

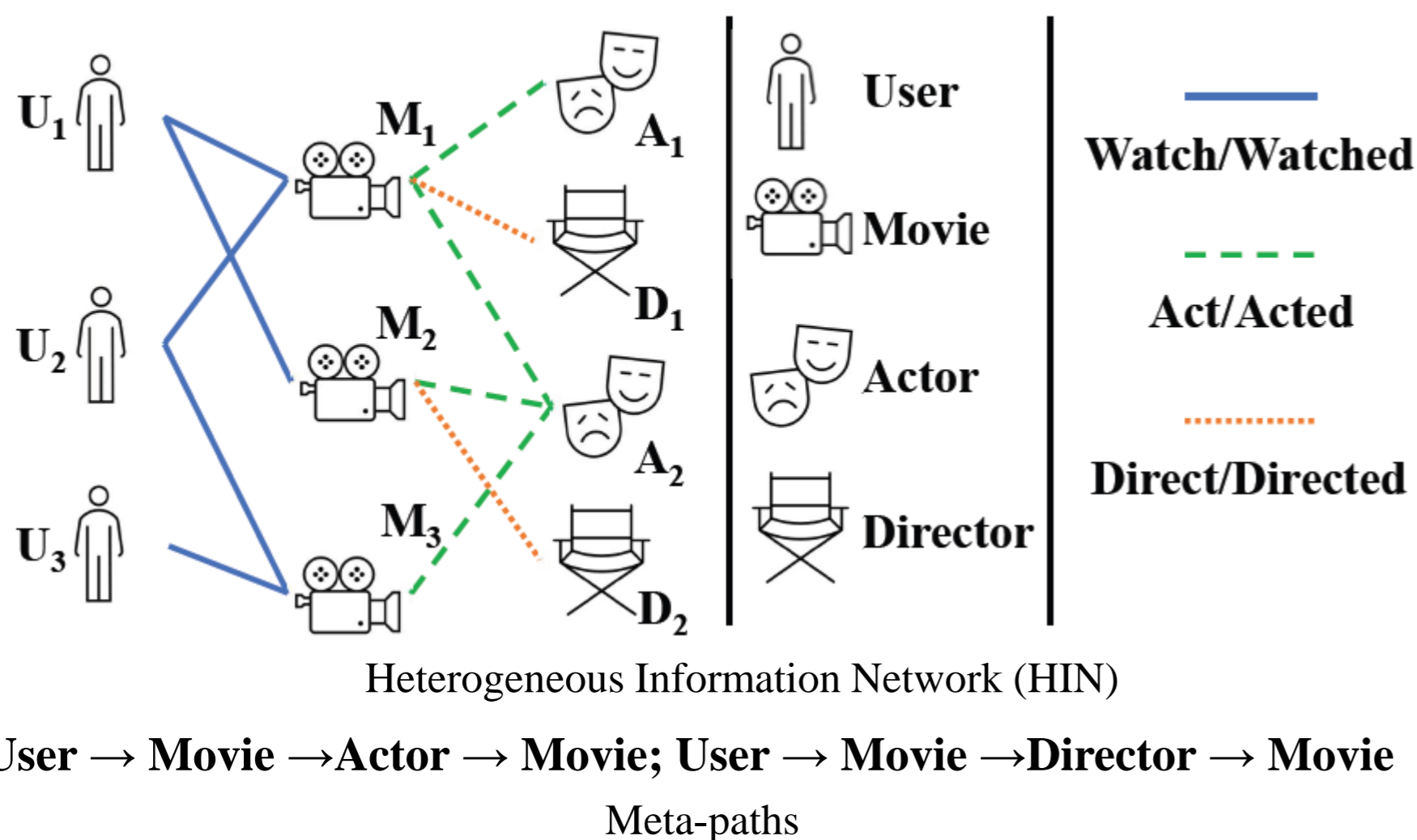
Using Knowledge Graphs for Long-Tail Keyword Query Recommendation in Video Search

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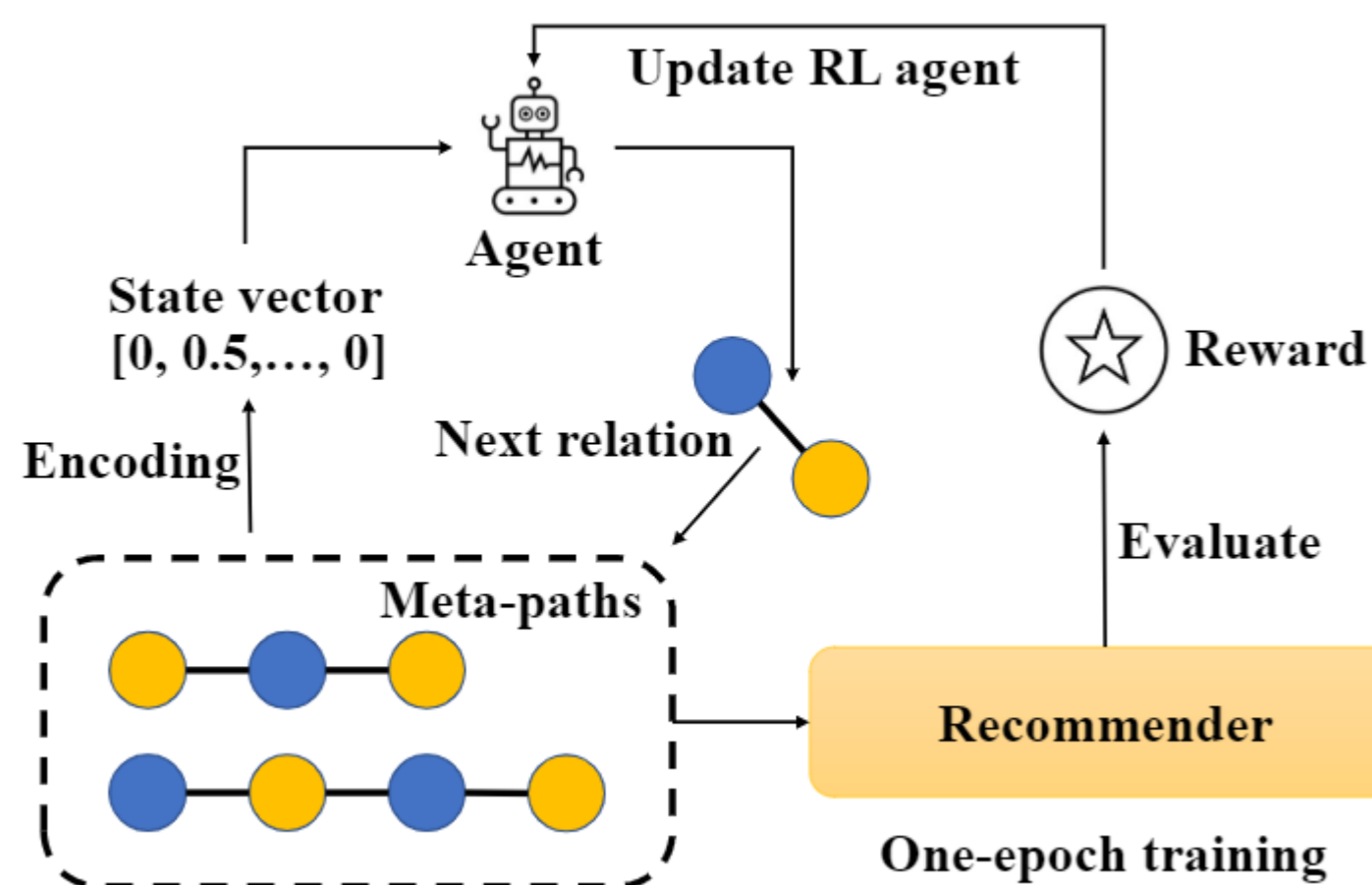
Background & Objectives

- Background: Most current recommendation algorithms are based on the Heterogeneous Information Network (HIN). HIN extracts semantic and structural information using meta-paths, which are manually specified. [VLDB11, WWW19]
- Objectives: Develop a meta-path automatic searching framework to enhance recommendation performance.

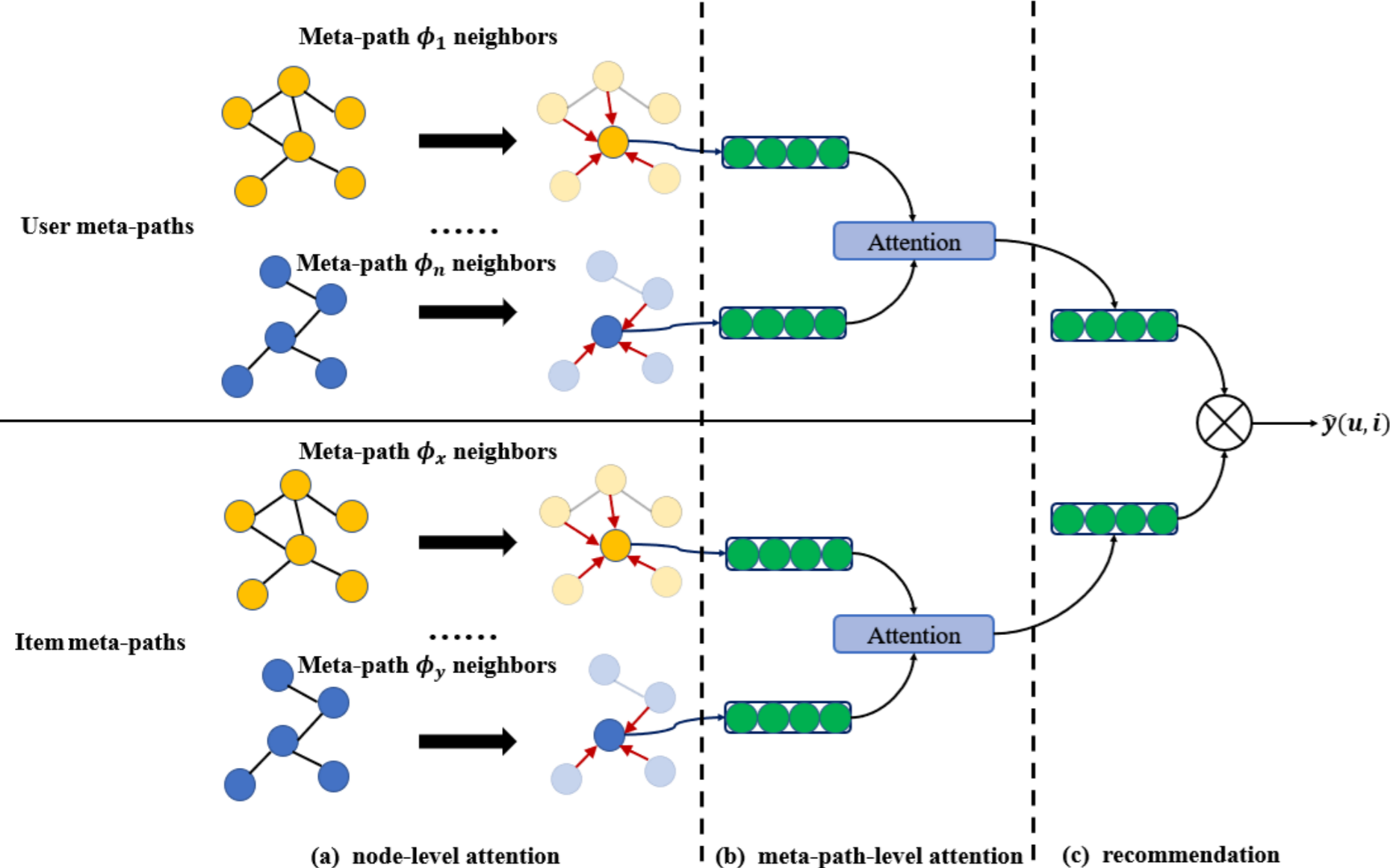


Methodology

- RMS: Reinforcement Learning (RL)-based Meta-path Selection Framework.
 - State: The encoding of current meta-path set.
 - Action: A relation in current HIN.
 - Policy: Decision model based on Multi-Layer Perceptron.
 - Reward: The performance improvement after using new meta-path set.

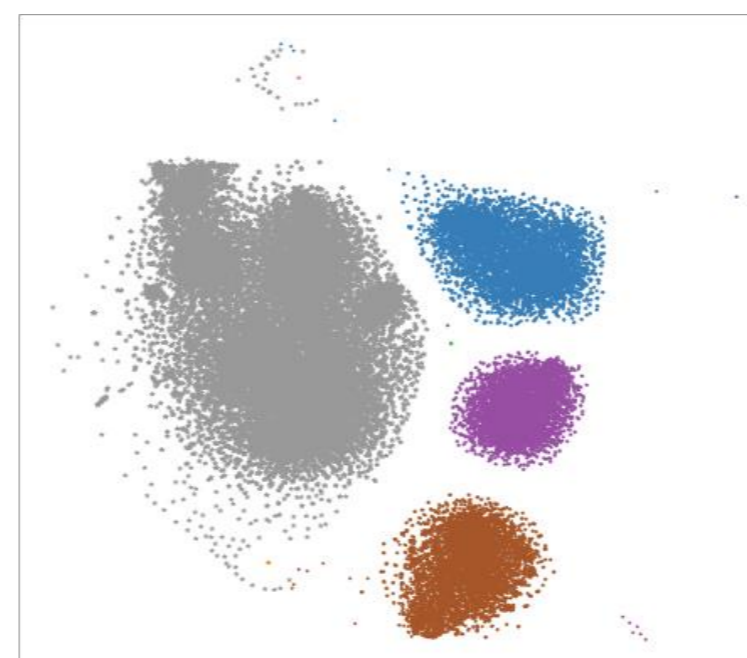


- HRec: A meta-path-based recommendation model
 - Apply HAN [WWW19] in recommendation tasks.
 - Apply Neighbor Sampling during training to prevent out of memory.

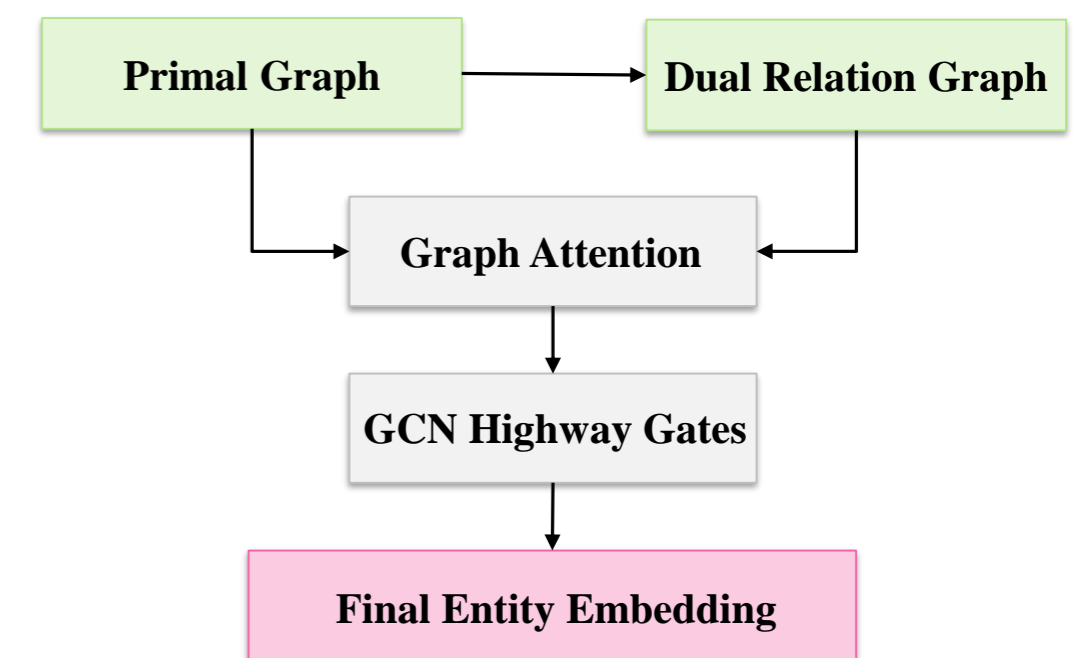


Data Processing

- KG Nodes Visualization



- RDGCN Model Framework [IJCAI19]



- Performance of Entity Alignment Models

	BootEA	mTransE	GCN-Align	RDGCN
Hit Rate @ 1	7.25	3.27	19.75	85.45
Hit Rate @ 10	13.83	6.16	34.72	90.36
Hit Rate @ 50	16.34	8.09	28.55	91.02
Hit Rate @ 100	24.30	16.21	46.61	91.37

Experiments

- Comparison of RMS and Baselines (Random and Greedy)
 - Integrate RMS into existing meta-path-based recommenders (HRec, MCRec).
 - Results show RMS can always find better meta-paths than baseline methods.

Dataset	Model	Strategy	HR1	HR3	NDCG10
Yelp	HRec	RMS	0.0648	0.1484	0.1740
		Greedy	0.0489	0.1181	0.1449
		Random	0.0589	0.1381	0.1633
	HERec	RMS	0.0389	0.0979	0.1215
		Greedy	0.0374	0.0918	0.1166
		Random	0.0344	0.0922	0.1167
	MCRec	RMS	0.0548	0.1317	0.1540
		Greedy	0.0516	0.1234	0.1504
		Random	0.0526	0.1229	0.1451

- Comparison of RMS-HRec and existing recommendation models.
 - RMS-HRec outperforms all the existing methods.

	Yelp					Douban Movie				
	HR1	HR3	HR10	NDCG10	NDCG20	HR1	HR3	HR10	NDCG10	NDCG20
RMS-HRec	0.0648	0.1484	0.3213	0.1740	0.2095	0.0997	0.2131	0.4258	0.2400	0.2802
BPR	0.0388	0.1025	0.2592	0.1301	0.1638	0.0529	0.1421	0.3502	0.1768	0.2218
NCF	0.0514	0.1251	0.2927	0.1522	0.1872	0.0622	0.1605	0.3854	0.1974	0.2438
CFKG	0.0456	0.1092	0.2630	0.1360	0.1710	0.0574	0.1495	0.3668	0.1862	0.2323
CKE	0.0572	0.1246	0.2721	0.1477	0.1791	0.0634	0.1646	0.3930	0.2015	0.2479
HERec	0.0389	0.0979	0.2381	0.1215	0.1528	0.0594	0.1613	0.3910	0.1984	0.2424
MCRec	0.0548	0.1317	0.2887	0.1540	0.1876	0.0928	0.1961	0.3985	0.2236	0.2631
GEMS	0.0100	0.0294	0.0868	0.0408	0.0583	0.0270	0.0603	0.1293	0.0742	0.0945
KGAT	0.0415	0.1151	0.2718	0.1388	0.1733	0.0630	0.1644	0.3922	0.2009	0.2469

Current Work

- We are now constructing a HIN for movie data and using the latest HIN data cleaning methods [IJCAI'19] to obtain a qualified movie HIN.
- Next, we will use RMS-HRec in this HIN.

References

- [WWW19] W. Xiao, J. Houye, S. Chuan, W. Bai, C. Peng, Y. P., and Y. Yanfang. Heterogeneous graph attention network. WWW, 2019.
- [VLDB11] Y. Sun, J. Han, X. Yan, P. S. Yu, and T.Wu. Pathsim: Meta path-based top-k similarity search in heterogeneous information networks. PVLDB, 2011.
- [IJCAI19] Wu, Y., Liu, X., Feng, Y., Wang, Z., Yan, R., & Zhao, D. (2019, July). Relation-Aware Entity Alignment for Heterogeneous Knowledge Graphs. IJCAI.