Joint Global-Local Representations via Relation-Entity Pair Encoding for Hyper-Relational Knowledge Graphs

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Hyper-relational Knowledge Graphs

Representation of complex n-ary facts by **extending conventional triples with qualifiers**:

H-fact #1: ((Brad_Pitt, associated_with, **F1**), {(**in_year**, **Y2025**), (at_event, F1_the_Movie)})

H-fact #2: ((Max_Verstappen, driver_in, **F1**), {(**in_year**, **Y2025**)})

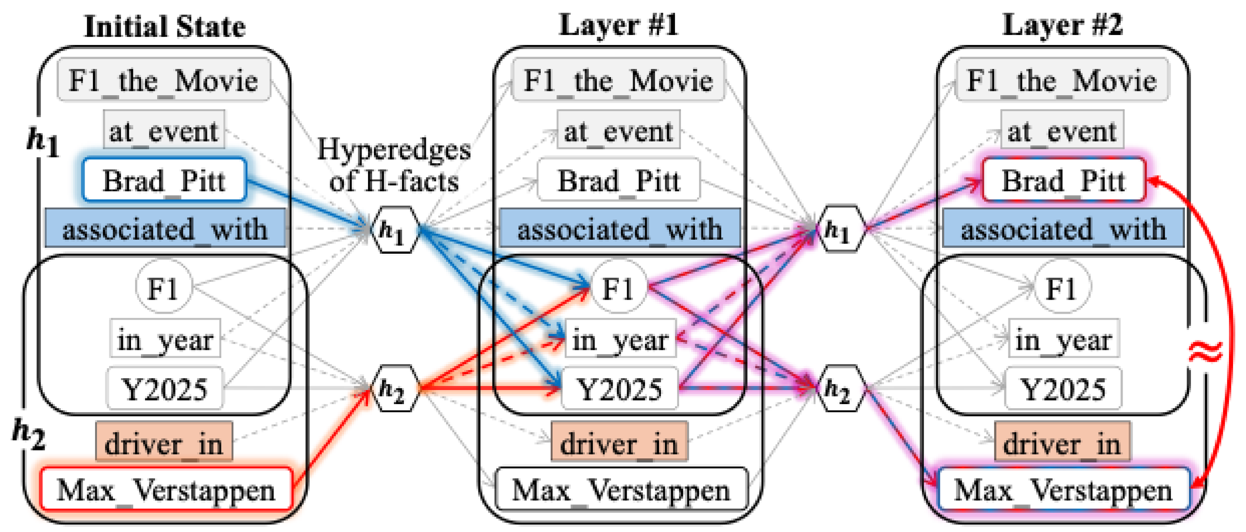
Two complementary views of each H-fact:

- **Global**: cross-fact structure
- **Local**: intra-fact semantics

Challenges

[C1] Relation-Agnostic Global Aggregation

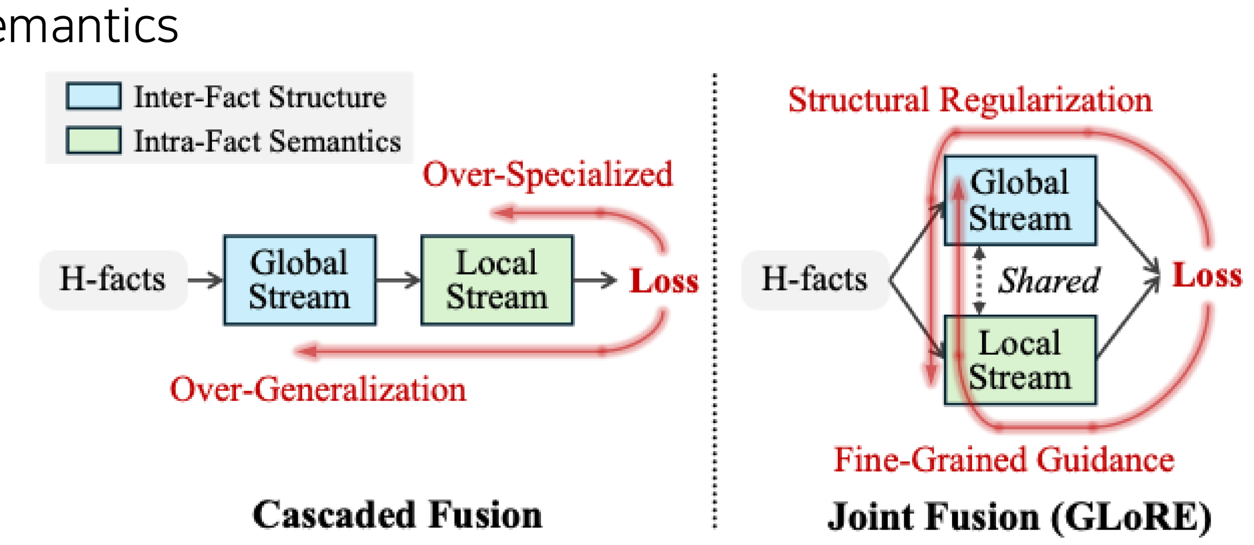
Mixing relation- and role-specific evidence into a single entity state, **leading to entity-role ambiguity** and **representation concentration**



✓ *GLoRE: Preserving relation identity and entity roles through pair-centric aggregation*

[C2] Insufficient Global-Local Fusion

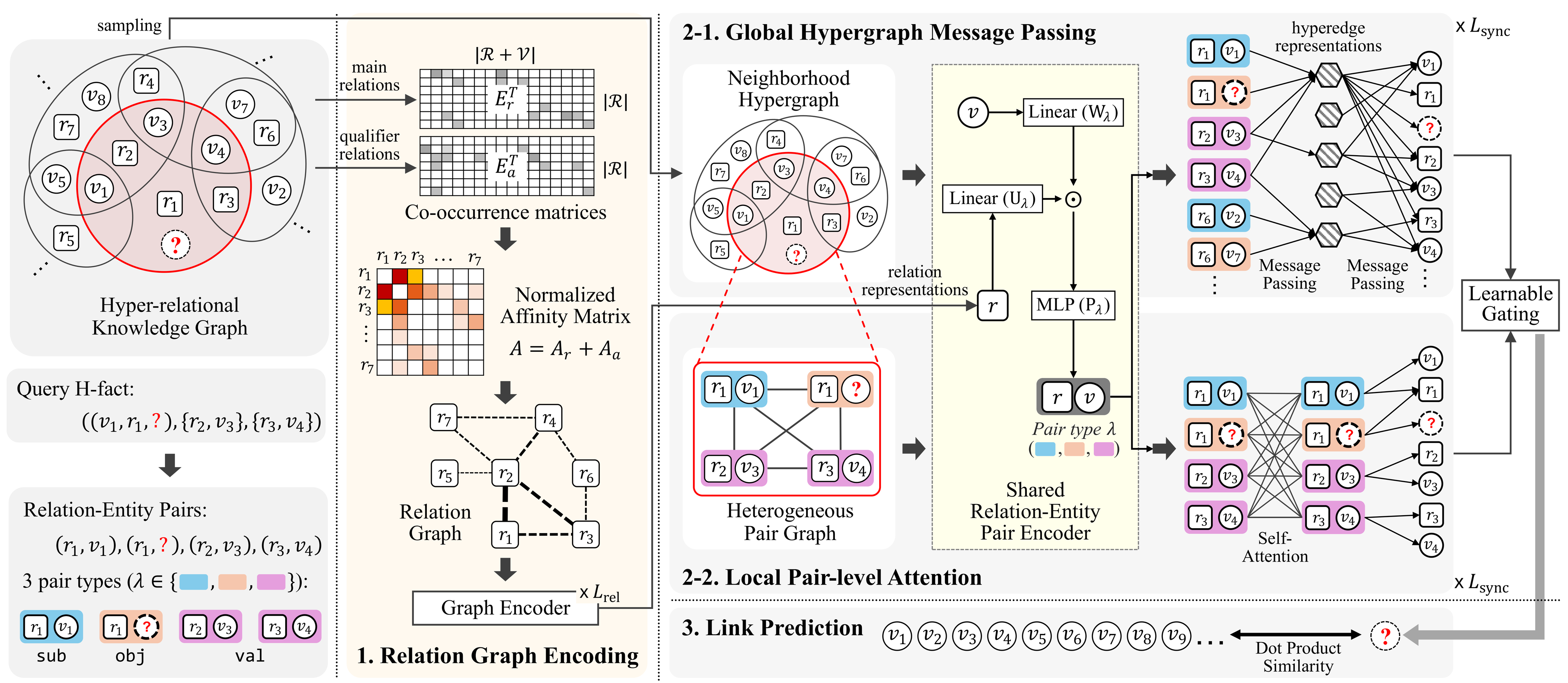
Relying on a single view or a **one-way global→local cascade**, **limiting mutual refinement** between global structure and local semantics



✓ *GLoRE: Jointly coupling global structure and local semantics through shared pair encoding*

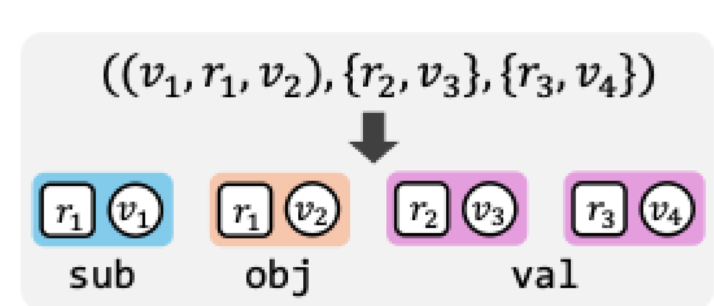
Proposed Method: GLoRE

- **Pair-centric modeling:** Global propagation and local interaction over relation-entity pairs
- **Relation affinity:** Co-occurrence-weighted relation graph for refining relation representations
- **Joint global-local learning:** Global hypergraph propagation and local pair-level self-attention jointly optimized through a shared pair encoder



① Relation-Entity Pairs

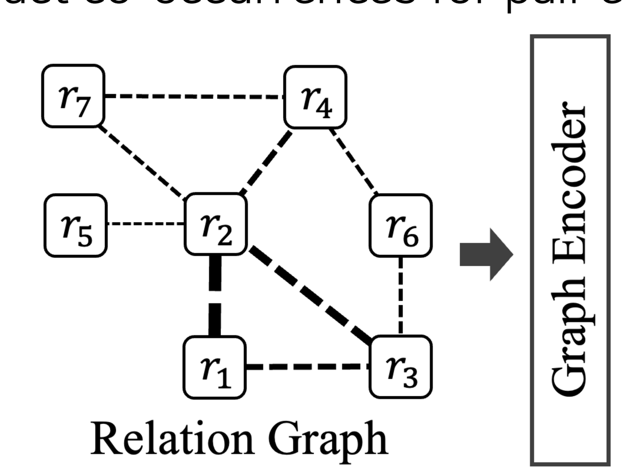
Preserving **relation identity** and **within-fact roles** before aggregation



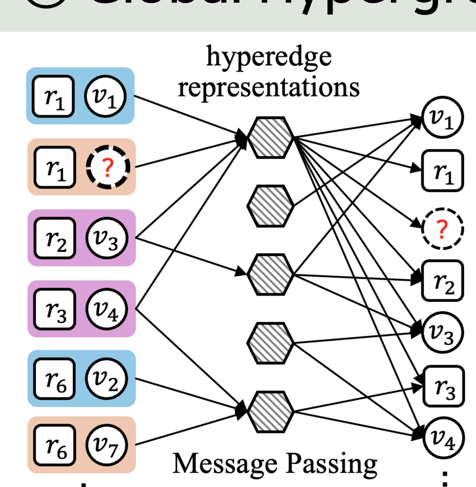
$$p_{(r,v)} = P_{\lambda_h(v)}\left(W_{\lambda_h(v)}\,\mathbf{v} \odot U_{\lambda_h(v)}\,\mathbf{r}\right)$$

② Relation Graph Encoding

Providing **relation affinity priors** from within-fact co-occurrences for pair encoding

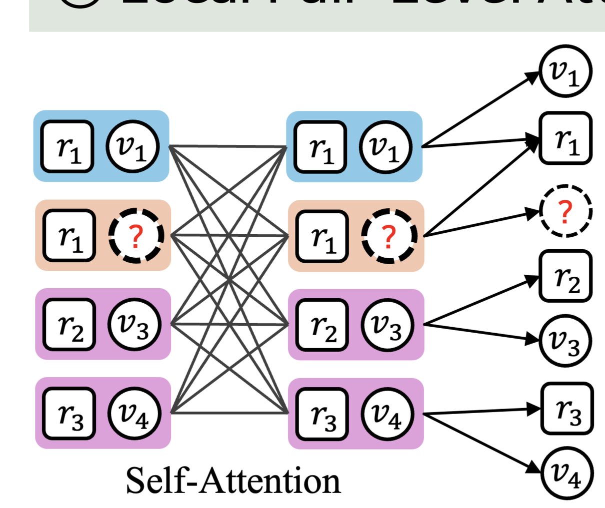


③ Global Hypergraph Propagation



Pair-based message passing across neighboring H-facts

④ Local Pair-Level Attention



Pair-level self-attention over a heterogeneous pair graph within each H-fact

⑤ Joint Global-Local Learning

Joint optimization through a **shared pair encoder**, followed by **gated fusion** for link prediction

Experiments

Best performance in all 18 reported metric columns

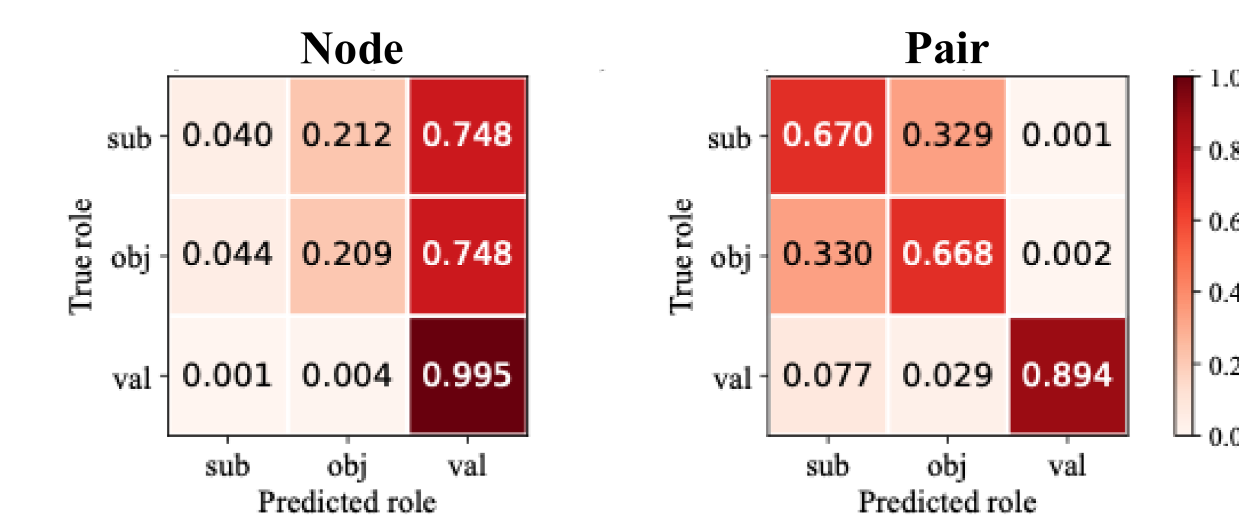
All entities	JF17K MRR(↑)	WikiPeople- MRR(↑)	WD50K MRR(↑)
Best Baselines	0.668	0.521	0.411
GLoRE	0.719	0.555	0.512
Improvement	+7.6%	+6.5%	+24.6%

Global Aggregation Unit: Pair vs. Node

Agg. Unit	Embedding Concentration		Role Separability	
	CCIc(↓)	Top-10(↓)	RSS(↑)	RNCA(↑)
Pair (GLoRE)	0.0022	0.251	0.2210	0.698
Node	0.0383	0.564	0.0521	0.236

※ **Node** replaces only the global stream with **node-centric** aggregation

CCIc: centered cosine concentration index; Top-10: variance captured by the top-10 principal components
RSS: distance between role centroids; RNCA: nearest-centroid role classification accuracy



➤ **Node** concentrates entity embeddings and confuses roles
➤ **Pair** keeps roles separable, empirically supporting the role-mixing claim in [C1]

Global-Local Fusion Strategies: Joint vs. Cascaded

WD50K (MRR)	Main entities	All entities
GLoRE	0.478	0.512
w/o sharing pair encoder	0.449	0.479
GLoRE (cascaded)	0.332	0.364
w/o sharing pair encoder	0.352	0.383

➤ Joint fusion consistently outperforms cascaded fusion
➤ Sharing the pair encoder helps only under joint fusion and hurts under cascading

Ranked first across all qualifier-density settings