Semantic Time-Geographic Modelling and Analysis

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Abstract

Time geography is a powerful framework that provides a set of well-defined space-time entities and relationships for representing human activity-travel behaviors under various space-time constraints. The classical time-geographic framework focuses on only the geometric aspect of activity-travel behaviors in the space and time dimensions but ignores rich semantic contexts of activity-travel behaviors (e.g., activity goals, transport modes, and individual emotions and feelings). This study introduces a novel time-geographic framework by explicitly incorporating semantic contexts of activity-travel behaviors. The introduced framework provides rigorous definitions for full spectrum of semantically rich space-time entities (e.g., semantic prisms and lifelines) and relationships (e.g., semantic space-time intersection relationships). The introduced framework is implemented by using two types of database approaches: relational and graph databases. Experimental results demonstrate the capabilities of the introduced semantic time-geographic framework for representing both geometric and semantic perspectives of human activity-travel behaviors. The graph database approach can achieve various queries on a large number of semantic time-geographic entities within reasonable computational times.

1. Introduction

Time geography is a powerful analytical framework for understanding individual-level activity-travel behaviors under various space-time constraints (Miller, 2005). It provides a set of well-defined space-time entities and relationships to analyze activity-travel behaviors in the space and time dimensions. This framework of time geography has been applied in broad applications, such as travel demand modelling, accessibility studies, social equity, social segregation, and etc. (Farber et al., 2012; Chen et al., 2018; Huang and Kwan, 2021; Chen et al., 2024).

The concept of time geography was initially proposed by Torsten Hägerstrand in the 1970s (Hägerstrand, 1970). Hägerstrand mainly focused on the understanding of individual activities through the lens of constraints. He defined a set of conceptual space-time entities to represent activity-travel behaviors, such as space-time paths, prisms and lifelines.Researchers developed effective and efficient spatiotemporal data models and index structures to store, manage, query and process huge number of time-geographic entities in the era of big data (Chen et al. 2016a; 2023). Data mining techniques were further developed for knowledge discovery from time-geographic entities (Yuan et al., 2018; Miller et al., 2019).

Although classical time-geographic entities and relationships are general enough to describe any kind of individual, they were criticized for being materialistic and geometric, but ignoring rich context information of activity-travel behaviors, such as home and work locations, transport modes, weather conditions, activity goals, and individual thoughts, emotions and feelings (Ellegård, 1999, 2018). Ignoring these semantic contexts undermines analytical capabilities of the existing geometric framework to understand complicated human activity-travel behaviors in the physical and institutional environments. In view of this, several researchers have suggested to incorporate context information in the time-geographic studies (Kwan and Ding, 2008; Ellegård, 1999). However, to best our knowledge, such semantic contexts have not been formally represented and

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integrated in the notation system of time geography. The time-geographic framework integrating with semantic contexts is hereafter referred as “semantic time geography” to distinguish it from the classical framework of time geography.

In the literature, research efforts have been devoted to developing effective data models for representing semantic space-time paths, also called semantic trajectories (Alvares et al. 2007; Renso et al. 2013; Noureddine et al. 2022). A popular semantic trajectory model is the episode (or stop-move) model (Spaccapietra et al. 2008; Fileto et al. 2013). This model separates a raw trajectory (with only geometric data) into a set of stop and move episodes, which are segments with the homogeneous status (Spaccapietra et al. 2008; Nogueira et al. 2018). Then, the semantic trajectory is constructed through a semantic enrichment process by attaching the corresponding semantic information onto episodes (Parent et al. 2013). Following this model, various methods have been developed to implement semantic enrichment process by linking to additional background data, such as open street map, points of interest (POIs) and social media data (Yan et al. 2013). Querying methods and data mining techniques were also developed for semantic trajectories (Wan et al 2018; Liu and Guo 2020; Izquierdo et al. 2021). However, current semantic trajectory techniques focused on only semantic space-time paths but ignored other time-geographic entities (e.g., semantic space-time prisms and lifelines). In addition, current semantic trajectory techniques seldom integrate with the GIS platforms.

In view of this, the present study aims to introduce a comprehensive framework of semantic time geography, and to develop techniques for implementing the introduced framework. It contributes to existing time-geographic literature in following aspects.

Firstly, a novel framework of semantic time geography is introduced. The introduced framework provides rigorous full spectrum of semantically rich time-geographic entities, namely semantic space-time paths, stations, prisms and lifelines. Further, it defines several semantic space-time relationships between entities by considering only the coexistence of entities in space and time dimensions but also the match of activity semantics. Therefore, the introduced framework extends the existing time-geography framework (Miller, 2005) by explicitly incorporating the semantic contexts of activity-travel behaviors.

Secondly, two approaches are developed for implementing the introduced semantic time-geographic framework. The first approach uses the classical relational databases (e.g., MySQL) and integrates with the existing GIS platforms (e.g., ArcGIS Pro). The second approach utilizes the emerging graph databases (e.g., Nebula Graph), which are more flexible to represent the high heterogeneity of semantic contexts and more efficient for querying big datasets. The implementation details of three types of queries on Nebula Graph are introduced, including entity-based, space-time-based, semantic-based, and relationship-based queries. Therefore, the second implementation approach extends the existing time-geographic implementation built on the spatial databases (Chen et al., 2016a) by using the high-performance graph databases.

Thirdly, computational experiments are conducted using real activity-diary data. Experimental results highlight the capabilities of the introduced semantic time-geographic framework for representing both geometric and semantic perspectives of human activity-travel behaviors. The implementation approach of using Nebula Graph could perform various queries on large number of semantic time-geographic entities within a reasonable computational time.

2. Proposed framework of semantic time geography

2.1 Semantic time-geographic entities

A sematic type, denoted by smt, represents a categorization of a semantic context. It can be formally defined as

$$smt = \langle ATT, smt_{supertype} \rangle \quad (1)$$

where $ATT = \{a_1, \dots, a_u, \dots, a_w\}$ is the set of attributes corresponding to the category; and $smt_{supertype}$ is the super-type of this sematic type and could be empty if no super-type. Subsequently, a semantic meaning, denoted by sm, can be defined as

$$sm_i = \langle smt_i, ATV_i \rangle \quad (2)$$

where smt_i is the associated sematic type; and $ATV_i = \{v_1, \dots, v_u, \dots, v_w\}$ is the non-empty set of values corresponding to attributes defined in ATT of smt_i.

Using these definitions of semantic contexts, we introduce two types of semantic spatial entities, namely $SemPOI$ and $SemPlace$. A POI represents a point of interest in the physical environment, such as a shopping center, school, and gym. Each POI, denoted by $SemPOI_i$, is expressed as a tuple:

$$SemPOI_i = \{\langle x_i, y_i\rangle, sm\_POI_i\} \quad (3)$$

A $SemPlace$ represents the physical environment with personal semantic contexts, such as Home, Workplace, Frequently Visited Place, and etc. Each Semantic Place, denoted by $SemPlace_j$, is expressed as a tuple:

$$SemPlace_j = \{SemPOI_i, sm\_SemPlace_j\} \quad (4)$$

Using the concepts of semantic contexts, we then introduce a series of semantic time-geographic entities including semantic space-time paths, semantic space-time stations, semantic space-time prisms and semantic space-time lifelines. The overview of the introduced spatiotemporal data model is given in Figure 1; and their detailed descriptions are given in following sections.

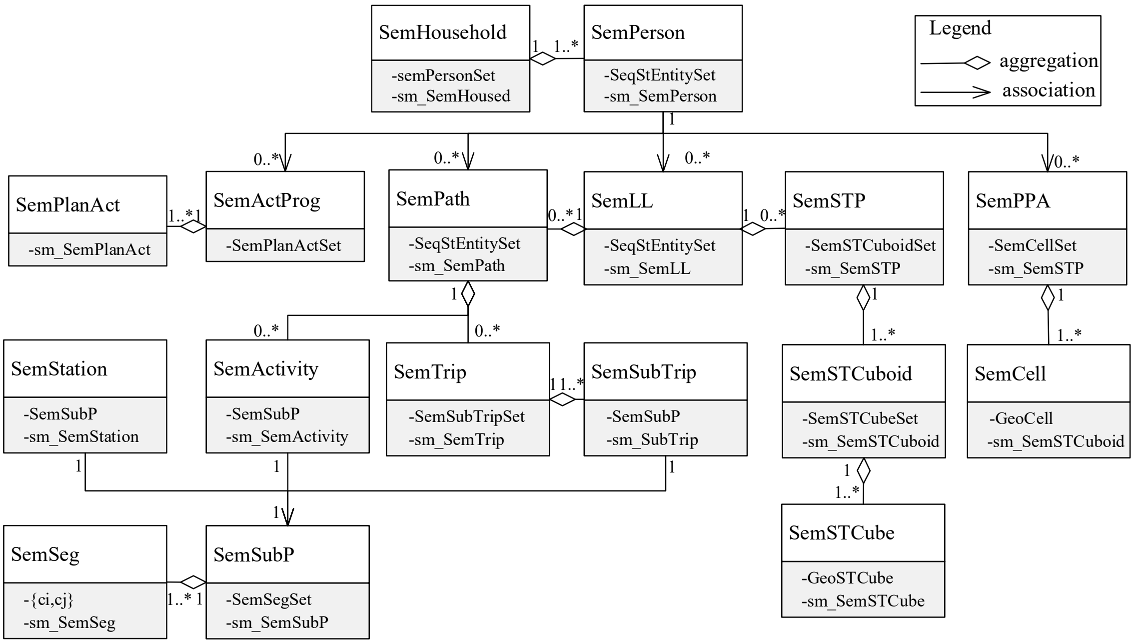

Figure 1. Overview of spatiotemporal data model for semantic time-geographic entities.

2.1.1 Semantic space-time paths: Following the episode model (Spaccapietra et al. 2008; Fileto et al. 2013), we firstly define the semantic straight-line segment, denoted by $SemSeg_i^q$, represents a straight-line movement with homogeneous status on multiple semantic contexts. It can be expressed as a tuple:

$$SemSeg_i^q = \{GeoSeg_{ij}, sm\_SemSeg_i^q\} \quad (5)$$

where $GeoSeg_{ij} = \{c_i, c_j\}$ is the classical straight-line segment representing the straight-line movement from space-time points c_i to c_j.

Following the literature of activity-based travel demand modelling (Wang and Cheng 2001; Timmermans et al., 2002), we then introduce two semantic space-time entities: SemActivity and SemTrip. A SemActivity represents the activity carried out at a place including the waiting time before or after the activity. The ith activity made by individual q, dented by $SemActivity_i^q$, can be expressed as a tuple:

$$SemActivity_i^q = \{SemSubP_i^q, sm\_SemActivity_i^q\} \quad (6)$$

where $SemSubP_i^q$ is the semantic space-time sub-path entity which consists a set of consecutive straight-line segments as

$$SemSubP_i^q = \{SemSeg_j^q, \cdots, SemSeg_k^q\} \quad (7)$$

A SemTrip is defined as the trip from an origin to an activity destination and it is also a sub-type of $SeqStEntity$. In real applications, a trip can be made by multiple transport modes, e.g., walking, bus, subway, and taxi. We define a subtrip entity representing a part of trip using a specific transport mode. The ith trip made by individual q, denoted by $SemTrip_i^q$, is expressed as a tuple:

$$SemTrip_i^q = \{SubTripSet_i^q, sm\_SemTrip_i^q\} \quad (8)$$

where $SubTripSet_i^q$ is a set of consecutive subtrip entities. The jth subtrip of $SemTrip_i^q$, denoted by $SemSubTrip_j^i$, is expressed as a tuple:

$$SemSubTrip_j^i = \{SemSubP_i^j, sm\_SemSubTrip_j^i\} \quad (9)$$

With the above definitions of activities and trips, we then define the concept of semantic space-time path. A semantic space-time path, denoted by $SemPath_k^q$, is defined as an activity pattern performed by an individual q during a particular day k. It can be expressed as a tuple:

$$SemPath_k^q = \{SeqStEntitySet_k^q, sm\_SemPath_k^q\} \quad (10)$$

where $SeqStEntitySet_k^q$ is a set of consecutive activities and/or trips, and $sm\_SemPath_k^q$ is the semantic meaning of the semantic space-time path.

The semantic space-time paths have spatial and time dimensions as well as multiple contextual dimensions. Along the line of classical time-geographic studies, we can project a semantic space-time path, $SemPath_k^q$, onto the spatial dimensions by removing the time dimension. This projection can be achieved by simply converting every 3D straight-line segment $GeoSeg_{ij} = \{c_i, c_j\}$ of the path into the 2D straight-line segment $LineSeg_{ij} = \{\langle x_i, y_i\rangle, \langle x_j, y_j\rangle\}$. Accordingly, the result of this projection is a 2D polyline with semantic contexts. We can further remove spatial and time dimensions for the path $SemPath_k^q$. This projection generates an activity program, denoted by $SemActProg_k^q$, which consists of a list of planned activities to be performed as

$$SemActProg_k^q = \left\{SemPlanAct_1^q, \dots, SemPlanAct_j^q\right\} \quad (11)$$

where $SemPlanAct_j^q$ is a planned activity to be performed and can be defined as

$$SemPlanAct_j^q = \{sm\_SemPlanAct_i^q\} \quad (12)$$

Using the similar representation technique, we introduce the semantic space-time station entity (denoted by $SemStation^f$) to incorporate semantic contexts into the classical space-time station entity (i.e., $GeoStation^f$). This $SemStation^f$ entity represents a physical facility (e.g., shopping center), in which activities can be conducted. It is expressed as a tuple:

$$SemStation^f = \{SemSubP^f, sm\_SemStation^f\} \quad (13)$$

2.1.2 Semantic space-time prisms: This section describes the semantic space-time prism by incorporating semantic contexts into the classical space-time prism. In the time geography, the space-time prism is to delimit all feasible space-time regions for scheduling a flexible activity between two fixed activities at the origin and destination respectively. Following this concept, we firstly introduce fixed and flexible activity entities. A fixed activity, denoted by $SemFixedAct_i^q$, is a sub-type of the planned activity with the fixed space and time location, and it can be expressed as

$$SemFixedAct_i^q = \{sm\_SemFixedAct_i^q\} \quad (14)$$

A flexible activity, denoted by $SemFlexibleAct_i^q$, is another sub-type of the planned activity to be scheduled and it can be expressed as

$$SemFlexibleAct_i^q = \{sm\_SemFlexibleAct_i^q\} \quad (15)$$

Using these concepts of fixed and flexible activity entities, a semantic space-time prism of individual q, denoted by $SemSTP_i^q$, is defined as a tuple:

$$SemSTP_i^q = \{SemSTCuboidSet_i^q, sm\_SemSTP_i^q\} \quad (16)$$

In Eq. (16), $SemSTCuboidSet_i^q$ is a discrete version of $GeoSTP_i^q$ enriched with spatial-varying semantic contexts. It consists of a set of semantic space-time cuboids as $\left\{SemSTCuboid_1^q, \dots, SemSTCuboid_j^q\right\}$. Each semantic space-time cuboid, $SemSTCuboid_j^q$, represents the potential space-time regions for conducting the flexible activity at a specific grid j and it can be expressed as:

$$SemSTCuboid_j^q = \left\{SemSTCubeSet_j^q, sm\_SemSTCuboid_j^q\right\} \quad (17)$$

In Eq. (17), the $SemSTCubeSet_j^q$ element is a set of semantic space-time cubes $\{SemSTCube_1^q, \dots, SemSTCube_i^q\}$ located at grid j. Each semantic space-time cube, $SemSTCube_i^q$, can be expressed as

$$SemSTCube_i^q = \{GeoSTCube_i^q, sm\_SemSTCube_i^q\} \quad (18)$$

We can project a semantic space-time prism, $SemSTP_i^q$, onto the spatial dimensions by removing the time dimension to generate a semantic potential path area, denoted by $SemPPA_i^q$. This $SemPPA_i^q$ entity is an extension of classical PPA by enriching with semantic contexts. It can be expressed as

$$SemPPA_i^q = \{SemCellSet_i^q, sm\_SemSTP_i^q\} \quad (19)$$

where $sm\_SemSTP_i^q$ is the semantic meaning of the prism $SemSTP_i^q$; and $SemCellSet_i^q$ is the set of semantic spatial cells. Each semantic spatial cell, $SemCell_j^q$, can be expressed as

$$SemCell_j^q = \left\{GeoCell_j^q, sm\_SemSTCuboid_j^q\right\} \quad (20)$$

2.1.3 Semantic space-time lifeline: This section describes the semantic space-time lifeline semantic space-time lifeline ($SemLL^q$) to incorporate semantic contexts into the classical space-time lifeline ($GeoLL^q$). The $SemLL^q$ entity consists of a series of semantic space-time paths (trips and/or activities) and prisms during the whole day, and it can be expressed as

$$SemLL^q = \{SeqStEntitySet^q, sm\_SemLL^q\} \tag{21}$$

where $SeqStEntitySet^q$ consists of the series of consecutive activities, trips and prisms.

2.1.4 Person and household: This section describes the person and household entities. A person, denoted by $semPerson^q$, could have semantic information in terms of socio-economic attributes, residential location and workplace. It can be expressed as:

$$semPerson^q = \{SeqStEntitySet^q, sm\_semPerson^q\} \tag{22}$$

A household, denoted by $semHousehold^h$, consists of multiple persons and could have several household attributes. It can be expressed as

$$semHousehold^h = \{semPersonSet^h, sm\_semHousehold^h\} \tag{23}$$

2.2 Semantic space-time relationships

This section describes semantic space-time relationships by incorporating semantic dimensions into the classical time-geographic relationships. we refine the bundling relationship between two semantic space-time paths $SemPath_i^q$ and $SemPath_j^p$ as:

$$\delta_{Bundle}(SemPath_i^q, SemPath_j^p) = \delta_{Bundle}^{Geo}(SemPath_i^q, SemPath_j^p)\delta_{Bundle}^{Sem}(SemPath_i^q, SemPath_j^p) \tag{24a}$$

$$\delta_{Bundle}^{Geo}(SemPath_i^q, SemPath_j^p) = \begin{cases} 1, if\ GeoD\left(SemPath_i^q(t), SemPath_j^p(t)\right) \le \omega_G, \forall t \in [t_s, t_e] \\ 0, \quad otherwise \end{cases} \tag{24b}$$

where δ_{Bundle} is a binary function, $\delta_{Bundle} = 1$ indicates a semantic space-time bundling relationship and $\delta_{Bundle} = 0$ otherwise.

The semantic space-time intersection of two prisms can be defined as

$$\delta_{Intersect}(SemSTP_i^q, SemSTP_j^p) = \delta_{Intersect}^{Geo}(SemSTP_i^q, SemSTP_j^p)\delta_{Intersect}^{Sem}(SemSTP_i^q, SemSTP_j^p) \tag{25a}$$

$$\delta_{Intersect}^{Geo}(SemSTP_i^q, SemSTP_j^p) = \begin{cases} 1, if\ SemSTP_i^q(t) \cap SemSTP_j^p(t) \ne \emptyset, \exists t \\ 0, \quad otherwise \end{cases} \tag{25b}$$

where $\delta_{Intersect}$ is a binary function, $\delta_{Intersect} = 1$ indicates a semantic space-time intersection relationship between two paths and $\delta_{Intersect} = 0$ otherwise.

3. Computational experiments

This section describes two approaches to implement the semantic time-geographic framework introduced in the previous section. The first approach uses the classical relational databases (e.g., Oracle, SQL Server or Access), which can be easily integrated with the most existing GIS platforms, such as ArcGIS Pro. The second approach utilizes the emerging graph databases (e.g., Neo4J or Nebula Graph), which are more flexible to represent the high heterogeneity of semantic contexts and more efficient for managing big datasets.

3.1. Data collections

Two datasets were collected for the case study. The first dataset was a small open dataset of activity-diary surveys of COVID-19 cases in Wuhan, China. During the early stage of pandemic, activity-diary surveys were conducted in Wuhan city to record trajectories and activity participations of COVID-19 cases. In this study, activity-diary data of 44 individuals were collected from a website of Wuhan government (http://wh.bendibao.com) during 20 July and 10 August 2021.

3.2. Visual analysis results using the relational database approach

We implemented the semantic time-geographic framework using relational database approach based on the MySQL database and ArcGIS Pro software. The first dataset with activity-diary data of 44 individuals was utilized for visual analysis. Figure 2 (a) visualizes activity-travel patterns of three household members in Family #1. It consists of a semantic space-time path of the daughter (i.e., Daisy) and two semantic lifelines of both household heads (i.e., Nancy and John). As shown, the family chose the residential location near to the wife. The husband commuted a long distance in the morning by using the subway mode. He spent a long out-of-home activity time (i.e., >11 hours) and conducted five out-of-home activities. Semantic space-time prisms based on the walking mode were constructed for three activities (i.e., having breakfast, lunch and dinner), since they were flexible activities. Further, no activity location was provided in the dataset for these three activities. Compared to her husband, the wife spent less out-of-home activity time (i.e., <7 hours) and took more household duties, including three joint-activities with her daughter and one food purchase activity. A semantic space-time prism based on the private car mode was constructed for the food purchase activity. It can be observed that the size of this semantic space-time prism was much larger than that of three prisms of her husband using the walking mode. This is because the family only had one car and it was used by the wife. It reveals a typical pattern of duty and resource allocations in many households in China and beyond (Kwan, 1999; Chen et al., 2011). Therefore, this illustrative example highlights the capabilities of the proposed semantic time-geographic framework for representing both geometric and semantic perspectives of human activity-travel behaviors.

Figure 2(b) visualizes a semantic space-time intersection relationship between two paths of the wife and daughter during 13:25 to 14:30, i.e., $\delta_{Intersect}\left(SemPath_i^{Nancy}, SemPath_j^{Daisy}\right) = 1$. As can be seen, these two paths not only intersected at the space and time dimensions (i.e., $\delta_{Intersect}^{Geo}\left(SemPath_i^{Nancy}, SemPath_j^{Daisy}\right) = 1$) but also had the same activity goal (i.e., $\delta_{Intersect}^{Sem}\left(SemPath_i^{Nancy}, SemPath_j^{Daisy}\right) = 1$). This relationship was the result of a joint activity between the wife and daughter. Figure 2(c) visualizes a classical space-time intersection relationship between two prisms of the couple during 17:00 to 19:00. As shown, two prisms intersected at the space and time dimensions, i.e., $\delta_{Intersect}^{Geo}\left(SemSTP_i^{Nancy}, SemSTP_j^{John}\right) = 1$. However, they have different activity goals with $\delta_{Intersect}^{Sem}\left(SemSTP_i^{Nancy}, SemSTP_j^{John}\right) = 0$. Accordingly, the semantic space-time intersection relationship did not hold, i.e., $\delta_{Intersect}\left(SemSTP_i^{Nancy}, SemSTP_j^{John}\right) = 0$; and cannot be feasible to schedule a joint activity between the couple during this time period. Therefore, compared to the classical time-geographic relationships, the introduced semantic time-geographic relationships can be used to analyze the human activity-travel behaviors in a more accurate way by explicating incorporating the semantic contexts of activities.

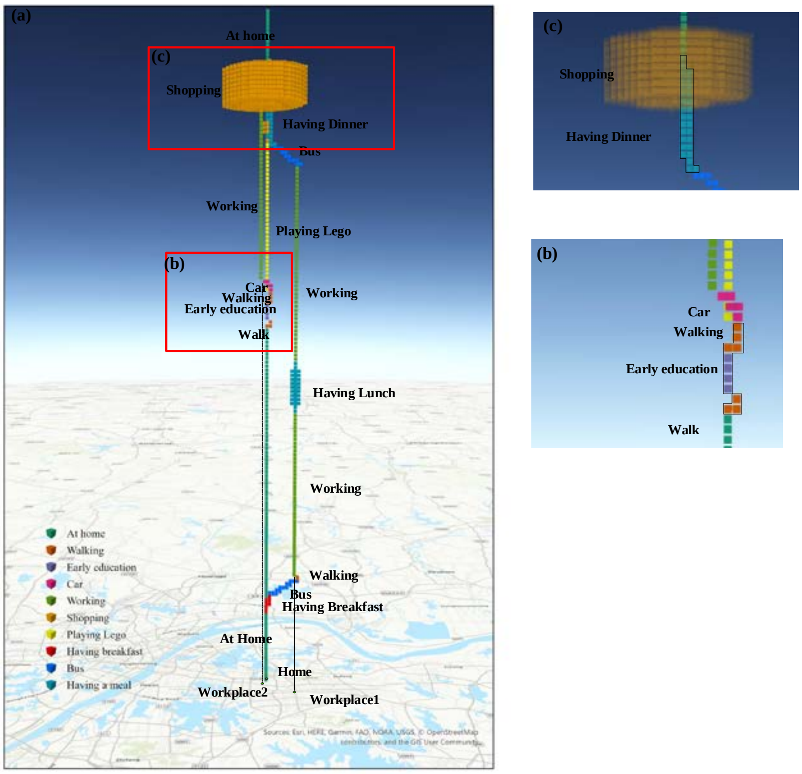

Figure 2. Activity-travel behaviors of three household members in Family #1: (a) semantic time-geographic entities; (b) semantic space-time intersection relationship between two paths; (c) classical space-time intersection relationship between two prisms.

3.3. Querying performance using the graph database approach

We implemented a semantic time-geography framework using a graph database approach based on the Nebula Graph database. Based on the existing data, we simulated the activity-travel data of 2,000 households for performance analysis and query. We set up four queries as follows:
llustrative query (a): Where is John and what is he/she doing at 12:00?
Illustrative query (b): Who had lunch Restaurant A during 12:00 to 13:00?
Illustrative query (c): Where do families with a monthly income of more than 10,000 live?
Illustrative query (d): Who is likely to meet Jhon while shopping between 18:00 and 19:00 in the evening?
In order to extract semantic information from the semantic time geographic entities, we typically utilize nGQL queries.

To evaluate the query efficiency of Nebula Graph, we conducted experiments involving four types of queries on datasets of varying sizes: 250, 500, 750, and 1000 households were stored, respectively. The query efficiency for these four types of queries is depicted in Table1. It can be seen that as the amount of data increases, the performance of queries (a) (b) (d) becomes more stable. This is because the graph database supports concurrent graph traversal operations to execute these queries. The results of query (c) show linear growth because as the number of storages increases, the number of households with incomes exceeding 10,000 that we query will also increase, so the number of queries for their residences will increase.

Number of Household		250	500	750	1000
Query Time(s)	Query(a)	3.01	1.16	1.04	0.65
	Query(b)	1.33	1.28	1.29	1.15
	Query(c)	2.09	3.34	4.98	6.72
	Query(d)	3.27	3.05	3.34	3.10

Table 1. Efficiency of four categories of queries with different storage level

4. Conclusion

This study introduces semantic information and proposes a semantic time-geographic framework. The framework combines semantic knowledge to define semantic time-geographic entities and relationships, and then can better explain human spatiotemporal behavior in combination with spatiotemporal constraints such as capability, authority, and combination. This framework has been tested and verified based on relational databases and graph databases. The results show that the semantic time-geographic framework can display individual travel activities in multiple dimensions and granularity, and can further enrich the applied research of time geography.

Much future work on semantic time geography still needs to be attended to. First, we only proposed a conceptual model of semantic time geography and performed simple storage management. However, further research is needed on its storage management in universities. The modeling and management techniques of semantic trajectories are relatively mature (Mello et al. 2019; Yan et al. 2011). The modeling and management techniques of space-time bodies such as space-time prisms and space-time lifelines are still in the initial stage of research. The only model currently available is the compressed linear reference model proposed by Chen et al (Chen et al. 2016a). However, this model only considers the geometric form of space-time bodies and does not consider the semantic information of space-time bodies. Therefore, there is a need for efficient storage management and indexing of objects in semantic time geography. In addition, we have not done further application research on real data sets, such as reachability, social interaction, etc. The application of the proposed semantic geographical framework in human mobility studies and advanced time-geographic analysis deserves further study.

References

Alvares, L. O., et al. 2007. Towards semantic trajectory knowledge discovery. *Data Mining and Knowledge Discovery*, 12.

Chen, B.Y., et al., 2016a, Spatiotemporal data model for network time-geographic analysis in the era of big data. *International Journal of Geographical Information Science,* 30, pp. 1041-1071.

Chen, B.Y., et al., 2018, Understanding the impacts of human mobility on accessibility using massive mobile phone tracking data. *Annals of the American Association of Geographers*, 108, pp. 1115-1133.

Chen, B.Y., et al., 2023a, A spatiotemporal data model and an index structure for computational time geography. *International Journal of Geographical Information Science*, 37, pp. 550-583.

Ellegård, K., 1999, A time-geographic approach to the study of everyday life of individuals: a challenge of complexity. *GeoJournal*, 48, pp. 167-175.

Ellegård, K., 2018. *Thinking time geography: Concepts, methods and applications.* Taylor & Francis.

ESRI. ArcGIS Pro Documentation: Fundamentals of netCDF data storage. Available online: https://pro.arcgis.com/en/pro-app/latest/tool-reference/multidimension/fundamentals-of-netcdf-data-storage.htm (accessed on 3 January 2024).

Farber, S., et al., 2013, The social interaction potential of metropolitan regions: A time-geographic measurement approach using joint accessibility. *Annals of the Association of American Geographers*, 103, pp. 483-504.

Fileto, R., M. et al., 2013, Baquara: A holistic ontological framework for movement analysis using linked data. *Lecture Notes in Computer Science* 8217:342-355.

Hägerstrand, T., 1970, What about people in regional science? *Papers in Regional Science*, 24, pp. 7-24.

Huang, J., and M.-P. Kwan. 2021. Uncertainties in the Assessment of COVID-19 Risk: A Study of People’s Exposure to High-Risk Environments Using Individual-Level Activity Data. *Annals of the American Association of Geographers*, 112 (4):968-987.

Kwan, M.-P. and Ding, G., 2008, Geo-Narrative: Extending Geographic Information Systems for Narrative Analysis in Qualitative and Mixed-Method Research. *The Professional Geographer,* 60, pp. 443-465.

Liu, C., and C. Guo. 2020. STCCD: Semantic trajectory clustering based on community detection in networks. *Expert Systems with Applications*, 162:113689.

Miller, H.J., 2005, A measurement theory for time geography. *Geographical Analysis*, 37, pp. 17-45.

Miller, H.J., Jaegal, Y. and Raubal, M., 2019, Measuring the geometric and semantic similarity of space-time prisms using temporal signatures. *Annals of the American Association of Geographers*, 109, pp. 730-753.

Nogueira, T. P., R. B. Braga, C. T. de Oliveira, and H. Martin. 2018. FrameSTEP: A framework for annotating semantic trajectories based on episodes. *Expert Systems with Applications*, 92:533-545.

Parent, C., S. Spaccapietra, C. Renso, G. Andrienko, N. Andrienko, V. Bogorny, M. L. Damiani, A. Gkoulalas-Divanis, J. Macedo, and N. Pelekis. 2013. Semantic trajectories modeling and analysis. *ACM Computing Surveys*, 45 (4):1-32.

Renso, C., M. Baglioni, J. A. F. de Macedo, R. Trasarti, and M. Wachowicz. 2013. How you move reveals who you are: understanding human behavior by analyzing trajectory data. *Knowledge and Information Systems*, 37 (2):331-362.

Spaccapietra, S., C. Parent, M. L. Damiani, J. A. de Macedo, F. Porto, and C. Vangenot. 2008. A conceptual view on trajectories. *Data & Knowledge Engineering*, 65 (1):126-146.

Wan, C., Y. Zhu, J. Yu, and Y. Shen. 2018. SMOPAT: Mining semantic mobility patterns from trajectories of private vehicles. *Information Sciences*, 429:12-25.

Yan, Z.X., Chakraborty, D., Parent, C., Spaccapietra, S. and Aberer, K., 2013, Semantic trajectories: Mobility data computation and annotation. *ACM Transactions on Intelligent Systems and Technology*, 4, p. 49.

Yuan, H., et al., 2018, Toward space-time buffering for spatiotemporal proximity analysis of movement data. *International Journal of Geographical Information Science*, 32, pp. 1211-1246.