A Prompt-Based Knowledge Graph Foundation Model for Universal In-Context Reasoning

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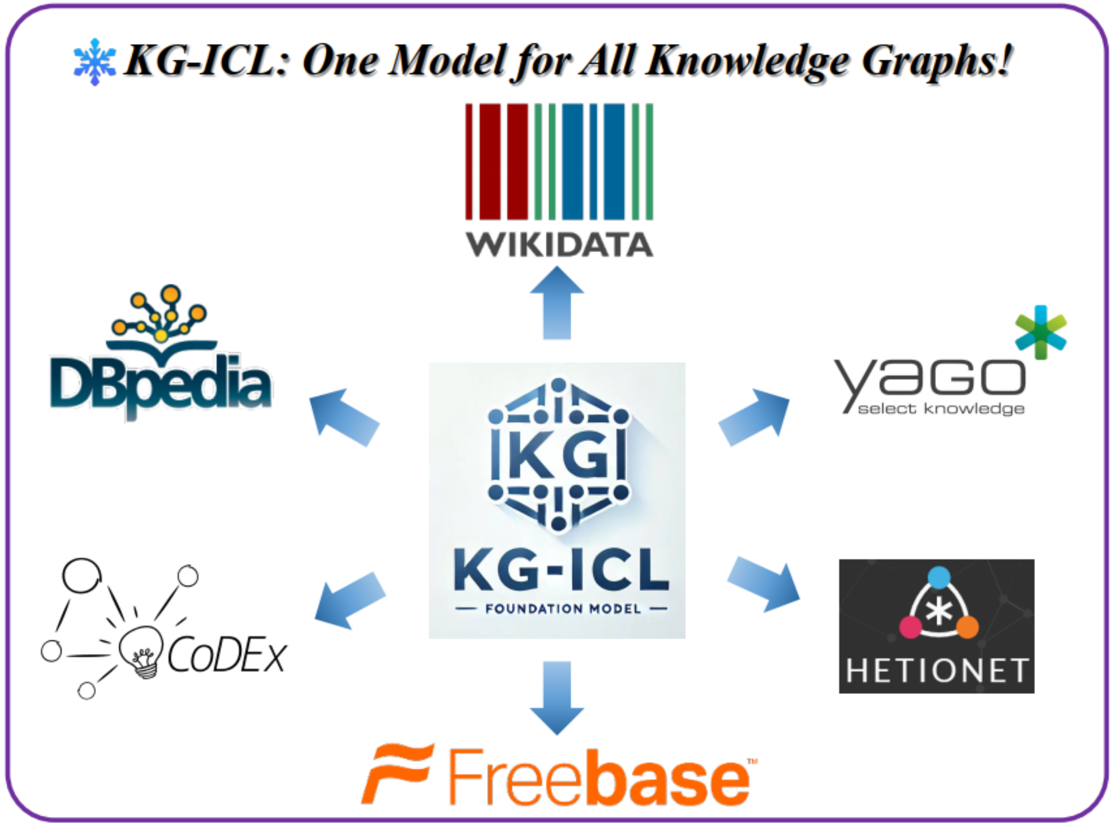
https://github.com/nju-websoft/KG-ICL

Motivation

- Recent advancements in NLP and computer vision have been largely driven by foundation models.
- Can we also develop a foundation model for reasoning on knowledge graphs?
- Inspired by the in-context learning capabilities of LLMs, we propose a new foundation model, **KG-ICL**.

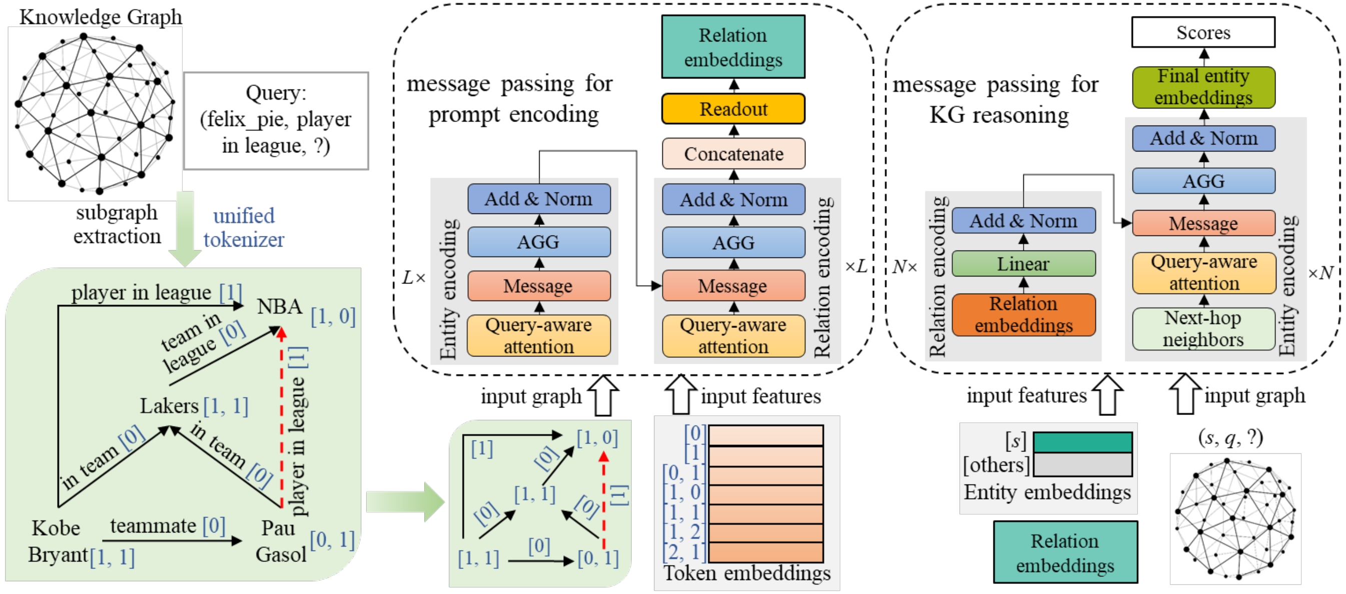


Challenges

- Different KGs do not share a common symbolic system, including entities and relations.
  - ➢ We defined a unified tokenizer to map entities and relationships from different KGs onto predefined tokens.

- A foundational model requires strong generalization capabilities among diverse datasets. How can it perform reasoning on unseen relations?
  - ➢ We defined a prompt graph that describes the reasoning patterns of a relation based on a set of example subgraphs.

Pipeline



(A) Prompt graph generation (B) Prompt graph encoding (C) Knowledge graph reasoning

- Given the query and KG, we extract prompt graphs as context for the query relation ``player in league''.The entities and relations in the prompt graphs are mapped to the unified tokens.
- We employ a message passing neural network to encode the prompt graph and readout the relation representations as the prompts.
- Then we use the prompts to initialize the representations of entities and relations in the KG.After KG encoding, we score the candidate entities according to their embeddings in the last layer.

Experiments

- Datasets: 43 datasets in three settings.
- Baseline: Supervised SOTA & ULTRA
- Results: KG-ICL outperforms baseline models on most datasets.

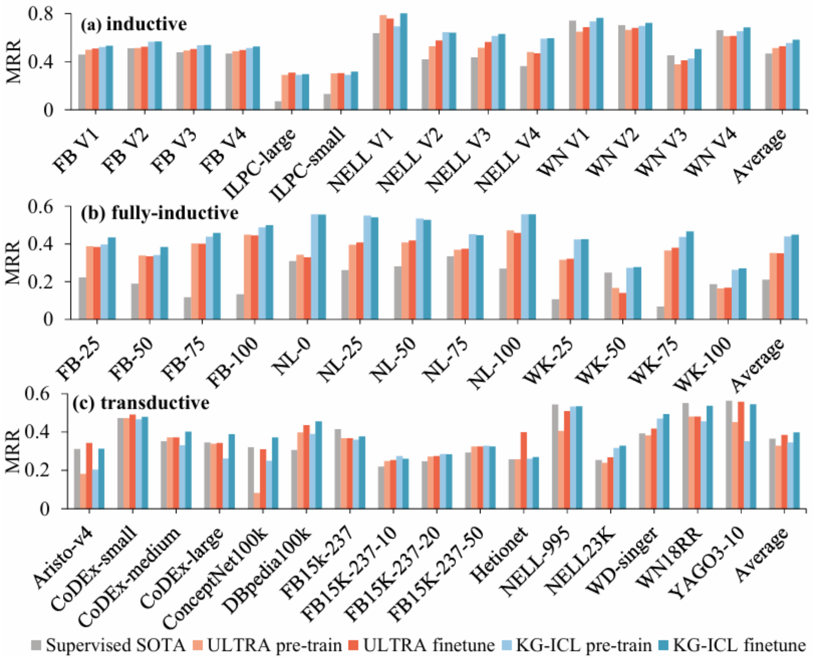


Figure 2: MRR results on various KGs.

Table 11: Detailed results on 43 datasets.

Datasets	Supervised SOTA		ULTRA pre-train		KG-ICL pre-train		ULTRA finetune		KG-ICL finetune	
	MRR	H@10	MRR	H@10	MRR	H@10	MRR	H@10	MRR	H@10
FB V1	0.457	0.589	0.498	0.656	0.520	0.678	0.509	0.670	**0.531**	**0.700**
FB V2	0.510	0.672	0.512	0.700	0.565	0.749	0.524	0.710	**0.568**	**0.768**
FB V3	0.476	0.637	0.491	0.654	0.535	0.695	0.504	0.663	**0.537**	**0.704**
FB V4	0.466	0.645	0.486	0.677	0.513	0.699	0.496	0.684	**0.525**	**0.706**
ILPC-large	0.070	0.146	0.290	0.424	0.288	0.412	**0.308**	**0.431**	0.295	0.411
ILPC-small	0.130	0.251	0.302	0.443	0.288	0.446	0.303	0.453	**0.316**	**0.473**
NELL V1	0.637	0.866	0.785	0.913	0.693	0.915	0.757	0.878	**0.841**	**0.995**
NELL V2	0.419	0.601	0.526	0.707	**0.644**	**0.835**	0.575	0.761	0.641	0.835
NELL V3	0.436	0.594	0.515	0.702	0.613	0.792	0.563	0.755	**0.631**	**0.799**
NELL V4	0.363	0.556	0.479	0.712	0.590	0.791	0.469	0.733	**0.594**	**0.802**
WN V1	0.741	0.826	0.648	0.768	0.733	**0.838**	0.685	0.793	**0.762**	0.827
WN V2	0.704	**0.798**	0.663	0.765	0.696	0.783	0.679	0.779	**0.721**	0.787
WN V3	0.452	0.568	0.376	0.476	0.425	0.548	0.411	0.546	**0.503**	**0.626**
WN V4	0.661	0.743	0.611	0.705	0.652	0.722	0.614	0.720	**0.683**	**0.749**
FB-25	0.223	0.371	0.388	0.640	0.396	0.656	0.383	0.635	**0.434**	**0.694**
FB-50	0.189	0.325	0.338	0.543	0.341	0.559	0.334	0.538	**0.384**	**0.598**
FB-75	0.117	0.218	0.403	0.604	0.438	0.633	0.400	0.598	**0.458**	**0.664**
FB-100	0.133	0.271	0.449	0.642	0.487	0.694	0.444	0.643	**0.499**	**0.703**
NL-0	0.309	0.506	0.342	0.523	**0.557**	**0.777**	0.329	0.551	0.555	0.765
NL-25	0.261	0.464	0.395	0.569	**0.550**	**0.736**	0.407	0.596	0.540	0.730
NL-50	0.281	0.453	0.407	0.570	**0.534**	0.704	0.418	0.595	0.528	**0.708**
NL-75	0.334	0.501	0.368	0.547	**0.452**	0.673	0.374	0.570	0.446	**0.681**
NL-100	0.269	0.431	0.471	0.651	0.556	0.762	0.458	0.684	**0.557**	**0.766**
WK-25	0.107	0.169	0.316	0.532	0.423	0.621	0.321	0.535	**0.425**	**0.628**
WK-50	0.247	0.362	0.166	0.324	0.273	0.430	0.140	0.280	**0.277**	**0.432**
WK-75	0.068	0.135	0.365	0.537	0.437	0.602	0.380	0.530	**0.466**	**0.626**
WK-100	0.186	0.309	0.164	0.286	0.262	0.409	0.168	0.286	**0.270**	**0.415**
AristoV4	0.311	0.447	0.182	0.282	0.203	0.306	**0.343**	**0.496**	0.313	0.480
CoDEx-small	0.473	0.663	0.472	0.667	0.465	0.654	**0.490**	**0.686**	0.479	0.662
CoDEx-medium	0.352	0.490	0.372	0.525	0.330	0.474	0.372	0.525	**0.402**	**0.565**
CoDEx-large	0.345	0.473	0.338	0.469	0.261	0.376	0.343	0.478	**0.388**	**0.508**
ConceptNet100K	0.320	0.553	0.082	0.162	0.249	0.416	0.310	0.529	**0.371**	**0.584**
DBpedia100K	0.306	0.418	0.398	0.576	0.390	0.541	0.436	0.603	**0.455**	**0.604**
FB15k-237	**0.415**	**0.599**	0.368	0.564	0.359	0.541	0.368	0.564	0.376	0.538
FB15k-237-10	0.219	0.337	0.248	0.398	**0.274**	**0.433**	0.254	0.411	0.260	0.416
FB15k-237-20	0.247	0.391	0.272	0.436	**0.285**	0.454	0.274	0.445	0.284	**0.456**
FB15k-237-50	0.293	0.458	0.324	0.526	**0.329**	0.520	0.325	**0.528**	0.324	0.499
Hetionet	0.257	0.403	0.257	0.379	0.260	0.371	**0.399**	**0.538**	0.269	0.402
NELL-995	**0.543**	0.651	0.406	0.543	0.532	0.653	0.509	0.660	0.534	**0.672**
NELL23K	0.253	0.419	0.239	0.408	0.317	0.532	0.268	0.450	**0.329**	**0.552**
WD-singer	0.393	0.500	0.382	0.498	0.470	0.582	0.417	0.526	**0.493**	**0.599**
WN18RR	**0.551**	**0.666**	0.480	0.614	0.455	0.527	0.480	0.614	0.536	0.637
YAGO3-10	**0.563**	0.708	0.451	0.615	0.352	0.503	0.557	**0.710**	0.545	0.688
Average	0.351	0.493	0.396	0.557	0.442	0.606	0.421	0.590	**0.473**	**0.638**

Thanks

The source code are available at https://github.com/nju-websoft/KG-ICL.

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