Visual Enhanced Entity-Level Interaction Network for Multimodal Summarization

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Abstract

MultiModal Summarization (MMS) aims to generate a concise summary based on multimodal data like texts and images and has wide application in multimodal fields. Previous works mainly focus on the coarse-level textual and visual features in which the overall features of the image interact with the whole sentence. However, the entities of the input text and the objects of the image may be underutilized, limiting the performance of current MMS models. In this paper, we propose a novel Visual Enhanced Entity-Level Interaction Network (VE-ELIN) to address the problem of underutilization of multimodal inputs at a fine-grained level in two ways. We first design a cross-modal entity interaction module to better fuse the entity information in text and the object information in vision. Then, we design an object-guided visual enhancement module to fully extract the visual features and enhance the focus of the image on the object area. We evaluate VE-ELIN on two MMS datasets and propose new metrics to measure the factual consistency of entities in the output. Finally, experimental results demonstrate that VE-ELIN is effective and outperforms previous methods under both traditional metrics and ours. The source code is available at https://github.com/summoneryhl/VE-ELIN.

1 Introduction

Multi**M**odal **S**ummarization (MMS) takes multimodal data like texts and images as input and aims to generate a concise summarization as output. This task has attracted much attention in the research community (Li et al., 2019, 2018b; Zhu et al., 2018) because it can be widely used in various real-world applications, such as social media (Zhang et al., 2022a), meeting (Zhong et al., 2021), and e-commerce products (Li et al., 2020a).

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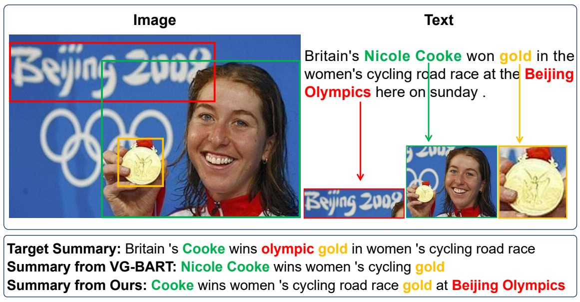

Figure 1: Illustration of multimodal summarization task. The bottom part is the target summary, a summary from the previous method, and ours. The previous method can not adequately leverage fine-grained entity information.

Recent studies primarily concentrate on the cross-modal interaction and filtering of visual features, which have achieved promising performances. For instance, Yu et al. (2021) explores various ways of image-text fusion to utilize multimodal information based on the application of generative Pre-trained Language Models (PLMs) to the task. Zhang et al. (2022b) adopts knowledge distillation from the vision-language pre-trained model to improve image selection. Liang et al. (2023) designs a target-oriented contrastive objective to discard needless visual information. Despite their effectiveness, current methods mainly focus on the coarse-level rather than fine-grained visual and textual features, which conduct interactions between the global image and sentence semantics. This might lead to an insufficient utilization of crucial local information. As shown in Figure 1, there are three fine-grained entities "Nicole Cooke", "Gold", and "Beijing Olympics" in the input text, and three object regions in the image corresponding to them while previous methods are not able to extract the fine-grained information adequately.

Thus, we consider utilizing the inherent entity information in the text and object information in the image so that the output summary maintains

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key entities with high coherence. In this paper, we propose a novel Visual Enhanced Entity-Level Interaction Network (VE-ELIN) for Multimodal Summarization. The proposed VE-ELIN addresses the problem of incomplete generation of entity information in two ways. Firstly, we design the cross-modal Entity Interaction (EI) module which can better fuse the entity information in text and the object information in vision and provide richer multimodal representation. In particular, the EI module includes three levels of features, namely sentence, entity, and object level. We encode the input text using a textual encoder to obtain sentence-level features and use a pre-trained Named Entity Recognition model (Yan et al., 2021) to get entity-level features. Moreover, we use the image object detection model (Carion et al., 2020) to capture the objects in the image and encode them to obtain the object-level features. Secondly, to further distill features from vision information, we apply CLIP (Radford et al., 2021) and integrate it into our object-guided Visual Enhancement (VE) module. The VE module can fully extract the visual features and enhance the focus of the image on the object area to better inject visual information into the multimodal decoder.

In addition to conventional evaluation methods, we introduce novel metrics to measure the factual consistency of entities in the output summarization. Specifically, we count the number of entities in the output and compare it with the entities in the target summary. Then, we compute the proportion of entities named EntityScore and the similarity between entities named SimilarScore.

We evaluate VE-ELIN on two MMS datasets, which have different text lengths and input image numbers. The experimental results demonstrate that VE-ELIN is effective and outperforms previous methods under both traditional metrics and ours.

In summary, our contributions are as follows:

- To the best of our knowledge, we are the first to identify the significance of fine-grained entity information for the multimodal summarization task.
- We propose a unified Visual Enhanced Entity-Level Interaction Network (VE-ELIN) to generate high-quality summaries while capturing key entity information in the original text.
- We propose two new metrics EntityScore and SimilarScore to further assess the factual consistency of entities in the output. The experimental results demonstrate the effectiveness of our proposed VE-ELIN.

2 Related Work

2.1 Multimodal Interaction

Object detection aims to predict a set of bounding boxes and corresponding category labels for the targeted objects in an image, which is a fundamental task in computer vision. Named Entity Recognition aims to identify the named entities in the text and can be widely used in information retrieval (Brandsen et al., 2022), and knowledge graphs (Zamini et al., 2022). Due to the rapid development of social media platforms such as Twitter, Multimodal Named Entity Recognition (MNER) (Zhao et al., 2022) has attracted increasing attention. Given image-text pairs, MNER aims to recognize the named entities in the text and classify the corresponding types. In the study of MNER, aligning the instance information in images with entities in text is an intuitive idea. However, in the field of multimodal summarization, there has been limited research on fine-grained interaction between visual and textual modalities.

2.2 Multimodal Summarization

Text summarization aims to extract important information from text and generate a concise summary. With the increasing of multimodal data on the internet, researchers have shown a growing interest in multimodal summarization. Different from traditional text summarization, multimodal summarization aims to generate summaries based on data from various modalities, e.g., video, image, audio, and text.

Existing multimodal summarization tasks contain sports summarization (Tjondronegoro et al., 2011), movies summarization (Evangelopoulos et al., 2013), video summarization (Sanabria et al., 2018), meeting summarization (Erol et al., 2003; Li et al., 2019), multimodal sentence summarization (Li et al., 2018b), multimodal summarization with multimodal output (Zhu et al., 2018), e-commerce products summarization (Li et al., 2020a) and so on. Previous studies on multimodal summarization tackle the tasks from different aspects. Palaskar et al. (2019) explore the hierarchy attention between the textual article and visual features. Consequent studies utilize fusion forget gate (Liu et al., 2020), visual selective gates (Li et al., 2020b), and contribution network (Xiao et al., 2023), directing the attention of models towards the most salient parts in the visual features for summarization.

3 Methodology

In this section, we introduce the overview of our framework. We first present the brief task formulation and describe the method overview. Then, we detail our proposed module and introduce the training and generation process.

3.1 Task Formulation

In this paper, we focus on the multimodal summarization task, involving a dataset comprising n triplets $\langle t_i, v_i, s_i \rangle$, where t_i represents the i-th text input, v_i represents the i-th image input, and the MMS model is tasked with generating a summary s_i based on both t_i and v_i.

3.2 Method Overview

We use VG-GPLM (Yu et al., 2021) as the backbone, which is built upon generative pre-trained language models (e.g., BART), and injects visual features on the encoder side. As shown in Figure 2, the VE-ELIN takes text and image as inputs and generates a summary as output. The multimodal encoder part of VE-ELIN consists of a Cross-modal Entity Interaction (EI) module that can better fuse the entity features in textual and visual information and an Object-guided Visual Enhancement (VE) module that can fully extract the visual features and enhance the focus of the image on the object area. Then, in the multimodal decoder, we fuse the features of different modalities from EI module and VE module and use it as extra input to the decoder.

3.3 Multimodal Encoder

3.3.1 Object-guided Visual Enhancement

Given an image, we first utilize the visual encoder of CLIP (Radford et al., 2021) to extract visual local grid features. CLIP is a dual-stream vision-language pre-trained model that has undergone pre-training with a contrastive loss using 400 million image-text pairs. This model comprises a Transformer (Vaswani et al., 2017) text encoder and an image encoder which could be either Vision Transformer (ViT) (Dosovitskiy et al., 2020) or Residual Convolutional Neural Network (ResNet) (He et al., 2016). In this paper, we apply the ViT image encoder of CLIP and obtain visual features $V \in \mathbb{R}^{s_v \times d_v}$, where s_v is the patch numbers and d_v is the hidden dimension of image features.

Previous studies indicate that different regions of visual features contribute unequally to summary generation (Li et al., 2020b; Liu et al., 2020; Xiao et al., 2023). For instance, given the input sentence and image, the target summary is "Britain's Cooke wins Olympic gold in women's cycling road race.", as shown in Figure 1. In the image, the People, Gold Medal, and Olympic Logo components are more relevant to the target summary, while the features corresponding to the rest of the sections are less important. Thus we design a simple feature filter to enhance the focus on the image objects and the better utilization of input visual features.

In practice, we follow Carion et al. (2020) to detect the objects in the image using ResNet-101 as a backbone. As shown in Figure 2(b), two features are obtained after going through DETR, one is the visual features of each object marked with the bounding box: $ObjectFeatures{=}V_o \in \mathbb{R}^{n \times 1 \times d_v}$, where n is the object numbers. For instance, there are three objects in the image, then n=3. In addition, we set the maximum number of objects to 64. The other is the attention score matrix of the whole image: $AttentionScore{=}A_{i,j}{=}(a_{i,j}) \in \mathbb{R}^{m \times m}$, where $a_{i,j} \in [0, 1]$, $i, j \in [0, m]$ and m is the dimension of the matrix, the closer the value is to the object area the closer it is to 1. We design a simple features filter through the attention score matrix, in practice, we transform $A_{i,j}$ through a linear layer to the same dimension as the image features, and then fuse it with the image features:

$$\hat{A}_{i,j} = \text{Linear}(A_{i,j}) \tag{1}$$

$$V_{filtered} = V + \hat{A}_{i,j} \tag{2}$$

where $V_{filtered} \in \mathbb{R}^{s_v \times d_v}$. The filtered visual features are represented in Figure 2 as visual-enhanced features.

3.3.2 Cross-modal Entity Interaction

We design this module to capture entity-related textual and visual information through three features: sentence-level features, entity-level features, and object-level features. Finally, get the entity-related feature as output and add it to the text-vision fusion in Section 3.4.

Sentence-level Features. At the entry of the framework, the input text is first tokenized and converted to a sequence of token embeddings $X_t \in \mathbf{R}^{N \times d_t}$, and the positional encodings $E_{pe} \in$

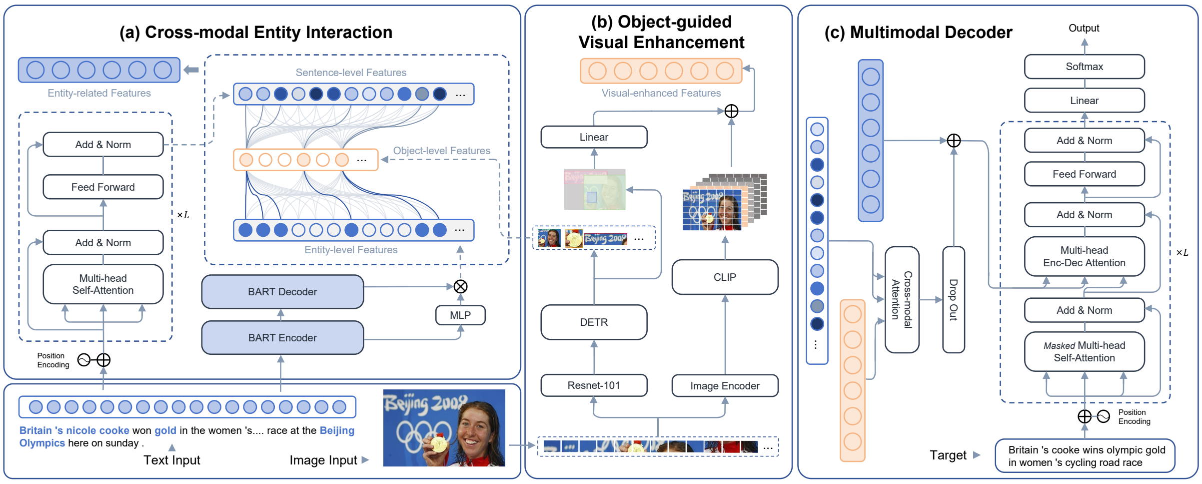

Figure 2: The overview of our model. Given input text and image, our model generates summaries as output through three modules: the cross-modal entity interaction module, object-guided visual enhancement module, and multimodal decoder.

$\mathbb{R}^{N\times d_t}$ are added to it, in which N is the sequence length and d_t is the textual dimension:

$$Z_0^{enc} = X_t + E_{pe} \tag{3}$$

As illustrated in Figure 2(a), the encoder is composed of a stack of L encoder layers, each containing two sub-layers: Multi-head Self-Attention (MSA) and Feed-Forward Network (FFN). After each sub-layer, there is a residual connection (Wang et al., 2019) followed by a layer normalization (LN). We obtain the sentence-level features T_s through the encoder:

$$Z_l' = \mathrm{LN}(\mathrm{MSA}(Z_{l-1}^{enc}) + Z_{l-1}^{enc}) \tag{4}$$

$$T_s = \mathrm{LN}(\mathrm{FFN}(Z_l') + Z_l') \tag{5}$$

where $T_s \in \mathbb{R}^{N\times d_t}$.

Entity-level features. Following Yan et al. (2021), we use the Seq2Seq model with the pointer mechanism to generate the entity index sequences, which are then mapped to sentence-level features to obtain entity-level features. This part includes two components.

(1) BART Encoder encodes the input sentence $X = t_i$ into vectors $\mathbf{H}^e$:

$$\mathbf{H}^e = \mathrm{Encoder}(X) \tag{6}$$

where $\mathbf{H}^e \in \mathbb{R}^{N\times d_t}$, and d_t is the hidden dimension.

(2) BART Decoder is to get the index probability distribution for each step $P_t = P\left(y_t \mid X, Y_{<t}\right)$. However, since $Y_{<t}$ contains the pointer and tag index, it cannot be directly inputted to the Decoder. We use the Index2Token conversion to convert indexes into tokens:

$$\hat{y}_t = \begin{cases} X_{y_t}, & \text{if} y_t \leq n, \\ G_{y_t-n}, & \text{if} y_t > n \end{cases} \tag{7}$$

After converting each y_t this way, we can get the last hidden state $\mathbf{h}_t^{d_t} \in \mathbb{R}^{d_t}$ with $\hat{Y}_{<t} = [\hat{y}_1, ..., \hat{y}_{t-1}]$ as follows:

$$\mathbf{h}_t^{d_t} = \mathrm{Decoder}(\mathbf{H}^e; \hat{Y}_{<t}) \tag{8}$$

Then, we can use the following equations to achieve the index probability distribution P_t:

$$\mathbf{E}^e = \mathrm{TokenEmbed}(X) \tag{9}$$

$$\hat{\mathbf{H}}^e = \mathrm{MLP}(\mathbf{H}^e) \tag{10}$$

$$\bar{\mathbf{H}}^e = \alpha \times \hat{\mathbf{H}}^e + (1-\alpha) \times \mathbf{E}^e \tag{11}$$

$$\mathbf{G}^{d_t} = \mathrm{TokenEmbed}(G) \tag{12}$$

$$P_t = \mathrm{Softmax}([\bar{\mathbf{H}}^e \otimes \mathbf{h}_t^{d_t}; \mathbf{G}^{d_t} \otimes \mathbf{h}_t^{d_t}]) \tag{13}$$

where TokenEmbed is the embeddings shared between the Encoder and Decoder; $\mathbf{E}^e$, $\hat{\mathbf{H}}^e$, $\bar{\mathbf{H}}^e \in \mathbb{R}^{n\times d_t}$; $\alpha \in [0, 1]$ is a hyper-parameter; $\mathbf{G}^{d_t} \in \mathbb{R}^{l\times d_t}$; $[\cdot;\cdot]$ means concatenation in the first dimension; $\otimes$ means the dot product. Finally, we map the index P_t to the sentence-level features Eq.(5) to get entity-level features:

$$T_e = \mathrm{Map}(P, T_s) \tag{14}$$

During the training phase, we use the same negative log-likelihood loss and the teacher forcing method as Yan et al. (2021). During the inference, we use an autoregressive manner to generate the target sequence. In the overall framework of our model, the NER part is pre-trained in advance, and in the overall model training, it is used for inference.

Cross-modal Entity Interaction. Firstly, we employ multi-head self-attention on the interaction features to exploit contexts of the same modality:

$$D_m = \text{MultiHeadAttn}(H_m, H_m, H_m) \quad (15)$$

where H_m is the interaction features, $m \in \{T_e, V_o, T_s\}$. Then, we interact entity features with object features via a gated cross-attention module:

$$R_e = \text{MultiHeadAttn}(H_{T_e}, D_{V_o}, D_{V_o}) \quad (16)$$

$$\alpha_e = \text{Sigmoid}(W_{e1} R_e + W_{e2} H_{T_e}) \quad (17)$$

$$M_e = \alpha_e \cdot R_e + (1 - \alpha_e) \cdot H_{T_e} \quad (18)$$

where M_e is object-aware entity representations. Similarly, we obtain entity-aware object representations M_o. After that, we fuse visual information from M_e to the sentence-level features T_s:

$$\alpha_s = \text{Sigmoid}(W_{s1} M_e + W_{s2} H_{T_s}) \quad (19)$$

$$M_s = \alpha_s \cdot R_s + (1 - \alpha_s) \cdot H_{T_s} \quad (20)$$

Finally, we add M_s and M_o to get the output entity-related features Z_{er} of the cross-modal entity interaction module:

$$Z_{er} = M_s + M_o \quad (21)$$

3.4 Multimodal Decoder

We inject visual information through the vision-guided multi-head attention mechanism. The query Q is from the obtained filtered visual features $V_{filtered}$ in Section 3.3.1, and the key K and value V are from the obtained sentence-level features T_s in Section 3.3.2. Then, we apply a cross-modal multi-head attention (CMA) to get the visual queried text features Z_v. Finally, we add the entity-related features Z_{er} and Z_v to get the text-vision fusion features Z_k:

$$Z_v = \text{CMA}(V_{filtered}, T_s, T_s) \quad (22)$$

$$Z_k = Z_{er} + Z_v \quad (23)$$

The text-vision fusion features will be input into the decoder of BART to generate the corresponding summary:

$$\log p_\theta(y) = \sum_{i=1}^{n} \log p_\theta(y_i | Z_k, y_i, \ldots, y_{i-1}) \quad (24)$$

Dataset	Size	S.Len (M/A/M)	T.Len (M/A/M)	I.Num (M/A/M)
MMSS				
train	$62,000$	11/21.68/63	2/7.72/25	1/1/1
dev	$2,000$	11/24.35/47	3/7.68/17	1/1/1
test	$2,000$	11/22.97/51	3/7.67/24	1/1/1
average	-	23.00	7.69	1
MM-Sum-En				
train	$303,828$	7/461.82/$39,282$	1/22.12/172	0/2.35/118
dev	$11,437$	55/440.59/$1,686$	8/21.15/41	0/2.24/30
test	$11,460$	61/438.11/$1,667$	7/21.23/42	0/2.09/26
average	-	446.84	21.50	2.23

Table 1: The statistics of MMSS and MM-Sum-En datasets. "S.Len" and "T.Len" refer to the number of words in the source text and the target summary. "I.Num" denotes the number of images corresponding to each text. "M/A/M" means Minimum/Average/Maximum.

where y_i is the i_{th} generated token on the decoder side. For the text-vision fusion process above, the training loss is the commonly used cross-entropy loss function $\mathcal{L}_{ce}$.

4 Experiments

4.1 Dataset

We evaluate our method on the MultiModal Sentence summarization (MMSS) (Li et al., 2018a) and Multilingual Multimodal abstractive Summarization for English (MM-Sum-En) dataset on mid-high-resource scenario (Liang et al., 2022). The MMSS dataset contains 62,000 samples in the training set, $2,000$ in the validation set, and $2,000$ in the test set, and each sample is a triplet of $\langle sentence, image, summary \rangle$. The MM-Sum dataset for English contains $326,725$ samples and $867,817$ images in total which crawled from the BBC News, where each sample is constructed of a news article and some images and presented as $\langle article, images, summary \rangle$. We count some basic information about the dataset, which is shown in Table 1.

4.2 Experimental Settings

For image processing, we utilize the vision encoder of the "ViT-B/32" version of CLIP (Radford et al., 2021), the image patches are 7×7 and the dimension of output visual features is 768. We apply the "Resnet-101" version of DETR (Carion et al., 2020) for object detection with $threshold = 0.95$. For textual generative pre-trained language models, we adopt BART-base (Lewis et al., 2020) as our textual encoder and decoder, where the textual dimension is also 768. We train the Named Entity

Model	ROUGE-1	ROUGE-2	ROUGE-L	BLEU	BERTScore	MoverScore
MMSS						
$Lead^{\star\top}$	33.64	13.40	31.84	-	-	-
$Compress^{\star\top}$	31.56	11.02	28.87	-	-	-
$ABS^{\star\top}$	35.95	18.21	31.89	-	-	-
$SEASS^{\star\top}$	44.86	23.03	41.92	-	-	-
$Multi\text{-}Source^{\star}$	39.67	19.11	38.03	-	-	-
$Doubly\text{-}Attention^{\star}$	41.11	21.75	39.92	-	-	-
$MAtt^{\star}$	47.28	24.85	44.48	-	-	-
$MSE^{\star}$	45.63	23.68	42.97	-	-	-
$CFSum^{\star}$	47.86	25.64	44.64	48.83	86.98	32.36
$VG\text{-}BART$	52.02	29.67	49.45	57.94	91.86	47.36
$Ours$ $(VE\text{-}ELIN)$	**54.20**	**31.24**	**51.47**	**60.16**	**92.22**	**49.15**
MM-Sum-En						
$mT5^{\wedge\top}$	36.99	15.18	29.64	-	-	-
$VG\text{-}mT5^{\wedge}$	37.17	14.88	29.41	-	-	-
$SOV\text{-}MAS^{\wedge}$	37.26	15.02	29.61	-	-	-
$VG\text{-}BART$	37.39	15.99	30.35	40.81	90.11	27.37
$Ours$ $(VE\text{-}ELIN)$	**39.97**	**18.09**	**32.47**	**45.44**	**90.61**	**30.85**

Table 2: Experimental results on test set of multimodal sentence summarization (MMSS) dataset and test set of Multilingual Multimodal abstractive Summarization for English (MM-Sum-En) dataset. "$\star$" marks the experimental results reported by Xiao et al. (2023) and "$\wedge$" indicates that they were reported by Liang et al. (2022). "$\top$" denotes this method only leverages text modality data.

Recognition (NER) model proposed by Yan et al. (2021) as a tool for extracting text entities. During training, for MMSS, we set the dropout to 0.1, the batch size is 120, the maximum training epochs is 50, and the beam size is 5. The learning rate is $2e$-5 and the loss function is cross entropy. We leverage AdamW (Loshchilov and Hutter, 2018) as optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.999$ and a weight decay of $1e$-2. Additionally, we apply a scheduler to decay the learning rate to 95% of the current one after every 10 epochs. The maximum input length is 64 and the maximum output length is 32. For the MM-Sum-En dataset, the parameters are the same as in MMSS except that the maximum input length is 1024, the maximum output length is 256, the batch size is 10, and the maximum training epochs is 20. We save our best model checkpoint according to the best ROUGE-2 score on the validation set. All models are trained and tested on a single NVIDIA 3090Ti GPU.

4.3 Compared Methods

Our base model is VG-BART (Yu et al., 2021), which utilizes PLMs as the backbone and injects visual features into the encoder layer through dot production.

We also compare our method with other works using the same two datasets. For MMS dataset: 1) **Lead**: The initial eight words are employed as the summary. 2) **Compress** (Clarke and Lapata, 2008): A methodology centered on sentence compression, utilizing syntactic structure as a basis. 3) **ABS** (Rush et al., 2015): An attentive CNN encoder in conjunction with a neural network language model decoder to proficiently summarize sentences. 4) **SEASS** (Zhou et al., 2017): A summarization framework distinguished by its incorporation of textual selective encoding. 5) **Multi-Source** (Libovický and Helcl, 2017): This method integrates multiple source modalities utilizing hierarchical attention mechanisms, addressing challenges in multimodal machine translation. 6) **Doubly-Attention** (Calixto et al., 2017): This approach leverages two distinct attention mechanisms to incorporate visual features, narrowing the gap between image and translation. 7) **MAtt** (Li et al., 2018b): This approach proposes modality attention and image-filtering techniques tailored for multimodal summarization. 8) **MSE** (Li et al., 2020a): This approach advocates for the application of visual selective gates in multimodal summarization. 9) **CFSum** (Xiao et al., 2023): This approach proposes a contribution network that selects more important parts of images for multimodal summarization, which is a strong baseline.

For MM-Sum-En dataset: 1) **mT5** (Xue et al., 2020): This approach is a multilingual language model pre-trained on a large dataset of 101 languages that is a text-only baseline. 2) **VG-mT5** (Liang et al., 2022): This approach implements the vision-guided multi-head attention fusion method to inject visual features into the mT5 model. 3) **SOV-MAS** (Liang et al., 2022): This approach applies two summary-oriented visual modeling tasks to enhance the MMS model based on the pre-trained language models (*e.g.*, BART).

For all the above models trained on MM-Sum-En, we follow the same monolingual experimental settings in the mid-high-resource scenario, as employed by Liang et al. (2022).

4.4 Main Results

Following Xiao et al. (2023) and Liang et al. (2022), we report our experiment results with 6 automatic metrics: ROUGE-1, ROUGE-2, ROUGE-L (Lin, 2005), BLEU (Papineni et al., 2002), MOVER (Zhao et al., 2019) and BERTScore (Zhang et al., 2019).

Overall, compared with previous works on MMSS as shown in Table 2, our proposed method demonstrates significant improvements across all 6 reported evaluation metrics. Compared with the strong baseline CFSum (Xiao et al., 2023), our method achieves 6.64 higher points on ROUGE-1, demonstrating the effectiveness of our proposed method. Comparing VG-BART with those that design gate-based pre-filters or other networks based on the vision-language pre-trained encoder (*e.g.*, MSE (Li et al., 2020b) and CFSum (Xiao et al., 2023)), we find that our base model, which straightforwardly employs a PLM and integrates visual features, proves to be more effective in enhancing model performance. Furthermore, VE-ELIN outperforms the base model VG-BART, showing that the image processing and visual enhancement we use in the model and the added entity-level features complement each other and significantly improve the quality of the output summarization. The experimental effects of each module are specified in the ablation study 5.1. In the MM-Sum-En dataset, we observe the same results as in MMSS dataset, the performance of our proposed method is improved compared to others.

As shown in Table 1, the average length of input sentences in MMSS is 23, and the average number of input images is 1. In contrast, the length and image number of MM-Sum-En are 446.84 and 2.23. Also, MMSS is from the headlines of article pairs from Gigaword (Graff and Cieri, 2003; Napoles et al., 2012), and MM-Sum-En is sourced from BBC website [1]. This indicates that there is a huge difference between the two MMS datasets. Our method still generates high-quality summaries, further demonstrating the robustness and effectiveness of our proposed VE-ELIN.

Model	R-1	R-2	R-L
MMSS			
Ours(VE-ELIN)	**54.20**	**31.24**	**51.47**
- w/o $\mathcal{M}_{VE}$&$\mathcal{M}_{EI}$&V_f	52.02	29.67	49.45
- w/o $\mathcal{M}_{VE}$&$\mathcal{M}_{EI}$	53.60	31.10	50.80
- w/o $\mathcal{M}_{VE}$	53.42	31.03	51.02
- w/o $\mathcal{M}_{EI}$	53.30	30.97	50.85
MM-Sum-En			
Ours(VE-ELIN)	**39.97**	**18.09**	**32.47**
- w/o $\mathcal{M}_{VE}$&$\mathcal{M}_{EI}$&V_f	37.39	15.99	30.35
- w/o $\mathcal{M}_{VE}$&$\mathcal{M}_{EI}$	39.30	17.60	31.90
- w/o $\mathcal{M}_{VE}$	39.74	17.96	32.28
- w/o $\mathcal{M}_{EI}$	39.51	17.84	32.04

Table 3: Ablation study on two datasets, the top row of each model shows the experimental results from the MMSS dataset and the bottom row shows the results from the MM-Sum dataset. R-1/2/L denotes ROUGE-1/2/L, "$\mathcal{M}_{VE}$" denotes visual enhancement module, "$\mathcal{M}_{EI}$" denotes entity interaction module, and "V_f" denotes visual features.

5 Analysis

5.1 Ablation Study

We conduct ablation studies on both MMSS dataset and MM-Sum-En dataset to prove the effectiveness of the different components of our model. The results are shown in Table 3. We have the following conclusions:

The absence of visual features means that it is a text-only model based on pre-trained language models (PLMs) like BART. It shows a decrease in performance across all ROUGE metrics, demonstrating the incorporation of visual information within the MMS model yields noticeable enhancements in performance.

Without the visual enhancement module and entity interaction module, we find a performance

[1] https://www.bbc.com/

Dataset	Source	Target			VG-BART			Ours (VE-ELIN)		
	E.Num	E.Num	E.Score	S.Score	E.Num	E.Score	S.Score	E.Num	E.Score	S.Score
MMSS										
dev	$3,013$	$1,422$	100	100	616	48.80	91.53	703	**61.87**	**93.74**
test	$3,117$	$1,429$	100	100	620	58.47	93.35	641	**59.60**	**93.47**
average	$3,065$	$1,425.5$	100	100	618	53.64	92.44	672	**60.74**	**93.61**
MM-Sum-En										
dev	$72,412$	$19,300$	100	100	$6,461$	37.96	90.27	$7,293$	**43.28**	**91.31**
test	$72,403$	$19,200$	100	100	$6,310$	37.02	90.14	$7,272$	**43.01**	**91.20**
average	$72,407.5$	$19,250$	100	100	$6,385.5$	37.49	90.21	$7,282.5$	**43.15**	**91.26**

Table 4: The Entity evaluation metrics in the output summarization. "Source" refers to the input text of the datasets, and "Target" refers to the reference summary. "E.Num" denotes the number of entities in the text, "E.Score" refers to the EntityScore, which is the proposed evaluation metric, and the "S.Score" means SimilarScore metric, which is obtained by doing similarity calculations between the entities in the summaries generated by Target/VG-BART/Ours and the entities in the "Target" respectively.

degradation of about 1%, this verifies the effectiveness of our proposed modules.

As for the model without the visual enhancement module compared with the previous methods, we find an improvement in the metrics, which shows that the image features filter does help to improve the quality of the output summaries. The results show that the visual enhancement module further improves the model performance, indicating that the objects in the images are beneficial to the visual modality information.

The model without entity interaction module makes relative contributions to the MMS model. We can see a certain growth of three ROUGE metrics compared with others in Section 4.4, showing that focusing on the object visual features of the image is effective. The results indicate that our entity interaction module improves the quality of the output summaries and has a large improvement on the model performance.

5.2 Entity Consistency

As shown in Table 4, we formulate some new metrics to assess the quality of output summarization. Specifically, we utilize the NER model trained with BART with an accuracy of 93.8% to count the number of entities in the output summarization generated by the proposed method and the baseline, which is represented in Table 4 by "E.Num". In the process of counting, if an entity in the generated summary is also among the entities in the corresponding target summary, the entity is recorded as a valid entity. Then, the ratio of the number of valid entities to the number of entities in the target summary is calculated and named EntityScore, which is expressed as "E.Score" in Table 4:

$$\text{EntityScore} = \frac{N_{generated}}{N_{target}} \tag{25}$$

where $N_{generated}$ and N_{target} is the entity numbers in generated summary and target summary. Statistical results indicate a significant improvement in the number of entities recognized by our approach. Moreover, we concatenate the entities in the model output summary into one sentence X=$\langle x_1, x_2, ..., x_k \rangle$ and the entities in the target summary into another sentence $\hat{X}$=$\langle \hat{x}_1, \hat{x}_2, ..., \hat{x}_l \rangle$. Following Zhang et al. (2019), the SimilarScore is then used to calculate the similarity of the two sentences:

$$\text{SimilarScore} = \text{BERTScore}(X, \hat{X}) \tag{26}$$

The computational results demonstrate that our proposed method indeed improves the number and quality of entities in the output summarization, thus proving the effectiveness of our model.

5.3 Case Study

We compare the summary output of VG-BART with the results of the VE-ELIN model to show that our method is able to accurately generate entities while generating complete summaries. To better characterize the consistency of our proposed metrics with the real world, the entities appearing in the original text and those in the output are bolded and marked in different colors. In order to make the overall format of the Figure 3 consistent and easy to read, we omit some parts of the original texts and the complete original inputs will be shown in Appendix A.

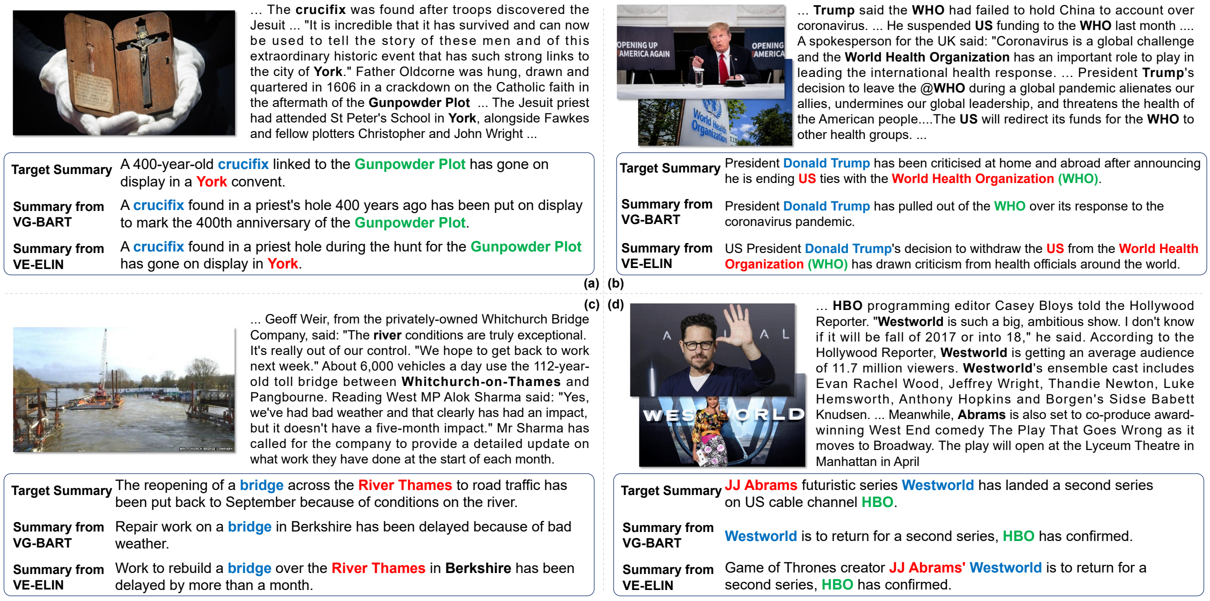

Figure 3: Case study of our proposed VE-ELIN. The top part of each column is the input texts and images, and the bottom part is the output summaries of the different methods and the corresponding target summaries.

Figure 3 shows four representative examples that intuitively demonstrate the effectiveness of our method. a) For the first example, VG-BART does not generate the corresponding location information, which in the original text is the entity "York", and it incorrectly misinterprets "400-year-old crucifix" as "400th anniversary" in the original text. The summary from VE-ELIN accurately covers all the entities in the target summary and is semantically consistent with it. This indicates that our approach can better focus on the entities that appear in the original text and assign higher weights to them when generating summaries. b) For the second example, VE-ELIN accurately generates the entity "US". In addition, the full name of WHO appears only once in the article compared to the abbreviation, but our method generates the full name of WHO with the contribution of the object area in the input images correctly. c) For the third example, the entity "River Thames" is not explicitly mentioned in the input article, however, since the Cross-modal Entity Interaction module in our approach can fuse semantic information from different modalities to form new features, VE-ELIN can combine separate and inherently related entities to generate the semantically complete entity "River Thames". d) For the last example, similarly to the second example, "Westworld" and "HBO" are successfully generated with the help of entities that appear several times in the text. In addition to this, the entity "JJ Abrams" (the person appearing in the image) is in the summary from ours, since our Visual Enhancement module can fully extract the visual features and enhance the focus of the image on the object area to better inject visual information to the whole model.

6 Conclusion

In this paper, we propose a novel framework VE-ELIN for multimodal summarization to alleviate the incomplete generation of entity information in summary. We design a cross-modal entity interaction module to better utilize the entity features in texts and images, and an object-guided visual enhancement module to enhance the focus on the objects while taking full advantage of useful image information. To further evaluate the factual consistency of entities in the output summary, we also propose two new metrics named EntityScore and SimilarScore. Experimental results on two different types of datasets demonstrate that our method is effective and outperforms previous methods under both traditional evaluation metrics and our proposed new metrics.

Limitations

Our approach is limited by the underlying performance of the generative pre-trained language model. In addition, the accuracy of the object detection model DETR and named entity recognition model also limit our performance. For images without valid object areas, our method does not utilize the visual information well. Also in the face of single modal inputs, such as text-only inputs or image-only inputs, our model fails to do the appropriate adaptation for this type of data and performs poorly. So improving the ability to adapt to different kinds of data is a future research direction.

Ethics Statement

We affirm that our work here does not deepen the biases already inherent in the models and the datasets we used are open-sourced. Thus we expect no ethical concerns associated with this research.

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A Original Inputs of Case Study

a: The cross was owned by Catholic priest Father Edward Oldcorne, who was friends with Guy Fawkes and some of the other plotters. He was arrested in 1605 after the failed attempt to blow up Parliament and kill King James I. Oldcorne was later executed, despite no evidence linking him to the assassination attempt. The crucifix was found after troops discovered the Jesuit hiding inside a priest hole at Hindlip Hall - a stately home in Worcestershire. It is now on display at the Bar Convent Living Heritage Centre. 'Historic event' Sister Patricia Harriss described the cross housed in a wooden case as "one of the most remarkable items in our possession." "Today, Bonfire Night is a celebration with fireworks but in 1605 it was an event that had a profound effect on Catholics and shocked the whole country," she said. "This crucifix, now more than 400 years old, was hidden in the priest's hole with Blessed Edward Oldcorne and would have offered him comfort in his final days. "It is incredible that it has survived and can now be used to tell the story of these men and of this extraordinary historic event that has such strong links to the city of York." Father Oldcorne was hung, drawn and quartered in 1606 in a crackdown on the Catholic faith in the aftermath of the Gunpowder Plot. He was beatified, the first step to becoming a saint, by the Vatican in 1929. The Jesuit priest had attended St Peter's School in York, alongside Fawkes and fellow plotters Christopher and John Wright. The school has a ban on the burning of guys on Bonfire Night after a former headmaster declared that it should not burn effigies of former pupils. Follow BBC Yorkshire on Facebook, Twitter and Instagram. Send your story ideas to yorkslincs.news@bbc.co.uk or send video here.

b: The EU urged him to reconsider the decision, while Germany's health minister called it a "disappointing setback for international health". The head of the US Senate's health committee, a Republican like Mr Trump, said now was not the time to leave. Mr Trump said the WHO had failed to hold China to account over coronavirus. The WHO, a UN agency that helps countries promote healthcare and tackle outbreaks of disease, has faced regular criticism from the US president over its handling of the outbreak. He suspended US funding to the WHO last month and on Friday permanently halted the payment, which last year stood at more than $\$400m$ (£324m; €360m), the largest single contribution at around 15% of its total budget. What has the response been to the US move? European Commission President Ursula von der Leyen and top EU diplomat, Josep Borrell, said in a statement: "In the face of this global threat, now is the time for enhanced co-operation and common solutions. Actions that weaken international results must be avoided. "We urge the US to reconsider its announced decision." German Health Minister Jens Spahn described the setback as "disappointing" although he accepted the WHO "needs reform". "The EU must take a leading role and engage more financially," he said. A spokesperson for the UK said: "Coronavirus is a global challenge and the World Health Organization has an important role to play in leading the international health response. We have no plans to withdraw our funding." The chair of the US Senate Health Committee, Lamar Alexander, said the move could hamper the discovery of a vaccine against Covid-19 and urged a reversal of the decision in the "strongest terms possible". "Certainly there needs to be a good, hard look at mistakes the World Health Organization might have made in connection with coronavirus, but the time to do that is after the crisis has been dealt with, not in the middle of it," he said. Ex-presidential candidate and US Senator Elizabeth Warren tweeted: "President Trump's decision to leave the @WHO during a global pandemic alienates our allies, undermines our global leadership, and threatens the health of the American people." Anders Nordstrom, a former WHO acting director general, said he was "deeply concerned" the move would increase political tension at a time when "we need to have global solidarity". South African Health Minister Zweli Mkhize called the decision "unfortunate". WHO member states agreed on 19 May to set up an independent inquiry into the global response to the pandemic. What was behind Trump's decision? Speaking at the White House, Mr Trump said: "Because they have failed to make the requested and greatly needed reforms, we will be today terminating our relationship with the World Health Organization and redirecting those funds to other worldwide and deserving urgent global public health needs." It is not clear when any US withdrawal might take place. A 1948 agreement between the US and WHO allows for one year's notice before pulling out. Mr Trump has accused China of trying to cover up the outbreak of coronavirus, which occurred in the city of Wuhan late last year. He also says that "China has total control over the World Health Organization". The president accused China of pressurising the WHO to "mislead the world" about the virus, without elaborating. "The world is now suffering as a result of the malfeasance of the Chinese government," he said. The US will redirect its funds for the WHO to other health groups. More than 102,000 people in the US have lost their lives to Covid-19 - by far the biggest death toll in the world. Opponents say Mr Trump is trying to deflect criticism of his handling of the pandemic ahead of his re-election bid this year. Meanwhile, Chinese Foreign Ministry spokesman Zhao Lijian has said that Mr Trump is trying to mislead the public, smear China and "shift the blame for [the US's] own incompetent response". What is the WHO - and who funds it?

c: Work on Whitchurch Bridge's £4.3m reconstruction which began in October and was originally due to finish in April, stopped on 20 December. Environment Agency red board warnings are in place due to strong stream flows stopping the contractors from working. Its operator said it regretted the delay to residents and businesses. Geoff Weir, from the privately-owned Whitchurch Bridge Company, said: "The river conditions are truly exceptional. It's really out of our control. "We hope to get back to work next week." About 6,000 vehicles a day use the 112-year-old toll bridge between Whitchurch-on-Thames and Pangbourne. Reading West MP Alok Sharma said: "Yes, we've had bad weather and that clearly has had an impact, but it doesn't have a five-month impact." Mr Sharma has called for the company to provide a detailed update on what work they have done at the start of each month.

d: Another 10 episodes of the big budget drama will air in 2017 or 2018, HBO programming editor Casey Bloys told the Hollywood Reporter. "Westworld is such a big, ambitious show. I don't know if it will be fall of 2017 or into 18," he said. According to the Hollywood Reporter, Westworld is getting an average audience of 11.7 million viewers. Westworld's ensemble cast includes Evan Rachel Wood, Jeffrey Wright, Thandie Newton, Luke Hemsworth, Anthony Hopkins and Borgen's Sidse Babett Knudsen. The first series is being broadcast on Sky Atlantic in the UK on Tuesday evenings. Co-creators Jonathan Nolan and Lisa Joy said in a statement: "During the lengthy journey to the screen, our incredibly talented actors, staff and crew became a family, and we look forward to the privilege of continuing this experience with them. "We're also thankful to all of our amazing partners at HBO, WBTV and Bad Robot for their steadfast support, imagination and ambition. We simply couldn't have made this show anywhere else." Bloys would not reveal whether the stars of the current series will return for a second season. "I don't want to speculate about cast because there's still three episodes left to air," he said. Meanwhile, Abrams is also set to co-produce award-winning West End comedy The Play That Goes Wrong as it moves to Broadway. The play will open at the Lyceum Theatre in Manhattan in April.