Learning Temporal Rules from Knowledge Graph Streams

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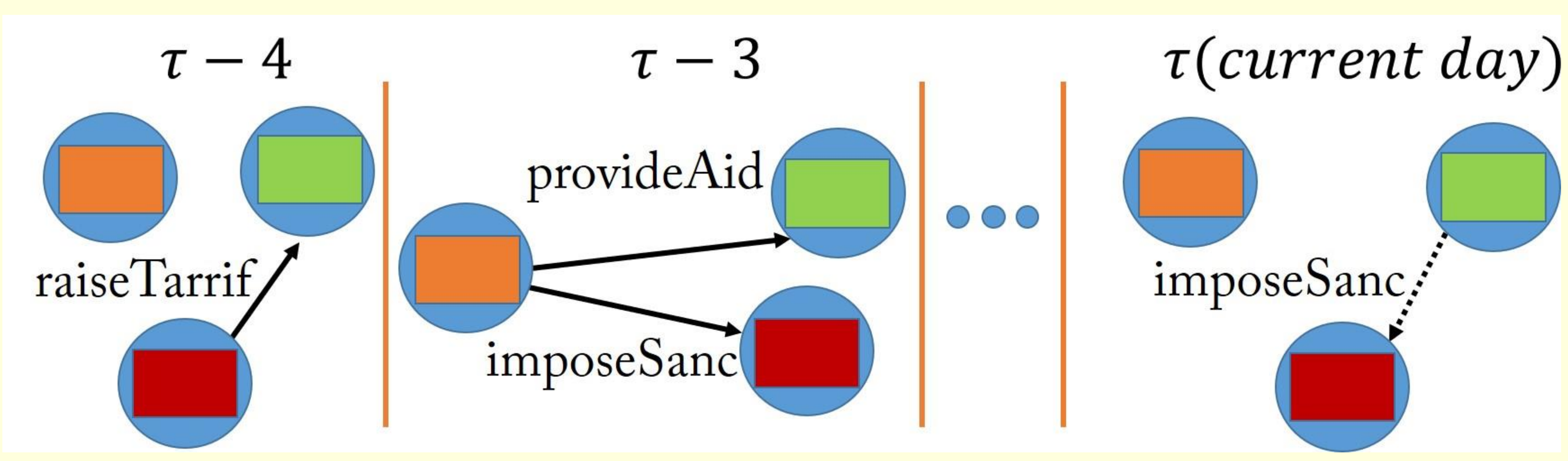
Abstract

Knowledge Graphs (KGs) are a prevailing data management approach and have found extensive applications in recent years. While several methods have been proposed for learning schema information for KGs in the form of logical rules, they are not suitable for KGs with constantly evolving data. This paper makes the first attempt to address the problem by presenting an approach to learning temporal rules from KG streams. The learned temporal rules can be applied in link prediction and event prediction over KG streams. Based on the proposed method, a system StreamLearner has been implemented. Our experimental results show that StreamLearner is effective and efficient in learning temporal rules on real-life datasets and significantly outperforms some state-of-the-art systems that do not account for temporal knowledge or evolving data.

Knowledge Graph Stream



A stream of KGs (e.g. Integrated Crisis Early Warning System)
Exemplary relations between countries (i.e. orange, green and red ones) in deferent times

Temporal Rule:

$$imposeSanc(y, x, \tau) \leftarrow raiseTarrif(x, y, \tau - 4)$$

$$imposeSanc(y, x, \tau) \leftarrow provideAid(z, y, \tau - 3), imposeSanc(z, x, \tau - 3)$$

Dynamic Rule Qualities

$$r: P_t(x, y) \leftarrow P_1(x, z), P_2(z, y)$$

$$r^0: P_t(x, y, \tau) \leftarrow P_1(x, z, \tau), P_2(z, y, \tau)$$

$$r^1: P_t(x, y, \tau) \leftarrow P_1(x, z, \tau - 1), P_2(z, y, \tau - 1)$$

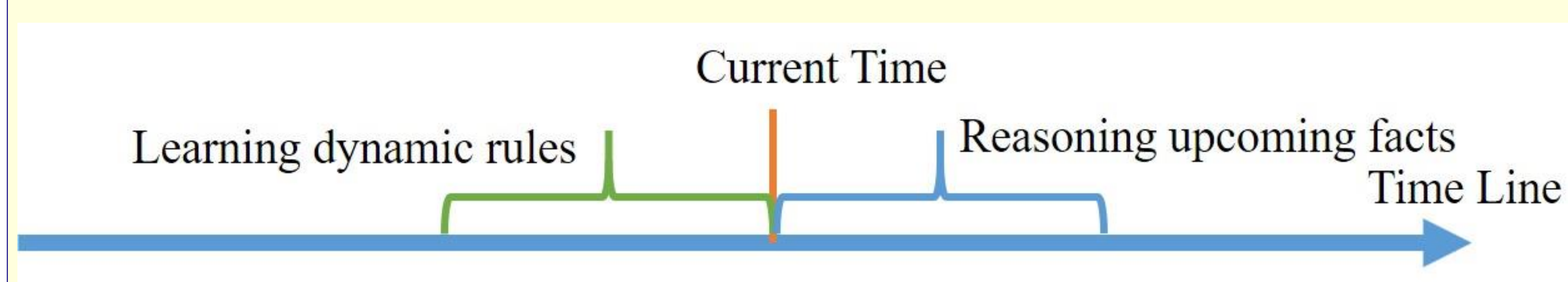
$$r^2: P_t(x, y, \tau) \leftarrow P_1(x, z, \tau - 2), P_2(z, y, \tau - 2)$$

$$supp(r^{(k)}, \tau) = \begin{cases} 0, & \text{if } \tau < k \\ \#(e, e') : head(r, e, e', \tau) \\ \wedge body(r, e, e', \tau - k), & \text{otherwise} \end{cases}$$

$$SC(r^{(k)}, \tau) = \frac{supp(r^{(k)}, \tau)}{\#(e, e') : body(r, e, e', \tau - k)}$$

$$DSC(\gamma, \tau) = \begin{cases} SC(\gamma, \tau), & \text{if } \tau = 0 \\ (1 - \alpha) \times DSC(\gamma, \tau - 1) \\ + \alpha \times SC(\gamma, \tau), & \text{otherwise} \end{cases}$$

Learning and Reasoning

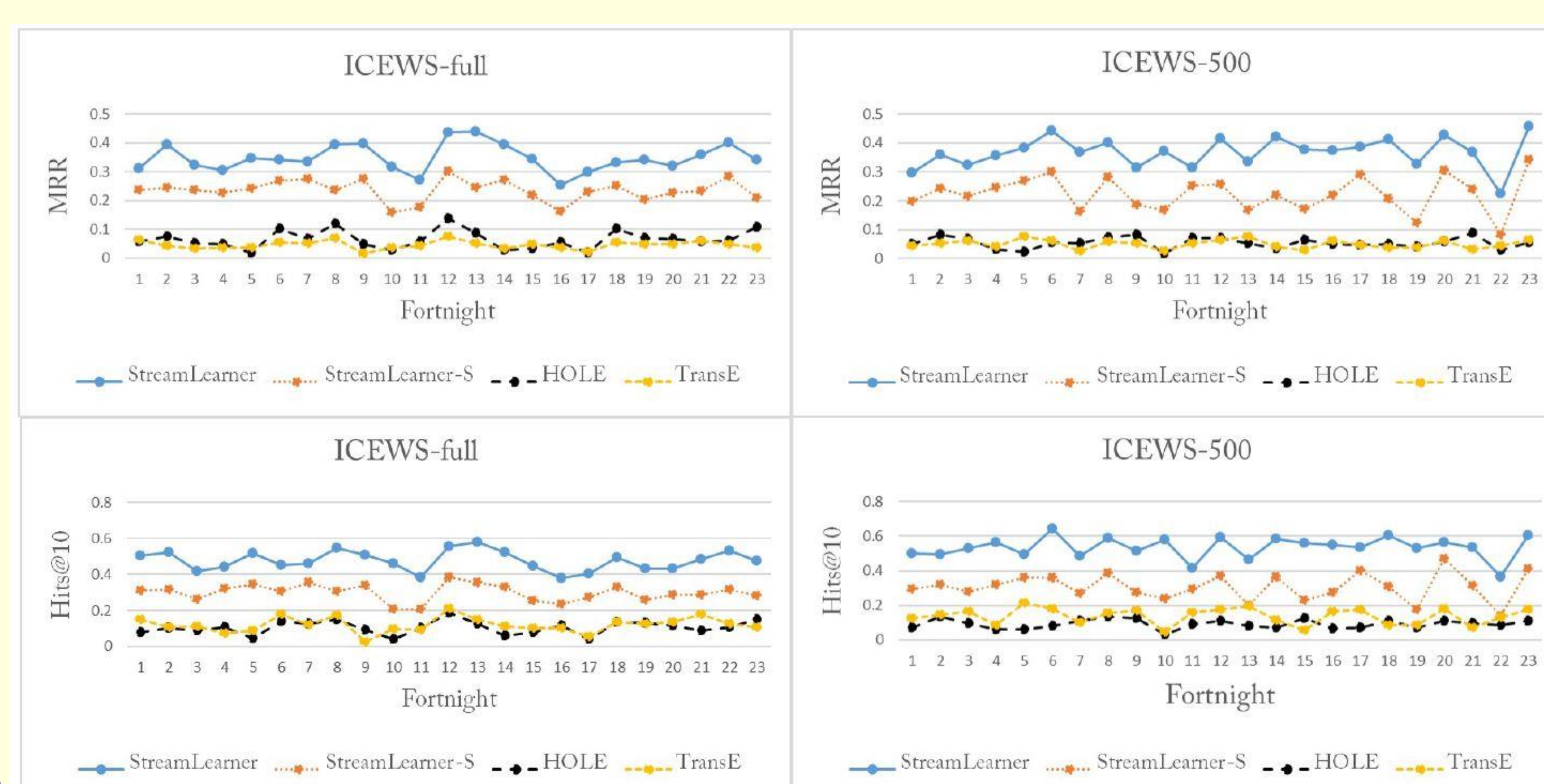


- StreamLearner uses a combination of learning and reasoning of temporal rules in a dynamic manner over KG streams.
- The method learns temporal rules r^i, for each structure rule r regarding facts of limited previous time points.
- It reasons new upcoming facts regarding future time points by learned temporal rules.

Experiments

Dataset	#Entity	#Event	#Pred.	#TPoint
ICEWS	12498	668080	260	365
ICEWS-500	500	445665	260	365

Dataset	StreamLearner			StreamLearner-S			TransE		HOLE	
	#TR	MRR	H@10	#SR	MRR	H@10	MRR	H@10	MRR	H@10
ICWEC	1748	0.35	0.48	568	0.24	0.30	0.05	0.12	0.07	0.10
ICWEC-500	1728	0.37	0.54	535	0.22	0.31	0.05	0.14	0.05	0.09



- StreamLearner learns temporal rules from KG streams and infers the upcoming events by the learned rules.
- It can handle KG streams with over 600K events and 12K entities.
- It evaluates candidate rules efficiently by proposed novel dynamic measurements.
- StreamLearner outperforms some state-the-art static link predictors including HOLE and TransE.
- The learned model (temporal rules) is understandable standalone knowledge.