Modeling Paragraph-Level Vision-Language Semantic Alignment for Multi-Modal Summarization

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Abstract

Most current multi-modal summarization methods follow a cascaded manner, where an off-the-shelf object detector is first used to extract visual features, then these features are fused with language representations to generate the summary with an encoder-decoder model. The cascaded way cannot capture the semantic alignments between images and paragraphs, which are crucial to a precise summary. In this paper, we propose ViL-Sum to jointly model paragraph-level Vision-Language Semantic Alignment and Multi-Modal Summarization. The core of ViL-Sum is a joint multi-modal encoder with two well-designed tasks, image reordering and image selection. The joint multi-modal encoder captures the interactions between modalities, where the reordering task guides the model to learn paragraph-level semantic alignment and the selection task guides the model to selected summary-related images in the final summary. Experimental results show that our proposed ViL-Sum significantly outperforms current state-of-the-art methods. In further analysis, we find that two well-designed tasks and joint multi-modal encoder can effectively guide the model to learn reasonable paragraphs-images and summary-images relations.

1 Introduction

The dramatic increase of multi-modal data (including text, image, audio, and video) on the Internet makes research on multi-modal summarization necessary. Multi-modal summarization aims to generate a condensed summary, which can cover salient information from one or more modalities inputs (Evangelopoulos et al., 2013; Li et al., 2017). Different from traditional pure text summary, Zhu et al. (2018) pointed out that generated summary with both text and images can effectively increase the satisfaction of users. Intuitively, people can grasp key information easier from multiple modalities than only from the text. This task is defined as multi-modal summarization with multi-modal outputs task (MSMO). Figure 1 shows an example of this task.

Recent single-modal summarization models employ transformers-based encoder-decoder framework (Zhang et al., 2019; Lewis et al., 2020). Existing multi-modal models always add separate encoders for different modalities into the single-modal encoder-decoder framework (Li et al., 2017, 2018; Chen and Zhuge, 2018; Zhu et al., 2018; Khullar and Arora, 2020; Zhu et al., 2020; Im et al., 2021). We show the structure of them in Figure 2a and 2b. The representation of different modalities is obtained separately from single-modal encoders, which leads to the model can not effectively capture the interaction between them. Recently, some works have paid attention to how to...
enhance image-text interaction (Zhu et al., 2020; Zhang et al., 2021a).

However, previous works all ignored paragraph-level vision-language semantic alignment, where an example is shown in Figure 1. The semantic of each paragraph is highly corresponding to the image on the left. Besides, visual-language joint encoding are not well-applied for multi-modal summarization task, which has been proved effective on many multi-modal natural language understanding (NLU) tasks (e.g. Visual Question Answering) (Li et al., 2020a,b,c; Zhang et al., 2021b; Xu et al., 2021; Zhou et al., 2020).

To improve these deficiencies, in this paper, we propose the Vision-Language Summarization model ViL-Sum with a universal transformer-based encoder-decoder structure. The core of ViL-Sum is a joint multi-modal encoder with two well-designed tasks, image reordering and image selection, which aims to guide the model to learn better vision-language representations and capture the alignment of paragraph-level vision-language semantic. Specifically, we use a backbone (e.g. ViT (Dosovitskiy et al., 2021)) to convert images into visual token embeddings and concatenate it with document token embeddings as the input of the joint multi-modal encoder. The ViL-Sum structure with the joint multi-modal encoder is shown in Figure 2c. To model paragraph-level vision-language semantic alignment, we propose a simple but effective image reordering task. It forces the model to reorder shuffled input images, which guides the model to learn the corresponding relation between paragraphs and images. To further enhance vision-language representation, we also train ViL-Sum with image selection task, which selects several summary-related images as part of the multi-modal summary. We follow (Zhu et al., 2020) used image caption construct pseudo labels. Finally, we train ViL-Sum with text summary generation, image selection, and image reordering tasks in a multi-task manner.

Experiments show that our ViL-Sum with multi-task training can outperform baselines by a wide margin. And further analysis demonstrates that the improvement is exactly from the joint modeling and multi-task training. However, the caption of the image is not always available. So the image selection task is not generalization for all datasets. It is deserved to mention that if we remove the image selection task, our proposed multi-modal encoder and the image reordering task still help the model beat all comparison models.

2 Methodology

We show the main architecture of our ViL-Sum model in Figure 3. Firstly, we employ a backbone network as the image tokenizer to convert images into visual token embeddings in Figure 3a. Then, text embeddings and visual token embeddings are concatenated as the input of the main encoder-decoder framework in Figure 3b. Finally, we train the ViL-Sum model in a multi-task manner. In the following sections, we will first introduce vision-language joint representation in section 2.1. Then, we will describe the details of multi-task learning in section 2.2.

2.1 Vision-Language Joint Representation

We formalized the input and output of our ViL-Sum as \( (D, I) \) and \( (S, I_S) \), where \( D = \{t_1, t_2, \ldots, t_T\} \) refers to the sequence of tokens from the input document, \( I = \{img_0, img_1, \ldots, img_M\} \) refers to the sequence of input images from the input document, \( S = \{t_1, t_2, \ldots\} \) refers to the sequence of tokens from gold text summary, and \( I_S = \{img_1, img_2, \ldots, img_K\} \) refers to \( K \) selected images for the summary.

2.1.1 Document Embeddings

Each document is firstly converted into the sequence of tokens \( \{t_1, t_2, \ldots, t_T\} \) and then two special tokens “\(<s>\)” and “\(<\backslash s>\)” are added to represent the start and end of the document. After that, we map each token into vector representation \( E_D = \{e_{\text{start}}, e_1, \ldots, e_T, e_{\text{end}}\} \).

2.1.2 Image Embeddings

Different from previous methods, which extract many image features via existing object detection models. We employ ViT (Dosovitskiy et al., 2021)
Figure 3: The overall framework of our proposed ViL-Sum model. Figure a) is the detail of ViT-based image tokenizer. Figure b) is the encoder-decoder framework with multi-task learning.

2.1.3 Multi-modal Encoder

The input of the multi-modal encoder is the concatenation of visual token embeddings \( E_v \) and token embeddings \( E_D \). We can formalize the input as \( H_0 = \{ E_v; E_D \} \) and then encode visual and text embeddings with 12 transformer blocks. Finally, we can obtain vision-language representation \( H_L = \{ h_{v1}, \ldots, h_{vM}, h_{start}, h_1, \ldots, h_{end} \} \) from last layer output of this encoder.

2.2 Enhanced by Multi-task Learning

We train our ViL-Sum with text summary generation task and two well-designed auxiliary tasks in a multi-task manner, which are used to enhance vision-language representation and paragraph-level semantic alignment.

2.2.1 Visual-enhanced Summary Generation

We feed the vision-language representation \( H_L \) from the multi-modal encoder as input of decoder with 12 transformer blocks. The target of the model is to minimize the negative log-likelihood of label text \( y \) tokens given input document \( D \) and images \( I \) via updating model parameters \( \theta \). The loss function of summary generation task is as follows:

\[
L^\text{GEN}_\theta = - \sum_{j=1}^{\text{|y|}} \log P_{\theta}(y_j|y_{<j}, D, I) \quad (3)
\]
2.2.2 Images Selection

We also train our ViL-Sum with multi-modal output reference following (Zhu et al., 2020). To build pseudo image selection labels of training data, we employ similarity between image caption and gold summary to select top-$K$ images as labels $\hat{y}$ ($K$ is empirically set as 3). The similarity is the average of ROUGE-1, ROUGE-2 and ROUGE-L scores. The probability to select each image is $y_i = P(img_i) = \sigma(W \cdot hv_i + b)$ and loss function of the image selection task is as follows:

$$L_{IS}^\theta = \frac{1}{M} \sum_{i=1}^{M} -[\hat{y}_i \log y_i + (1 - \hat{y}_i) \log(1 - y_i)]$$ (4)

2.2.3 Images Reordering

To model the paragraph-level semantic alignment, we proposed the image reordering task to joint train ViL-Sum. Specifically, we shuffle the order of input images and then force ViL-Sum model to predict the original position of each image through $y_i = P(pos_i) = \text{softmax}(W \cdot hv_i + b)$ and minimize the objective function:

$$L_{IR}^\theta = \frac{1}{M} \sum_{i=1}^{M} \sum_{c=1}^{C} -\hat{y}_{ic} \log y_{ic}$$ (5)

where $C$ is the number of categories, depending on the number of input images. We set $C = 10$. If the number of input images is greater than 10, we only keep the first 10 images as input images.

2.2.4 Joint Training

Finally, ViL-Sum is trained with previous three tasks: summary generation, image selection, image reordering, jointly by simultaneously minimizing three loss functions as follows:

$$L_{\theta}^{TOTAL} = L_{\theta}^{GEN} + L_{\theta}^{IS} + L_{\theta}^{IR}$$ (6)

3 Experimental Setup

3.1 Dataset

We employ the MSMO dataset (Zhu et al., 2018) to evaluate the effectiveness of our proposed ViL-Sum. MSMO dataset is a large-scale dataset for the Multi-modal Summarization with Multi-modal Output task. Each example in the dataset is a triplet (document, images, summary). This dataset contains online news articles (723 tokens on average) paired with multiple image-caption pairs (6.58 images on average) and multi-sentence summaries.

|               | train  | valid | test  |
|---------------|--------|-------|-------|
| #Documents    | 293,965| 10,355| 10,261|
| #AvgTokens(D)| 721    | 766   | 731   |
| #AvgTokens(S)| 70     | 70    | 72    |
| #Images       | 1,928,356| 68,520| 71,509|
| #AvgImgs     | 6.56   | 6.62  | 6.97  |

Table 1: Statistical information of MSMO dataset. D refers to the input document. S refers to the summary.

(70 tokens on average). For test data, based on text reference, at most three images are annotated to produce a multi-modal reference by humans. The detailed statistical information of MSMO dataset is shown in Table 1.

3.2 Baseline Methods

We report the existing multi-modal summarization methods (ATG, ATL, HAN, GR) (Zhu et al., 2018) and MOF$_{RR}^{dec}$ (Zhu et al., 2020) using multiple metrics. We also report the result of PGC (See et al., 2017), which is a single-modal summarization model.

To prove the effectiveness of our proposed joint representation and multi-task learning, we mainly compare with BART-base (Lewis et al., 2020) model and a reproduced two-stream model BART-cross which has the same structure with MOF$_{RR}^{dec}$ and replace GRU and VGG19 (Liu and Deng, 2015) with BART and ViT (Dosovitskiy et al., 2021) respectively. To be fair, we mainly compare our model with BART-base and BART-cross due to previous methods did not employ pre-trained models. The details of these models are as follows:

1) **PGC** is the BiGRU-based pointer-generator network that allows both copying words from the input text and generating words from a fixed vocabulary.

2) **ATG** is based on the PGC model. It fuses static visual features from VGG19 with text features after the BiGRU encoder. Besides, ATG selects final images by the visual-text attention weight.

3) **ATL** replaces the image global features of ATG with local features (multiple pooling features), which select images by measuring the sum of visual attention distribution over the local patch features of each image.

4) **HAN** is based on the ATL model and adds a hierarchical attention mechanism. This attention mechanism first attends to the image patches to get the intermediate vectors to represent images.
and then attends to these vectors to get the visual context vector.

5) **GR** is an extractive method that employs LexRank (Erkan and Radev, 2004) to rank captions of images and select images based on the rank score. The text summary of it is generated by the PGC model.

6) **MOF** is based on ATG model. This model first constructs pseudo-labels of image selection for the final summary. Specifically, it employs ROUGE score to measure the relevance of image caption and summary text.

7) **BART-base** is a pre-trained seq2seq generation model, which achieved promising results in many generations NLP tasks, especially on text summarization. We employ this model to confirm visual features’ contribution to a summary generation.

8) **BART-cross** is a BART-based model with the same model structure as previous ATG, ATL, HAN, GR, and **MOF**. It first encodes images with ViT and then fuses with text representation from the BART encoder. The fusion of image and text representations employs cross attention like the ATG model. For a fair comparison, we construct this BART-cross model to prove the effectiveness of joint multi-modal encoder and multi-task training in our ViL-Sum.

### 3.3 Implementation Details

We train our model for 10 epoches on 8 V100 GPUs using Adam (Kingma and Ba, 2015) with $\beta_1 = 0.9$, $\beta_2 = 0.99$, a batch size of 64. We also use linear learning rate warm-up with 1,000 steps. The weight-decay is set as $10^{-4}$. The model is initialized with ViT-B/16 and BART-base parameters. The max length of input images and tokens are 10 and 512 respectively. For image tokenizer, we employ the same setting with ViT-b/16 in (Dosovitskiy et al., 2021). When testing, we generate the summary with a beam size of 3, and the minimum and maximum decoding lengths are set as 15 and 150 separately.

### 3.4 Evaluation Metrics

We evaluate the pictorial summary with the MMAE metric (Zhu et al., 2018).

MMAE consists of three sub-metrics: ROUGE score (ROUGE-L), Image Precision (IP), and Image Text Relevance (MAXsim). ROUGE (Lin, 2004) score can measure the salience of text in generated summary, which is widely used for measuring summarization systems. The image precision can measure the salience of selected images and is computed as Eq. (7).

$$\text{IP} = \frac{|\text{ref}_\text{img} \cap \text{rec}_\text{img}|}{|\text{rec}_\text{img}|}$$

where $\text{ref}_\text{img}$ and $\text{rec}_\text{img}$ denote reference images and recommended images by MSMO systems respectively. MAXsim can measure the relevance between selected images and generated text summary, which trains an image-text retrieval (Faghri et al., 2018) model with max-margin loss to evaluate Image-Text relevance. Finally, Zhu et al. (2018) choose the linear regression results of 3 metrics as MMAE with human judgments and the weight for ROUGE-L, MAXsim, and IP is 1.641, 0.854, 0.806 respectively, the intercept is 1.978.

We report the results of ROUGE-1/2/L, MAXsim, IP, and MMAE of each model to comprehensively measure their performance. The results of our model are all the averages of three different checkpoints.

### 4 Results and Analysis

#### 4.1 Overall Performance

The main results of all models are shown in Tab. 2. We can see that compared with the baselines, our ViL-Sum gains significant improvement on all metrics and ViL-Sum+selection, reordering achieves the best comprehensive performance. Compared with BART-cross, we can see that the joint representation and multi-task training both bring satisfactory improvement, which proved the effectiveness of our proposed methods.

#### 4.2 Ablation Study

##### 4.2.1 Performance of Joint Representation

Firstly, we can see that the performance of ATG, ATL, HAN, and GR all hurt ROUGE scores by simply introducing images as independent visual features. Through the multi-modal objective optimization, **MOF** has a significant improvement on IP and does not decrease the quality of generated text summary. This situation proves that modeling vision and language information independently did...
not bring in the revenue for text summary generation. The results of BART-cross, which also introduces images as independent features, also has lower ROUGE scores than BART-base. This situation proved again previous conclusion.

Different from previous performance on ROUGE score, our ViL-Sum with joint vision-language representation obtains better ROUGE scores and the Image Precision (IP) and MAX$_{sim}$ both have a significant improvement. This demonstrated that using the joint multi-modal encoder to obtain vision-language representation is better than using separate encoders with cross-attention to fuse multi-modal features.

### 4.2.2 Performance of Multi-task Learning

The result of ViL-Sum without multi-task learning has achieved new state-of-the-art performance and is better than BART-cross. In this section, we will analyze the influence of our proposed multi-task learning. From the results, we can see that the introduction of images selection and reordering bring a slight decrease in ROUGE scores. Meanwhile, the IP and MAX$_{sim}$ scores increase significantly, which makes the overall score MMAE is better than ViL-Sum without multi-task training.

We report the ablation study results of two auxiliary tasks in the second block of Table 2. From the results, we can see that image selection and reordering both can bring improvement on IP and MAX$_{sim}$ scores. The combination of two tasks can push the overall score MMAE higher. The comparison of these models demonstrated that the introduction of multi-task learning exactly improved the vision-language representation and semantic alignment, which is reflected in the improvement of the multi-modal metrics: IP, MAX$_{sim}$ and MMAE.

### 4.3 Human Evaluation

We randomly sample 100 examples from the test set to conduct the human evaluation. The multi-modal summary of golden reference, BART-base, BART-cross, and our ViL-Sum (best) are evaluated by three human annotators. Each annotator will score each example with a rating scale from 1 (worst) to 5 (best). Table 3 shows the average scores from three annotators ($t$-test, $p < 0.05$). We can see that annotators tend to give the multi-modal summary higher scores and our ViL-Sum outperforms two strong baselines by a wide margin.

### 4.4 Impact of Different Numbers of Images

Tab. 4 depicts the experimental results of our model performance varying with different $K$ (the image
number at the final summary). Since the golden reference in the test set contains three images, the consistency between training and test makes the model perform best when $K$ is 3. Overall, our model is not very sensitive with $K$. With different $K$, our ViL-Sum all achieve excellent performance, which prove our method can identify the real importance images from multi-modal inputs.

### 4.5 Impact of Different Image Tokenizer

To further evaluate the effectiveness of joint modeling and multi-task learning, we replace the backbone of the image tokenizer to observe the performance of vilsum. We replace ViT backbone with Linear Layer and an image tokenizer from Vision Transformer (Wu et al., 2020). Both of them have much smaller parameters than ViT backbone. Specifically, linear is the simple version of ViT which replaces the transformer image encoder with a simple linear layer to map the images into visual token embeddings. Vision is an image tokenizer from Vision Transformer (Wu et al., 2020), which can convert one image into several visual tokens embeddings. Table 5 reports the results of them. We can see that the ViT exactly provides better visual features than the other two backbones. However, the performance does not drop sharply with the replacement of the image tokenizer. This proves that Our proposed two strategies are robust and the ViL-Sum is flexible with different image tokenizers.

|       | ROUGE-L | MAX$_{sim}$ | IP  | MMAE |
|-------|---------|-------------|-----|------|
| ViT   | 41.21   | 34.52       | 71.73 | 3.55 |
| Linear| 40.18   | 33.89       | 70.44 | 3.51 |
| Vision| 41.10   | 34.28       | 71.04 | 3.54 |

Table 5: Results of ViL-Sum with different image tokenizer. Linear means image tokenizer which replace transformer blocks with linear layer. Vision is an image tokenizer from Vision Transformer.

### 4.6 Case Study and Relevance Visualization

We select one typical example from the test set and visualize the relevance of 1) summary sentences and selected images; 2) selected paragraphs and images; 3) all tokens and images in Figure 4 and 5. Each color block means cosine similarity between image and text object. The darker color refers to a higher similarity in the heatmap. From 3 different relevant visualizations, we can see that our ViL-Sum can effectively align semantic representation of summary sentences and selected images as shown in Figure 4b. The input images can be aligned with paragraphs by training with image re-ordering as shown in Figure 4c. We also report the heatmap of all input tokens and images in Figure 5, which is consistent with Figure 4b and 4c. This case proves that the multi-task training really helps ViL-Sum learn reasonable relation between images and input paragraphs.

### 5 Related Work

#### 5.1 Vision-Language Representation

Large-scale Transformers-based (Vaswani et al., 2017) vision and language representation models (Radford et al., 2019; Devlin et al., 2019; Lewis et al., 2020) have achieved the state-of-the-art results on many Natural Language Processing (NLP) tasks, which always pre-train on a large corpus with self-supervised tasks and then fine-tune on specific NLP tasks. Most existing vision and language pre-training (VLP) models (Tan and Bansal, 2019; Li et al., 2021) adopt two different encoders to model vision and language separately, which extracts visual features by an object detection model and then combines the derived object-centric representation of the image and text embedding. Recently, large-scale vision and language representation learning has achieved promising improvements (Li et al., 2020a,b,c; Zhang et al., 2021b; Xu et al., 2021; Zhou et al., 2020) by jointly encoding different modalities with the same encoder and achieved better performance on many NLU tasks.

#### 5.2 Multi-modal Summarization

Recently, text summarization models have achieved remarkable performance on different type methods (Liu and Lapata, 2019; Zhong et al., 2020; Lewis et al., 2020; Zhang et al., 2019; Liang et al., 2021b,a) with the development of pre-trained language models. Different from text summarization, multi-modal summarization is a task to generate a condensed summary to cover the main information from multimedia data. One of the most significant characteristics of this task is it is not only based on text information, but can also employ rich visual information from images, audio, and videos. Multi-modal summarization task can be divided into two types with different output: single-modal output (Evangelopoulos et al., 2013; Chen and Zhuge, 2018; Li et al., 2018) and multi-modal output (Bian et al., 2015; Zhu et al., 2018, 2020). Compared with
[1] Sergio Aguero is Manchester City's greatest striker ... Sergio Aguero became Manchester City's all-time leading goalscorer on Wednesday when he netted his 178th goal for the club to break Eric Brook’s record, which had stood for 78 years ... Sportsworld’s Jamie Redknapp. Martin Keown and Chris Sutton have had their say.

[2] JAMIE REDKNAPP: 1. Thierry Henry Simply the greatest ... 2. Cristiano Ronaldo He didn’t play as a striker for all of his Manchester United career but towards the end he was out of this world ... 3. Sergio Aguero An assassin from the Gerry Muller school of ... 4. Didier Drogba The perfect target man and a monster who bullied defenders ... 5. Luis Suarez The ultimate street footballer.

[3] MARTIN KEOWN: 1. Thierry Henry He was like an Olympic ... 1. Sergio Aguero He’s an all-time Premier League’s greatest foreign striker ... 2. Didier Drogba The best four strikers ... 4. Daniele Bergamini A Rolls-Royce player. Not only did he score great goals but he set them up, too. He benefited Henry to play with such a great technician.

[3] CHES SUTTON: 1. Thierry Henry He really was world class. Never mind just strikers ... 2. Didier Drogba The ultimate No 9. Physically, running in behind, link-up play – he had the lot ... 3. Sergio Aguero A ruthless finisher. While he may not be as good as Henry or Drogba in terms of all-round contribution, you think of Aguero and you think of goals, goals and goals! 4. Eric Cantona Iconic, influential and possibly the greatest carlery for ... 5. Daniele Bergamini He was the master of creativity and had a wonderful eye for a pass at Arsenal.

Figure 4: Example from the test set with the generated multi-modal summary. Figure a) is the full example. Figure b) is the heatmap that shows the relevance of the summary and selected images. Figure c) is the heatmap that shows the relevance of selected paragraphs and images. Each color block means cosine similarity between image and text object. The darker color refers to higher similarity.

Figure 5: The heatmap shows the relevance of all input tokens and images. The darker color refers to higher similarity.

A novel vision-language summarization ViL-Sum model with a multi-task learning framework to tackle these issues.

6 Conclusion

In this paper, we propose a novel (ViL-Sum) model, which can enhance the vision-language representation and the paragraph-level semantics alignment by multi-task training. Our ViL-Sum achieves new state-of-the-art results on automatic and manual evaluation metrics. The further analysis demonstrates the improvement is from the joint multi-modal encoder and multi-task training. Our proposed image reordering task is very simple yet effective. We believe it can be extended to more scenarios (e.g. vision-language pre-training models) and modalities (e.g. audio and video).

Limitations

The amount of parameters of ViL-Sum is relatively large. To reduce the parameters is one vital problem that needs to be considered. Besides, due to lack of multi-modal summarization corpus, we verify ViL-Sum on the only available dataset in this version. In the future work, we will consider open domain datasets for more verification.

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