Zero-Shot Aspect-Based Sentiment Analysis
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Abstract

Aspect-based sentiment analysis (ABSA) typically requires in-domain annotated data for supervised training/fine-tuning. It is a big challenge to scale ABSA to a large number of new domains. This paper aims to train a unified model that performs zero-shot ABSA without using any annotated data for a new domain. We propose a method called contrastive post-training on review Natural Language Inference (CORN). In this method, ABSA tasks are cast as natural language inference for zero-shot transfer. We evaluate CORN on ABSA tasks, ranging from aspect extraction (AE), aspect sentiment classification (ASC), to end-to-end aspect-based sentiment analysis (E2E ABSA), which show ABSA can be conducted without any human annotated ABSA data.

1 Introduction

Aspect-based sentiment analysis (Liu, 2012; Vaswani et al., 2017; Zhang et al., 2018; Xu et al., 2020) is challenging because it typically requires supervised training data that differs domain-by-domain. Given a review sentence “The battery life of this laptop is superb,” if we want to extract the aspect “battery life”, one needs to have a large quantity of annotated data with terms such as “screen”, “keyboard” for the laptop domain/category. When it comes to a new domain (e.g., restaurant), these annotated data can hardly be re-used, so a new annotation in the restaurant domain is required.

In this paper, we study the problem of how to learn a unified model that can be zero-shot transferred to tasks in ABSA, ranging from aspect extraction (AE) (Shu et al., 2017; Xu et al., 2018; Shu et al., 2019), aspect sentiment classification (ASC) (Xu et al., 2019b), to end-to-end aspect-based sentiment analysis (E2E ABSA) (Li et al., 2019a), without requiring any human annotated ABSA data.

Although the rising of pre-training/post-training\textsuperscript{1} on language models (LM) like BERT (Devlin et al., 2019) and GPT (Radford et al., 2018), prompt engineering (Gao et al., 2021a; Seoh et al., 2021) has been proposed for few-shot or zero-shot transfer in sentiment classification, ABSA problems are more domain-dependent than sentiment classification. Also, certain LM losses such as those in masked language model (MLM) and next sentence prediction (NSP) in BERT (Devlin et al., 2019) may not be suitable for zero-shot transfer to ABSA tasks. This is because the fine-grained correlations between aspect-opinion terms and aspect-entity terms are critical, and MLM’s noisy masked tokens or NSP’s easy negative examples may not capture aspect-opinion and aspect-entity dependencies well. Therefore, an ideal model must be trained on a general task and learns representations (e.g., regarding aspect-opinion terms and aspect-entity dependencies) to cover all downstream ABSA tasks and do-

\textsuperscript{1}post-train takes pre-trained weights as the initialization for further training before fine-tuning using end-task annotated data.
This paper proposes a method called CORN (contrastive post-training on review natural language inference). This method casts all ABSA problems into Natural Language Inference (NLI) to infer domain-invariant relations on aspect-opinion and aspect-entity dependencies. The intuition of using NLI is to detect the logical connection between mentioned/inferred aspects and their correlated opinion polarities. We can create a hypothesis that includes the hypothesis aspect and hypothesis opinion polarity. If the review (premise) can entail the hypothesis, we can infer the aspect and its correlated opinion. Note that the NLI task typically requires supervised training data with human annotation. To learn domain knowledge in reviews into CORN, we pre-process reviews into review NLI (RNLI) without human annotation.

As the example in Figure 1, a unified model can solve all ABSA tasks. The review sentence is “I do enjoy Windows 8”. This sentence contains the aspect “Windows 8” and its opinion polarity is positive. For a true AE hypothesis like “The product has Window 8”, the NLI predicts the review sentence entails this hypothesis. For a negative hypothesis like “The product has I.”, where “I” could be a token from this review sentence but not an aspect, NLI may predict that the hypothesis contradicts the review because “I” is not an entity associated with the product. Thus, we enumerate all possible text spans $S$ in the review like “I”, “do”, “enjoy”, “Windows 8” to create a set of hypotheses “The product has $\langle S \rangle$” and then transfer their NLI predictions to AE label set \{B, I, O\}. For ASC, we form hypotheses “Windows 8 is great” from the span, which is predicted as an aspect like “Windows 8” in this example. Likewise, the NLI predicts the review sentence entails this hypothesis for a true ASC hypothesis. And then, we transfer the NLI prediction to ASC label set \{positive, negative, neutral\} sentiment. Finally, we combine the prediction of AE and ASC and infer the E2E ABSA prediction.

The work makes two main contributions. (1) It proposes to perform zero-shot transfer to 3 ABSA tasks. To the best of our knowledge, zero-shot AE and E2E ABSA have not been attempted before. (2) It proposes a unified model CORN post-trained on RNLI to solve zero-shot ABSA tasks. Experimental results show the effectiveness of our approach without human annotation.

2 Related Work

Zero-shot Sentiment Analysis. Sentiment analysis has been widely studied (Hu and Liu, 2004; Pang and Lee, 2008; Liu, 2012). Zero-shot learning was introduced for text classification tasks using entailment as the solution (Yin et al., 2019). Later, (Yin et al., 2020; Sainz et al., 2021) extended entailment approaches to zero-shot and few-shot open NLP tasks and relation extraction. Hu et al. (2021) focused on few-shot aspect category detection, which is a simplified few-shot aspect extraction. Seoh et al. (2021) considered zero-shot and few-shot learning on ASC and DSC through fine-tuning NLI and language modeling. This work comprehensively solves three ABSA tasks (ASC, AE, and E2E ABSA) in a zero-shot fashion with a unified model. Best to our knowledge, zero-shot AE and E2E ABSA, which belong to sequence labeling tasks, have not been studied before.

Natural Language Inference (NLI). NLI considers the textual entailment problem. The problem is determining whether a textual hypothesis can be inferred from a premise. Dagan et al. (2005) introduced the task of textual entailment. Several NLI benchmarks are proposed to facilitate the research. Bentivogli et al. (2009) developed the 3-way decision task that considers text contradiction. Zhang and Chai (2009) created a conversational entailment dataset that requires dialogue interpretation. Bowman et al. (2015) proposed a large NLI dataset and Williams et al. (2018) expanded the idea to 10 genres including both formal and informal corpora. These human annotation datasets incur a large labor cost. Besides, none of these works focuses on the review corpus. The approaches to solving NLI range from earlier rule-based approaches to recent deep neural network approaches (MacCartney and Manning, 2007; Chen et al., 2017). Several works explored the transformation of NLI tasks to other tasks. Zhang et al. (2020) transferred the NLI knowledge on few-shot intent detection. Seoh et al. (2021) transferred the NLI information to zero-shot, few-shot intent, and DSC. Wang et al. (2021) uses entailment in a few-shot scenario on 15 text classification...
datasets and a regression dataset.

**Contrastive Learning.** In our method, we adopt contrastive learning, which has been widely used in computer vision tasks (Wu et al., 2018). Recently, contrastive learning has also been used to learn representations of input sentences in NLP (Radford et al., 2021). These works use data augmentation to construct pairwise data, which helps feature learning. Gunel et al. (2021) directly used the contrastive loss to make the prediction. We use contrastive learning (Khosla et al., 2020) to pull expressions with the same NLI labels together and push expressions with different NLI labels apart.

## 3 Method

### Overview

As discussed in the introduction section, the critical point of allowing one model to perform multiple tasks in ABSA without supervised learning is to formulate a general learning task to post-train on. We adopt natural language inference (NLI) as the general task to capture subtle differences in pairs of texts. This section consists of three parts. In Section 3.1, we first revisit the NLI problem. Then, we describe how three (3) ABSA tasks can be cast into three forms of NLI problems via prompting. Table 2 summarizes our problem transformation. In Section 3.2, we describe how we process reviews into the NLI form with pseudo labels from metadata and reviews. We name our curated review NLI data as RNLI. Lastly, in Section 3.3, we introduce the details of post-training on RNLI following the transformation in Section 3.1. Table 1 summarizes a (non-exhaustive) list of notations, used repeatedly in the subsequent sections.

### 3.1 ABSA to NLI

**Natural Language Inference (NLI).** NLI is a core NLP problem. Specifically, a sentence, a document, or paragraph might be given as the premise $P$; the task then is to infer whether a given hypothesis $H$ is implied by (entailment), irrelevant to (neutral) or contradicted (contradiction) by the premise. The three relations are labeled with $Y_{\text{NLI}}$ which takes one of the labels in \{entailment, neutral, contradiction\}.

**Intuition of ABSA to NLI.** As described in Section 1, aspect-opinion and aspect-entity dependencies are the core problems for all ABSA tasks. Specifically, ASC aims to find the opinion polarity of a given aspect. AE and E2E ABSA aim to find aspects and their associated opinion polarities. We observe that when a hypothesis expresses a true aspect-opinion or aspect-entity dependency in the review, an NLI model may predict that the review entails this hypothesis.

ASC is a text classification task. Gao et al. (2021b) designed a simple yet effective prompt/template `<aspect> is <label>` to cast the aspect and the label into a natural language sentence. From the NLI perspective, the prompt is the hypothesis $H$, and the input text/review is the premise $P$. As such, by inferencing multiple `<label>`s of different sentiment polarities, NLI can perform aspect-based sentiment classification. Further, AE and E2E are sequence labeling problems, which is more challenging to formulate as an NLI problem given NLI is a 3-class classification task. The idea is to propose multiple candidates of spans (either aspect, e.g., “Window 8” or other chunks of words, e.g., “I”). Then, NLI can find aspects that entail aspect-opinion dependency (e.g., finding Window 8 is an aspect). As such, we chunk words into candidates of spans and create hypotheses for every candidate. Then, we summarize the predictions from all candidate spans to get the final AE/E2E ABSA prediction. Table 2 is a summary of how we cast ABSA tasks as NLI. The details of the transformations are as follows.
Table 2: The summary of casting ABSA tasks as natural language inference (NLI). X indicates a review sentence, S corresponds to a (pre-chunked) span and A corresponds to a given aspect. Taking the restaurant domain as examples, we use the domain label Restaurant when constructing hypotheses. entail., neutral, contra. indicates entailment, neutral and contradiction in NLI. Aspect, Outside indicates the span S’s label in AE; POS, NEU, NEG indicate the given aspect A’s sentiment label in ASC; T-{POS, NEU, NEG}, Outside indicate the span S’s aspect/outside labels in E2E ABSA.

| Task   | Input  | Premise | Hypothesis                  | NLI labels → ABSA labels                          |
|--------|--------|---------|------------------------------|---------------------------------------------------|
| AE     | (X, S) | X       | Restaurant has S.            | entail. → T, [neutral, contra.] → Outside          |
| ASC    | (X, A) | X       | A is great.                  | entail. → POS, neutral → NEU, contra. → NEG       |
| E2E(step1) | (X, S) | X       | Restaurant has S.            | entail. → <go to step2>, {neutral, contra.} → Outside |
| E2E(step2) | (X, S) | X       | S is great.                  | entail. → T-POS, neutral → T-NEU, contra. → T-NEG  |

Aspect Sentiment Classification (ASC). ASC aims to classify sentiment polarity $Y_{ASC}$ associated with a known aspect $A$ in an input review sentence $X$. The sentiment polarity can be one of {positive, neutral, negative} (we abbreviate the label set as {POS, NEU, NEG}). To cast this problem into an NLI problem, we take the review $X$ as premise $P$ and take prompt $<aspect>$ is great as hypothesis $H$. If the hypothesis prompt can be implied by the premise (entailment), ASC prediction is POS. Similarly, contradiction of NLI is mapped to NEG and neutral is mapped to neutral, respectively.

Aspect Extraction (AE). Aspect extraction (AE) aims to find aspects that may have associated opinions in the review sentence $X$. It is typically modeled as a sequence labeling task, where each token of the review sentence is labeled as one of {Begin, Inside, Outside} (or {B, I, O} for brevity). Spans that are labeled as one B and followed by zero or more I are treated as an aspect. We cast AE into multiple entailment problems between the input review sentence and spans. Specifically, we take the review sentence $X$ as the premise $P$ of NLI. We first produce multiple candidates of spans via choosing chunked tokens of length within 6 (Cui et al., 2021), where each candidate $S$ will later be included in a prompt to compose one hypothesis $H$. Note that we craft different prompts for different domains. For example, for the restaurant domain, we use Restaurant has $S$ as the template prompt. During prediction, we simplify B and I as a single label $T$. If the hypothesis prompt can be implied by the premise (entailment), the AE prediction of the span is mapped to $T$. Otherwise, the prediction is $O$. We predict all possible $(X, S)$ pairs and summarize them to predictions of all tokens in the review $\hat{Y}_{AE}$. Note, if two spans have text overlapping and yet are assigned with different labels, we choose the span with the higher score as the final prediction to avoid conflicts.

End-to-end ABSA (E2E). Li et al. (2019b) conducts end-to-end aspect-based sentiment analysis which treats the two tasks AE and ASC as one unique task. For example, given input $X$, end-to-end ABSA aims to predict whether a token is part of an aspect. If so, it further predicts the sentiment polarity associated with that aspect. Following the implementation of (Xu et al., 2019a), each token of the review sentence can be labeled as one of {T-POS, T-NEU, T-NEG, O}, which is a combined label space of AE and ASC and $T$ implies the token is a part of aspect $A$. Inspired by the previous formulation for AE and ASC, we propose to perform zero-shot E2E ABSA in two steps, a combination of AE and ASC as shown in Table 2 E2E(step1) and E2E(step2). Specifically, we predict all possible $(X, S)$ pairs in the review. We first perform zero-shot AE by using the hypothesis “$<Entity>$ has $S$”. If the span $S$ is predicted as an aspect $T$, we go to E2E(step2) and use the hypothesis “$S$ is great” to perform zero-shot ASC. The final E2E prediction is one of {T-POS, T-NEU, T-NEG}. If during zero-shot AE, the span $S$ is predicted as $O$, its final E2E prediction is $O$.

3.2 Review NLI (RNLI)

Existing NLI datasets are very labor-intensive to annotate, which is not scalable to a large number of domains. Instead, we pre-process reviews using simple yet effective rules (Qiu et al., 2011) to curate a review NLI data with pseudo labels, without prior knowledge of any
domains. We name such pre-processed data as RNLI for simplicity.

An RNLI example is composed of a premise and hypothesis pair curated from reviews. We define the sentiment clause as a language expression for an aspect and its associated opinion. The opinion can be positive, negative, and neutral, not presented (unknown). Our hypotheses and premises are composed of sentiment clauses that express sentiment on aspects. We detail the process as follows.

**Aspect Extraction.** We extract aspects using double propagation (Qiu et al., 2011; Shu et al., 2016). Note that double propagation requires seed aspects that could be domain-specific. To avoid building seed aspects domain-by-domain, we leverage the metadata from products’ feature description in Amazon dataset (Ni et al., 2019). With double propagation, we can extract “price” and “Windows 10” from “The price for windows 10 is great !”.

**Aspect Polarity Extraction.** Given every category’s aspect set, we extract clauses that contain an aspect in the aspect set from the review data under the same category. Then we infer aspect’s polarity with one of \{PO

pro 11 a shot. [C3] I am still struggling with **Windows 8**.

More examples of mapping from hypothesis to NLI label is shown in Table 3. In the example premise, learning tool is an aspect with positive polarity. When the hypotheses mentioned the aspect and the positive opinion like “a good learning tool”, the NLI label is entailment. If the hypotheses mention the aspect but with no opinion term like “it is a learning tool”, the NLI label is still entailment. The reason is that a premise consisting of an aspect with a positive or negative opinion can infer a hypothesis that only mentions the aspect without opinion. However, the premise that only consists of an aspect without any opinion mentioned cannot entail the hypotheses consisting of positive or negative opinions.

### 3.3 Post-training

**Transformer Encoder.** We adopt BART encoder (Lewis et al., 2020) as the pre-trained model and post-train it on RNLI. For each RNLI input \((H_i, P_i)\), we format the input as \(I_i = [CLS]+P_i+[SEP]+H_i+[SEP]\). We feed the input \(X_i\) into the encoding model as follows:

\[
z_i = \text{BART}(I_i).
\]

**Supervised Contrastive Learning (SCL).** Supervised contrastive learning on class labels Khosla et al. (2020) trains the model to pull samples in the same class together and meanwhile push samples with different class labels away. We use this form of contrastive learning to pull expressions with the same entailment orientation closer and push expressions with different entailment orientations apart. The loss function of SCL \(L_{SCL}\) is:

\[
L_{SCL,i} = \frac{1}{|A_i|} \sum_{j \in A_i} \log \frac{\exp(z_i \cdot z_j / \tau)}{\sum_{k=1, k \neq i}^N \exp(z_i \cdot z_k / \tau)}
\]

\[
L_{SCL} = \frac{1}{N} \sum_{i=1}^N L_{SCL,i}.
\]

where \(N\) is the number of examples, \(\tau\) is the temperature, \(A_i = \{j \in \{1...N\} | i \neq j, Y_i = Y_j\}\).
4 Experiments

We aim to answer the following research questions in the experiment: (1) What is the performance difference between CORN and other pre/post-trained models? (2) Upon ablation studies of different post-train datasets and training losses, what are their respective contributions to the whole post-training performance gain? (3) What are the challenges and future directions of zero-shot ABSA? We answer them in Section 4.4.

4.1 Dataset and Evaluation

We pre-process 29 categories of data from the Amazon review dataset (Ni et al., 2019) into RNLI data. To make our RNLI data generic, we generate 50k examples per category. Besides, to avoid imbalanced distribution over product features, we take at most ten clauses, given an aspect and a sentiment polarity. The final RNLI data contains 100k examples for each label {entailment, neutral, contradiction}, which sum up to 300k examples. In comparison, broad-coverage human-annotated MNLI dataset Williams et al. (2018) has 433k examples. We split 85%, 5% for training and validation, respectively.

Testing Datasets. To test the performance of our post-trained model, we evaluate their zero-shot transfer performance over ASC, AE, and E2E. Table 4 provides the statistics.

We follow (Xu et al., 2019a) and use SemEval 2014 Task 4 for laptop domain and SemEval 2016 Task 5 for restaurant domain to evaluate zero-shot AE. We use SemEval 2014 Task 4 for laptop and restaurant reviews to evaluate zero-shot ASC. For E2E, we follow (Li et al., 2019a) and use their merged SemEval data to evaluate zero-shot E2E.

Metric. We report the accuracy and Macro-F1 for ASC. For AE, we compute accuracy over three AE labels. For E2E, we also compute Macro-F1 over four E2E labels.

4.2 Hyper-parameter Settings

We take BART-large as the backbone. In the SCL loss Eq. 2, we set the temperature \( \tau = 0.1 \). To accelerate the training process, we use fp16 to speed up computation. The maximum length of model pre-training is 512, and the batch size is 16. We use Adam optimizer and set the learning rate to be \( 1 \times 10^{-5} \). We train 10 epochs with early termination. We report the averaged score and standard deviation of 5 random seeds.

4.3 Compared Methods

We compare our model with available zero-shot baselines.

BERT\textsubscript{base}+MNLI: is proposed in (Seoh et al., 2021) that finetunes the BERT-base pre-trained model on MNLI datasets for zero-shot ASC. GPT-2 is a baseline compared in this work (Seoh et al., 2021).

In the following paper, BART refers to BART-large, BERT refers to uncased-bert-large, and Roberta refers to Roberta-large. To enable these transformer models to predict
Table 5: Comparison of CORN with other baselines for zero-shot transfer to 3 ABSA tasks. Rest., Lap. corresponds to restaurant and laptop domains, respectively. † are results from Seoh et al. (2021).

| Model          | ASC (Accuracy/Macro-F$_1$) | AE (Accuracy) | E2E (Macro-F$_1$) |
|----------------|-----------------------------|---------------|-------------------|
|                | Rest. | Lap.  | Rest. | Lap.  | Rest. | Lap.  |
| Pre-training only |      |      |      |      |      |      |
| BERT           | 56.9/45.5 | 57.9/50.7 | 44.9 | 46.6 | 10.7 | 25.3 |
| Roberta        | 59.3/49.1 | 58.8/54.4 | 43.1 | 44.5 | 18.5 | 27.6 |
| GPT-2          | **71.4**/45.5 $^* $ | 60.5/39.6 | -    | -    | -    | -    |
| Post-training  |      |      |      |      |      |      |
| BERT+PT        | 61.0/49.2 | 60.6/53.4 | 45.8 | 48.2 | 27.3 | 31.4 |
| BERT+ITPT      | 60.3/49.1 | 60.2/52.4 | 45.3 | 48.6 | 27.5 | 32.6 |
| Post-training on MNL1 |      |      |      |      |      |      |
| BERT+MNLI      | 61.8/57.9 $^†$ | 58.9/54.9 $^†$ | -    | -    | -    | -    |
| BART+MNLI      | 67.5±5.6/69.3±0.3 | 70.5±0.3/70.9±0.4 | 56.7±0.5 | 59.6±0.3 | 32.5±0.8 | 36.1±0.6 |
| BART+SCL+MNLI  | 68.8±5.6/69.2±0.4 | **71.3±0.3**/70.3±0.2 | 56.9±0.3 | 60.0±0.3 | 33.9±0.5 | 36.8±0.4 |
| Post-training on MNL1 |      |      |      |      |      |      |
| BART+CE+RNLI   | 67.0±0.4/69.7±0.7 | 70.5±0.4/70.3±0.4 | 57.6±0.7 | 60.7±0.5 | 35.4±0.6 | 38.9±0.5 |
| CORN           | 69.7±0.4/70.0±0.5 | 70.9±0.5/71.0±0.8 | **58.0±0.6** | 61.5±0.7 | **37.2±0.5** | 40.3±0.6 |

Table 6: The precision ($P$) and recall ($R$) of CORN and baselines.

| Model          | ASC ($P/K$) | AE ($P/K$) | E2E ($P/K$) |
|----------------|-------------|------------|-------------|
|                | Rest. | Lap.  | Rest. | Lap.  | Rest. | Lap.  |
| Pre-training only |      |      |      |      |      |      |
| BERT           | 58.0/37.4 | 61.9/33.2 | 49.2/21.9 | 51.0/16.6 | 32.7/6.4 | 37.1/19.2 |
| Roberta        | 57.4/41.1 | 61.2/34.8 | 47.8/29.8 | 50.3/16.3 | 28.9/11.9 | 40.9/21.0 |
| Post-training  |      |      |      |      |      |      |
| BERT+PT        | 56.9/41.8 | 66.1/41.9 | 58.9/45.1 | 60.6/40.7 | 34.7/22.5 | 41.7/28.7 |
| BERT+ITPT      | 56.0/41.0 | 65.7/41.5 | 56.5/44.3 | 59.3/42.9 | 31.8/24.2 | 44.9/30.4 |
| Post-training on MNL1 |      |      |      |      |      |      |
| BART+MNLI      | 71.5±0.5/66.6±0.4 | **74.6±0.4**/71.0±0.4 | 54.3±0.6/49.5±0.4 | **65.0±0.4**/54.4±0.3 | 35.3±0.7/30.4±0.1 | 43.9±0.7/30.8±0.6 |
| BART+SCL+MNLI  | 72.0±0.3/66.9±0.3 | 74.3±0.3/66.5±0.3 | 55.4±0.3/49.9±0.4 | 64.1±0.3/54.9±0.3 | 35.9±0.9/31.9±0.6 | 44.9±0.9/31.5±0.4 |
| Post-training on MNL1 |      |      |      |      |      |      |
| BART+CE+RNLI   | 72.3±0.5/66.5±0.4 | 74.1±0.4/67.1±0.3 | 54.9±0.6/55.3±0.5 | 57.9±0.6/54.4±0.4 | 36.3±0.6/54.3±0.5 | 44.1±0.6/54.3±0.5 |
| CORN           | 72.0±0.6/66.7±0.6 | 74.6±0.6/67.5±0.7 | 55.6±0.6/55.4±0.5 | 60.3±0.6/54.7±0.8 | 38.0±0.6/53.2±0.7 | 45.0±0.6/53.8±0.8 |

zero-shot ABSA tasks, we use manually created prompts, which proved to be effective in Gao et al. (2021b).

BERT (Vaswani et al., 2017): this is the original uncased BERT-large model.

BERT+PT (Xu et al., 2019a): this is post-trained BERT-large with amazon and yelp reviews on general tasks including masked-language modeling (MLM) and next sentence prediction (NSP).

Robert (Liu et al., 2019): this is the original Roberta-large model.

BERT+ITPT (Sun et al., 2019): This is post-trained BERT on Amazon20 (Chen et al., 2015), IMDB (Maas et al., 2011), YELP (Zhang et al., 2015) and SST-2 (Socher et al., 2013).

BART+MNLI: fine-tune BART with MNLI datasets (Williams et al., 2018). The trained model is available online3. Note that this baseline uses an extra output layer to fine-tune on cross-entropy loss.

CORN: our contrastive post-pretraining on RNLI. The details of CORN are in Section 3. To gain further insight, we ablate various components of our model. First, we are interested in the contribution of RNLI. Then, we compare our model with the same post-training approach using the human-annotated NLI data MNLI and denote this method as BART+SCL+MNLI. Second, we are interested in the contribution of different types of losses. We train RNLI with cross-entropy loss and denote this method as BART+CE+RNLI.

4.4 Results

Comparison with baselines. Tables 5 and 6 report scores of all models’ zero-shot transfer performance for the three ABSA tasks. We observe the following: (1) BART+MNLI turns out to be the strongest baseline. This shows the importance of finetuning on the NLI dataset for ABSA tasks. (2) Post-trained models achieve higher performances for all three ABSA tasks than pre-trained models, especially on E2E tasks, by 6.3% at least (BERT+PT outperforms Roberta). This suggests that domain adaptation is essential for ABSA tasks. (3) Overall,
Table 7: Qualitative study, with predictions from three models over E2E ABSA. In the AE NLI prediction, we use NE to indicate non-entailment (neutral or contradiction) in NLI label space. Red texts indicate wrong predictions. (Best view in color.)

| Model          | BERT+PT                                                                 | BART+MNLI                                                             | CORN                                                                 |
|----------------|-------------------------------------------------------------------------|-----------------------------------------------------------------------|-----------------------------------------------------------------------|
| Review Premise | I was given a demonstration of Windows 8                               | I was given a demonstration of Windows 8                               | I was given a demonstration of Windows 8                               |
| True Label     | O O O O O O T-NEU T-NEU                                                 | O O O O O O T-NEU T-NEU                                              | O O O O O O T-NEU T-NEU                                              |
| AE Hypothesis  | Product has I.                                                          | Product has demonstration...Product has Windows.                       | Product has windows 8.                                               |
| AE Prediction  | O O O O R O R R                                                        | O O O O R O R R                                                        | O O O O R O R R                                                        |
| ASC Hypothesis | Product has demonstration...Product has Windows.                        | Product has demonstration...Product has Windows.                       | Product has demonstration...Product has Windows.                       |
| ASC Prediction | POS POS                                                               | POS NEU                                                               | POS NEU                                                               |
| E2E Prediction | O O O O T-POS T-NEU                                                     | O O O O T-NEU T-NEU                                                  | O O O O T-NEU T-NEU                                                  |

our model performs the best, especially on AE and E2E tasks.

BART+MNLI outperforms BERT, Roberta, and post-trained BERTs on all three tasks. The MNLI dataset contains human-annotated examples for sentiment analysis and possession. Thus we use them to infer aspect-opinion and aspect-entity relations mentioned in the premise. However, MLM and NSP loss-based pre-trained and post-trained methods are self-supervised and cannot reflect the aspect-opinion and aspect-entity dependency well. BART+MNLI mostly performs better than GPT-2 and BERTbase+MNLI (Seoh et al., 2021) on ASC. It may be due to the pre-trained model configurations, prompts, and post-processing methods on NLI predictions.

In the second observation, we compare post-trained BERTs (on domain corpus) to pre-trained methods, BERT and Roberta. Their training losses are the same. Nevertheless, BERT+PT and BERT+ITPT perform slightly better than BERT and Roberta because the domain corpus contains a higher density of sentiment words and aspect words than the corpus used in BERT and Roberta.

Last but not least, CORN outperforms the baselines. In ASC, we observe that CORN performs close to the models finetuned on MNLI (BART+MNLI and BART+SCL+MNLI) in all metrics (accuracy, macro-F1, precision, and recall). Considering that MNLI is human-annotated while RNLI’s sentiment analysis examples are curated from rules, we think that rule-based sentiment-related NLI examples can achieve a similar effect as human-annotated examples. CORN performs slightly better in the AE task than MNLI-based models on accuracy. Diving deep into Table 6, we find that MNLI-based models have higher precision but lower recall than CORN. This suggests that RNLI can enrich the aspect terms; however, the precision of possession cannot achieve a human-annotated level as MNLI. E2E ABSA is an aggregation task over AE and ASC. CORN performs better than MNLI-based models because of its high recall of AE.

Ablation study. To evaluate how contrastive post-training and RNLI contribute respectively, firstly, we compare CORN to BART+SCL+MNLI. From Table 5, CORN has performance gains on AE and E2E. This indicates that RNLI feeds the model more domain-specific information for AE and E2E ABSA tasks. We validate our post-training approach by comparing it with BART+CE+RNLI. CORN outperforms BART+CE+RNLI on all three tasks. This shows the effectiveness of contrastive post-training.

Qualitative Analysis We provide a case study to show the effectiveness of our model by comparing it with two baseline models, BART+MNLI and BERT+PT. Table 7 shows a sample in the E2E task. There are two steps: (1) identifying “Windows 8” as an aspect (2) determining the sentiment polarity as neutral. BART+MNLI fails to extract “8” due to its lack of domain-specific information. The E2E prediction of BERT+PT is the worst. It fails to classify the sentiment polarity of “Windows 8” correctly, probably because it lacks knowledge about aspect-opinion dependencies. CORN performs the best. However, its overall performance cannot achieve supervised models. There are limitations on the prompts used in testing and the rules used in RNLI curation. Furthermore, there exists a gap between them. As shown in Table 2, the prompt for AE is “<Entity> has S”. It indicates a possession relation. However, not all possession samples contribute to AE. For example, the “demonstration” in the case study “I was given a demonstration of Windows 8.” has the possession relation with the entity while it is not an as-
pect. Another premise example is that “It does not come with the keyboard”. The “keyboard” is an aspect. However, the NLI prediction on the hypotheses “The product has keyboard” is a contradiction and indicates “keyboard” is not an aspect. This example suggests that the possession relation cannot cover all AE. Nevertheless, the weaknesses aforementioned are the future directions.

5 Conclusion

This paper proposed contrastive post-training on review NLI. This method casts three ABSA tasks (AE, ASC, E2E ABSA) into natural language inference (NLI) to allow zero-shot transfer. We pre-process reviews into NLI form based on rules. As a result, our method alleviates the need for human annotation for both ABSA and NLI. Furthermore, experimental results show that our approach achieves promising results.

References

Luisa Bentivogli, Bernardo Magnini, Ido Dagan, Hoa Trang Dang, and Danilo Giampiccolo. 2009. The fifth PASCAL recognizing textual entailment challenge. In Proceedings of the Second Text Analysis Conference, TAC 2009, Gaithersburg, Maryland, USA, November 16-17, 2009. NIST.

Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015. A large annotated corpus for learning natural language inference. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015, pages 632–642. The Association for Computational Linguistics.

Qian Chen, Xiaodan Zhu, Zhen-Hua Ling, Si Wei, Hui Jiang, and Diana Inkpen. 2017. Enhanced LSTM for natural language inference. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers, pages 1657–1668. Association for Computational Linguistics.

Zhiyuan Chen, Nianzu Ma, and Bing Liu. 2015. Lifelong learning for sentiment classification. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, pages 750–756. The Association for Computer Linguistics.

Leyang Cui, Yu Wu, Jian Liu, Sen Yang, and Yue Zhang. 2021. Template-based named entity recognition using BART. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 1835–1845.

Ido Dagan, Oren Glickman, and Bernardo Magnini. 2005. The PASCAL recognizing textual entailment challenge. In Machine Learning Challenges, Evaluating Predictive Uncertainty, Visual Object Classification and Recognizing Textual Entailment, First PASCAL Machine Learning Challenges Workshop, MLCW 2005, Southampton, UK, April 11-13, 2005, Revised Selected Papers, volume 3944 of Lecture Notes in Computer Science, pages 177–190. Springer.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 4171–4186. Association for Computational Linguistics.

Tianyu Gao, Adam Fisch, and Danqi Chen. 2021a. Making pre-trained language models better few-shot learners. In Association for Computational Linguistics (ACL).

Tianyu Gao, Adam Fisch, and Danqi Chen. 2021b. Making pre-trained language models better few-shot learners. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and
Beliz Gunel, Jingfei Du, Alexis Conneau, and Veselin Stoyanov. 2021. Supervised contrastive learning for pre-trained language model fine-tuning. In 9th International Conference on Learning Representations. OpenReview.net.

Mengting Hu, Shiwan Zhao, Honglei Guo, Chao Xue, Hang Gao, Tiegang Gao, Renhong Cheng, and Zhong Su. 2021. Multilabel few-shot learning for aspect category detection. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing. ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021, pages 6330–6340. Association for Computational Linguistics.

Minqing Hu and Bing Liu. 2004. Mining and summarizing customer reviews. In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, pages 168–177.

Prannay Khosla, Piotr Teterwak, Chen Wang, Aaron Sarna, Yonglong Tian, Phillip Isola, Aaron Maschiotto, Ce Liu, and Dilip Krishnan. 2020. Supervised contrastive learning. In Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020, pages 7871–7880. Association for Computational Linguistics.

Xin Li, Lidong Bing, Piji Li, and Wai Lam. 2019a. A unified model for opinion target extraction and target sentiment prediction. Proceedings of the AAAI Conference on Artificial Intelligence, 33:6714–6721.

Xin Li, Lidong Bing, Wenzuan Zhang, and Wai Lam. 2019b. Exploiting BERT for end-to-end aspect-based sentiment analysis. In Proceedings of the 5th Workshop on Noisy User-generated Text (W-NUT 2019), pages 34–41, Hong Kong, China. Association for Computational Linguistics.

Bing Liu. 2012. Sentiment Analysis and Opinion Mining. Synthesis Lectures on Human Language Technologies. Morgan & Claypool Publishers.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. CoRR, abs/1907.11692.

Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. 2011. Learning word vectors for sentiment analysis. In The 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, Proceedings of the Conference, pages 142–150. The Association for Computer Linguistics.

Bill MacCartney and Christopher D. Manning. 2007. Natural logic for textual inference. In Proceedings of the ACL-PASCAL@ACL 2007 Workshop on Textual Entailment and Paraphrasing, Prague, Czech Republic, June 28-29, 2007, pages 193–200. Association for Computational Linguistics.

Jianmo Ni, Jiacheng Li, and Julian J. McAuley. 2019. Justifying recommendations using distantly-labeled reviews and fine-grained aspects. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong.
Bo Pang and Lillian Lee. 2008. Opinion mining and sentiment analysis. *Found. Trends Inf. Retr.*, 2(1-2):1–135.

Guang Qiu, Bing Liu, Jiajun Bu, and Chun Chen. 2011. Opinion word expansion and target extraction through double propagation. *Comput. Linguistics*, 37(1):9–27.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. 2021. Learning transferable visual models from natural language supervision. In *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pages 8748–8763. PMLR.

Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by generative pre-training. *openai*.

Oscar Sainz, Oier Lopez de Lacalle, Gorka Labaka, Ander Barrena, and Eneko Agirre. 2021. Label verbalization and entailment for effective zero and few-shot relation extraction. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 1199–1212.

Ronald Seoh, Ian Birle, Mrinal Tak, Haw-Shiuan Chang, Brian Pinette, and Alfred Hough. 2021. Open aspect target sentiment classification with natural language prompts. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, EMNLP 2021, Punta Cana, Dominican Republic November 7-11, 2021. Association for Computational Linguistics.

Lei Shu, Bing Liu, Hu Xu, and Annice Kim. 2016. Lifelong-rl: Lifelong relaxation labeling for separating entities and aspects in opinion targets. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 225–235.

Lei Shu, Hu Xu, and Bing Liu. 2017. Lifelong learning crf for supervised aspect extraction. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 148–154.

Lei Shu, Hu Xu, and Bing Liu. 2019. Controlled cnn-based sequence labeling for aspect extraction. *arXiv preprint arXiv:1905.06407*.

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Y. Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1631–1642. ACL.

Chi Sun, Xipeng Qiu, Yige Xu, and Xuanjing Huang. 2019. How to fine-tune BERT for text classification? In *Chinese Computational Linguistics - 18th China National Conference*, volume 11856 of *Lecture Notes in Computer Science*, pages 194–206. Springer.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems*, pages 5998–6008.

Sinong Wang, Han Fang, Madian Khabsa, Hanzi Mao, and Hao Ma. 2021. Entailment as few-shot learner. *CoRR*, abs/2104.14690.

Adina Williams, Nikita Nangia, and Samuel R. Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers), pages 1112–1122. Association for Computational Linguistics.
Zhirong Wu, Alexei A. Efros, and Stella X. Yu. 2018. Improving generalization via scalable neighborhood component analysis. In European Conference Computer Vision, volume 11211 of Lecture Notes in Computer Science, pages 712–728. Springer.

Hu Xu, Bing Liu, Lei Shu, and S Yu Philip. 2018. Double embeddings and cnn-based sequence labeling for aspect extraction. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 592–598.

Hu Xu, Bing Liu, Lei Shu, and S Yu Philip. 2020. Dombert: Domain-oriented language model for aspect-based sentiment analysis. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, pages 1725–1731.

Hu Xu, Bing Liu, Lei Shu, and Philip S. Yu. 2019a. BERT post-training for review reading comprehension and aspect-based sentiment analysis. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 2324–2335. Association for Computational Linguistics.

Hu Xu, Bing Liu, Lei Shu, and Philip S Yu. 2019b. A failure of aspect sentiment classifiers and an adaptive re-weighting solution. arXiv preprint arXiv:1911.01460.

Wenpeng Yin, Jamaal Hay, and Dan Roth. 2019. Benchmarking zero-shot text classification: Datasets, evaluation and entailment approach. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3914–3923.

Wenpeng Yin, Nazneen Fatema Rajani, Dragomir Radev, Richard Socher, and Caiming Xiong. 2020. Universal natural language processing with limited annotations: Try few-shot textual entailment as a start. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 8229–8239.

Chen Zhang and Joyce Yue Chai. 2009. What do we know about conversation participants: Experiments on conversation entailment. In Proceedings of the SIGDIAL 2009 Conference, The 10th Annual Meeting of the Special Interest Group on Discourse and Dialogue, 11-12 September 2009, London, UK, pages 206–215. The Association for Computer Linguistics.

Jianguo Zhang, Kazuma Hashimoto, Wenhao Liu, Chien-Sheng Wu, Yao Wan, Philip S. Yu, Richard Socher, and Caiming Xiong. 2020. Discriminative nearest neighbor few-shot intent detection by transferring natural language inference. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020, pages 5064–5082. Association for Computational Linguistics.

Lei Zhang, Shuai Wang, and Bing Liu. 2018. Deep learning for sentiment analysis: A survey. Wiley Interdiscip. Rev. Data Min. Knowl. Discov., 8(4).

Xiang Zhang, Junbo Jake Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. In Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems, pages 649–657.