers and Gurevych, 2019), can be utilized in a similar manner for this purpose. We follow the  

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$^2$SentiHood: https://github.com/uclnlp/jack/tree/master.

$^3$SemEval-2014 Task 4: https://alt.qcri.org/semeval2014/task4/.
settings of the original BERT-base model (Devlin et al., 2019); our model consists of 12 heads and 12 layers with a hidden layer size of 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 (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 a value of 0.3 and 0.4 for the 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: The 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. The aspect-based sentiment classification subtask aims to associate each detected aspect (i.e., ignore the 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 the 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 (i.e., negative, neutral, or positive), and 4-class classification (i.e., negative, neutral, positive, or conflict). 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 that relied on features extracted from a syntactic information parser and BOW. For the 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 the 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., 2019). 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 a method to learn how to distribute 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., $y \in \{yes, no\}$) to obtain the probability distribution.

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

#### 4.3.1 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...
1.07% improvement over the previous state-of-the-art model.

For the aspect categorization task, our solution achieves state-of-the-art performance with a 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’s performance on the ABSA task.

We conducted additional experiments on various PLMs, including BERT_{large}, BART, and RoBERTa, as shown in Table 6. From these experiments, we made the following observations. (1) BERT-ASC shows significant improvements over BERT-NLI in aspect detection. We attribute these improvements to the proficient generation of auxiliary sentences, which facilitates the model’s ability to more effectively map the category to its corresponding representatives in the sentence. (2) However, these improvements are modest in aspect sentiment. (3) We also observe that BERT-ASC improves the stability measure in standard deviation, which is an important metric in multi-label classification scenarios.

### 4.3.2 Ablation Study

We conducted an ablation study to assess the contribution of each component of BERT-ASC to the final performance, as shown in Table 7. The analysis includes three versions of the model: BERT-
Table 7: Ablation study by eliminating semantic information (BERT-ASC W/O Semantic) and syntactic information (BERT-ASC W/O Syntactic). BERT-ASC W/O Semantic demonstrates a greater contribution to the final performance due to the effective ability of DNNs to model implicit information. However, BERT-ASC W/O Syntactic may leave many examples with opinion words due to the inaccuracy of the dependency parser as shown in Table 12.

ASC without semantic information (BERT-ASC W/O Semantic), BERT-ASC without syntactic information (BERT-ASC W/O Syntactic), and the full BERT-ASC model. The results demonstrate that the BERT-ASC W/O Semantic model contributes more to the final performance, as performance drops when it is eliminated. This is expected for the following reasons: syntactic information heavily relies on the accuracy of the parser, which may not always be reliable as shown in Table 12. Sentences with implicit aspects (see Table 2) are left without opinion words, as we depend on the semantic latent space to generate the modifiers. The results show that the full BERT-ASC model outperforms its ablated versions across all metrics. Specifically, the BERT-ASC model achieves the highest Precision (96.17), Recall (92.04), and F1 score (94.05), indicating the significant contribution of both semantic and syntactic information to the model’s performance.

4.4 Exp-II: TABSA

We validate the effectiveness of the proposed solution with the TABSA task on the SentiHood dataset. For a 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., the most frequently appearing in the corpus) are considered (i.e., price, transit-location, safety, and general). For the aspect categorization subtask, we report the results of the strict accuracy metric, Macro-F1 score, and AUC. Strict accuracy requires the model to correctly detect all aspect categories for a given target, while Macro-F1 is the harmonic mean of the Macro-precision and Macro-recall of all targets. For the sentiment classification subtask, we report accuracy and AUC metrics.

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 regarded 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., 2017) that exploited the external memory chains with a delayed memory update mechanism to track entities.

4.5 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 for the SentiHood dataset in Table 8 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 and 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 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
particularly, we use the baseline BERT-NLI when it comes to aspect sentiment analysis. To better illustrate the effectiveness of BERT-ASC, we perform a case study shown in Table 4.6. However, these improvements are relatively modest in terms of mapping implicit aspects to their indicators. Table 9 presents the performance results of various PLMs, including BERT-Large, BART, and RoBERTa. Consistent with the SemEval, BERT-ASC demonstrates significant improvements over BERT-NLI in aspect detection. However, these improvements are relatively modest when it comes to aspect sentiment analysis.

### 4.6 Case Study

To better illustrate the effectiveness of BERT-ASC in terms of mapping implicit aspects to their indicators, we perform a case study shown in Table 10. 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., 2019), 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 10 depicts some examples where BERT-NLI fails to accurately predict. As can be seen in s1, the presence of the word “air” leads BERT-NLI to wrongly associate the sentence with the aspect of ambience, while BERT-ASC does not construct an auxiliary-sentence for ambience. Similarly, BERT-NLI assigned an extra aspect of ambience to the sentence s2 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 be readily available in real scenarios. s3 is an illustrative example of such a scenario; the word “saag”, which indicates food, may rarely occur in reviews and thus leads BERT-NLI to wrongly classify the sentence.
Table 10: A case study where the letters F, S, and A denote the aspects of food, service, and ambience, respectively, while POS and NEG represent positive and negative sentiments, respectively.

Table 11: An illustrative example of the error analysis.

Table 12: The percentage of auxiliary-sentences that are automatically constructed.

4.7 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 often 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 in error analysis Table 11, where the atmosphere in the sentence $s_1$ is modified by both nice and dark, but only nice is detected by the parser and thus leads to incorrect polarity prediction.

2. **Inaccurate semantic candidates.** This type of error generally 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 an 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 targeted 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 tasks. For future work, it is interesting to note that incorporating prior knowledge with pre-trained language models, e.g., BERT, is potentially applicable to other classification tasks; however, technical solutions need further investigation.

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