A Survey on Temporal Knowledge Graph Completion: Taxonomy, Progress, and Prospects

Jiapu Wang et al

November 30, 2023

1 What?

This is a survey paper about the task of temporal knowledge graph completion.

2 Why?

TKGs or KG in general, ften suffer from incompleteness for three main reasons:

- the continuous emergence of new knowledge.
- he weakness of the algorithm for extracting structured information from unstructured data.
- the lack of information in the source dataset.

3 How?

The temporal knowledge graph completion task can be divided into two main kinds:

- Interpolation: estimates and predicts the missing elements or set of elements through the relevant available information.
- Extrapolation: focuses on continuous TKGs and predicts future events, and then classifies all extrapolation methods based on the algorithms they utilize.

JOURNAL OF LATEX CLASS FILES, VOL. ??, NO. ??, AUGUST 20YY 4

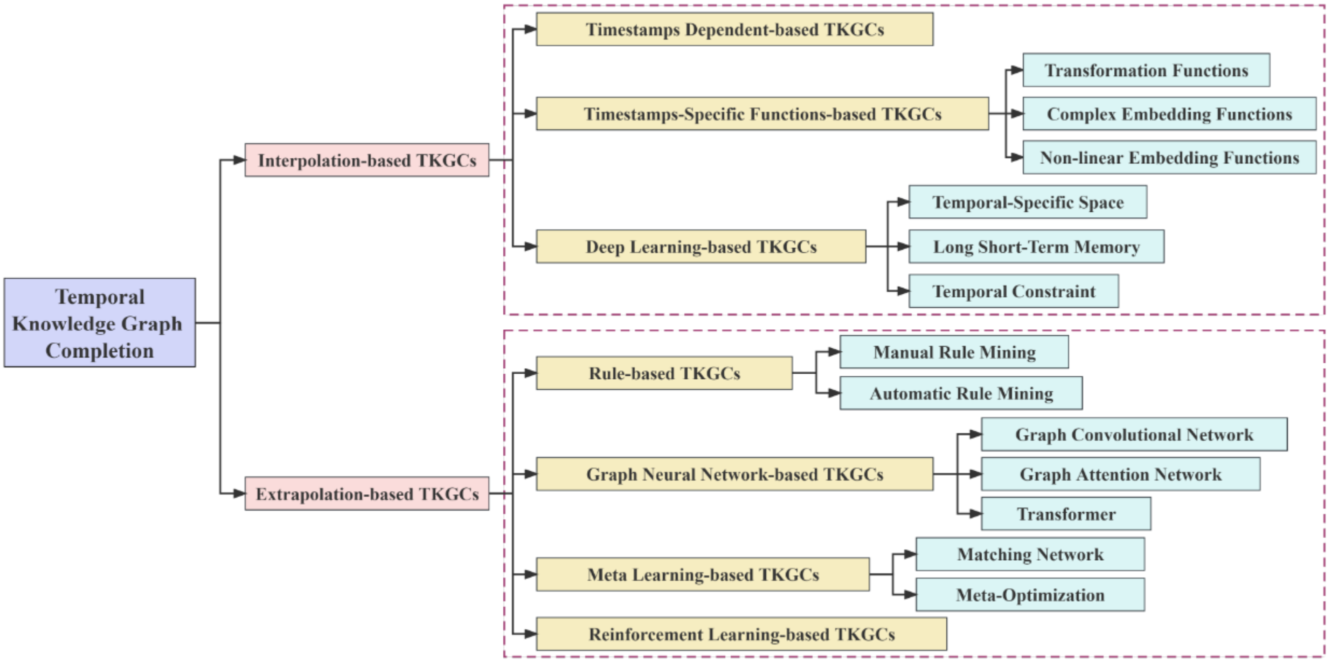

Fig. 2. Fine-grained categorization of *Temporal Knowledge Graph Completion (TKGC)* methods.

Figure 1: Tổng quan hướng tiếp cận bài toán hoàn thiện đồ thị tri thức động.

3.1 Interpolation-based TKGCs

3.1.1 Timestamps dependent-based TKGC methods

These methods typically do not perform operations on timestamps. They just simply associate the timestamps with the corresponding entity or relation to accomplish the evolution of entities and relations.

- TuckERTNT (Shao et al. 2022)
- TTransE, ST-TransE
- T-SimplE
- TKGFrame
- TBDRI

3.1.2 Timestamps-specific functions-based TKGC methods

These methods typically exploit the specific function to learn the embeddings of timestamps or the evolution of entities and relations.

There are various useful functions can be used:

- Diachronic embedding functions
- Gaussian functions
- Transformation functions

Transformation functions: encoding timestamps via one/ or some transformation functions

- TransE-ILP (Jiang et al. 2016) utilize the time-aware embedding model and Integer Linear Programming (ILP) to encode temporal order information and temporal consistency information.
- HTTR utilize Householder transformation
- BoxTE -> model-agnostic based on BoxTE
- SPLIME
- TARGCN
- TASTER
- Time-LowFER
- DE-SimplE, DE-DistMult
- DEGAT

Complex functions: using complex spaces or special coordinate system to capture various relational patterns.

- ChronoR (an extended version of RotatE)
- TComplEx and TNTComplEx
- TeRo
- TGeomE (using hypercomplex space, i.e., quaternion)
- TeLM (based on TGeomE)
- RotateQVS (quaternion space)

- ST-NewDE (Dihedron algebra)
- BiQCap
- HA-TKGE
- STKE (spherical coordinate system)
- HTKE

Non-linear embedding functions: tilize non-linear functions, such as Gaussian and non-Euclidean functions, to embed TKGs.

- DyERNIE, HERCULES
- ATiSE
- TKGC-AGP

3.1.3 Deep learning-based TKGC methods

Timestamps-specific space

- HyTE, HTKE, TRHyTE, BTHyTE
- ToKEi
- SANe
- QDN

Long short-term memory

- TA-TransE, TA-DistMult
- TDG2E
- TRHyTE
- CTRIEJ
- TeCre

Temporal constraint

- Kgedl

- T-GAP
- TempCaps
- RoAN
- TAL-TKGC

3.2 Extrapolation-based TKGCs

3.2.1 Rule-based TKGC methods

- ALRE-IR
- TLogic
- TILP
- TFLEX

3.2.2 Graph neural network-based TKGC methods

Graph convolutional network

- RE-NET
- Glean
- TeMP
- DACHA
- RE-GCN
- CyGNet
- TiRGN
- HiSMatch
- SPA
- TANGO
- HGLS

Graph attention network

- TPmod
- EvoKG
- DA-Net
- TAE
- EvoExplore
- CRNet
- CENET
- MP-KD
- Know-Evolve
- RTFE
- CyGNet
- xERTE
- T-GAP

Transformers

- HSAE
- rGalT
- GHT

3.2.3 Meta learning-based TKGC methods

Matching network

- FTAG
- FTMF
- TFSC

Meta-optimization

- MOST
- MetaTKG
- MetaTKGR

3.2.4 Reinforcement learning-based TKGC methods

- TAgent (Tao, Li, and Wu 2021)
- TPath (Bai et al. 2021)
- TITer (Sun et al. 2021)
- CluSTeR (Li et al. 2021)
- DREAM (Zheng et al. 2023)
- RLAT (Bai, Chai, and Zhu 2023)

References

Bai, Luyi, Die Chai, and Lin Zhu (2023). "RLAT: Multi-hop temporal knowledge graph reasoning based on Reinforcement Learning and Attention Mechanism". In: *Knowledge-Based Systems* 269, p. 110514.

Bai, Luyi et al. (2021). "Multi-hop reasoning over paths in temporal knowledge graphs using reinforcement learning". In: *Applied Soft Computing* 103, p. 107144.

Jiang, Tingsong et al. (Dec. 2016). "Towards Time-Aware Knowledge Graph Completion". In: *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*. Ed. by Yuji Matsumoto and Rashmi Prasad. Osaka, Japan: The COLING 2016 Organizing Committee, pp. 1715–1724. URL: https://aclanthology.org/C16-1161.

Li, Zixuan et al. (2021). "Search from history and reason for future: Two-stage reasoning on temporal knowledge graphs". In: *arXiv preprint arXiv:2106.00327*.

Shao, Pengpeng et al. (2022). "Tucker decomposition-based temporal knowledge graph completion". In: *Knowledge-Based Systems* 238, p. 107841.

Sun, Haohai et al. (2021). "Timetraveler: Reinforcement learning for temporal knowledge graph forecasting". In: *arXiv preprint arXiv:2109.04101*.

Tao, Ye, Ying Li, and Zhonghai Wu (2021). "Temporal link prediction via reinforcement learning". In: *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, pp. 3470–3474.

Zheng, Shangfei et al. (2023). "DREAM: Adaptive Reinforcement Learning based on Attention Mechanism for Temporal Knowledge Graph Reasoning". In: *arXiv preprint arXiv:2304.03984*.