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## Supplementary Material for DRUM: End-to-End Differentiable Rule Mining on Knowledge Graphs

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**Theorem 1.** *If  $R_o, R_s$  are two rules of length  $T$  obtained by optimizing the objective related to  $\Omega_H^I$ , with confidence values  $\alpha_o, \alpha_s$ , then there exists  $\ell$  rules of length  $T$ ,  $R_1, R_2, \dots, R_\ell$ , with confidence values  $\alpha_1, \alpha_2, \dots, \alpha_\ell$  such that:*

$$\begin{aligned} d(R_o, R_1) = d(R_\ell, R_s) = 1 \quad \text{and} \quad d(R_o, R_s) \leq \ell + 1, \\ d(R_l, R_{l+1}) = 1 \quad \text{and} \quad \alpha_l \geq \min(\alpha_o, \alpha_s) \quad \text{for} \quad 1 \leq l \leq \ell, \end{aligned}$$

where  $d(.,.)$  is a distance between two rules of the same size defined as the number of mismatched atoms between them.

*Proof.* Define:

$$\mathbf{a}^* \doteq \arg \max_{\mathbf{a}} O_H^I(\mathbf{a}) = \sum_{(x,H,y) \in KG} \mathbf{v}_x^T \Omega_H^I(\mathbf{a}) \mathbf{v}_y,$$

where  $O_H^I(\mathbf{a})$ , is the objective related to the  $\Omega_H^I(\mathbf{a})$  model. The confidence value of a rule of length  $T$ , for instance  $S$ , with body  $B_{r_1} \wedge B_{r_2} \wedge \dots \wedge B_{r_T}$ , is

$$\alpha_S^* = \prod_{i=1}^T a_{i,r_i}^*.$$

Therefore changing a body atom  $B_{r_i}$  to  $B_{r'_i}$  in  $S$ , does not decrease the confidence value iff  $a_{i,r'_i}^* \leq a_{i,r_i}^*$ . Let  $a_{i,r_i}^*$  be the maximum element of the sequence  $a_{i,1}^*, \dots, a_{i,|\mathcal{R}|}^*$ . By consequently changing  $B_{r_i}$  in  $S$  to  $B_{r_i^*}$  (for  $i$ 's where  $r_i^* \neq r_i$ ) we obtain a sequence of rules of length  $T$ , with non-decreasing confidence values. The distance between any two consecutive elements in that sequence is 1. The last element of the sequence ( $S^*$ ) is the rule with the highest confidence value among length  $T$  rules, and the length of the sequence is  $d(S, S^*) + 1$ .

To prove the theorem, it is sufficient to substitute  $S$  with  $R_o$  and  $R_s$  to obtain two sequences of rules, with lengths  $d(R_o, S^*) + 1$  and  $d(R_s, S^*) + 1$ , respectively. by reversing the sequence related to  $R_s$  and concatenate it with the other sequence, we have a sequence of length  $d(R_o, S^*) + d(R_s, S^*) + 1$ , satisfying the conditions required to prove the theorem (after excluding  $R_o$  and  $R_s$ ).

The confidences values for the rules in the sequence satisfy the condition  $\alpha_l \geq \min(\alpha_o, \alpha_s)$ , because all the rules in the sequence related to  $R_s$  ( $R_o$ ) and  $S^*$  have larger or equal confidence value to  $R_s$  ( $R_o$ ). And since  $d(.,.)$  is a valid distance function it satisfies the triangle inequality; therefore  $d(R_o, R_s) \leq d(R_o, S^*) + d(R_s, S^*)$ , which implies  $d(R_s, R_o) \leq \ell + 1$ .  $\square$

Table 1: Comparison with other reasoning methods, an extension to the table 2 in the paper

Datasets	UMLS				Kinship			
	MRR	Hits@1	Hits@3	Hits@10	MRR	Hits@1	Hits@3	Hits@10
ConvE	0.94	0.92	0.96	0.99	0.83	0.98	0.92	0.98
ComplEx	0.89	0.82	0.96	1	0.81	0.7	0.89	0.98
MINERVA	0.82	0.73	0.90	0.97	0.72	0.60	0.81	0.92
NTP <sup>1</sup>	0.88	0.82	0.92	0.97	0.6	0.48	0.7	0.78
NTP- $\lambda^1$	0.93	0.87	0.98	1	0.8	0.76	0.82	0.89
NTP 2.0	0.76	0.68	0.81	0.88	0.65	0.57	0.69	0.81
DRUM	0.81	0.67	0.94	0.98	0.61	0.46	0.71	0.91

Table 2: Transductive link prediction results

	WN18				FB15K			
	MRR	Hits			MRR	Hits		
		@10	@3	@1		@10	@3	@1
DistMult	.822	.936	.914	.728	.XXX	.XXX	.XXX	.XXX
ComplEx	.941	.947	.936	.936	.XXX	.XXX	.XXX	.XXX
Gaifman	–	.939	–	.761	–	–	–	–
R-GCN	.814	.964	.929	.697	.XXX	.XXX	.XXX	.XXX
TransE	.495	.943	.888	.113	.XXX	.XXX	.XXX	.XXX
ConvE	.943	.956	.946	.935	.XXX	.XXX	.XXX	.XXX
Neural LP	.94	.945	–	–	.XXX	.XXX	–	–
DRUM	.944	.954	.943	.939	.XXX	.XXX	.XXX	.XXX

Table 3: Transductive link prediction results

	WN18			
	MRR	Hits		
		@10	@3	@1
DistMult	.822	.936	.914	.728
ComplEx	.941	.947	.936	.936
Gaifman	–	.939	–	.761
R-GCN	.814	.964	.929	.697
TransE	.495	.943	.888	.113
ConvE	.943	.956	.946	.935
Neural LP	.94	.945	–	–
DRUM	.944	.954	.943	.939

Head	brother(., .)	wife(., .)	son(., .)
NeuralLP	(B, A) $\leftarrow$ inv_sister(B, A) (C, A) $\leftarrow$ inv_sister(B, A), inv_sister(C, B) (C, A) $\leftarrow$ inv_brother(B, A), inv_sister(C, B) (B, A) $\leftarrow$ inv_brother(B, A) (C, A) $\leftarrow$ inv_sister(B, A), inv_brother(C, B) (C, A) $\leftarrow$ inv_brother(B, A), inv_brother(C, B) (B, A) $\leftarrow$ son(B, A) (C, A) $\leftarrow$ inv_sister(B, A), son(C, B) N/A N/A	(C, A) $\leftarrow$ inv_husband(B, A), inv_husband(C, B) (B, A) $\leftarrow$ inv_husband(B, A) (C, A) $\leftarrow$ daughter(B, A), inv_husband(C, B) (C, A) $\leftarrow$ wife(B, A), inv_husband(C, B) (C, A) $\leftarrow$ inv_husband(B, A), mother(C, B) (C, A) $\leftarrow$ mother(B, A), inv_husband(C, B) N/A N/A N/A N/A	(C, A) $\leftarrow$ son(B, A), brother(C, B) (B, A) $\leftarrow$ brother(B, A) (C, A) $\leftarrow$ son(B, A), inv_mother(C, B) (C, A) $\leftarrow$ inv_mother(B, A), brother(C, B) (B, A) $\leftarrow$ inv_mother(B, A) (C, A) $\leftarrow$ inv_mother(B, A), inv_mother(C, B) (C, A) $\leftarrow$ inv_husband(B, A), brother(C, B) (C, A) $\leftarrow$ inv_father(B, A), brother(C, B) (C, A) $\leftarrow$ inv_husband(B, A), inv_mother(C, B) (C, A) $\leftarrow$ inv_father(B, A), inv_mother(C, B)
DRUM	(C, A) $\leftarrow$ nephew(A, B), uncle(B, C) (C, A) $\leftarrow$ nephew(A, B), inv_nephew(B, C) (C, A) $\leftarrow$ brother(A, B), sister(B, C) (C, A) $\leftarrow$ brother(A, B), inv_sister(B, C) (C, A) $\leftarrow$ brother(A, B), inv_brother(B, C) (C, A) $\leftarrow$ brother(A, B), brother(B, C) (C, A) $\leftarrow$ nephew(A, B), inv_niece(B, C) (C, A) $\leftarrow$ nephew(A, B), aunt(B, C) (C, A) $\leftarrow$ inv_uncle(A, B), uncle(B, C) (C, A) $\leftarrow$ inv_uncle(A, B), inv_nephew(B, C)	(A, B) $\leftarrow$ inv_husband(A, B) (C, A) $\leftarrow$ mother(A, B), inv_father(B, C) (C, A) $\leftarrow$ inv_son(A, B), inv_father(B, C) (C, A) $\leftarrow$ mother(A, B), son(B, C) (C, A) $\leftarrow$ inv_son(A, B), son(B, C) (C, A) $\leftarrow$ mother(A, B), daughter(B, C) (C, A) $\leftarrow$ inv_son(A, B), daughter(B, C) (C, A) $\leftarrow$ inv_daughter(A, B), inv_father(B, C) (C, A) $\leftarrow$ inv_daughter(A, B), son(B, C) N/A	(C, A) $\leftarrow$ nephew(A, B), brother(B, C) (C, A) $\leftarrow$ brother(A, B), inv_mother(B, C) (C, A) $\leftarrow$ brother(A, B), daughter(B, C) (C, A) $\leftarrow$ brother(A, B), son(B, C) (C, A) $\leftarrow$ brother(A, B), inv_father(B, C) (C, A) $\leftarrow$ inv_sister(A, B), inv_mother(B, C) (C, A) $\leftarrow$ inv_sister(A, B), daughter(B, C) (C, A) $\leftarrow$ inv_sister(A, B), son(B, C) (C, A) $\leftarrow$ inv_sister(A, B), inv_father(B, C) (C, A) $\leftarrow$ inv_uncle(A, B), brother(B, C)

Table 4: Examples of top rules obtained by each system learned on *family* dataset