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Spatial Analytics Techniques: Concepts and Importance

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Abstract

Spatial analysis is an essential component of Geographic Information Systems (GIS) and is widely used for various purposes. One of its primary applications is to assess the suitability of a location for specific systems or to make accurate weather predictions for a particular geographic area. By utilizing spatial analysis, users can effectively model problems and find comprehensive solutions that incorporate geographical attributes.

At its core, spatial analysis relies on spatial data, which provides a numerical representation of physical entities within a geographic coordinate system. This spatial data serves as the fundamental unit of a map. There are two main types of spatial data: geometric and geographic.

Geometric data involves mapping spatial information onto two-dimensional surfaces. On the other hand, geographic data represents the latitude and longitude of a location or entity and is overlaid on a sphere to represent the Earth. For instance, applications utilize two-dimensional data to provide navigational routes, while GPS devices offer detailed geographic information.

In addition to geometric and geographic data, georeferencing and geocoding are crucial aspects of geospatial analysis. Georeferencing involves modelling the Earth's surface by assigning data coordinates to vectors or raster data. On the other hand, geocoding precisely identifies addresses such as states, countries, and other locations on the planet's surface.

Keywords: Georeferencing; Spatial Analysis; Geographic Information Systems; Model; Prediction

Introduction

Spatial analysis is the systematic examination of attributes, locations, and interrelationships among spatial data features. It leverages analytics, computational models, and algorithms to address challenges or extract valuable insights. This analytical approach yields actionable information from spatial data and finds diverse applications in fields such as emergency management, urban planning, logistics modelling, disease mapping, and natural resource management [1]. The utility of spatial analysis extends to enhancing urban resilience, fostering improved quality of life, managing urban traffic, controlling disease spread, and strategizing mass vaccination campaigns during pandemics. The benefits of spatial analysis are manifold and are applicable across both private and public sectors, contributing to local community development, habitat preservation, and addressing global challenges. Analysing temporal patterns in spatial data, it facilitates the identification of trends and the prediction of future events with high precision [2,3]. Besides, traditional manual analysis of satellite imagery is labour-intensive, costly, and error-prone. In contrast, spatial data analytics harness artificial intelligence (AI) and machine learning (ML) technologies to process vast datasets efficiently, economically, and with remarkable accuracy. It enables users to make well-informed decisions by providing a comprehensive view of the area under consideration, offering historical context for present occurrences, and supporting contingency planning [4]. Moreover, spatial analysis simplifies the comprehension of complex spatial data and its significance, aiding in the formulation and implementation of strategies that serve diverse interests. It transcends basic mapping by enabling users to visualize the interactions among variables and consolidating information from multiple sources to offer decision-makers a unique perspective for informed action. On the other hand, the widespread integration of spatial analysis into daily activities, such as using navigation apps, tracking deliveries, or utilizing GPS for travel, underscores its integral role in modern life. While spatial data, including satellite imagery, has existed for some time, the challenge lies in extracting actionable insights from massive datasets. The contemporary applications of AI and ML have revolutionized spatial analysis by enabling efficient data processing and the generation of critical insights that have the potential to enhance profitability and save lives [5].

A distinguishing feature of Geographic Information Systems (GIS) is its capacity for conducting various types of spatial analysis. Spatial analysis, a crucial application of GIS, encompasses the geographic modelling of spatial predicaments. This involves the utilization of sophisticated processing techniques by experts to derive results, which are subsequently subjected to detailed analysis for practical implementation. Notably, this form of analysis serves to ascertain the geographic suitability of locations for diverse interventions [6]. Geospatial information systems (GIS) specifically focus on the physical mapping of data within a visual representation. For instance, when a hurricane map displaying location and time is overlaid with another layer showing potential areas for lightning strikes, GIS is being utilized [7]. In addition, different categories of spatial analysis play a pivotal role in enabling planners to forecast outcomes, comprehend alterations, and unveil distinctive insights concealed within spatial data. Importantly, the utilization of spatial analysis is not confined to experts, as even individuals at a novice level in GIS can readily initiate its application. The accessibility and versatility of spatial analysis render it an invaluable tool for diverse users within the GIS domain [8].

Geospatial data

Geospatial data refers to information that describes objects, events, or features with a location on or near the Earth's surface. It combines location information, usually in the form of coordinates, with attribute information that describes the characteristics of the object or event. Additionally, geospatial data includes temporal information, indicating the time or lifespan at which the location and attributes exist [9]. Furthermore, the location provided by geospatial data can be either static or dynamic. Static locations refer to fixed positions, such as the location of a piece of equipment or the occurrence of an earthquake event. On the other hand, dynamic locations involve moving entities like vehicles, pedestrians, or the spread of infectious diseases [10]. Geospatial data is derived from various sources and can encompass large sets of spatial data in different formats. These sources may include census data, satellite imagery, weather data, cell phone data, drawn images, and social media data. To fully utilize geospatial data, it is important to discover, share, analyse, and combine it with traditional business data [11]. Additionally, geospatial analytics is a technique used to enhance traditional data by incorporating timing and location information. By creating data visualizations such as maps, graphs, statistics, and cartograms, geospatial analytics provides a comprehensive view of historical changes and current shifts. These visual representations enable the identification of patterns and insights that might be overlooked in a large spreadsheet, making predictions faster, easier, and more accurate [12].

Geospatial analysis, facilitated by Geographic Information Systems (GIS), was initially associated with life sciences such as geology, ecology, and epidemiology. However, its widespread applications now encompass diverse industries, including defence and social sciences. The insights derived from geospatial analysis are integral to critical matters such as natural resource management and national intelligence [13]. Moreover, the versatility of geospatial analysis enables the simultaneous study and monitoring of numerous events, allowing for the collection of relevant data from these events. This capability provides organizations of varying sizes with the opportunity to utilize data in making well-informed business decisions. For instance, the proliferation of the Internet of Things (IoT) has led to a surge in the volume of data, presenting a significant challenge in analysing vast quantities of information. This trend is advantageous for geospatial analysis, which relies on an abundance of data to extract valuable insights [14]. Besides, geospatial analytics involves the integration of data obtained through geospatial analysis with a heightened visual approach that organizes the data based on time and space. This visual representation facilitates the identification of underlying trends and provides a comprehensive depiction of evolving situations. As more data is gathered, geospatial analytics enables the detection of subtle nuances within the scenario [15].

GIS (Geographic Information Systems)

Introduction and Definition

The process of urbanization in recent decades has resulted in the formation of intricate urban structures that cannot be adequately represented by traditional two-dimensional models. Consequently, there is a growing necessity to establish a multi-layered, three-dimensional model to comprehensively depict and document urban areas, capturing their three-dimensional reality. Rapid technological advancements have facilitated the optimization of multi-dimensional (nD) modelling and the realistic portrayal of urban spaces in various applications.

Furthermore, geographic Information Systems (GIS) have garnered significant global attention in recent years, primarily driven by the escalating demand for the acquisition, processing, and storage of geospatial data [16]. This demand has prompted the development of specialized software and databases tailored to these tasks. GIS technology encompasses both hardware and software components and is defined as a comprehensive set of tools designed for the collection, storage, processing, analysis, management, retrieval, and dissemination of real-world spatial datasets to serve specific purposes or facilitate decision-making processes. The essential components of a GIS system comprise spatial data (digital maps), logical operators (commands and functions), and a database designed to accommodate various methods of retrieving information to address inquiries relating to geographic space [17]. Also, in the context of GIS, spatial data refers to phenomena, observations, or events associated with space that can be encoded. Specifically, spatial data within a GIS encompasses location information, topology, and thematic features. These data are represented as points (pairs of coordinates), lines (sequences of coordinate pairs), and polygons (closed paths composed of a finite sequence of lines), and are structured at a hardware level based on the user's perception, the method of importation, and their deployment within the database [18]. The data sources may include graphic information such as existing maps, GIS files, processed or raw satellite images, rural data, or non-graphic information such as namespaces, statistical metrics, etc. These data may be linked to correlation tables of graphical and non-graphical features. Each mapping attribute corresponds to an entry in an accompanying database, and each entry may encompass multiple descriptive features. GIS possesses the capability to establish connections between spatial graphic information and non-graphical data, thereby empowering the system to fulfil specific requirements effectively [19].

Three-Dimensional Representation of Geospatial Data

The incorporation of logical and numerical operations between maps is a notable feature within GIS systems. Furthermore, advanced GIS programs encompass topology, which serves as a form of cartographic logic, enabling independent cartographic features to possess an awareness of their spatial relationships based on geographic coordinates. Unlike non-digital maps, topology is absent in traditional cartography. While certain GIS users, particularly those focused on cartographic imaging, may not necessitate topology, specialized users seeking to conduct map-related queries, compare cartographic information levels, or analyse market data often require a certain level of topological representation [20]. Similarly, the analysis of geospatial data in two dimensions within GIS is constrained when visualizing specific scenarios such as urban planning, environmental assessments, telecommunications, architectural design, and landscaping. Consequently, there is an escalating demand for three-dimensional representations to address these limitations effectively. Three-dimensional representation can be broadly categorized as follows:

Modelling of 3D Objects Using Solid Shapes

This category involves the modelling of three-dimensional objects utilizing solid shapes such as spheres, cubes, and cylinders, employing a variety of parameters and functions such as intersection, union, and difference to capture the three-dimensional nature of objects [21]. A key advantage of utilizing solid shapes lies in their facile translation into images using computers. However, a potential drawback is the potential complexity arising from the representation of intricate objects and their interrelationships [22].

Voxel-Based Representation

This category focuses on the representation of the spatial imprint through voxels. A voxel, which stands for "volume element," represents a three-dimensional pixel and is depicted as a cubic or spherical field. Each voxel element may contain one or more data values, allowing for the representation of volumetric data within a three-dimensional space. Voxels are predominantly utilized for modelling continuous phenomena such as geology, soil composition, and other analogous entities. The utilization of voxels offers several advantages, primarily enabling a more detailed analysis of the data. However, a notable drawback of voxels lies in the substantial storage space required to accommodate high-resolution data [23]. Another method for visualizing three--dimensional data involves the use of tetrahedrons (TEN). A tetrahedron, comprising four triangles that form a closed object within three-dimensional space, represents the simplest 3D primitive (3-simplex). Its fundamental structure allows for the relatively straightforward formulation of the requisite functions. Additionally, the defined nature of a tetrahedron, with the three points of each triangle consistently positioned at the same level, facilitates its practical application. Nevertheless, a significant limitation of this approach pertains to the necessity of employing multiple tetrahedra to construct an object [24]. On the other hand, the final method for three-dimensional object imaging is through boundary representation, where the 3D object is delineated by specific boundaries-elements such as vertices (0 Dimension), lines (1D), polygons (2D), and polyhedra (3D)-that are organized and stored within data structures. These boundaries may encompass flat faces and straight edges akin to border representations on a map, or more intricate representations such as curved surfaces and edges [25]. The primary advantage of this method lies in its comprehensive and precise representation of real-world objects, with the boundaries being derived from actual measurements. Additionally, many rendering engines are based on triangle representations with specific constraints, thereby aligning with this method. However, a notable disadvantage of boundary representations is their lack of uniqueness, as multiple objects may share the same boundaries, necessitating the imposition of additional constraints and rules for modelling [26]. Consequently, this process can become exceedingly intricate, requiring the definition of constraints such as flatness, number of points and arcs, order of edges, and relationships with adjacent neighbours when describing geometrically defined triangles or polygons.

Voxel enables highly detailed 3D representations of geological characteristics that can be of crucial importance for understanding complex structures. In addition, voxels can simulate real behaviours of complex objects, which is useful for geological simulations. They offer a more precise 3D component than other modelling types because they imitate particles. However, the Voxel modelling lacks the mathematical precision of the Boundary Representation (BREP) modelling. In addition, modern computers are not optimized for the rendering of Voxel, which can heavily strain the current hardware.

Types of Geospatial Data

Geospatial data constitutes information that is intricately linked to a geographic reference or indicator. This data is predominantly categorized into two primary forms: vector data and raster data, each serving distinct purposes in geospatial analysis and representation.

- Vector Data: In the realm of geospatial data, vector data encompasses the representation of features through points, lines, and polygons, delineating various geographic entities such as properties, cities, roads, mountains, and bodies of water. For instance, in a visual depiction utilizing vector data, houses may be delineated by points, roads by lines, and entire towns by polygons. This form of data is pivotal for conveying discrete spatial features and their attributes [27].

-Raster Data: Contrasting with vector data, raster data is characterized by its pixelated or gridded structure, wherein cells are delineated based on row and column identifiers. Raster data facilitates the creation of intricate imagery, including photographs and satellite images, by employing a grid-based representation that captures detailed spatial information. This form of data is particularly instrumental in portraying continuous and high-resolution spatial phenomena, offering a comprehensive view of the Earth's surface and its diverse attributes [28].

Spatial Big Data Analysis

Spatial big data pertains to geo-referenced data characterized by its substantial volume, velocity, and variety, surpassing the processing capacity of contemporary spatial computing platforms. Noteworthy examples of spatial big data encompass GPS trajectories, earth observation imagery, and check-in location history. The analysis of spatial big data involves the intricate process of unveiling compelling, previously undiscovered, yet potentially valuable patterns inherent within spatial big data [29]. Figure 1 illustrates the process of spatial data exploration.

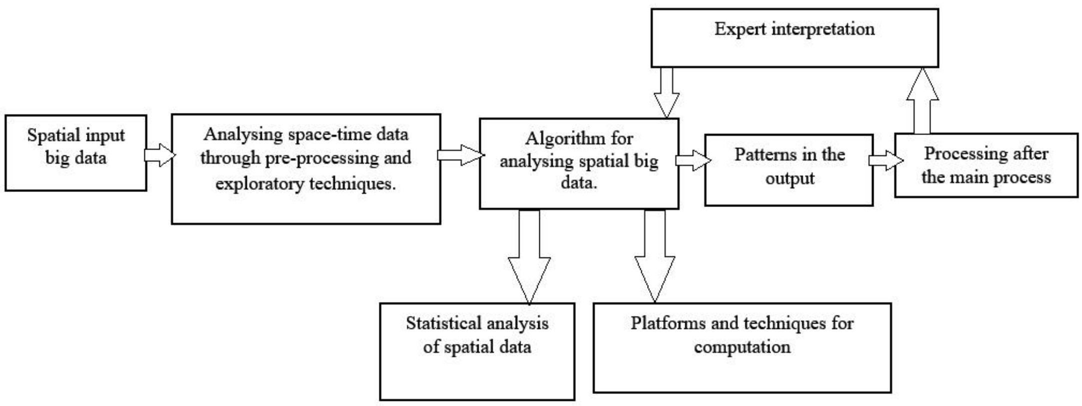

Figure 1: Spatial big data analytics process

The comprehensive knowledge discovery process encompasses various stages, with the central component being spatial big data analytic algorithms. These algorithms are designed to assimilate input spatial big data and generate desired output pattern families, encompassing spatial or spatiotemporal outliers, associations and teleconnections, predictive models, partitions and summarizations, hotspots, as well as change patterns. For instance, spatial prediction techniques can be employed to categorize earth observation images into distinct land cover types, while spatial colocation patterns can identify correlated event types. These algorithms are underpinned by statistical principles and incorporate scalable computational methodologies and platforms [30].

The selection of appropriate algorithms is contingent upon the nature of the input data and the desired output patterns, dictating the suitability of specific algorithmic approaches.

Machine Learning and Geospatial data

Machine learning is a prominent field within the realm of artificial intelligence. It aims to replicate the cognitive abilities of humans to acquire knowledge about the environment using machines. While humans and animals possess an innate learning capacity, machine learning endeavours to develop machines that can efficiently gather information from the environment and subsequently comprehend the data in some manner [31]. The ultimate objective is to create machines that are capable of making decisions or predicting outcomes based on input data. This can be achieved through the utilization of Machine Learning Classifiers. In the context of machine learning, classification refers to the process of predicting the class or category to which a given set of data belongs. Classification predictive modelling involves approximating a mapping function that connects input variables to discrete output variables [32]. To accomplish this, a classifier leverages training data to discern the relationship between the input variables and the various classes or categories. By analysing the training data, the classifier can learn patterns and make accurate predictions about the class of new, unseen data. Overall, machine learning plays a crucial role in advancing artificial intelligence by enabling machines to learn from data and make informed decisions or predictions. With classification techniques and classifiers, machines can effectively analyse and understand complex datasets, contributing to the development of intelligent systems [33].

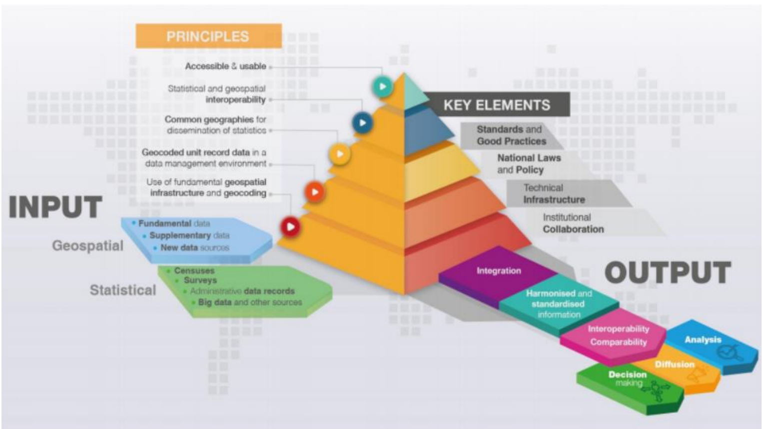

Figure 2: Global Statistical Geospatial Framework [34]

Geospatial data, also known as spatial data, is a type of information that is associated with specific geographic locations. It involves the association of objects, events, and real-world phenomena with precise geographical coordinates defined by latitude and longitude. This enables the mapping of various elements in the physical world. Figure 2 illustrates the Geospatial Global Statistics Framework. For example, geospatial data can be used to identify the location of a parked car or to monitor its movement in real-time [35]. Besides, geospatial visualization is a technique that transforms spatial data into visually engaging representations, such as maps and 3D models. It goes beyond static data maps and utilizes advanced technologies to create interactive visualizations. These dynamic representations unveil patterns, trends, and themes on the Earth's surface, allowing for a deeper understanding of our surroundings. Decision-makers can gain valuable insights into various fields, including environmental management, urban planning, and disaster response, by utilizing geospatial visualization [36]. The following figure (Figure 3) establishes the Global Statistical Geospatial Framework's guiding principles.

Figure 3: Principles of the Global Statistical Geospatial Framework [34]

At the core of leveraging geospatial data is the concept of geospatial intelligence. Geospatial intelligence involves the collection, analysis, and interpretation of geospatial data for informed decision-making. It combines geographic data with other forms of intelligence, such as imagery, signals intelligence, and human intelligence, to provide accurate representations of locations and their physical environments. Geospatial intelligence plays a vital role in various domains, including military planning, emergency response, and environmental management. It enables the identification of patterns, assessment of emerging trends, mitigation of risks, and data-driven decision-making [37]. Overall, geospatial data and geospatial intelligence provide valuable insights and understanding of our world by mapping and analysing objects, events, and phenomena in specific geographical areas [38, 39]. These tools have wide-ranging applications across industries and play a crucial role in decision-making processes.

Machine learning classifiers are applied such as predicting flood-prone areas. Artificial neuronal networks (ANN) can be trained to predict flood events by analyzing historical precipitation data, river levels and other environmental factors. You can recognize patterns and relationships that may not be recognizable using conventional methods. In addition, Support Vector Machines (SVM) can classify regions based on their flood risk by analysing various characteristics such as topography, soil type and land use. This helps with the creation of precise flood crisis cards. Finally, decision trees can be used to predict the occurrence of floods by analysing factors such as precipitation, river drainage and weather conditions. They offer a clear and interpretable model for the flood forecast.

Machine learning classifiers also are employed, such as optimizing delivery routes. The clustering algorithm groups deployment locations based on proximity and other factors, which minimize the optimization of the delivery routes by minimizing travel distance and time. In addition, genetic algorithms optimize the tax routes by simulating the process of natural selection. They can find almost optimal solutions for complex routing problems. Furthermore, algorithms for learning reinforcement can learn to make intelligent routing decisions by interacting and receiving feedback from the surroundings. This approach can adapt to changing traffic conditions and other variables.

Conclusion

Experts anticipate the evolution of geospatial technology, particularly as it intersects with machine learning and Artificial Intelligence. Geospatial Artificial Intelligence is expected to emerge, incorporating a geographic element into machine learning processes. Moreover, the concept of "mapping as a service" is anticipated, wherein custom, high-resolution maps can be tailored to meet consumer or industrial requirements. Additionally, the development of vehicles reliant on geospatial technology, such as drones for aerial mapping and autonomous vehicles for ground transportation, is envisaged. These advancements will lead to new applications and expanded utilization of geospatial technologies in various domains.

Conflict of Interest

The authors have no conflicts of interest to declare and no financial interest to report.

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