Interventional Aspect-Based Sentiment Analysis

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Abstract

Recent neural-based aspect-based sentiment analysis approaches, though achieving promising improvement on benchmark datasets, have reported suffering from poor robustness when encountering confounder such as non-target aspects. In this paper, we take a causal view to addressing this issue. We propose a simple yet effective method, namely, Sentiment Adjustment (SENTA), by applying a backdoor adjustment to disentangle those confounding factors. Experimental results on the Aspect Robustness Test Set (ARTS) dataset demonstrate that our approach improves the performance while maintaining accuracy in the original test set\textsuperscript{1}.

1 Introduction

Aspect-Based Sentiment Analysis (ABSA) is the task of classifying the sentiment polarity (positive, negative, neutral) on an aspect from a sentence or extracting aspects that reviewers have made comments on (Hu and Liu, 2004). Recently neural models have dominated the ABSA task, including memory networks (Wang et al., 2018; Tang et al., 2016), convolution methods (Li et al., 2018; Huang and Carley, 2018), attention mechanism (Ma et al., 2017) and dependency trees (Bai et al., 2020).

However, open issues remain as neural models lack robustness for ABSA since they are sensitive to only the sentiment words of the target aspect, and therefore not be interfered with by the sentiment of any non-target aspect (Xing et al., 2020). For example, when there are multiple aspects in a review sentence, such as “The pizza is good and waiters are friendly.”. The key challenge behind this phenomenon is caused by spurious correlations of statistical learning (Zeng et al., 2020). From a causal perspective, spurious correlations are caused by confounding factors such as those other aspects in the same sentences. Based on the structural causal model (SCM) theory (Pearl, 2019), if we intervene on the precursor variable in spurious correlations, we can eliminate those spurious correlations to some degree.

Motivated by this, we propose the SENtiment Adjustment (SENTA), which intervene between confounding factor and target aspect for ABSA. Firstly, we rethink the ABSA in the causal view in § 3.1 and introduce backdoor adjustment (Halpern, 2019) in SCM, which try to intervene between confounding factor and target aspect in ABSA as shown in Figure 1. Secondly, we introduce our Sentiment Adjustment approach in § 3.2. We train a confounding model without prior knowledge achieving good performance on the training and original test data. Then, we optimize a combination model to alleviate confounding effects by using decomposed confounding features. We evaluate our model’s effectiveness in Aspect Robustness

Figure 1: The causal graph of ABSA. We build our causal model over three main variables: target feature $X$, predictions $Y$ and confounding factor $C$. Our goal is to alleviate confounding factors, which is caused by $X \leftarrow C$, $Y \leftarrow C$. 

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\textsuperscript{1} The code and dataset are available in https://github.com/zjunlp/SENTA.
Test Set (ARTS), and our proposed method exhibits good performance compared with baselines. Our major contributions are summarized as:

- We make the first attempt to take the causal view of ABSA to address the confounding factors.
- We propose a simple causal framework, Sentiment Adjustment, for ABSA, which obtain better performance than baselines.

2 Related Work

ABSA has recently emerged as an active research area with lots of approaches (Ma et al., 2017; Li et al., 2018; Huang and Carley, 2018; Bai et al., 2020), yet challenges remain for robustness. Xing et al. (2020) introduce a new benchmark ARTS and probe the aspect robustness of neural models, and reveal up to 69.73% performance drop compared with the original test set. Previous work leverage re-weighting (Xu et al., 2019b) to address this issue. Differently, we take the causal view of ABSA. Note that, causal inference has been applied to various fields, including semantic segmentation (Zhang et al., 2020), few-shot learning (Yue et al., 2020), etc. However, there are only a few works for natural language processing (NLP). (Pryzant et al., 2020) propose an estimator and proves bias is bounded when performing an adjustment for the text. (Madaan et al., 2020) introduce a framework to generate counterfactual samples in text generation. To the best of our knowledge, we are the first to apply causal inference to ABSA.

3 Methodology

In ABSA task, given a aspect \( t = (t_1, t_2, ..., t_m) \) about a product and a review sentence \( s = (s_1, s_2, ..., s_n) \) containing the information about \( t \). Aspect \( t \) appears as a text span in sentence \( s \) and a sentence may contain more than one aspect. The goal is to find polar sentiment (positive, neutral, negative) about specific aspect \( t \).

3.1 ABSA in the Causal View

Causal relations describe the causal effect among variables, which exist as the edge between nodes in SCM. Such relations are written using the assignment operator \( \leftarrow \) and deterministic function notation \( f \), labeling the variable they affect. For example, we use \( X \leftarrow u_x \) represent the causal relationship of an unobserved variable on variable \( X \).

All causal relations in SCM is a directed acyclic graph (DAG). As shown in Figure 1, the SCM presented in the paper can be shown as follows:

\[
X \leftarrow f_x(C, U_X) \\
Y \leftarrow f_y(X, C, U_Y) \\
C \leftarrow f_c(U_C)
\]

We build our causal model over three observed variables target feature \( X \), predictions \( Y \) and confounding factor \( C \). Variable \( U \) is called extraneous or unobserved variable, and \( u_c, u_x \) and \( u_y \) independent and unobserved noise variables. As confounding factor \( C \) has impacts on \( X \), we can get \( X \leftarrow f_x(C, U_X) \). Variable \( C \) also has causal impact on predictions \( Y \), so conditional distribution \( P(Y \mid X, Y, U) \) can be converted into \( Y \leftarrow f_y(X, C, U_Y) \). To find the inner causal connection between \( X \) and \( Y \), we need to eliminate the influence of confounding factor \( C \).

Backdoor Adjustment

To intervene in SCM, do operation is used to describe the whole process. We use \( do(X = x) \) to express the intervention. When we do intervention to make \( X = x \), this process is denoted as \( P(Y = y \mid do(X = x)) \). If there are a set of variables \( C \) that satisfies the backdoor criterion (Appendix A), we can estimate the causal effect of \( X \) on \( Y \). As confounding factor meets the requirement, to know the effect of \( X \) (target feature) on \( Y \) (predictions), we regard variable \( C \) as the control, then make backdoor adjustment:

\[
P(Y = y \mid do(X = x)) = \sum_c P(Y = y \mid X = x, C = c)P(C = c)
\]

Suppose there are \( m \) classes in classification, then:

\[
= \sum_{i=1}^{m} P(Y = y \mid X = x, c_m)P(c_m)
\]

⇒ \[
P(Y \mid x \oplus \frac{1}{m} \sum_{i=1}^{m} P(c_i \mid x) \bar{x}_i)
\]

Note that \( P(c_i \mid x) \), which we denote as the output of corresponding class. The key point is that, we make adjustment to original input \( x \) by adding the decomposed class-level features of the trained confounding model.
3.2 Sentiment Adjustment

STEP1: Training a Confounding Model

Since ABSA is to classify the sentiment of a specific aspect from a review sentence, it is similar to QA tasks. However, the output of ABSA is the polarity of aspect instead of a text span. We leverage BERT to encode the input as ([CLS], q_1, ..., q_N, [SEP], s_1, ..., s_M, [SEP]). Then we apply the hidden representation of h_{CLS} to the linear transformation to predict the sentiment polarity. The first step aims to obtain a model with good performance on the original test set but significantly deteriorates the new test set’s performance.

STEP2: Training an Interventional Model

As shown in Figure 2, we build an interventional framework. h(\bar{x}_i) is the mean hidden feature of the confounding model from class c_i. h_{x_i} is the hidden states of main model.

There are m classifying polarities C = \{c_1, ..., c_m\}, given a training sample \{x, y\}, then

\[ \alpha_i = f_{\text{classifier}}(h(x_i)) \]

\[ h_C = \sum_i \alpha_i h(\bar{x}_i) \]

\[ h_{\text{adjust}} = f_{\text{concat}}(h_M, h_C) \]

Figure 2: Framework of SENtiment Adjustment (SENTA).

4 Experiments

4.1 Datasets and Settings

For evaluating our SENTA model, we use SemEval-2014 Task 4 in both laptop and restaurant domains for training, which is a popular benchmark for ABSA. Specifically, we use the SemEval-2014 original (Ori) test set as well as ARTS (Change) which is a aspect robustness probing test set from (Xing et al., 2020). Statistics about test sets is shown in Table 1. Ori is the original test set in SemEval-2014 and Change is ARTS.

|                | Laptop | Restaurant |
|----------------|--------|------------|
|                | Ori    | Change     |
| Positive       | 341    | 883        |
| Negative       | 128    | 587        |
| Neutral        | 169    | 407        |

|                | Ori    | Change     |
|----------------|--------|------------|
| Positive       | 728    | 1,953      |
| Negative       | 196    | 1,104      |
| Neutral        | 196    | 473        |

Table 1: Statistics of test sets

4.2 Baselines

We compare with several baseline methods with the same hyper-parameters for fairness as follows: BERT (Devlin et al., 2019) is BERT-base-uncased, which is regarded as a baseline pretraining model in our experiment. BERT-PT (Xu et al., 2019a) is
a post-training language model, post-trained (fine-tuned) on a combination of Amazon reviews and all Yelp data. BERT-PT remains almost SOTA in ARTS so far and BERT(-PT)-Distill (Hinton et al., 2015) is a distillation method to combine confounding model with ABSA model. The training epochs for all models is set according to the evaluation in Ori, instead of Change which is unseen in a real scenario.

4.3 Results Analysis

Results are shown in Table 2, including accuracy of six models on Laptop and Restaurant test sets as well as corresponding ARTS test set. Apparently, all methods perform worse in Change than Ori. For example, in Laptop BERT shows a sharp decline in Change test set from 75.07% to 63.71%, and BERT-SENTA declines from 75.08% to 67.23%. It shows that all methods still suffer from bias from confounding factors in new test set, which is hard to remove completely.

SENTA outperforms other methods while maintaining accuracy in the original test set. Since SENTA is pluggable, we demonstrate its effectiveness with BERT and BERT-PT as the backbone, which improve the baseline model in Change test set. It is worth noting that post-training helps alleviate the confounding bias in Change test set.

We also list the declining accuracy (red numbers) of all methods in new test set. If BERT is the baseline model, BERT-SENTA has the least performance drop (\(\downarrow 7.85\) in Laptop and \(\downarrow 6.00\) in Restaurant) than others. If BERT-PT is the baseline model, the falling range of BERT-PT-SENTA is the least (\(\downarrow 6.72\) in Laptop). SENTA shows weaker performances (80.91% \(\downarrow 5.43\) in Restaurant), due to the effect of post-training.

4.4 Ablation Study

REVNON (Xing et al., 2020) is a strategy in generating ARTS, which could test whether a model is sensitive enough by perturbing the sentiments of the non-target aspects. We split the ARTS and get REVNON subset results are shown in Table 3. The more detailed case study is shown in Appendix B.

There are 444 and 135 REVNON’s instances in Laptop and Restaurant domains. We compare SENTA with BERT and BERT-PT. Although we change the relative contents of non-target aspects, SENTA is still robust enough to bias from non-target aspects. Our model performs better than other methods, further confirming the effectiveness of its mechanism.

5 Conclusion and Future Work

In this paper, we take the causal view of ABSA to address the robustness issue. We propose a novel Sentiment Adjustment (SENTA) model based on the backdoor adjustment to weaken confounding effects. Experimental results demonstrate that our approach yields better performance on the robust set while maintaining accuracy in the original test set. Our framework is general in the sense that any backbone models with different architectures can be employed. In the future, we plan to 1) apply our approach to more NLP tasks with robustness issues and 2) find more reasonable metrics in evaluating the robustness of ABSA.
Broad Impact Statement

The causal inference has a wide range of applications, presenting researchers with an effective method to deeply understand relations between observed and unobserved variables. Our work proves causal inference helps to analyze fine-grained sentiment classification task. Sentiment bias is a challenging and unsolved problem. Some social bias in sentiment analysis, including specific attributes (race, genders, occupations) is sensitive. However, data-driven neutral models tend to fail in prediction because of bias from human annotation, bringing about unnecessary perplexity and trouble. If researchers do not consider biases, it will be unfair for those with specific background or identification. Therefore we are supposed to provide the public with a qualified analyzing model in the application robust enough to harmful biases.

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A Backdoor Criterion

If we want to know the effect of $X$ on $Y$ and have a set of variables $S$ as control, and $S$ satisfies the backdoor criterion if

- $S$ blocks every path from $X$ to $Y$ that has an arrow to $X$.
- No node in $C$ is a descendant of $X$.

Then

$$Pr(Y = y \mid do(X = x)) = \sum_s Pr(Y = y \mid X = x, S = s)Pr(S = s)$$

B Case Study

We choose cases from REVNON in Laptop domain, results are shown in Table 4 and Table 5.

C Experiments Details

We detail the training procedures and hyperparameters for each of the datasets. We utilize Pytorch to conduct experiments with one NVIDIA 1080 Ti 12GB GPU and support parallel training. All optimization was performed with the Adam optimizer. The max length for encoders is 64. More details can be seen in README.md in the supplementary material.
The SD card reader is slightly recessed but upside down (the nail slot on the card can be accessed), if this was not a self ejecting slot this would not be an issue, but it's not.

The SD card reader is slightly not recessed but not upside down (the nail slot on the card can be accessed), if this was a self ejecting slot this would not be an issue, but it's not.

The SD card reader is slightly not recessed but not upside down (the nail slot on the card cannot be accessed), if this was not a self ejecting slot this would not be an issue, but it's not.

Table 4: The REVNON cases from Laptop domain. Underlined words are target aspects.

| CASE ID   | SENTENCE                                                                 | POLARITY |
|-----------|---------------------------------------------------------------------------|----------|
| 1053:13_0 | The SD card reader is slightly recessed but upside down (the nail slot on the card can be accessed), if this was not a self ejecting slot this would not be an issue, but it's not. | negative |
| 1053:13_1 | The SD card reader is slightly not recessed but not upside down (the nail slot on the card can be accessed), if this was a self ejecting slot this would not be an issue, but it's not. | negative |
| 1053:13_2 | The SD card reader is slightly not recessed but not upside down (the nail slot on the card cannot be accessed), if this was not a self ejecting slot this would not be an issue, but it's not. | negative |

Table 5: Comparison with different methods. Case statistics is shown in table 4. ✓ denotes correct prediction and ✗ denotes wrong prediction.

| Method      | CASE 0 | CASE 1 | CASE 2 |
|-------------|--------|--------|--------|
| BERT        | ✗      | ✗      | ✓      |
| BERT-SENTA  | ✓      | ✓      | ✓      |
| BERT-PT     | ✗      | ✗      | ✓      |
| BERT-PT-SENTA | ✓  | ✓      | ✓      |