Chapter

A Spatial-Temporal Knowledge Management Framework

Catherine Inibhunu

Abstract

With the rise of complex systems and devices equipped with sensors that generate exponential data within seconds, most organizations still use methods and frameworks designed for static or historical data warehouses and therefore lack the capability to harness such high-frequency data streams on time. Effective management of time-oriented data requires much more work to be completed particularly if one needs to discern any special temporal relationships in data that may exist in space (region) and quantify how those relationships could impact other spaces (regions). A fusion of time and space (spatial temporal) data dimensions in knowledge systems can enable the discovery of untapped information that can be central to tackling many open research questions in vast domains. This chapter first, describes a collection of spatial-temporal knowledge management and sharing methods from the literature highlighting existing shortcomings where systems designed lacks capabilities to effectively harness data critical for making data-driven decisions on time. To address some of these challenges, an overarching spatial-temporal knowledge processing framework named Sesat is introduced. This new framework outlines principles adopted for designing effective spatial-temporal knowledge systems that can be effectively managed. A theoretical use case scenario within cyber security is demonstrated utilizing the Sesat framework thus highlighting the potential for such effective spatial-temporal knowledge management in many data domains.

Keywords: knowledge frameworks, spatial-temporal knowledge, data-driven intelligence, knowledge systems, knowledge management, expert systems

1. Introduction

Fundamentals of knowledge creation, dissemination, and utilization are topics studied heavily in theoretical literature stimulating research in different kinds of social dynamics of knowledge and practice [1]. Others have focused on defining the different types of knowledge, "know-that" and "know-how" [2]. Within the vast scientific literature, "know-that" is referred to as factual knowledge or explicit knowledge while "know-how" is referred to as practical knowledge, tactile knowledge, or implicit knowledge [1].

Tactile knowledge is referred to as intuitive knowledge and rooted in experience, practice, values and it is hard to communicate as it resides in the mind of the person [1]. In the age of big data, explicit knowledge can be characterized as known facts that can be in documents or stored in the database, etc. The process of finding optimal methods to identify, create, organize, and share factual knowledge is at the

IntechOpen

core of vast knowledge management systems. In many organizations, their effective functioning depends on many aspects in particular on the factual knowledge that can be derived from data about products, services, and customer base.

Within explicit knowledge, a combination of context, space, and time intro¬duces new aspects of knowledge that can be created to understand relationships of time within a specific space. Such knowledge is defined as spatial temporal and can be utilized in multiple domains. In this chapter we pay special attention to spatial-temporal knowledge with respect to how it is created, managed, shared, and applied to many real-world scenarios.

There are several questions that arise within spatial-temporal knowledge; how can it be created? How can one represent it? How can it be managed and shared?

To answer these questions, first Section 2 evaluates key elements in knowledge management which involve; knowledge creation, representation, processing, sharing, and application. Section 3 presents an overview of existing frameworks for spatial-temporal knowledge management and sharing and highlights existing challenges, Section 4 presents an innovative framework and outline principles that can be adopted in designing spatial-temporal knowledge systems. Section 5 demonstrates a theoretical application of the proposed framework using a use case scenario in a cyber-network domain.

2. Temporal knowledge management methods

To answer the question of how can spatial-temporal knowledge be created in a given business domain, this section explores the aspect of time and space in knowledge creation.

2.1 Spatial-temporal knowledge creation process

In natural sciences, the standard concept of time is determined by what is specified and measured [3]. With respect to the temporal aspects of time, this is measuring time with respect to the temporal duration of an interval or event. Galton in [3] notes that time flows in one direction thus moving forward.

Space is the geographical representation of a real-world object, a place, or a region. Space is said to be moving in any direction.

The creation of knowledge that contains aspects of space and time involves building what is known about spatial-temporal knowledge. This is described as a profoundly interactive process that is affected by other people, the environment, and the actions of objects or individuals. As noted in [4], knowledge is considered inseparable from the temporal process of creation, interaction, interpretation as well as context and space of where creation is completed. It is important to look at how space and time are interconnected within intervals of time or events in a certain geographical space or region.

The creation of space and time-based knowledge has been described in many aspects. The study on how space and time are intertwined within the knowledge creation process is described in [4]. As the researchers noted, knowledge is not information as it requires interpretation and exists between explicit and tactile dimensions. The creation of knowledge involves a combination of various elements of time and the context for which space and time exist. In the creation of knowledge, there are several dimensions to consider (a) object space as to where an object resides, (b) object time as the time when an object is engaged in some event, and (c) the process of deriving the object space and time can be termed as knowledge creation that can then be communicated through various means.

The creation of knowledge can be about relationships as noted in [5], where set-oriented relationships on moving objects can enable the creation of knowledge with respect to properties of movement such as time, speed, direction, accelera¬tion, deceleration, accumulated time intervals as well as the distance within the instance of time.

Others like Yuan [6] highlights events and processes as key to the creation of event-driven knowledge within geospatial research. The researcher discusses the importance of events in scientific inquiries and reviews event-based data modeling and computing. Instead of just applying machine learning (ML) algorithms to readily available data, Yuan highlights the need to add curiosity by asking why events are important and how these can be computed within geospatial research [6]. Events are important to understanding the world and the objects involved in the events.

Based on the domain of service, there are several methods detailed in the literature with respect to the creation of spatial-temporal knowledge. We give an example of a few here.

In social media with the increase in location-based services, massive data sets are generated that contain text, the context of time and geography, that is in social media tweets which can be termed as spatial-temporal messages and contain a vast amount of information (comments, reviews). Users may be interested in knowing information about something they care about but do not want to be bombarded with tweets. To this respect, researchers are looking at methods to get the top-k relevant tweets to a user's interest such as the work in [7] where approximation top k relevant spatial-temporal knowledge can be published and others can subscribe to.

2.2 Temporal knowledge representation

Knowledge representation was initiated as a discipline within artificial intelligence (AI) with a focus on symbolic forms of representation of knowledge so that it can be manipulated and stored on a computer as noted in [3] and most knowledge representation research problems focus on finding a process to encode knowledge so that machines can use it.

There are several factors that are considered in the process of temporal representation. This includes; (a) the ability to include relative and absolute sense of time, (b) relationships between intervals of time, (c) an ability to have context sense of now, and (d) the context of persistence. Allen outlines derived principles for representing temporal knowledge with logic statements that can be used for interference and deduction to enable reasoning about the knowledge represented [8].

Galton highlights several aspects of reasoning that are employed in knowledge representation as rule-based methods using "if… then…" rules which can be used to formulate either data-driven or goal-driven conclusions in the development of expert systems [3].

Model-based reasoning approaches are other forms of knowledge representation that form the explicit encoding of a domain with structural models. Case by case uses existing known solutions for which to build new structures, while hybrid methods combine any of the above representations.

On spatial representation, a landmark paper by Randall et al. [9] details a formal treatment of space and spatial relations within the aspects of time. The researchers introduced the region connection calculus while the work in [10] focused on geographical information systems. A region is an extended potion of space and can be applied at any time. An example using cyberspace, suppose there are two regions R1 and R2, Galton in [3] details relationships that can be used to define the two regions. Now integrating those definitions with time, one can represent the two regions in any event or interval of time. There is some expectation that geographical regions have valid durability within a specific snapshot of the world. As such, it is possible to represent a region in temporal snapshots of time.

With domain-specific encoding of entities of a region, aspects of time can enable representation of critical knowledge that is not obvious. To complete this process requires a comprehensive framework for processing of space and time knowledge and this can be implemented within information systems [3]. Next, we discuss an overview of knowledge processing methods within the spatial-temporal paradigm.

2.3 Spatial-temporal knowledge processing

After creating and representation of spatial-temporal knowledge, next, we examine how knowledge is processed.

Processing knowledge involves the use of information systems. There are several elements to consider in the processing of spatial-temporal knowledge specifically when it comes to the era of big data where exponential volumes of data streams are generated from connected devices and sensors every second from social media, e-commerce, energy, and healthcare among others.

The complexity of processing time-oriented data streams was noted in [11], adding a new dimension of space adds even more complexity in the process of deducing knowledge.

Historically knowledge processing has been characterized within a framework comprised of six phases in data mining literature; business understanding, data collection, data processing, modeling, evaluation, and deployment [12]. Several methods have been suggested in the literature that utilizes this framework particularly in processing spatial-temporal data already created in database systems [6]. However, as noted in [4], data within a database only contain a geometric representation of time and space but not the relationships that are derived by knowledge representation. As such frameworks for processing that data to derive any hidden knowledge are needed.

In recognition that historical knowledge processing frameworks that use [12] do not incorporate methods for processing temporal aspects of data, researchers in [13] designed a temporal knowledge framework by incorporating techniques in temporal abstraction and data mining. This work was later enhanced in [11] to incorporate components for deriving temporal relationships in time-oriented high-frequency data within the data processing and modeling phases. Although the researchers demonstrated their work in clinical case studies in [14], their work did not specify the potential for the inclusion of spatial data and the wealth of extra spatial knowledge that can be added to the knowledge discovery process.

2.3.1 Current focus on spatial-temporal knowledge processing

In most of the research that seeks to process knowledge that incorporates both space and time, the focus has been mostly on data processing and modeling phases. We highlight some of the works here.

Classification: Spatial-temporal access methods for classifying knowledge are detailed in [15] where the researchers note that classification is based on the data indexing. The researchers indicate that there are indexes for historical, current and recent, future as well as the process for which data is processed in parallel or distributed systems.

Clustering: There are various clustering approaches for processing spatial-temporal data. A good review is presented in [16] where researchers defined clustering based on the purpose of use such as hotspots for identifying the high density of some phenomena or cluster trajectories in finding groups of elements that have similar trajectories. An example would be a group of taxis that follow similar routes, or in weather, hurricanes that show similar trajectories, and in the combination of time and space, there are clusters that can be developed for identifying locations that have similar spatial maps.

Rule-based techniques: These are normally termed as methods for temporal associations rooted in sequence mining. In particular, mining relationships in spatial-temporal data aims to identify relations among pairs of regions which may vary by time as noted in [17]. The researchers identify interrelating windows as well as the windows of time within which the interactions happen.

Information flow: In quantifying information flow within a network, then temporal ordering among elements within the network is to be considered. Multiple works have considered the Lagrangian reference frame to study information flow thus quantifying the state of a physical system [18].

Spatiotemporal outlier: This is a technique that has been applied in extracting information that differs significantly from others. As noted in [19], detecting spatial-temporal outliers has many applications, in transportation, ecology, public health, security, and location-based services.

While traditional ML algorithms have been demonstrated as efficient in analyzing and modeling spatially and temporally variable environmental data, automated feature representation and learning in deep learning (DL) models are noted as able to capture spatial, temporal, and spatial-temporal dependencies [20]. These are demonstrated in traffic prediction, where researchers in [21] use deep neural networks to model spatial dependencies and temporal dynamics on large-scale traffic data to predict accurate taxi demand. Neuro networks (NN) are also utilized in [22] where graphical convolutional networks (CNN) are proposed to forecast urban planning and traffic management. Reinforcement learning has been proposed in [23] for spatial-temporal pricing in ride-sharing services by using two feed-forward neural networks. Once spatial models are generated, they are evaluated using some testing dataset and then deployed. The derived special models are the knowledge that has been generated from spatial data and deployment of that knowledge is known as knowledge sharing.

We discuss some of the elements that are involved in spatial-temporal knowledge sharing next.

2.4 Temporal knowledge sharing methods

There are various methods discussed in the literature for knowledge sharing. In this section, we discuss some of the key aspects in spatial-temporal knowledge sharing and highlight limitations still to be addressed.

The competitive advantage of any organization can be greatly enhanced with a well-defined process of knowledge exchange among individuals, teams, and units within the organization. There are several enablers for the seamless flow of knowledge within an organization including secure communication channels that enable dissemination and flow of information to those who require it.

There can be resistance to sharing knowledge among knowledge workers as noted in [24]. These include lack of communication, lack of trust, cultural differences, and personal difference among others.

The creation and processing of spatial-temporal knowledge can generate critical information that would benefit a business, organization, or even a community, therefore, there has to be a well-defined process for which that information is shared.

With the rise of critical questions about how and what are the results generated from models, there needs to be a process to freely share the knowledge creation process including what data was used and how it was acquired, what are the features included in models as well as explaining the results of the models.

Sharing spatial-temporal knowledge also raises the bar on how trustworthy that knowledge can be taken, interpreted, and applied within any domain.

With sharing more information about the spatial-temporal knowledge creation process, this can contribute to user buying when the results of models are to be utilized to make a critical decision about people, places, and communities. For this to be accomplished requires well-structured frameworks for knowledge creation, processing, and sharing. We present some of the existing frameworks suggested from the literature in the next section.

3. Frameworks for temporal knowledge management and knowledge sharing and their applications

There are several frameworks proposed in the literature for spatial-temporal knowledge processing in multiple domains, we highlight a few in this section. Within social media, researchers in [25] developed a framework for discovering spatial-temporal patterns from Twitter data. The researchers describe temporal representation using triangulation and clustering to capture twitter events and demonstrated their technique using datasets related to civic unrest in Mexico. The researchers indicate that such a framework can be used to accurately predict the temporal evolution of events depicted in tweets, especially in the age of big data. The researchers indicate the central challenge remains on selecting the optimal window for which to characterize a temporal event. Another challenge is the ability to process spatial-temporal data from multiple sources concurrently. Visualization of temporal patterns is also another issue noted by the researchers.

In recognition that spatial-temporal knowledge can be utilized in the analysis of projects that span territories and time frames, Allais and Gobert in [26], proposed a conceptual framework for spatial-temporal analysis of territorial projects. The researchers partially tested the theoretical framework on several territorial projects. Implementation of such a framework within information systems could provide much temporal knowledge that can be integrated into many territorial-based research and projects.

In modeling climate data, Amato et al. [20] introduced a framework of spatial-temporal prediction using deep learning. The researchers demonstrated their framework through the simulation of two case studies to show coherent temporal fields. One case study was in modeling to predict the temperature in a complex Alpine region in Europe.

Integration of contextual information in the spatial-temporal knowledge process is described in [27] where researchers propose a collaborative framework for planning highway projects by the state highway agencies in the development and maintenance of transportation infrastructure. The framework integrates multiple factors from budgeting, spatial conflict analysis, and their classification which allow the development of response actions. The framework was developed to mitigate incompatible information systems, especially in facilitating dynamic contextual information generated. The researchers claimed that the framework was rated very high by expert users with respect to being easy to use, intuitive, and complete.

Using more than textual data in [28] integrates images in spatiotemporal models geared to person re-identification thus combining visual semantic information and spatial-temporal information into a unified framework.

A meta-learning paradigm is detailed in [29] where researchers create a framework for learning about different cities using spatial-temporal network data and claim that knowledge from one city can be adapted in other cities with respect to factors, such as traffic and water quality. Another framework for analysis of water, energy, and food is described in [30] where an engagement of academics, practitioners, and policymakers are engaged in studying to understand barriers to critical water, energy, and food.

On the visualization of spatial-temporal knowledge, researchers have proposed several techniques. The work in [31] proposed a visual analytics platform that supports large space spatial-temporal data by redefining spatial-temporal attributes in a data-intensive computing environment. This allows distributed storage, data reorganization, query distribution, spatial indices, and fetch segmentations.

The rise of mobile technologies has led to vast amounts of location information generated by individuals. This is quite valuable information in knowledge frameworks, but that data contains a lot of personal information raising data privacy concerns. Frameworks have been suggested for tackling spatial-temporal data privacy such as the works in [32] where researchers use anonymization and probabilistic techniques to mask underlying data map. Recent work introduced temporal hierarchies in the combination of differential privacy to protect temporal data attributes when publishing data about patients [33].

All these frameworks use static data and little attention is paid to the urgency of processing data as is generated or captured. As Shekhar et al. note in [19] extracting interesting and useful patterns from spatiotemporal datasets is more difficult than extracting corresponding patterns from traditional numeric and categorical data due to the complexity of spatiotemporal data types and relationships.

As most of the proposed frameworks focus lies on the percentage of accuracy of model predictions with minimal attention paid to the knowledge creation process, they inherit most of the problems that affect existing knowledge systems with an inability to effectively generate and share knowledge that is actionable in real time. In current frameworks, spatial-temporal data generated lacks privacy protection, is plagued with data quality issues, and models generated are mostly not explainable and are mostly biased. Although knowledge generated from static data is important for lesson learning, it is imperative that on-time knowledge is created, processed, and shared for it to have a clear impact in any business domain while maintaining the privacy of data sources and context. This is particularly critical in cyber networks, critical infrastructure, energy, banking, transportation, and healthcare.

Big data frameworks that recognize the need for real-time processing of data streams have been suggested in the healthcare domain [34]. Though the researcher's methods are demonstrated as effective at processing high-frequency data streams from bedside monitors and sensors, they have yet to be integrated with spatial information that would enhance any resulting knowledge.

In the next section, we describe a conceptual framework for spatial-temporal knowledge generation, processing, and sharing that incorporates components for end-to-end real-time processing of spatial-temporal data streams. This is an overarching spatial-temporal framework that embeds privacy by design, integrates data quality modules, models outputs are encapsulated with explainable details as well as seamless knowledge sharing and application. Design principles adopted in this framework acknowledge the volume, variety, velocity, and richness of spatial-temporal data that is generated every second from multiple domains and as noted in [35], new innovative frameworks for spatial-temporal knowledge management that are actionable are needed to improve lives.

4. Spatial-temporal knowledge management framework in the phase of big data

In this section, a spatial-temporal knowledge management framework named Sesat is introduced. Sesat name is adopted from Seshat, the Egyptian goddess of knowledge, wisdom, and writing, and was seen as a record keeper and illuminator [36]. In recognition that for spatial-temporal knowledge to be effectively harnessed, there has to be end-to-end processing of space and time data from multiple sources to application efficiently. To this respect, Sesat is a framework designed as a multi-layered process flow with agents that continuously enable data ingestion from multiple sources, processing to sharing and application. To accomplish this, Sesat multi-agents are designed with tasks for accomplishing many complex tasks simultaneously as presented pictorially in **Figure 1** and described next.

There are seven layers within Sesat as follows:

a. Data acquisition layer: Within this layer, there are agents tasked with workflows for acquiring data from a variety of data sources, devices, sensors as well as any historical data.

b. Data preparation layer: This layer contains agents that effectively ingest the data that is streaming from multiple devices and sensors. Other agents within this layer filter, enrich as well as integrate multiple data sources generating unified information about phenomena or object. There are also agents for segmenting and reducing the dimension of data reducing backlogs in buffers. Another key aspect within this layer involves preserving the privacy of data sources and context. This is accomplished with the data de-identification and masking agents.

c. Temporal data preparation layer (TDPL): The integrated and de-identified data from the data preparation layer being passed on to the TDPL where quantification of temporal aspects within data is completed. This layer contains agents that generate temporal data, spatial data, and a combination of space and time to generate spatial-temporal data streams.

d. Knowledge creation layer (KCL): This layer contains agents that utilize the data from the TDPL for the creation of spatial-temporal knowledge. KCA contains vast agents for knowledge creation; agents that utilize traditional learning and mining algorithms, agents that can utilize newer methods from deep learning, agents for knowledge classification, prediction, and forecasting, agents for integrating statistical null hypothesis tests and inference as well as hybrid agents that combine multiple knowledge creation algorithms.

e. Knowledge management layer (KML): After the creation of knowledge from the KCL, the KML has agents that facilitate the storage of all the spatial-temporal knowledge created. There are also agents to verify the accuracy and quality of knowledge created. This is also the layer where created knowledge is made available for others to access. There are also agents to facilitate encryption of the created knowledge thus ensuring further privacy preservation of context and knowledge generated.

f. Knowledge sharing layer (KSL): This is the layer where all the encrypted knowledge from the KML is made available for sharing to internal or external systems and processes.

g. Knowledge application layer (KAL): This is the layer that contains agents that facilitated the application of knowledge shared from the KSL to many business problems internally and externally.

DOI: http://dx.doi.org/10.5772/intechopen.101797

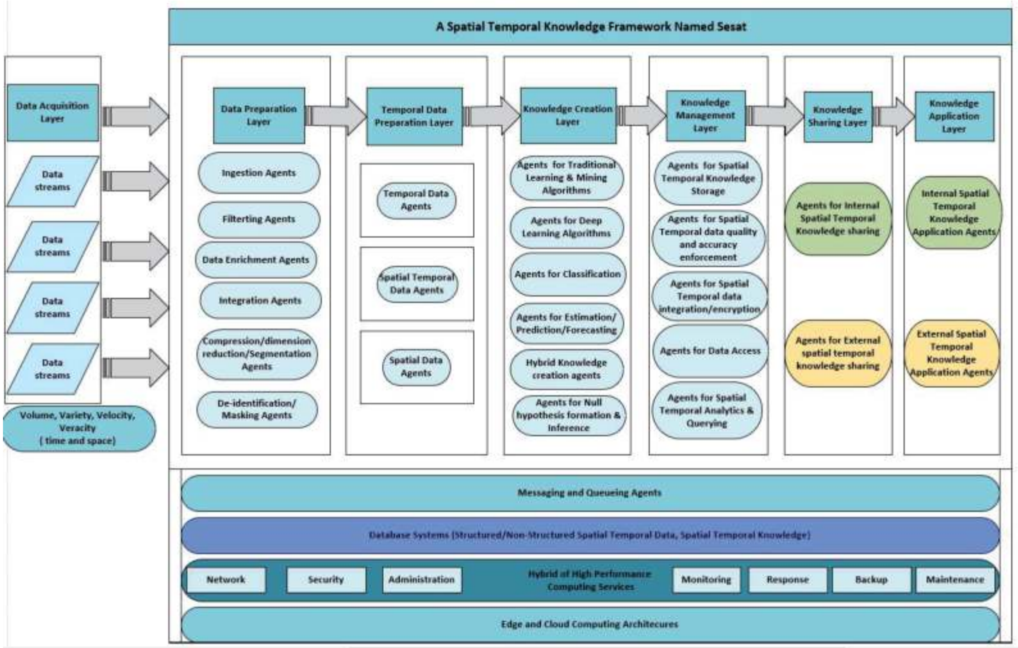

Figure 1.
Spatial-temporal knowledge management framework (Sesat).

The multiple agents adopted in Sesat address many challenges in existing knowledge frameworks that are still designed from a static data mindset. We argue that by incorporating streamed lined layers of data flow and agents, such a framework if adopted in spatial-temporal knowledge creation, management and sharing provides a unified end-to-end process flow on real-time knowledge management applicable to any data domain.

Next, we demonstrate a theoretical application of Sesat to a cyber-network domain with a use case scenario.

5. Theoretical application of the Sesat framework in a cyber network: a use case scenario

Spatiotemporal outlier detection is a technique noted in [19] that can be utilized for identifying abnormality in data, within a cyber-network, we theorize how the proposed Sesat framework can be utilized in real-time spatiotemporal outlier detection in a use case scenario detailed next.

A fictitious organization named "XYZ" is located in North America and has branches and workers scattered all over the seven continents. It is the early days of the pandemic, workers in many countries are still commuting to work while others work remotely. There are meetings held regularly virtually among different groups within the company stemming from different time zones, some of those meetings could include potential or existing clients during product launches, webinars, or conferences. The organization has several high-performance computing architectures that service all the network activities and log all the network flow between all devices communicating in its network.

The time is 12:00 PM Eastern Standard Time (EST) and a webinar is scheduled for all employees to attend as a new product is about to be launched. As usual, all are logged in to listen to the product team who have diligently been working on the new product and have been preparing for weeks to present in the webinar. Thirty minutes into the webinar, all is going well, then suddenly, all are logged out of the webinar, no emails are going through, the network monitoring team are diligently plowing through the millions of log files generated over the last few hours and more data stored in databases. After 4 hours, the network is back but the webinar has to be rescheduled for another day and product launch has to be delayed as feedback from internal employees is vital for ensuring critical aspects of the products can go-ahead for the public deployment.

How can XYZ utilize the Sesat framework to derive, manage, and share real-time knowledge about the network and effectively mitigate such long network failures?

A simulation of Sesat in XYZ is adopted with a pictorial representation in **Figure 2**. The spatial-temporal knowledge derived from vast network logs acquired from multiple devices in the company's network and processed within the seven layers of the Sesat framework is detailed next.

a. Data acquisition layer: This layer contains agents that continuously gather network logs from the multiple devices logged in the company XYZ network.

This data is queued within the messaging queues for ingestion from the data ingestion agents win the DPL.

b. Data preparation layer: Within this layer, multiple agents consume the data from the data ingestion, network logs are filtered, enriched with metadata of time, space and then integrated based on context similarity. The dimension reduction and segmentation agents are also involved to partition the data based on their temporal aspects.

c. Temporal data preparation layer: This is the layer where temporal aspects of time and space about the network logs are quantified. This is accomplished using temporal relation formulation principles. This data is then passed on to the next layer.

d. Knowledge creation layer: This layer utilizes the temporal relations of time and space from the TDPL and then utilizes multiple algorithms to generate spatial-temporal knowledge about the underlying network. This process involves the classification of abnormal logs as specifically temporal intervals at various regions. This is critical information that is passed on to the KML.

e. Knowledge management layer: Within this layer, the knowledge created is checked for quality and accuracy, encrypted and sent to storage as well as made available for others within the company to access it.

f. Knowledge sharing layer: This layer has agents utilized by the network monitoring team at XYZ as well as others that the XYZ company works with including clients and customers.

g. Knowledge application layer: The agents in this layer allow XYZ to apply mitigations to the affected networks internally, as well as inform any external parties of the network problems.

There are many advantages for a company like XYZ to utilize the Sesat framework that includes; the ability for real-time data ingestion and processing, spatial-temporal data formulation and knowledge creation, preservation of privacy, on-time management, sharing of key facts about the network, and on-time application of

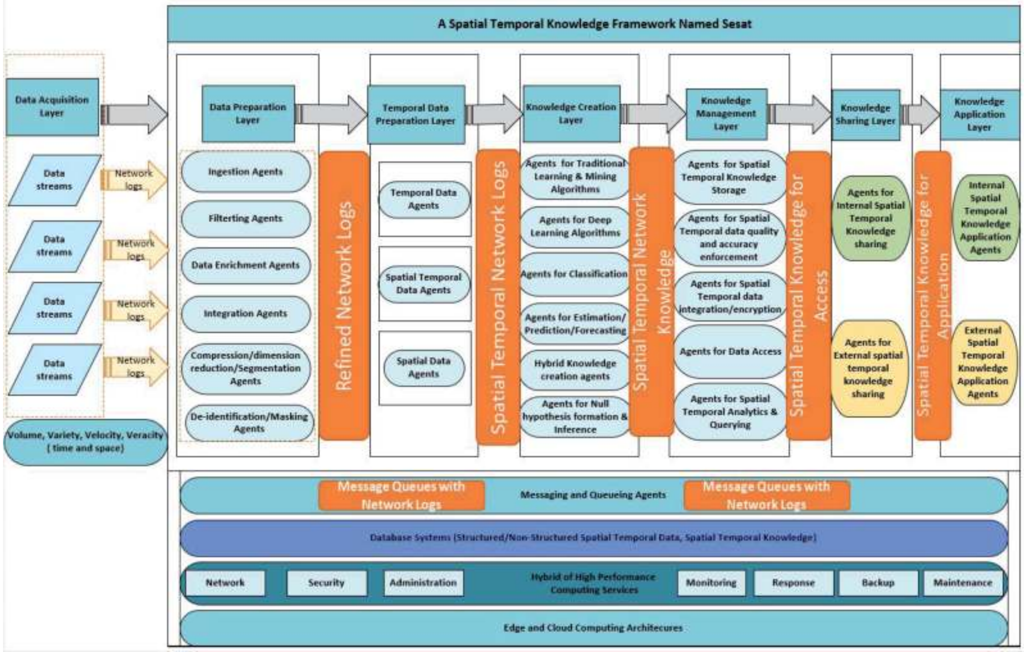

Figure 2.
Adopting Sesat framework for processing spatial-temporal knowledge from network logs data streams.

spatiotemporal knowledge strategically. Within XYZ, this process would allow targeting network mitigation instead of shutting down the entire company network given that the right spatial-temporal knowledge would be created, managed, shared, and effectively applied on time to the right parties internally and externally.

We argue that Sesat can be applied to multiple other domains where on-time spatial-temporal knowledge needs to be created, managed, and shared efficiently and effectively.

6. Conclusion

As large volumes of data are been generated every second from social media, cyber networks, healthcare, banking, etc., there is a heightening need for any organization, community, or country to have a good understanding of any knowledge that may exist in data specifically within aspects of time and space.

Although there are many frameworks designed to harness space and time data as noted in Section 3, most of the existing works are geared toward historical or static datasets. While the use of static data in existing frameworks provides important information of what has happened in the past, it is crucial that on-time knowledge is also created, processed, and shared for it to have a clear impact in any business domain. This is particularly critical in cyber networks, critical infrastructure, energy, banking, transportation, and healthcare.

The ability to extract interesting and useful patterns from spatiotemporal datasets is noted in [19] as more difficult than extracting corresponding patterns from traditional numeric and categorical data due to the complexity of spatiotemporal data types and relationships.

In recognition of the need for real-time processing of data streams, big data frameworks have been introduced in domains, such as healthcare [34]. Though the researcher's methods are demonstrated as effective at processing high-frequency data streams from bedside monitors and sensors, they have yet to be integrated with spatial information that would enhance any resulting knowledge. This is especially critical for many high-frequency data domains where exponential data streams from multiple devices and sensors capture the world phenomena within seconds. There is a need to develop frameworks that can effectively derive knowledge from such high-frequency spatial-temporal data streams and efficiently share those for application in critical domains, such as cyber networks in real time.

This chapter has provided a highlight of methods in the literature that describes spatial-temporal knowledge creation, representation, processing, sharing, and application. Additionally, a high-level overview of current spatial-temporal knowledge frameworks is presented highlighting current shortcomings. To address some of these challenges, an overarching spatial-temporal knowledge processing framework named Sesat is introduced. Sesat framework contains a generalized design applicable to multiple data domains and a theoretical illustration is described using a cyber-network use case scenario thereby demonstrating the potential for such a framework to be applicable in multiple data domains.

Conflict of interest

The author declares no conflict of interest.

Author details

Catherine Inibhunu
Ontario Tech University, Ontario, Canada

*Address all correspondence to: kathy174ca@gmail.com

References

[1] Boshoff N. Types of knowledge in science-based practices. Journal of Science Communication. 2014;**13**:A06

[2] Tang R. Knowing that, knowing how, and knowing to do. Frontiers of Philosophy in China. 2011;**6**(3):426-442

[3] Galton A. Spatial and temporal knowledge representation. Earth Science Informatics. 2009;**2**:169-187

[4] Hautala J, Jauhiainen JS. Spatio-temporal processes of knowledge creation. Research Policy. 2014;**43**(4): 655-668

[5] Geocomputation: A Practical Primer [Online]. 1st ed. 55 City Road, London: SAGE Publications, Inc.; 2015. Available from: https://methods.sagepub.com/book/geocomputation [Accessed: August 22, 2021]

[6] Yuan M. Why are events important and how to compute them in geospatial research? Journal of Spatial Information Science. 2020;**21**:47-61

[7] Chen L, Shang S. Approximate spatio-temporal top-k publish/subscribe. World Wide Web. 2019;**22**

[8] Allen JF. An interval-based representation of temporal knowledge. IJCAI'81: Proceedings of the 7th International Joint Conference on Artificial Intelligence; Vol.1. 1981. pp. 221-226

[9] Randall DA et al. Intercomparison and interpretation of surface energy fluxes in atmospheric general circulation models. Journal of Geophysical Research. 1992;**97**:3711-3724

[10] Egenhofer M, Franzosa R. Point set topological spatial relations. International Journal of Geographical Information Systems. 1991;**5**:161-174

[11] Inibhunu C. A method to detect and represent temporal patterns from time series data and its application for analysis of physiological data streams [PhD Dessertation]. Canada: Ontario Tech University; 2020

[12] CRISP-DM. Available from: https://www.sv-europe.com/crisp-dm-methodology/

[13] Catley C, Smith K, McGregor C, Tracy M. Extending CRISP-DM to Incorporate Temporal Data Mining of Multidimensional Medical Data Streams: A Neonatal Intensive Care Unit Case Study. 22nd, IEEE International Symposium on Computer-Based Medical Systems; 2009. pp. 1-5

[14] Inibhunu C, McGregor C. Identification of temporal changes on patients at risk of LONS with TPRMine: A case study in NICU. In: 33rd International Symposium on Computer-Based Medical Systems (CBMS). Rochester, MN, USA: IEEE; 2020. pp. 33-36

[15] Mahmood AR, Punni S, Aref WG. Spatio-temporal access methods: A survey (2010—2017). GeoInformatica. 2019;**23**(1):1-36

[16] Atluri G, Karpatne A, Kumar V. Spatio-temporal data mining: A survey of problems and methods. ACM Computing Surveys. 2018;**51**(4):83

[17] Atluri G, Steinbach M, Lim K, MacDonald A, Kumar V. Discovering groups of time series with similar behavior in multiple small intervals of time. In: Proceedings of the 2014 SIAM International Conference on Data Mining (SDM) (Proceedings: Society for Industrial and Applied Mathematics). 2014. pp. 1001-1009

[18] Gunturi VMV, Shekhar S. Fundamental concepts for

spatio-temporal graphs. In: Gunturi VMV, Shekhar S, editors. Spatio-Temporal Graph Data Analytics. Cham: Springer International Publishing; 2017. pp. 5-11

[19] Shekhar S et al. Spatiotemporal data mining: A computational perspective. ISPRS International Journal of Geo-Information. 2015;**4**(4)

[20] Amato F, Guignard F, Robert S, et al. A novel framework for spatio-temporal prediction of environmental data using deep learning. Scientific Reports. 2020;**10**

[21] Yao H, Tang X, Wei H, Zheng G, Li Z. Revisiting spatial-temporal similarity: A deep learning framework for traffic prediction. Proceedings of the AAAI Conference on Artificial Intelligence. 2019;**33**(01):5668-5675

[22] Song C, Lin Y, Guo S, Wan H. Spatial-temporal synchronous graph convolutional networks: A new framework for spatial-temporal network data forecasting. Proceedings of the AAAI Conference on Artificial Intelligence. 2020;**34**(01):914-921

[23] Chen C, Yao F, Mo D, Zhu J, Chen X. Spatial-temporal pricing for ride-sourcing platform with reinforcement learning. Transportation Research Part C: Emerging Technologies. 2021; **130**:103272

[24] Hassan NH, Ismail Z. Investigation of key resistance factors in knowledge sharing towards information security culture in healthcare organization. In: The 8th International Conference on Knowledge Management in Organizations. Dordrecht: Springer Netherlands; 2014. pp. 593-601

[25] Shi Y, Deng M, Yang X, Liu Q, Zhao L, Lu C-T. A framework for discovering evolving domain related spatio-temporal patterns in Twitter. ISPRS International Journal of Geo-Information. 2016;**5**(10)

[26] Allais R, Gobert J. Conceptual framework for spatio-temporal analysis of territorial projects. Environmental Impact Assessment Review. 2019;**77**:93-104

[27] France-Mensah J, Kothari C, O'Brien WJ, Khwaja N, Gonzalez R. Framework for spatial-temporal cross-functional planning of projects by highway agencies. Frontiers in Built Environment. 2019;**5**:120. DOI: 10.3389/fbuil.2019.00120

[28] Wang G, Lai J, Huang P, Xie X. Spatial-temporal person re-identification. Proceedings of the AAAI Conference on Artificial Intelligence. 2019;**33**(01):8933-8940

[29] Yao H, Liu Y, Wei Y, Tang X, Li Z. Learning from multiple cities: A meta-learning approach for spatial-temporal prediction. In: The Web Conference 2019 - Proceedings of the World Wide Web Conference, WWW 2019. San Francisco, CA, USA: Association for Computing Machinery, Inc, 2019. pp. 2181-2191

[30] Scott MA, McGrane J, Artioli F, Chen P-Y, Comber R, Cottee J, et al. Scaling the nexus: Towards integrated frameworks for analysing water, energy and food. The Geographical Journal. 2018;**185**(4)

[31] Guo D, Du Y. A Visualization Platform for Spatio-Temporal Data: A Data Intensive Computation Framework, in 23rd International Conference on Geoinformatics; 2015. pp. 1-6

[32] Cicek AE, Nergiz ME, Saygin Y. Ensuring location diversity in privacy-preserving spatio-temporal data publishing. The VLDB Journal. 2014;**23**(4):609-625

[33] Olawoyin AM, Leung CK, Choudhury R. Privacy-preserving spatio-temporal patient data publishing. In: Database and Expert Systems Applications. Cham: Springer International Publishing; 2020. pp. 407-416

[34] Inibhunu C, Jalali R, Doyle I, Gates A, Madill J, McGregor C. Adaptive API for real-time streaming analytics as a service. In: 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2019. pp. 3472-3477

[35] Yang C, Clarke K, Shekhar S, Tao C. Big spatiotemporal data anlyatics: A research and innovation frontier. International Journal of Geographical Science. 2020;**34**(6):1075-1088

[36] Wilkinson RH. The Complete Gods and Goddesses of Ancient Egypt. Thames & Hudson; 2003. p. 166. ISBN: 100500284245