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ATHENS-GREECE

Rethinking Uncertainly Missing and Ambiguous Visual Modality in Multi-Modal Entity Alignment

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https://github.com/zjukg/UMAEA

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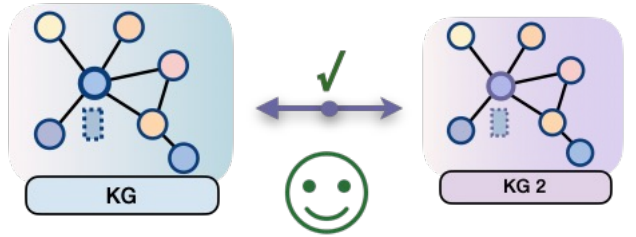
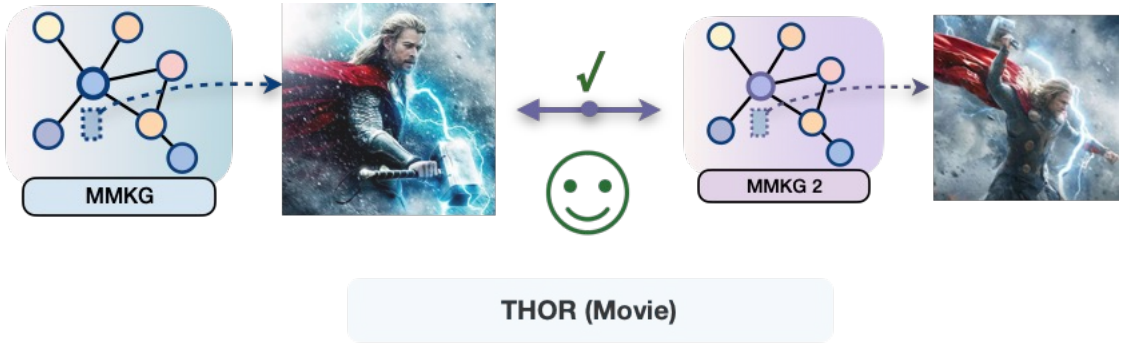
Background: MMEA

- **Entity Alignment (EA):**
  - ***Identify equivalent entities across knowledge graphs (KGs)***:
    - *Addressing challenges such as disparate naming conventions, multilingualism, and heterogeneous graph structures*

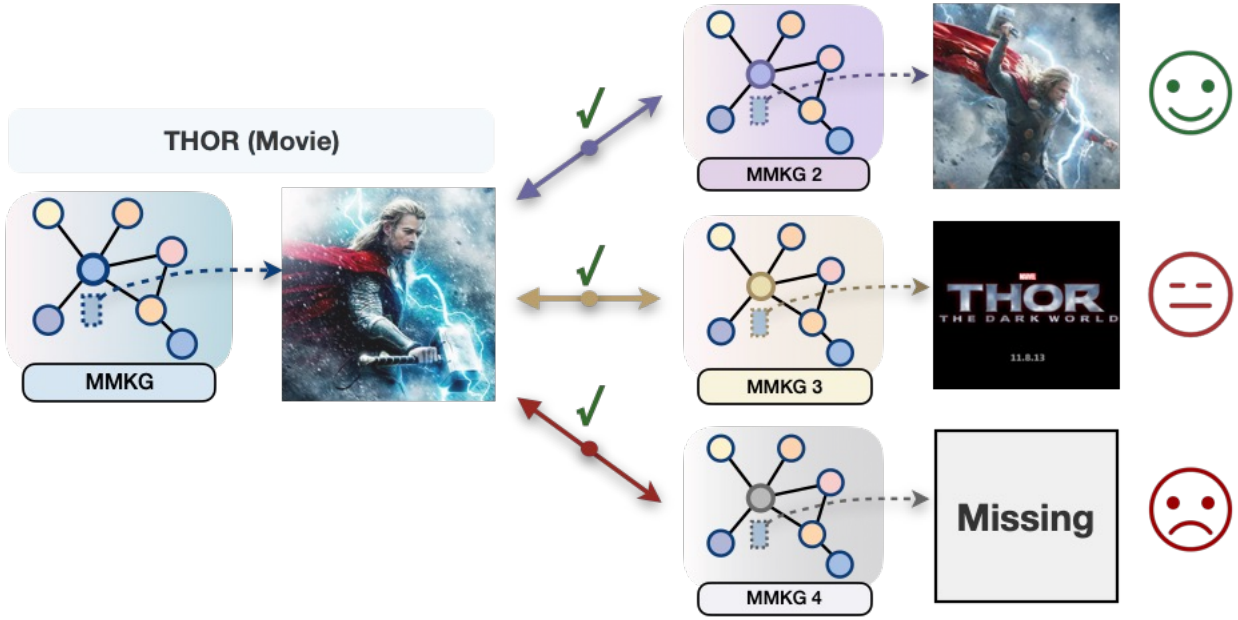


- **Multi-modal Entity Alignment (MMEA):**
  - ***Leverage visual modality***:
    - *From the Internet as supplementary information for EA*
    - *Entity is associated with its name-related images*
  - ***Current emphasis for MMEA approaches***:
    - *Modality-specific attention weights*
    - *Visual-guided relational learning*
    - *Intra-modal enhancement via contrastive learning*
    - *Image filtering via ontology*



Challenge: Missing and Ambiguous Visual Modality

- **Two Ideal Assumptions:**
  - ***One-to-one correspondence***:
    - *A single image sufficiently encapsulates and conveys all the information about an entity.*
  - ***Images are always available***:
    - *An entity consistently possesses a corresponding image.*



- **Practical Scenario:**
  - ***Uncertainly missing visual modality***:
    - *A varying degree of image absence*
  - ***Uncertainly ambiguous visual modality***:
    - *A single entity might have heterogeneous visual representations*

Contribution

- ***Propose the MMEA-UMVM dataset:***
  - *Contain seven separate datasets with a total of **97 splits***
- ***Benchmark latest MMEA models:***
  - *Standard (non-iterative) and iterative training paradigms*
- ***Identify two critical phenomena:***
  - *Models may succumb to **overfitting noise** during training*
  - *Models exhibit performance **oscillations or even declines** at high missing modality rates*
- ***Propose our model UMAEA:***
  - *multi-scale modality hybrid and circularly missing modality imagination*
  - *Consistently achieve SOTA results across **all** benchmark splits*
  - *limited parameters and runtime*

Dataset: UMVM

- **UMVM (uncertainly missing visual modality) Datasets:**

  - ***Basic MMEA datasets***:
    - ***DBP15K***: *multilingual versions of DBpedia*
      - *$DBP15K_{ZH\text{-}EN}$, $DBP15K_{JA\text{-}EN}$ and $DBP15K_{FR\text{-}EN}$*
    - ***Multi-OpenEA***: *multi-modal variants of the OpenEA*
      - *EN-FR-15K, EN-DE-15K, D-W-15K-V1, D-W-15K-V2*

Dataset	KG	# Ent.	# Rel.	# Attr.	# Rel. Triples	# Attr. Triples	# Image	# EA pairs
$DBP15K_{ZH\text{-}EN}$	ZH (Chinese)	19,388	1,701	8,111	70,414	248,035	15,912	15,000
	EN (English)	19,572	1,323	7,173	95,142	343,218	14,125	
$DBP15K_{JA\text{-}EN}$	JA (Japanese)	19,814	1,299	5,882	77,214	248,991	12,739	15,000
	EN (English)	19,780	1,153	6,066	93,484	320,616	13,741	
$DBP15K_{FR\text{-}EN}$	FR (French)	19,661	903	4,547	105,998	273,825	14,174	15,000
	EN (English)	19,993	1,208	6,422	115,722	351,094	13,858	
$OpenEA_{EN\text{-}FR}$	EN (English)	15,000	267	308	47,334	73,121	15,000	15,000
	FR (French)	15,000	210	404	40,864	67,167	15,000	
$OpenEA_{EN\text{-}DE}$	EN (English)	15,000	215	286	47,676	83,755	15,000	15,000
	DE (German)	15,000	131	194	50,419	156,150	15,000	
$OpenEA_{D\text{-}W\text{-}V1}$	DBpedia	15,000	248	342	38,265	68,258	15,000	15,000
	Wikidata	15,000	169	649	42,746	138,246	15,000	
$OpenEA_{D\text{-}W\text{-}V2}$	DBpedia	15,000	167	175	73,983	66,813	15,000	15,000
	Wikidata	15,000	121	457	83,365	175,686	15,000	

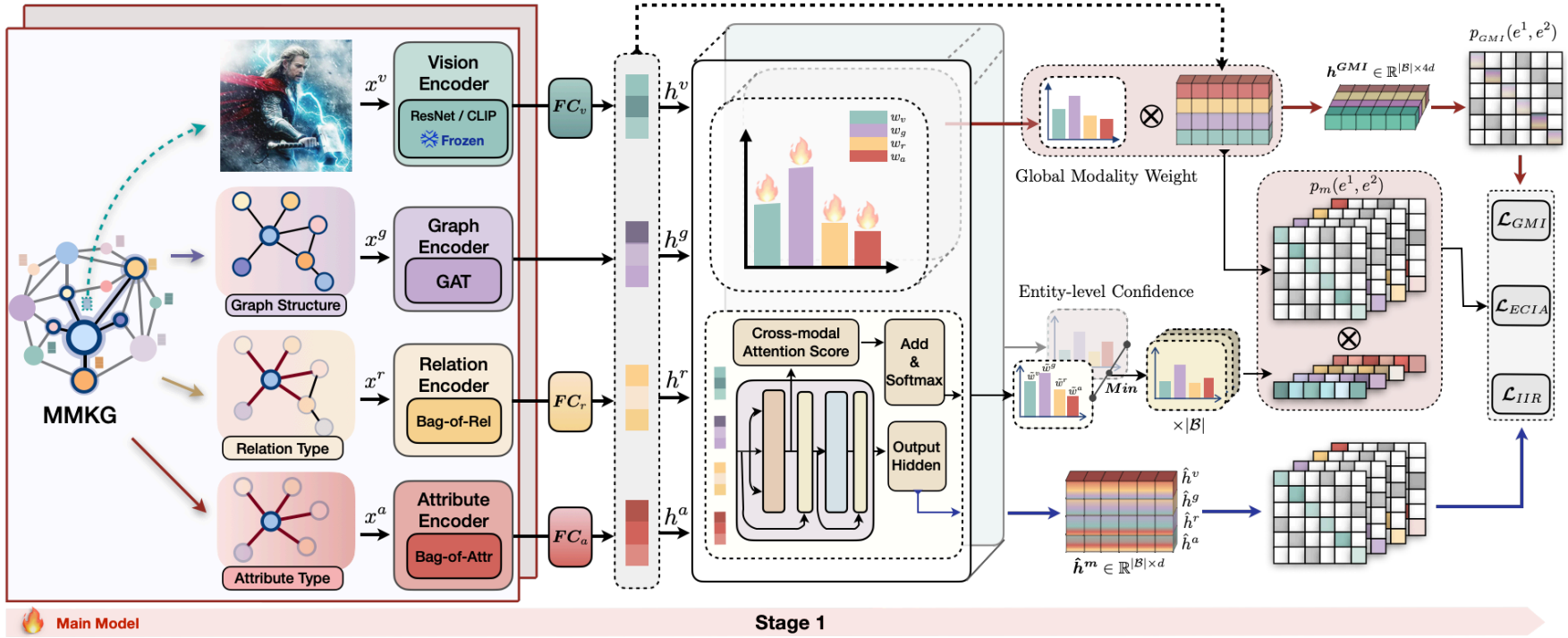
  - ***Random image dropping on MMEA datasets***:
    - *Varying degrees of visual modality missing*
    - *Range from 0.05 to the maximum R_{img} of the raw datasets*

Dataset	R_{img}
$DBP15K_{ZH\text{-}EN}$	0.05, 0.1, 0.15, 0.2, 0.3, 0.4, 0.45, 0.5, 0.55, 0.6, 0.7, 0.75, 0.7829 (STD)
$DBP15K_{JA\text{-}EN}$	0.05, 0.1, 0.15, 0.2, 0.3, 0.4, 0.45, 0.5, 0.55, 0.6, 0.7, 0.7032 (STD)
$DBP15K_{FR\text{-}EN}$	0.05, 0.1, 0.15, 0.2, 0.3, 0.4, 0.45, 0.5, 0.55, 0.6, 0.6758 (STD)
$OpenEA_{EN\text{-}FR}$	0.05, 0.1, 0.15, 0.2, 0.3, 0.4, 0.45, 0.5, 0.55, 0.6, 0.7, 0.8, 0.9, 0.95, 1.0 (STD)
$OpenEA_{EN\text{-}DE}$	0.05, 0.1, 0.15, 0.2, 0.3, 0.4, 0.45, 0.5, 0.55, 0.6, 0.7, 0.8, 0.9, 0.95, 1.0 (STD)
$OpenEA_{D\text{-}W\text{-}V1}$	0.05, 0.1, 0.15, 0.2, 0.3, 0.4, 0.45, 0.5, 0.55, 0.6, 0.7, 0.8, 0.9, 0.95, 1.0 (STD)
$OpenEA_{D\text{-}W\text{-}V2}$	0.05, 0.1, 0.15, 0.2, 0.3, 0.4, 0.45, 0.5, 0.55, 0.6, 0.7, 0.8, 0.9, 0.95, 1.0 (STD)

◎ **The proportion R_{img} of entities containing images in our setting, with "STD" refers to the standard R_{img} in raw datasets**

UMAEA

- **Multi-scale Modality Hybrid:**
  - ***Global Modality Integration (GMI)***
  - ***Entity-level Modality Alignment***
  - ***Late Modality Refinement***



UMAEA

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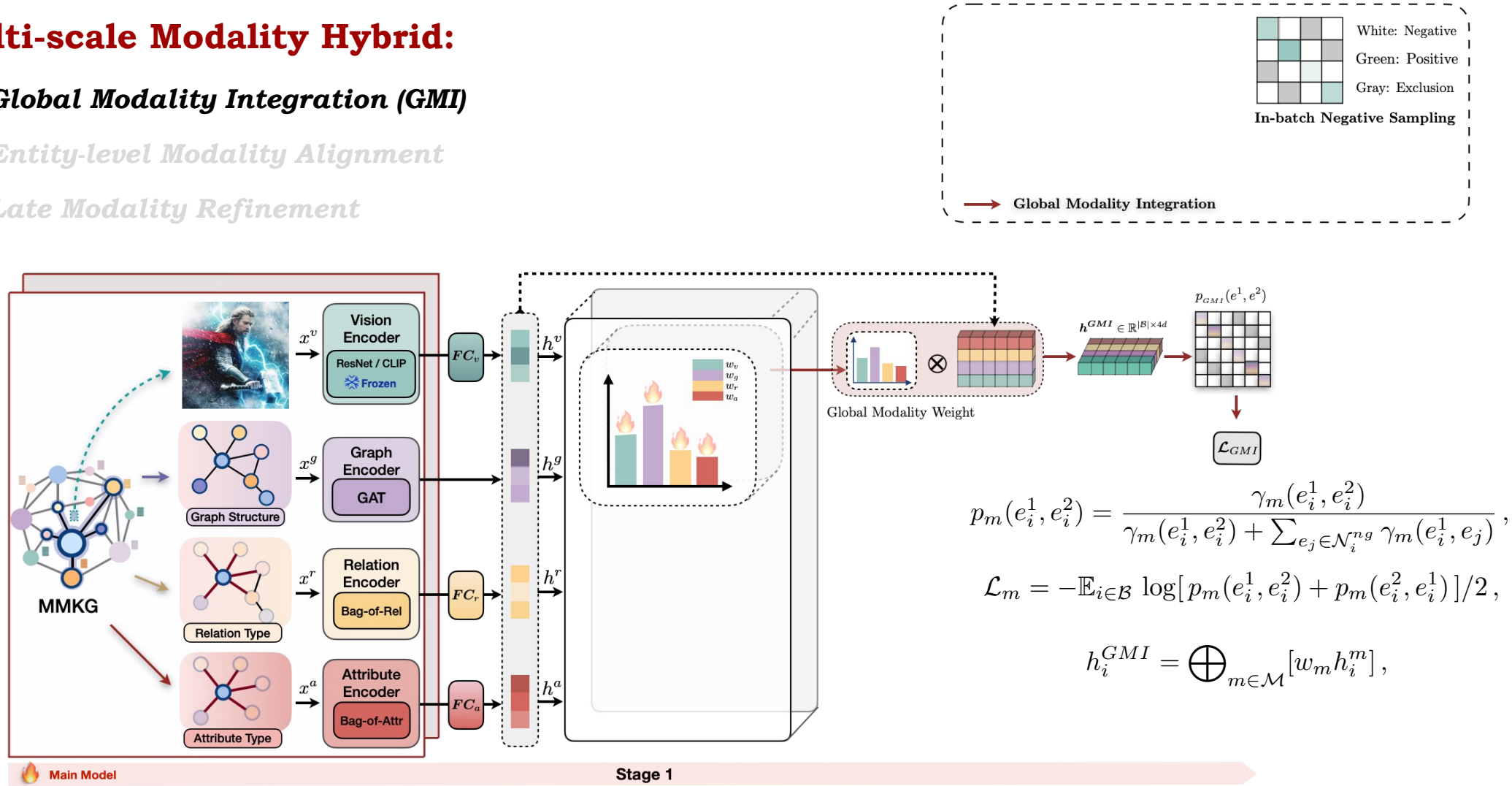


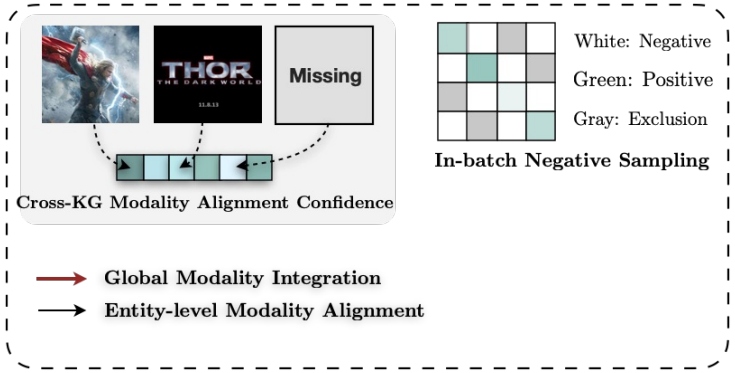
$$p_m(e_i^1, e_i^2) = \frac{\gamma_m(e_i^1, e_i^2)}{\gamma_m(e_i^1, e_i^2) + \sum_{e_j \in \mathcal{N}_i^{ng}} \gamma_m(e_i^1, e_j)},$$

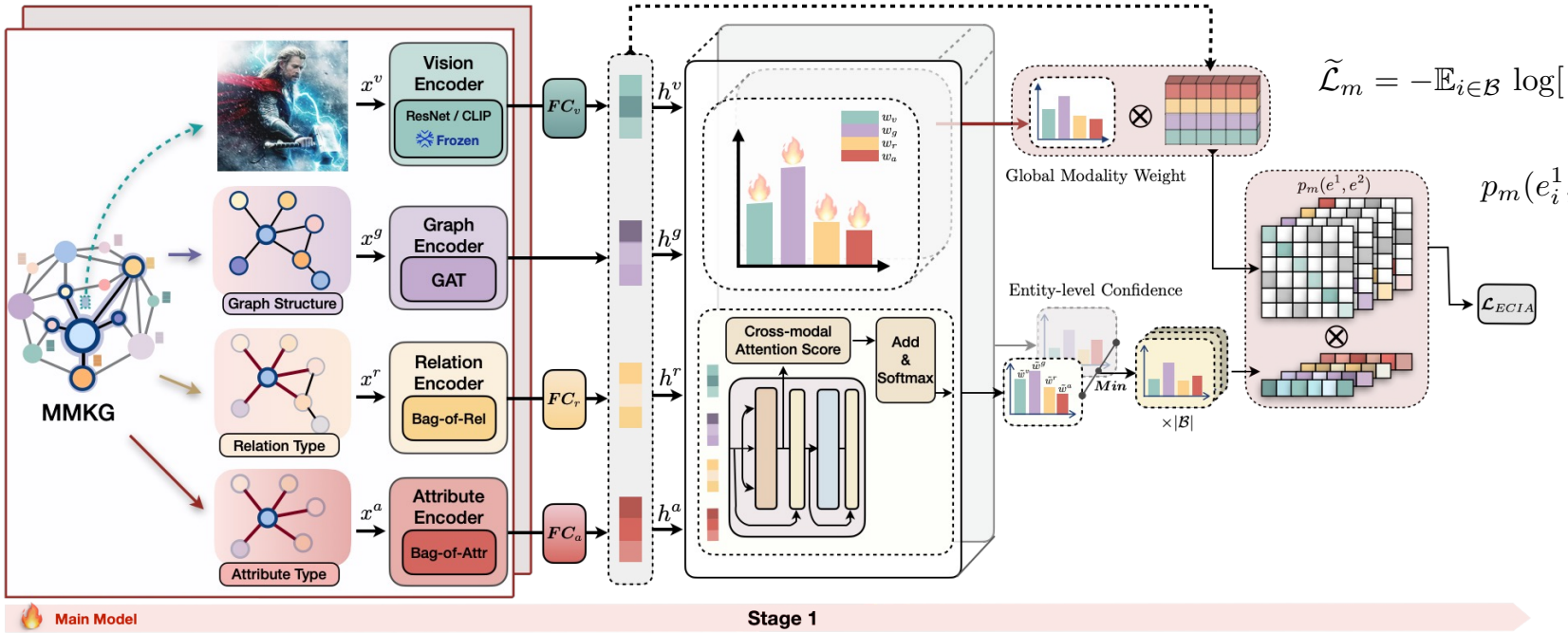
$$\mathcal{L}_m = -\mathbb{E}_{i \in \mathcal{B}} \log[\, p_m(e_i^1, e_i^2) + p_m(e_i^2, e_i^1)\,]/2\,,$$

$$h_i^{GMI} = \bigoplus\nolimits_{m \in \mathcal{M}} [w_m h_i^m]\,,$$

UMAEA

- **Multi-scale Modality Hybrid:**
  - *Global Modality Integration (GMI)*
  - ***Entity-level Modality Alignment***
    - ***Explicit confidence-augmented intra-modal alignment (ECIA)***
    - *Implicit inter-modal refinement (IIR)*
  - *Late Modality Refinement*





$$\mathcal{L}_{ECIA} = \sum_{m \in \mathcal{M}} \widetilde{\mathcal{L}}_m \ ,$$

$$\widetilde{\mathcal{L}}_m = -\mathbb{E}_{i \in \mathcal{B}} \log[\, \phi_m(e_i^1, e_i^2) * (p_m(e_i^1, e_i^2) + p_m(e_i^2, e_i^1))\,]/2 \,.$$

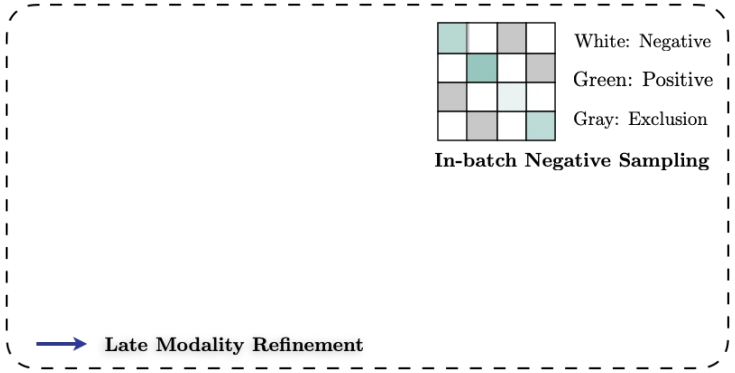
$$p_m(e_i^1, e_i^2) = \frac{\gamma_m(e_i^1, e_i^2)}{\gamma_m(e_i^1, e_i^2) + \sum_{e_j \in \mathcal{N}_i^{ng}} \gamma_m(e_i^1, e_j)} \ ,$$

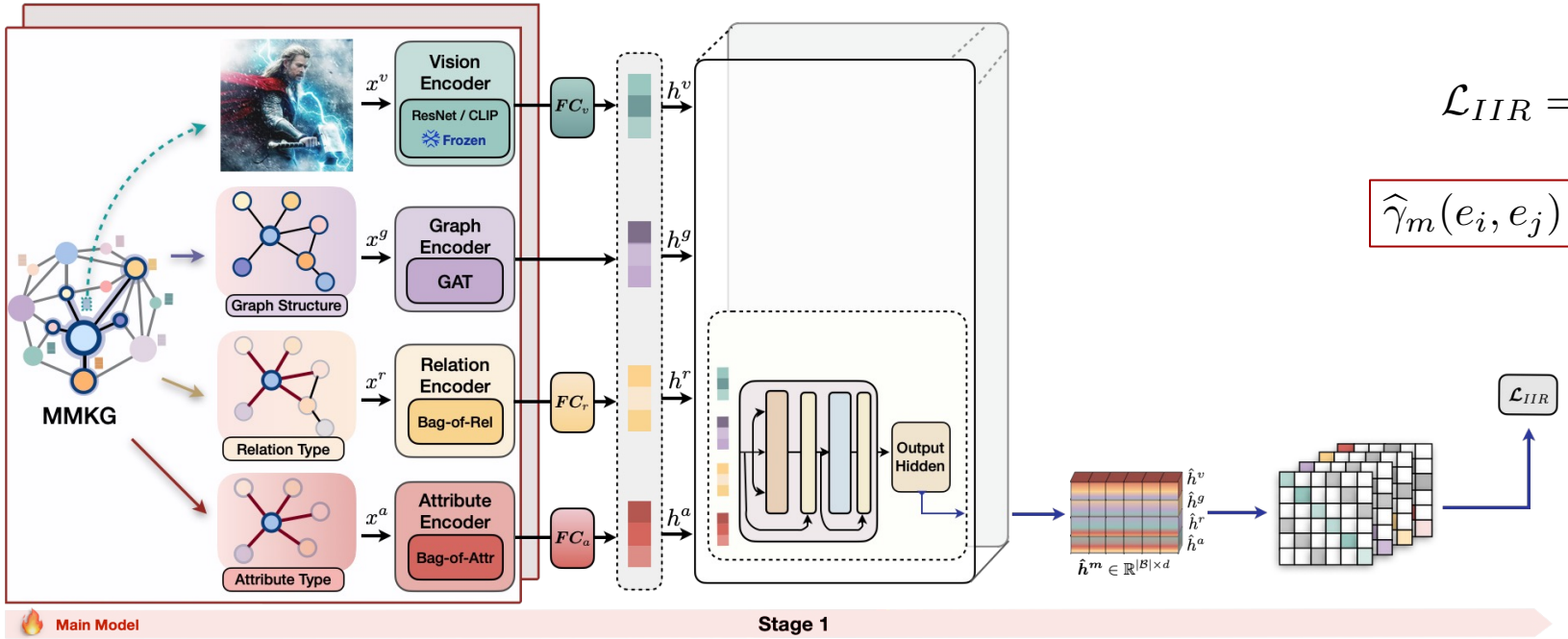
$$\phi_m(e_i, e_j) = Min(\tilde{w}_i^m, \tilde{w}_j^m)$$

$$\gamma_m(e_i, e_j) = \exp(h_i^{m\top} h_j^m / \tau)$$

UMAEA

- **Multi-scale Modality Hybrid:**
  - *Global Modality Integration (GMI)*
  - *Entity-level Modality Alignment*
    - *Explicit confidence-augmented intra-modal alignment (ECIA)*
    - *Implicit inter-modal refinement (IIR)*
  - ***Late Modality Refinement***



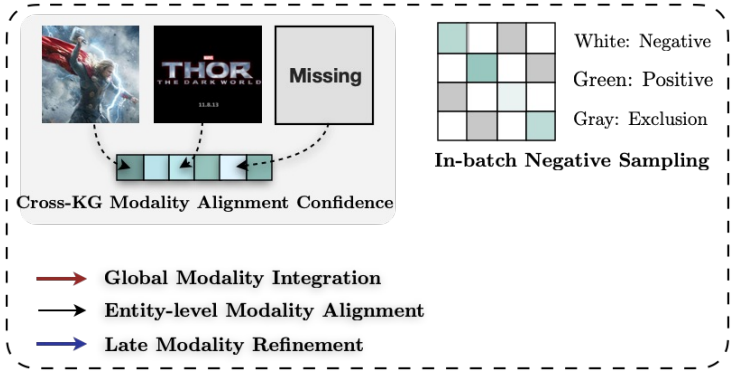


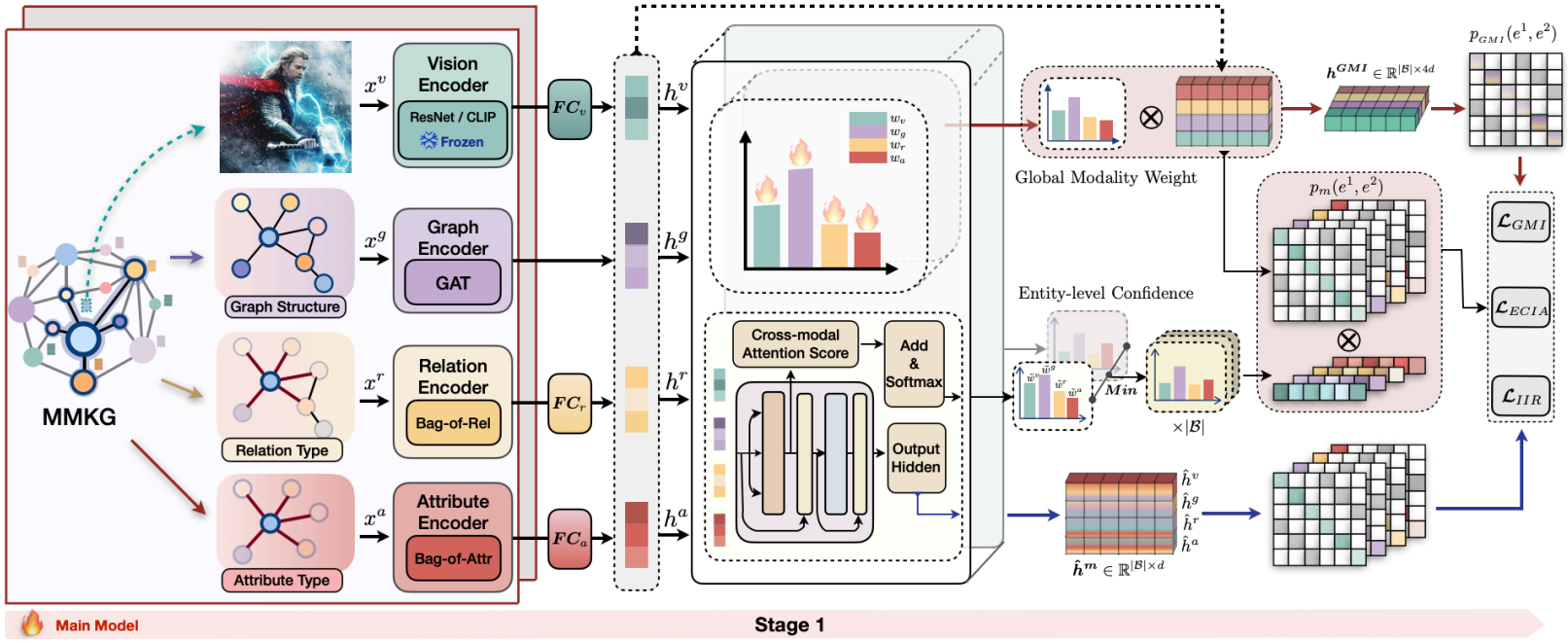
$$\mathcal{L}_{IIR} = \sum_{m \in \mathcal{M}} \widehat{\mathcal{L}}_m \,,$$

$$\widehat{\gamma}_m(e_i, e_j) = \exp(\hat{h}_i^{m\top} \hat{h}_j^m / \tau).$$

UMAEA

- **Multi-scale Modality Hybrid:**
  - ***Global Modality Integration (GMI)***
  - ***Entity-level Modality Alignment***
  - ***Late Modality Refinement***





$$\mathcal{L}_1 = \mathcal{L}_{GMI} + \mathcal{L}_{ECIA} + \mathcal{L}_{IIR}\,.$$

UMAEA

- **Circularly Missing Modality Imagination:**
  - ***Global Modality Integration (GMI)***
  - ***Entity-level Modality Alignment***
  - ***Late Modality Refinement***

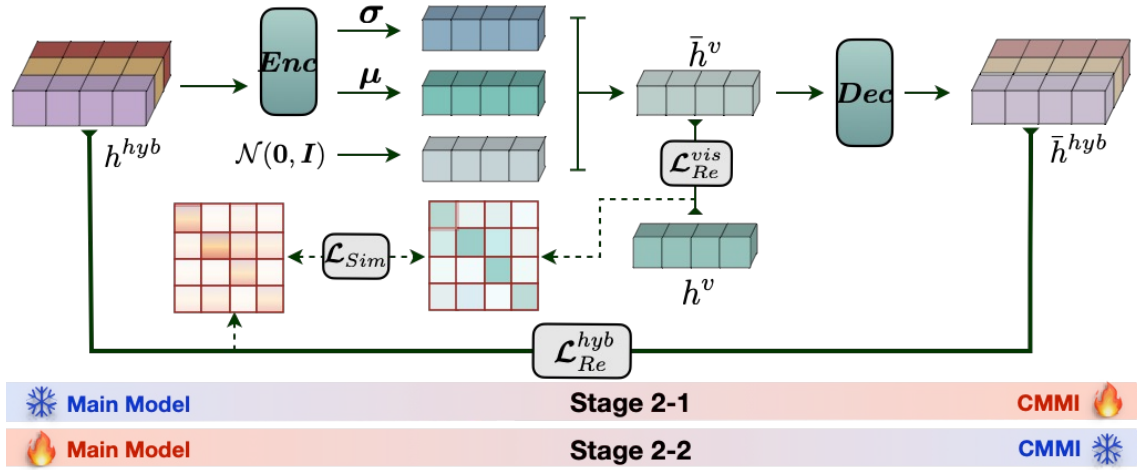
$$h_i^{hyb} = [h_i^r \oplus h_i^a \oplus h_i^g]$$

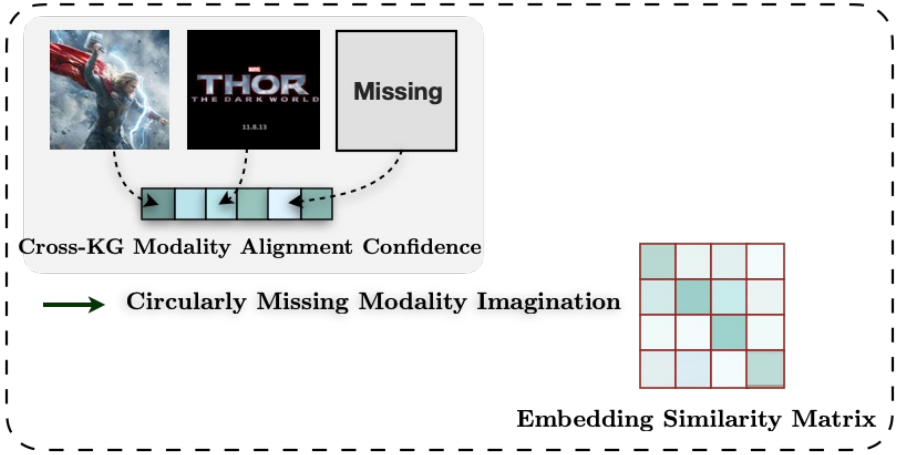
$$[\,\mu_i \oplus \log(\sigma_i)^2\,] = MLP_{Enc}(h_i^{hyb})\,,$$
$$\bar{h}_i^v = z \odot \sigma_i + \mu_i\,,\quad z \sim \mathcal{N}(\mathbf{0}, \boldsymbol{I})\,,$$
$$\bar{h}_i^{hyb} = MLP_{Dec}(\bar{h}_i^v)\,.$$

$$\mathcal{L}_{KL} = \mathbb{E}_{i\in\bar{\mathcal{B}}}\,((\mu_i)^2 + (\sigma_i)^2 - \log(\sigma_i)^2 - 1)/2\,,$$

$$\mathcal{L}_{Sim} = \mathbb{E}_{i\in\bar{\mathcal{B}}}\,D_{KL}(p_{hyb}(e_i^1, e_i^2)||\bar{p}_v(e_i^1, e_i^2))\,,$$

$$\mathcal{L}_2 = \mathcal{L}_{KL} + \mathcal{L}_{Re}^{vis} + \mathcal{L}_{Re}^{hyb} + \mathcal{L}_{Sim}\,.$$

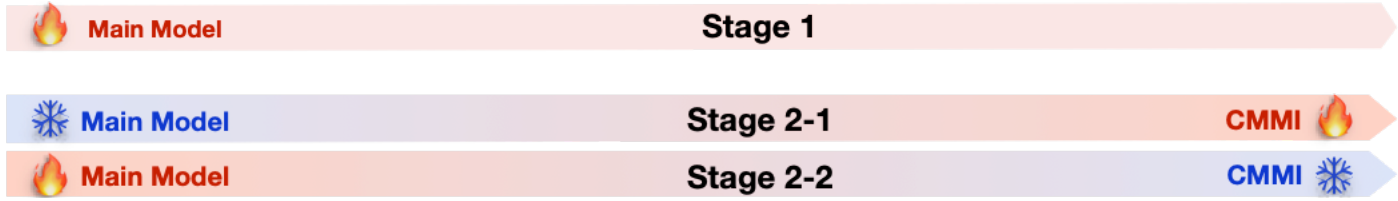




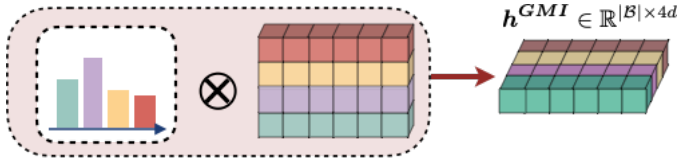
Training Details

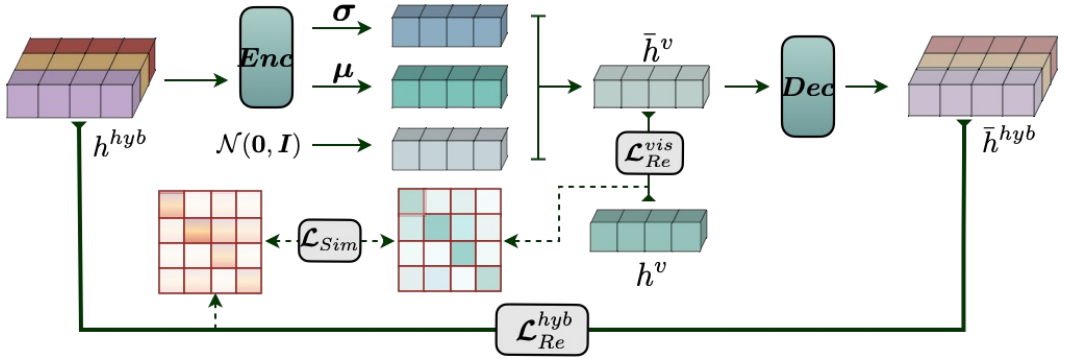
- **Pipeline:**

$$Stage\ 1 : \mathcal{L} \leftarrow \mathcal{L}_1\ ,$$
$$Stage\ 2\text{-}1/2\text{-}2 : \mathcal{L} \leftarrow \mathcal{L}_1 + \mathcal{L}_2\ ,$$



- **Entity Representation:**
  - ***For those entities without images:***
    - ***Evaluation****: replace the original random vectors with the generated* μ_i
    - ***Training****: pseudo-visual embedding* $\bar{h}_i^v$
  - *Final multi-modal entity representation:* h_i^{GMI}





Experiments

◎ Iterative Training

- *Concretely, every K_e (where K_e = 5) epochs, we propose cross-KG entity pairs that are **mutual nearest neighbors** in the vector space and add them to a **candidate list** N_{cd}*
- *An entity pair in N_{cd} will be added into the training set if it **remains a mutual nearest neighbor** for K_s (= 10) consecutive rounds.*

Main Experiments

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- **Non-iter. Results on Bilingual Datasets**

	Models	$R_{img}=0.05$ H@1	H@10	MRR	$R_{img}=0.2$ H@1	H@10	MRR	$R_{img}=0.4$ H@1	H@10	MRR	$R_{img}=0.6$ H@1	H@10	MRR
DBP15K$_{ZH-EN}$	MSNEA [7]	.413	.722	.517	.411	.725	.518	.446	.743	.546	.520	.786	.611
	EVA [30]	.623	.878	.715	.624	.878	.716	.623	.875	.714	.625	.876	.717
	MCLEA [29]	.638	.905	.732	.588	.865	.686	.611	.874	.704	.661	.896	.744
	w/o CMMI	.703	.934	.787	.710	.937	.793	.721	.939	.801	.753	.949	.825
	UMAEA	**.720**	**.938**	**.800**	**.727**	**.941**	**.806**	**.727**	**.941**	**.806**	**.758**	**.951**	**.829**
	Improve ↑	8.2%	3.3%	.068	10.3%	6.3%	.090	10.4%	6.6%	.092	9.7%	5.5%	.085
DBP15K$_{JA-EN}$	MSNEA [7]	.313	.643	.425	.311	.644	.422	.369	.678	.472	.480	.744	.569
	EVA [30]	.615	.877	.708	.616	.877	.710	.616	.878	.711	.624	.881	.716
	MCLEA [29]	.599	.897	.706	.579	.846	.675	.613	.867	.703	.686	.898	.761
	w/o CMMI	.708	.943	.794	.712	.947	.798	.730	.950	.810	.772	.962	.843
	UMAEA	**.725**	**.949**	**.807**	**.726**	**.949**	**.808**	**.732**	**.952**	**.813**	**.775**	**.963**	**.845**
	Improve ↑	11.0%	5.2%	.099	11.0%	7.2%	.098	11.6%	7.4%	.102	8.9%	6.5%	.084
DBP15K$_{FR-EN}$	MSNEA [7]	.297	.690	.427	.304	.690	.428	.360	.710	.474	.478	.772	.574
	EVA [30]	.624	.895	.720	.624	.895	.720	.626	.898	.721	.634	.900	.728
	MCLEA [29]	.634	.930	.741	.582	.863	.682	.601	.879	.702	.675	.901	.757
	w/o CMMI	.727	.956	.813	.733	.960	.817	.746	.961	.828	.790	.968	.857
	UMAEA	**.752**	**.970**	**.830**	**.755**	**.960**	**.832**	**.763**	**.962**	**.838**	**.792**	**.970**	**.859**
	Improve ↑	11.8%	4.0%	.089	13.1%	6.7%	.112	13.7%	6.4%	.117	11.7%	6.9%	.102

	Models	$R_{img}=0.05$ H@1	H@10	MRR	$R_{img}=0.2$ H@1	H@10	MRR	$R_{img}=0.4$ H@1	H@10	MRR	$R_{img}=0.6$ H@1	H@10	MRR
OpenEA$_{EN-FR}$	MSNEA [7]	.200	.431	.278	.213	.439	.290	.260	.477	.334	.360	.560	.427
	EVA [30]	.528	.833	.634	.533	.835	.638	.539	.835	.642	.547	.830	.647
	MCLEA [29]	.545	.852	.653	.547	.852	.655	.531	.839	.637	.597	.852	.688
	w/o CMMI	.587	.893	.695	.590	.893	.697	.614	**.900**	.715	.664	.912	.753
	UMAEA	**.605**	**.898**	**.708**	**.604**	**.896**	**.708**	**.618**	.899	**.718**	**.665**	**.914**	**.753**
	Improve ↑	6.0%	4.6%	.055	5.7%	4.4%	.053	7.9%	6.1%	.076	6.8%	6.2%	.065
OpenEA$_{EN-DE}$	MSNEA [7]	.242	.486	.323	.253	.495	.333	.309	.542	.387	.412	.622	.484
	EVA [30]	.717	.917	.787	.718	.918	.788	.721	.920	.791	.734	.921	.800
	MCLEA [29]	.723	.918	.791	.721	.915	.789	.697	.907	.771	.745	.906	.803
	w/o CMMI	.752	.938	.818	.757	.941	.822	.771	.946	.833	**.804**	.954	.858
	UMAEA	**.757**	**.942**	**.823**	**.759**	**.943**	**.824**	**.774**	**.947**	**.835**	**.804**	**.957**	**.860**
	Improve ↑	3.4%	2.4%	.032	3.8%	2.5%	.035	5.3%	2.7%	.044	5.9%	3.6%	.057
OpenEA$_{D-W-V1}$	MSNEA [7]	.238	.452	.31	.254	.465	.326	.318	.514	.385	.432	.601	.490
	EVA [30]	.570	.801	.653	.575	.806	.658	.567	.797	.650	.595	.811	.673
	MCLEA [29]	.585	.834	.675	.574	.824	.663	.581	.813	.665	.655	.848	.726
	w/o CMMI	.640	.879	.727	.644	.882	.730	.667	.891	.749	.722	**.908**	.790
	UMAEA	**.647**	**.881**	**.733**	**.649**	**.882**	**.735**	**.669**	**.892**	**.750**	**.724**	**.908**	**.791**
	Improve ↑	6.2%	4.7%	.058	7.4%	5.8%	.072	8.8%	7.9%	.085	6.9%	6.0%	.065
OpenEA$_{D-W-V2}$	MSNEA [7]	.397	.690	.497	.405	.695	.503	.454	.727	.546	.545	.781	.626
	EVA [30]	.775	.952	.839	.767	.947	.832	.773	.950	.837	.788	.954	.848
	MCLEA [29]	.771	.965	.842	.753	.957	.827	.757	.935	.822	.800	.948	.855
	w/o CMMI	.828	.983	.883	.829	**.982**	.885	**.844**	**.984**	**.896**	.857	.986	**.905**
	UMAEA	**.840**	**.984**	**.890**	**.832**	**.982**	**.887**	**.844**	**.984**	**.896**	**.859**	**.987**	**.905**
	Improve ↑	6.5%	1.9%	.048	6.5%	2.5%	.055	7.1%	3.4%	.059	5.9%	3.3%	.050

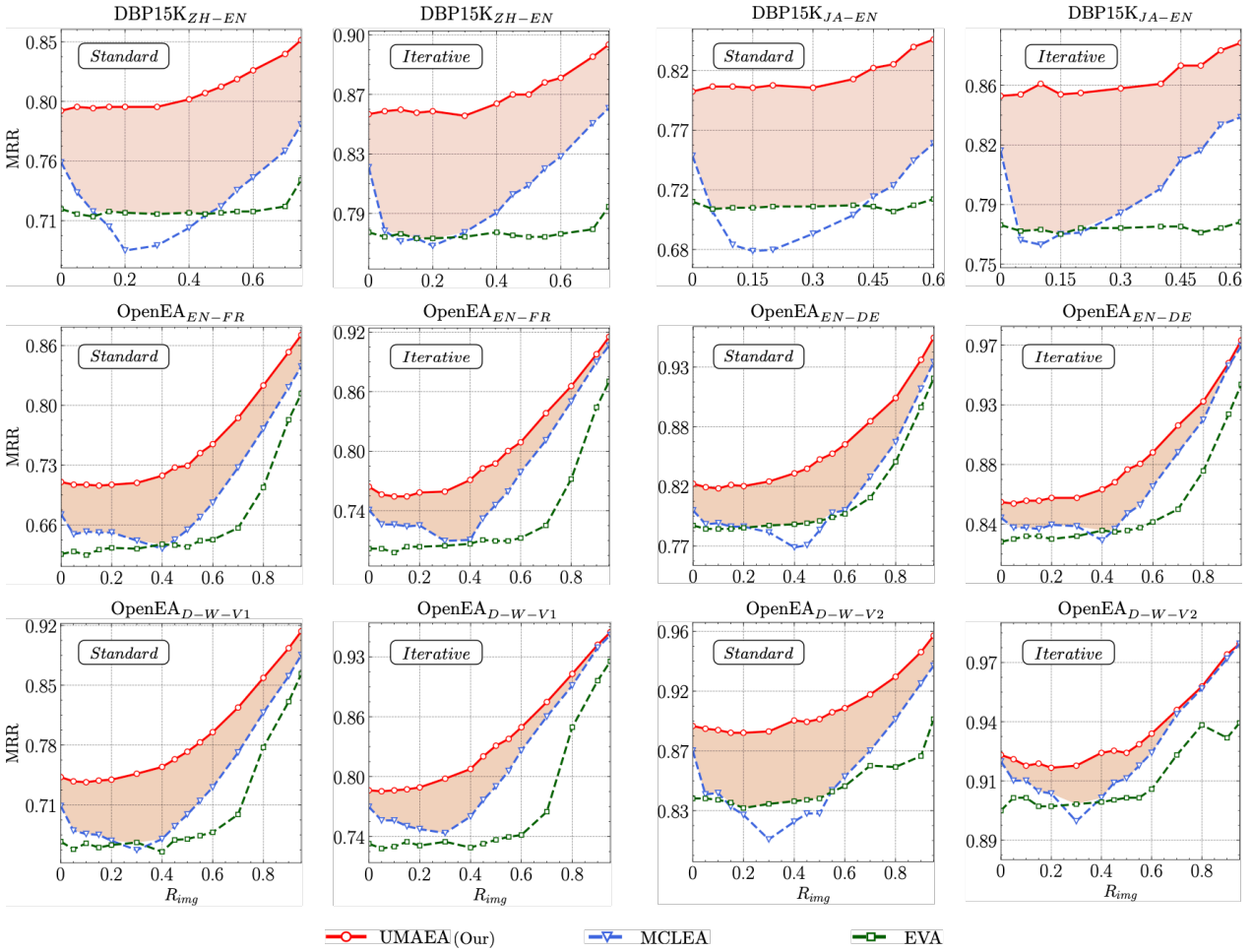
➢ *Non-iterative results of four models with "w/o CMMI" setting indicating the absence of the Stage-2. The best results within the baselines are marked with underline, and we highlight our results with **bold** when we achieve SOTA.*

Main Experiments

- **Model Overall Performance**

  - *Existing models exhibit performance oscillations (EVA) or declines (MCLEA) at higher modality missing*
    - *Introducing images for half of the entities means that the remaining half may become noise*

  - *Our method can gain benefits with fewer visual modality data in entity.*
    - *Less oscillation and greater robustness than other methods*



Main Experiments

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- **Complete Visual Modality**
  - *Prove the robustness of the models against ambiguous images*

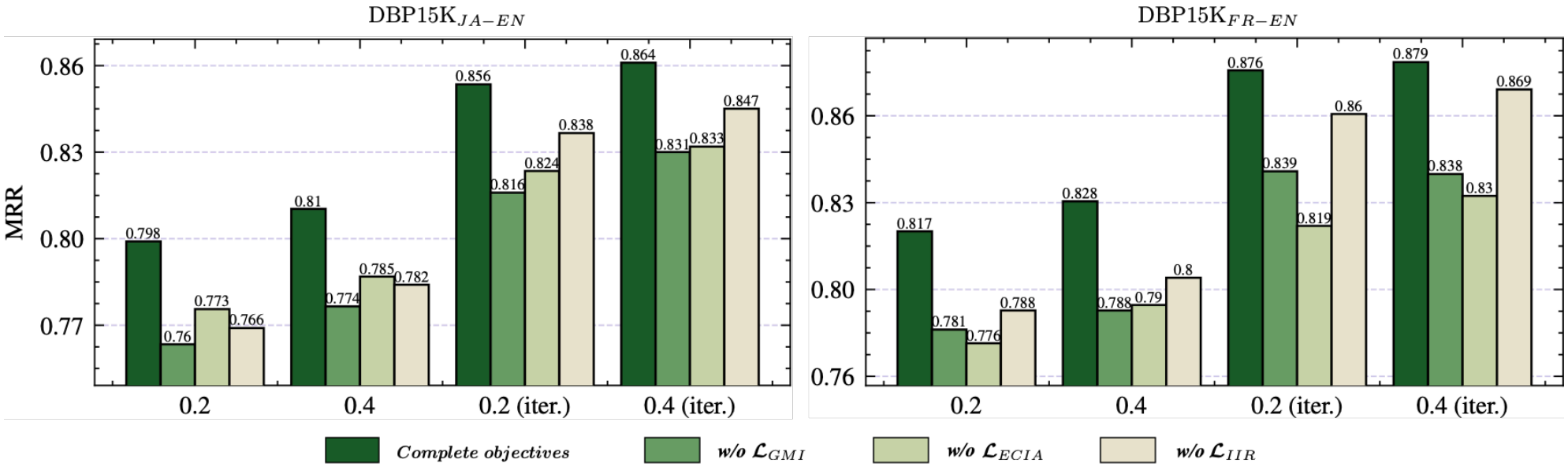
	Models	DBP15K$_{ZH-EN}$			DBP15K$_{JA-EN}$			DBP15K$_{FR-EN}$		
		H@1	H@10	MRR	H@1	H@10	MRR	H@1	H@10	MRR
Non-iter.	AlignEA [39]	.472	.792	.581	.448	.789	.563	.481	.824	.599
	KECG [27]	.478	.835	.598	.490	.844	.610	.486	.851	.610
	MUGNN [3]	.494	.844	.611	.501	.857	.621	.495	.870	.621
	AliNet [41]	.539	.826	.628	.549	.831	.645	.552	.852	.657
	MSNEA* [7]	.609	.831	.685	.541	.776	.620	.557	.820	.643
	EVA* [30]	.683	.906	.762	.669	.904	.752	.686	.928	.771
	MCLEA* [29]	.726	.922	.796	.719	.915	.789	.719	.918	.792
	UMAEA*	**.800**	**.962**	**.860**	**.801**	**.967**	**.862**	**.818**	**.973**	**.877**
	w/o IMG	**.718**	**.930**	**.797**	**.723**	**.941**	**.803**	**.748**	**.956**	**.826**
Iter.	BootEA [39]	.629	.847	.703	.622	.854	.701	.653	.874	.731
	NAEA [62]	.650	.867	.720	.641	.873	.718	.673	.894	.752
	MSNEA* [7]	.648	.881	.728	.557	.804	.643	.583	.848	.672
	EVA* [30]	.750	.912	.810	.741	.921	.807	.765	.944	.831
	MCLEA* [29]	.811	.957	.865	.805	.958	.863	.808	.963	.867
	UMAEA*	**.856**	**.974**	**.900**	**.857**	**.980**	**.904**	**.873**	**.988**	**.917**
	w/o IMG	**.793**	**.952**	**.852**	**.794**	**.960**	**.857**	**.820**	**.976**	**.880**

	Models	OpenEA$_{EN-FR}$			OpenEA$_{EN-DE}$			OpenEA$_{D-W-V1}$			OpenEA$_{D-W-V2}$		
		H@1	H@10	MRR	H@1	H@10	MRR	H@1	H@10	MRR	H@1	H@10	MRR
Non-iter.	MSNEA* [7]	.692	.813	.734	.753	.895	.804	.800	.874	.826	.838	.940	.873
	EVA* [30]	.785	.932	.836	.922	.983	.945	.858	.946	.891	.890	.981	.922
	MCLEA* [29]	.819	.943	.864	.939	.988	.957	.881	.955	.908	.928	.983	.949
	UMAEA*	**.848**	**.966**	**.891**	**.956**	**.994**	**.971**	**.904**	**.971**	**.930**	**.948**	**.996**	**.967**
Iter.	MSNEA* [7]	.699	.823	.742	.788	.917	.835	.809	.885	.836	.862	.954	.894
	EVA* [30]	.849	.974	.896	.956	.985	.968	.915	.986	.942	.925	.996	.951
	MCLEA* [29]	.888	.979	.924	.969	.993	.979	.944	.989	.963	.969	.997	.982
	UMAEA*	**.895**	**.987**	**.931**	**.974**	**998**	**.984**	**.945**	**.994**	**.965**	**.973**	**.999**	**.984**

➢ *Non-iterative (Non-iter.) and iterative (Iter.) results on seven MMEA datasets (complete version), where " * " refers to involving the visual information for EA. The DBP15K dataset (left table) only has part of the entities with images attached (e.g., 78.29% in DBP15K$_{ZH-EN}$, 70.32% in DBP15K$_{FR-EN}$, and 67.58% in DBP15K$_{JA-EN}$)*

Experiments: Details Analysis

- **Component Analysis**



- *IIR serves as an enhancement for ECIA, and its influence is comparatively less significant than that of GMI and ECIA*

Experiments: Details Analysis

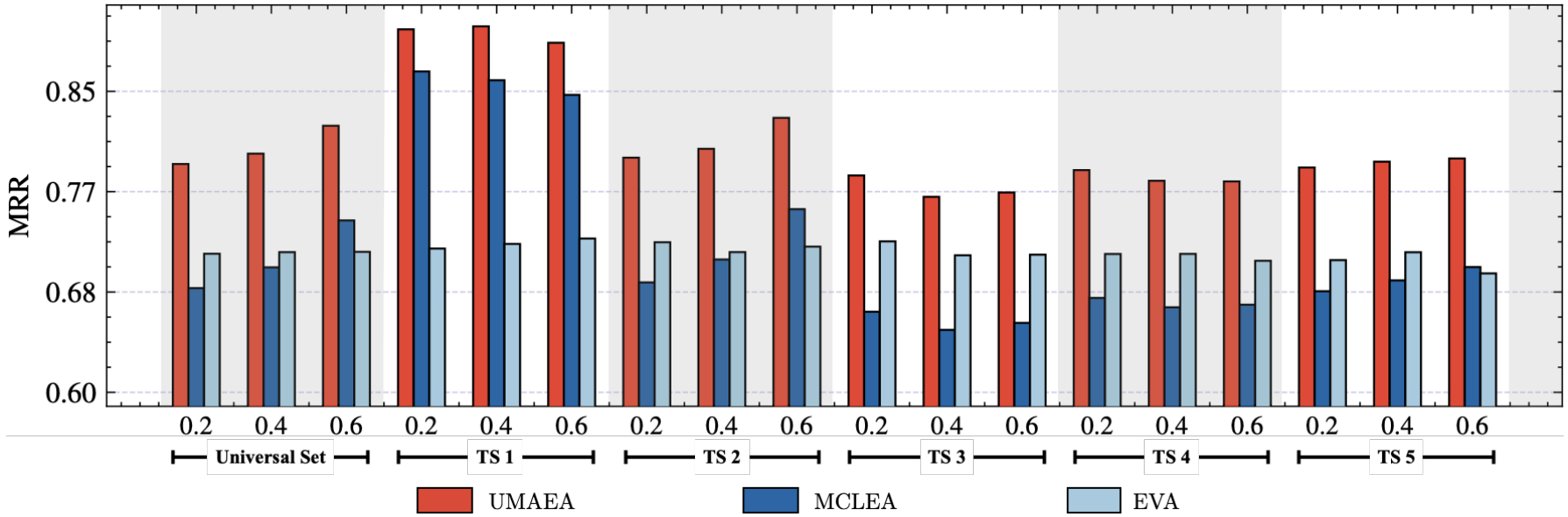
- **Efficiency Analysis**

Models	DBP15K_{JA-EN}			DBP15K_{FR-EN}			OpenEA_{EN-FR}		
	Para. (M)	Time (Min)	MRR	Para. (M)	Time (Min)	MRR	Para. (M)	Time (Min)	MRR
EVA* [30]	13.27	30.9	.711	13.29	30.8	.721	9.81	17.8	.642
MCLEA* [29]	13.22	15.3	.703	13.24	15.7	.702	9.75	19.5	.637
w/o CMMI	13.82	30.2	.810	13.83	28.8	.828	10.35	17.9	.715
UMAEA	14.72	33.4	.813	14.74	32.7	.838	11.26	23.1	.718

- *Relationship between model parameter size (Para.), training time (Time), and performance (MRR)*
- *UMAEA improves the performance with only a minor increase in parameters and time consumption*

Experiments: Details Analysis

- **Entity Distribution Analysis**



- *Models (EVA) succumb to **overfitting noise** during training*
- *Models (MCLEA) exhibit performance **oscillations or even declines** at high missing modality rates*

➢ *EA prediction distribution analysis on DBP15K ZH–EN(non-iterative), with $R_{img} \in \{0.2, 0.4, 0.6\}$. "TS" denotes the testing set, where:*

- *TS 1 (both entities in an alignment pair have images);*
- *TS 2 (at least one entity in an alignment pair has images);*
- *TS 3 (only one entity in an alignment pair has images);*
- *TS 4 (at least one entity in an alignment pair loss images);*
- *TS 5 (neither entity in an alignment pair has images).*

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Thank you!

https://github.com/zjukg/UMAEA

Rethinking Uncertainly Missing and Ambiguous Visual Modality in Multi-Modal Entity Alignment

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