Entity Spatio-temporal Evolution Summarization in Knowledge Graphs

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***Abstract*—Knowledge graph has been growing in popularity with extensive applications in recent years, such as entity alignment, entity summarization, question answering, etc. However, the majority of research only focuses on one snapshot of the knowledge graph and neglects its dynamicity in nature, which often causes missing important information contained in other versions of the knowledge graph. Even worse, the incompleteness of the data in the knowledge graph is a challenge issue, which hinders the further utilization of the data. Considering that knowledge graph can evolve with time as well as the changing locations, it is necessary to summarize and integrate the entity temporal and spatial evolution information. To address this challenge, this paper pioneers to formulate the problem of entity spatio-temporal evolution summarization, capturing the entity evolution with time and location changes and integrating the data from two groups of various knowledge graphs. Further, we propose a two-stage approach: 1) generate entity temporal summarization and spatial summarization by utilizing the Triadic Formal Concept Analysis; 2) produce the spatio-temporal evolution summarization of the entity by adopting a fusion strategy. The obtained summarization results can be used to the visualization of the entity spatio-temporal evolution, data integration, and question answering.**

***Index Terms*—RDF Knowledge Graph, Spatio-temporal Evolution, Triadic Formal Concept Analysis**

I. INTRODUCTION

Knowledge Graph (KG) describes the entities and their relationships in the real world using the Resource Description Framework (RDF)-style triples $< s, p, o >$, where s, p, and o represent the subject, predicate, object of the entity in the KG, respectively. KG has received numerous attention in recent years, due to its powerful ability in characterizing concepts and their interrelationships in the physical world. Many publicly available knowledge graphs, such as DBpedia [1], Yago [2], have been successfully applied to various applications, including entity alignment [3], entity summarization [4], [5] and question answering [6], [7], etc.

However, due to the considerable scale of the surging data in the KG, searching for important information is a computationally complex task. Thus, Entity Summarization (ES) has emerged and attracted considerable attention [4], [5], [8], [9], which aims to extract compact and key information from a complex KG. Most existing approaches, however, only focus on the snapshot of the latest version of the KG, which may miss important information contained in previous versions of the KG. Considering the dynamicity of the KG in nature, for the same entity, new properties may be added and existing properties may change in the next versions of the KG along its evolution. In such a scene, important properties contained in the previous versions of the KG may be neglected when only the latest version of the KG is considered.

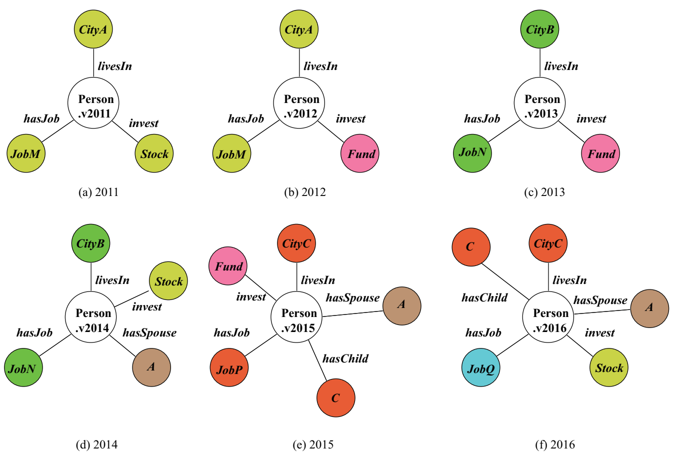

Fig. 1. Visual representation of the information of a person obtained from six yearly KGs.

Example 1: Fig. 1 depicts the information of a person across diverse versions of a KG as the time evolves. In different time stamps, the person has various properties. Some properties of the person may alter and new properties may be added in different time stamps. For example, the person lived in city A in 2011 and 2012, afterwards moved to city B in 2013 and 2014. The person has spouse A in 2014 and has child C in 2015. In addition, some important properties of the person may be neglected if we only focus on the latest version of the KG. For instance, the person invested fund in 2015 while invested stock in 2016.

To overcome the above issue, the literature [10] has attempted to discover the entity evolution information from diverse versions of a KG. In terms of dynamicity in the evolution, the spatial changes of the entity can also be seen as a form of evolution dynamics. Location information is as important

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as time information, because the behaviors of the entity on the web can also differ as the location changes, indicating that the underlying information can also be extracted from the dimension of locations using clustering approaches.

Example 2: Fig. 2 describes the same person in diverse versions of a KG as the location evolves. We can discover that the person has various properties in different locations. For instance, we can obtain that the person went to $Disney$ in city A and B, and bought a house in city C.

More importantly, the data in Fig. 1 and Fig. 2 are all incomplete. For example, comparing the data in the two figures, Fig. 1 lacks the properties (went to $Disney$ and buy $house$), while Fig. 2 misses the properties (has spouse A and has child C).

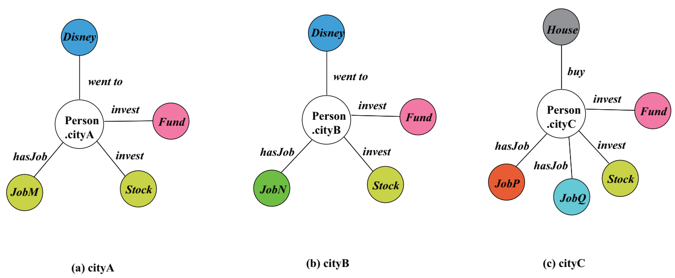


Fig. 2. Visual representation of the information of a person obtained from three locational KGs.

Formal Concept Analysis (FCA) [11] is a complete mathematical tool for mining the binary relations between objects and attributes and further building concept lattice according to the partial ordering relation of the concepts (paired sets of object and attribute). FCA reflects the generalization and generalization relation of the concepts through the Hasse diagram. As its extension, Triadic Formal Concept Analysis (TFCA) [12] targets at clustering and modeling the features of the triadic data. The triadic formal context is represented as a quadruple (G, M, C, R) with G, M, C, and R denoting object, attribute, condition and their relation, respectively. Triadic concept is a triple including extent (object set), intent (attribute set), and mode (condition set), which refers to the relations between objects and attributes under the conditions. Considering its powerful ability for clustering triadic data, TFCA has been utilized in various domains [13], [14].

To capture entity temporal evolution from different versions of a KG, Tasnim et al. [10] proposed an FCA-based approach to generate a compact summary graph. Nevertheless, to the best of our knowledge, there has been no attempt to dynamic entity summarization from time and location dimensions. The obtained summarization results have numerous applications, such as visualization of the entity spatio-temporal evolution, data integration, and question answering. For instance, considering that time and location are the two most important contextual factors in the users' decision-making process for choosing a Point of Interest (POI) to visit in recommendation systems [15], the entity spatio-temporal evolution can be utilized to recommend POIs for the users with the similar underlying pattern. Therefore, this paper presents a two-stage approach to generate the entity spatio-temporal evolution summarization adopting a TFCA algorithm and a fusion strategy.

Specifically, we employ a TFCA algorithm to obtain the entity temporal and spatial summarization, respectively. Then, we present a fusion strategy to generate the entity spatio-temporal evolution summarization. The generated summarization of the entity S is a set of 4-tuples (P, O, T, L), indicating that the entity S has the property set (P, O) at a certain time T and a given location L.

The main contributions of this paper are summarized as follows:

- **Formalization of Entity Spatio-temporal Evolution Summarization**. To better reveal the entity spatio-temporal evolution patterns, we pioneer to present and formulate the novel problem of entity spatio-temporal evolution summarization. The aim is to integrate two diverse KGs from the dimensions of time and location and summarize the evolution characteristics of the entities in the KGs. As a matter of fact, this problem is to obtain a tetrad set (P, O, T, L) of the entity e from the RDF triple sets $< S_t, P_t, O_t >$ at diverse times and $< S_l, P_l, O_l >$ at different locations, indicating that the entity e has the properties (paired predicate and object) at a certain time T and at a given location L.
- **TFCA-based Entity Spatio-temporal Evolution Summarization Approach**. We propose a two-stage approach to obtain the entity spatio-temporal evolution summarization. Firstly, the temporal and spatial evolution summarizations of the entity are generated using TFCA. More specifically, to construct the triadic context, the predicate and object and time/location of the entity are considered as object, attribute, and condition in TFCA, respectively. Then, the time-centric triadic concepts and location-centric triadic concepts of the entity are generated. Secondly, a fusion strategy is proposed for generating the entity spatio-temporal evolution summarization by integrating the obtained entity temporal and spatial evolution summarizations. In addition, a case study is provided for illustrating the effectiveness of the proposed approach.

The rest of this paper is organized as follows: Section II introduces the related work. The problem formalization and proposed solution framework are presented in Section III. The details of the proposed approach are provided in Section IV. Section V illustrates a case study. Finally, Section VI concludes the paper.

II. Related Work

In terms of FCA-based entity summarization, Kim and Choi [16] have put forward an entity summarization approach based on FCA, where the object and predicate in RDF triples are deemed as the object and attribute in FCA, respectively. Also, the formal context is constructed by the relation between the attribute and tokenized object, and outputs $top-k$ RDF triples that are ranked by the cardinality of extent of the concepts.

As for the entity temporal summarization, Tasmin et al. [10] proposed an approach to generate compact entity temporal summarization from different versions of a KG leveraging FCA and a fusion policy.

For the given entity in a KG, the predicate, the object, and the time can be viewed as a type of the ternary data. Through this transformation, it is more feasible to discover the evolution dynamics of the entity in a KG. Time and location are of equal importance in the evolution of the KG. However, the evolution from the spatial dimension remains silent in all of these summarization methods. In addition, the investigation of the entity spatio-temporal evolution can be useful for other applications, such as recommendation systems [15]. Hence, the main objective of our paper is to present a solution for this problem using TFCA. In what follows, the preliminaries of TFCA and the problem formalization are provided.

III. Problem Formulation

In this section, we firstly provide the fundamental definitions about TFCA [17] and then formulate the definition of Entity Spatio-temporal Evolution Summarization. Then, we formulate the novel problem of entity spatio-temporal evolution summarization.

A. Triadic Formal Concept Analysis

Let K_1, K_2, and K_3 denote objects, attributes, and conditions, respectively. The following four definitions hold [17]:

Definition 1: (**Triadic Context**) A Triadic Context is a quadruple (K_1, K_2, K_3, Y) where K_1, K_2, and K_3 are sets and Y is a ternary relation between K_1, K_2, and K_3, i.e., $Y \subseteq K_1 \times K_2 \times K_3$. For instance, $(k_1, k_2, k_3) \in Y$ indicates that the object k_1 has the attribute k_2 under the condition k_3.

Definition 2: Let $K := (K_1, K_2, K_3, Y)$ be a triadic context, for $\{i, j, k\}$ = $\{1, 2, 3\}$ with $j < k$ and for $X \subseteq K_i$ and $Z \subseteq K_j \times K_k$, the (i)-derivation operators are defined by:
$X \mapsto X^{(i)}$
$:= \{(a_j, a_k) \in K_j \times K_k | a_i, a_j, a_k$ are related by Y for all $a_i \in X\}$,
$Z \mapsto Z^{(i)}$
$:= \{a_i \in K_i | a_i, a_j, a_k$ are related by Y for all $(a_j, a_k) \in Z\}$.

Definition 3: (**Underlying Triadic Contexts**)
$K^{(1)} := (K_1, K_2 \times K_3, Y^{(1)})$,
$K^{(2)} := (K_2, K_1 \times K_3, Y^{(2)})$,
$K^{(3)} := (K_3, K_1 \times K_2, Y^{(3)})$, where $gY^{(1)}(m, b) :\Leftrightarrow mY^{(2)}(g, b) :\Leftrightarrow bY^{(3)}(g, m) :\Leftrightarrow (g, m, b) \in Y$.

Definition 4: (**Triadic Concept**) Let $K := (K_1, K_2, K_3, Y)$ be a triadic context, $A_i \subseteq K_i, i = 1, 2, 3$. If $A_i = (A_j \times A_k)^{(i)}$, for $\{i, j, k\}$ = $\{1, 2, 3\}$ and $j < k$, then (A_1, A_2, A_3) is called a triadic concept, where A_1, A_2, and A_3 are called the extent, the intent, and the modus of (A_1, A_2, A_3), respectively.

B. Problem Description

Entities in the KG are described by RDF triples. Entity spatio-temporal evolution summarization is to obtain the temporal and spatial evolution summarization by integrating and summarizing two groups of evolving KGs as time and location of the entity change, respectively.

Definition 5: [18] (**RDF subject-molecule**) Given an RDF knowledge graph G, an RDF subject-molecule $M \subseteq G$ is a set of triples $\{t_1, t_2, ..., t_n\}$ in which subject(t_1) = subject(t_2) = ... = subject(t_n).

Definition 6: (**Temporal Entity Summarization**) Given the RDF triple set $< S_t, P_t, O_t >$ of the entity e from diverse versions of the KG at time $T_1, T_2, T_3, ...$, temporal entity summarization is to generate a triple set (P_t, O_t, T), depicting that the entity e has the property (i.e., predicate and object) set at certain times.

Definition 7: (**Spatial Entity Summarization**) Given the RDF triple set $< S_l, P_l, O_l >$ of the entity e from diverse versions of the KG at location $L_1, L_2, L_3, ...$, spatial entity summarization is to generate a triple set (P_l, O_l, L), depicting that the entity e has the property (i.e., predicate and object) set at certain locations.

Entity Spatio-temporal Evolution Summarization in the KG aims to integrate two groups of evolving KGs and discover evolution characteristics as time and location of the entity change. We formulate the problem as follows:
Given two RDF triple sets $< S_t, P_t, O_t >$ and $< S_l, P_l, O_l >$ of the entity e from two groups of diverse versions of the KG at time $T_1, T_2, T_3, ...$ and location $L_1, L_2, L_3, ...$, entity spatio-temporal evolution summarization is to generate a 4-tuples set (P, O, T, L), depicting that the entity e has the property (i.e., predicate and object) set at certain times and locations. Specifically, the problem can be divided into two subproblems: 1) obtaining the temporal and spatial entity summarization, and 2) producing the spatio-temporal entity summarization. To tackle the problem, a two-stage approach is proposed and elaborated in the following section.

IV. The Proposed Approach

This section discusses: the framework of entity spatio-temporal evolution summarization; the approach of the temporal and spatial entity summarization; the fusion strategy; the algorithm description.

A. Framework of Entity Spatio-temporal Evolution Summarization

Fig. 3 illustrates the framework of Entity Spatio-temporal Evolution Summarization. Firstly, two groups of various versions of KGs with time and location changes are the input. Then, these KGs are converted into RDF subject-molecule for the equivalent entities using the entity recognition technique, which is beyond the scope of this paper. This paper emphatically discusses how to generate an entity spatio-temporal evolution summarization using the obtained equivalent entities

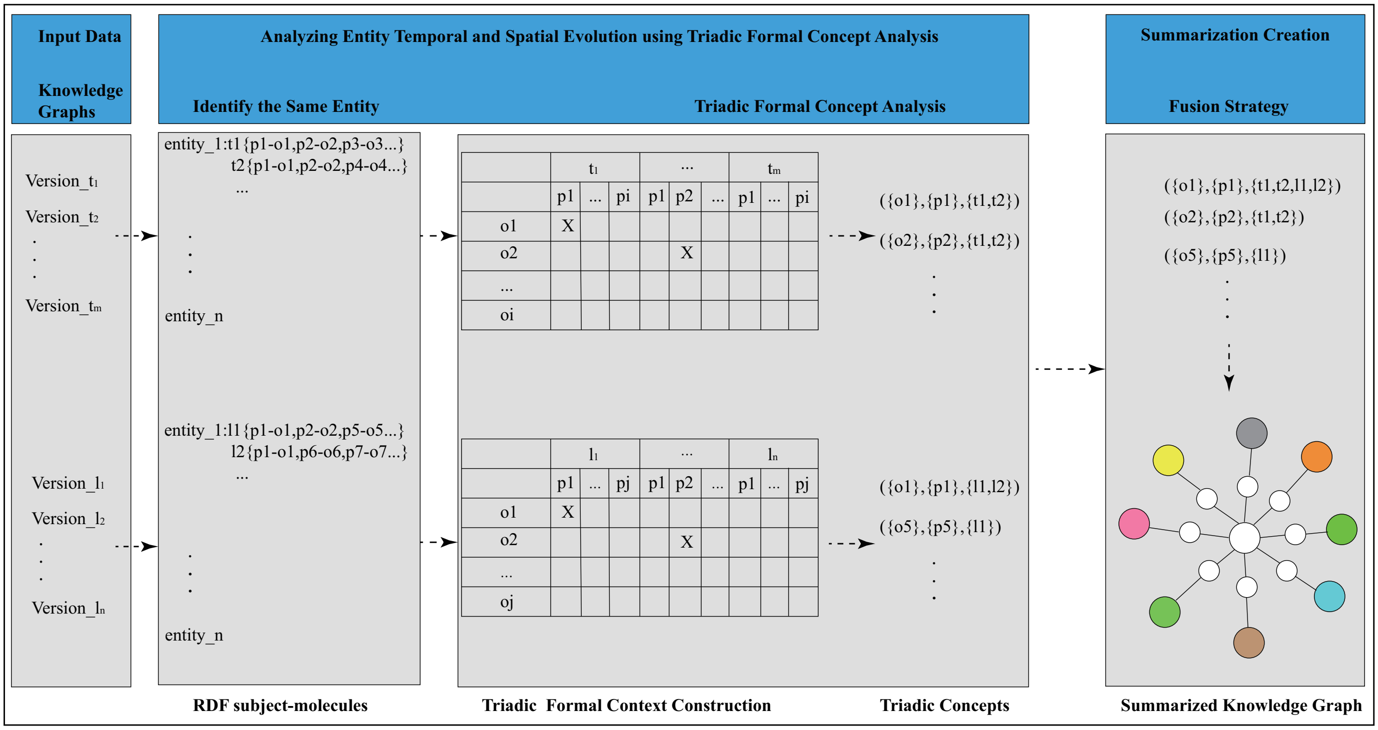


Fig. 3. The framework of the entity spatio-temporal evolution summarization.

TABLE I
THE CONSTRUCTED TRIADIC FORMAL CONTEXT OF THE ENTITY IN THE VERSIONS OF 2015 AND 2016.

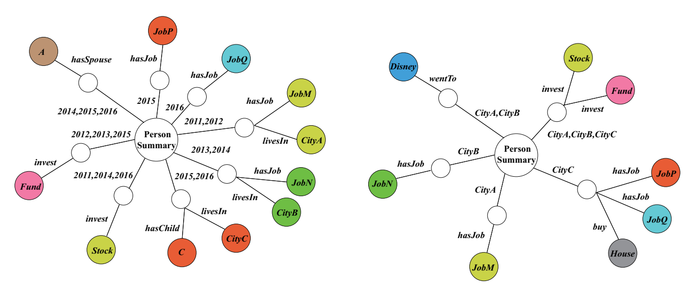
	$t2015$											$t2016$										
	JobM	*CityA*	*Stock*	*Fund*	*JobN*	*CityB*	*A*	*JobP*	*CityC*	*C*	*JobQ*	*JobM*	*CityA*	*Stock*	*Fund*	*JobN*	*CityB*	*A*	*JobP*	*CityC*	*C*	*JobQ*
hasJob	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
livesIn	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0
invest	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
hasSpouse	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
hasChild	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0

from diverse versions of KGs. As shown in Fig. 1 and Fig. 2, two groups of the RDF subject-molecules in diverse versions of KGs are provided for the equivalent entity. Secondly, the two groups of the obtained molecules are then converted into the triadic formal context, which is used for generating time-centric triadic concepts and location-centric triadic concepts, respectively. Finally, we propose a fusion strategy to integrate the obtained two groups of triadic concepts and produce the entity spatio-temporal evolution summarization.

B. Temporal and Spatial Entity Summarization

As the first stage of the proposed approach, time-centric triadic concepts (i.e., predicate set, object set, and time set) and location-centric triadic concepts (i.e., predicate set, object set, and location set) are generated using the TRIAS algorithm [19]. The obtained summarization of the entity not only contains all the information, but also is compact signifying that each property of the entity is distinct.

Firstly, we construct the triadic formal context of the entity temporal evolution, as shown in TABLE I. For the sake of simplicity, we only list the formal context of the entity in version 2015 and 2016, and other versions of the entity is constructed in the same way. To be more precise, the relations between the predicates and objects are denoted by "0" and "1", where "0" and "1" represent that there exist no relation and there is relation between the predicates and objects,



(a) Entity Temporal Summarization Representation (b) Entity Spatial Summarization Representation

Fig. 4. The Entity Temporal Summarization and Spatial Summarization.

respectively. Then, time-centric triadic concepts are generated by the TRIAS algorithm [19] according to the obtained triadic formal context, and the results are shown in Fig. 4 (a). The obtained time-centric triadic concepts are shown as TABLE II.

TABLE II
THE OBTAINED TIME-CENTRIC TRIADIC CONCEPTS.

extent	intent	modus
$hasJob$	$JobQ$	$t2016$
$hasJob$	$JobP$	$t2015$
$hasJob$	$JobM$	$\{t2011, t2012\}$
$livesIn$	$CityA$	$\{t2011, t2012\}$
$hasJob$	$JobN$	$\{t2013, t2014\}$
$livesIn$	$CityB$	$\{t2013, t2014\}$
$livesIn$	$CityC$	$\{t2015, t2016\}$
$hasChild$	C	$\{t2015, t2016\}$
$invest$	$Stock$	$\{t2011, t2014, t2016\}$
$invest$	$Fund$	$\{t2012, t2013, t2015\}$
$hasSpouse$	A	$\{t2014, t2015, t2016\}$

Along similar lines, the results of spatial entity summarization are shown in Fig. 4 (b), and the corresponding location-centric triadic concepts are generated as shown in TABLE III.

TABLE III
THE OBTAINED LOCATION-CENTRIC TRIADIC CONCEPTS.

extent	intent	modus
$hasJob$	$JobM$	$CityA$
$hasJob$	$JobN$	$CityB$
$hasJob$	$\{JobP, JobQ\}$	$CityC$
buy	$House$	$CityC$
$invest$	$\{Stock, Fund\}$	$\{CityA, CityB, CityC\}$
$wentTo$	$Disney$	$\{CityA, CityB\}$

C. Fusion Strategy

For integrating and summarizing the obtained temporal and spatial entity summarizations, we propose a fusion strategy to generate the spatio-temporal evolution summarization of the entity. The idea of the fusion strategy is to generate an entity summarization that contains all evolution information with time and location changes. Moreover, each property of the summarization results occurs only once, which enables its compactness. In other words, if the pairs of predicate and object are same, we merge the corresponding time and location labels. For the unique pairs of predicate and object, we add them to the final summarization results. ***Algorithm 1*** details the fusion process. Using the proposed fusion algorithm, we can obtain the final triadic concepts, as shown in TABLE IV. Fig. 5 illustrates the final result of entity spatio-temporal evolution summarization using the fusion strategy.

D. Algorithm

The algorithm we employed for generating time-centric triadic concepts and location-centric triadic concepts can be obtained in [19].

With regard to the fusion strategy, ***Algorithm 1*** aims at integrating and summarizing the entity temporal summarization and spatial entity summarization. Firstly, the time-centric

Algorithm 1 Fusion Algorithm

Input:
The time-centric triadic concepts TC and location-centric triadic concepts LC

Output:
Entity spatio-temporal summarization result LT

1: Initialize $TCM = \emptyset$, $LCM = \emptyset$
2: **begin**
3: Converting the time-centric triadic concepts TC and location-centric triadic concepts LC into time-centric concepts map TCM and location-centric concepts map LCM, respectively
4: **end**
5: **for** each location-centric concept $lc \in LCM$
6: $keyLocation \leftarrow lc.getKey()$
7: **if** $TCM.containsKey(keyLocation)$
8: $value \leftarrow TCM.get(keyLocation)$
9: $+LCM.get(keyLocation)$
10: $LT \leftarrow LT \cup (keyLocation, value)$
11: $TCM \leftarrow TCM.remove(keyLocation)$
12: $LCM \leftarrow LCM.remove(keyLocation)$
13: **end if**
14: **end**
15: **begin**
16: Removing the time-centric concepts whose key contains location information from TCM
17: **end**
18: **begin**
19: $LT \leftarrow LT \cup TCM$
20: $LT \leftarrow LT \cup LCM$
21: **end**
22: **Return** LT

TABLE IV
THE OBTAINED FINAL TRIADIC CONCEPTS.

extent	intent	modus
$hasSpouse$	A	$\{t2014, t2015, t2016\}$
$hasChild$	C	$\{t2015, t2016\}$
$wentTo$	$Disney$	$\{CityA, CityB\}$
buy	$House$	$CityC$
$invest$	$Stock$	$\{t2011, t2014, t2016\}$, $\{CityA, CityB, CityC\}$
$hasJob$	$JobQ$	$\{t2016\}, CityC$
$hasJob$	$JobP$	$\{t2015\}, CityC$
$hasJob$	$JobN$	$\{t2013, t2014\}, CityB$
$hasJob$	$JobM$	$\{t2011, t2012\}, CityA$
$invest$	$Fund$	$\{t2012, t2013, t2015\}$, $\{CityA, CityB, CityC\}$

triadic concepts TC and location-centric triadic concepts LC are as input, and the output is the entity spatio-temporal summarization result LT. Line 1 initializes the time-centric concepts map TCM and location-centric concepts map LCM. Then, Lines 2-4 assign values to TCM and LCM by converting TC and LC, respectively. Particularly, the key and value of TCM and LCM are the property (predicate and object pair) and the time set (location set), respectively. After that, the

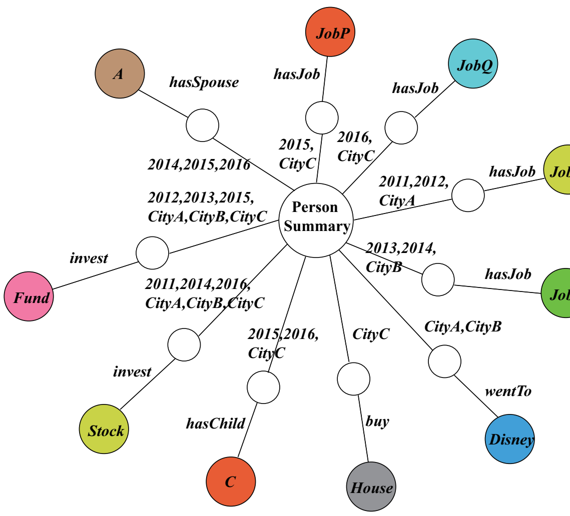


Fig. 5. The Entity Spatio-temporal Entity Summarization.

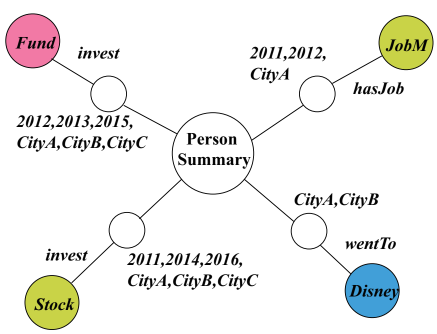


Fig. 6. The Result of the Query "*What behaviors or properties a person has in City A?*".

operation of integrating TCM and LCM is shown in Lines 5-13 according to whether TCM and LCM have the same properties. Afterwards, to ensure the summarization compact, the time-centric concepts with redundant location properties are removed (Lines 14-16), because the location properties are contained in other properties. Finally, the remainder concepts of TCM and LCM are merged into the final results at Lines 17-20.

V. Case Study

In this section, a case study is presented to illustrate the potential applications of the obtained summarization. The proposed approach can be used for extracting valuable information from KGs and visualizing the query results, which can facilitate the querying efficiency on large-scale knowledge graphs.

For the summarization results in Fig. 5, one can search the compact answer for the requests that focus on temporal-spatial attributes from the summarization result. For instance, when asking the query "*What behaviors or properties a person has in City A in 2011 and 2012?*", we can clearly find that the answer is $hasJobM$. When asking the query "*What behaviors or properties a person has in City A?*", the results can be exhibited as shown in Fig. 6.

The spatio-temporal summarization of entity has the following merits: 1) the summarization contains all the information from various versions of the KG, and thus providing the better results in search systems; 2) the summarization is compact, which can dramatically reduce computational costs in search systems.

VI. Conclusions

In this paper, we have presented an approach to generate the entity spatio-temporal evolution summarization in the KG. Concretely, we have firstly constructed the triadic formal context of the entity in the KG, where the predicate, object, and time/location of the entity are regarded as object, attribute, and condition in TFCA, respectively. Then, the entity temporal summarization and spatial summarization have been produced by employing a TFCA algorithm. Finally, based on the obtained entity temporal summarization and spatial summarization, a fusion strategy has been proposed to generate the spatio-temporal summarization of the entity. In the future, we plan to compare the proposed approach with other ternary clustering algorithms using real-world datasets to evaluate its performance advantages and effectiveness.

References

[1] J. Lehmann, R. Isele, M. Jakob, A. Jentzsch, D. Kontokostas, P. N. Mendes, S. Hellmann, M. Morsey, P. Van Kleef, S. Auer *et al.*, "Dbpedia–a large-scale, multilingual knowledge base extracted from wikipedia," *Semantic Web*, vol. 6, no. 2, pp. 167–195, 2015.

[2] F. M. Suchanek, G. Kasneci, and G. Weikum, "Yago: A large ontology from wikipedia and wordnet," *Web Semantics: Science, Services and Agents on the World Wide Web*, vol. 6, no. 3, pp. 203–217, 2008.

[3] F. He, Z. Li, Y. Qiang, A. Liu, G. Liu, P. Zhao, L. Zhao, M. Zhang, and Z. Chen, "Unsupervised entity alignment using attribute triples and relation triples," in *International Conference on Database Systems for Advanced Applications*. Springer, 2019, pp. 367–382.

[4] K. Gunaratna, K. Thirunarayan, and A. Sheth, "Faces: diversity-aware entity summarization using incremental hierarchical conceptual clustering," in *Twenty-Ninth AAAI Conference on Artificial Intelligence*, 2015.

[5] A. Thalhammer, N. Lasierra, and A. Rettinger, "Linksum: using link analysis to summarize entity data," in *International Conference on Web Engineering*. Springer, 2016, pp. 244–261.

[6] D. Lukovnikov, A. Fischer, J. Lehmann, and S. Auer, "Neural network-based question answering over knowledge graphs on word and character level," in *Proceedings of the 26th international conference on World Wide Web*. International World Wide Web Conferences Steering Committee, 2017, pp. 1211–1220.

[7] Y. Zhang, H. Dai, Z. Kozareva, A. J. Smola, and L. Song, "Variational reasoning for question answering with knowledge graph," in *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.

[8] S. Pouriyeh, M. Allahyari, K. Kochut, G. Cheng, and H. R. Arabnia, "Es-lda: Entity summarization using knowledge-based topic modeling," in *Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 2017, pp. 316–325.

[9] Q. Liu, G. Cheng, K. Gunaratna, and Y. Qu, "Entity summarization: State of the art and future challenges," *arXiv preprint arXiv:1910.08252*, 2019.

[10] M. Tasnim, D. Collarana, D. Graux, F. Orlandi, and M.-E. Vidal, "Summarizing entity temporal evolution in knowledge graphs," in *Companion Proceedings of The 2019 World Wide Web Conference*. ACM, 2019, pp. 961–965.

[11] B. Ganter and R. Wille, *Formal concept analysis: mathematical foundations*. Springer, 1999.

[12] F. Lehmann and R. Wille, "A triadic approach to formal concept analysis," in *International Conference on Conceptual Structures*. Springer, 1995, pp. 32–43.

[13] F. Hao, D.-S. Park, D.-S. Sim, M. J. Kim, Y.-S. Jeong, J.-H. Park, and H.-S. Seo, "An efficient approach to understanding social evolution of location-focused online communities in location-based services," *soft Computing*, vol. 22, no. 13, pp. 4169–4174, 2018.

[14] F. Hao, D.-S. Park, G. Min, Y.-S. Jeong, and J.-H. Park, "k-cliques mining in dynamic social networks based on triadic formal concept analysis," *Neurocomputing*, vol. 209, pp. 57–66, 2016.

[15] T. Qian, B. Liu, Q. V. H. Nguyen, and H. Yin, "Spatiotemporal representation learning for translation-based poi recommendation," *ACM Transactions on Information Systems (TOIS)*, vol. 37, no. 2, p. 18, 2019.

[16] E.-k. Kim and K.-S. Choi, "Entity summarization based on formal concept analysis," 2018.

[17] R. Wille, "The basic theorem of triadic concept analysis," *Order*, vol. 12, no. 2, pp. 149–158, 1995.

[18] J. D. Fernández, A. Llaves, and O. Corcho, "Efficient rdf interchange (eri) format for rdf data streams," in *International Semantic Web Conference*. Springer, 2014, pp. 244–259.

[19] R. Jaschke, A. Hotho, C. Schmitz, B. Ganter, and G. Stumme, "Trias–an algorithm for mining iceberg tri-lattices," in *Sixth International Conference on Data Mining (ICDM'06)*. IEEE, 2006, pp. 907–911.