



Learning Rule-Induced Subgraph Representations for Inductive Relation Prediction

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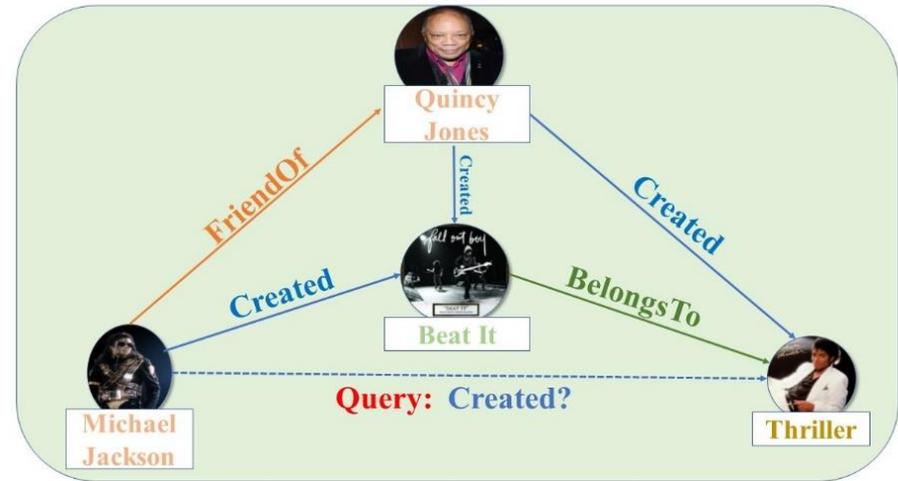
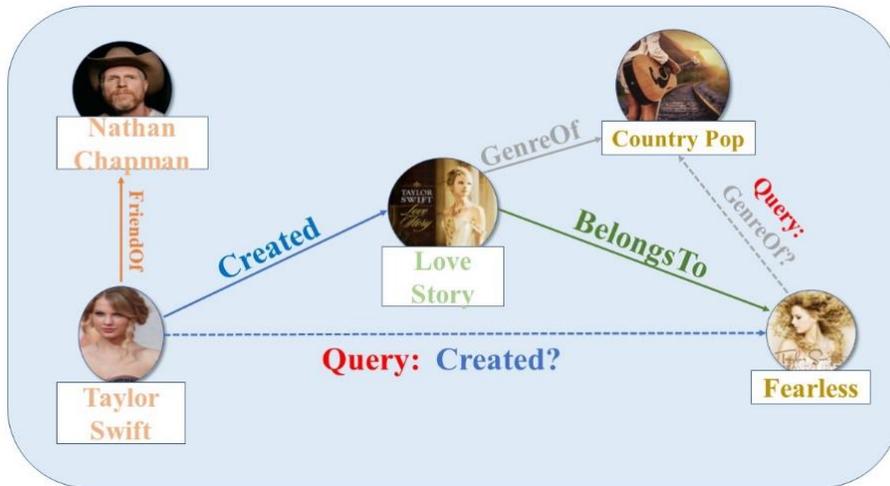


Overlook

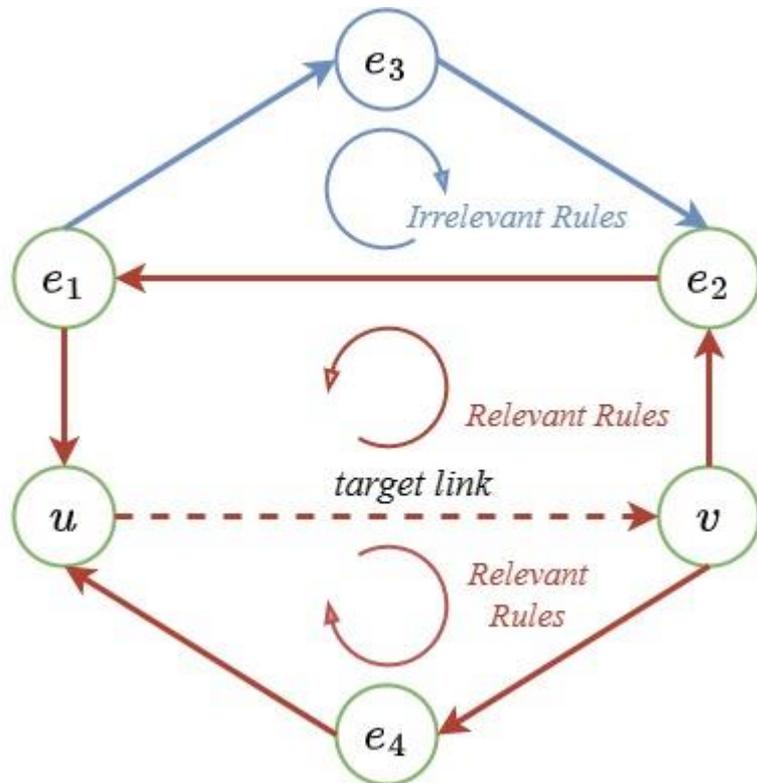
- Introduction and Motivation
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Introduction and Motivation

- Objective: Predicting missing relations in evolving knowledge graphs.
- Goal: Training on one graph and test on another graph.



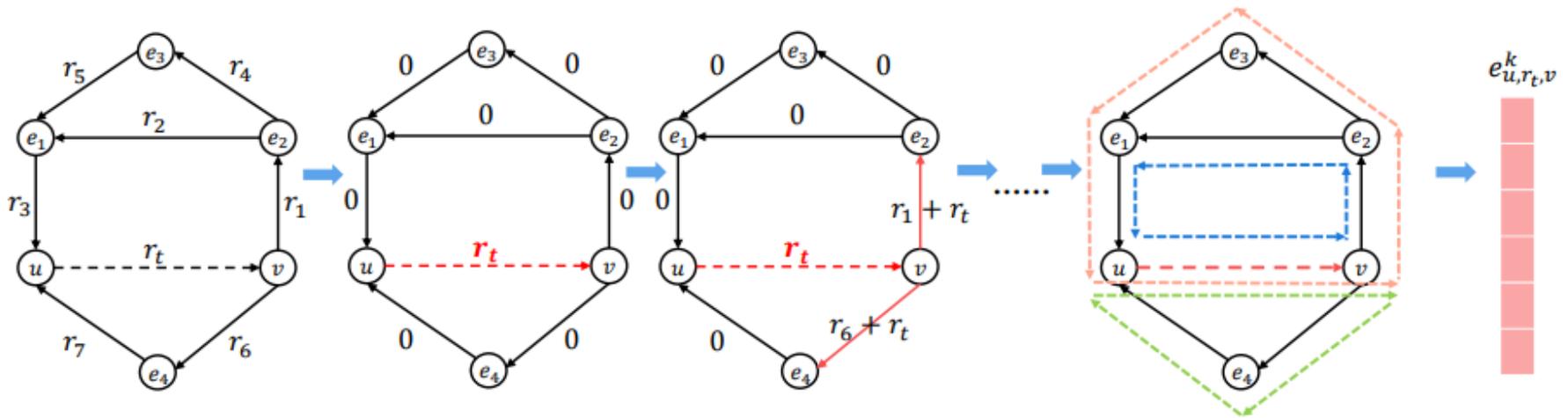
Introduction and Motivation



- *Relevant rules* are cycles that pass the target link, while *irrelevant rules* are on the contrary.
- Existing methods cannot **differentiate** relevant rules from irrelevant ones, resulting in suboptimal representations with irrelevant information.

Method

- We propose a novel single-source edge-wise GNN REST, which **encodes** relevant rules and **eliminates** irrelevant rules within the subgraph.



1. Extracted local subgraph for the target link (u, r_t, v) .

2. Single-source initialization for all edges within the subgraph.

3. Edge-wise message passing to update edge representations. Finally, we output the representation of the target link $e_{u,r_t,v}^k$ to calculate its plausibility.



Method

□ Single-source Initialization:

$$\mathbf{e}_{x,y,z}^0 = \mathbb{1}_{(u,r,v)}(x,y,z) \odot \mathbf{r}_y = \begin{cases} \mathbf{r}_y, & \text{if } (x,y,z) = (u,r_t,v) \\ \mathbf{0}, & \text{if } (x,y,z) \neq (u,r_t,v) \end{cases} \quad (1)$$
$$\mathbf{h}_v^0 = \mathbf{0} \quad \text{for } \forall v \in \mathcal{E},$$

□ Edge-wise Message Passing:

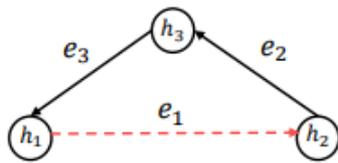
$$\mathbf{m}_{x,y,z}^k = \text{MESSAGE}(\mathbf{h}_x^{k-1}, \mathbf{e}_{x,y,z}^{k-1}, \mathbf{r}_y) = (\mathbf{h}_x^{k-1} \otimes^1 \mathbf{r}_y) \uplus (\mathbf{e}_{x,y,z}^{k-1} \otimes^2 \mathbf{r}_y) \quad (2)$$

$$\mathbf{h}_z^k = \text{AGGRAGATE}(\mathbf{m}_{x,y,z}^k) = \bigoplus_{(x,y,z) \in \mathcal{T}} \mathbf{m}_{x,y,z}^k \quad (3)$$

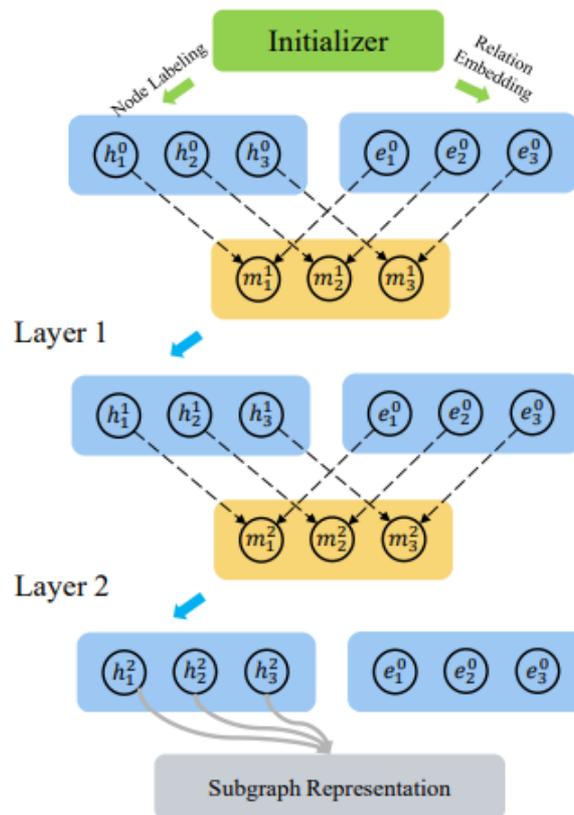
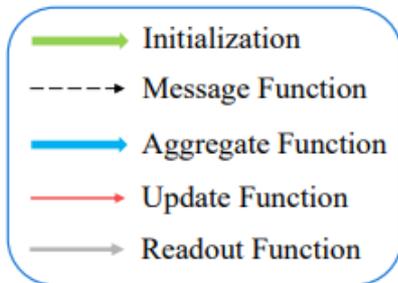
$$\mathbf{e}_{x,y,z}^k = \text{UPDATE}(\mathbf{h}_x^k, \mathbf{e}_{x,y,z}^{k-1}) = \mathbf{h}_x^k \diamond \mathbf{e}_{x,y,z}^{k-1} \quad (4)$$

Theoretical Analysis and Findings

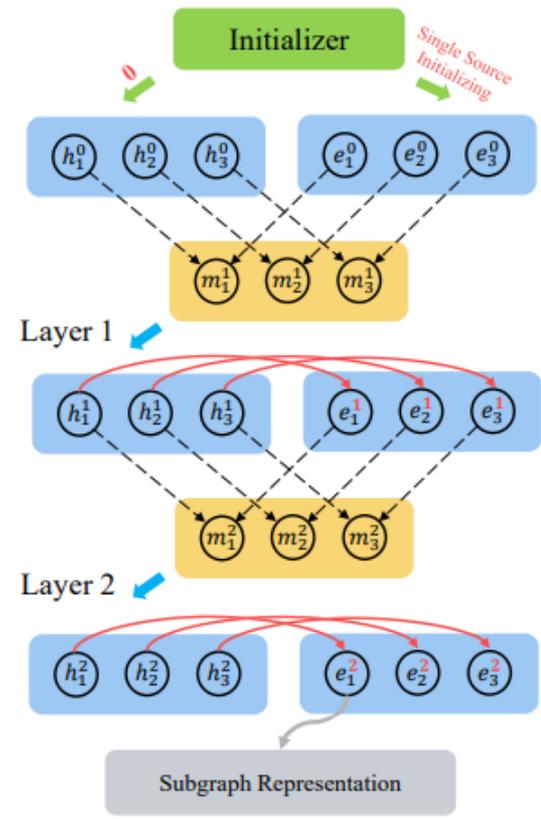
- Our REST is basically different with GraLL.



(a) Original Graph



(b) Conventional Message Passing Framework



(c) Edge-wise Message Passing Framework



Theoretical Analysis and Findings

- Our REST is theoretically effective.

Definition 1 (Rule-induced subgraph representation.) Given a subgraph $\mathcal{SG}_{u,r_t,v}$, its rule-induced subgraph representation is defined as follows:

$$\mathcal{S}_{u,r_t,v} = \bigoplus_{i=1}^k \underbrace{\bigoplus_{(u,r_t,v) \ (v,y_0,x_0) \ \dots \ (x_{i-3},y_{i-2},u)} \alpha_{i1}\mathbf{r}_{r_t} \otimes \alpha_{i2}\mathbf{r}_{y_0} \otimes \dots \otimes \alpha_{ii}\mathbf{r}_{y_{i-2}}}_{i} \quad (11)$$

where i denotes the length of the cycle, \mathbf{r}_{y_i} is the representation of relation y_i , (x_i, y_i, x_{i-1}) is an existing triple in $\mathcal{SG}_{u,r_t,v}$. $\{(u, r_t, v), (v, y_0, x_0), \dots, (x_{i-3}, y_{i-2}, u)\}$ is a cycle at length i .

Theorem 2 Single-source edge-wise GNN can learn rule-induced subgraph representation if $\uplus = \oplus, \oplus = \oplus, \diamond = \oplus, \otimes^1 = \otimes, \otimes^2 = \otimes$, where \oplus and \otimes are binary operators that satisfy $0 \oplus a = a, 0 \otimes a = 0$. i.e., there exists nonzero $\alpha_{i,j}$ such that

$$\mathbf{e}_{u,r_t,v}^k = \bigoplus_{i=1}^k \underbrace{\bigoplus_{(u,r_t,v) \ (v,y_0,x_0) \ \dots \ (x_{i-3},y_{i-2},u)} \alpha_{i1}\mathbf{r}_{r_t} \otimes \alpha_{i2}\mathbf{r}_{y_0} \otimes \dots \otimes \alpha_{ii}\mathbf{r}_{y_{i-2}}}_{i} \quad (13)$$

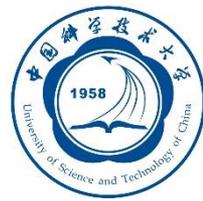


Experiments

- REST is effective:

		WN18RR				FB15k-237				NELL-995			
		v1	v2	v3	v4	v1	v2	v3	v4	v1	v2	v3	v4
Rule-Based	Neural LP	74.37	68.93	46.18	67.13	52.92	58.94	52.90	55.88	40.78	78.73	82.71	80.58
	DRUM	74.37	68.93	46.18	67.13	52.92	58.73	52.90	55.88	19.42	78.55	82.71	80.58
	RuleN	80.85	78.23	53.39	71.59	49.76	77.82	87.69	85.60	53.50	81.75	77.26	61.35
Subgraph-Based	GraIL	82.45	78.68	58.43	73.41	64.15	81.80	82.83	89.29	59.50	93.25	91.41	73.19
	CoMPiLE	83.60	79.82	60.69	75.49	67.64	82.98	84.67	87.44	58.38	93.87	92.77	75.19
	TACT	84.04	81.63	67.97	76.56	65.76	83.56	85.20	88.69	79.80	88.91	94.02	73.78
	SNRI	87.23	83.10	67.31	83.32	71.79	86.50	89.59	89.39	-	-	-	-
	ConGLR	85.64	92.93	70.74	92.90	68.29	85.98	88.61	89.31	81.07	94.92	94.36	81.61
	REST(ours)	96.28	94.56	79.50	94.19	75.12	91.21	93.06	96.06	88.00	94.96	96.79	92.61

- REST outperforms existing rule-based and subgraph-based methods by a large margin



Experiments

- REST is efficient:

		WN18RR				FB15k-237				NELL-995			
		v1	v2	v3	v4	v1	v2	v3	v4	v1	v2	v3	v4
Enclosing Subgraph	GraIL	121.77	537.42	1127.14	194.98	949.48	2933.04	8423.59	15089.74	136.55	1197.24	6112.77	1303.97
	REST	54.01	251.97	617.16	91.76	111.34	338.24	868.79	1,626.77	61.19	213.45	688.14	219.33
	Efficiency	2.25×	2.13×	1.83×	2.12×	8.53×	8.67×	9.70×	9.28×	2.23×	5.61×	8.88×	5.95×
Unclosing Subgraph	GraIL	127.69	517.94	1194.18	199.00	1287.35	4166.63	11499.32	21738.29	167.06	1611.97	8044.53	1542.82
	REST	56.27	260.20	631.71	95.23	123.36	386.55	985.81	1890.54	64.72	245.41	858.23	248.00
	Efficiency	2.27×	1.99×	1.89×	2.09×	10.44×	10.78×	11.66×	11.50×	2.58×	6.57×	9.37×	6.22×

- REST significantly accelerates the subgraph preprocessing time by up to $11.66\times$ ($6.02\times$ on average).



Experiments

□ Case study

Table 3: Some relations and their top-3 relevant relations. The relations are taken from WN18RR.

Rule Head	Rule Body	Scores
<i>_hypernym</i>	<i>_similar_to</i> -> <i>_hypernym</i> ⁻¹	0.89
	<i>_also_see</i> -> <i>_hypernym</i> ⁻¹	0.84
	<i>_hypernym</i> ⁻¹ -> <i>_also_see</i> -> <i>_verb_group</i>	0.67
<i>_derivationally_related_form</i>	<i>_derivationally_related_form</i> -> <i>_also_see</i>	0.82
	<i>_has_part</i> - > <i>_also_see</i>	0.76
	<i>_derivationally_related_form</i> -> <i>_also_see</i> -> <i>_has_part</i>	0.66
<i>_member_meronym</i>	<i>_has_part</i> -> <i>_synset_domain_topic_of</i>	0.77
	<i>has_part</i> -> <i>_synset_domain_topic_of</i> -> <i>_derivationally_related_form</i>	0.76
	<i>_has_part</i> -> <i>_derivationally_related_form</i>	0.71
<i>_synset_domain_topic_of</i>	<i>_has_part</i> -> <i>_also_see</i>	0.95
	<i>_synset_domain_topic_of</i> ⁻¹ -> <i>_similar_to</i>	0.91
	<i>_has_part</i> -> <i>_synset_domain_topic_of</i> ⁻¹	0.81



Thank You!