Dual-Encoder Transformers with Cross-modal Alignment for Multimodal Aspect-based Sentiment Analysis

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Abstract

Multimodal aspect-based sentiment analysis (MABSA) aims to extract the aspect terms from text and image pairs, and then analyze their corresponding sentiment. Recent studies typically use either a pipeline method or a unified transformer based on a cross-attention mechanism. However, these methods fail to explicitly and effectively incorporate the alignment between text and image. Supervised finetuning of the universal transformers for MABSA still requires a certain number of aligned image-text pairs. This study proposes a dual-encoder transformer with cross-modal alignment (DTCA). Two auxiliary tasks, including text-only extraction and text-patch alignment are introduced to enhance cross-attention performance. To align text and image, we propose an unsupervised approach which minimizes the Wasserstein distance between both modalities, forcing both encoders to produce more appropriate representations for the final extraction. Experimental results on two benchmarks demonstrate that DTCA consistently outperforms existing methods. For reproducibility, the code for this paper is available at: https://github.com/windforfurture/DTCA.

1 Introduction

Human experience of the world is multimodal, e.g., seeing objects, hearing sounds, feeling textures, and tasting flavors. Multimodal experiences are usually mutually associated to some extent. For example, images are usually associated with tags and text explanations, and text often contains images to more clearly express the main intent of the author.

With the widespread availability of smart phones with digital cameras, social media posts have become increasingly multimodal. To practically apply the existing aspect-based sentiment analysis, one must be able to interpret such multimodal attributes together (Yu et al., 2022; Ling et al., 2022).

Figure 1 (a) shows an example: What do health heroes look like? Dr Lucille Corti died AIDS 1996, Dr Lukwiya died Ebola 2000. An intelligent system is expected to extract four aspect-sentiment pairs from this text, i.e., (Dr Lucille Corti, positive), (AIDS, negative), (Dr Lukwiya, positive) and (Ebola, negative). Notably, if only the language modality is used for inference, the model tends to predict (Dr Lucille Corti, negative) and (Dr Lukwiya, negative). Related to the vision modality, the expression of the text will become more ironic, and thus tends to be positive. Figure 1 (b) shows another example: Kevin Durant says Kyrie Irving has more skill than Allen Iverson. It is difficult to infer from the image that this person is necessarily good at basketball, while a direct understanding of the text seems to recognize the attitude of the author towards Kyrie Irving and Allen Iverson.

Based on this, existing methods for multimodal aspect-based sentiment analysis are typically composed of two subtasks in a pipeline model, including multimodal aspect term extraction (MATE) and multimodal aspect sentiment classification (MASC). The former tries to identify all the as-
pect terms from texts (Wang et al., 2021), while the latter aims to classify the sentiment for each identified aspect term (Hosseini-Asl et al., 2022; Zhang et al., 2021b; Yuan et al., 2022). Unfortunately, the pipeline approach ignores the innate relationship between the two subtasks and is prone to error propagation.

Alternatively, another obvious solution is to apply multitask learning to integrate both subtasks into a joint framework (Vazan and Razmara, 2021). Combining different modalities or types of information to improve performance seems intuitively appealing, but it is challenging in practice to reconcile the varying levels of noise and conflicts between modalities. A series of convolution-based models are usually applied to extract image features, including VGG (Simonyan and Zisserman, 2015) and ResNet (He et al., 2015). To extract region-of-interest (ROI) features, several subsequent works have used a Fast R-CNN (Girshick, 2015) to learn the image representation (Zhang et al., 2021a). For text, Transformer-based models, such as BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), XLNet (Yang et al., 2019) and ELECTRA (Clark et al., 2020) have greatly improved the capability of language understanding and generation.

Taking the obtained representation of both modalities as input, recent studies applied different attentions to compose the features for the final classification. For examples, Ju et al. (2021) and Xu et al. (2022) applied a cross-modal self-attention approach to learn text-image interaction and obtain image-aware text representations and text-aware image representations. However, the image-text pairs present different kinds of knowledge. Thus, different modalities may contribute differently to the final classification, and do not have equivalent amounts of information in each modality, with the language modality tending to dominate with more information. For training, the gradients from the dominant modality will overwhelm the other, effectively preventing the entire model from being trained. It is difficult to encode explicit cross-modal information by superficially measuring the attention distribution.

Based on the universal Transformer architecture, the unified vision-and-language pretrained models can simultaneously encode both modalities, e.g., OSCAR (Li et al., 2020) and UNITER (Chen et al., 2020). However, they are insensitive to aspect extraction and sentiment detection from both language and vision modalities. Finetuning these models with a supervised learning still require a certain number of aligned image-text pairs.

In this study, a dual-encoder transformer with cross-modal alignment (DTCA) is proposed for multimodal aspect-based sentiment analysis. Instead of extracting ROI features, we apply the ViT strategy (Dosovitskiy et al., 2021), which tokenizes the image by slicing it into a sequence of patches. Both ViT and RoBERTa are initialized from pretrained checkpoints, and were used to encode the vision and language modalities. To align the learned features, a multitask learning architecture containing three subtasks was applied, including text-only extraction, co-attention interaction, and token-patch matching. Aside from the co-attention module, we propose minimizing the Wasserstein distance between tokens and images to improve the training effectiveness of the proposed model.

Comparative experiments were conducted on two different benchmarks. The empirical results show that the proposed model outperforms the existing unimodal and multimodal models for MABSA tasks. The effects on different subtasks were further evaluated, finding that the different subtasks all play an indispensable role in performance improvement.

The remainder of this paper is organized as follows. Section 2 presents a detailed description of the proposed DTCA model. Section 3 summarizes the implementation details and experimental results. Conclusions are drawn in Section 4.

2 Dual-Encoder Transformers

Figure 2 shows the overall architecture of the proposed dual-encoder transformers with cross-modal alignment. Two individual transformer-based models, i.e., RoBERTa (Liu et al., 2019) and ViT (Dosovitskiy et al., 2021), were respectively applied for text and image encoding. Notably, both RoBERTa and ViT share the same encoder architecture, which is initialized from a well pretrained checkpoint. Three subtasks were applied for cross-modal alignment to enhance the performance of cross-modal attention for MABSA.

2.1 Modality-specific Encoder

Tokenizer. An input sample $x$ consists of two modalities, including an image $v$ and a text $s$. The objective of MABSA is to perform sequence la-
belong to predict the labels $y = \{y_1, y_2, \ldots, y_N\}$ where $N$ is the length of the text. Following the ViT, the image was first sliced into a sequence of patches $v = [v_1, v_2, \ldots, v_M] \in \mathbb{R}^{M \times (P^2 \times C)}$, where $(P, P)$ is the resolution of each patch, $C$ is the number of channels, and $M = HW/P^2$ is the resulting number of patches. Each patch was then flattened and prepended with a special token, i.e., $v_{[CLS]}$, followed by a linear projection $V \in \mathbb{R}^{(P^2 \times C) \times d_h}$. The result patch embeddings $\bar{v} \in \mathbb{R}^{(M+1) \times d_h}$ can be formulated as,

$$\bar{v} = [v_{[CLS]}, v_1 V, v_2 V, \ldots, v_M V] + V^{\text{pos}}$$  \hspace{1cm} (1)

where $d_h$ is the dimensionality and $V^{\text{pos}} \in \mathbb{R}^{(M+1) \times d_h}$ is the position embeddings.

For language modality, the input text is tokenized by the WordPiece (Wu et al., 2016) tokenizer as same as in the RoBERTa model to obtain a sequence of token embeddings $t \in \mathbb{R}^{(N+1) \times d_h}$ with a word embedding matrix $T \in \mathbb{R}^{N \times |V|}$ as follows,

$$\bar{t} = [t_{[CLS]}, t_1 T, t_2 T, \ldots, t_N T, t_{[SEP]}] + T^{\text{pos}} + T^{\text{seg}}$$  \hspace{1cm} (2)

where $T^{\text{pos}} \in \mathbb{R}^{(N+1) \times d_h}$ and $T^{\text{seg}} \in \mathbb{R}^{(N+1) \times d_h}$ are respectively the position and segment embeddings, and $|V|$ is the number of the vocabulary items. Here, the [CLS] and [SEP] tokens respectively respond to $<s>$ and $<\$/s>$ tokens in the RoBERTa model. We did not apply any extra embeddings to annotate the type of modality, since

Figure 2: The overall architecture of the proposed dual-encoder Transformers with cross-modal alignment for MABSA.
Token-Patch Alignment

Figure 3: The conceptual diagram of the proposed Token-Patch Alignment.

The steak is really great ……

2.2 Cross-modal Alignment

To align the features of both the vision and language modalities, we propose a cross-modal alignment to train both the image and text encoders for the final cross-modal extraction. It mainly consists of three subtasks: text-only extraction, co-attention interaction, and token-patch matching.

Text-only Extraction. The textual representation obtained from RoBERTa, i.e., \( z_T^{(L)} = [\hat{t}_{CLS}, \hat{t}_1, \hat{t}_2, ..., \hat{t}_N, \hat{t}_{SEP}] \) was fed to a fully-connected layer with softmax activation to predict the auxiliary tags for the tokens, defined as,

\[
\hat{y}_n = \text{softmax}(W^t \hat{t}_n + b^t)
\]

where \( W^t \in \mathbb{R}^{K \times d_h} \) and \( b^t \in \mathbb{R}^K \) are trainable parameters, and \( K \) is the number of the candidate tags. Given a training dataset of \( \{x^{(j)}, y^{(j)}\}_{j=1}^J \), the loss function is a categorical cross-entropy,

\[
L_{TO} = -\frac{1}{J \times N} \sum_{j=1}^{J} \sum_{n=1}^{N} \mathbb{I}(y^{(j)}_n) \circ \log \hat{y}^{(j)}_n
\]

where \( y^{(j)}_n \) is the ground-truth label, \( \mathbb{I}(y_n) \) denotes a one-hot vector with the \( y \)-th component being one, and \( \circ \) represents the element-wised multiplication operation.

For token classification, BIO schema was applied. Instead of using 7 tags as in previous works, we used only 5 tags, i.e., B–POS, B–NEU, B–NEG, I and O. For example, the sequence of \( \{B–POS, I–POS\} \) can be converted to \( \{B–POS, I\} \), so that the number of class \( K \) can be compressed by half, thus decrease the prediction error caused by sentiment analysis.

Vision-aware Text Extraction. Multi-head cross-attention was applied to integrate the textual and visual features, where the text representation \( z_T^{(L)} = [\hat{t}_1, \hat{t}_2, ..., \hat{t}_N] \) is regarded as the query, while the image representation \( z_V^{(L)} = [\hat{v}_1, \hat{v}_2, ..., \hat{v}_M] \) was
used as the key and the value, 
\[
\hat{p} = W^p [\text{Att}_1, \text{Att}_2, ..., \text{Att}_U]^\top
\]
where \(W^p \in \mathbb{R}^{d_h \times u \times N}\) and \(\{W^Q_k, W^V_k\} \in \mathbb{R}^{d_h / u \times M}\) are matrices of the query, key and value. 

By passing a MLP and two-layer normalization with two residual connections, the resulting representation is \(\hat{p} = [\hat{p}_1, \hat{p}_2, ..., \hat{p}_N]\). To ensure the consistency of representation size, the first residual added the text-only representation. 

Different from the text-only tasks, the output layer is a CRF to predict sequence \(y\) as follows,
\[
P(\hat{y} | x) = \frac{\exp(\text{score}(x, y))}{\sum_{y' \in \mathcal{Y}_x} \exp(\text{score}(x, y'))}
\]
\[
\text{score}(x, y) = \sum_{n=0}^{N} A_{y_n, y_{n+1}} + \sum_{n=0}^{N} w_{y_n} \hat{p}_n
\]

Token-Patch Alignment. For matching tokens and patches, there are no annotated labels to supervise the training. Thus, we propose minimizing the Wasserstein distance, also called the earth mover distance (EMD), a measure of the distance between two probability distributions, as shown in Figure 3. Regarding the distribution as a certain amount of earth, the EMD is the minimum cost of turning one pile into another; where the cost is assumed to be the amount of dirt moved times the distance by which it is moved. Based on this, the hidden representation of both text and image for the \(j\)-th sample can be assigned with a moving weight, 

\[
t^{(j)} = [(\hat{t}_1^{(j)}, w_1^t), (\hat{t}_2^{(j)}, w_2^t), ..., (\hat{t}_N^{(j)}, w_N^t)]
\]
\[
v^{(j)} = [(\hat{v}_1^{(j)}, w_1^v), (\hat{v}_2^{(j)}, w_2^v), ..., (\hat{v}_M^{(j)}, w_M^v)]
\]

where \(w_1^t\) and \(w_1^v\) denote the moving weight, respectively initialized as \(1/N\) and \(1/M\). The cost of moving \(\hat{t}_n\) to \(\hat{v}_m\) is a normalized mean squared error (MSE), denoted as,
\[
\delta_{m,n} = \text{MSE}(\hat{t}_n, \hat{v}_m)
\]
\[
= \frac{1}{d_h} \sum_{n} \left\| \hat{t}_n \right\|_2 - \left\| \hat{v}_m \right\|_2^2
\]

According to Rubner et al. (2000), the target of the token-patch alignment is to find a transfer flow \(F\) that maps the features from \(\hat{t}_n\) to \(\hat{v}_m\) by minimizing the cumulative cost, defined as,
\[
\text{WORK}(\hat{t}_n, \hat{v}_m, F) = \sum_{n=1}^{N} \sum_{m=1}^{M} f_{m,n} \delta_{m,n}
\]
\[
s.t. \quad f_{m,n} \geq 0
\]
\[
\sum_{m=1}^{M} f_{m,n} \leq w_n^t
\]
\[
\sum_{n=1}^{N} f_{m,n} \leq w_n^v
\]
\[
\sum_{n=1}^{N} \sum_{m=1}^{M} f_{m,n} = \min \left( \sum_{n=1}^{N} w_{n}^\gamma, \sum_{m=1}^{M} w_{m}^\gamma \right)
\]

where \(1 \leq n \leq M\) and \(1 \leq m \leq M\) respectively denote the indices of the tokens and image patches. Here, Eq. (17) ensures there is no negative value to impact the result. Eqs. (17) and (18) limit that the number of features which can be sent and received were less than their weights. Eq. (19) ensures the maximum number of features possible are moved. The optimal problem can be solved by the optimal transportation problem, and the cost of token-patch alignment is then defined as the work normalized by the total flow,

\[
\mathcal{L}^{WD} = \frac{\sum_{n=1}^{N} \sum_{m=1}^{M} f_{m,n} \delta_{m,n}}{\sum_{n=1}^{N} \sum_{m=1}^{M} f_{m,n}}
\]

2.3 Joint Training
The final objective is a combination over the main task and two auxiliary tasks as follows,

\[
\mathcal{L} = \mathcal{L}^{CM} + \alpha \mathcal{L}^{TD} + \beta \mathcal{L}^{WD}
\]

where \(\alpha\) and \(\beta\) are tradeoff hyper-parameters to control the contribution of each task. For inference, the output of vision-aware text extraction was applied as the results.

3 Experiments
3.1 Datasets and Evaluation Metrics
To evaluate the performance of the dual-encoder transformer with cross-modal alignment, two MABSA benchmark datasets are used, mainly consisting of reviews on Twitter. These datasets are Twitter-2015 and Twitter-2017, originally provided by Zhang et al. (2018) for multimodal named entity recognition and annotated with the sentiment polarity for each aspect by Lu et al. (2018). Table 1 summarizes the statistical characteristics of these two datasets.

Precision, recall, and micro \(F_1\)-score are used as evaluation metrics for MABSA. An aspect is regarded as correctly predicted only if the aspect term and polarity respectively match the ground-truth aspect term and corresponding polarity.

3.2 Implementation Details
To evaluate the proposed DTCA model, several baseline models are implemented for comparison, including text-based methods and multimodal methods.

1) Textual methods
- **SPAN** (Hu et al., 2019) is a span-based extract-then-classify framework, where targets are directly extracted from the sentence under the supervision of target span boundaries.
- **D-GCN** (Chen et al., 2020) is a directional graph convolutional network to jointly perform aspect extraction and sentiment analysis with encoding syntactic information.
- **RoBERTa** (Liu et al., 2019) is a pretrained transformer-based model, used as text encoder in the proposed DTCA model.

2) Multimodal methods


| Modality       | Approaches     | Twitter-2015 F | Twitter-2015 P | Twitter-2015 R | Twitter-2017 F | Twitter-2017 P | Twitter-2017 R |
|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
|                |                | F  | P  | R  | F  | P  | R  |
| Text           | SPAN           | 53.8 | 53.7 | 53.9 | 60.6 | 59.6 | 61.7 |
|                | D-GCN          | 59.4 | 58.3 | 58.8 | 64.1 | 64.2 | 64.1 |
|                | RoBERTa        | 63.3 | 62.9 | 63.7 | 65.6 | 65.1 | 66.2 |
| Text+ Image    | UMT-collapse   | 59.8 | 58.4 | 61.3 | 62.4 | 62.3 | 62.4 |
|                | OSCGA-collapse | 62.5 | 61.7 | 63.4 | 63.7 | 63.4 | 64.0 |
|                | JML            | 64.1 | 65.0 | 63.2 | 66.0 | 66.5 | 65.5 |
|                | DTCA           | 68.4 | 67.3 | 69.5 | 70.4 | 69.6 | 71.2 |

Table 2: The results of the DTCA model and other models with comparison.

- **UMT-collapse** (Yu et al., 2020) is a directional graph convolutional network used to jointly perform aspect extraction and sentiment analysis with encoding syntactic information.

- **OSCGA-collapse** (Wu et al., 2020) combines object-level image information and character-level text information to predict entities.

- **JML** (Ju et al., 2021) uses a hierarchical framework to bridge the multi-modal connection between MATE and MASC with an auxiliary text-image relation module to ensure the proper exploitation of visual information.

The hyperparameters of all models were finetuned using a grid-search strategy according to the performance on the development set. The hidden size $d_h$ is 768 for both RoBERTa and ViT model. The number of heads in cross-modal self-attention is 8. AdamW optimizer (Loshchilov and Hutter, 2019) with a base learning rate of 2e-5 and warmup decay of 0.1 was used to update all trainable parameters. The maximum length and batch size were respectively set to 60 and 4. For training epochs, we leveraged an early stopping strategy with a patience of 3 to avoid overfitting.

### 3.3 Hyper-parameters Finetuning

The tradeoff hyper-parameters $\alpha$ and $\beta$ may impact the final performance of the proposed DTCA method for MABSA. Figure 4 shows the optimal settings according to the final performance on the dev set. We successively fine-tuned each parameter in turn by fixing the other to 1. For both $\alpha$ and $\beta$, we used a candidate set of {0.1, 0.3, 0.6, 0.9, 1.0}.

The performance of the proposed DTCA model is optimized when $\alpha$ and $\beta$ are respectively 0.6 and 0.6 on the Twitter-2015 dataset and 0.3 and 0.9 on the Twitter-2017 dataset, the performance of the proposed DTCA model is the best. The results indicate that the use of appropriate parameters can improve the performance.

### 3.4 Comparative Results

Table 2 summarizes the comparative results of the proposed DTCA model against several previous methods in terms of precision (P), recall (R), and $F_1$-score. As indicated, the proposed model outperforms all the baseline models. Compared with the multi-modal baseline with the best performance, i.e. JML, DTCA still shows absolute $F_1$-score increases of 6.71% and 6.67%. Compared with text-based models, DTCA provides far better results. The $F_1$-score of the DTCA model on the test set outperforms RoBERTa by 8.06% and 7.32% respectively on Twitter-2015 and Twitter-2017. This indicates that vision-aware text extraction can enable the proposed DTCA model to learn an appropriate representation for MABSA.

### 3.5 Ablation Study

Table 3 shows the results of an ablation study to further demonstrate the effectiveness of the two auxiliary subtasks, i.e., text-only extraction (TE) and token-patch alignment (TPA). By doing so, we remove TE (w/o TE) and set hyperparameter $\beta$ as 1.0. Then, we remove TPA (w/o TPA) and set $\alpha$ as 1.0. As indicated, the removal of either one or both subtasks (w/o Both) produce varying degrees of performance decline, indicating that both text-only
Figure 5: Two results of different modality encoders.

3.6 Effect of Different Encoder

To investigate the effect of using different encoders, Figure 5 shows the performance of different transform-based encoders for the DTCA model. BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), ALBERT (Lan et al., 2020) and ELECTRA (Clark et al., 2020) were applied as text encoder, while ViT (Dosovitskiy et al., 2021), Swin Transformer (Liu et al., 2021) and DeiT (Touvron et al., 2021) were applied as image encoder. As shown, RoBERTa achieved the best performance for language modality. For vision modality, the performance margins between different encoders were not obvious, indicating that the text contains enough features to identify the aspect-sentiment pairs, whereas the image sometimes fails to provide complementary information and may even induce noise.

3.7 Case Study

Figure 6 shows a case study of two randomly selected examples. For comparison, both text-only RoBERTa and JML were introduced as baselines. For example (a), although JML can accurately predict the correct aspect term Chris Sale, the sentiment of the Chris Sale aspect was wrongly predicted. The main reason is the misleading influence of the image. For example (b), RoBERTa only predicts some aspect terms correctly because of the lack of the image relation. In contrast, DTCA can obtain all correct aspect terms and aspect-related sentiment using cross-modal alignment between text and image.

4 Conclusion

This work proposes a dual-encoder transformer with cross-modal alignment for encoding text-image features into the representations for MABSA tasks. A multitask learning architecture containing three subtasks was applied to integrate both text and image modalities. In addition to the co-attention module, the token-patch alignment was introduced to improve model training effectiveness. Empirical experiments show the model improved the performance for MABSA in the Twitter-2015 and Twitter-2017 datasets. In addition, ablation and case studies further indicate the effectiveness of the proposed model.

Future work will extend the proposed method to more multi-modal tasks, such as multi-modal
MRC, ASTE and dialogue.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (NSFC) under Grant Nos. 61966038 and 62266051, and the Ministry of Science and Technology, Taiwan, ROC, under Grant No.MOST 111-2628-E-155-001-MY2. The authors would like to thank the anonymous reviewers for their constructive comments.

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