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# "Spatial Thinking" in Curriculum

In an era where governments rely increasingly on data-driven decisions, one critical skill remains underdeveloped in our education: spatial thinking.

Today, when data are available at multiple spatial and temporal scales, it is appropriate to have them in location-specific form. Once data are available with reference to their location, typically in a gridded form or in an amorphous form (which is usually irregular, e.g., geopolitical units), there are numerous techniques as well as off-the-shelf software from advanced fields, such as spatial statistics, geostatistics, neural networks, graph theory, fractal geometry, mathematical morphology, fuzzy and rough set theories, computer vision, digital image processing and analysis, and so on, for retrieving information in a variable-specific map from variable-specific data (in short, referred to as *spatial data*) in multiple spatial and temporal scales, for quantitative characterization, quantitative reasoning, simulation, modeling, and spatiotemporal visualization. Such well-reasoned and characterized information from spatial data is invaluable for preparing accurate spatial social policies.

Gone are the years when modelers and policy makers could blame source data inaccuracies, gaps across spatial and temporal scales, data nonavailability, and so on for wrong or inaccurate policies and decisions. Data scientists today can rely on data that are better structured, curated, represented with location tags, and acquired by reliable governmental organizations, such as sampling survey organizations, statistics and program implementation organizations, economic development and resource planning organizations, unique digital identification organizations, thematic mapping agencies, telecom authorities, census and income survey organizations, survey and space agencies, informatics centers, federal banks, agricultural banking departments, and nongovernmental organizations. Now, datasets acquired via various acquisition mechanisms—ranging from survey based, remotely sensed, biometric based, and physical sensing based—are more reliable, less misleading, better curated, interoperable, and hierarchical.

Spatial data are similar to and can be considered a 2D landscape that possesses, for instance, topographic highs and lows, valleys and ridges, troughs and crests, foreground and background, watersheds, and plateaus. Understanding such data, or landscapes, requires the data to be normalized like a gray-scale image that consists of values between zero and 255, which respectively represent shades of gray from black (zeros) to white (255). Such data, for example, representing the lowest-to-highest population density over 2D space, can be subjected to various operations and transformations, drawn from the toolbox of the mathematical, statistical, and computational sciences. Such data are dynamic. They change over time as a living being and react to perturbations. They can be stored, abstracted, and eventually exploited to prepare spatial policies.

Mathematicians, statisticians, computational geographers, and spatial dynamists have discovered numerous ways to tease out dynamic data available in multispatial and multitemporal modes in order to derive spatial social policies that are more objective than the qualitative approaches of the past.

Geographic information science experts are familiar with spatial modeling based on layered maps; spatial statisticians analyze spatial data with spatial statistical tools and techniques; space scientists acquire data using both passive and active sensing mechanisms at multiple spatial, spectral, and temporal scales; nonlinear dynamists analyze the complexity

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of data; and information scientists look for scientific and engineering outcomes from information mapped from data. They all need to come together in a joint endeavor of deriving the basics of spatial science and policies.

Data partitioning is the first postacquisition step in the quest for finding patterns that may be simple (indicating a specific point), periodic (oscillating between a few points), and chaotic (when the trajectories are nonoverlapping). A crude partitioning is to place a grid on the data; a more scientific approach is to place shapefiles of coarse-to-finer scales, whose boundaries delineate zones, states, districts, counties (administrative divisions), villages, streets, and households. The most scientific is via hierarchical biogeographic boundaries that follow terrestrial characteristics, once the variable-specific data are grid or boundary based, using shapefiles or biogeographic boundaries.

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Understanding the spatial relationships between the partitioned-specific data and information for different variables paves the way to derive parameters and, eventually, attractors that explain the relationships, similarities, correlations, and synchronizations among behavioral patterns.

Data come from broad disciplines, often in a sparser form than needed, and spatial interpolations help researchers and policy makers transform sparser data into denser data, from low resolution to superresolution and, eventually, to hyperresolution.

While students learn calculus, probability, or algebra, they are rarely trained to interpret data in spatial form, to analyze patterns across regions, scales, and time. As a result, graduates may understand numbers but not the geography of those numbers. It is imperative to introduce "spatial thinking" in a firm manner, and consider it as important as learning mathematics and statistics, at the high-school and higher secondary school levels. The "spatial" component added to each datum and each specific variable measured at a particular time provide a new flavor for talking about the "science of where." The addition of the spatial component assists scientists and academics in processing spatial data through spatial clustering, spatial interpolation and extrapolation, spatial optimization, spatial analysis, and so on.

The variables mentioned here, some highly time varying and some time invariant, include, to name a few, population; gross domestic product; land values; natural resources; climate parameters; air quality indices; crime rates; livability; numbers of migrants, immigrants, and out-migrants; mobile data; and the ratio of male to female workers. In some cases, variable-specific spatial—temporal behavior prediction is close to accurate. In turn, one can find patterns in the behavior, ranging from simple to strange. Simple patterns observed in spatiotemporal behavior at a global scale may exhibit a strange pattern at a regional scale. The same might occur at coarser and finer spatial and temporal scales.

The aim of this article is to alert educators, researchers, and policy makers to ponder spatial thinking, which is a way forward, as all its ingredients are already available to address (spatial) data-driven spatial policies. Our policy makers of the future must be prepared to glean essential information when available in visual form, retrieve this information, conduct quantitative reasoning based on the information, and carry out spatiotemporal modeling across spatial and temporal scales. If we expect future policy makers to design effective evidence-based policies, we must teach them not only how to analyze numbers but how to understand where those numbers live. Spatial thinking must become a foundational pillar of modern education.

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