

Joint Multimodal Entity-Relation Extraction Based on Edge-enhanced Graph Alignment Network and Word-pair Relation Tagging

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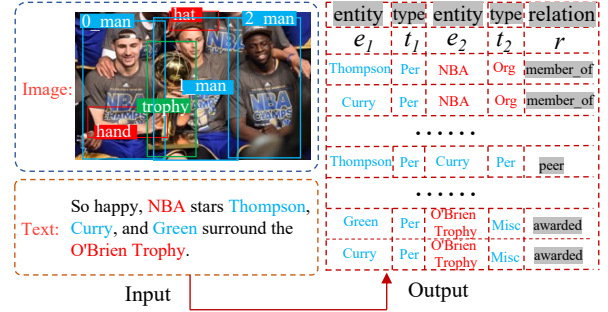
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Abstract

Multimodal named entity recognition (MNER) and multimodal relation extraction (MRE) are two fundamental subtasks in the multimodal knowledge graph construction task. However, the existing methods usually handle two tasks independently, which ignores the bidirectional interaction between them. This paper is the first to propose jointly performing MNER and MRE as a joint multimodal entity-relation extraction task (JMERE). Besides, the current MNER and MRE models only consider aligning the visual objects with textual entities in visual and textual graphs but ignore the entity-entity relationships and object-object relationships. To address the above challenges, we propose an edge-enhanced graph alignment network and a word-pair relation tagging (EEGA) for the JMERE task. Specifically, we first design a word-pair relation tagging to exploit the bidirectional interaction between MNER and MRE and avoid error propagation. Then, we propose an edge-enhanced graph alignment network to enhance the JMERE task by aligning nodes and edges in the cross-graph. Compared with previous methods, the proposed method can leverage the edge information to auxiliary alignment between objects and entities and find the correlations between entity-entity relationships and object-object relationships. Experiments are conducted to show the effectiveness of our model¹.

Introduction

Multimodal named entity recognition (MNER) and multimodal relation extraction (MRE) are two fundamental subtasks for the multimodal knowledge graph construction (Liu et al. 2019; Chen, Jia, and Xiang 2020), which aims to extend the text-based models by taking images as additional inputs. Previous works usually consider MNER and MRE as two independent tasks (Lu et al. 2018; Moon, Neves, and Carvalho 2018; Wu et al. 2020b; Yu et al. 2020; Zheng et al. 2021c; Zhang et al. 2021a), which ignore the interaction between these two tasks. Recently, jointing NER and RE as joint entity-relation extraction tasks have attracted much attention in text scenarios, which can exploit the bidirectional



Joint Multi-Modal Entity-Relation Extraction (JMERE)

Figure 1: An illustrative example of the joint multimodal entity-relation extraction (JMERE) task, where the Per, Org, and Misc are denoted as the entity types of person, organization, and miscellaneous.

interaction between tasks and improve their performance (Wei et al. 2020; Yuan et al. 2020a,b). As shown in Figure 1, if we extract the entity type of (Curry, NBA) is Per and Org, then their relation should not be peer. Otherwise, if we know the relation of entity pair (Curry, Thompson) is the peer, then their entity types should be Per and Per. Thus, the NER can facilitate RE. Meanwhile, RE is also beneficial for NER.

However, to the best of our knowledge, joining the MNER and MRE as a joint multimodal entity-relation extraction task (JMERE) has not been studied in the multimodal scenario. Compared with separate tasks, the JMERE task requires extracting different characteristic information from vision. As shown in Figure 1, for the MNER task, if the model can capture the people objects from the image, e.g., outlines of multiple people (blue boxes), it helps to identify the person entity in the text. Meanwhile, the MRE task needs to extract the object-object relationships, e.g., if we know the holding is the relationship between man_0 and trophy, we can understand the relation awarded between entities Thompson and O'Brien Trophy. Thus, we consider that the JMERE task should align entities with objects and entity-entity relationships (in text) with object-object relationships (in image). Most recent MNER and MRE studies (Zhang et al. 2021a; Zheng et al. 2021a) align the entities with objects in the visual and textual graphs constructed by the latent relationships

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¹The code and appendix are available at <https://github.com/YuanLi95/EEGA-for-JMERE>

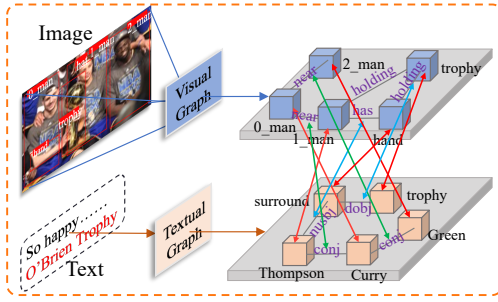


Figure 2: An example for illustrating node (red line) and edge alignment (blue and green lines) in the cross-graph.

of objects and words, as shown by the red lines in Figure 2. However, this method only considers node alignment in the cross-graph but ignores edge alignment. As shown in the blue and green lines in Figure 2, the edge information in the cross-graph can auxiliary align the nodes and contain clues about the relations between textual entities.

In addition, the pipeline framework method is an intuitive way to solve the JMERE task. It extracts the entities using MNER method and then classifies their relations by MRE method. However, the pipeline framework only benefits MRE through the results of MNER and suffers from error propagation (Ju et al. 2021). As shown in Figure 1, if the MNER extracts the entity type of (**Curry**, **NBA Stars**) is *Per* and *Misc*, the result should be incorrect. Inspired by the grid tagging scheme in the aspect-based sentiment triplet extraction task (Wu et al. 2020a), we first adopt a word-pair (w_i, w_j) classification scheme for the JMERE task, namely the word-pair relation tagging. This scheme simultaneously trains MNER and MRE tasks to exploit the interaction between them and avoid the error propagation caused by the pipeline framework. As shown in Figure 3, the word-pair relation tagging of word pairs (**Curry**, **Curry**) and (**Thompson**, **Curry**) is *Per* and *Peer*, which denotes **Curry** belongs to a person and the *peer* denotes this the relation between **Curry** and **Thompson**.

To address the above challenges, we propose an edge-enhanced graph alignment network (EEGA) and word-pair relation tagging to enhance JMERE by simultaneously aligning objects with entities (e.g., **0 man** with **Curry** and **trophy** with **trophy**) and object-object relationships with entity-entity relationships (e.g., *near* with *conj* and *holding* with *dobj*) in the cross-graph. The overall framework of EEGA is shown in Figure 4. Specifically, we use a graph encoder layer to construct the textual and visual graphs from the input text-image using pre-trained models. Then, we propose an edge-enhanced graph alignment module with Wasserstein distance to align the nodes and edges in the cross-graph. Meanwhile, the module can leverage the edge information to auxiliary alignment between objects and entities and find the correlations between entity-entity relationships and object-object relationships. Finally, we design a multi-channel layer by mining word-word relationships from different perspectives to obtain the final word pair representations.

Our main contributions can be summarized as follows:

- We are the first to propose the joint multimodal entity relation extraction (JMERE) task to handle the multimodal

	So	happy	NBA	stars	Thompson	Curry	O'Brien	Trophy
So	N	N	N	N	N	N	...	N	N
happy	N	N	N	N	N	N	...	N	N
NBA	N	N	T ₃	N	R ₁	N	R ₁	...	N
stars	N	N	N	N	N	N	...	N	N
Thompson	N	N	N	N	N	N	...	N	N
Curry	N	N	N	N	N	N	...	N	N
.....	N	N	N	N	N	N	...	N	N
O'Brien	N	N	N	N	N	N	...	N	N
Trophy	N	N	N	N	N	N	...	N	N
	:	:	:	:	:	:	...	:	:
	N	N	N	N	R ₃	N	R ₃	...	T ₁ T ₁
	N	N	N	N	R ₃	N	R ₃	...	N T ₁

T₁: Misc

T₂: Per

T₃: Org

R₁: Member of

R₂: Peer

R₃: Awarded

Figure 3: A word-pair relation tagging example for the JMERE task.

NER and RE tasks. Meanwhile, we design a word-pair relation tagging for JMERE. This scheme can exploit the bidirectional interaction between MNER and MRE and avoid the error propagation caused by the pipeline framework.

- We propose an edge-enhanced graph alignment network (EEGA) to enhance the JMERE task by aligning nodes and edges simultaneously in the cross-graph. Compared with previous methods, the EEGA can leverage the edge information to auxiliary alignment between objects and entities and find the correlations between entity-entity relationships and object-object relationships.
- We conduct extensive experiments on the collected JMERE dataset, and the experimental results demonstrate the effectiveness of our proposed model.

Related works

The crucial components of the knowledge graphs construction task (Chen, Jia, and Xiang 2020; Chen et al. 2022b,a), named entity recognition (NER) and relation extraction (RE), have attracted much attention from researchers (Vashishth, Joshi, and Suman 2018; Wen et al. 2020; Li et al. 2020; Ren et al. 2020; Nasar, Jaffry, and Malik 2021; Zhao et al. 2021). Previous researches have mainly focused on a single modality. With the increasing popularity of multimodal data on social platforms, some studies have begun to focus on multimodal NER (MNER) and multimodal RE (MRE), which aim to consider the image as a supplement to text and better recognize the entities and their relations. According to the object of image-text alignment, the current methods of MNER and MRE can be divided into image alignment methods, object alignment methods, and node alignment methods.

Image Alignment Methods

Previous studies usually used RNN (Recurrent Neural Networks) to encode text and CNN (Convolution Neural Network) to encode image as a vector. Then, designing an implicit interaction module to model the information between

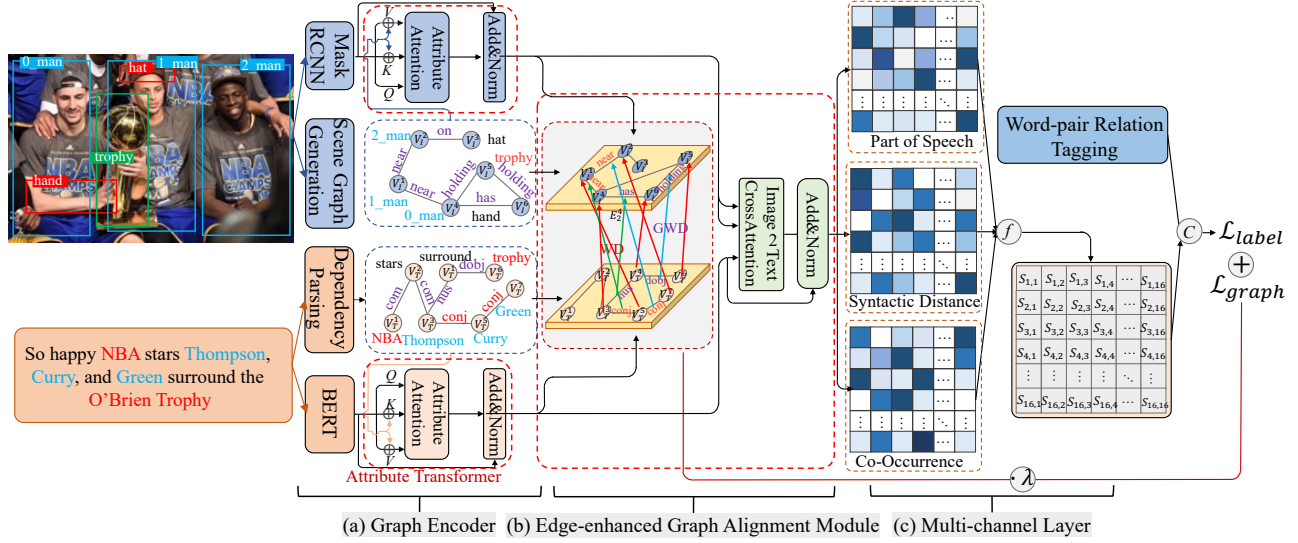


Figure 4: The overall framework of EEGA for JMERE, where com and nus denote the syntactic dependency relationships compound and nsubj.

modalities for the MNER task (Zhang et al. 2018; Lu et al. 2018; Moon, Neves, and Carvalho 2018). For example, Zhang et al. (2018) constructed an MNER dataset and proposed a baseline model based on a bi-directional long-term memory network using an attention mechanism to align the image representation with text. However, encoding image as a vector cannot benefit extract different type entities, e.g., **Curry** (*Per*) and **O’Brien Trophy** (*Misc*).

Object Alignment Methods

To address limitation of image alignment methods, the previous models extracted different visual objects using Mask-RNN or Fast-RNN (He et al. 2017) and aligned visual objects with the text representation (Wu et al. 2020b; Yu et al. 2020; Zheng et al. 2021c; Zhang et al. 2021a; Xu et al. 2022). Wu et al. (2020b) proposed an interactive attention structure to align text with visual objects. In addition, Zheng et al. (2021c) designed a gated bilinear attention network (Kim, Jun, and Zhang 2018) with an adversarial strategy to better extract the fine-grained objects from the image. However, the object alignment method does not consider the relations of entity-entity and object-object, and the model will ineffectively match overlapping visual objects with textual entities. For example, the **trophy** of text may align with the **1_man**, since the **1_man** contains the region of **trophy**.

Node Alignment Methods

To address the above limitation, the most current researches align the entities with objects in the visual and textual graphs constructed by the latent relationships of objects and words (Zhang et al. 2021a,b; Zheng et al. 2021a). Zhang et al. (2021a) proposed a graph-based multimodal fusion model based on the syntactic dependency text graph and full connection visual graph to exploit the fine-grained semantic alignment different modalities. In the MRE task (Zheng et al. 2021b), Zheng et al. (2021a) designed a graph alignment

module to align nodes in textual graph and visual graphs. However, the node alignment methods only consider the nodes in the cross-graph and ignore the edge information. The edge information in the cross-graph can effectively improve the matching precision of nodes and contain some clues about the classifying relation between entities.

Task Definition and Word-pair Relation Tagging

Task Definition

The joint multimodal entity-relation extraction task is defined: given an input text $w = \{w_1, w_2, \dots, w_n\}$ with a corresponding image I , the model is required to extract a set of quintuples $y = \{(e_1, t_1, e_2, t_2, r)_c\}_{c=1}^C$, where $(e_1, t_1, e_2, t_2, r)_c$ represents the c -th quintuple, consisting of two entities e_1 and e_2 with the corresponding entity types t_1 and t_2 , where $e_1 \neq e_2$. Furthermore, r represents the relation between the entities e_1 and e_2 . Figure 1 gives an example to better understand the JMERE task, which aims to extract all quintuples, e.g., (**Thompson**, *Per*, **NBA**, *Org*, *Member_of*), where *Per* and *Org* indicate the entity types of **Thompson** and **NBA**, and *Member_of* denotes their relation type.

Word-pair Relation Tagging

Inspired by the grid tagging scheme in aspect-based sentiment triplet extraction (Wu et al. 2020a), we design a word-pair relation tagging to extract all elements of JMERE in one step. By word-pair relation tagging, the JMERE task is converted into extracting the relations Y between each word-pair (w_i, w_j) and avoid the error propagation caused by the pipeline framework. These relations can be explained below, and we also give an example in Figure 3 to better understand the word-pair relation tagging.

- N indicates that the word-pair does not have any relation.

- T indicates that the word-pair belongs to an entity type, which is contained 4 defined types in the previous work (Zheng et al. 2021c)
- R indicates that the word-pair belongs to defined relation (Zheng et al. 2021a) and each word is an entity.

Edge-enhanced Graph Alignment Network

Figure 4 shows the overall architecture of the proposed model, consisting of three parts: a graph encoder, an edge-enhanced graph alignment module, and a multi-linguistic channel layer. The graph encoder layer uses the pre-trained models to construct the textual and visual graphs from the input. To enhance the ability to capture edge information, we do not directly send textual and visual representations to the next module but an attribute transformer. Then, to match the objects with entities more precisely and capture the entity-entity relation clues from the visual graph, we use a cross-graph optimal transport method (Chen et al. 2020) with Wasserstein distance and Gromov-Wasserstein distance to simultaneously align the nodes and edges in the cross-graph. Finally, we propose a multi-channel layer that uses a weighted graph convolution network (W-GCN) to mine the latent relationships for word pairs from multi-perspectives. A detailed description of each component is provided below. The code of the manuscript will publish in the final version.

Graph Encoder

Textual Graph. Formally, we first use the dependency parse toolkit² to construct the textual graph. As shown in Figure 4 (a), after parsing, the given sentence is converted into a textual graph $G_T = \{V_T, E_T\}$, where $V_T \in \mathbb{R}^n$ and $E_T \in \mathbb{R}^{n \times n}$ denote syntactic dependency nodes and edges, respectively, and G_T is an un-directed self-loop graph. Meanwhile, we use $A_T \in \mathbb{R}^{n \times n}$ to denote the adjacent mask matrix for textual graph, where $A_T^{i,j} \in \{0, 1\}$ indicate whether there is an edge between w_i and w_j or not. Furthermore, the nodes V_T are fed into BERT to obtain $X_T \in \mathbb{R}^{n \times d_T}$. Meanwhile, an edge transition matrix is used to map the edge type $E_T^{i,j}$ into a trainable vector and obtained edge trainable matrix $Z_T \in \mathbb{R}^{n \times n \times d_{zT}}$,

$$X_T = \text{BERT}(w) \quad (1)$$

where BERT denotes the BERT as the text encoder and d_T is the dimension of the BERT output.

Visual Graph. In previous multimodal tasks, the objects were considered the semantic information of images. As shown in Figure 4 (a), we convert the image into a visual graph $G_I = \{V_I, E_I\}$ by using the scene graph generation model (Tang et al. 2020) (the Mask-RCNN used as the backbone). Furthermore, we only consider the top k salient objects with the highest object classification scores as the valid visual objects and exploit the adequate visual information while ignoring the irrelevant ones. Thus, the final node represents $V_I \in \mathbb{R}^k$ salient objects detected by Mask-RCNN and $E_I \in \mathbb{R}^{k \times k}$ denotes the visual relationship set, such as position relationships (e.g., *near* and *in front of*) and affiliation

relationships (e.g., *holding* and *wearing*). We use $A_I \in \mathbb{R}^{k \times k}$ to denote the adjacent matrix of the visual graph. Thus, the final node vectors in visual graph $X_I \in \mathbb{R}^{k \times d_I}$ are defined as,

$$X_I = \text{Mask-RCNN}(I) \quad (2)$$

where d_I is the hidden dimension of Mask-RCNN and the final edge vectors $Z_I \in \mathbb{R}^{k \times k \times d_{zI}}$ are obtained in the same way as the textual graph.

Attribute Transformer. we propose the attribute attention ($At\text{-}Att$) by incorporating the edge types into keys and values in the self-attention of the transformer as the attribute transformer, which can update the node state in the inter-model while effectively incorporating relationship edges in the cross-graph (e.g., *nsubj* and *acom* in the textual graph, and *holding* and *wearing* in the visual graph).

Since the visual and textual graphs are two semantic units containing information in different modalities, we model them using similar operations but with different parameters. Thus, the hidden representation of the i -th token $\tilde{H}_T^i \in \mathbb{R}^{n \times d_T}$ in text modalities is defined as,

$$\begin{aligned} \tilde{H}_T^i &= At\text{-}Att(X_T^i, Z_T^i, A_T^i) \\ &= \text{Softmax}\left(A_T^i \cdot \frac{Q_T^i(K_T^i)^\top}{\sqrt{d_T}}\right)V_T^i \end{aligned} \quad (3)$$

where $A_T^i \in \mathbb{R}^{1 \times n}$ is the adjacency mask set of the i -th node, $Q_T^i \in \mathbb{R}^{1 \times d_T}$, $K_T^i \in \mathbb{R}^{n \times d_T}$, and $V_T^i \in \mathbb{R}^{n \times d_T}$ are matrices that package the queries, keys, and values for the i -th word in text correspondingly, which are defined as,

$$\begin{aligned} Q_T^i &= W_Q X_T^i \\ K_T^i &= W_K X_T + W_z Z_T^i \\ V_T^i &= W_V X_T + W_r Z_T^i \end{aligned} \quad (4)$$

The other operations of the attribute transformer are consistent with the vanilla transformer: \tilde{H}_T is added to X_T using a feed-forward network (FFN) and layer normalization (Layer-Norm) to obtain the text representation $H_T \in \mathbb{R}^{n \times d_T}$.

We use similar operations to obtain the visual representation. In particular, we use a variable-dimensional FFN to match the dimension of object H_I and token H_T . Thus, the image representation of graph encoder can be denoted as $H_I \in \mathbb{R}^{k \times d_T}$.

Edge-enhanced Graph Alignment Module

Given the textual graph $G_T = \{H_T, Z_T\}$, and the visual graph $G_I = \{H_I, Z_I\}$. We aim to align the nodes and edges of the cross-graphs simultaneously and to transfer the matched semantic information from objects into entities. Formally, an optimal transport method (Chen et al. 2020) is first used to match the nodes and edges in the cross-graph. Furthermore, we use image2text attention to transfer matched semantic information from the visual object to text modality and obtain the refined textual representation.

Edge-enhanced Graph Optimal Transport. To explicitly encourage simultaneously aligning the nodes and edges in the cross-graph, we apply the optimal transport method initially

²<https://spacy.io/models>.

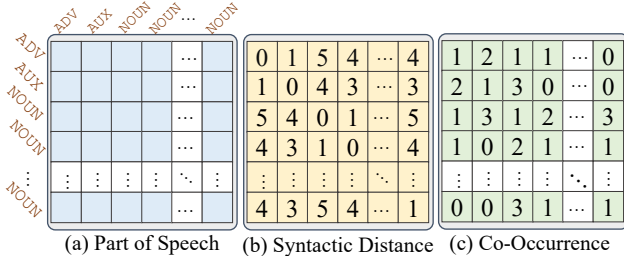


Figure 5: The multi-channel matrices of the given sentence.

proposed in transfer learning. As illustrated in Figure 4 (b), unlike the original optimal transport method considering text and image as full-connected graphs, we only consider the nodes and edges of having adjacency relationships in the cross-graph. Particularly, two types of distance are adopted for cross-graph matching: (1) Wasserstein Distance (WD) (Peyré, Cuturi et al. 2019) for node matching (the red lines); (2) Gromov-Wasserstein Distance (GWD) (Peyré, Cuturi, and Solomon 2016) for edge matching (the blue and green lines). Formally, the $D_{wd}(H_I, H_T)$ is measured the optimal transport distance to match the nodes H_I to H_T , which is defined as:

$$D_{wd}(H_I, H_T) = \min \sum_{i=1}^k \sum_{j=1}^n T_{i,j} \cdot c(H_I^i, H_T^j) \quad (5)$$

where $c(H_I^i, H_T^j)$ denotes the cosine distance between X_I^i to X_T^j , which is defined as $c(H_I^i, H_T^j) = 1 - \frac{(H_I^i)^T H_T^j}{\|H_I^i\| \|H_T^j\|}$. The matrix T is the transport information flow, where $T_{i,j}$ represents the amount of cost shifted from node X_I^i to X_T^j .

Then, we use the Gromov-Wasserstein distance (Peyré, Cuturi, and Solomon 2016) to measure the similarity scores D_{gwd} of the edge in the cross-graph by calculating distances between node-pairs, which is defined as,

$$D_{gwd}(H_I, H_T, H_I', H_T') = \min \sum_{i=1}^k \sum_{j=1}^n \hat{T}_{i,j} \hat{T}_{i',j'} \cdot L(H_I^i, H_I'^{i'}, H_T^j, H_T'^{j'}) \quad (6)$$

where $H_T^{j'}$ and $H_I'^{i'}$ are adjacent nodes sets in the textual and visual graphs of H_T^j and H_I^i respectively, and $L(\cdot)$ is considered as the distance cost of the cross-graph edges $(H_I^i, H_I'^{i'})$ to $(H_T^j, H_T'^{j'})$, i.e. $L(H_I^i, H_I'^{i'}, H_T^j, H_T'^{j'}) = \|c(H_I^i, H_I'^{i'}) - c(H_T^j, H_T'^{j'})\|$. The learned matrix \hat{T} now denotes a transport plan that aids in aligning edges in the cross-graph.

We use a unified solver and use the Sinkhorn algorithm (Cuturi 2013) with an entropic-regularizer (Benamou et al. 2015) to iteratively optimize costs D_{wd} and D_{gwd} . Thus, the object loss function of optimizing the cross-graph is,

$$\mathcal{L}_{graph} = \alpha \cdot D_{wd}(H_I, H_T) + (1 - \alpha) \cdot D_{gwd}(H_I, H_I', H_T, H_T') \quad (7)$$

where α is the hyper-parameter for balancing the importance of costs. Then, we use image2text attention to effectively transform the visual semantic information into the textual representation, which is denoted as,

$$\tilde{O} = ATT_{cross}(H_T, H_I, H_I) \quad (8)$$

where ATT_{cross} denotes the cross-modal multihead attention (Ju et al. 2020). Then, the \tilde{O} is added with H_T and sends a layer normalization to obtain the final contextual representation O .

Multi-channel Layer

In this subsection, we aim to mine the different dependency features between w_i and w_j to help detect relations between them. As shown in Figures 5: (a) we consider that part of speech (Pos) can provide lexical information for word pairs. For example, the Pos of most entities belong to the NOUN and PEROPN, e.g., **NBA**, **Curry**, and **Thompson**; (b) encoding the syntactic distance (Sd) between word-pair can improve the ability of the model to capture long-range syntactic information; (c) the word co-occurrences matrix (Co) can provide corpus-level information between word pairs. For example, **Curry** and **NBA** appear some times in the corpus. The details about constructing each feature matrix are added in Appendix-A.

After data preprocessing, three feature matrices are obtained, $M^l \in \mathbb{R}^{n \times n}$, $l \in \{Pos, Sd, Co\}$. We propose a W-GCN module to model each matrix, obtaining each channel representation. Each matrix M^l firstly sends an embedding layer yielding a trainable representation $R^l \in \mathbb{R}^{n \times n \times d_l}$ and d_l is the dimension of representation. The calculation W-GCN process of i -th word in l -th matrix is shown as,

$$S_i^l = \text{W-GCN}_l(R_i^l, O) = \text{Softmax}(\text{ReLU}(W_l^{r1} R_i^{r1} + b_l)) \cdot (W_l^{r2}(O)) \quad (9)$$

where $R_i^l \in \mathbb{R}^{n \times d_l}$ is the i -th word in l -th linguistic matrix and $W_l^{r1} \in \mathbb{R}^{1 \times d_l}$ and $W_l^{r2} \in \mathbb{R}^{d_T \times d_T}$ are shared weights used to perform a linear layer to learn linguistic features and representational abilities. We combine the representations and send them to the MLP (MultiLayer Perception) layer for obtaining the final word representation,

$$S_i = \text{MLP}[S_i^{Pos}; S_i^{Sd}; S_i^{Co}] \quad (10)$$

where $S_i \in \mathbb{R}^{d_T}$ is the i -th word representation. Thus, the output representation of the multi-channel layer is denoted as $S = [S_1, S_2, \dots, S_n]$. Finally, we concatenate the enhanced representations of S_i and S_j to represent the word-pair (w_i, w_j) , i.e., $r_{i,j} = [S_i; S_j]$. Then, send the $r_{i,j}$ to a linear prediction layer and obtain the probability distribution,

$$p_{i,j} = \text{Softmax}(W_p r_{i,j} + b_p) \quad (11)$$

where $W_p \in \mathbb{R}^{d_y \times 2d_T}$ and $b_p \in \mathbb{R}^{d_y}$ are trainable parameters and d_y is the number of tags. Then, we used the cross-entropy error to measure the ground truth distribution \mathcal{Y} and predicted tagging distribution,

$$\mathcal{L}_{main}(\theta) = - \sum_{s=1}^S \sum_{i=1}^n \sum_{j=1}^n \mathcal{Y}_{i,j}^s \log(p_{i,j}^s \theta) \quad (12)$$

where S and θ denote the number of training samples and all trainable parameters, respectively.

Methods		JMERE			#MNER		
		#P	#R	F1	#P	#R	F1
Pipeline Methods	AdapCoAtt+MEGA	48.44	47.06	47.74	74.32	72.11	73.20
	OCSGA+MEGA	48.21	47.99	48.10	75.27	72.32	73.77
	AGBAN+MEGA	47.87	48.28	48.57	74.78	73.69	74.23
	UMGF+MEGA	49.28	50.76	50.01	75.02	76.77	75.88
Word-pair Relation Tagging Methods	AdapCoAtt*	50.22	47.67	48.91	77.32	73.28	75.25
	OCSGA*	52.11	47.41	49.64	77.13	75.03	76.07
	AGBAN*	51.07	48.89	49.95	76.57	75.82	76.19
	UMGF*	52.76	50.22	51.45	77.51	76.01	76.75
	MEGA*	55.08	51.40	53.18	77.78	76.67	77.22
	MAF*	52.56	54.73	<u>53.62</u>	76.07	77.57	76.81
	EEGA(<i>ours</i>)	58.26 †	<u>52.61</u>	55.29 †	78.27	78.91 †	78.59 †

Table 1: The experiment results on the JMERE task (%) and the #MNER denote the MNER results computed by the JMERE results. AGBAN* means using the word-pair relation tagging in the AGBAN model. The marker † refers to significant test $p - value < 0.05$. The best result is in bold and #P, #R, and F1 denote the precision, recall, and F1-score.

Methods	#P	#R	F1
EEGA(<i>All</i>)	58.26	52.61	55.29
<i>w/o edge-enhanced</i>	51.85	50.31	51.07
<i>w/o attribute transformer</i>	55.69	51.07	53.28
<i>w/o multi-channel</i>	55.48	52.13	53.75

Table 2: Results of ablation study for the JMERE task.

Join Training

The final objective is a combination of the main task and optimizing the cross-graph as follows,

$$\mathcal{L} = \mathcal{L}_{main} + \lambda \cdot \mathcal{L}_{graph} \quad (13)$$

where λ are trade off hyper-parameters to control the contribution of optimizing the cross-graph.

Experiments

Comparative experiments were conducted to evaluate and compare the performance of the EEGA method against several prior works. Furthermore, more detailed experiments (e.g., datasets, setting, and parameter sensitivity) are presented in Appendix B-D.

Comparative Results

Compared Methods. We summarize the MNER and MRE studies and combine the state-of-the-art methods as our strong JMERE baselines, as shown in Table 1. They include AdapCoAtt (Zhang et al. 2018), OCSGA (Wu et al. 2020b), AGBAN (Zhang et al. 2021a), and MAF (Xu et al. 2022) for extraction of the entity and the corresponding type, and UMGF (Zheng et al. 2021a) for relation extraction of entities. In addition, we apply the word-pair relation tagging to the above baseline models to investigate the effectiveness of the word-pair relation tagging and the proposed method, e.g., AdapCoAtt*, OCSGA*, and MEGA*.

Overall Results. Observing pipeline methods, we find that the UMGF+MEGA performs better than other pipeline methods, which shows that aligning the nodes in the cross-graph

can benefit matching the entities with objects. The word-pair relation tagging methods outperform the pipeline methods in JMERE and #MNER, such as OCSGA, AGBAN, and UMGF, showing that the word-pair relation tagging can improve performance by leveraging task relationships and reducing error propagation issues caused by the pipeline framework.

Furthermore, the EEGA surpasses all baselines. Compared with the best results of existing baselines, EEGA still achieves absolute F1-score increases of 1.67% and 1.37% on JMERE and #MNER. The experimental results strongly prove that simultaneously aligning the nodes and edges in the cross-graph can effectively improve the precision of matching the objects with entities and capture more relationships between entities. In addition, the proposed attribute transformer enhances the ability to mine relations between nodes by incorporating edge information into the key and value in the transformer. Meanwhile, the multi-channel layer can take linguistic relations between word pairs to refine the final representation and improve prediction performance.

Ablation Study. To investigate the effectiveness of different components in EEGA, edge-enhanced graph optimal transport (edge-enhanced), attribute transformer, and multi-channel layer, we conduct an ablation study for the JMERE task in Table 2. *W/o attribute transformer* means that a vanilla transformer replaces the attribute transformer. The F1-score dropped 2.01%, indicating that integrating the edge information into the key and value in the transformer can enhance the ability to capture the relations between nodes and benefit the edge alignment in the cross-graph. The performance is decreased after removing the multi-channel layer (*w/o multi-channel*), indicating the multi-channel layer can mine relationships of word pairs from different perspectives and refine the final representation.

W/o edge-enhanced means removing the edge-enhanced graph optimal transport from EEGA. The performance of the model is highly degraded after removing the edge-enhanced, showing that simultaneously aligning nodes and edges in the cross-graph can be beneficial for matching the visual objects with textual entities more precisely and finding the entity classification clues from the relationship between objects.

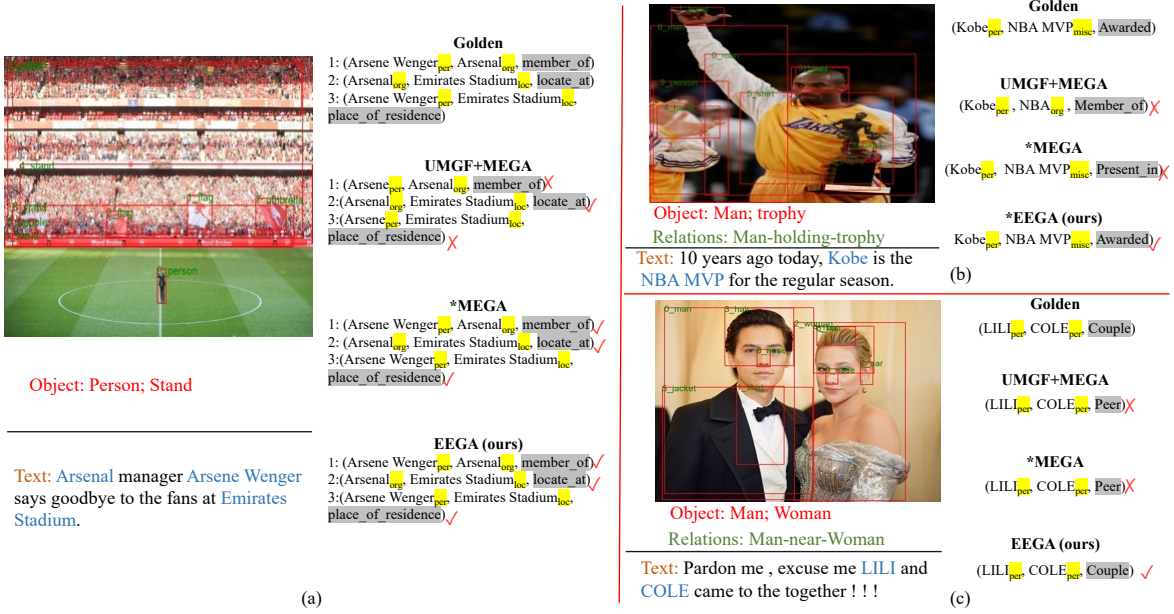


Figure 6: Three cases of the predictions by UMGF+MEGA, *MEGA, and EEGA.

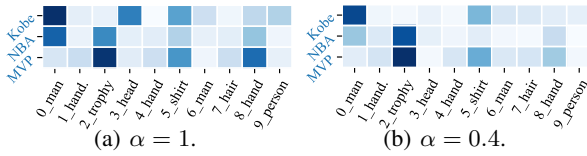


Figure 7: A comparison of Attention visualization on entity-object pair from $\alpha = 1$ (only node alignment) and $\alpha = 0.4$ (best performance setting) in Eq. (7)

Case Study

To understand the effectiveness of our proposed model, Figure 6 presents three examples with the predicted results. Meanwhile, the important objects and relations are detected from images. In example (a), only the pipeline-based model UMGF+MEGA extracts incorrectly since the pipeline model easily suffers from error propagation, i.e., the extraction entity **Arsene** by UMGF is incomplete, and the final model UMGF+MEGA extract the incorrect quintuple. In example (b), UMGF+MEGA imprecisely extracts **NBA** as an entity, and *MEGA incorrectly predicts the relationship between **Kobe** and **NBA MVP** as the *Present_in*. In example (c), the situation is similar to example (b). Since lacking effective ways to map the semantic relationship of objects *Man-near-Woman* to entities (*LILI-COLE*), the UMGF+MEGA and *MEGA incorrectly predicts relations *peer* between entities.

For these three examples, the proposed EEGA makes accurate judgments. Benefiting from the edge-enhanced graph optimal transport module, the EEGA can align the nodes and edges in the cross-graph to match the entities with objects more precisely. Meanwhile, the EEGA also effectively captures the relation clue from the visual graph to the textual graph shown in examples (b) and (c). In addition, the attribute transformer and multi-channel layer can further enhance the

ability to model the relationships of objects and word pairs.

Visualization Analysis

In this section, we visualize the example (b) of Figure 6 at $\alpha = 1$ and $\alpha = 0.4$ to test whether our edge alignment strategy helps to learn fine-grained entity-object matching. As shown in Figure 7 (a), when only node alignment means $\alpha = 1$, since the proposed model lacks the edge constraints, the attention weight is relatively scattered and affects the precision of matching entities with objects. Particularly, the model easily classifies the type of entity **NBA** as *Per*. Meanwhile, as shown in the **NBA** and **Kobe** in Figure 7 (b), benefiting from the edge alignment can find the mapping between the object-object relationships and entity-entity relationship; the EEGA effectively reduces the ambiguity and match objects with entities more precisely.

Conclusion

In this paper, we are the first to propose a joint multimodal entity relation extraction (JMERE) task to handle the multimodal NER and RE tasks. To tackle this task, we propose an edge-enhanced graph alignment network and a word-pair relation tagging. Specifically, we design a word-pair relation tagging to avoid the error propagation caused by the pipeline framework. Then, we propose an edge-enhanced graph alignment network (EEGA) to enhance the JMERE task by aligning nodes and edges simultaneously in the cross-graph. The EEGA can leverage the edge information to auxiliary alignment between objects and entities and find the correlations between entity-entity relationships and object-object relationships. The detailed evaluation demonstrates that our proposed model significantly outperforms several state-of-the-art baselines. We will extend our approach to multi-label multimodal tasks in our future work and investigate other methods (e.g., the self-supervised model) to better model JMERE.

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Appendix

Appendix A: Detail about the Multi-channel Layer

In this section, we introduce the process of constructing three feature matrices: part of speech (Pos), syntactic distance (Sd), and word co-occurrences matrix (Co).

Part of Speech (Pos). To obtain the lexical-level information between word pairs (w_i, w_j) , we use the spaCy to obtain the Pos sequence of the input sentence, as shown in Figure 8. Then, an embedding layer is used to embed the Pos sequence into trainable vectors $R^{Pos} \in \mathbb{R}^{n \times d_l}$. We add the i -th to j -th Pos vector of the corresponding element as the final lexical-level representation $R_{i,j}^{Pos} \in \mathbb{R}^{d_l}$.

Syntactic Distance (Sd). To model the syntactic-level information for word pairs, we use the syntactic relative distance $M_{i,j}^{Sd} \in \mathbb{R}^1$, which is defined as the number of hops on path from the token x_i to token x_j in a dependency tree. As shown in Figure 8, the absolute distance between **Thompson** and **Trophy** is 7, while the syntactic relative distance is 2.

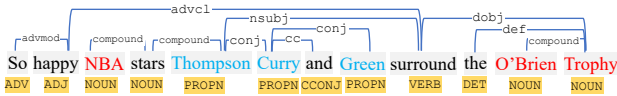


Figure 8: The dependency parse tree of the given example.

Statistics	JMERE			
	#S	Entity	Words	#AL
Train	3,617	9,006	15,981	16.31
Dev	495	1,248	3,535	16.57
Test	474	1,280	4,678	16.28

Table 3: The statistics of the JMERE dataset. Here #S and Entity respectively denote the numbers of sentence and entity. The #AL is the average length of the sentence.

Co-occurrences matrix (Co). To incorporate the corpus-level information into the word pairs, such as **Curry** and **NBA** co-appearing many times in the corpus, we use the word frequency co-occurrence matrix with the Pointwise Mutual Information (PMI) (Bouma 2009) to calculate the word-pair correlation. Thus, the correlation of PMI for the i -th token with the j -th token is denoted as $PMI_{i,j}$. To encoding $PMI_{i,j}$ as a trainable vector, we round up the $PMI_{i,j}$ and obtain the final correlation value $M_{i,j}^{Co} \in \mathbb{R}^1$. Especially for negatively correlated values, we uniformly set them as -1.

Appendix B: Dataset

To verify the effectiveness of the proposed model, we collect the joint multimodal entity-relation extraction dataset (JMERE) by the MNER (Zheng et al. 2021a) and MRE datasets (Zheng et al. 2021c). In addition, we merge samples of the same sentence but with different annotations for entities and relations. Each sample contains the original sentence, corresponding image, and sets of quintuples. If the corpus contains many unlabeled data, the model will learn some meaningless information. Thus, we eliminate the original dataset samples with no entity type or relationship between entities. Table 3 shows the static of our collated JMERE.

To evaluate the performance of different methods, we use precision, recall, and F1-score as the evaluation metrics. The extract quintuple is regarded as correct only if predicted, and ground truth spans match precisely.

Appendix C: Implementation Details

We apply the spaCy³ with *en_core_web_trf* version to parse the given sentence into a dependency tree, then built both text graph and adjacency matrix from the dependency tree. We initialize the textual representation by BERT-based-Uncased⁴ and set the dimension D_T is 768. Besides, the dimension D_I of visual object extracting by scene graph generation model (Tang et al. 2020) (the Mask-RCNN used as the backbone) is 4096. In addition, the dimension of the other features, e.g., edge features d_{zT} and d_{zI} and linguistic features d_l , are initialized 100. The iteration number of the Sinkhorn algorithm is 20, and the maximum number of token sequences and objects is 70 and 10, respectively. Adam (Kingma and Ba 2015) optimizer with a learning rate of $2e-5$ and a decay factor of 0.5. The early stopping strategy is also applied to determine the number of epochs with the patience of 5. We implement our model

³<https://github.com/explosion/spaCy>

⁴<https://huggingface.co/bert-base-uncased>

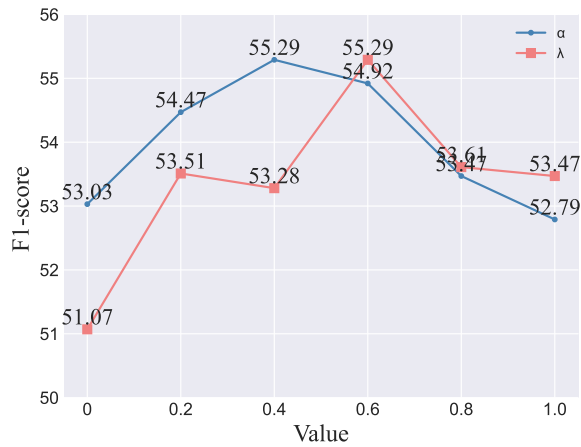


Figure 9: The effect of different parameters about balance coefficients, where α in Eq. (7) and λ in Eq. (13).

with the PyTorch framework and conduct experiments on the machine with NVIDIA RTX 3090.

Appendix D: Parameter Sensitivity

In this section, we further discuss the different settings of the parameters. We are concerned about the influence of two balance coefficients α in Eq.(7) and λ in Eq. (13). The $\lambda = 0$ means *w/o edge-enhanced*, the model cannot effectively match the objects with entities and achieves the worst performance. When $\lambda = 0.6$ the proposed EEGA achieved the best performance; After λ is over 0.6, the cross-graph alignment has interfered with the training process of the main task, resulting in slightly lower performance. In addition, the $\alpha = 0$ and $\alpha = 1$ mean only aligned nodes and edges in the cross-graph alignment and achieve a lower performance, especially when $\alpha = 1$. This shows that edge alignment can effectively improve the precision of matching entities with objects and the ability to capture latent semantic relationships between objects. When $\alpha = 0.4$, the result of EEGA is better than other settings.