# A Survey on Temporal Knowledge Graph Embedding

**Abstract.** Knowledge Graph (KG) embedding has emerged as an active area of research. Recently, we note that KG beliefs are not universally true, as they tend to be valid only in a specific time period. However, most algorithms for KG embedding have been designed for static data, which lead to low efficiency and high error rate. Therefore, modeling dynamically-evolving, multi-relational graph data has received a surge of interests with the rapid growth of heterogeneous event data. And recent research has focused on temporal knowledge graph and its temporal information. In this survey, we first describe the standard definition of temporal knowledge graph. And then we provide a comprehensive review on temporal knowledge graph embedding covering overall research topics about temporal information and embedding models. We also introduce some prominent downstream tasks with the widely used data sets and evaluation protocol. Finally, we summarize recent challenges and highlight directions to facilitate future research.

**Keywords:**Temporal knowledge graph embedding, temporal information, translational distance models, semantic matching models, downstream tasks

# 1 introduction

From document interconnection in the "Web1.0" era, to data interconnection in the "Web2.0" era, to knowledge interconnection in the "Web3.0" era [1], the development of Web technology pushes the Net toward intelligence and machines understand the human world better. However, in the era of big data, the explosive growth of global information, the multi-source heterogeneous information content and the loose information structure have brought huge challenges to the realization of knowledge interconnection. Therefore, it’s important to explore appropriate knowledge organization principles [2] and seek knowledge interconnection methods that that meet both the changes of network information and the needs for user cognitive [3], so that we can reveal the integrity and relevance of human cognition from a deeper level [4]. Then the Knowledge Graph (KG) that mainly uses for organizing, managing and retrieving structured information [6] arises under this situation. It can collect dispersed human knowledge and organize these data into the structured knowledge system [7].

On May 17, 2012, KG was formally proposed by Google [5]. It is a knowledge base used to enhance the search engine functionality and improve the quality of the search content, which can enhance the user experience and satisfaction. Then, the KG has been widely used in many applications related to natural language processing (NLP), such as information retrieval, question answering system, recommendation system. The open link knowledge bases represented by Freebase, Wikidata, DBpedia, YAGO and the vertical industry knowledge bases represented by

IMDB, MusicBrainz, and ConceptNet has been gradually set up[10].

KG is a multi-directional graph with labeled edges [15], which is composed of nodes and edges. It can be formalized as $G = (E,R)$, where E is a set of labeled nodes called entities, representing entities in the objective world, and R is a set of labeled edges called relations (relation types or predicates) [6], which represents a certain connection between entities. The elements in the KG are often in the form of triples, i.e. $(h,r,t)$, which includes two basic forms of (head entity, relation, tail entity) and (concept, attribute, attribute value). In the second one, the concepts mainly refer to collections, categories, object types and so on. Attribute mainly refer to the attributes, characteristics and parameters that the object may have, and attribute values mainly refer to the value of the specified attributes of the object [10]. The relationship description of triples is shown in Figure 1.


**Figure 1:** The relationship description of triples

However, most of the researches on existing knowledge graph embedding(KGE) models ignore the temporal information of facts, and mainly focus on static relational data that is time-unaware [6]. In the real world, KG beliefs are not universally true, as they tend to be valid only in a specific time period [9]. And with the rapid growth of heterogeneous event data, the KG is always in a dynamic state [13]. For example, the triple (Kobe, played for, Lakers) is only valid in the time span of 1996 to 2016. The triple (Kobe, winning champion, Lakers) is valid in the time span of 1999 to 2002 and 2008 to 2010. And the triple (Kobe, died, California) occurred on January 26, 2020... If there is no limitation and modification of temporal information, these triples will cause errors in practice.

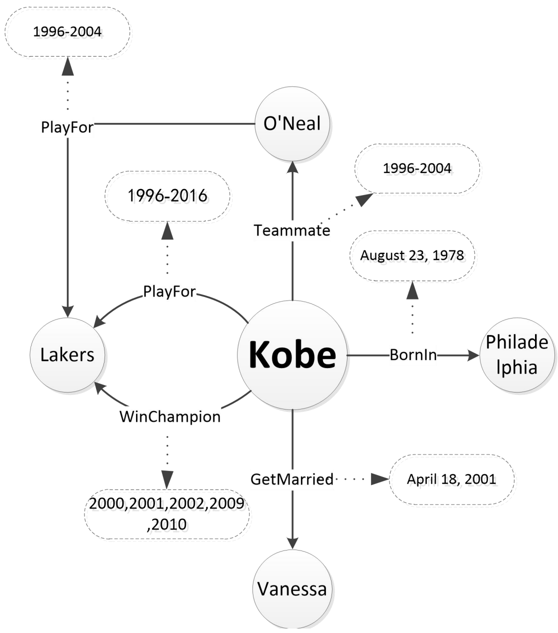


**Figure 2:** The KG of Kobe, the content in the dotted line represents the temporal information of each fact triple

Therefore, if the temporal information is not introduced as a new dimension into the KG, the data will quickly become outdated and invalid, no matter the data is generated and maintained by users or computer programs. What's worse, some most popular formats for data distribution (including RDF, JSON or CSV) do not provide a built-in mechanism to capture and retain the information that changes over time, so that errors and omissions can easily spread [8].

In order to improve the quality of the KG and enable the "knowledge" in the KG to keep pace with the time, the temporal knowledge graph embedding(TKGE) technology has become a hotspot in the field of knowledge graph research, but the degree of exploration is relatively low, and the use of time series information Still not perfect. The rest of this article is organized around the time series knowledge graph as follows. In section 2, we describe the standard definition of temporal knowledge graph. And then we provide a comprehensive review on temporal knowledge graph embedding covering overall research topics about temporal information and embedding models in section 3. We also introduce some prominent downstream tasks with the widely used data sets and evaluation protocol in section 4. Finally, we summarize recent challenges and highlight directions to facilitate future research.

# 2 Preliminaries

## 2.1 Temporal knowledge graph

In the real world, KG beliefs are not universally true, as they tend to be valid only in a specific time period [9]. Therefore, knowledge is time-labeled and changes significantly over time [17]. The introduction of temporal information as a new dimension into the knowledge graph will not only make the knowledge graph more real and effective, but also improve the quality of the information from the KG .

Formally speaking, the temporal knowledge graph (TKG) can be formalized as $\mathrm{G} = (\mathrm{E,R,T})$[6], where the new set T relative to KG represents time-aware information (temporal information or time predicate). The "knowledge" originally represented by triples $(\mathrm{h,r,t})$ has become a quadruple $(\mathrm{h,r,t},[\tau_s, \tau_e])$ [9] due to the addition of separate time dimension information, that is, each relational fact $(\mathrm{h,r,t})$ corresponds to a time range label $[\tau_s, \tau_e]$ (that is, the triple $(\mathrm{h,r,t})$ is valid within $[\tau_s, \tau_e]$ ), where h represents the head entity, r represents the relationship, t represents the tail entity, $\tau_s$ and $\tau_e$ represent the start time and end time respectively.

Given a timestamp, the graph can be decomposed into several static graphs composed of valid triples in each time step. For example, the knowledge graph G can be expressed as $\mathrm{G} = \mathrm{G}_{\tau_1} \cup \mathrm{G}_{\tau_2} \cup \cdots \mathrm{G}_{\tau_T}$, where $\tau_i$, $\mathrm{i} \in 1,2,\cdots,\mathrm{T}$ are discrete time points, which $\mathrm{G}_{\tau_i}$ are called time component diagram [9].

In many studies, as a dynamic knowledge graph that also carries time information, it is easy to confuse it with the concept of temporal knowledge graph. In fact, the two are both related and different.

Dynamic Knowledge Graph (Dynamic KG) is essentially a type of dynamic graph (that is, when G in the formal representation is KG), dynamic graphs include continuous-time dynamic graphs (CTDG) and discrete-time dynamic graphs (DTDG). Type [16]. We denote CTDG as

$\mathrm{CTDG} = (\mathrm{G},\mathrm{O})$, where G is a static graph representing the initial state of the dynamic graph at time $t_0$, and O is a set of observations/event sequences, where each observation is a tuple (event type, event, timestamp), event The type can be edge addition, edge deletion, node addition, node deletion, node splitting, node merging, etc. [16].

At any point in time $t \geqslant t_0$, CTDG updates G sequentially according to the observation value O that occurred before (including t) at time t, and we can obtain a snapshot $G_t$ from CTDG, which corresponds to a static picture. DTDG is a sequence of snapshots of dynamic graphs, and these snapshots are sampled at regular intervals. Formally, $\mathrm{DTDG} = \{\mathrm{G}_1,\mathrm{G}_2,\cdots,\mathrm{G}_T\}$, where $\mathrm{G}_t = \{\mathrm{V}_t,\mathrm{E}_t\}$ [16].