Structure Is All You Need: Structural Representation Learning on Hyper-relational Knowledge Graphs

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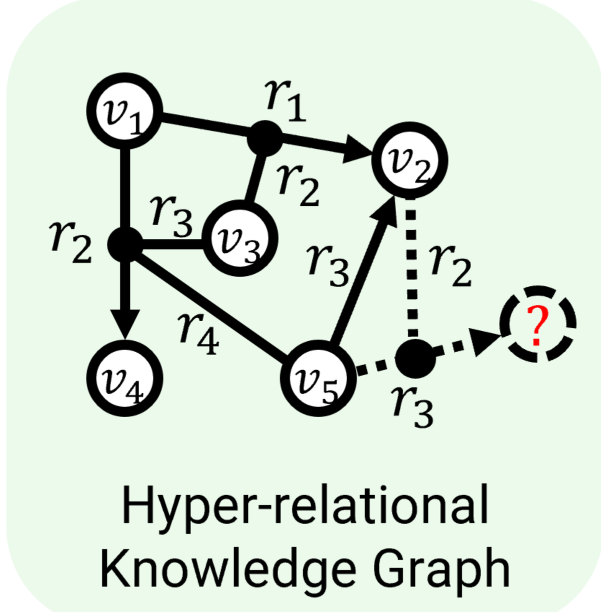
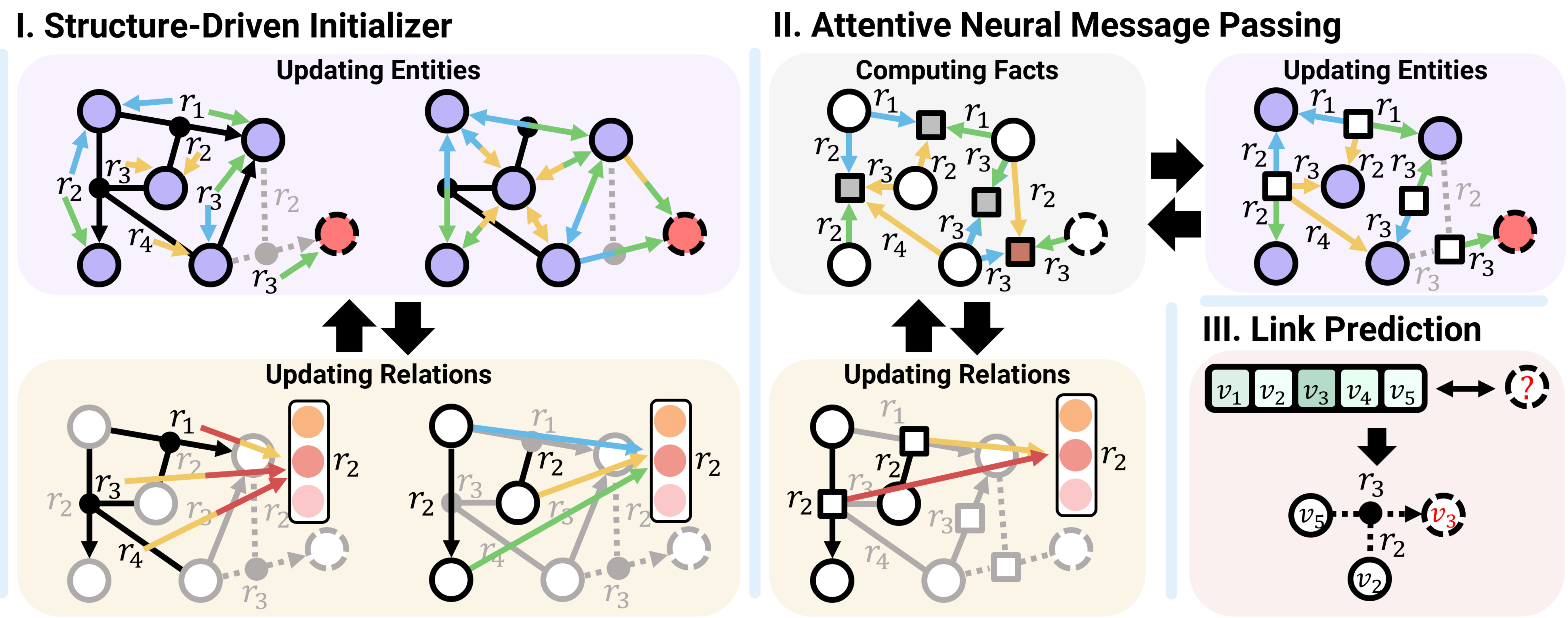


MAYPL

Message P**A**ssing framework for h**Y**per-relational knowledge graph re**P**resentation **L**earning

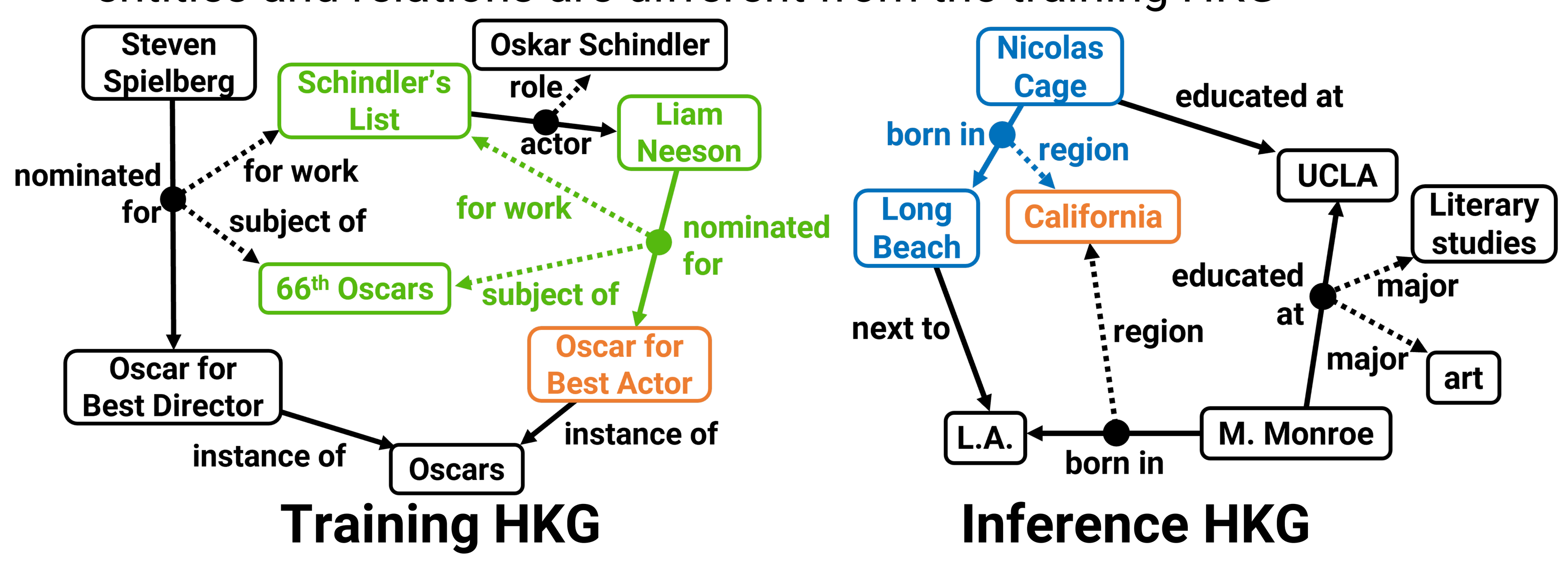


Main Findings and Contributions

- Employing the **structure of an HKG is crucial** for HKG reasoning
  - Purely structure-based learning can successfully solve link prediction
- Propose **MAYPL**, **the first structural representation learning method**
  - Can be applied in both transductive and inductive learning settings
- MAYPL outperforms **41 different baseline methods** on 3 **transductive HKG** datasets, 12 **inductive KG** datasets, and 4 **inductive HKG** datasets
  - Compared with different baseline methods on different datasets

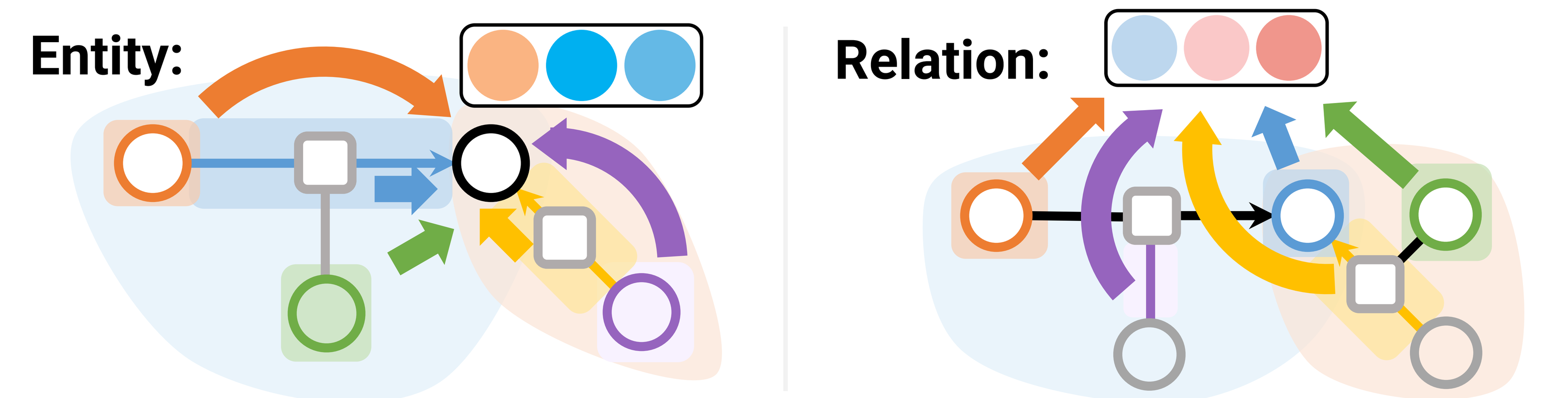
Hyper-relational Knowledge Graphs (HKGs)

- **Hyper-relational Knowledge Graphs**
  - Adds auxiliary details to triplets by adding qualifiers
- **Link Prediction on HKGs**
  - Predict a missing entity in an incomplete hyper-relational fact
  - **Transductive Inference**: predict missing links in the training HKG
  - **Inductive Inference**: predict missing links in an inference HKG whose entities and relations are different from the training HKG



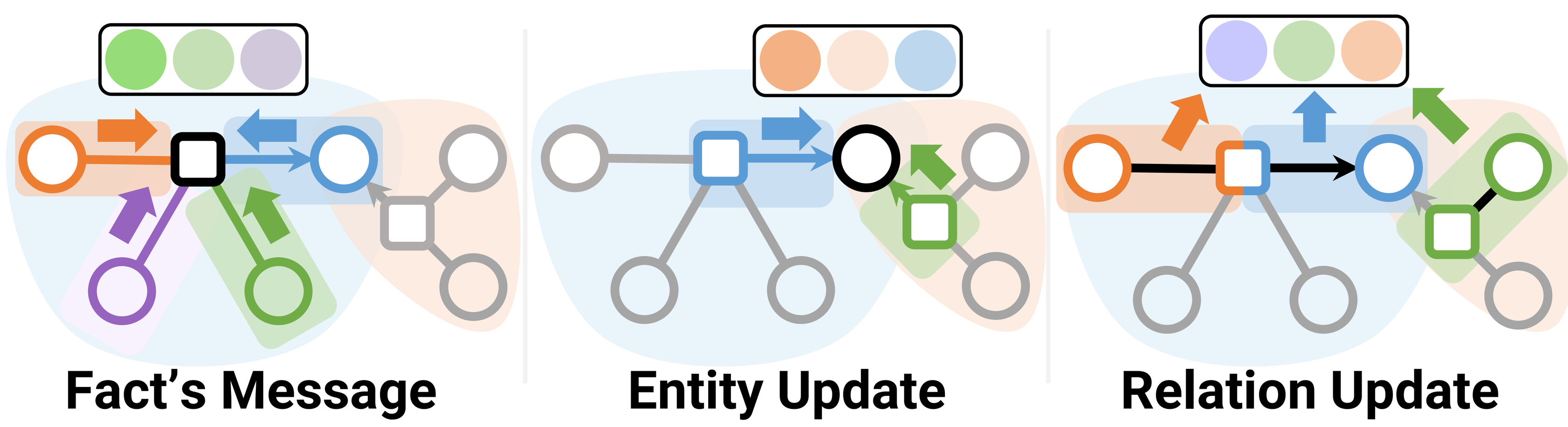
Structure-driven Initializer

- Exploits the **interconnections**, **co-occurrence**, and **positions**
- Entity: messages of the **co-occurring entities** and **incident relations**
- Relation: messages of the **co-occurring relations** and **incident entities**



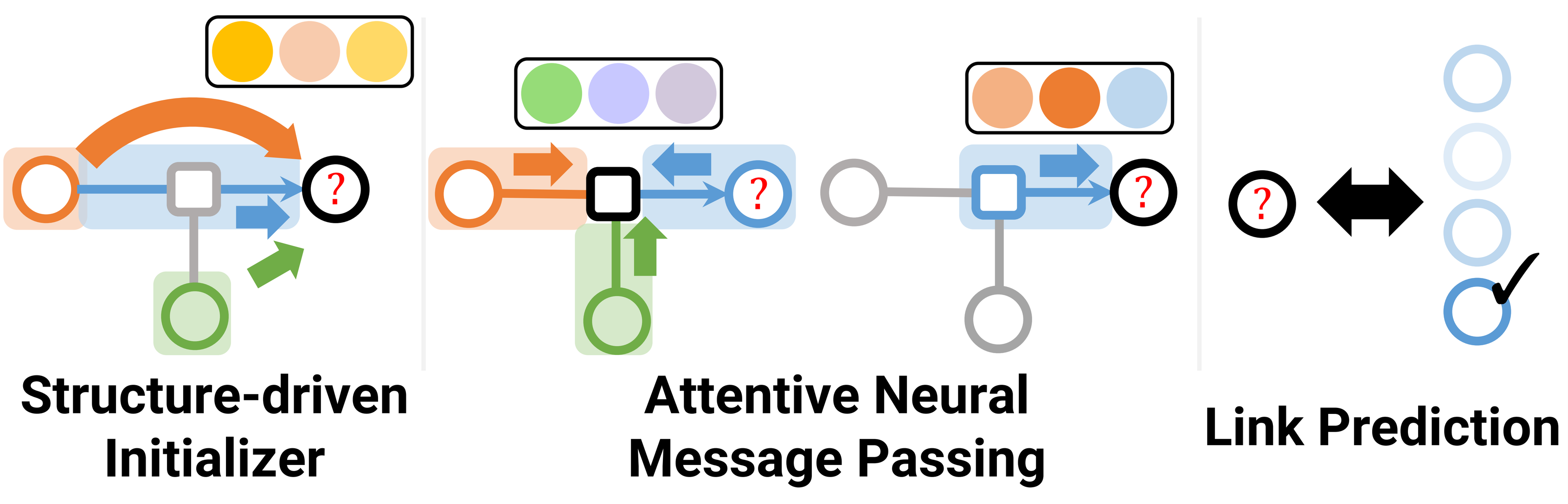
Attentive Neural Message Passing

- Updates representations by attentively aggregating facts' messages
- Fact Message: considers which **entities** and **relations** comprise the fact
- Entity: **attentive aggregation** of the **facts** and **corresponding relations**
- Relation: **attentive aggregation** of the **facts** and **corresponding entities**



Link Prediction on HKGs

- Representation of a query entity x is computed using **structure-driven initializer** and **attentive neural message passing** module
- Predict by computing the **dot product** between final representations



Experiments

- Datasets: **19 benchmark datasets**
  - 3 Transductive HKG, 12 Inductive KG, and 4 Inductive HKG datasets
- Baselines: **41 baseline methods** in total
- **Transductive Link Prediction on HKGs**

	WD50K (Pri)		WikiPeople⁻ (Pri)		WikiPeople (All)	
	MRR (↑)	Hit@10 (↑)	MRR (↑)	Hit@10 (↑)	MRR (↑)	Hit@10 (↑)
Best-baseline	0.368	0.516	0.509	0.648	0.450	0.592
MAYPL	**0.381**	**0.544**	**0.519**	**0.657**	**0.488**	**0.635**

- **Inductive Link Prediction on KGs**

	WK-50		FB-50		NL-50	
	MRR (↑)	Hit@10 (↑)	MRR (↑)	Hit@10 (↑)	MRR (↑)	Hit@10 (↑)
Best-baseline	0.076	0.164	0.204	**0.376**	0.315	**0.529**
MAYPL	**0.109**	**0.230**	**0.205**	0.361	**0.343**	0.508

- **Inductive Link Prediction on HKGs**

	WD20K(100)v1 (Pri)		WD20K(100)v2 (Pri)		MFB-IND (All)	
	MRR (↑)	Hit@10 (↑)	MRR (↑)	Hit@10 (↑)	MRR (↑)	Hit@3 (↑)
Best-baseline	0.113	0.245	0.067	0.129	0.368	0.417
MAYPL	**0.486**	**0.662**	**0.298**	**0.518**	**0.550**	**0.582**

Conclusion

- MAYPL learns to compute representations based on **how facts, entities, and relations are connected, positioned, and organized** in HKGs
  - Can effectively compute representations on a new HKG
- MAYPL outperforms **41 different baseline** methods on **19 benchmark datasets** in varied settings: transductive HKG, inductive KG/HKG
- **Thoroughly learning and exploiting the structure** of an HKG is necessary and sufficient for learning representations on HKGs

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