A Survey on Temporal Knowledge Graphs-Extrapolation and Interpolation Tasks

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1 What?

This paper provided a comprehensive study of temporal knowledge graph, discussing the main existing temporal models and techniques which divided into extrapolation tasks and interpolation tasks.

2 Why?

The traditional KGE methods do not consider the time factor. And in the real world, data always involves larger and larger through the time. These old method get hard to expand on the new scenarios.

3 How?

TKG: $\{(e_i, r, e_j, t)\}$

In context of learning and KGC, entities and relationships of the KG undergo dynamic modifications over time.

3.1 Backgrounds

Temporal point processes can be represented based on the conditional strength function $\lambda(t)$ as stochastic model of the next event time given all previous events,

$$\lambda(t)dt := \mathbf{P}\{eventin[t, t+dt] \mid T(t)\} = \mathbf{E}[dN(t) \mid T(t)] \tag{1}$$

where:

- $\lambda(t)dt$ the conditional probability of observing an event in a small window given the history up to t.
- A small window = $[t, t + dt]$.
- The history up to t, i.e, $T(t) := \{t_\tau < t\}$.
- dt is a small window of size which only one event can occur, i.e, $dN(t) \in \{0, 1\}$.

The conditional density of the event occurring at moment t is defined as:

$$h(t) = \lambda(t)S(t) \tag{2}$$

where:

- $S(t)$ is the conditional probability that no event occurs.

3.2 Extrapolation .vs Interpolation

Extrapolation and interpolation are both used to estimate hypothetical values for a variable based on other observations.

- In interpolation setting, we could use our model to predict/ estimate the value of the dependent variable for an independent variable that in our data.
- In extrapolation setting, we could use our model to predict/ estimate the value of the dependent variable for an independent variable that is outside the range of our data.

Note that: In extrapolation, we are making the assumption that our observed trend continues for values in the outside the range we used to form our model.

3.3 Temporal knowledge graphs - Extrapolation setting

3.3.1 Temporal point process

The combination of temporal point process and deep networks to procedure neural point process which demonstrated powerful capabilities.

- Know-Evolve (Trivedi et al. 2017)
- DeRep

3.3.2 Time series models

- RE-Net
- CyGNet
- HIPNET
- CluSTeR
- DySAT
- TemporalGAT
- FTAG
- xERTE

3.3.3 Others

- TGAT

3.4 Temporal knowledge graphs - Interpolation setting

3.4.1 Translational distance model

- t-TransE, TTransE are based on TransE model.
- HyTE is based on TransH model.

3.4.2 Semantic matching model

- TComplEx
- TIMEPLEX
- TeLM

3.4.3 Neural network model

- TeMP

3.4.4 Relational rotation model

- TeRo
- ChronoR

3.4.5 Hyperbolic geometric model

- DyERNIE (Han et al. 2020)
- HERCULES ()

References

Han, Zhen et al. (2020). "Dyernie: Dynamic evolution of riemannian manifold embeddings for temporal knowledge graph completion". In: *arXiv preprint arXiv:2011.03984*.

Trivedi, Rakshit et al. (2017). "Know-evolve: Deep temporal reasoning for dynamic knowledge graphs". In: *international conference on machine learning*. PMLR, pp. 3462–3471.