LGC-CR: Few-shot Knowledge Graph Completion with Local Global Contrastive Learning and LLM Guided Refinement

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Background

In real-world knowledge graphs, many entities/relations show a long-tail distribution (with very few triples), which is defined as **few-shot problem**.

Long-tail distribution(few-shot KG)

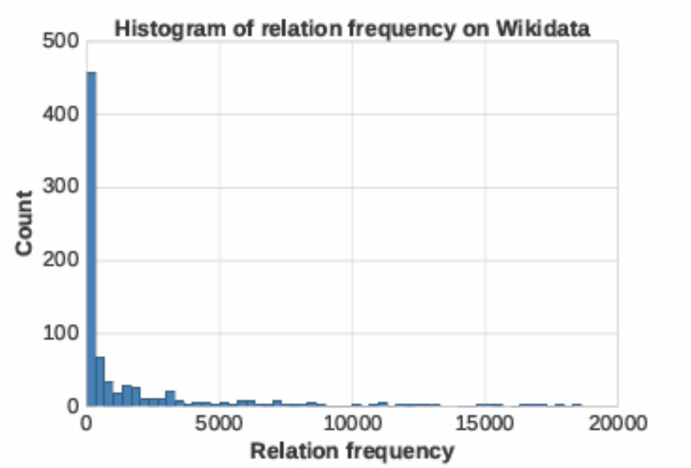
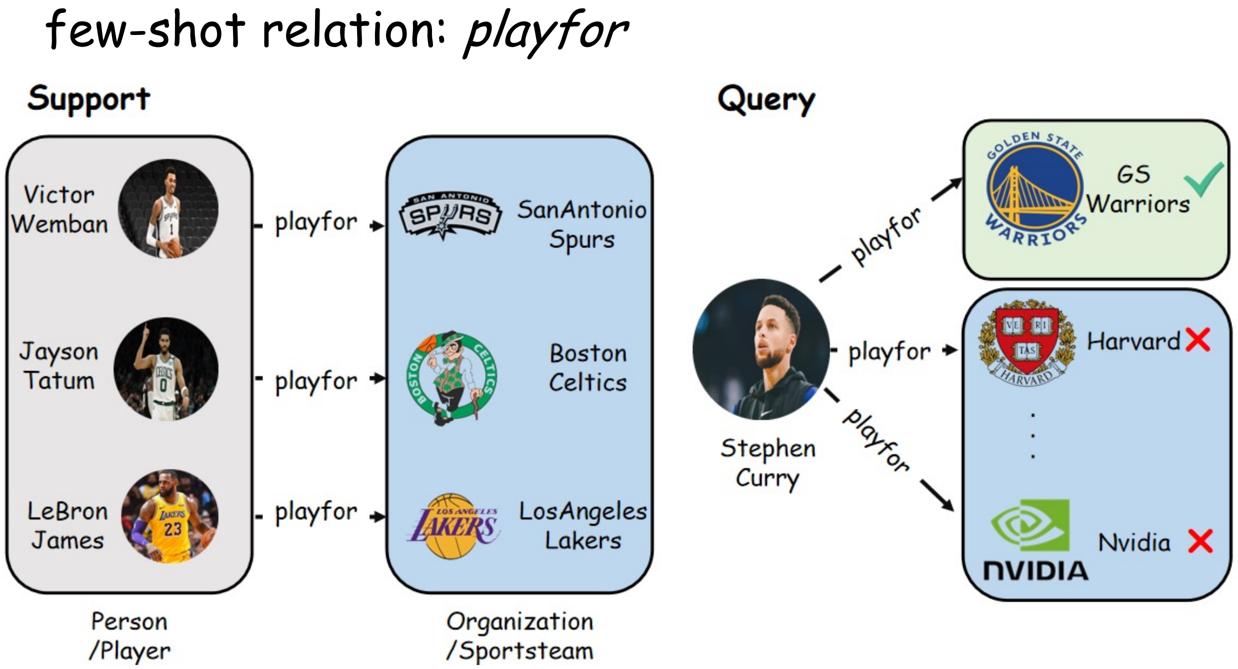


Figure 1: The histogram of relation frequencies in Wikidata. There are a large portion of relations that only have a few triples.

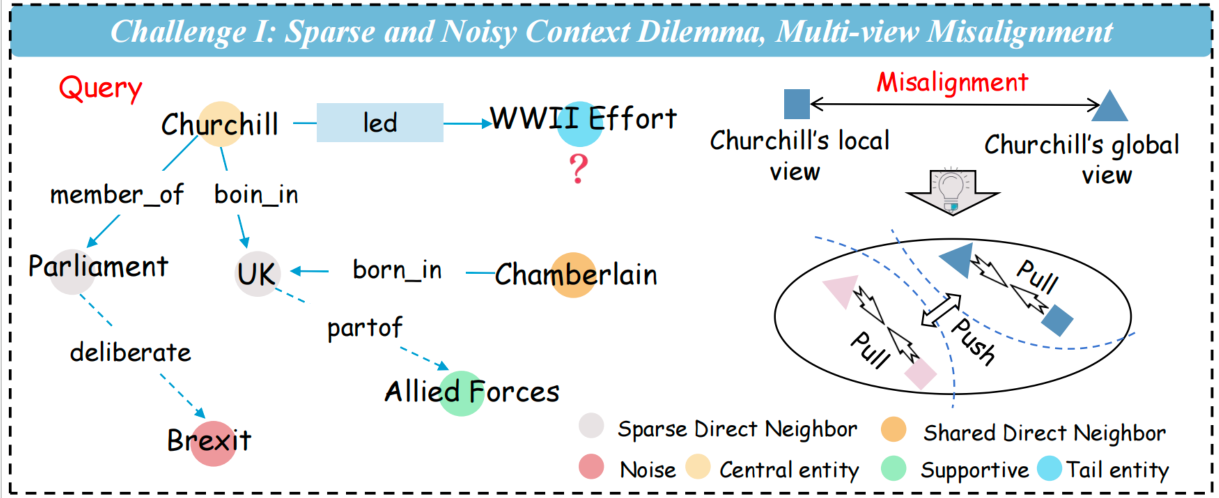
[Xiong, Wenhan and et al. One-shot relational learning for knowledge graphs. EMNLP 2018]

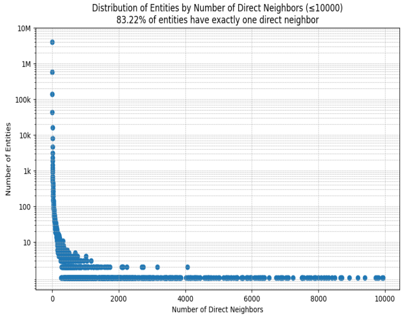
How to effectively achieve knowledge graph completion under few-shot conditions?



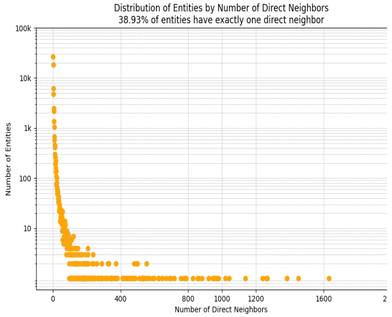
Meta Learning Framework

Motivation

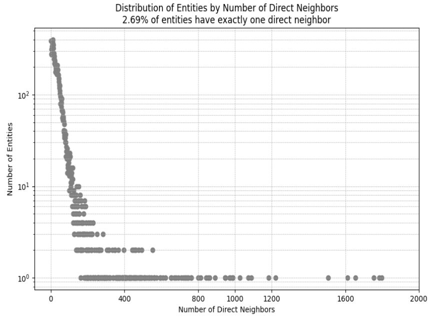




Wikidata



NELL



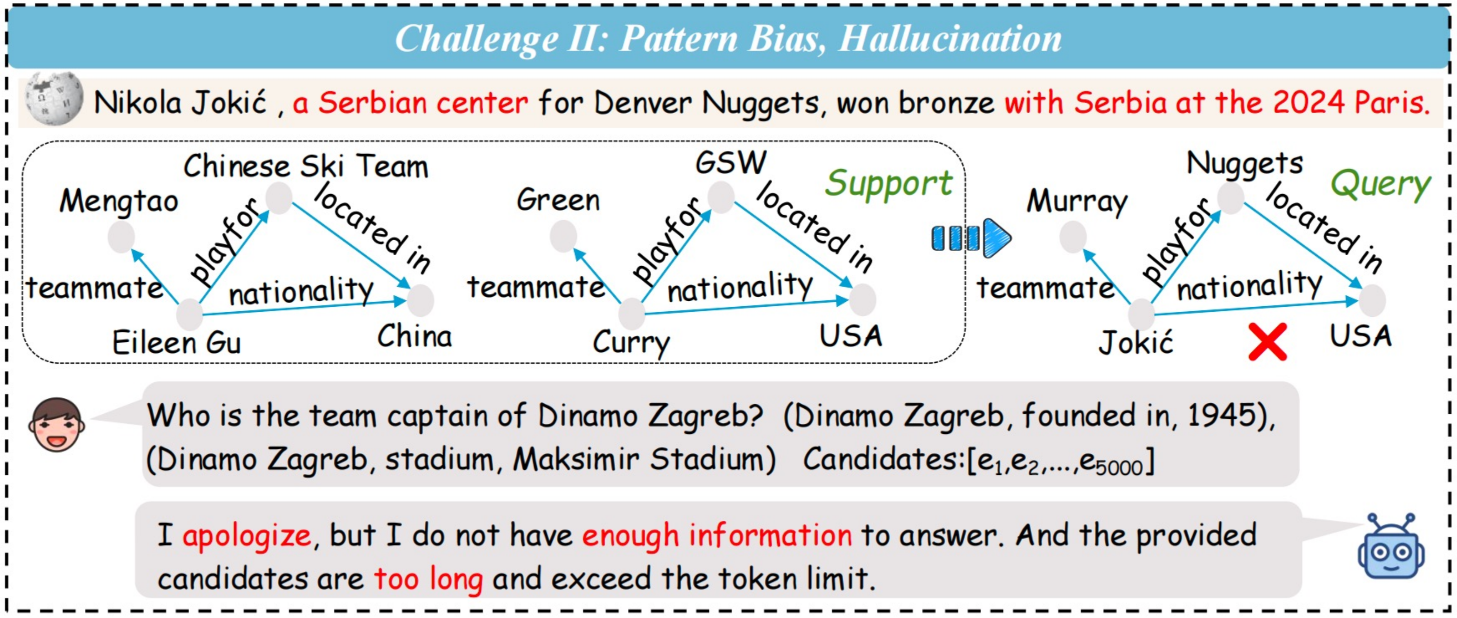
FB15K

Sparse One-hop Neighborhoods!

1. Existing methods over-rely on local neighbors to enhance entity embedding, which struggle to **leverage noisy high-order neighborhoods** and **align multi-view neighbor information**.

Need to Enrich and Align Neighbor Information.

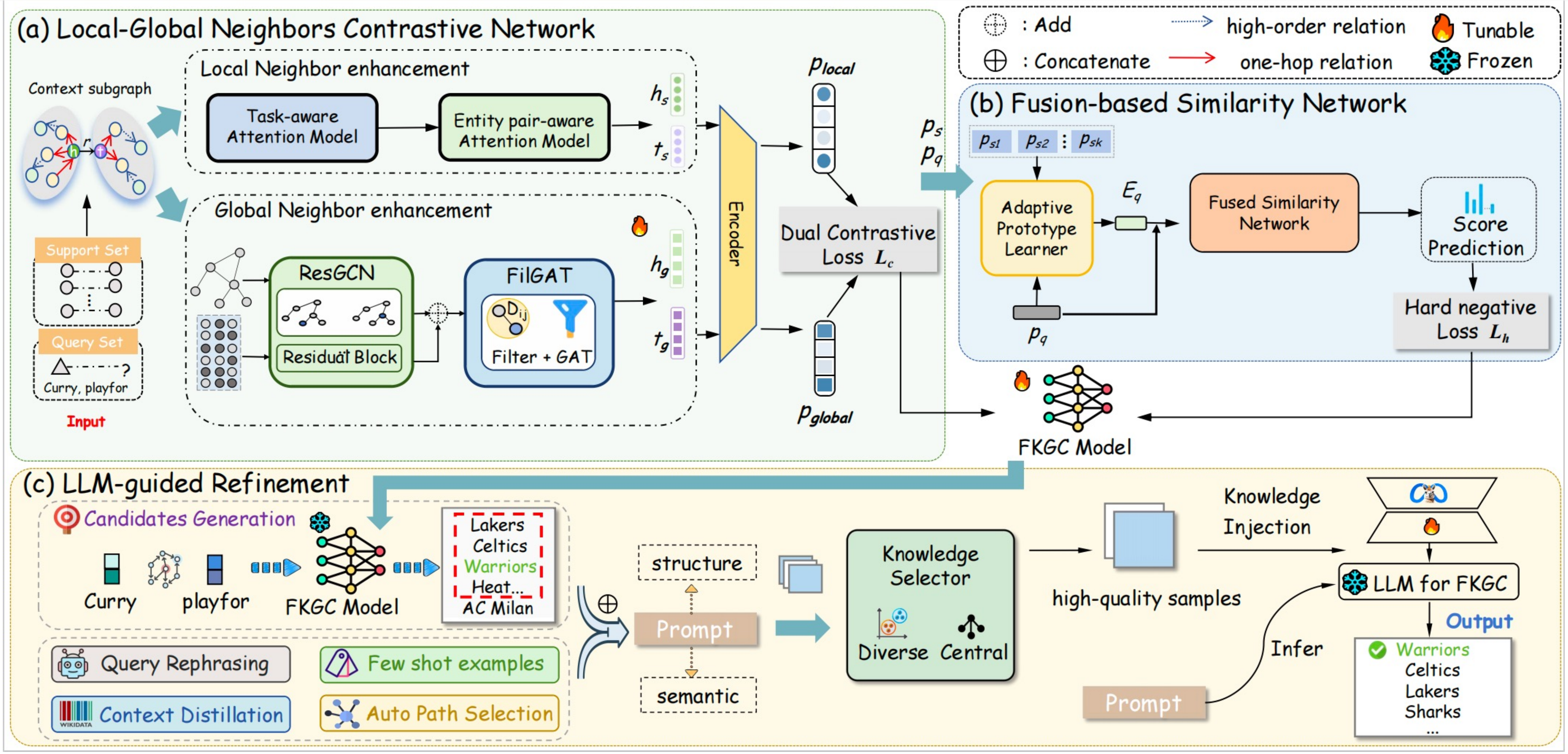
Motivation



2. Embedding-based meta-learning may overfit to **frequent relational patterns** in the support set, while LLMs suffer from **hallucination and input constraints**.

Need more knowledge to Refine the bias.

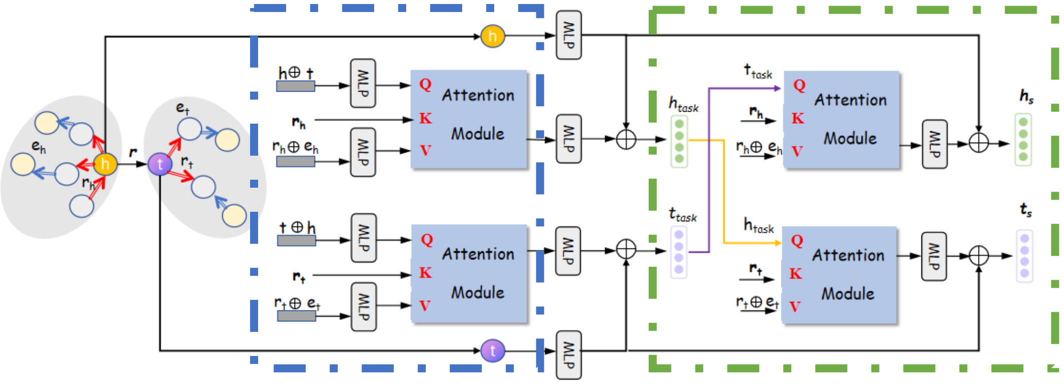
Framework



(a) Local-Global Neighbors Contrastive Network (b) Fusion-based Similarity Network
(c) LLM-guided Refinement

Local-Global Contrastive Network

Cross-Attention Local Enhancement.

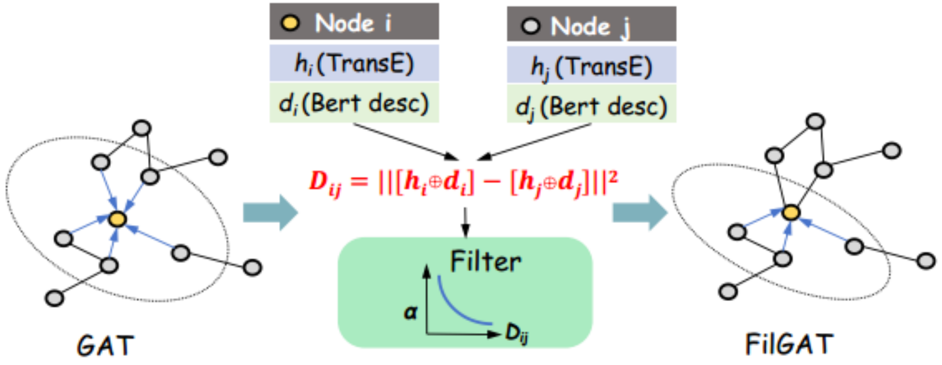


(1)Task-aware (2)Entity pair-aware

(1) Neighbors more task-relevant receive higher weights.

(2) Neighbors more similar to paired entities receive higher weights.

ResGCN-FilGAT Global Enhancement.



ResGCN $$H^{(1)} = \mathrm{ReLU}\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}XW^{(0)}\right) + W^r X,$$

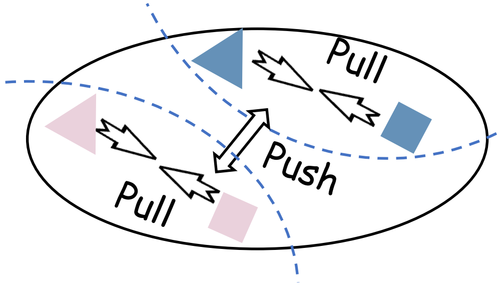
one-hop: stable and comprehensive

FilGAT $$\alpha_{ij} = \frac{o_{ij} \cdot \mathrm{sigmoid}(-\beta D_{ij})}{\sum_{k \in N_i} o_{ik} \cdot \mathrm{sigmoid}(-\beta D_{ik})},$$

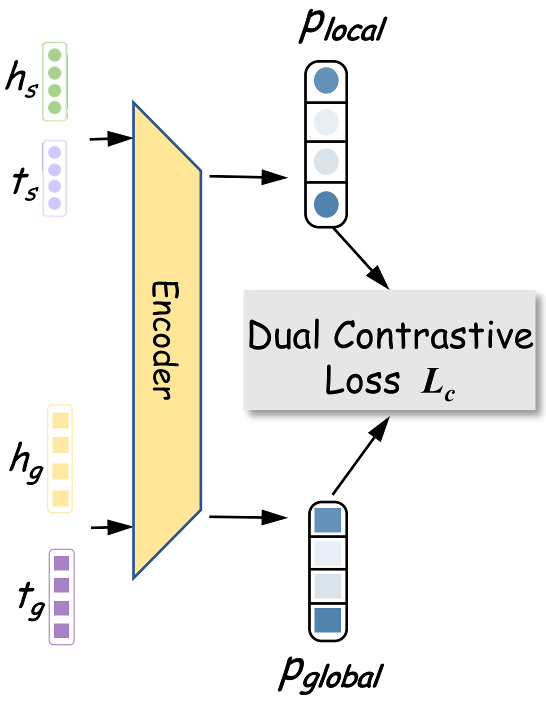
$$H_i^{(2)} = \sum_{j \in N(i)} \alpha_{ij} W^l H_j^{(1)},$$

high-order: Not all neighbors matter: adaptive filtering based on structure-semantic dissimilarity.

Local-Global Contrastive Network



- Local and global neighbors from different views may generate embeddings with **certain gaps**.
- Optimizing from a single perspective (local or global only) may **overfits to noise in the current view**.
- **Maximize local–global neighborhood consistency** for the same entity pair.
- **Interactive alignment**.



□ Project to the same semantic space

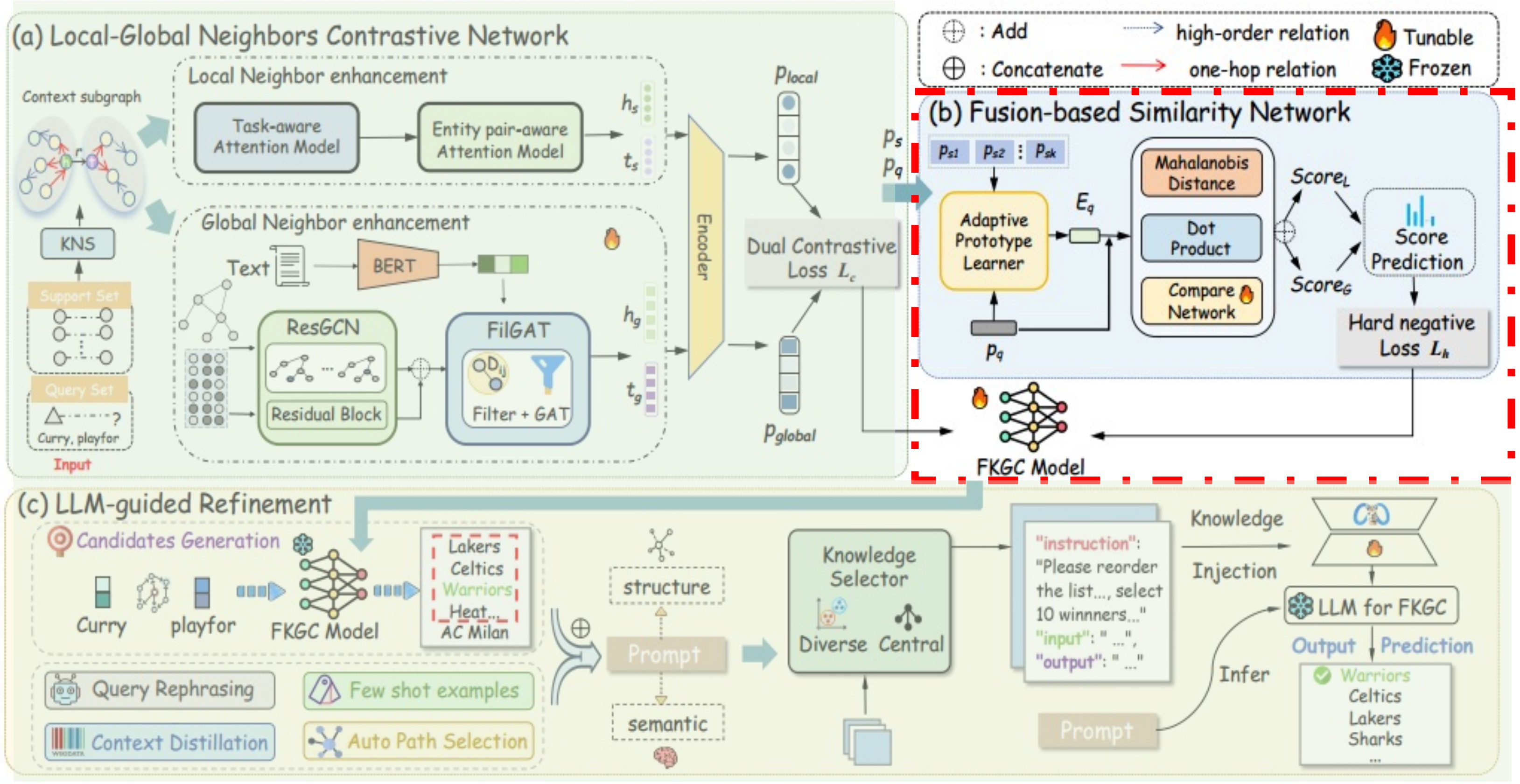
□ Dual Neighbor Contrastive Loss

$$L_{local} = \frac{1}{|Q_r|} \sum_{q \in Q_r} -\log \frac{\exp(sim(p_{local}^{q}, p_{global}^{q})/\tau)}{\sum_i \exp(sim(p_{local}^{q}, p_{global}^{q_i^-})/\tau)}$$

$$L_{global} = \frac{1}{|Q_r|} \sum_{q \in Q_r} -\log \frac{\exp(sim(p_{global}^{q}, p_{local}^{q})/\tau)}{\sum_i \exp(sim(p_{global}^{q}, p_{local}^{q_i^-})/\tau)}$$

$$L_{cl}$$

Fusion based Similiarity Network

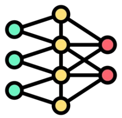


- A fusion similarity network integrates three **complementary similarity metrics**, which constructs a **learnable non-linear** metric space.

- Hard Negative Loss
Instead of treat all negative samples equally, we **focus more on hard negative samples** that are difficult to distinguish during training.

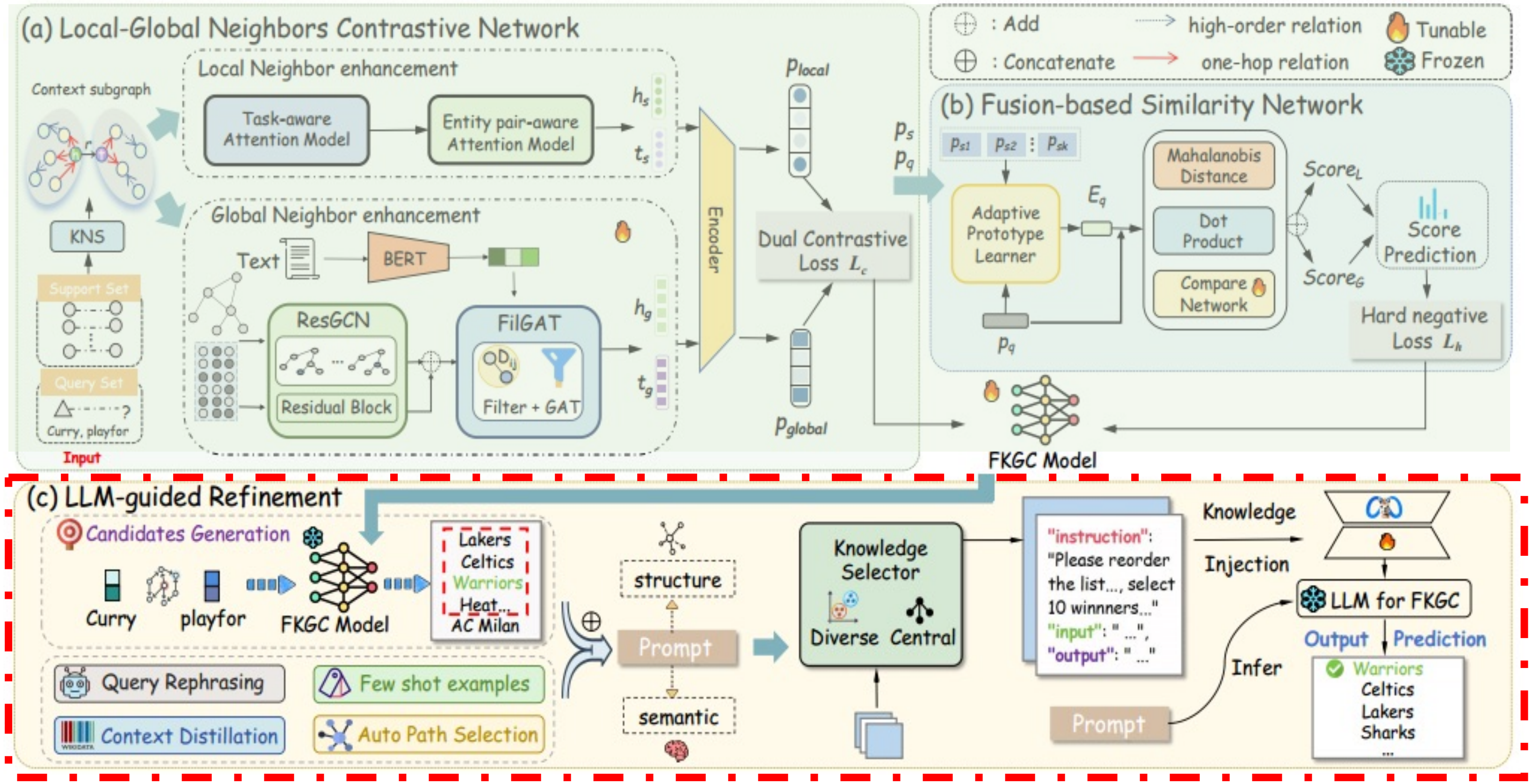
Dual Contrastive Loss

Hard Negative Loss



Optimize FKGC Model

LLM-guided Refinement



- **Instruction Retrieval**

Retrieve query-relevant **structural and semantic knowledge**.

- **Knowledge Selector**

Diversity-aware Sampling: selects **representative relations** covering diverse KG information.

Centrality-aware Sampling: focusing on **high-centrality relations** while avoiding noise.

> Prompt Template

You are an expert in refining initial meta-learning outputs. Please refine the list of tail entities based on the given information, select 10 winnners and output as ent1 | ent2...

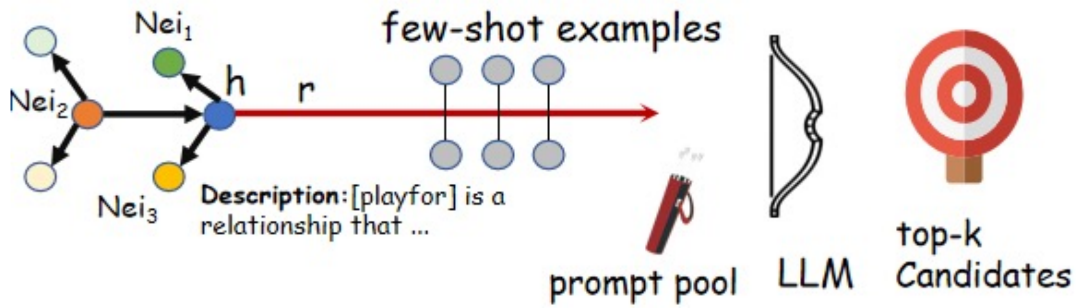
Query: Which team does Curry play for?
What team is Curry currently on?

few-shot examples:
Lebron James, playfor, Lakers...

Entity Des: American basketball....
Relation Des: [playfor] is a relation...

Path triples:
Draymond Green, teammates, Curry
Curry, team_location, San Francisco, venue_of, Chase

top-m entities:
Lakers, Celtics, Warriors, Heat, ...



High quality Facts

Train LLM to Learn Refining efficiently!

Datasets and Settings

Datasets

Datasets	*Entities(E)*	*Triples*	*Relations(R)*	*Task(Train/val/Test)*	*Avg.Description Length (E/R)*
NELL-One	68,545	181,109	358	67(51/5/11)	30.5/10.2
Wiki-One	4,838,244	5,859,240	822	183(133/16/34)	24.7/8.4
FB15K-One	14,478	309,621	237	45(32/8/5)	19.6/7.1

Implementation Details

platform	4 NVIDIA RTX A800 GPUs
base model	Deepseek-R1-Distill-Qwen-14B
fine-tuning approach	LoRA

Experiments

Model	Nell-One MRR 3-shot	Nell-One MRR 5-shot	Nell-One Hit@5 3-shot	Nell-One Hit@5 5-shot	Nell-One Hit@1 3-shot	Nell-One Hit@1 5-shot	Wiki-One MRR 3-shot	Wiki-One MRR 5-shot	Wiki-One Hit@5 3-shot	Wiki-One Hit@5 5-shot	Wiki-One Hit@1 3-shot	Wiki-One Hit@1 5-shot	FB15K-One MRR 5-shot	FB15K-One Hit@5 5-shot	FB15K-One Hit@1 5-shot
GMatching(2018)[37]	-	0.176	-	0.233	-	0.113	-	0.263	-	0.337	-	0.197	0.189	0.274	0.101
MetaR (2019)[4]	0.245	0.261	0.360	0.350	0.144	0.168	0.317	0.323	0.379	0.385	0.261	0.270	0.203	0.291	0.107
FSRL(2020)[40]	0.219	0.195	0.296	0.279	0.139	0.108	0.102	0.113	0.131	0.135	0.050	0.056	0.223	0.364	0.102
FAAN(2020)[30]	0.247	0.279	0.309	0.364	0.183	0.200	0.298	0.341	0.368	0.395	0.228	0.281	0.259	0.424	0.178
GANA(2021)[26]	0.322	0.344	0.432*	0.437	0.225	0.246	0.331	0.351	0.389	0.407	0.283	0.299	0.209	0.334	0.107
CIAN(2022)[19]	0.344*	0.373*	0.417	0.453	0.266*	0.294*	0.358	0.383	0.438	0.453	0.284	0.318	0.248	0.426	0.144
TransAM(2023)[23]	0.235	0.263	0.361	0.311	0.175	0.205	0.315	0.330	0.345	0.405	0.273	0.258	-	-	-
APINet(2023)[20]	0.305	0.318	0.405	0.412	0.208	0.225	0.342	0.347	0.419	0.428	0.283	0.297	-	-	-
SuperRL(2024)[12]	0.312	0.330	0.404	0.441	0.223	0.234	0.359*	0.388*	0.446*	0.458*	0.297*	0.320*	-	-	-
MVSE(2024)[25]	0.302	0.332	0.405	0.465*	0.178	0.211	0.349	0.351	0.382	0.422	0.295	0.296	0.285*	0.458*	0.195*
HNII(2024)[21]	-	0.365	-	0.453	-	0.283	-	0.352	-	0.457	-	0.315	-	-	-
NFAA(2025)[8]	0.303	0.332	0.368	0.409	0.233	0.263	0.332	0.341	0.384	0.416	0.285	0.282	-	-	-
LGC-FKGC	0.382	0.390	0.467	0.488	0.304	0.311	0.362	0.377	0.458	0.473	0.301	0.304	0.310	0.469	0.208
LGC+DeepSeek-R1	-	0.392	-	0.473	-	0.322	-	0.486	-	0.525	-	0.459	0.396	0.518	0.300
LGC-CR	**0.428**	**0.440**	**0.515**	**0.523**	**0.342**	**0.375**	**0.544**	**0.567**	**0.573**	**0.606**	**0.511**	**0.537**	**0.474**	**0.566**	**0.401**

Best results are **bolded**, runner-up results are underlined, and * indicates the SOTA baseline metrics. Missing metrics are due to unavailability in the original papers.

- ✓ LGC-CR outperforms the state-of-the-art methods on three benchmark datasets.
  NELL: **8.1%** Hit@1 Wiki: **21.7%** Hit@1 FB15K: **20.6%** Hit@1
- ✓ LGC-FKGC is also competitive, particularly under 3-shot setting.
  Stable and denoised global neighbor information compensate for lack of support set.
- ✓ With the addition of LLM refinement, our method significantly outperforms embedding-based meta-learning.

Experiments-Ablation Study

Table 3: Ablation study results on Nell-One and Wiki-One.

Models	Nell-One		Wiki-One	
	MRR	Hit@1	MRR	Hit@1
Full Model	**0.440**	**0.375**	**0.567**	**0.537**
w/o. KS	0.420	0.356	0.538	0.508
w/o. KS&sft	0.392	0.322	0.485	0.459
w/o. CR	0.390	0.311	0.377	0.304
w/o. CR&FS	0.384	0.302	0.364	0.295
w/o. CR&DCL	0.376	0.286	0.359	0.288
w/o. CR&LGC	0.353	0.269	0.342	0.280
LLM-only(shuffle)	0.267	0.282	0.336	0.269
LLM-only(generate)	0.110	0.135	0.110	0.226

1. Knowledge selector **selects high diversity, high-centrality facts** helps reduce noise from marginal relations.

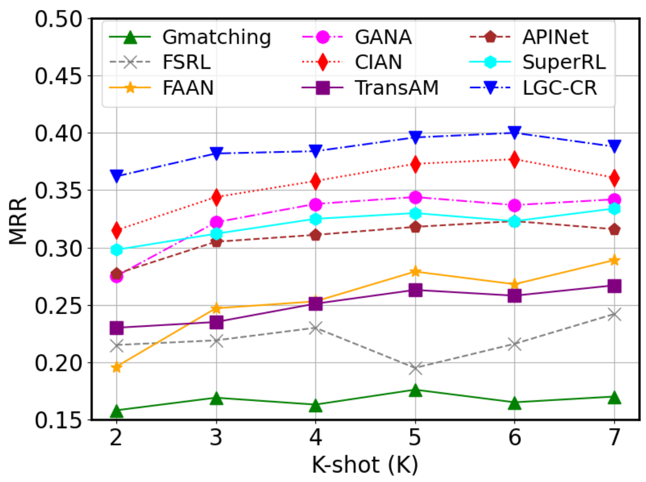
2. **Knowledge injection** through fine-tuning enhances LLM performance and contributes to better refinement results.

3. Dual contrastive learning show its effectiveness in **aligning local-global neighbors** and enhancing model robustness.

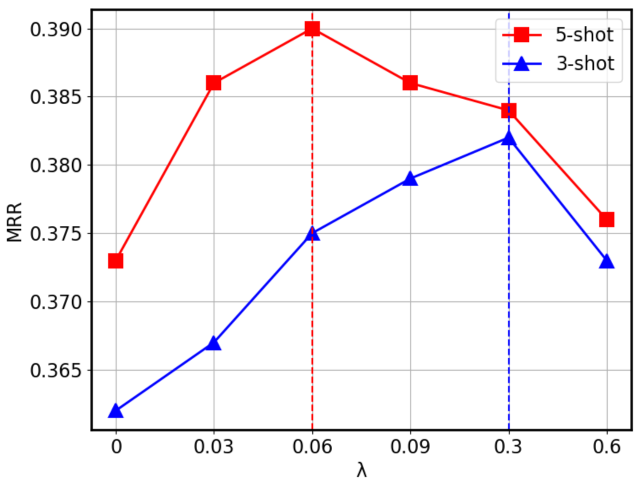
4. Relying solely on a single metric can **introduce similarity bias.**

5. Rich **high-order neighbor information and noise filtering** are crucial to model effectiveness.

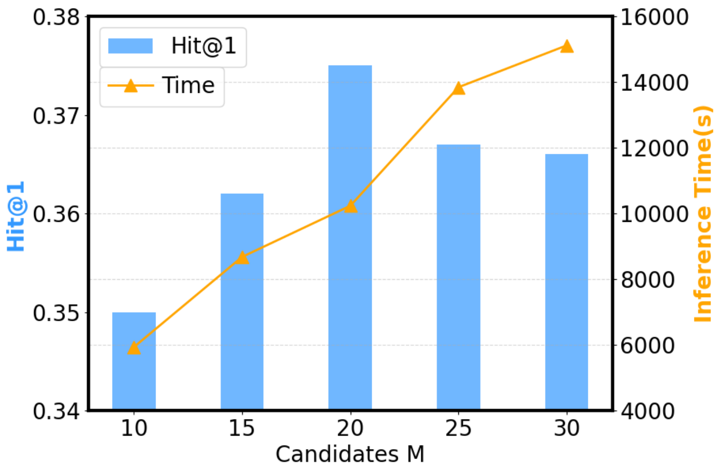
Experiments-Parameter Analysis



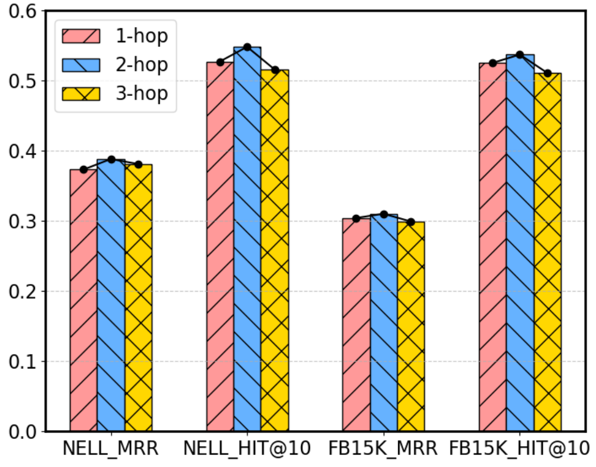
Impact of few-shot size K on NELL dataset



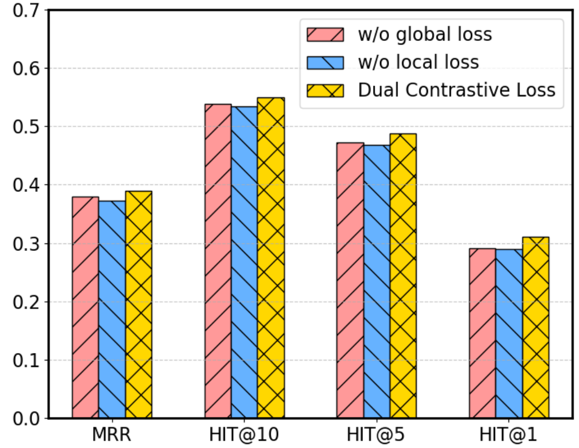
Impact of hyperparameter λ



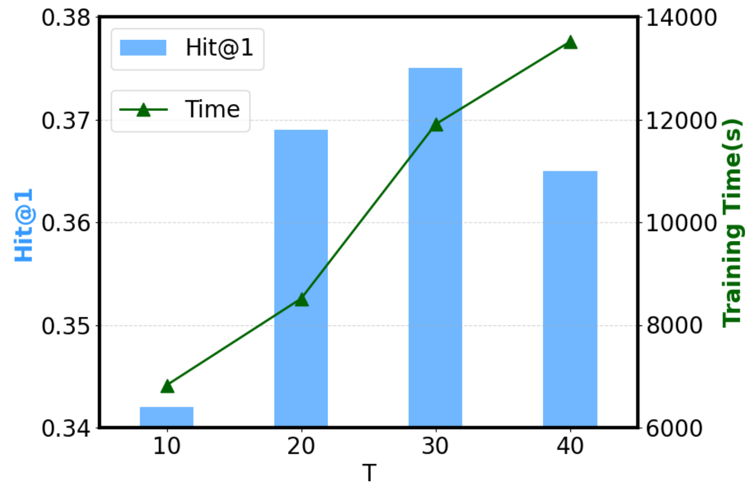
Impact of number of candidates



Impact of neighbor hop



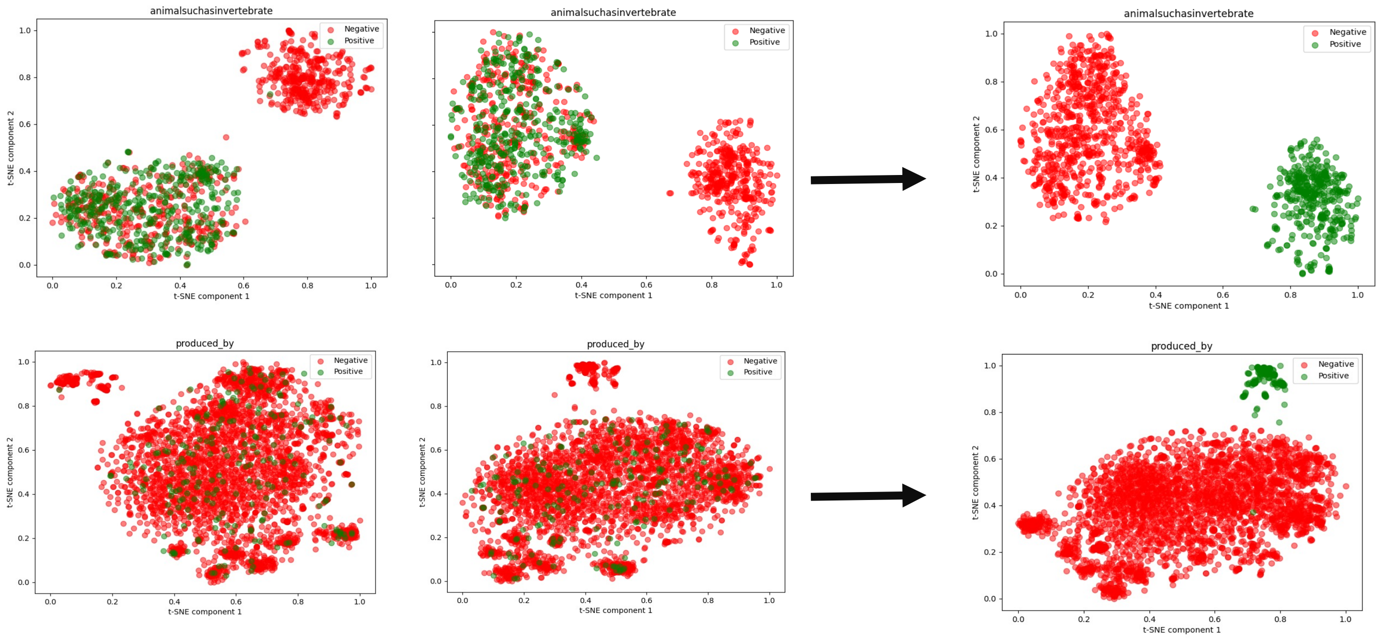
Impact of Contrastive Learning Strategies



Impact of Knowledge Selector ratio

Experiment-Case Study

- Our LLM-Guided Refinement integrates **textual evidence and factual knowledge** to promote the correct answer to the top, effectively **mitigating the pattern bias** of meta-learning methods.



CIAN(2022) MVSE(2024) Ours

Table 5: Case study of Top-5 candidate rankings for two relation types. Correct entities are in bold.

Query Task	LGC-FKGC	LGC-CR
(dallas_mavericks, teamcoach, ?) *True:* coach:jason_kidd	phil_jackson gregg_popovich scott_skiles rick_carlisle **jason_kidd**	**jason_kidd** rick_carlisle gregg_popovich scott_skiles marc_iavaroni
(possible_agrippina_major, location_of_discovery, ?) *True:* béziers	siselen müllheim **béziers** labastide_marnhac isarrnig	**béziers** siselen müllheim labastide_marnhac river_ness

- Our model excels at producing highly **distinctive and well-separated** represen- -tations for different types of entity pairs.

Conclusion

01 02 03 04

Conclusion

- We introduced LGC-CR, a novel few-shot knowledge graph completion framework that integrates an *enhanced meta-learning model with LLM knowledge.*
- At the data level-to address Challenge 1, we design a *local-global contrastive network* to enrich and align neighborhood information.
- At the model level-to address Challenge 2, we introduce *LLM refinement*, which retrieves relevant contexts and selects diverse, knowledge-centric facts to fine-tune LLMs for optimizing meta learning results.
- Experiments on three benchmark datasets demonstrate that LGC-CR outperforms the state-of-the-art baselines by **8.1-20.6%** in terms of Hit@1 and shows robust performance in few-shot scenarios.

Future Work : - Inject long-tail knowledge into LLMs in a more effective manner.
- More modalities knowledge (such as image) could be considered.

Thanks

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Yiming Xu would like to **thank** all the collaborators and the team members.