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

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01. Introduction

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Aspect term Extraction (AE) and Sentiment Classification (SC) :

Example: Amazing Spanish Mackeral special appetizer and perfect box sushi (that eel with avodcao – um um um).

Positive

Positive

Challenge:

Longer Terms(contain multiple words), ambiguity and fluidity of language usage, …

01. Introduction

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Diffusion Model:

1. Impressive capabilities in controlled generation tasks

2. Remarkable performance in various domains, including text-to-image , and text generation.

01. Introduction

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DiffusionABSA:

STEP 1	Amazing $\overbrace{\text{Spanish Mackeral special appetizer}}^{\text{ASPECT ✓ POSITIVE ✓}}$ and perfect $\overbrace{\text{box sushi}}^{\text{MISSING ✗}}$ (that eel with avodcao – um um um).
STEP 2	Amazing $\overbrace{\text{Spanish Mackeral special appetizer and perfect box sushi}}^{\text{ASPECT ✗ POSITIVE ✓}}$ (that eel with avodcao – um um um).
STEP 3	Amazing $\overbrace{\text{Spanish Mackeral special appetizer}}^{\text{ASPECT ✓ POSITIVE ✓}}$ and perfect $\overbrace{\text{box sushi}}^{\text{ASPECT ✓ POSITIVE ✓}}$ (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.

02. Methods

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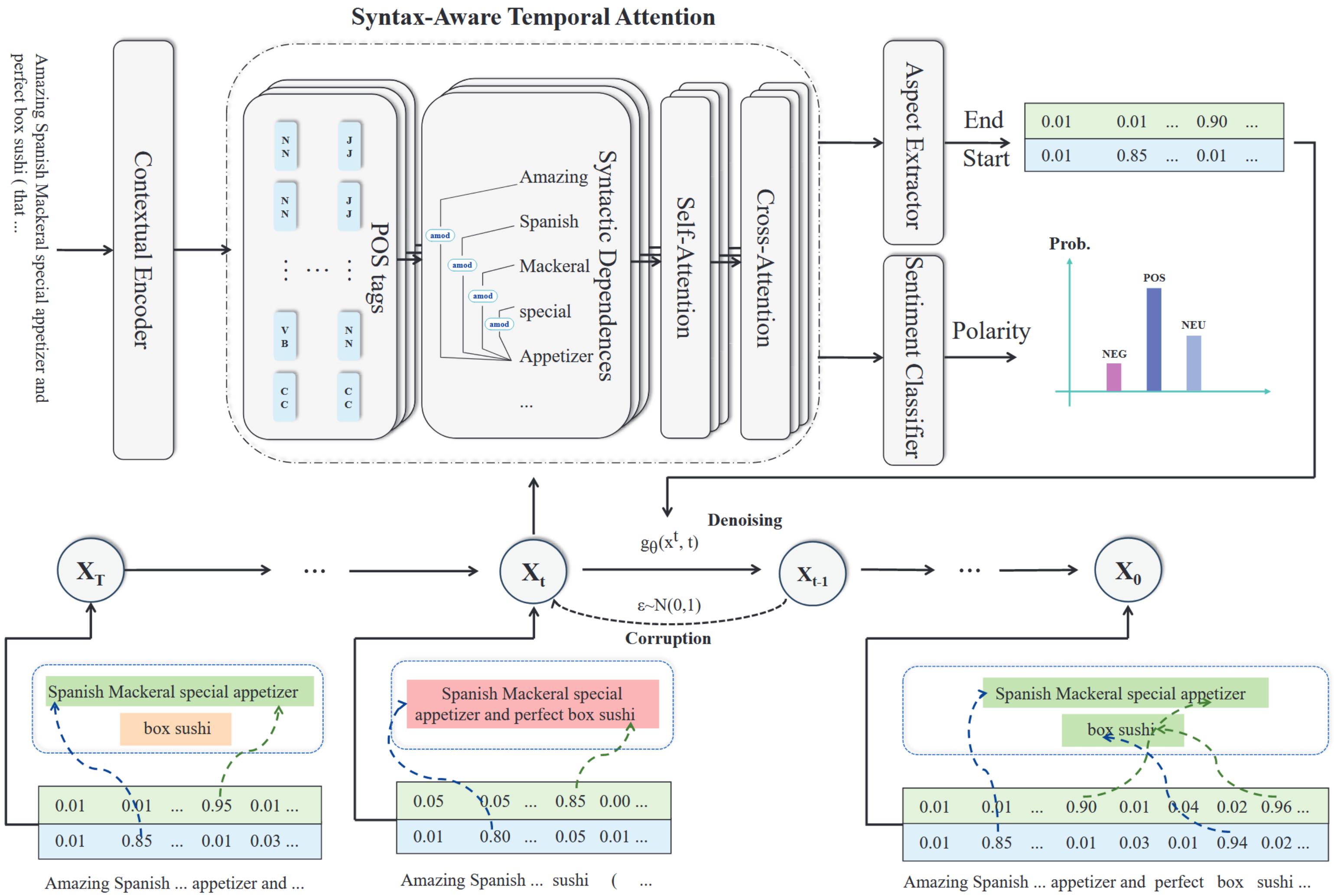
Framework of DiffusionABSA:



03. Experiments

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Datasets:

Restaurant and laptop reviews in two version

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.

03. Experiments

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Effectiveness of Our Model:

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).

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).

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.

03. Experiments

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Effectiveness of Our Model:

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.

04. Conclusions

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Conclusions:

- 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 module.
- A series of experiments on eight widely-used benchmark datasets show that DiffusionABSA achieves new SOTA performance in most cases.

Thanks!

Q&A

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