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Cross-Temporal Snapshot Alignment for Dynamic Multi-Relational Networks

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Abstract. A dynamic network is often represented as a sequence of snapshots evolving over time. In certain real-world scenarios, the identities of nodes in snapshots of a dynamic network are unknown and need to be figured out. To deal with such a challenge, recently, the task of cross-temporal snapshot alignment for dynamic networks is proposed, which aims to match equivalent nodes across temporal snapshots of a dynamic network given a small set of identified nodes. However, in many dynamic multi-relational networks like temporal knowledge graphs, the relation type information of edges, which can be useful for the alignment task, is neglected by existing methods. In this paper, we focus on a similar task but pay special attention to dynamic multi-relational networks. We propose a Relation-Aware Cross-Temporal Snapshot Alignment model (RCTSA) that incorporates time-dependent topological structure information into temporal node embeddings and temporal relation embeddings. To disentangle time-dependent information and time-independent information of the dynamic multi-relational network, RCTSA maintains a time embedding for each snapshot to preserve the temporal information which is incorporated into entity embeddings and relation embeddings to get the temporal embeddings. After training, the learned entity embeddings of unidentified nodes together with time embeddings can be used for the alignment task. Experimental results on real-world dynamic multi-relational networks demonstrate the effectiveness of our model.

1. Introduction

A dynamic network refers to a network whose topological structure changes dynamically over time, and is often represented as a sequence of snapshots in chronological order. Different from the fact that each entity corresponds to exactly one node in the static network scenario, an entity usually participates in a dynamic network multiple times and is referred to by nodes in different snapshots with time-dependent interaction behaviors, exhibiting complex and informative temporal patterns. In certain real-world scenarios, due to the difficulties in data collection or data corruption, the entities that nodes refer to (i.e., the identities of nodes) are unknown and need to be figured out. To deal with such a challenge, recently, the task of cross-temporal snapshot alignment for dynamic networks ("snapshot alignment" for short) has been studied. Specifically, it aims to match equivalent nodes across temporal snapshots of a dynamic network referring to the same entities given a small set of identified nodes. In dynamic multi-relational networks, edges are attached with heterogeneous types of relations indicating the

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semantic information of the connections, which can help characterize the interaction behaviors of nodes more precisely compared to all edges with a homogeneous type of relation in dynamic single-relational networks studied in [1–3]. We argue that such relation type information can be helpful when aligning snapshots of a dynamic multi-relational network and propose to study the task of snapshot alignment for dynamic multi-relational networks.

To integrate relation type information which is neglected in [1], we propose a Relation-Aware Cross-Temporal Snapshot Alignment (RCTSA) model for dynamic multi-relational networks. our RCTSA model can not only leverage relation type information of edges to refine node embeddings used for the alignment task but also perform cross-snapshot mining to learn temporal pattern information. The key design of our model is to learn two embedding vectors for each node: (1) the entity embedding, which preserves time-invariant characteristics of the entity across snapshots and is shared among any other node (in other snapshots) referring to the same entity; and (2) the temporal node embedding encoding time-dependent behaviors of a node in its snapshot. Using two kinds of embeddings for each node allows the model to disentangle the time-dependent feature and the time-independent feature of a node. To serve as a bridge between these two types of embeddings, time embeddings, each of which captures temporal information of a snapshot, are introduced to transform time-independent entity embeddings into temporal node embeddings. Additionally, temporal topological information is encoded into temporal node embeddings with the help of temporal relation embeddings. Finally, the learned entity embeddings of unidentified nodes together with time embeddings can be used for alignment.

Overall, we make the following contributions in this paper. (1) **New Task**: To the best of our knowledge, we are the first to study the task of snapshot alignment for a dynamic multi-relational network; (2) **New Algorithm**: To address this novel task, we propose a model called Relation-Aware Cross-Temporal Snapshot Alignment (RCTSA); (3) **Empirical Evaluations**: Experimental evaluations on two real-world dynamic multi-relational network datasets demonstrate the superior performance of our proposed RCTSA over the baseline models.

2. Related Work

The task of network alignment is to find equivalent nodes of different networks [4]. As for multi-network alignment, CrossMNA [4] is proposed to jointly learn structural information across diversities of networks. Knowledge graph alignment aims to find entities in different knowledge graphs representing the same real-world entity, which is a special case of network alignment in that edges in knowledge graphs are with heterogeneous relation types. Compared to all edges with the homogeneous type in network alignment, such additional relation type information can help characterize the interaction behavior of the nodes more precisely and has been shown useful for improving the performance of knowledge graph alignment [5]. JAPE [5] jointly embeds the structures of two knowledge bases into a unified vector space for alignment. CompGCN [6] is a graph convolutional framework for incorporating multi-relational information, which can be employed to embed different knowledge graphs into the same embedding space for alignment.

Different from research in network alignment and knowledge graph alignment described above focusing on aligning different separate networks, CTSA [1] is the first to study the task of cross-temporal snapshot alignment for dynamic networks, which aims to discover the cross-temporal links connecting the equivalent unidentified nodes in the source and target snapshots, by considering both the structural and temporal information. Although it achieves state-of-the-art performance on cross-temporal snapshot alignment for dynamic single-relational networks, it neglects relation type information of edges which carries useful semantic information. In this paper, we propose to incorporate such relation type information to enhance alignment performance for dynamic multi-relational networks.

3. Relation-Aware Cross-Temporal Snapshot Alignment

3.1. Problem Formulation

Let $\mathcal{R} = \{r_l\}_{l=1}^{M}$ be a set of M categorical relations. A dynamic multi-relational network $\mathcal{G}_{\leq T}$ can be represented as a sequence of network snapshots, i.e., $\mathcal{G}_{\leq T} = \{\mathcal{G}_t\}_{t=1}^{T}$, with the time steps evolving from 1 to T. Specifically, the snapshot at time t is defined as $\mathcal{G}_t = (\mathcal{V}_t, \mathcal{E}_t)$, where $\mathcal{V}_t$ and $\mathcal{E}_t$ represent the set of nodes and edges at time t, respectively. A relation tuple $(s, r, o, t) \in \mathcal{E}_t$ denotes a directed edge with relation type $r \in \mathcal{R}$ from a subject node $s \in \mathcal{V}_t$ to an object node $o \in \mathcal{V}_t$ at time step t. Given two snapshots $\mathcal{G}_{t_1}, \mathcal{G}_{t_2}$ at two different time steps and their corresponding node sets $\mathcal{V}_{t_1}, \mathcal{V}_{t_2}$ respectively, the pre-aligned nodes between the two snapshots are described by an anchor link set $\mathcal{A}_{(t_1,t_2)} = \left\{\left(v_{t_1}^a, v_{t_2}^a\right) \mid v_{t_1}^a \in \mathcal{V}_{t_1}, v_{t_2}^a \in \mathcal{V}_{t_2}\right\}$. Specifically, each element $\left(v_{t_1}^a, v_{t_2}^a\right)$ is an anchor link connecting two nodes $v_{t_1}^a, v_{t_2}^a$ referring to the same entity a. All anchor links of the dynamic network $\mathcal{G}_{\leq T}$ across snapshots can be obtained by the union of all anchor link sets, i.e., $\mathcal{A}_{\leq T} = \bigcup_{t_1 \neq t_2} \mathcal{A}_{(t_1,t_2)}$. Given a dynamic multi-relational network $\mathcal{G}_{\leq T} = \{\mathcal{G}_t\}_{t=1}^{T}$ and the pre-align anchor links $\mathcal{A}_{\leq T}$, the task of cross-temporal snapshot alignment for a dynamic network is to find the remaining undiscovered cross-temporal links between $\mathcal{G}_{t_1}$ and $\mathcal{G}_{t_2}$ that connect the equivalent unidentified nodes, $\mathcal{A}'_{(t_1,t_2)} = \left\{\left(v_{t_1}^{a'}, v_{t_2}^{a'}\right) \notin \mathcal{A}_{(t_1,t_2)} \mid v_{t_1}^{a'} \in \mathcal{V}_{t_1}, v_{t_2}^{a'} \in \mathcal{V}_{t_2}\right\}$, which in essence is to learn a function F satisfying:

$$\mathcal{G}_{\leq T}, \mathcal{A}_{\leq T}, (t_1, t_2) \xrightarrow{F} \mathcal{A}'_{(t_1,t_2)}. \tag{1}$$

Following [1], we assume that known anchor nodes are identified across all snapshots $\{\mathcal{G}_t\}_{t=1}^{T}$.

3.2. The Proposed Model

To incorporate relation information to resolve the problem of snapshot alignment for a dynamic multi-relational network, we propose the **RCTSA** model.

Three types of basic embeddings with the same dimension size d, i.e., time embeddings, entity embeddings and relation embeddings, are used in our model. To capture snapshot-specific temporal information, RCTSA maintains a time embedding $\mathbf{e}_t$ for each snapshot $\mathcal{G}_t$ (time step t). In order to capture time-agnostic information, it makes use of entity embeddings and relation embeddings to capture time-independent features of nodes and relations. Specifically, RCTSA allocates a distinct relation embedding $\mathbf{e}_r$ for each relation type $r \in \mathcal{R}$. As for the entity embeddings, identified nodes in different snapshots referring to the same entity v share one entity embedding $\mathbf{e}_v$ while each unidentified node has its own entity embeddings since its identity is unknown.

Through the basic entity embeddings and relation embeddings, we can capture the common characteristics of entities and relations across times (i.e., information invariant in all snapshots). However, we are also interested in the specific pattern of entities and relations at a specific time. On the one hand, the interaction behaviors of an entity may be dependent on time steps. On the other hand, the meaning of relations may also change as time progresses. Inspired by research in temporal knowledge embedding techniques, we employ HyTE [7] to transform both entity embeddings and relation embeddings to their temporal-aware counterparts. The main idea is to embed representations of nodes and relations of different snapshots into different time-specific hyperplanes. More specifically, for each time step t we model its corresponding time embedding $\mathbf{e}_t$ to be a normal vector of the hyperplane $\mathcal{P}_t$ by restricting its norm to be 1, i.e., $\|\mathbf{e}_t\|_2 = 1$, and then representations of nodes and relations within snapshot $\mathcal{G}_t$ can be obtained by projecting their basic embeddings onto $\mathcal{P}_t$. Given a tuple $(s, r, o, t) \in \mathcal{E}_t$ and the basic embeddings of its elements $(\mathbf{e}_s, \mathbf{e}_r, \mathbf{e}_o, \mathbf{e}_t)$, the projected embeddings are calculated as follows:

$$\mathcal{P}_t(\mathbf{e}) = \mathbf{e} - \left(\mathbf{e}_t^\top \mathbf{e}\right) \mathbf{e}_t, \quad \mathbf{e} \in \{\mathbf{e}_s, \mathbf{e}_o, \mathbf{e}_r\} \tag{2}$$

Table 1. Statistics of the dynamic multi-relational networks.

Dataset	#Entities	#Relations	#Edges	#Snapshots
Wikidata	11,285	24	68,780	10
YAGO	8,727	10	34,687	10

In this way, there will be T hyperplanes $\{\mathcal{P}_t\}_{t=1}^{T}$ in the whole embedding space $\mathbb{R}^d$. And representations of nodes and relations at different times can capture time-specific information as they locate in different hyperplanes. To encourage these projected time-aware embeddings to capture the interactional patterns of nodes at specific times, we represent temporal relation embeddings as the translations from subject embeddings to object embeddings, i.e.,$\mathcal{P}_t(\mathbf{e}_s) + \mathcal{P}_t(\mathbf{e}_r) \approx \mathcal{P}_t(\mathbf{e}_o)$. Thus, we use the following non-parametric scoring function f to measure the plausibility of a tuple (s, r, o, t):

$$f(s,r,o,t) = \|\mathcal{P}_t(\mathbf{e}_s) + \mathcal{P}_t(\mathbf{e}_r) - \mathcal{P}_t(\mathbf{e}_o)\|_2^2, \tag{3}$$

where we expect a low score of $f(s,r,o,t)$ if $(s,r,o,t) \in \mathcal{E}_t$ is a positive tuple, and a high score of $f(s',r,o',t)$ if $(s',r,o',t) \notin \mathcal{E}_t$ is a negative tuple constructed by replacing s or o with $v \in \mathcal{V}_t$ randomly and is not part of the snapshot structure on the contrary. All learnable parameters of our RCTSA model (i.e., three types of basic embeddings) are optimized by minimizing the above loss across all snapshots:

$$\mathcal{L} = \sum_{t=1}^{T}\left(\sum_{(s,r,o,t)\in\mathcal{E}_t} f(s,r,o,t) - \lambda \sum_{(s',r,o',t)\notin\mathcal{E}_t} f(s',r,o',t)\right), \quad \text{s.t. } \|\mathbf{e}_v\|_2 \le 1, \|\mathbf{e}_t\|_2 = 1 \tag{4}$$

where λ is the hyper-parameter balancing the loss for positive and negative tuples. Besides enforcing the norm of each time embedding to be 1, we also restrict the norm of each entity embedding no greater than 1 as suggested in [7].

After training, all the entity embeddings capture common characteristics of the entities across times and the time embeddings encode temporal information of snapshots. Now we can perform nearest neighbor search based on the distances of temporal node embeddings to aligning nodes. More specifically, let $\mathcal{V}'_{t_1}$ and $\mathcal{V}'_{t_2}$ be the unidentified node sets in snapshots $\mathcal{G}_{t_1}$ and $\mathcal{G}_{t_2}$ respectively, to find the equivalent node (target unidentified node) $v_{t_2}^{a'} \in \mathcal{V}'_{t_2}$ for the source unidentified node $v_{t_1}^{a'} \in \mathcal{V}'_{t_1}$, we first project the entity embedding of the source node into the time hyperplane $\mathcal{P}_{t_2}$ and perform alignment based on the distances between the projected embedding and temporal node embeddings of the unidentified nodes in snapshot $\mathcal{G}_{t_2}$:

$$v_{t_2}^{a'} = \arg\min_{v\in\mathcal{V}'_{t_2}} \|\mathcal{P}_{t_2}(\mathbf{e}_v) - \mathcal{P}_{t_2}(\mathbf{e}_{a'})\|_1. \tag{5}$$

4. Experiments

4.1. Datasets

For evaluation purposes, we process two widely used knowledge graph datasets Wikidata [8] and YAGO [9] to construct dynamic multi-relational networks following the procedure in [10, 11]. Since the attribute information of nodes (especially unidentified nodes) is usually missing, even unavailable in real-life applications [4], only structural features are used to train models for alignment. Statistics of the constructed dynamic multi-relational networks are provided in Tab.1.

4.2. Baselines

We compare our model with the following baseline models:

- JAPE [5]: This model jointly embeds the structures of two knowledge bases into a unified vector space and performs entity alignment based on the embeddings. For fair comparison, here we only use the structural part of JAPE which does not use any attribute information.
- CompGCN [6]: It is a graph convolutional framework for incorporating multi-relational information which can be employed to embed different knowledge graphs into the same embedding space for alignment.
- CrossMNA [4]: This is a network alignment method for the multi-network scenarios which leverages the cross-network information. Two types of node embedding are optimized via a skip-gram based objective to maximize the likelihood of all edges of multiple networks.
- CTSA [1]: It is a state-of-the-art framework for cross-temporal snapshot alignment for dynamic single-relational networks. It designs a framework that employs parameter-share GNNs to infer structural representation of nodes and self-attention mechanism to enhance these representations with temporal information.
- RCTSA: This is our proposed model which uses temporal node embeddings for alignment.

4.3. Experimental Settings

Three types of commonly used metrics for evaluating alignment methods, i.e., $P@k$ (Precision@k), MR (Mean Rank) and MRR (Mean Reciprocal Rank), are reported in the experiments. As for the $P@k$ metric, k is chosen as $1, 10$ and 30 as in [1]. In short, a good method should achieve lower MR, higher MRR, and higher $P@K$. The parameters of our model are optimally tuned to be $\lambda = 0.2, d = 600$ in Wikidata dataset and $\lambda = 0, d = 600$ in YAGO dataset. We train our model by Adam [12] optimizer with a learning rate $lr = 0.01$. The chosen source and target snapshots for alignment are $\mathcal{G}_2$ and $\mathcal{G}_7$ on Wikidata, $\mathcal{G}_3$ and $\mathcal{G}_8$ on YAGO. For each dynamic multi-relational network, all the pre-aligned node pairs between the two snapshots are divided into a training set (30%) and a testing set (70%).

4.4. Results and Analysis

The overall performance of our RCTSA and the baseline models on snapshot alignment for dynamic multi-relational networks is reported in Tab. 2 from which we can have the following findings:

(1) Our proposed RCTSA surpasses all baseline methods in terms of different evaluation metrics for the snapshot alignment task on both dynamic multi-relational network datasets. Particularly, RCTSA achieves significant improvement in terms of $P@1$ and MRR metrics, which suggests that it can precisely locate the counterparts of the nodes. As for other metrics, e.g., $P@10$, $P@30$, and MR, it also achieves superior performance. This experimental result demonstrates the effectiveness and advantages of our RCTSA by incorporating relation type information and structural information of multi-snapshots.

(2) Aligning methods originally designed for knowledge graph alignment tasks, i.e JAPE and CompGCN, generally outperform alignment methods proposed for single-relational networks like CrossMNA and CTSA. The empirical results strongly suggest that incorporating relation types information into embeddings can greatly help distinguish the interaction behavior of different entities and improve the performance for entity alignment, which is consistent with our motivation.

(3) After utilizing structural information from other snapshots, our RCTSA model achieves significant improvement over those knowledge graph alignment methods which only consider information from the source and target snapshots. This shows the importance of learning temporal behaviors of entities with temporal information in the task of snapshot alignment, which is coincident with findings reported in the literature [1].

Table 2. Overall performance. The best results per metric per dataset are marked in boldface.

Method	Wikidata					YAGO				
	$P@1$	$P@10$	$P@30$	MRR	MR	$P@1$	$P@10$	$P@30$	MRR	MR
JAPE	22.6	52.8	71.6	0.324	33.4	30.0	46.8	55.4	0.359	172.8
CompGCN	19.8	51.4	70.5	0.300	49.1	29.8	47.6	57.9	0.361	168.4
CrossMNA	14.6	46.3	63.6	0.246	179.6	26.5	43.8	48.7	0.324	287.6
CTSA	18.8	41.6	55.0	0.263	248.8	28.3	39.4	43.5	0.324	206.0
RCTSA	**25.8**	**55.7**	**73.6**	**0.357**	**33.2**	**31.9**	**51.5**	**67.3**	**0.386**	**72.0**

5. Conclusion

In this paper, we propose the RCTSA model to tackle the task of cross-temporal snapshot alignment for a dynamic multi-relational network. RCTSA leverages time embeddings to capture temporal information of snapshots and employ entity embeddings to embed time-invariant feature of nodes. In addition, RCTSA uses temporal relation embeddings to help learn time-dependent interaction behaviors of nodes together with temporal node embeddings. Finally, the learned entity embeddings of unidentified nodes together with time embeddings can be used for the alignment task. Experimental results demonstrate the effectiveness of our model.

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