Let's Rectify Step by Step: Improving Aspect-based Sentiment Analysis with Diffusion Models

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Abstract

Aspect-Based Sentiment Analysis (ABSA) stands as a crucial task in predicting the sentiment polarity associated with identified aspects within text. However, a notable challenge in ABSA lies in precisely determining the aspects' boundaries (start and end indices), especially for long ones, due to users' colloquial expressions. We propose `DiffusionABSA`, a novel diffusion model tailored for ABSA, which extracts the aspects progressively step by step. Particularly, `DiffusionABSA` gradually adds noise to the aspect terms in the training process, subsequently learning a denoising process that progressively restores these terms in a reverse manner. To estimate the boundaries, we design a denoising neural network enhanced by a syntax-aware temporal attention mechanism to chronologically capture the interplay between aspects and surrounding text. Empirical evaluations conducted on eight benchmark datasets underscore the compelling advantages offered by `DiffusionABSA` when compared against robust baseline models. Our code is publicly available at https://github.com/Qlb6x/DiffusionABSA.

1. Introduction

Aspect-Based Sentiment Analysis (ABSA) (Fan et al., 2018), a prominent text analysis technique of the past decade, has garnered significant research attention. ABSA involves extracting aspect terms and discerning the sentiment associated with each aspect. The ABSA landscape encompasses four pivotal sentiment subtasks, namely aspect term extraction (AE), aspect category detection, opinion term extraction (OE), and sentiment classification (SC) (Zhang et al., 2022). Within this paper, our primary focus centers on two of these subtasks: AE and SC, collectively referred to as AESC. For example, in the sentence "Amazing *Spanish Mackeral special appetizer* and perfect *box sushi* (that eel with avodcao – um um um).", there are two sets of aspect terms and their sentiment polarities, (*Spanish Mackeral special appetizer*, Positive) and (*box sushi*, Positive).

Some previous studies perform AE and SC independently in a pipeline, potentially leading to error propagation (Fan et al., 2019; Hu et al., 2019). Recently, end-to-end models are designed to address two subtasks jointly via unified tagging schema (Mitchell et al., 2013; Zhang et al., 2015; Li et al., 2019a) or machine reading comprehension framework (Yang and Zhao, 2022). Furthermore, generative techniques have emerged as a powerful tool in tackling ABSA challenges (Zhang et al., 2022; Yan et al., 2021). These methods often involve the generation of sentiment element sequences adhering to specific formats, thereby harnessing

the nuances of label semantics. However, a recurring limitation across these approaches lies in their struggle to precisely delineate the boundaries of aspects due to the inherent diversity of language expression. The ambiguity and fluidity of language usage can lead to indistinct boundaries, where one aspect term might encompass multiple words (e.g., "Spanish Mackeral special appetizer"), and a single sentence could encompass multiple aspect terms.

In response to this intricate challenge, we introduce an innovative solution by integrating a diffusion model (Sohl-Dickstein et al., 2015) – a paradigm that has showcased impressive capabilities in controlled generation tasks. Notably, diffusion models have demonstrated remarkable performance in various domains, including text-to-image generation (Zhang et al., 2023; Nichol et al., 2022), and text generation (Nachmani and Dovrat, 2021; He et al., 2022). These achievements stand as testaments to the potential of diffusion models in facilitating token-level controls (Zou et al., 2023). At its core, a diffusion model orchestrates the process of generation in a stepwise manner. During training, it introduces noise to the input, progressively refining the generation process. Subsequently, it learns a complementary denoising procedure to accurately restore the original input. Leveraging this underlying mechanism, we propose an ingenious fusion of the diffusion model with ABSA, harnessing its capabilities to enhance the inference of the aspects.

This paper introduces `DiffusionABSA`, a novel architecture for diffusion architecture for ABSA which effectively marries the controlled generation

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	ASPECT ✓POSITIVE ✓	MISSING ✗
STEP 1	Amazing [Spanish Mackeral special appetizer] and perfect [box sushi] (that eel with avodcao – um um um).	
	ASPECT ✗POSITIVE ✓	
STEP 2	Amazing [Spanish Mackeral special appetizer and perfect box sushi] (that eel with avodcao – um um um).	
	ASPECT ✓POSITIVE ✓	ASPECT ✓POSITIVE ✓
STEP 3	Amazing [Spanish Mackeral special appetizer] and perfect [box sushi] (that eel with avodcao – um um um).	
	...	

Table 1: The boundary of aspect terms gradually changes during the denoising process in `DiffusionABSA`. The spans annotated with green , orange , and red respectively signify the correct, missing, wrong results.

process of diffusion models with the intricate aspect detection challenge characteristic of ABSA. `DiffusionABSA` is structured around two fundamental processes: corruption and denoising. The corruption process gradually adds Gaussian noise to the aspect terms according to a fixed variance schedule. The denoising process undoes the added noise at each time step iteratively and learns to faithfully reconstruct the original data by reversing this noising process. Illustrative insights from Table 1 underscore the distinctive features of `DiffusionABSA` in handling intricate aspect boundaries. Specifically, the model demonstrates iterative refinement in aspect extraction: initially missing an aspect ("box sushi"), then combining two aspects into one ("Spanish Mackeral special appetizer and perfect box sushi"), and finally, accurately extracting both aspects ("Spanish Mackeral special appetizer" and "box sushi"). To further bolster `DiffusionABSA`'s capabilities, we introduce a denoising neural network equipped with a syntax-aware temporal attention strategy. This strategic augmentation facilitates the model's adeptness in capturing the temporal evolution of aspect-text interactions, resulting in a more effective aspect modeling process.

To comprehensively assess the efficacy of our proposed `DiffusionABSA`, we conduct a series of experiments across eight diverse datasets, benchmarked against several state-of-the-art (SOTA) baselines. The empirical findings affirm the superiority of `DiffusionABSA` in most cases. Additionally, ablation studies provide nuanced insights into the contributions of key components within our model, further validating its effectiveness in addressing the ABSA challenge.

The principal contributions are summarized as follows.

- We propose `DiffusionABSA`, a novel framework that adapts diffusion models to refine the aspect progressively through a dynamic interplay of corruption and denoising processes.

- We design a denoising neural network enhanced by a syntax-aware temporal attention strategy,

which estimates the boundaries temporally in the reverse diffusion process.

- A series of experiments on eight widely-used benchmark datasets show that `DiffusionABSA` achieves new SOTA performance in most cases. Notably, our model showcases superior performance over ChatGPT, highlighting its efficacy in ABSA.

2. Related Work

2.1. Aspect-based Sentiment Analysis

Aspect-Based Sentiment Analysis (ABSA) is a pivotal endeavor that identifies sentiment-related components within a sentence (Schouten and Frasincar, 2015; Ma et al., 2019; Li et al., 2020; Zhou et al., 2020a). These components encompass aspects, opinions, and sentiments, collectively contributing to a comprehensive understanding of the textual content. In the nascent stages of ABSA research, the focus predominantly gravitated toward individual subtasks, namely aspect terms extraction (AE), opinion extraction (OE), or sentiment classification (SC) (Zhang et al., 2022; Zhou et al., 2020b). This includes the convergence of multiple subtasks, such as the simultaneous treatment of aspect extraction and sentiment classification (AESC) (Yan et al., 2021), aspect-opinion pair extraction (AOPE) (Fan et al., 2019) and triplet extraction (TE) (Peng et al., 2020), to model the relationships among them.

This study primarily centers its attention on AESC. Previous efforts, exemplified by Hu et al. (2019); Zhou et al. (2019), introduced span-based AESC techniques that amalgamated AESC at the span level. These models that merged AE and SC in a pipeline framework are susceptible to error propagation, as highlighted by Hu et al. (2019). Recent efforts (Li et al., 2019b,a) have aimed to handle the entire ABSA task using end-to-end models and a unified tagging schema. Nonetheless, the intricacies of language expression's diversity often hinder the accurate detection of as-
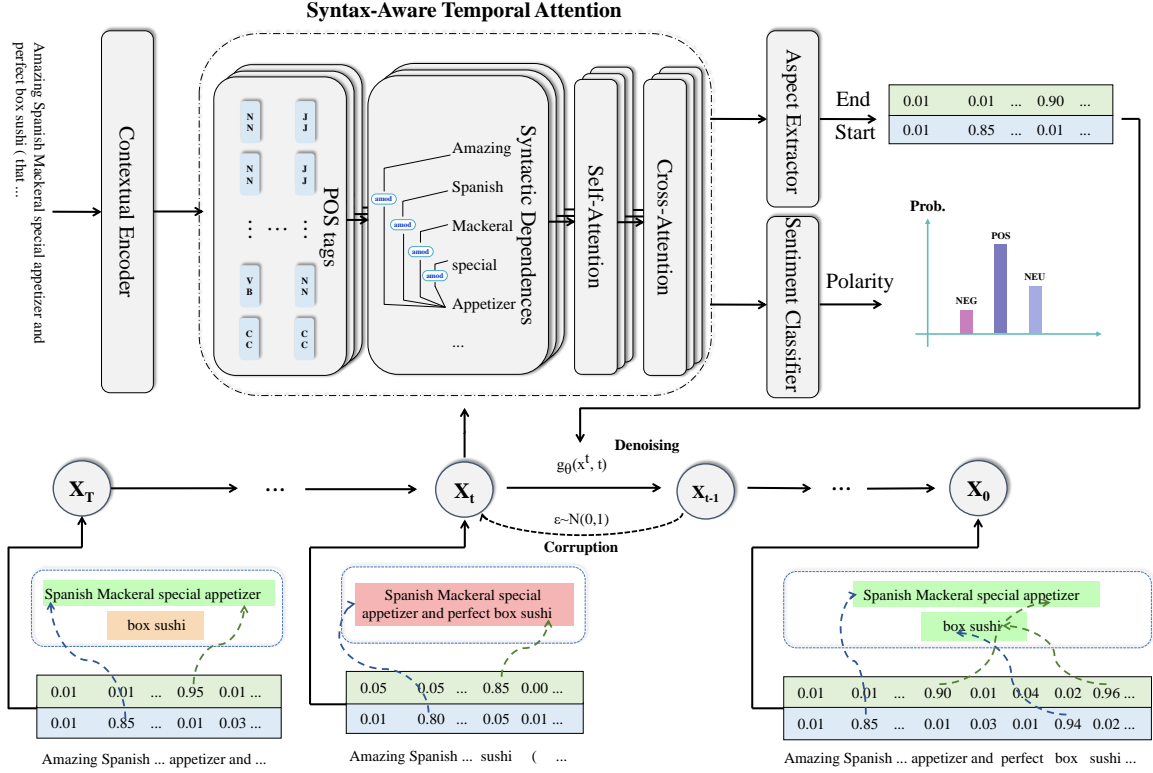
Figure 1: The framework of `DiffusionABSA`.

pects in these models. This paper contributes a novel `DiffusionABSA` framework that tactfully integrates diffusion models to advance ABSA by modeling the aspects progressively.

2.2. Diffusion Models

Diffusion models (Sohl-Dickstein et al., 2015; Ho et al., 2020; Song et al., 2021) which have recently emerged as a new one of SOTA generative models, have achieved impressive synthesis results on image data. Denoising diffusion probabilistic models (DDPMs) were initially introduced by Sohl-Dickstein et al. (2015), and Ho et al. (2020) brought theoretical breakthroughs and innovations. DDPMs contain two major processes: adding noise in a forward diffusion process and restoring the original data in a denoising process. The forward process corrupts information by gradually adding Gaussian noise:

$$q(\boldsymbol{x}_{1:T}|\boldsymbol{x}_0) = \prod_{t=1}^{T} q(\boldsymbol{x}_t|\boldsymbol{x}_{t-1}) \tag{1}$$

$$q(\boldsymbol{x}_t|\boldsymbol{x}_{t-1}) = \mathcal{N}(\boldsymbol{x}_t; \sqrt{1-\beta_t}\boldsymbol{x}_{t-1}, \beta_t \boldsymbol{I}). \tag{2}$$

Notably, the forward process allows sampling $\boldsymbol{x}_t$ at an arbitrary time step t directly based on the initial data sample $\boldsymbol{x}_0$:

$$q(\boldsymbol{x}_t|\boldsymbol{x}_0) = \mathcal{N}(\boldsymbol{x}_t; \sqrt{\bar{\alpha}_t}\boldsymbol{x}_0, (1-\bar{\alpha}_t)\boldsymbol{I}) \tag{3}$$

where $\alpha_t = 1 - \beta_t$ and $\bar{\alpha}_t = \prod_{t=1}^{T} \alpha_t$.

Diffusion models learn the reverse process to restore the original data step by step. If β_t is small enough, that is, the added noise at each step is relatively small the reverse process can be modeled as a Markov chain with learned conditional Gaussians (Song et al., 2021), parameterized by a neural network:

$$p_{\boldsymbol{\theta}}(\boldsymbol{x}_{0:T}) = p(\boldsymbol{x}_T) \prod_{t=1}^{T} p_{\boldsymbol{\theta}}(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t) \tag{4}$$

$$p_{\boldsymbol{\theta}}(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t) = \mathcal{N}(\boldsymbol{x}_{t-1}; \boldsymbol{\mu}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, t), \boldsymbol{\Sigma}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, t)) \tag{5}$$

where $\boldsymbol{\mu}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, t)$ and $\boldsymbol{\Sigma}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, t)$ is the predicted covariance and mean of $p_{\boldsymbol{\theta}}(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t)$ computed by a neural network.

Recently, the application of the diffusion model in the realm of natural language processing (NLP) has garnered notable attention from researchers, as evident in works such as Nachmani and Dovrat (2021); He et al. (2022). This application can be broadly categorized into two directions: 1) Continuous Diffusion Models: This line of research involves encoding discrete tokens into a continuous space and subsequently executing both the forward and reverse diffusion processes (Li et al., 2022); 2) Discrete Diffusion Models: Operating within the discrete token space, this direction extends the principles of diffusion models to encompass discrete state-spaces (Reid et al., 2022). Leveraging the potent capabilities of the diffusion model

in a controlled generation, our paper introduces `DiffusionABSA` to tackle the intricate challenges of aspect extraction and sentiment classification.

3. Our Proposed Framework

In this paper, we propose `DiffusionABSA`, which learns a denoising neural network for ABSA based on a diffusion architecture (Figure 1). First, `DiffusionABSA` adds noise ϵ into aspect representation at each step in the forward corruption process. Next, `DiffusionABSA` recovers the input using a denoising neural network g_θ in the backward denoising process. Particularly, we design a denoising neural network with a syntax-aware temporal attention mechanism to estimate the boundaries $g_\theta(x_t, t, S)$ at the time step t.

Formally, ABSA aims to extract aspects and the corresponding sentiment polarities $Y = \{(a_i, p_i)\}_{i=1}^{|Y|}$ from the given sentence $S = \{w_1, w_2, ... w_{|S|}\}$, where a_i and p_i are the i-th aspect and its sentiment polarity (neutral, positive or negative). $|Y|$ is the number of aspects in sentence S and $|S|$ is the length of the sentence. Each aspect $a_i = (s_i, e_i)$ is defined by all the tokens between s_i and e_i, where s_i and e_i are the start and end indices of aspect a_i, $1 \le s_i \le e_i \le |S|$.

3.1. Aspect Diffusion

As shown in Table 1, we extract the aspects progressively via a diffusion model under the Markov chain assumption, where each step x_t only depends on the previous step x_{t-1} with T steps. `DiffusionABSA` adds noise to the aspects to model $p(x_t|x_{t-1})$ in the forward corruption process while recovering them from the noise to model $q_\theta(x_{t-1}|x_t)$ in the backward denoising process.

Forward Corruption Process The forward corruption process is a process of adding a small amount of Gaussian noise by a fixed schedule to the aspect term boundaries step by step. We normalize the start and end indices as initial step x_0:

$$x_0 = \lambda \left(\frac{[[s_1, e_1], ..., [s_i, e_i], [s_N, e_N]]}{|S|} - 0.5 \right) \quad (6)$$

where λ is a hyper-parameter to scale the value to $(-\lambda, \lambda)$ and N is the max $|Y|$ in the dataset.

Instead of applying the forward process multiple times repeatedly to get the desired data point x_t at $t < T$, we apply a simple reparameterization to get the desired output by precomputing the variances

and certain parameters:

$$
\begin{aligned}
x_t &= \sqrt{\alpha_t} x_{t-1} + \sqrt{1 - \alpha_t} \epsilon_{t-1} \\
&= \sqrt{\alpha_t \alpha_{t-1}} x_{t-2} + \sqrt{1 - \alpha_t \alpha_{t-1}} \bar{\epsilon}_{t-2} \\
&= ... \\
&= \sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon \quad (7)
\end{aligned}
$$

where $\alpha_t = 1 - \beta_t$, $\bar{\alpha}_t = \prod_{t=1}^{T} \alpha_t$ and $\epsilon \sim \mathcal{N}(0, I)$. In accordance with this equation, we can directly compute the x_t from x_0 in the corruption process.

Backward Denoising Process During the backward process, `DiffusionABSA` progressively refines the aspect boundaries by the learned denoising process. Specifically, we restore the x_0 from the noisy x_T based on the conditional Gaussian $p_\theta(x_{t-1}|x_t)$:

$$
\begin{aligned}
x_{t-1} = &\sqrt{\alpha_{t-1}} \cdot g_\theta(x_t, t, S) \\
&+ \sqrt{1 - \alpha_{t-1}} \cdot \frac{x_t - \sqrt{\alpha_t} g_\theta(x_t, t, S)}{\sqrt{1 - \alpha_t}} + \sigma_t \cdot \epsilon_t
\end{aligned}
$$
$$(8)$$

where $g_\theta(x_t, t, S)$ represents a denoising neural network used to predict the distribution of start and end indices, where θ is the learnable parameters of the denoising neural network.

To expedite the reverse process of `DiffusionABSA`, we adopt DDIMs (Song et al., 2021) which is a straightforward scheduler that converts the stochastic process into a deterministic one, requiring a small number of sampling steps. DDIMs construct a class of non-Markovian diffusion processes that lead to the same training objective, but whose reverse process can be much faster to sample from. We define τ as an increasing sub-sequence of $[1, 2, \ldots, T]$, where γ is the length of τ and $\tau_\gamma = T$:

$$
\begin{aligned}
x_{\tau_{t-1}} = &\sqrt{\alpha_{\tau_{t-1}}} g_\theta(x_{\tau_t}, \tau_t, S) \\
&+ \sqrt{1 - \alpha_{\tau_{t-1}}} \frac{x_{\tau_t} - \sqrt{\alpha_{\tau_t}} g_\theta(x_{\tau_t}, \tau_t, S)}{\sqrt{1 - \alpha_{\tau_t}}} + \sigma_{\tau_t} \epsilon_{\tau_t}
\end{aligned}
$$

where σ_{τ_t} is commonly chosen as zero. Finally, to calculate the boundaries of aspect terms at each step, we design a denoising neural network $g_\theta(x_t, t, S)$.

3.2. Denoising Neural Network

This section presents a denoising neural network $g_\theta(x_t, t, S)$, comprising four components: contextual encoder, syntax-aware temporal attention, aspect extractor, and sentiment classifier. Utilizing the sentence representation learned by the contextual encoder, we introduce a syntax-aware temporal attention mechanism to sequentially model connections between aspects and text. Then, we use an aspect extractor and sentiment classifier to predict the boundaries and sentiments of the aspects based on the sentence representation learned by syntax-aware temporal attention.

Contextual Encoder Pre-trained language models (PLM) (Devlin et al., 2019; Liu et al., 2019) have been shown prominent in retrieving the contextualized features for various NLP tasks. Hence we utilize PLM (e.g., BERT, RoBERTa) as the underlying encoder to encode the sentence S into vectors:

$$H = \text{Encoder}(\{w_1, w_2, ..., w_{|S|}\}). \qquad (9)$$

The start of sentence ([CLS]) and the end of sentence ([SEP]) tokens are added to the start and end of S, which are disregarded in the equations for the sake of simplification.

Syntax-aware Temporal Attention (SynTA) Within the denoising process, we devise a syntax-aware temporal attention method tailored for the temporal inference of aspect boundaries. This involves combining part-of-speech (POS) tags and dependency trees to capture the interaction between text and aspects. Furthermore, we incorporate time features to capture the temporal information.

To initiate, we get POS tags $\{p_1, p_2, ..., p_{|S|}\}$ by StandfordCoreNLP tool, where p_i is word w_i' POS tag. POS features hold significant importance in identifying potential boundaries, thereby guiding the model to appropriately identify aspects. We use a learnable POS embedding layer to embed the POS tags, where $E^p \in \mathbb{R}^{|S| \times d}$:

$$E^p = \text{POSEmbedding}(\{p_1, p_2, ..., p_{|S|}\}). \qquad (10)$$

To further integrate the syntactic dependency, we adopt a graph convolution network (GCN) model. We define an undirected graph $G = <V, E>$ with self-loop edges, where E is a list of dependency edges between each pair of words and V is a list of words. The adjacency matrix $\mathbf{M} \in \mathbb{R}^{|S| \times |S|}$ is defined as follows:

$$M_{ij} = \begin{cases} l_{i,j}, & \text{if a dependency edge between } w_i, w_j, \\ 0, & \text{otherwise}, \end{cases} \qquad (11)$$

where $l_{i,j}$ is the index of dependency label between w_i and w_j. Then, the hidden representation of the word w_i at the k-th layer of GCNs is computed as:

$$H_i^k = \text{ReLU} \left(\sum_{j=1}^{|S|} u_{i,j}^{k-1} \cdot (W_1 \cdot [H_j^{k-1}; E_{i,j}^d; E_j^p] + b) \right)$$

$$u_{i,j}^{k-1} = M_{i,j} \cdot \text{Softmax}(W_2 \cdot [H_j^{k-1}; E_{i,j}^d; E_j^p]) \qquad (12)$$

where $E_{i,j}^d$ is the embedding of dependency label $l_{i,j}$, H_i^0 is the word embedding H_i learned by contextual encoder. W_1 and W_2 are learnable parameters. The final representation is defined as $\hat{H} = H^K$, where K is the number of layers.

Based on syntax-enhanced representation $\hat{H}$, we obtain aspect representation H^a via average pooling. In order to explore the internal connection between sentence representations $\hat{H}$ and span representations H^a, we utilize a self-attention and a cross-attention layer to model the interaction.

$$\hat{H}^a = \text{SelfAttention}(W_1^Q H^a, W_1^K H^a, W_1^V H^a) \qquad (13)$$

$$\hat{H}^a = \text{CrossAttention}(W_2^Q \hat{H}^a, W_2^K \hat{H}, W_2^V \hat{H}). \qquad (14)$$

To consider the timestep, we incorporate the sinusoidal embedding E_t of timestep t using sine and cosine functions (Vaswani et al., 2017). The final time-related representations of the aspects are calculated as follows:

$$\hat{H}^a = \text{TimeEmbedding}(\hat{H}^a, E_t) \qquad (15)$$

where $\text{TimeEmbedding}(\cdot, \cdot)$ is an operation to combine two vector representations. In this paper, we use addition or multiple interactions with scale and shift (Dumoulin et al., 2018; Perez et al., 2018); other operations can also be used.

Aspect Extractor We use an aspect extractor to predict the start and end indices of the aspects. In precise terms, we calculate the probability of the aspect span boundary P^b and $b \in \{\text{start}, \text{end}\}$ with $\hat{H}^a$ and $\hat{H}$:

$$P^b = \text{Sigmoid}(\hat{H}^a W_a^b + \hat{H} W_s^b). \qquad (16)$$

Sentiment Classifier And probability P^y of the sentiment polarity, $y \in (\text{positive}, \text{negative}, \text{neutral})$ is calculated by the classifier:

$$P^y = \text{Softmax}(\text{MLP}(\hat{H}^a)). \qquad (17)$$

Utilizing the aforementioned extractor and classifier, we can decode the predicted probabilities of P^{start}, P^{end} and P^y to get the outputs $Y_i = ((s_i, e_i), p_i)$ for the i-th aspect.

Loss Function DiffusionABSA progressively refines the aspect boundaries based on x_t through the learned denoising process. Like traditional DDPMs, loss will be computed in each intermediate step. We use the cross-entropy (CE) losses between the ground truth $((s_i, e_i), p_i)$ and predicted aspect probabilities of the left and right boundary indexes and type of entity, $P_i^{start}, P_i^{end}, P_i^y$:

$$\mathcal{L} = -\sum_{i=1}^{K} (CE(P_i^{start}, s_i) + CE(P_i^{end}, e_i) + CE(P_i^y, p_i)) \qquad (18)$$

Dataset	14res		14lap		15res		16res	
	#S	#T	#S	#T	#S	#T	#S	#T
D_{20a}								
Train	1300	2145	920	1265	593	923	842	1289
Dev	323	524	228	337	148	238	210	316
Test	496	862	339	490	318	455	320	465
D_{20b}								
Train	1266	2338	906	1460	605	1013	857	1394
Dev	310	577	219	346	148	249	210	339
Test	492	994	328	543	322	485	326	514

Table 2: Statistics of the datasets pertinent to the ABSA task. #S and #T denote the quantities of sentences and targets within the respective datasets.

4. Experiment Setting

4.1. Datasets and Metrics

We conducted an extensive evaluation using four distinct ABSA datasets, each comprising two versions denoted as D_{20a} (Peng et al., 2020), D_{20b} (Xu et al., 2020), which contain restaurant (res) and laptop (lap) reviews. Detailed statistical summaries of these datasets can be found in Table 2. Following Yan et al. (2021), we employ micro-F1 scores as the evaluation metric in our experiments. In our evaluation methodology, the correctness of a predicted aspect term and its associated sentiment polarity is contingent upon the precise alignment of its span with the corresponding boundaries delineated by the ground truth. Additionally, the polarity classification must concord with the actual sentiment polarity. This rigorous evaluation approach ensures a stringent validation of the predictive efficacy of our proposed method.

4.2. Baselines

To ensure a comprehensive comparative analysis, we have meticulously outlined the most proficient baseline models for AE and AESC subtasks. This comprehensive delineation is aimed at facilitating a thorough assessment of the proposed experimental framework against existing benchmarks, including the pipeline, joint, end-to-end, and large language models.

We first compare our `DiffusionABSA` against the pipeline methods:

- **SPAN-BERT** (Hu et al., 2019) is a pipeline method for AESC which takes BERT as the backbone network. A span boundary detection model is used for AE subtask, and then followed by a polarity classifier for SC.

- **Peng-two-stage** (Peng et al., 2020) is a two-stage pipeline model. Peng-two-stage extracts both aspect-sentiment pairs and opinion terms in the first stage. In the second stage, a classifier

is used to find the valid pairs from the first stage and finally construct the triplet prediction.

Some methods investigate ABSA using joint models:

- **MIN** (Yu et al., 2021) is a multi-task learning method named to make flexible use of subtasks for a unified ABSA.

- **SPAN** (Hu et al., 2019) is a span-based extract-then-classify model, where opinions are directly extracted from the sentence based on supervised target boundaries and corresponding polarities are then classified by extracted spans.

- **Dual-MRC** (Mao et al., 2021) is a joint training model that incorporates two machine reading comprehension (MRC) modules used separately for AE and AESC.

The summation of significant findings from end-to-end ABSA endeavors is detailed below:

- **SynGen** (Yu et al., 2023) adds syntactic inductive bias to attention assignment and thus directs attention to the correct target words which apply to AESC, Pair, and Triplet subtasks.

- **SyMux** (Fei et al., 2022) is a multiplex decoding method. It improves the framework by using syntactic information to identify term boundaries and pairings, transferring sentiment layouts and clues from simpler tasks to more challenging ones.

- **Li-unified** (Li et al., 2019a) addresses target-based sentiment analysis as a complete task in an end-to-end manner. The model introduces a novel unified tagging scheme to achieve this goal.

- **RINANTE+** (Peng et al., 2020), is modified from the work (Ma et al., 2018). RINANTE+ is an LSTM-CRF model which first uses dependency relations of words to extract opinions and aspects with the sentiment. Then, all the candidate aspect-opinion pairs with position embedding are fed into the Bi-LSTM encoder to make a final classification.

- **CMLA+** (Peng et al., 2020) is adjusted from the one (Wang et al., 2017) which is an attention-based model following the same two-stage processing with dependency relations as RINANTE+.

- **GEN** (Yan et al., 2021) converts all ABSA subtasks into a unified generative formulation, and provides a real unified end-to-end solution for the whole ABSA subtasks, which could benefit multiple tasks.

MODEL	14res	14lap	15res	16res
CMLA+	70.62	56.90	53.60	61.20
RINANTE+	48.15	36.70	41.30	42.10
Li-unified	73.79	63.38	64.95	70.20
Peng-two-stage	74.19	62.34	65.79	71.73
Dual-MRC	76.57	64.59	65.14	70.84
SPAN-BART	78.47	68.17	69.95	75.69
SyMux	78.68	70.32	69.08	77.95
SynGen	79.72	70.06	71.61	77.51
ChatGPT (Zero-shot)	59.08	45.48	53.91	55.40
ChatGPT (5-shot ICL)	65.98	49.50	63.66	63.11
ChatGPT (5-shot COT)	62.82	48.87	66.07	65.93
DiffusionABSA	**80.93**	**72.81**	**76.70**	**81.72**
w/o SynTA	80.84	72.39	74.26	80.53

Table 3: Results of AESC over D_{20a} datasets. We use the results of baselines reported in Yu et al. (2023).

- **GTS** (Wu et al., 2020) is a tagging scheme different from pipeline methods, to address the Aspect-oriented Fine-grained Opinion Extraction (AFOE) task in an end-to-end fashion only with one unified grid tagging task.

- **RCAL** (Chen and Qian, 2020) allows the sub-tasks to work coordinately via the multi-task learning and relation propagation mechanisms in a stacked multi-layer network.

  Furthermore, our scope of comparative analysis was broadened to encompass Large Language Models (LLMs):

- **ChatGPT** (OpenAI, 2023) is one of the best-known examples of LLMs from OpenAI's GPT (Generative Pre-Training Transformer) series, and is capable of generating human-like text based on context and past conversations. Additionally, we explore zero-shot (Zero-shot) prompts, few-shot in-context learning (ICL) prompts (Brown et al., 2020), and chain-of-thought (COT) prompts (Wei et al., 2022) settings.

4.3. Implementation

Our experimental evaluations encompass eight benchmark datasets. For the AE and AESC tasks, we incorporate dependency trees and POS tags as an integral preprocessing step. We adopt the RoBERTa as our pre-trained language model. The optimization process is orchestrated using the AdamW optimizer, initialized with a learning rate of 0.0002. All experiments are conducted on a potent 24GB RTX3090 GPU. The training regimen, comprising 100 epochs, is concluded within an hour, employing a batch size of 16. This streamlined experimental setup enables us to efficiently explore

MODEL	14res	14lap	15res	16res
SPAN	86.71	82.34	74.63	74.68
RACL	86.38	81.79	73.99	74.91
MIN	87.91	83.22	-	-
CMLA	81.22	79.53	76.03	74.20
RINANTE	81.34	80.40	73.38	72.82
Li-unified	81.62	78.56	74.65	73.36
GTS	83.82	82.48	78.22	75.80
GEN	87.07	83.52	75.48	81.35
SyMux	**89.02**	84.42	79.73	82.41
ChatGPT (Zero-shot)	55.65	43.03	40.33	-
ChatGPT (5-shot ICL)	70.99	48.19	53.49	-
ChatGPT (5-shot COT)	72.41	54.50	59.27	-
DiffusionABSA	87.15	**86.66**	**85.40**	**87.87**
w/o SynTA	86.93	86.01	83.15	86.23

Table 4: Results of AE over D_{20a} datasets. We use the results of baselines reported in Fei et al. (2022).

the model's performance across various tasks and datasets.

5. Results and Analyses

5.1. Main Results

In Tables 3 and 4, we present the results of `DiffusionABSA` on dataset D_{20a} as well as the baselines on AE and AESC tasks. Based on the outcomes, we deduce the ensuing observations. **First**, our method achieves significant improvements against almost all the baselines on micro-F1 score. Impressively, our approach outperforms the SOTA model, exhibiting an average improvement of 3.31% on AESC. We also extend our analysis to the D_{20b} dataset, as illustrated in Table 6. Similar trends emerge, as our methodology consistently demonstrates a competitive edge over baselines. This consistent pattern of superior performance substantiates our model's capacity to leverage the SynTA encoder effectively, resulting in the proficient distinction of aspect term representations. **Second**, it is worth noting that in comparison to the performance reported in (Han et al., 2023) for ChatGPT, which incorporates ICL prompts and COT prompts, our `DiffusionABSA` stands out as a robust contender. Despite the reported enhancements achieved by ChatGPT through these prompt-based strategies, it remains evident that ChatGPT falls short of both SOTA and `DiffusionABSA` in terms of competitive performance and consistent achievement.

5.2. Ablation Studies

As delineated in Tables 3, 4, and 6, we conduct the ablation studies by removing the SynTA (w/o SynTA) on the AE and AESC tasks. Upon metic-

MODEL	14res				16res			
	ALL	LEN=1	LEN=2	LEN>2	ALL	LEN=1	LEN=2	LEN>2
SeqLab	66.17	58.88	16.11	4.36	68.60	58.94	19.37	4.73
DiffusionABSA	79.13	71.68	20.82	7.51	78.87	68.97	21.61	8.49
Improvement	19.59%	21.74%	29.24%	72.25%	14.97%	17.02%	11.56%	79.49%

Table 5: Results over aspects with various lengths on D_{20a} datasets.

MODEL	14res		14lap		15res	
	AE	AESC	AE	AESC	AE	AESC
SPAN-BERT	86.71	73.68	82.34	61.25	74.63	62.29
IMN-BERT	84.06	70.72	77.55	61.73	69.90	60.22
RACL-BERT	86.38	75.42	81.79	63.40	73.99	66.05
Dual-MRC	86.60	75.95	82.51	65.94	75.08	65.08
DiffusionABSA	**86.17**	**80.64**	**88.37**	**74.90**	**84.62**	**77.26**
w/o SynTA	85.89	80.11	84.74	70.40	85.62	77.02

Table 6: Results of AE, AESC on D_{20b} datasets.

ulous experimentation, we observed a compelling trend: the direct omission of the SynTA module has a discernible adverse impact on model performance, reflected in a reduction of the F1 score over all the datasets. On datasets D_{20a} and D_{20b}, this omission respectively led to an average decline of 1.04% and 1.76%. These empirically substantiated findings reaffirm the pivotal role played by the SynTA strategy in fortifying the interaction between aspect terms and sentences. The synthesis of these outcomes underscores the effectiveness of SynTA in augmenting the cohesive integration of aspect terms within sentences, thus contributing significantly to the overall model performance.

5.3. Performance on Aspects with Various Lengths

To further assess the effectiveness of DiffusionABSA, we conduct an extensive analysis of its performance across varying aspect lengths. Our evaluation encompasses both our proposed framework and a fine-tuned BERT-large-based sequence labeling model (SeqLab) – a widely acknowledged and robust baseline for ABSA tasks. Due to space constraints, we present the experimental findings for aspect lengths on datasets 14res and 16res in Table 5. The results reveal the following insights: 1) Our model consistently demonstrates substantial performance enhancements across all aspect lengths. Notably, the average improvement over SeqLab surpasses 14%; 2) The magnitude of enhancements grows in tandem with the length of the aspect. For example, we observe remarkable enhancements exceeding 70% for datasets 14res and 16res. All these findings indicate the potency of our framework in facilitating token-level controlled generation, particularly as aspect lengths extend.
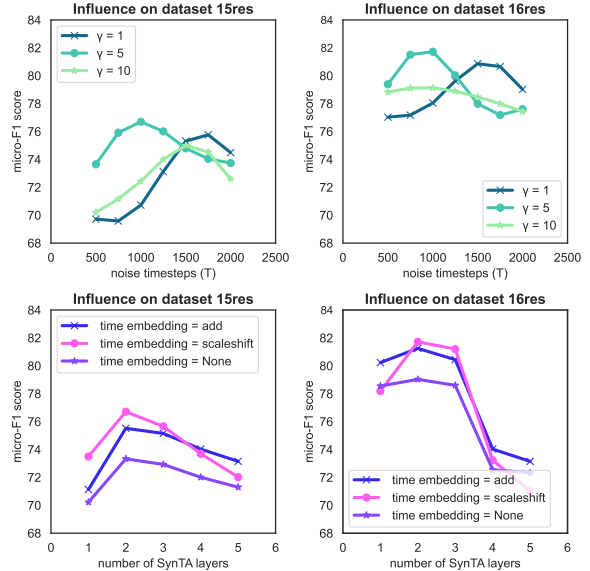

Figure 2: Further analysis of DiffusionABSA.

5.4. Further Analysis

Influence of Hyper-Parameter γ. Furthermore, our investigation extends to the examination of DiffusionABSA's performance in relation to the DDIMs sampling parameter γ during the reverse process, as well as the noise timesteps denoted as T within the forward process. Figure 2 vividly illustrates the outcomes of this ablation study. As the value of γ increases, there is a discernible convergence of the aspects' boundaries towards the ground truth. Particularly compelling is the fact that the most optimal performance is achieved when $\gamma = 5$ and $T = 1000$, specifically within the context of the AESC task. This empirical evidence underscores the effectiveness of our approach in progressively refining aspects' boundaries by leveraging increased sampling γ, ultimately culminating in a performance zenith characterized by greater alignment with the ground truth.

Influence of Number of SynTA Layers. To assess the efficacy of DiffusionABSA, we conducted a series of experiments to analyze its performance across varying numbers of SynTA layers. Our findings indicate that employing two layers yields superior results compared to a solitary layer, while employing excessively large values may potentially lead to overfitting.

Influence of Time Embedding. We delve into the impact of time embedding with various operations. Notably, we observe promising outcomes through the implementation of the scale and shift technique on time embeddings, as illustrated in Figure 2. A significant advantage of this method lies in its capacity to enhance results without substantially augmenting computational overhead.

6. Conclusions and Future Work

In this paper, we propose `DiffusionABSA` equipped with a syntax-aware temporal attention mechanism, which adapts the diffusion model to enhance ABSA by refining the aspect progressively through a dynamic interplay of corruption and denoising process. Through comprehensive experimentation across eight benchmark datasets, we empirically validate that `DiffusionABSA` excels over the compared strong baselines (e.g., ChatGPT), setting a new performance benchmark within the domain. Notably, the controlled generation inherent to diffusion models exhibits remarkable efficacy in facilitating the extraction of aspect terms with extended length. Specially, for aspects with lengths greater than two, our approach surpasses the SeqLab model with an impressive 70% enhancement in terms of F1 score. In the future, we will explore the potential of diffusion models to tackle more complex subtasks such as pair and triplet extraction.

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