Multi-perspective Improvement of Knowledge Graph Completion with Large Language Models

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Knowledge Graph Completion

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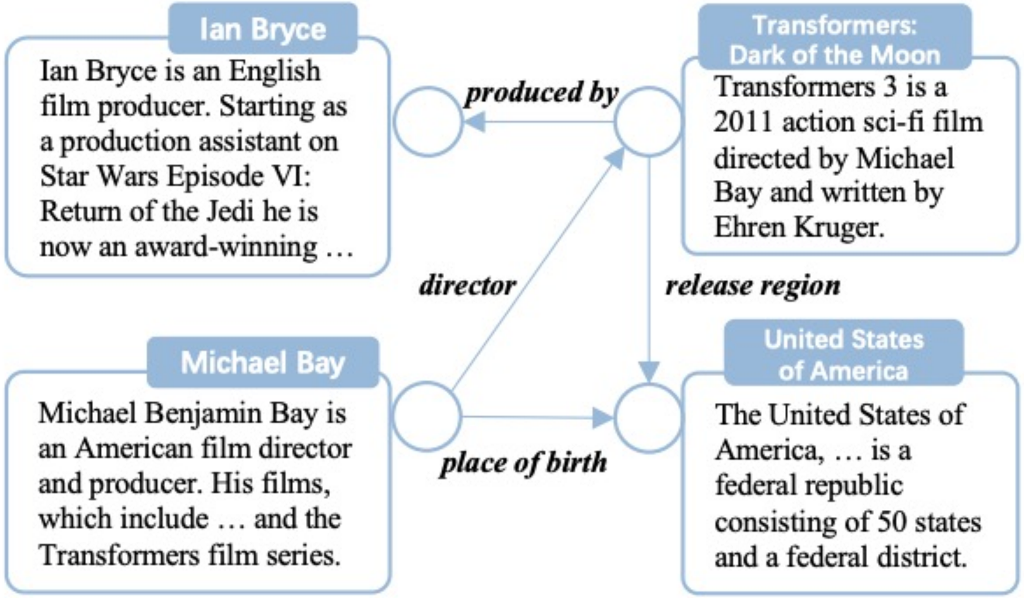
- **Knowledge Graph Completion (KGC):**
  - Predict missing links to address the incompleteness of knowledge graphs.
- **Challenges**: Limitations in text quality and incomplete graph structures.
  - Lack sufficient entity descriptions.
  - Rely solely on relationship names, resulting in a shallow understanding of relationship semantics.
  - Lack of structural information contained within long-tail entities leads to suboptimal results.

How to leverage the capabilities of LLMs to improve the graph learning?



MPIKGC

- **Approach**: We propose a general enhancement framework that addresses the limitations of contextual knowledge by leveraging multiple perspectives through querying LLMs.
- **MPIKGC-E**: Expanding entity descriptions using the reasoning capabilities of LLMs.
- **MPIKGC-R**: Understanding relationship semantics by leveraging the interpretive abilities of LLMs.
- **MPIKGC-S**: Enhancing structural information through the summarization capabilities of LLMs.

Strategies	Templates
MPIKGC-E	Please provide all information about {Entity Name}. Give the rationale before answering:
MPIKGC-R Global	Please provide an explanation of the significance of the relation {Relation Name} in a knowledge graph with one sentence:
MPIKGC-R Local	Please provide an explanation of the meaning of the triplet (head entity, {Relation Name}, tail entity) and rephrase it into a sentence:
MPIKGC-R Reverse	Please convert the relation {Relation Name} into a verb form and provide a statement in the passive voice:
MPIKGC-S	Please extract the five most representative keywords from the following text: {Entity Description}. Keywords:

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- **MPIKGC-E**:
  - Design a Chain-of-Thought (CoT) prompt strategy, that enables LLMs to break down complex queries into different directions and generate descriptions step-by-step.
  - Instructs LLMs to implicitly query relevant information on their own, resulting in more efficient and extensive responses.

Strategies	Templates
MPIKGC-E	Please provide all information about {Entity Name}. Give the rationale before answering:

MPIKGC

- **MPIKGC-R**:
  - **Global**: aims to deduce the significance of a relation from the perspective of the entire KG, thereby facilitating better association between two relations
  - **Local**: intends to infer the relation's meaning from the triplet perspective, thereby enhancing comprehension and suggesting possible types of head/tail entities while predicting missing facts
  - **Reverse**: entails LLMs to represent relations as verbs, and convert them to the passive voice

MPIKGC-R Global	Please provide an explanation of the significance of the relation {Relation Name} in a knowledge graph with one sentence:
MPIKGC-R Local	Please provide an explanation of the meaning of the triplet (head entity, {Relation Name}, tail entity) and rephrase it into a sentence:
MPIKGC-R Reverse	Please convert the relation {Relation Name} into a verb form and provide a statement in the passive voice:

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- **MPIKGC-S**:

To convert the LLMs generative text into graph-based data, we utilize the summarizing capability of LLMs to extract relevant keywords from description, then calculate a matching score s between entities keywork:

$$s = len(m)/min(len(k_h), len(k_t)),$$
$$m = intersection(k_h, k_t),$$

where k_h and k_t denote the keywords of head/tail entities, respectively, and m is the intersection of k_h and k_t .

MPIKGC-S	Please extract the five most representative keywords from the following text: {Entity Description}. Keywords:

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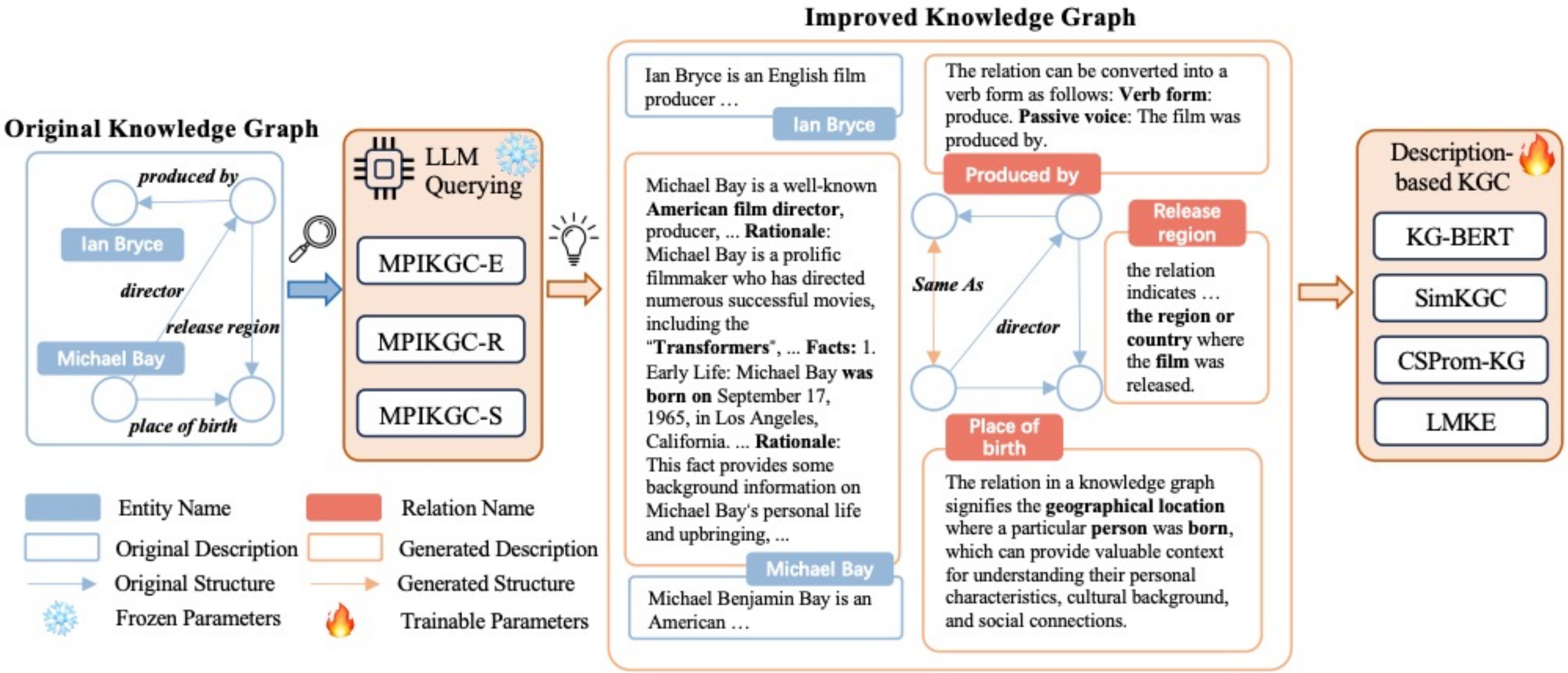
➢ The enhanced KG obtained through the aforementioned techniques is utilized in multiple KGC models to improve the performance of link prediction and triple classification tasks.



Link Prediction results

- Experimental results demonstrate that this enhancement approach improves the performance of multiple KGC models.

Models	FB15k237					WN18RR				
	MR↓	MRR↑	H@1↑	H@3↑	H@10↑	MR↓	MRR↑	H@1↑	H@3↑	H@10↑
Structure-based Approaches										
TransE (Bordes et al., 2013)	323	27.9	19.8	37.6	44.1	2300	24.3	4.3	44.1	53.2
DistMult (Yang et al., 2014)	512	28.1	19.9	30.1	44.6	7000	44.4	41.2	47.0	50.4
ConvE (Dettmers et al., 2018)	245	31.2	22.5	34.1	49.7	4464	45.6	41.9	47.0	53.1
RotatE (Sun et al., 2019)	177	33.8	24.1	37.5	53.3	3340	47.6	42.8	49.2	57.1
ATTH (Chami et al., 2020)	-	34.8	25.2	38.4	54.0	-	48.6	44.3	49.9	57.3
Description-based Approaches										
CSProm-KG (Chen et al., 2023)	188	35.23	26.05	38.72	53.57	545	**55.10**	**50.14**	**57.04**	64.41
+MPIKGC-E	195	35.51	26.38	38.96	53.74	1244	53.80	49.19	55.65	62.81
+MPIKGC-R	192	35.38	26.29	38.83	53.50	838	53.90	49.35	55.74	62.36
+MPIKGC-S	**179**	**35.95**	**26.71**	**39.52**	**54.30**	**528**	54.89	49.65	56.75	**65.24**
LMKE (Wang et al., 2022b)	**135**	30.31	21.49	33.02	48.07	**54**	55.78	42.91	64.61	79.28
+MPIKGC-E	138	30.83	21.89	33.67	48.75	57	56.35	43.27	65.54	**79.53**
+MPIKGC-R	145	**30.99**	**22.21**	**33.70**	48.83	59	**57.60**	**45.10**	**65.95**	79.35
+MPIKGC-S	**135**	30.68	21.67	33.35	**48.91**	70	50.71	36.91	59.65	76.13
SimKGC (Wang et al., 2022a)	146	32.66	24.13	35.42	49.65	148	65.64	57.08	71.20	80.33
+MPIKGC-E	**143**	33.01	24.37	35.80	50.29	**124**	65.64	57.10	71.09	80.41
+MPIKGC-R	156	31.05	22.63	33.62	47.65	129	**66.41**	**57.90**	**72.08**	**81.47**
+MPIKGC-S	**143**	**33.22**	**24.49**	**36.26**	**50.94**	170	61.48	52.81	66.77	76.94

Triplet classification results

➢ The overall results indicate our framework can enhance the performance of various KGC models in both link prediction and triplet classification tasks.

Models	FB13	WN11
Structure-based Approaches		
TransE (Bordes et al., 2013)	81.5	75.9
DistMult (Yang et al., 2014)	86.2	87.1
ConvKB (Nguyen et al., 2018)	88.8	87.6
Description-based Approaches		
KG-BERT (Yao et al., 2019)	84.74	93.34
+MPIKGC-E	**86.29**	**94.13**
+MPIKGC-R	84.51	93.36
+MPIKGC-S	85.35	93.61
LMKE (Wang et al., 2022b)	91.70	93.71
+MPIKGC-E	91.52	93.84
+MPIKGC-R	91.49	**93.93**
+MPIKGC-S	**91.81**	93.91

Ablation Study

➢ Ablation of Multi-perspective Prompts.

Models	FB15k237			
	MRR	H@1	H@3	H@10
LMKE	30.31	21.49	33.02	48.07
+MPIKGC-E	30.71	21.97	33.29	48.35
+MPIKGC-R	30.64	21.70	33.22	48.74
+MPIKGC-S	30.68	21.67	33.35	48.91
+MPIKGC-E&R	30.74	21.77	33.57	48.77
+MPIKGC-E&S	30.92	21.85	33.67	**49.50**
+MPIKGC-R&S	**31.21**	**22.26**	33.86	49.42
+MPIKGC-E&R&S	30.97	21.91	**33.90**	49.28

Table 5: Ablation of augmentation methods from different perspectives.

Parameter Analysis

➢ Analysis of hype-parameter k and the self-loop setting on FB15k237

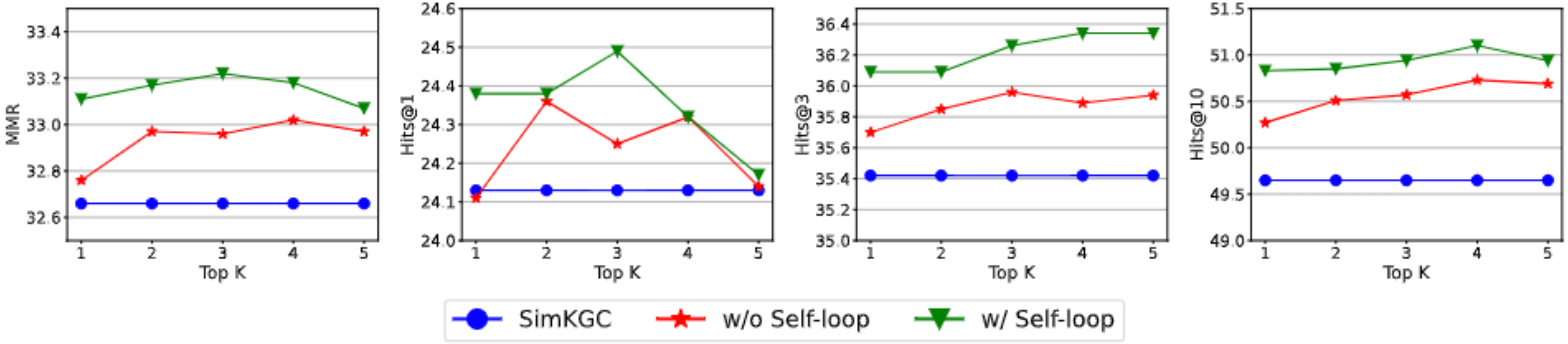


Figure 3: Analysis of hype-parameter k and the self-loop setting on FB15k237.

Ablation of Relation Understanding

- Combine MPIKGC-R Global & Local & Reverse

Models	WN18RR			
	MRR	H@1	H@3	H@10
SimKGC	65.64	57.08	71.20	80.33
+MPIKGC-R Global	66.41	57.90	**72.08**	81.47
+MPIKGC-R Local	64.45	54.87	70.65	**81.57**
+MPIKGC-R Reverse	66.53	59.28	70.72	80.09
+MPIKGC-R G&L	**66.97**	**59.88**	70.82	79.77
+MPIKGC-R G&R	65.56	57.00	70.98	80.90
+MPIKGC-R L&R	65.75	57.36	71.03	80.06
+MPIKGC-R G&L&R	65.85	57.47	70.98	80.64

Table 6: Ablation of different relation understanding strategies and combinations on WN18RR.

Comparison of LLMs

- Different LLMs as backbone for Data Augmentation

Models	FB15k237			
	MRR	H@1	H@3	H@10
LMKE	30.31	21.49	33.02	48.07
+MPIKGC-E (Llama-2)	30.56	21.62	33.47	48.15
+MPIKGC-E (ChatGLM2)	**30.83**	**21.89**	**33.67**	**48.75**
+MPIKGC-R (Llama-2)	30.64	21.70	33.22	48.74
+MPIKGC-R (ChatGLM2)	30.24	21.33	32.96	48.27
+MPIKGC-R (ChatGPT)	30.65	21.82	33.24	48.52
+MPIKGC-R (GPT4)	**30.99**	**22.21**	**33.70**	**48.83**
+MPIKGC-S (Llama-2)	30.68	21.67	33.35	**48.91**
+MPIKGC-S (ChatGLM2)	**31.07**	**22.26**	**33.81**	48.82

Table 7: Ablation of different LLMs on FB15k237.

Conclusion

- MPIKGC:
  - Expanding the entity descriptions by designing Chain-of-Thought prompt
  - Enhancing the understanding of relation by designing global, local, and reverse prompts
  - As well as extracting the structural data via keywords summarization and matching
- Extensive Experiments on four KGC models:
  - Link Prediction
  - Triplet Classification
  - Combination of Multi-perspective Prompts
  - Parameter Analysis
  - Combination of Relation Understanding
  - Comparison of LLMs