



Urban Science: Putting the “Smart” in Smart Cities

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Abstract: Increased use of sensors and social data collection methods have provided cities with unprecedented amounts of data. Yet, data alone is no guarantee that cities will make smarter decisions and many of what we call smart cities would be more accurately described as data-driven cities. Parallel advances in theory are needed to make sense of those novel data streams and computationally intensive decision support models are needed to guide decision makers through the avalanche of new data. Fortunately, extraordinary increases in computational ability and data availability in the last two decades have led to revolutionary advances in the simulation and modeling of complex systems. Techniques, such as agent-based modeling and systems dynamic modeling, have taken advantage of these advances to make major contributions to diverse disciplines such as personalized medicine, computational chemistry, social dynamics, or behavioral economics. Urban systems, with dynamic webs of interacting human, institutional, environmental, and physical systems, are particularly suited to the application of these advanced modeling and simulation techniques. Contributions to this special issue highlight the use of such techniques and are particularly timely as an emerging science of cities begins to crystallize.

Keywords: systems modeling; big data; smart cities; decision-making; urban science

1. Introduction

Technology is revolutionizing the way we think about and manage cities. The use of sensors, social media analytics, and mobile technology are providing cities with unprecedented quantities of data. Accompanying this explosion of data—and helping to fuel the revolution—are novel methods of data collection and analysis. Cities that embrace these novel data streams and analytic techniques to change the way they make decisions are often referred to as smart cities. And though there is no one agreed-upon definition of a smart city, the following captures commonly implied attributes:

“A smart city is a municipality that uses information and communication technologies to increase operational efficiency, share information with the public and improve both the quality of government services and citizen welfare.” [1]

A key assumption is that a smart city is one that uses data to improve something—the use of data leads to something better. Where did this assumption originate? Why do we assume that more and better data equals smarter decisions? Is this assumption valid or is something missing from this simple perspective?

Consider the historical analogy of medieval medical practitioners. In those times healers believed that many medical problems were the result of such conditions as too much blood or imbalances in the body’s “humors”. And removing blood, through bloodletting or the application of leeches, was a common remedy. Imagine, then, what would happen if those healers were suddenly given access to the types of data available to medical professionals today—monitor readouts, blood test results, MRIs, and numerous other data streams from various sensors. How would those medieval practitioners interpret and use this new data? Would they make smarter healthcare decisions? Would their patients

see improved quality of life? Or would healers, perhaps, use the data to change the placement of leeches, and assume they had made smarter decisions?

2. Discussion

Regardless of how decisions may have been affected in the analogy above, it is highly unlikely that more and better data would have equaled smarter healers. This is because practitioners at that time had no theory to guide the interpretation and use of new data. They had no reasonable model of the system they sought to improve. Urban systems today are not so different—new and better data may well lead to different decisions, but not necessarily smarter ones. Put succinctly, *“big data will only improve decision-making if leaders apply it correctly”* [2]. Thus, data alone does not necessarily improve decisions—it is the transformation of that data into information, information into knowledge, and ultimately knowledge into wisdom, that improves the quality of decisions [3]. And it is the development and application of theory that facilitate each stage of that transformation (Figure 1).

To be sure, highly effective models do exist for specific components of urban systems. For some decisions, a simple mental model is sufficient. For instance, armed with a simple model of a bridge a person can accurately anticipate that, if the bridge were destroyed, people and vehicles would be unable to cross a river. Other urban components require more formalized models. Consider a traffic planner who needs to know the regional ramifications of placing a new traffic control light at a previously unregulated intersection. A systems dynamic model, using fundamental principles of physical systems, might effectively identify such down-stream effects.

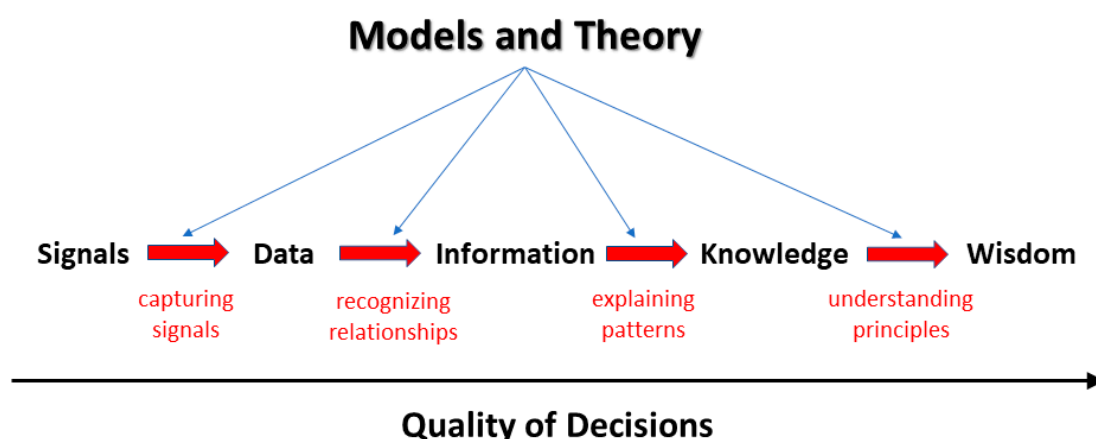


Figure 1. As signals are collected as data, processed into information, and ultimately converted to wisdom, the quality of evidence-based decisions increases. However, each transformation between raw signals and wisdom is facilitated by theoretical advances. Without accompanying theory, it is unlikely that collected data will lead to the knowledge and wisdom that improve decisions (adapted from [3]).

However, holistic models, that capture an urban system's functional dynamics, anticipate its responses to interventions, and allow decision-makers to run multiple future scenarios with some degree of certainty, are still largely aspirational. Such models must be able to describe and anticipate the breadth of cascading effects that result from changes to urban areas, such as natural disasters, military intervention, or economic shocks. They must also integrate the cryptic interdependencies and internal connectedness that are ubiquitous in cities.

Yet there is hope, as demonstrated by just how much medical practitioners today differ from their medieval counterparts. Doctors today not only tend to make smarter, life-prolonging decisions, but they do so even when they encounter patients they have never seen before. This is because doctors today are equipped with a fundamental understanding of what makes all patients similar—they employ a model of the human body. This mental model, when combined with expert intuition and

experience, enables today's doctor to respond to completely new scenarios with a high degree of confidence in desired results and to anticipate outcomes to alternative interventions.

Similarly, urban planners and managers require a model of the fundamental commonalities across all urban systems—how cities generally function, what is “normal”, and how they respond to shocks and interventions. It is that set of fundamental system commonalities and regularities that awaits discovery.

Thus, in parallel with deployment of new sensors, the collection of new data, and the execution of new decisions, we must also create new theories and holistic models of cities. As highlighted in a recent U.S. White House report, a new interdisciplinary “science of cities” is now emerging to address this need and to properly frame data-driven models of cities [4]. Fusing social sciences, biophysical sciences, public administration, and other established disciplines [5–7], this new science should embrace novel technologies and computational methods to drive the development of new theories that will be foundational to a science of cities.

3. Special Issue Highlights

To demonstrate to the scholarly community how modeling and simulation can contribute to novel urban theories, we present this special issue of *Urban Science*. The issue's contributions exemplify contemporary development and application of modeling and computational techniques for urban questions. In doing so the authors not only advance the frontiers of urban science but highlight the central role that modeling and simulation can play in the future of this new science.

A common theme among the issue's offerings is a realization of the immense complexity of cities. This is largely due to human activities and Wolfel et al. [8] offer an analysis of sociocultural factors that magnify the complexity of urban systems. In contrast to an environmental approach to studying cities, the authors argue that social, economic, cultural, and political factors attributable to humans necessitate a novel lens through which to analyze urban systems. In particular, Wolfel et al. explore the benefits of a social science view of a city as a multitude of overlapping and interacting networks, concluding that the future of modeling urban systems will depend on the willingness of researchers to embrace the social complexity of cities and to identify and understand the numerous sociocultural factors involved.

Yet the availability of such social-cultural data is an obstinate challenge for urban theorists, as Friesen et al. [9] find in their attempt to understand the drivers of slum growth as a byproduct of urbanization. The authors use data-mining techniques to develop a novel predictive model of slum growth and highlight one of the primary challenges facing the young discipline of urban science—the lack of city-level data required to inform theory and model development. This is particularly challenging for the informal settlements that are the focus of [9], and in developing-nation cities more generally. However, the authors deftly turn to surrogate nation-level metrics to inform their data-mining exercise.

In contrast, Lagrosa et al. [10] utilize an existing model for predicting land-use and land-cover change, demonstrating that carefully informed parameterization is crucial for the model's accuracy. The authors reinforce the notion that parameterizing models with existing data should be informed by relevant theory. Exploiting large data on a sub-basin of the greater Tampa Bay Watershed in US state of Florida, Lagrosa et al. parameterize and execute the Dyna-CLUE modeling framework. As in [8] the authors note that addressing urban systems with this level of complexity greatly increases the number of relevant variables that must be considered.

In an example of the transdisciplinary nature of urban science, Yamu and van Nes [11] argue that cities grow and self-organize much like living organisms and natural systems, creating a fractal pattern that can be modeled and understood for better planning. The authors demonstrate this approach with a multi-scale fractal model of the Vienna-Bratislava metro region of central Europe, and show how such models can improve planning for sustainability, sprawl, transportation, and other urban issues.

4. Conclusions

Taken together, the articles of this special issue offer a tantalizing glimpse of the breadth of modeling and simulation tools offered by multiple disciplines to advance urban science. They also highlight the central role that complexity plays both in the functioning of cities and in scientific approaches to understanding urban dynamics. The next few years will be an exciting time for those forging a new science of cities, characterized by unprecedented volumes of data flowing from urban systems. The types of tools highlighted in this special issue will be instrumental in transforming that data into knowledge and wisdom and ensuring that smart cities are truly more than just data-driven cities.

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