[DM-02-022] Events and Processes for Geospatial Computing

Abstract

Including a space-time perspective in geospatial data modeling is especially relevant for anyone working in a domain where dynamics, e.g., change or movement, are relevant and there is a desire to represent and analyze these dynamics. This entry discusses two key dynamics, events and processes, that have been identified by geospatial scientists as being relevant for many different geospatial applications. Events may be formally distinguished from objects, and events and processes may also be distinguished from each other, and researchers have formalized sets of relations that hold for each type of dynamic. With regard to geospatial computing and analyses with events and processes, researchers have used spatial and space-time clustering and time series analyses among other methods to understand the distribution of events over time and the impact of sequences of events or processes for a domain.

Keywords: processes

Author & citation

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Explanation

1. Overview
2. Fundamentals of Events and Processes
3. Event Computing in Geospatial Research

1. Overview

Since the late 1990's, discussions of ontologies for geospatial computing recognized that entities in the real world existed as either, continuants, i.e., entities that exist over time including e.g., lakes, mountains, roads, and buildings, or occurrents, i.e., entities that are more dynamic and that exist and then are often gone again, e.g., tornadoes, landslides, and traffic accidents (Worboys & Hornsby, 2004; Worboys, 2005). Continuants effectively map to objects that have always held a prominent place in geospatial modeling and around which many models are focused. Occurrents, on the other hand, are associated with dynamic happenings including events, processes, activities, and actions, and as recognition has grown regarding the importance of including a dynamic or space-time perspective for geospatial modeling (see e.g., Peuquet & Duan, 1995), designing both the ontologies that underlie contemporary models as well as the models themselves to handle occurrents as well as continuants has become accepted (Yuan, 2020; Claramunt, 2021). Here, we discuss the categories of occurrents commonly known as events and processes and how these two categories of dynamics are fundamental for geospatial computing.

2. Fundamentals of Events and Processes

The term 'event' has been described as an umbrella term representing all kinds of occurrents (Worboys, 2005). Events and processes together both represent dynamic happenings in the world such as when a vehicle crosses a street intersection, the expansion of a flood boundary, or the urban activity of gentrification where neighborhoods undergo change such that more resources become available and the economic value of homes and businesses in the neighborhood increase. Events and processes are important for countless applications, e.g., transportation, finance, sports, and lifetime milestones among other application domains. Previous research has distinguished events from processes by defining events as completed episodes of history, i.e., that these episodes effectively have both a start and end time (i.e., are bounded in time), while processes, on the other hand, are ongoing over time and at a coarse granularity may even be viewed as being homogenous (Galton & Worboys, 2005; Galton, 2016). The example of a vehicle crossing an intersection during a specific time interval such that once it is through the intersection, it no longer continues its crossing fits with an event-based view. Gentrification, on the other hand, is commonly characterized as a process that is ongoing with no specific end time. Deforestation and urban growth are additional examples of processes for which geospatial models are designed and applied. Processes, Galton and Worboys (2005) argue, may undergo change, while events do not undergo change in the same way (e.g., the spread of wildfires may change over space and time). Snapshots of underlying processes may be extracted with one snapshot differing from the next, e.g., traffic flow through an intersection at one time point is one snapshot from a sequence of snapshots that by itself does not capture dynamics but rather the world state at different times (Peuquet & Duan, 1995). However, considering change in the context of time and the temporal relationships that are essential to these changes allows for a representation of processes, e.g., the process of traffic flow in a city. Events are generated from processes, e.g., a traffic accident event arises from traffic flow, and are intrinsic to change and movement (Galton & Worboys, 2005; Yuan, 2020).

Together, events and processes, offer a lot of richness for the geospatial modeler or analyst who desires to capture and represent geospatial dynamics. While scholars have made a distinction between events and processes, it is sometimes the case in geospatial computing, that ontological development and modeling has been directed more towards events and sequences of events than processes. In review articles discussing why events are important for geospatial research, event is used to represent all classes of occurrents including processes (Worboys, 2005;Yuan, 2020). Instances and classes of geospatial events are understood to have a dynamic structure. They have attributes and subparts in a similar way as objects, including both spatial and temporal attributes and parts. The origins and destinations of vehicle trip events, for example, may be represented using both location and time-based information, while storm events are often modeled with spatial footprints and temporal durations. Events also participate in relationships with both objects as well as other events giving rise to object-event relations, e.g., between a new road and road construction, as well as event-event relations, e.g., between a flooding event and a landslide event (Worboys & Hornsby, 2004). Andrienko et al. (2011) discussed events for movement analyses, e.g., vehicle movements in traffic, where movement events are formally defined using object trajectories (a spatio-temporal construct) and are associated with spatial and temporal relations that provide a space-time construct and support the detection and visualization of movement events. He et al. (2022) describes a set of relationships useful for researchers modeling geographic scenes, i.e., dynamic geographic environments, where people, things (discrete distributions of geographic objects), events (sudden changes in a scene), and phenomena represented as continuous and variably distributed fields were elements of a scene. The relationships studied included scene-scene, scene-element, and element-element relationships. Processes also exist in this framework and further express dynamics associated with scenes and their elements (He et al., 2022). These authors modeled events as bounded and discrete while processes were continuous and within events. A case study based on a typhoon in China included typhoon landfall events and the process of flood incursion, and identified cause/give rise to, next/precede, and initialize/change relations among others.

Scholars working on the use of knowledge graphs for geospatial semantic reasoning and computing have also noted that without the capability to represent space-time processes and events, these graph structures will be limited in their application (Zheng et al., 2022). Extending knowledge graphs to handle elements including geo-events, activities, and participation relationships means that the evolutionary changes such those present with the formation of typhoons or tornadoes can be fully represented, and that the long-term evolution involving entities and events can capture spatiotemporal processes (Zheng et al., 2022).

3. Event Computing in Geospatial Research

Different approaches to event computing have been discussed for geospatial computing including understanding the spatial distribution of event occurrences and predicting the spatial distribution of further events. In general, clustering, i.e., the identification of statistically significant groupings of features is frequently used to either identify non-random groupings of events and/or understand patterns of events that have happened in the past, or more prospectively. These analyses include both cluster detection as well as analysis of patterns of clustering over space-time. In an analysis of new businesses openings in part of Tokyo where the new openings were modeled as events and the pattern of events was tracked over space and time, spatial clustering was used to detect the occurrence of sequential events (Sadahiro, 2023). In this study, cluster detection was applied to proximal events (i.e., two events that occur successively) that were spatially close using a probability density function and Monte Carlo simulation to determine patterns of events that were not simply random occurrences. A similar analysis was applied to the time intervals between events to discover if the pattern of events was increasing or decreasing over time.

Space-time cluster detection, has also been applied to geospatial events identified in social media data, for example, detecting events such as house fires, ongoing sporting events, or traffic jams, expressed in tweets for a given geographic area (Walther & Kaisser, 2013). In an analysis of a helicopter crash in London, UK and events related to this incident in Twitter data, space-time scan statistics were applied to generate clusters of tweets on event topics across space and time (Cheng & Wicks, 2014). In this study, geographic coordinates associated with tweets provided spatial data (note that privacy regulations for such message posts have changed since the publication of this article, making coordinate-level spatial data associated with social media data less available). Space-time clustering using SaTScan (Kulldorff, 1997) was applied to the tweets for different time periods and different temporal granularities (e.g., hours and days), and to relate the clusters to the events related to the helicopter crash, topic modeling using Latent Dirichlet Allocation (LDA) was used to classify the text content of clusters into topics (Cheng & Wicks, 2014). While some of the clusters referred to non-event topics, the methods were shown to reveal the space-time pattern of tweets associated with the helicopter accident, revealing both the geographic scope as well as the timescale for when the event remained significant in Twitter conversations. In addition to SaTScan, spatiotemporal density-based clustering using ST-DBSCAN (Birant & Kut, 2007) has also been applied to geotagged tweets to detect non-random clusters of small-scale events in Twitter data (Khazael et al., 2023). For this study, two different examples of events, gunshot events and St. Patrick's Day events in Columbus, OH were analyzed as domain examples. Using ST-DBSCAN incorporated the time dimension directly into the cluster detection step and then was followed by topic modeling using LDA to detect the topics within each space-time cluster.

Smart city applications require the capability to detect events and their spatial characteristics (e.g., the spatial footprint of an event) and monitor such events for different smart city needs, e.g., to monitor air quality and detect air pollution events when the concentration of certain pollutants increased above an identified threshold (Khazael et al., 2023). This application, which involved different kinds of pollutant events, e.g., PM2.5, NO2 and O3 events, applied the semantics of primitive events and complex events where primitive events referred to single sensor measurements that identified basic pollutants being present and complex events were aggregates of sensor types inferred from a predefined pattern or rule, e.g., an air quality index (Khazael et al., 2023). Smart city applications are examples of systems where complex event detection and analysis contribute to the design of early warning systems for citizens.

For a more process-based focus, dynamics involving for example, splitting, merging, expansion and contraction are at the heart of many geospatial processes (Claramunt & Theriault 1996). Researchers analyzing the processes of land cover change and subsequent urban expansion have examined how to go beyond simple density functions to capture changing distributions of urban land density, i.e., the proportion of urban land area (Jiao et al., 2021). In this analysis, the spatial growth of a city was modeled as a continuous process that assumed a series of sequential micro-processes over short time steps where the probability of new urban land decreased from the city center outwards following an inverse power function (Jiao et al., 2021). The process of urban expansion and urban land density change was revealed, including characteristics such as degree of compactness during different time periods. Xue et al. (2023) also used a process-oriented approach to monitor ocean dynamics using time series data from 1982 and 2021, a time period long enough to track changes in an ocean environment and form a process-level understanding of ocean dynamics. These dynamics included merging, splitting and related sequences of split-merge dynamics especially as they related to sea surface temperature (SST) anomalies, for example, ocean eddies associated with El Niño and La Niña climate events. A workflow using global satellite-derived remotely sensed imagery and a tracking algorithm were applied to track and map the evolution of ocean dynamics of SST anomalies from origination to dissipation of these entities modeled as marine objects over space and time (Xue et al., 2023).

Recent approaches using techniques from geospatial data science and geoAI that use e.g., machine learning, data mining and pattern recognition and take advantage of the increasing availability of big data (e.g., big mobile device data), open the door for analyses including event detection, prediction, and forecasting among others, offering additional insights about events and processes for traffic monitoring, climate fluctuations, and natural hazard alerting among other fields (Zhao, 2021).

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