LBMKGC: Large Model-Driven Balanced Multimodal Knowledge Graph Completion

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Abstract

Multi-modal Knowledge Graph Completion (MMKGC) aims to predict missing entities, relations, or attributes in knowledge graphs by collaboratively modeling the triple structure and multimodal information (e.g., text, images, videos) associated with entities. This approach facilitates the automatic discovery of previously unobserved factual knowledge. However, existing MMKGC methods encounter several critical challenges: (i) the imbalance of inter-entity information across different modalities; (ii) the heterogeneity of intra-entity multimodal information; and (iii) for a given entity, the informational contributions of different modalities are inconsistent across contexts. In this paper, we propose a novel Large model-driven Balanced Multimodal Knowledge Graph Completion framework, termed LBMKGC. Initially, LBMKGC employs the Stable Diffusion XL (a Large generative vision model) to augment the imbalanced information across modalities. Subsequently, to bridge the semantic gap between heterogeneous modalities, LBMKGC aligns the multimodal embeddings of entities semantically by using the CLIP (Contrastive Language-Image Pre-Training) model. Furthermore, LBMKGC adaptively fuses multimodal embeddings with relational guidance by distinguishing between the perceptual and conceptual attributes of triples. Finally, extensive experiments conducted against 21 state-of-the-art baselines demonstrate that LBMKGC achieves superior performance across diverse datasets and scenarios while maintaining efficiency and generalizability. Our code and data are publicly available at: https://github.com/guoynow/LBMKGC.

1 Introduction

Multimodal Knowledge Graphs (MMKGs) [14] represent an advanced semantic framework that extends traditional knowledge graphs. Unlike conventional knowledge graphs, which primarily consist of structured entity-relation-attribute triples, MMKGs integrate a variety of multimodal data associated with entities, including textual descriptions, images, audio, and videos. This comprehensive approach allows MMKGs to capture and describe complex real-world phenomena across multiple

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39th Conference on Neural Information Processing Systems (NeurIPS 2025).

dimensions. By fusing structural and multimodal information, MMKGs facilitate finer-grained reasoning in applications such as recommender systems [29], natural language processing [6], and computer vision [8]. Current mainstream MMKGC [31] methods can be categorized into two primary approaches. The first focuses on multimodal fusion mechanisms, aiming to achieve completion by systematically modeling the cross-modal correlations among structural topologies, visual representations, and textual semantics [24, 1, 35]. The second approach emphasizes negative sampling optimization algorithms, which enhance completion performance by improving the quality of negative samples through vision-text joint discrimination [2, 36, 34]. However, existing methods often overlook following critical challenges.

(1) **The imbalance of inter-entity information across different modalities.** In real-world MMKGs, modality distributions are diverse and complex. Some entities may possess rich multimodal information (e.g., images and text), while others suffer from modality scarcity (e.g., text-only entities with missing visual data). This imbalanced distribution complicates knowledge graph completion tasks, as missing modalities may lead to critical knowledge omissions, thereby compromising accuracy. Although existing MMKGC methods [38] employ frameworks like adversarial training to mitigate imbalance issues, they fail to explicitly model latent semantics in modality-missing scenarios.

(2)**The heterogeneity of intra-entity multimodal information.** Significant disparities exist in data structures and semantic comprehension across modalities. For instance, visual information is encoded as 2D pixel matrices in images, while textual modalities convey symbolic logic through word sequences. This dual gap in both data representation and semantic parsing mechanisms poses substantial challenges for cross-modal alignment. Existing MMKGC methods predominantly rely on single-modality pretrained models (e.g., VGG [21] for vision, BERT [5] for text) to independently extract visual or textual features, thereby neglecting the construction of a cohesive cross-modal representation space. Consequently, downstream tasks often struggle to fully capture the deep semantic interdependencies amongst modalities.

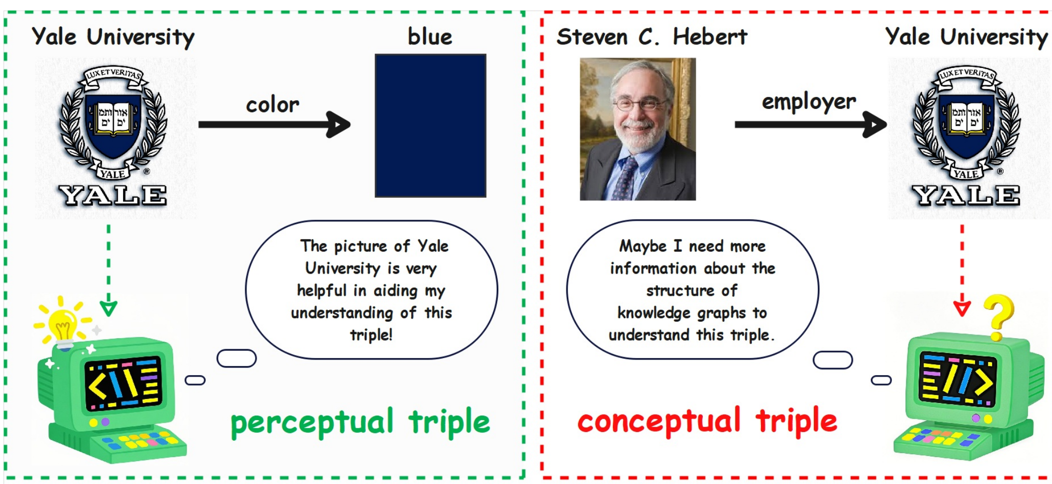


Figure 1: The salience of information carried by different modalities varies across different types of triples.

(3) **The inconsistency in the volume of information represented by various modalities for a given entity.** In knowledge graphs, triples can be categorized into perceptual (concrete) and conceptual (abstract) types. For the same entity, the salience of information carried by different modalities varies across these two types of triples. Taking the entity "Yale University" as an example, in the MKG-W dataset, the triple (Yale University, color, blue) is a perceptual triple. In this triple, the visual modality of Yale University provides discriminative evidence, and thus should be assigned higher weight during the feature fusion stage. However, the triple (Steven C. Hebert, employer, Yale University) is a conceptual triple, as it involves an employer relationship, which is a social construct and cannot be directly perceived. Therefore, Yale University in this context relies more on the structural information of the knowledge graph, and higher weight should be assigned to structural information during feature fusion. Similarly, for entities, "blue" is perceptual, where the visual modality provides discriminative evidence, while "law" is conceptual, relying more on symbolic reasoning from textual modalities. Existing MMKGC methods struggle to dynamically adjust inter-modal weights for entities based on

the perceptual or conceptual attributes of triples, leading to inefficient and imprecise utilization of multimodal information.

To address the aforementioned challenges, we propose a novel Large model-driven Balanced MMKGC framework, named LBMKGC. LBMKGC comprises three key modules called **Large Generative Visual Model-based Modality Completion** (LvMC) module, **Cross-Modality Alignment** (CMoA) module, and **Context-Guided Adaptive Fusion** (CGuAF) module, respectively. To address the imbalance issue, the LvMC module utilizes the large generative visual model SDXL (Stable Diffusion XL) [16] to augment the missing modality information. To address the heterogeneity issue, the CMoA module focuses on aligning the entities between various modalities by employing the pre-trained CLIP model. To address the inconsistency issue, the CGuAF module adaptively moderates the weight of each modality with relational guidance to learn joint cross-modality representations. Our major contributions are summarized as follows.

- We propose a novel MMKGC framework, named LBMKGC, designed to address issues of modality imbalance, modality heterogeneity, and the inconsistency of information quantity for entities across different modalities.
- We innovatively tackle the modality imbalance issue in MMKGC by leveraging the capabilities of the SDXL, a state-of-the-art large generative visual model, instead of relying on conventional adversarial training methods.
- We propose a CMoA module that dynamically adjusts the alignment of multimodal embeddings, which effectively mitigates biases arising from data heterogeneity, ensuring sufficient utilization of multimodal information.
- We first consider the impact of the perceptual and conceptual attributes of triples during joint cross-modality representation learning, and accordingly propose a novel context-guided adaptive fusion module.
- To evaluate the performance of LBMKGC, we conduct comprehensive experiments and further explorations on three public benchmarks. Empirical results demonstrate that LBMKGC outperforms 21 recent baselines, achieving new state-of-the-art MMKGC results.

2 Preliminaries

2.1 Problem Statement

MMKGs [14] provide a robust foundation for knowledge representation and reasoning by integrating structured triples with rich multimodal entity attributes (e.g., images, text, audio, video). In recent years, significant progress has been made in MMKGC [31], which aims to automatically discover new knowledge from incomplete MMKGs.

We define a MMKGs as $\mathcal{G} = (\mathcal{E}, \mathcal{R}, \mathcal{T}, \mathcal{M})$, where $\mathcal{E}$ is the set of entities, $\mathcal{R}$ is the set of relations, $\mathcal{T} = \{(h, r, t) | h, t \in \mathcal{E}, r \in \mathcal{R}\}$ is the set of triples, and $\mathcal{M}$ is the set of modalities, encapsulating different modalities in MMKGs (such as images, text, videos, audio, etc.). For an entity $e \in \mathcal{E}$ in a modality $m \in \mathcal{M}$, its modality information is denoted as e_m, such as text modality denoted as e_t, and visual modality denoted as e_v.

The MMKGC model embeds entities and relations into a continuous vector space. For each entity $e \in \mathcal{E}$, we define its structure, text, and visual embeddings as $e_s^{\text{emb}}, e_t^{\text{emb}}, e_v^{\text{emb}}$. For each relation $r \in \mathcal{R}$, we define its structure embedding as r_s^{emb}. Additionally, the MMKGC model can use a scoring function $\mathcal{F}$ to measure the plausibility of each triple (h, r, t). $\mathcal{F}$ calculates the score through the embedding representation of triples. In the inference phase of the MMKGC task, for a given query $(h, r, ?)$ or $(?, r, t)$, the model scores each candidate entity corresponding to the triple and ranks them to make predictions.

2.2 Related Work

In recent years, numerous KGC methods have been developed. Traditional unimodal approaches, e.g., TransE [1], TransD [10], RotatE [24], PairRE [4], DistMult [35] and ComplEx [26], learn knowledge graph embeddings (KGE) by projecting entities and relations into a continuous vector space that preserves the observed triple structure. To capture heterogeneous graph topology, DGS [9] first separately embeds the cyclic instance structure and hierarchical ontology structure of two-view knowledge graphs into spherical and hyperbolic spaces, unifying them via a bridge space.

On the multi-modal front, IKRL [33] first augments TransE with visual features; TBKGC [19] further incorporates textual cues. Building on KGE, MMKGC methods such as OTKGE [3], VISTA [11], RSME [28], TransAE [32], IMF [13] and QBE [30] leverage rich multi-modal signals to refine entity representations. MMRNS [34] and MANS [36] instead focus on exploiting modalities for higher-quality negative sampling. Modality-imbalance has also been tackled by generative adversarial schemes like MMKRL [15] and AdaMF-MAT [38], which synthesize missing-modal features and use RotatE-style scores as discriminators. Yet these models (i) capture only local semantics and ignore global cross-modal correlations, and (ii) require separate adversarial networks per modality, aggravating heterogeneity. Consequently, modality imbalance, structural heterogeneity and inconsistent saliency across modalities remain largely unresolved.

In this work, we propose LBMKGC to tackle these issues and achieve state-of-the-art performance.

3 Method

In this section, we will introduce our MMKGC framework, LBMKGC. An overview of LBMKGC is shown in the Figure 2. We will introduce the main components in the following paragraphs. These components are the Large Generative Visual Model-based Modality Completion module, Cross-Modal Alignment module, Context-Guided Adaptive Fusion module, and MMKGC Module.

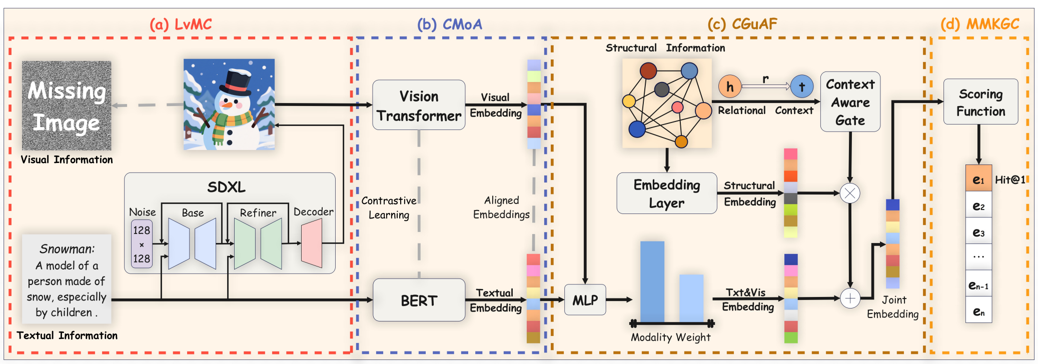


Figure 2: Architectural Overview of the LBMKGC Modal.

3.1 Large Generative Visual Model-based Modality Completion

To address the issue of imbalanced multimodal information, we propose a modality completion module based on SDXL (Stable Diffusion XL) [16] as shown in the Figure 2 (a). In the field of knowledge graph, obtaining visual information is usually more difficult than obtaining text information. Therefore, this paper focuses on the problem of multimodal information missing in visual modality, that is, given an entity $e \in \mathcal{E}$, LvMC populates the prompt template with e_t to generate e_v.

The core component of LvMC is the generative model SDXL. SDXL employs a two-stage generative process facilitated by two specialized models: a Base model and a Refiner model. The Base model is primarily responsible for generating a coherent initial image based on the text prompt, ensuring overall semantic accuracy and composition. Subsequently, the Refiner model operates on the output (typically in the latent space) of the Base model to enhance fine-grained details and visual fidelity. For clarity, a simplified representation of the overall generation process is provided as follows:

First, LvMC generates a text embedding vector by combining two CLIP encoders:

$$\mathbf{c}_t = \mathbf{W}_1 \cdot \text{CLIP}_{\text{bigG}}(\mathbf{e}_t) + \mathbf{W}_2 \cdot \text{CLIP}_{\text{ViT-L}}(\mathbf{e}_t), \tag{1}$$

where $\mathbf{W}_1$ and $\mathbf{W}_2$ are projection matrices, $\text{CLIP}_{\text{bigG}}$ and $\text{CLIP}_{\text{ViT-L}}$ are respectively OpenCLIP ViT-bigG [18] and OpenAI CLIP ViT-L [17] encoders.

The image resolution (w, h) is embedded as Fourier features:

$$\mathbf{f}_{\text{size}} = [\sin(2^k \pi n_w), \cos(2^k \pi n_w), \sin(2^k \pi n_h), \cos(2^k \pi n_h)]_{k=0}^{L-1}, \tag{2}$$

where $n_w = \frac{w}{1024}$, $n_h = \frac{h}{1024}$, and L is the number of frequency bands, and the final combined embedding vector is: $\mathbf{c} = \mathbf{c}_t \oplus \mathbf{f}_{\text{size}}$.

The Base model generates the initial resolution potential through DDIM sampling [22]:

$$\mathbf{z}_{t-1}^{\text{base}} = \sqrt{\bar{\alpha}_{t-1}} \left(\frac{\mathbf{z}_t^{\text{base}} - \sqrt{1-\bar{\alpha}_t} \cdot \epsilon_\theta(\mathbf{z}_t^{\text{base}}, t, \mathbf{c})}{\sqrt{\bar{\alpha}_t}} \right) + \sqrt{1-\bar{\alpha}_{t-1}} \cdot \epsilon_\theta(\mathbf{z}_t^{\text{base}}, t, \mathbf{c}), \tag{3}$$

where the initial noise sampled from a standard Gaussian distribution: $\mathbf{z}_T^{\text{base}} \sim \mathcal{N}(0, \mathbf{I})$. Then, at each reverse step t, the previous state $\mathbf{z}_{t-1}^{\text{base}}$ is computed by first estimating the predicted noise $\epsilon_\theta(\mathbf{z}_t^{\text{base}}, t, \mathbf{c})$ using its UNet, and then applying the DDIM update rule based on the cumulative noise schedule $\bar{\alpha}_t$ and the conditioning embedding $\mathbf{c}$, which combines text and size information.

The Refiner model adds noise to $\mathbf{z}_0^{\text{base}}$:

$$\mathbf{z}_{t_{\text{refine}}}^{\text{refine}} = \sqrt{\bar{\alpha}_{t_{\text{refine}}}} \mathbf{z}_0^{\text{base}} + \sqrt{1-\bar{\alpha}_{t_{\text{refine}}}} \epsilon, \quad \epsilon \sim \mathcal{N}(0, \mathbf{I}), \tag{4}$$

where t_{refine} denotes the running timestep variable in the Refiner's reverse diffusion process.

The Refiner model refines the image step by step:

$$\begin{aligned} \mathbf{z}_{t-1}^{\text{refined}} =& \sqrt{\bar{\alpha}_{t-1}} \left(\frac{\mathbf{z}_t^{\text{refined}} - \sqrt{1-\bar{\alpha}_t} \cdot \epsilon_\phi(\mathbf{z}_t^{\text{refined}}, t, \mathbf{c}, \mathbf{z}_0^{\text{base}})}{\sqrt{\bar{\alpha}_t}} \right) \\ &+ \sqrt{1-\bar{\alpha}_{t-1}} \cdot \epsilon_\phi(\mathbf{z}_t^{\text{refined}}, t, \mathbf{c}, \mathbf{z}_0^{\text{base}}), \end{aligned} \tag{5}$$

where ϵ_ϕ is the noise predictor of the Refiner model.

Finally, the high-resolution image in the variable $\mathbf{z}_0^{\text{refined}}$ is decoded through the VAE decoder to the real image space:

$$\mathbf{e}_v = \text{Decoder}_{\text{VAE}}(\mathbf{z}_0^{\text{refined}}). \tag{6}$$

3.2 Cross-Modal Alignment

To address the issue of heterogeneity in multimodal information within a single entity, we proposed a Cross-Modal Alignment (CMoA) module, as shown in the Figure 2 (b). This module leverages the pre-trained CLIP [17] model to achieve semantic alignment between an entity's image and text representations.

We first extract multimodal feature encodings from the original image and text description of the entity using a pre-trained model, which is a necessary step for all MMKGC methods. The text modality is encoded into text features $f_t = \{T_1, T_2, ..., T_N\}$ using BERT [5], and the visual modality is encoded into visual features $f_v = \{V_1, V_2, ..., V_N\}$ using ViT [7]. The cosine similarity matrix S between the two is calculated, where $S_{i,j}$ represents the similarity between the i-th visual feature V_i and the j-th text feature T_j:

$$S_{i,j} = \frac{V_i \cdot T_j}{\|V_i\| \cdot \|T_j\|}. \tag{7}$$

The symmetric contrastive loss function with a learnable temperature parameter τ is defined as:

$$\mathcal{L}_{\text{CLIP}} = -\frac{1}{2} \left(\frac{1}{N} \sum_{i=1}^{N} \log \frac{e^{S_{i,i}/\tau}}{\sum_{j=1}^{N} e^{S_{i,j}/\tau}} + \frac{1}{N} \sum_{i=1}^{N} \log \frac{e^{S_{i,i}/\tau}}{\sum_{j=1}^{N} e^{S_{j,i}/\tau}} \right). \tag{8}$$

Based on the cross-modality feature alignment, we obtain the aligned visual features f_v and text features f_t. Subsequently, through a projection layer, each entity $e \in \mathcal{E}$ in modality $m \in \mathcal{M}$ is embedded into a representation $e_m^{\text{emb}} = \mathcal{P}_m(f_m)$. Here $\mathcal{P}_m$ is a projection layer for modality m, aimed at projecting different modality embeddings into the same vector space. Each $\mathcal{P}_m$ consists of two MLP layers with ReLU as the activation function.

3.3 Context-Guided Adaptive Fusion

To address the issue that existing MMKGC methods struggle to adaptively adjust the weights of different modalities based on the specific characteristics of the three-element entities, leading to the inability to effectively utilize different modalities, we propose a Context-Guided Adaptive Fusion (CGuAF) module, as shown in the Figure 2 (c). This mechanism is divided into two stages. The first stage performs adaptive fusion of multiple modalities, and the second stage considers the upper and lower context information to generate a joint embedding representation for each entity in the three-element set.

The mechanism adjusts the weight ω_m of each modality based on the entity's (perception or concept) characteristics. For perceptual entities (such as color), if the visual modality can provide strong evidence, it is assigned a higher weight, and the text modality is assigned a lower weight. Conversely, for conceptual entities (such as force), it is difficult to express them with images, so a higher weight is assigned to the text modality, and a lower weight is assigned to the visual modality. Specifically, the weight of the modality m for entity e, $\omega_m(e)$, is calculated as follows:

$$\omega_m(e) = \frac{\exp\left(V \odot \tanh\left(e_m\right)\right)}{\sum_{n \in \mathcal{M}} \exp\left(V \odot \tanh\left(e_n\right)\right)}, \tag{9}$$

where V is a learnable vector and $\odot$ is the point-wise operator.

Based on these weights, we obtain the fused multimodal information h_{mm}:

$$h_{\text{mm}}^{\text{emb}} = \sum_{m \in \mathcal{M}} \omega_m e_m^{\text{emb}}. \tag{10}$$

For the same entity, the salience of information carried by different modalities varies across different types of triples (e.g., perceptual and conceptual). Accordingly, we design a relational temperature ζ_r that allows an entity to adapt its joint embedding based on the type of triple, rather than using a static one, thus providing a more effective relational context.

$$h_{\text{joint}}^{\text{emb}} = \zeta_r h_s^{emb} + (1 - \zeta_r) h_{\text{mm}}^{\text{emb}}. \tag{11}$$

Similarly, the joint embedding of the tail entity is derived using the same fusion method.

Traditional Multimodal Knowledge Graph Completion (MMKGC) approaches typically rely on static, entity-level modality fusion strategies, which overlook the specific context of the input triple. In comparison, our proposed context-guided adaptive fusion module dynamically recalibrates entity embeddings conditioned on the triple type. This fine-grained adaptive adjustment mechanism significantly enhances the model's ability to interact with multimodal features in different relationship contexts.

3.4 Multimodal Knowledge Graph Completion

As shown in the Figure 2 (d), based on the multimodal joint embedding representation of entities, we introduce the RotatE [24] score function based on complex space rotation operations to evaluate the rationality of triples (h, r, t), which has universal modeling capability for complex relationship patterns in knowledge graphs. Specifically, for a triple (h, r, t), its plausibility score is defined as the negative distance between the head entity embedding after rotation and the tail entity embedding, that is:

$$\mathcal{F}(h, r, t) = -||h_{\text{joint}}^{\text{emb}} \circ r - t_{\text{joint}}^{\text{emb}}||, \tag{12}$$

where $\circ$ is the rotation operation in complex space, and a higher score indicates greater rationality of the triple. In the training process, we use a loss function based on negative sampling to optimize the parameters, which can be expressed as:

$$\mathcal{L}_{\text{kgc}} = \sum_{(h,r,t) \in \mathcal{T}} -\log \sigma(\gamma + \mathcal{F}(h, r, t)) - \sum_{i=1}^{K} p(h_i', r_i', t_i') \log \sigma(-\mathcal{F}(h_i', r_i', t_i') - \gamma), \tag{13}$$

where σ is the sigmoid function; γ is a fixed boundary; $(h_i', r_i', t_i') \in \mathcal{T}'$, $(i = 1, 2, ..., K)$ are K negative samples of the triple (h, r, t). Additionally, $p(h_i', r_i', t_i')$ is the self-adversarial weight proposed in RotatE [24].

4 Experiments

In this section, we evaluate our method using a mainstream task in KGC - link prediction task. We first introduce the experimental setup and then present the results. We mainly explore the following four research questions (RQs) regarding LBMKGC:

- **RQ1:** Can our model LBMKGC surpass the existing baselines and make substantial progress in the MMKGC task in link prediction?
- **RQ2:** How much does the design of each module in LBMKGC contribute to performance?
- **RQ3:** When the multimodal information is imbalanced, can LBMKGC maintain stable performance in the MMKGC task?
- **RQ4:** Can LBMKGC adaptively adjust multimodal weights based on different entities?

4.1 Experimental Settings

Datesets. To better explore the MMKGC task in a diverse and complex environment, we conducted comprehensive experiments and further explorations on three public benchmarks. The DB15K [14] dataset was built by crawling search engine images and aligning them with DBpedia [12], while the MKG-W and MKG-Y [34] datasets were created by extracting subsets from Wikidata [27] and YAGO [23]. We used the pre-trained model of CLIP to extract multimodal features.

Baselines. To demonstrate the effectiveness of our method, we conducted a comprehensive comparison and analysis with 21 different state-of-the-art KGC and MMKGC models as our baselines. They can be categorized into three types:

(i) **Uni-modal KGC methods**, this paper employs 6 of the most advanced uni-modal KGC methods, including TransE [1], DistMult [35], ComplEx [26], RotatE [24], PairRE [4], GC-OTE [25], which designed elegant scoring functions and considered structural information in model design.

(ii) **Multi-modal KGC models**, this paper utilizes 12 MMKGC methods that consider multi-modal information and triple structural information, including IKRL [33], TBKGC [19], TransAE [32], MMKRL [15], RSME [28], OTKGE [3], IMF [13], AdamF [38], QEB [30], VISTA [11], AdamF-MAT [38] and MyGO [37].

(iii) **Negative sampling methods**, this paper compares our method with 3 different negative sampling methods, including KBGAN [2], MANS [36], MMRNS [34]. Among them, KBGAN is an adversarial sampling method designed for traditional KGC, applying reinforcement learning to optimize the model. MMRNS utilizes multi-modal information to enhance the negative sampling process.

Metrics. To evaluate our method, we conducted link prediction tasks on three datasets. Link prediction is an important task in knowledge graph completion, aiming to predict the missing entity for a given query $(h, r, ?)$ or $(?, r, t)$. The link prediction task consists of two parts: head prediction and tail prediction.

Following previous work, we use ranking-based metrics such as Mean Reciprocal Rank (MRR) and Hit@K (K = 1, 3, 10) to evaluate the results. MRR and Hit@K can be calculated as:

$$\text{MRR} = \frac{1}{|\mathcal{T}_{\text{test}}|} \sum_{i=1}^{|\mathcal{T}_{\text{test}}|} \left(\frac{1}{r_{h,i}} + \frac{1}{r_{t,i}} \right), \tag{14}$$

$$\text{Hit@K} = \frac{1}{|\mathcal{T}_{\text{test}}|} \sum_{i=1}^{|\mathcal{T}_{\text{test}}|} \left(1(r_{h,i} \leq K) + 1(r_{t,i} \leq K) \right), \tag{15}$$

where $r_{h,i}$ and $r_{t,i}$ are the results of head prediction and tail prediction, respectively.

To ensure fair comparisons, the filter setting [1] is applied to all results to remove candidate triples that already exist in the training set.

Implementation details. We implemented our LBMKGC model based on the famous open-source KGC library OpenKE. We conducted experiments on a Linux server with Ubuntu 24.04.01 operating system and a single NVIDIA GeForce 4090 GPU. We reproduced some advanced models, and some baseline results refer to MyGO [37].

In the LBMKGC, we fix the batch size to 512 and set the training epoch from {1000, 1250, 1500}. The embedding dimensions are tuned from {300, 400, 500} and the negative sampling number K is tuned from {32, 64, 128}. The margin γ is tuned from {8, 12, 16, 20, 24} and the temperature β is set to 4. We optimize the model with Adam and the learning rate is tuned from {1e-5, 2e-5, 5e-5}.

For baselines, we reproduce the results following the methodology and parameter setting described in the original papers and their open-source official code.

4.2 Main Results (RQ1)

We conducted link prediction experiments and presented the experimental results in Table 1. Our method, LBMKGC, achieved superior performance on all evaluation metrics across three public benchmarks. The experimental results of this method show that our approach enables the model to capture a richer set of candidate relation patterns, enhancing semantic coverage, and more stably retaining correct answers in the top region of the candidate set (Hit@3 and Hit@10), while still maintaining advanced performance in the exact first match metric (Hit@1). It has stronger practicality in real-world scenarios that require multi-candidate selection (such as recommendation systems, open-domain question answering).

4.3 Ablation Study (RQ2)

To provide a more detailed demonstration of the effectiveness of each module design and to answer RQ3, we conducted ablation studies, as shown in Table 2. We replaced the adaptive fusion guided by the context with mean fusion to verify the effectiveness of CGuAF. Furthermore, to verify the contribution of different information in MMKGC, we covered visual information (textual information/structural information) for link prediction tasks. Additionally, we used uni-modal pre-training models (VGG16 [21], BERT [5]) to independently extract visual and textual features to verify the effectiveness of cross-modal feature alignment. Finally, we randomly initialized the missing modal information to verify the importance of the real missing modal information in explicit modeling.

The results of the ablation study show that when each module or each modal information of our method is removed, the link prediction results will decrease, which demonstrates their effectiveness.

Table 1: Knowledge Graph Completion Models Comparison

Model	**DB15K**				**MKG-W**				**MKG-Y**			
	MRR	**Hit@1**	**Hit@3**	**Hit@10**	**MRR**	**Hit@1**	**Hit@3**	**Hit@10**	**MRR**	**Hit@1**	**Hit@3**	**Hit@10**
TransE	24.86	12.78	31.48	47.07	29.19	21.06	33.20	44.23	30.73	23.45	35.18	43.37
DistMult	23.03	14.78	26.28	39.59	20.99	15.93	22.28	30.86	25.04	19.33	27.80	35.95
ComplEx	27.48	18.37	31.57	45.37	24.93	19.06	26.69	36.73	28.71	22.26	32.12	40.93
RotatE	29.28	17.87	36.12	49.66	33.67	26.80	36.68	46.73	34.95	29.10	38.35	45.30
PairRE	31.13	21.62	35.91	49.30	34.40	28.24	36.71	46.04	32.01	25.53	35.84	43.89
GC-OTE	31.85	22.11	36.52	51.18	33.92	26.55	39.65	46.90	32.95	26.77	38.41	44.08
IKRL	26.82	14.09	34.93	49.09	32.36	26.11	34.75	44.07	33.22	30.37	34.28	38.26
TBKGC	28.40	15.61	37.03	49.86	31.48	25.31	33.98	43.24	33.99	30.47	35.27	40.07
TransAE	28.09	21.25	31.17	41.17	30.00	21.23	34.91	44.72	28.10	25.31	29.10	33.03
MMKRL	26.81	13.85	35.07	49.39	30.10	22.16	34.09	44.69	36.81	31.66	39.79	45.31
RSME	29.76	24.15	32.12	40.29	29.23	23.36	31.97	40.43	34.44	31.78	36.07	39.09
OTKGE	23.86	18.45	25.89	34.23	34.36	28.85	36.25	44.88	35.51	31.97	37.18	41.38
IMF	32.25	24.20	36.00	48.19	34.50	28.77	36.62	45.44	35.79	32.95	37.14	40.63
QEB	28.18	14.82	36.67	51.55	32.38	25.47	35.06	45.32	34.37	29.49	36.95	42.32
VISTA	30.42	22.49	33.56	45.94	32.91	26.12	35.38	45.61	30.45	24.87	32.39	41.53
AdaMF	32.51	21.31	39.67	51.68	34.27	27.21	37.86	47.12	38.06	33.49	40.44	45.48
KBGAN	25.73	9.91	36.95	51.93	29.47	22.21	34.87	40.64	29.71	22.81	34.88	40.21
MANS	28.82	16.87	36.58	49.26	30.88	24.89	33.63	41.78	29.03	25.25	31.35	34.49
MMRNS	32.68	23.01	37.86	51.01	35.03	28.59	37.49	47.47	35.93	30.53	39.07	45.47
AdaMF-MAT	35.14	25.30	41.11	52.92	35.77	28.87	38.85	48.71	38.57	34.34	40.59	45.76
MyGO	37.17	**29.62**	41.66	51.87	36.09	30.02	38.26	46.89	38.66	**34.85**	39.96	44.37
Ours	**37.23**	27.78	**42.75**	**54.71**	**38.46**	**31.20**	**41.78**	**51.46**	**40.03**	33.89	**43.11**	**50.81**
	+0.16%	-	+2.6%	+3.38%	+6.6%	+3.9%	+7.5%	+5.6%	+3.5%	-	+6.2%	+11.0%

Table 2: Ablation Study

Settings	**DB15K**				**MKG-W**				**MKG-Y**			
	MRR	**Hit@1**	**Hit@3**	**Hit@10**	**MRR**	**Hit@1**	**Hit@3**	**Hit@10**	**MRR**	**Hit@1**	**Hit@3**	**Hit@10**
LBMKGC	37.23	27.78	42.75	54.71	38.46	31.20	41.78	51.46	40.03	33.89	43.11	50.81
w/o LvMC	36.73	27.19	42.01	53.76	37.12	29.43	40.28	49.16	39.40	33.42	42.47	49.59
w/o CMoA	36.81	27.69	41.56	53.37	38.03	29.88	40.86	49.34	39.34	33.58	42.28	49.37
w/o CGuAF	36.36	26.55	42.39	54.48	37.53	30.51	41.76	50.77	39.29	33.01	42.92	50.86
w/o e_s^{emb}	31.21	16.96	41.12	54.60	34.76	23.84	41.86	51.97	37.79	29.33	42.43	51.02
w/o e_t^{emb}	36.51	27.09	41.45	53.19	36.72	30.01	40.02	48.79	38.33	32.72	40.95	47.67
w/o e_v^{emb}	37.08	27.34	42.01	53.92	37.89	30.63	41.05	50.89	39.24	33.13	41.76	49.73

4.4 Modality-missing Results (RQ3)

We conducted link prediction experiments with modality dropout on the DB15K dataset. The visual modality was discarded at rates of $\eta = \{0.25, 0.5, 0.75, 1.0\}$. Specifically, for LBMKGC, we used the LvMC module to fully compensate for the missing visual modality information. For other models, we used the commonly used random initialization method [20] to compensate for the missing information. The experimental results are shown in the Figure 3, as the missing modality rate increases, the baseline models (TBKGC [19] and AdaMF-MAT [38]) exhibit significant performance degradation, whereas our proposed LBMKGC demonstrates relatively stable performance. LBMKGC's explicit modeling of missing modalities based on large-scale pre-trained models (i.e., generating real modality information) boosts MMKGC's performance and robustness more effectively than strategies using adversarial training or random initialization.

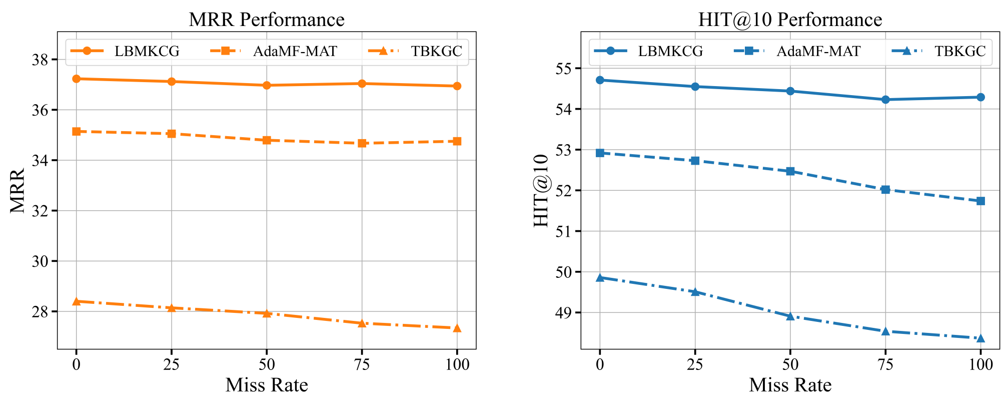
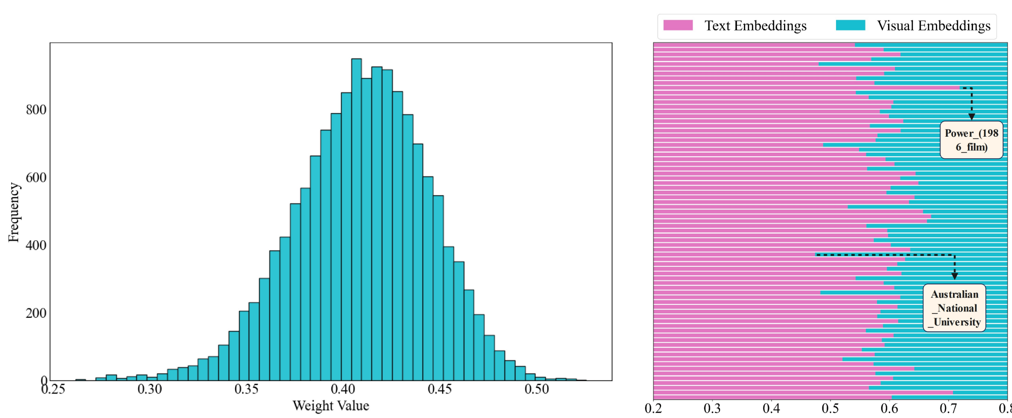


Figure 3: Link prediction results on modality-missing DB15K dataset.



(a) Histogram of Visual Modality Weights Distribution (b) Comparison Chart of Text and Visual Modality Weights

Figure 4: Fusion weights of different modalities.

4.5 Case Study (RQ4)

To intuitively demonstrate the effectiveness of CGuAF, we present the histogram of visual modality weight distribution for all entities in the MKG-W dataset in Figure 4 (a). Based on this, we randomly selected some entities' textual and visual modality weights for comparison in Figure 4 (b), for the conceptual entity "Power_(1986_film)", the weight of textual information is 71%, while that of visual modality is 29%, whereas for the perceptual entity "Australian_National_University", the weight of textual information is 47%, and that of visual modality is 53%. This reflects that CGuAF can dynamically adjust the weight of each modality according to the specific (perceptual) or abstract (conceptual) characteristics of different triad groups of entities, enhancing and retaining the truly important parts of multi-modal information, thereby significantly enhancing the model's ability to interact with multi-modal features under scenarios of complex relationships.

5 Conclusion and Future Work

In this paper, we mainly discussed the imbalance of multi-modal information among entities, the heterogeneity of multi-modal information within entities, and the issue of inconsistent information quantities across different modalities. We proposed a novel MMKGC framework, LBMKGC, to address the limitations of existing methods. LBMKGC consists of three core modules: LvMC, CMoA, and CGuAF, which sequentially solve the issues of imbalance, heterogeneity, and inconsistent information quantities. We conducted in-depth theoretical analysis to demonstrate the rationality of our design and comprehensive experiments on 21 benchmarks to show the effectiveness and robustness of our framework.

However, our study currently focuses on text and image modalities, without integrating semantically rich information such as audio and video into a unified framework. Additionally, our experiments have been conducted exclusively on general domain datasets, leaving the adaptability and robustness in specialized fields like biomedical data and social networks unverified. In the future, MMKGC tasks should more comprehensively consider these modalities in the real world and design generalizable and scalable model architectures to adapt to various tasks and modality combinations, thereby enhancing the ability to model complex relationships.

6 Acknowledgements

This work was supported by the National Natural Science Foundation of China (No.62002039, 62472062, U23B2019).

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A Technical Appendices and Supplementary Material

A.1 Dataset Analysis

In real-world multimodal knowledge graphs, the modal information is diverse and complex. Some entities may have rich multimodal information such as images and text, while others may have scarce modalities (e.g., containing only text modality with the absence of image modality). This uneven distribution makes the task of knowledge graph completion exceptionally challenging. The missing modal information can lead to the omission of key knowledge, thereby affecting the accuracy of the completion process. As shown in Figure 5, we present the phenomenon of imbalance across different datasets. Specifically, we focus on the imbalance of the image modality and calculate the proportion of entities containing image modality within the entire set of entities. Regarding the text modality, even if an entity lacks a corresponding textual description, the entity itself contains textual information (for example, the triple <snowman, state, stillness>, which consists of three words and is also considered a form of textual information), so we consider the text modality to be balanced.

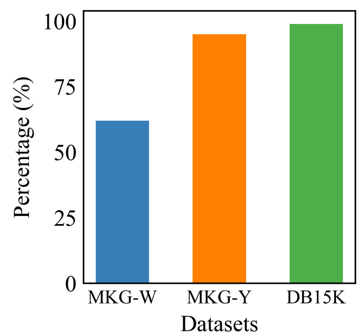

Figure 5: Imbalance Situations in Different Datasets

A.2 Generalization Experiments

We conducted generalization experiments on four different MMKGC models (namely TBKGC, IKRL, AdaMF and QEB) using the multimodal features obtained from the LvMC and CMoA modules. We employed the same parameters as LBMKGC on the DB15K dataset. In fact, with more meticulous parameter tuning tailored to different MMKGC models, these models could potentially exhibit even better performance. We report the Mean Reciprocal Rank (MRR) and Hit@10 results on the DB15K dataset, as shown in Figure 6. Based on the experimental results, we can conclude that by addressing the imbalance of multimodal information between entities and the heterogeneity of multimodal information within entities, MMKGC models can achieve significant performance gains. This indicates that the LvMC and CMoA modules can serve as universal components applicable to various models in downstream tasks.

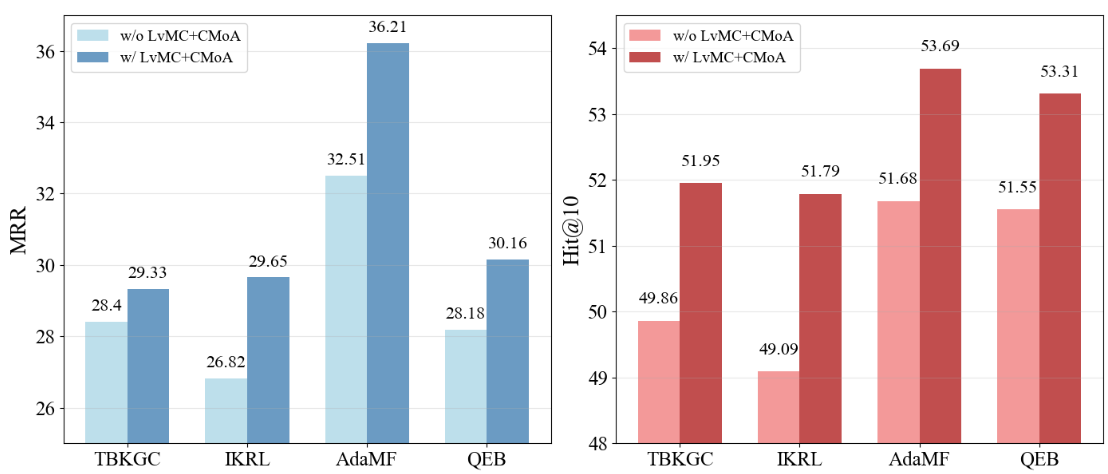

Figure 6: Imbalance Situations in Different Datasets

A.3 Statistical Testing

To rigorously evaluate the stability and reproducibility of our proposed LBMKGC method, we have conducted five independent experiments on each of the three benchmark datasets (MKG-W, MKG-Y, and DB15K) without fixing the random seed during training.

The comprehensive results across all datasets, as depicted in Figure 7, demonstrate highly consistent performance patterns throughout the evaluation metrics. On the MKG-W dataset, MRR values remain confined to a narrow interval of 0.3840–0.3866, while Hit@1 scores exhibit stability, ranging from 0.3119 to 0.3152. A similar degree of consistency is observed on the MKG-Y dataset, where MRR varies between 0.3992 and 0.4031, accompanied by Hit@1 scores spanning 0.3387–0.3449. The DB15K dataset also reflects minimal performance deviation, with MRR consistently maintained between 0.3707 and 0.3734. The standard deviations across all evaluation metrics on MKG-W, MKG-Y, and DB15K datasets remain below 0.0026, demonstrating the exceptional algorithmic stability of our proposed method.

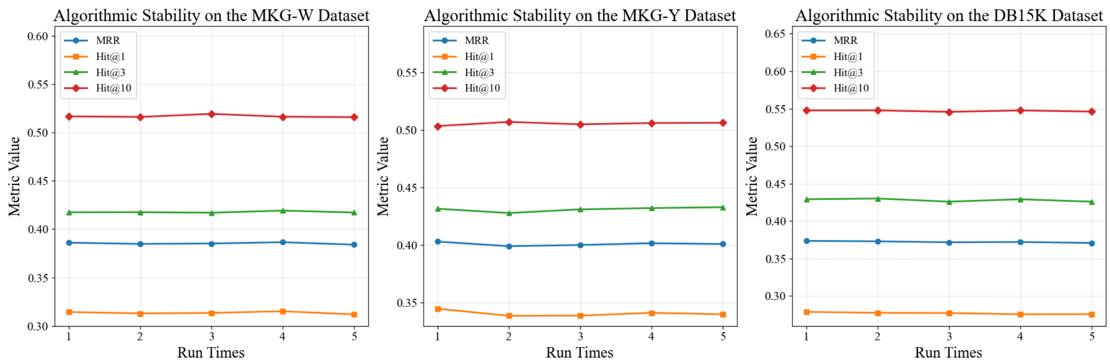

Figure 7: Algorithmic Stability on Different Datasets

A.4 Hyperparameter Sensitivity

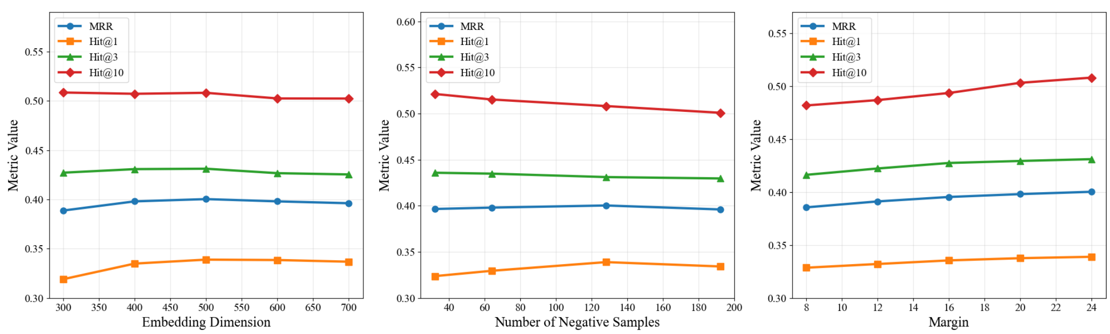

Figure 8: Hyperparameter Sensitivity on MKG-W Dataset

We have conducted experiments on the core hyperparameters (including embedding dimension, number of negative samples, and margin) using the MKG-Y dataset. To ensure the fairness of these experiments, we fixed the random seed at 42 and employed a controlled variable approach for multiple independent experiments. The experimental results are shown as Figure 8.

The experimental results indicate that while there is some variability in the outcomes under different hyperparameter settings, this variability is minor and does not significantly impact the model's performance.

A.5 Time Efficiency

We have conducted time efficiency experiments on the DB15K dataset using an NVIDIA GeForce 4090 GPU, employing the LBMKGC, TBKGC, QEB, RSME, and IKRL methods. The results are as Figure 9, this deceleration is within an acceptable range and leads to substantial performance improvements. The increased computational time is primarily due to the additional processing required for assigning weights to the text and image modalities, as well as to the graph structural information regulated by relational context.

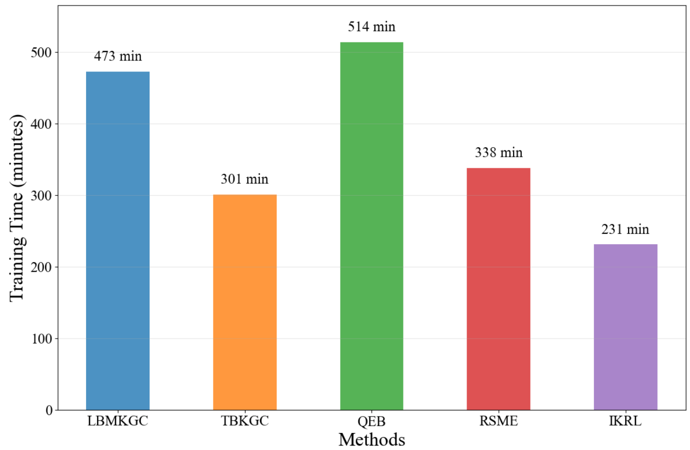

Figure 9: Training Time Efficiency on DB15K Dataset

Overall, the LBMKGC model achieves a commendable balance between efficiency, performance, and stability. The additional computational investment yields disproportionately valuable returns in terms of prediction accuracy and model robustness, making it particularly suitable for applications where performance is prioritized over minimal training time.