

Chapter 108

Space–Time Analytics for Spatial Dynamics

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ABSTRACT

The so-called Big Data Challenge poses not only issues with massive volumes of data, but issues with the continuing data streams from multiple sources that monitor environmental processes or record social activities. Many statistics tools and data mining methods have been developed to reveal embedded patterns in large data sets. While patterns are critical to data analysis, deep insights will remain buried unless we develop means to associate spatiotemporal patterns to the dynamics of spatial processes that essentially drive the formation of patterns in the data. This chapter reviews the literature with the conceptual foundation for space-time analytics dealing with spatial processes, discusses the types of dynamics that have and have not been addressed in the literature, and identifies needs for new thinking that can systematically advance space-time analytics to reveal dynamics of spatial processes. The discussion is facilitated by an example to highlight potential means of space-time analytics in response to the Big Data Challenge. The example shows the development of new space-time concepts and tools to analyze data from two common General Circulation Models for climate change predictions. Common approaches compare temperature changes at locations from the NCAR CCSM3 and from the CNRM CM3 or animate time series of temperature layers to visualize the climate prediction. Instead, new space-time analytics methods are shown here the ability to decipher the differences in spatial dynamics of the predicted temperature change in the model outputs and apply the concepts of change and movement to reveal warming, cooling, convergence, and divergence in temperature change across the globe.

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INTRODUCTION

The example given in the abstract demonstrates the idea of new space-time analytics to dig down into massive amounts of spatiotemporal data to derive understanding of spatial dynamics. While there is no unified definition, *analytics* is defined here as the science or method of examining something complex so as to determine its nature, structure, or essential features¹. The Oxford English Dictionary quoted from R. Bisset Douglas (1800) “I teach all the arts and sciences; Greek, Latin, Mathematics, Metaphysics, Analytics, Synthetics, and Arithmetic” which positions analytics in a progress of science’s emphases (Table 1). While mathematics and metaphysics provide the basics of conceptual and symbolic abstraction, analytics is the first step towards data and computing. Analytics gains increasing popularity with the ever growing volumes of data from remote sensing satellites, environmental sensor networks, social surveys, surveillance systems and cyber media. Data deluge pushes the demand for analytical ability to take data, visualize it, understand it, process it, extract value from it, and communicate it.

Space-time analytics extends the definition of analytics to the use of space and time as frames of processing, extraction, visualization, understanding, and communication to simplify the complexity of spatial dynamics into elements and structures in space and time. Because every object or process exists in some space and time, data that provide measures of spatial objects or spatial processes must have location and time references.

Table 1. Sciences of methodology and logics

Science	Emphases
Mathematics	Space, number, quantity, and arrangement
Metaphysics	First principles of things or reality
Analytics	Element and structure
Synthetics	Whole, consequence, or particular instance
Arithmetic	Numbers and features

Hence, space-time naturally serves as a common framework for data integration. However, data are static; observations or samples are taken at specific location and instance. Space-time analytics aims not only to uncover patterns of properties captured by the data but also to reveal the underlying processes that drive the patterns. For example, analysis of temperature observations can reveal distributions of high and low temperatures. Insights about temperature change in a region are acquired through the analyses of the movements of cold and warm fronts. Analyses of space-time tracks can lead to patterns of activities. Furthermore, analyses of the person’s social and environmental resources provide the underlying constraints with which the person is operating, and subsequently the constraints lead to an understanding of the person’s routine activity patterns.

Hence, the premise of the chapter posits the need of space-time analytics for understanding the underlying spatial dynamics. Ontological debates on spatiotemporal objects persist, but this chapter subscribes to the conceptual framework that consists of (1) change and movement as two fundamental spatiotemporal observables, and (2) activities, events, and processes are three spatiotemporal primitives that drive the observables (Yuan & Stewart, 2008). Change depicts the differentiation of properties or values over time, while movement involves changing locations over time. Humans observe change and movement to interpret the happening, transitions, or consequences of activities, events, and processes in space and time. In a nutshell, activities are actions taken by an agent, events denote what happens, and processes detail how it happens. The emphasis is to go beyond identification of space-time patterns of change and movement to the understanding of spatial dynamics about activities, events, and processes. The following sections include a conceptual framework for thinking about space-time analytics and highlights of space-time methods that represent key analytical emphases, arguments

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