CONTRASTE: Supervised Contrastive Pre-training With Aspect-based Prompts For Aspect Sentiment Triplet Extraction

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Objective

- To improve the aspect-aware sentiment understanding of a generative architecture that can **simultaneously benefit multiple ABSA tasks**.

ASTE As A Generative Task - What Templates To Choose For Decoding The Sequence Of Triplets?

PARAPHRASE TEMPLATE	It is great / ok / bad because *ASPECT* is *OPINION* [SSEP] ...
OUR TEMPLATE	<aspect> *aspect* <opinion> *opinion* <sentiment> *sentiment* [SSEP] ...
Sentence 1	While the sushi was tasty, the ambience sucked.
PARAPHRASE TARGET	It is great because sushi is tasty [SSEP] It is bad because ambience is sucked.
OUR TARGET	<aspect> sushi <opinion> tasty <sentiment> POS [SSEP] <aspect> ambience <opinion> sucked <sentiment> NEG.
Sentence 2	I was very disappointed with the chef.
PARAPHRASE TARGET	It is bad because chef is very disappointed.
OUR TARGET	<aspect> chef <opinion> very disappointed <sentiment> NEG.

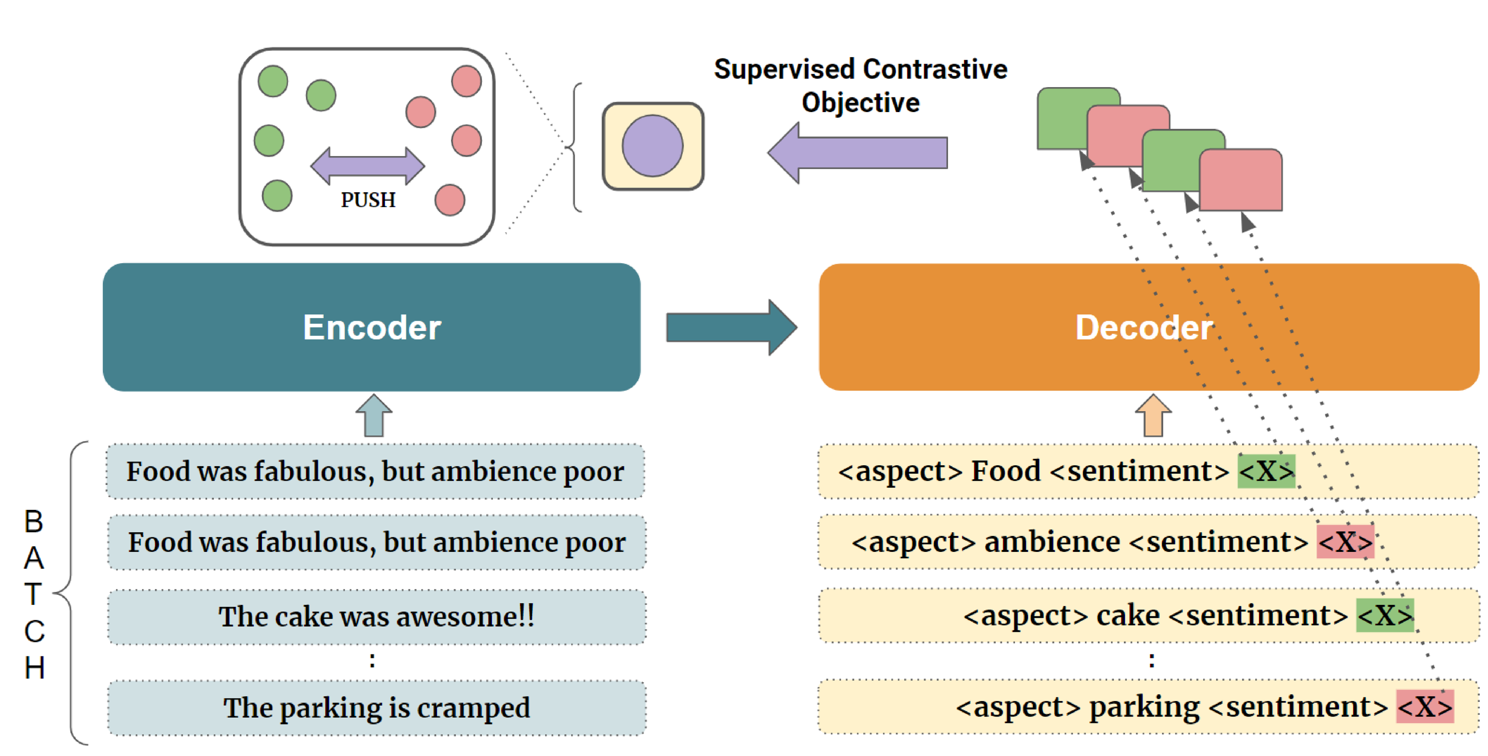
Table 1:Comparing our templates with *PARAPHRASE* [1] for training T5 to generate a sequence of (aspect, opinion, sentiment) triplets occurring in the given sentence. Target sequences highlighted in red are not semantically meaningful; especially for *Sentence 2* where the *customer* should be disappointed, and not the *chef*, contrary to the paraphrased sentence means.

Prompts to Continually Pre-Train T5 Using Supervised Contrastive Learning

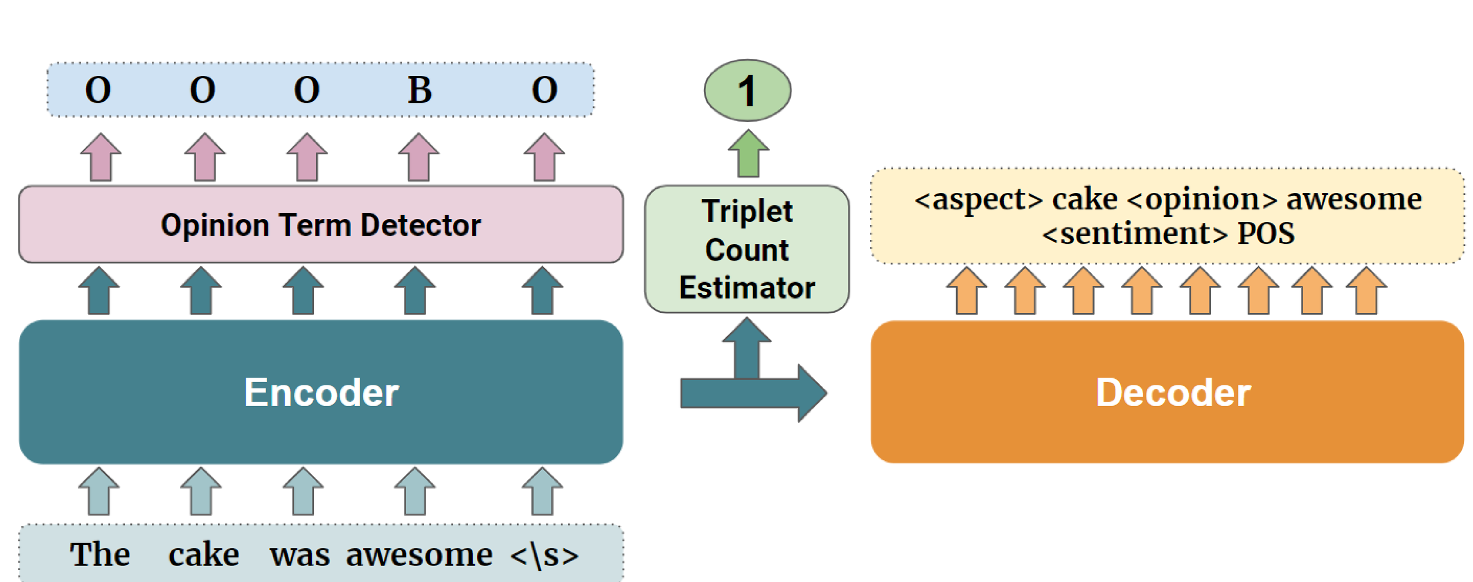
Sentence 1	The food was fresh.
PRE-TRAINING PROMPTS	<aspect> food <sentiment> [MASK]
Sentence 2	While the sushi was tasty, the ambience sucked.
PRE-TRAINING PROMPTS	<aspect> sushi <sentiment> [MASK] <aspect> ambience <sentiment> [MASK]

Table 2:ASPECT-BASED prompts derived from sentences to continually pre-train T5.

CONTRASTE Architecture



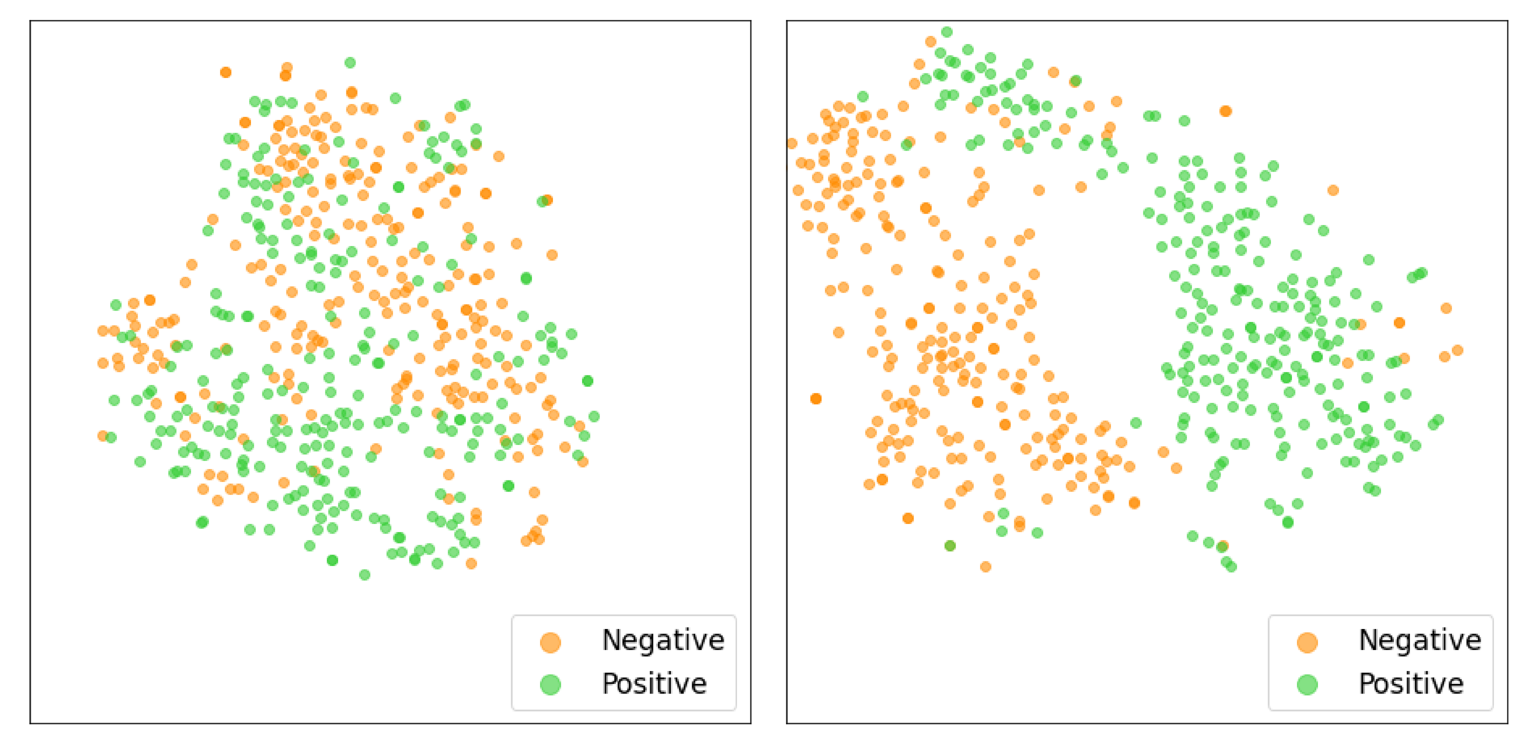
(a) Supervised contrastive pre-training



(b) Proposed multi-task model for ASTE

Figure 1:(a) Contrastive pre-training of T5 encoder-decoder model using aspect-based prompts. (b) Fine-tuning the continually pre-trained T5 model for ASTE in a multi-task setup.

Effect of Pre-Training Using Aspect-based Prompts



(a) Before Contrastive Pre-training (b) After Contrastive Pre-training

Figure 2:t-SNE visualization of decoder-generated [MASK] token embeddings. Performing supervised contrastive learning on aspect-based sentiment embeddings helps the decoder produce discriminable representations of different sentiment polarities.

ASTE Results on ASTE-Data-V2 Datasets

Model	14Res	15Res	16Res	Lap14
ChatGPT	0.565	0.495	0.520	0.409
PARAPHRASE [1]	0.715	0.621	0.719	0.605
Current SOTA [2]	**0.743**	<u>0.648</u>	0.721	<u>0.627</u>
ASTE-Base	0.720	0.634	0.722	0.608
w/ SCL-Sentence	0.722	0.645	0.724	0.611
CONTRASTE-Base	0.728	<u>0.648</u>	<u>0.730</u>	0.614
CONTRASTE-MTL	<u>0.740</u>	**0.661**	**0.742**	**0.629**

Key Takeaways

- **ChatGPT** is **not good enough** to produce SOTA results.
- **Placeholder-based templates** (as shown in Table 1) **are better** suited to train encoder-decoder models for ABSA tasks (Compare ASTE-Base with PARAPHRASE [1] in above).
- Performing contrastive pre-training on aspect-based sentiment embeddings is better than performing it on sentence-level sentiment embeddings (Compare CONTRASTE-Base with ASTE-Base w/ SCL-Sentence in the table above).
- We **do not use any external data** for pre-training.
- We achieve **SOTA results on multiple ABSA tasks** including ACOS, ASTE, TASD, and AESC (refer to paper).

CONTACT

PAPER

References

[1] Aspect Sentiment Quad Prediction as Paraphrase Generation; **EMNLP 2021**
[2] A Span-level Bidirectional Network for Aspect Sentiment Triplet Extraction; **EMNLP 2022**