Urban Informatics for Social Good: Definitions, Tensions, and Challenges

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ABSTRACT

The vast amount of data generated from diverse sources provides both an opportunity and a challenge to urban policymakers and decision-makers. The application of data science and analytics to parse the detailed data that city agencies continually collect offers the opportunity to identify new areas for operational efficiencies, enhanced service delivery, and better informed policy design and implementation. This exploratory paper articulates the theoretical, practical, and pedagogical foundations for the fields of urban informatics and civic analytics and the challenges and tensions to effectively applying computational approaches to urban management, policy, and planning. It describes the state of the field, defines the need for computational methods in cities, and presents the tensions in creating data-driven approaches that both acknowledge and capitalize on shifting modes of learning, working, and decision-making. The paper concludes with a discussion of connecting urban theory to informatics practice.¹

CCS CONCEPTS

• **Applied computing** → **Physical sciences and engineering**; Law, social and behavioral sciences;

KEYWORDS

Urban informatics, data science, city planning, data for social good, civic analytics

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1 INTRODUCTION

The convergence of two phenomena - the ability to collect, store, and process an expanding volume of data and the increasing level of global urbanization - has led to the opportunity and need to use large-scale datasets and analytics to address fundamental problems and challenges of city operations, policy, and planning. However, this opportunity has been constrained by the lack of trained specialists that have both the ability to manipulate and use large-scale datasets and the understanding of city functions within and across urban domains that are defined by complex sociotechnical systems. The challenge is how to apply the tools of informatics—data collection, management, integration, and analytics—in the urban context to improve decision-making, increase the efficiency of operations and service delivery, and support evidence-based policy and planning.

The vast amount of data generated from diverse data sources provides both an opportunity and a challenge to urban policy makers and decision-makers. The application of data technologies and data-driven analytics to parse the detailed data that city agencies continually collect offers the opportunity to identify new areas for operational efficiencies, enhanced service delivery, and better informed policy design and implementation. When combined with other, correlative data sources—pulled from social media feeds, transit cameras, and myriad sensors—the potential increases significantly to understand and improve quality-of-life in cities. A major challenge preventing city officials from unlocking these insights is the lack of personnel with specific training and deep expertise. What's more, individual agencies have been limited in their ability to conduct large-scale analytics by mandate, scope, and organizational structure. However, in an era of shrinking budgets and greater expectations for city services, many cities, including New York, have made new efforts to solve this problem by developing the capability for data investigation that can cross agency boundaries, with promising results.

While the marketing rhetoric around Smart Cities is replete with unfulfilled promises, and the persistent use (and misuse) of the term “big data” has generated confusion and distrust around potential applications, the reality remains that disruptive shifts in ubiquitous data collection (including mobile devices, GPS, social media, and synoptic video) and the ability to store, manage, and analyze massive datasets require new capabilities for urban policy makers that respond to these innovations. In the emerging field of urban informatics, and its corollary civic analytics, core competencies cross traditional boundaries of computer and data science, public policy and urban planning, and business and technology management. This results in requirements for both technical and non-technical

(or non-computing) skills, as well as breadth and depth across informatics disciplines and domain applications. These skills include knowledge of programming (Python, R, etc.), data mining and management (Hadoop, MapReduce), applied mathematics and statistics, machine learning, and visualization (CartoDB, D3).

The challenge of training scientists and practitioners to extract usable insight from data extends far beyond programming skills. They must be knowledgeable about a wide range of urban data—both structured and unstructured—and be aware of the biases inherent in its definition and collection. They must be able to manage and integrate large, disparate datasets of varying types, and use a range of analytical techniques to interpret and visualize outcomes in such a way that can be communicated effectively to non-technical audiences and drive decision-making and policy design. They must understand city governance, structure, and history sufficiently to identify and assess problems, collect and organize appropriate data, utilize suitable analytical approaches, and ultimately produce results that recognize the constraints faced by city agencies and policy makers. This is not an easy task, and requires an understanding of urban social and political dynamics and a significant appreciation of data governance, privacy, and ethics.

This paper articulates the theoretical, practical, and pedagogical foundations for the fields of urban informatics and civic analytics and the challenges and tensions to effectively applying computational approaches to urban management, policy, and planning. It describes the state of the field, defines the need for computational methods in cities, and presents the tensions in creating data-driven approaches that both acknowledge and capitalize on shifting modes of learning, working, and decision-making. The paper concludes with a discussion of connecting urban theory to informatics practice.

2 BACKGROUND ON THE FIELD AND STATE OF PRACTICE

2.1 State of the Field

Urban informatics brings together aspects of computer science, physics, operations research, management science, decision sciences, and the social sciences, particularly urban planning, policy, and economics. As such, the subject to date has appeared in the literature within several disciplines, often with researchers using a new language (or a lexicon from computing) to describe traditional, quantitative social science research, or researchers using traditional computer science tools or physical models applied to urban data [7], [22], [25].

An increasing chorus of researchers are demonstrating the uses of big data in the urban context. The focus of these articles tends to be on using new sources of data and computing methods from the computer and physical sciences to improve operational decisions in city management [3], [6], [15], [16], [19]. Others examine the influence of Information and Community Technologies (ICT) and the Internet of Things (IoT) on creating “Smart Cities” that track and automate many systems-level functions currently using manual or analog processes [5], [8], [24]. While the analysis of data is a necessary extension of IoT-enabled technologies, there is often a disconnect between the adoption of urban technologies

and needed changes in city agency organizational behavior and decision-making.

The research landscape for urban data technologies and data science applications to city management and policy is changing rapidly. The field remains relatively nascent; much as in the early days of neuroeconomics, computational biology, and genomics [14], [23]. The maturation of the field has led to greater clarity in the focus and meaning of various terms that have evolved over the past few years. The following are proposed definitions for common terminology encountered in urban big data and smart cities debates:

Urban science is the scientific study of cities through experimentation and inter-disciplinary research. It can be defined by its objective to understand urban dynamics using heterogeneous data, diverse computing capabilities and approaches, and scientific methods from physical, natural, and social sciences.

A science of cities seeks to apply models from the physical and natural sciences to discover universal principles of urban form and function. It is predicated on the use of observational data to inform and develop new theories of urban space.

Urban informatics is the study of urban phenomena through urban sensing, data mining and integration, modeling and analysis, and visualization to generate new insights that simultaneously advance methods in data science and address domain-specific challenges.

And, finally, *civic analytics* is the application of data science to enable data-driven and evidenced-based public sector decision-making in city operations, policy and planning.

The distinction between urban informatics and civic analytics rests on the emphasis of the respective research goals. Where urban informatics focuses on advances in computing and data science methods through the use of urban data, civic analytics focuses on new ways to solve persistent urban challenges using machine learning and other computational methods. A civic analyst must be able to understand the full analytical toolkit, recognize what methods are appropriate for what types of problems, and to translate analytical output to change organizational behavior and public management practices. Thus, the civic analyst needs to understand what tools are available, which tool works for the nature of the given problem, and how to communicate the output to impact the identified problem.

While competing or varying definitions exist, these definitions provide a starting point for the discussion of the skills needed by the next generation of city managers, planners, and policy-makers. The core competencies are a direct function of the nature of problems facing today’s cities, and the constraints that urban decision-makers face in balancing needs, goals, and priorities. These issues are considered in the next section.

2.2 State of the Practice

Cities, for their part, are becoming increasingly data-driven in their management approach, buoyed by open data mandates and the realization that the process of measure-verify-act-evaluate can result in more efficient delivery of services and management of infrastructure [4]. And the private sector has jumped in after recognizing the massive investment opportunity represented by civic technology and urban Internet-of-things. But there are non-trivial constraints

to the widespread adoption of data-driven practices, and to utilizing data technologies in service of citizen needs and well-being. Described below are three infrastructural issues that many cities now face:

Computing infrastructure: Most cities lack the fundamental computing and database infrastructure to support big data analytics. Antiquated information technology systems designed for storage rather than integration and analysis constrain city agencies' ability to access the rich data resources embedded in most cities' day-to-day operations. Furthermore, data collection efforts — from parking tickets to land use characteristics — were historically designed with a single use case in mind. Parking tickets were recorded in a way sufficient to enable the collection of fines; land use characteristics were coded and stored to allow for annual property tax assessments. However, the real opportunity for cities is to integrate and analyze these data to (1) explore patterns and discover unexpected correlations between seemingly unrelated aspects of urban operations and (2) to ask and answer a much wider range of potentially relevant policy and planning questions. As part of this infrastructural limitation, city database systems and access protocols severely impede the ability to take in data from other cities, universities, and the private sector to leverage the vast data repositories already in hand by multiple stakeholders. For instance, merging high-resolution building energy use data from private sector firms with public sector energy disclosure data could greatly enhance our knowledge of building energy efficiency and urban energy systems [17]. While this may not be a primary function of government data systems, the ability to share data effectively across sectors and domains remains a critical gap in bringing data to bear on urban challenges.

Human infrastructure: While city agencies no doubt attract very talented individuals, the skills needed by future generations of city managers and leaders have shifted dramatically. Functional capabilities in coding, data science, machine learning, database management, etc., should now be considered baseline requirements for city management. Couple these skills with the need to understand analytical problem-solving methods, to be able to communicate technical language to non-technical audiences, and to recognize that the problems facing cities cannot be solved through data alone. Several new degree programs have been created in recent years to address this skill gap. The emergence of programs at the intersection of data science and city management speaks to both the growing demand for these skills by students and employers and the need to build a technically-competent and socially-aware cadre of experts able to take on some of society's most pressing challenges.

Institutional infrastructure: The shift to a data-driven city governance model in many cases requires city agencies and leadership to overcome institutional capacity constraints and legacy bureaucracy. Most decision support systems and procedures were designed decades ago, and there is little incentive to innovate, perhaps understandably so, as city agencies are constantly focused on delivering city services on a daily basis. Data-driven approaches necessitate processes that combine analytical evidence with "ground-truth" experience and expertise. Combining the two is not any easy task, as shifting organizational behavior requires leaders that recognize the benefits of change and have the time, resources, and commitment

to see it through. Additionally, city agencies often operate in siloes, thus rendering the type of collaboration necessary for urban analytics difficult to achieve. These boundaries impact sharing of data and best practices and manifest themselves in the absence of data standards, common data definitions, and universal identifiers to easily merge data collected from different sources and for different purposes.

3 DATA-DRIVEN CITIES

3.1 A Typology of Problems and Applications

Urban informatics is driven by the nature of the problems to be solved. In the context of cities, these problems can be grouped into three bins: *operational*, *policy*, and *planning*. *Operational challenges* focus on efficient and effective systems operations and delivery of city services. These problems have been the focus of a majority of data-related research, primarily because they tend to involve problems with definable solutions, such as mapping disparities in 311 service complaints. These challenges lend themselves well to the application of data science methods, particularly machine learning, data exploration, and data visualization. Within the operational basket, three sub-groups emerge. First, situational awareness problems are those that require a greater understanding of the location, use, or movement of a given asset or resource. For instance, the GPS-mapping tool for the Department of Sanitation of the City of New York (DSNY) enables the agency to know where any vehicle in their fleet is at any given time. Second, the use of targeting to improve resource allocation is a common need among agencies. Given limited resources - whether it be police officers, building inspectors, or energy - cities must be able to deploy them in such a way that maximizes efficacy, while minimizing cost and time. An example of this is work between New York City Mayor's Office of Data Analytics (MODA) and the Fire Department of New York (FDNY) to predict the locations of illegally converted buildings [9]. Third, optimization problems seek to balance supply-demand at a given spatial and temporal resolution. These problems are more complex, as they require data and domain-level knowledge of both the supply chain for a resource and the drivers of its consumption. Energy demand response and efficiency programs provide one useful example [18].

Policy challenges revolve around broader social, economic, and environmental goals, and often require the ability to identify causal inference. An example is policy or program evaluation. Here, it is necessary to design appropriate experiments (or quasi-experiments) to effectively understand counterfactual scenarios and to identify suitable control and treatment groups. Policy challenges require a different set of analytical tools than operational ones, including more extensive use of regression modeling and Bayesian inference. In addition, effectively addressing policy-related questions typically requires the collection of new data specifically needed for the research. The availability of big data, and the ability to process large-scale datasets, represents a significant shift in public policy research [13]. The opportunity to evaluate policy decisions in near-real-time and simultaneously across multiple dimensions of impact creates new pressures on public decision-making processes built during a time when learning and evaluating interventions occurred,

if at all, through survey data with low temporal frequency and spatial granularity.

Planning challenges include two distinct aspects of data analytics and technology adoption. First, analytical applications are focused on issues of simulation and forecasting, thus estimating the impact of various decisions on land use, transportation, and other infrastructure-related investment choices over time. Thus, planners can use urban informatics to more fully understand how urban space is being used, and apply that knowledge to future expectations of demand or need [20]. Long-term scenario modeling requires both knowledge of how individual systems function, how these systems interact and create new functional relationships, and how changes to the systems result in changes in output. Urban modeling, reinforced by extensive domain knowledge, can be used to better inform planning decisions through more reliable estimates of future behaviors and outcomes. Second, information and communication technologies, and the computing processes that enable their widespread use, can be used to improve public engagement and individual empowerment in decision-making processes. Here the focus is not on analytical methods to solve problems; rather, it is to enhance substantive participation by a wider range of stakeholders in typical planning strategies of visioning, goal-setting, and value definition [2], [11].

3.2 Tensions

It has become clear that there is a bimodal distribution of interest in those drawn to this emerging field, a division that impacts the types of problems that receive the most attention. Some are focused on a deep exploration of the technical and data skills needed to manipulate urban big data; others are dedicated to solving persistent social problems, and recognize the value of analytical and data-driven approaches to identifying policy solutions. A coarse distinction can be made between those focused on the data and on the problems.

Developing a curriculum to train future urban data scientists inherently has to balance an exposure to data science and related technical skills with an understanding of an appropriate urban domain. Such tensions are also reflected in the field itself, which has emerged with competing visions for how best to approach scientific discovery. On one hand are those that emphasize the applied science component of the field, focused on identifying problems first. On the other hand, a large segment of researchers view the new streams of data generated by, in, and about cities as a powerful tool for scientific discovery and advancing the fundamental science of complex systems dynamics. This is, in many respects, a false choice, as advancements in basic science can be achieved through the process of problem-solving, commonly referred to as Pasteur's Quadrant [21]. Described below are several areas of tension where priorities need to be defined:

State of the art vs state of the agencies: One of the first tensions that emerge is the focus of learning objectives: should we train students to understand the state of the art, or the state of the practice in which city agencies operate? There is a distinct difference here that in several respects shifts the emphasis on which analytical tools are needed, what types of data to use, the nature of the problems addressed, and the measures of success. For instance, to train to

the state of the art, one would want to provide students with an in-depth understanding of computer vision, natural language process, even deep learning. The utilization of video for understanding city dynamics, as an example, provides a novel approach to common operational needs such as pedestrian counts and flows, situational awareness and anomaly detection, and behavior [12]. However, few agencies have the capabilities to do such analytics, those that do are severely constrained by privacy and other data ethics concerns, and most would have limited budget to hire someone specifically trained in such a specialized field.

On the other hand, many of the problems facing cities—particularly as they relate to service delivery—can be addressed with rather straightforward methods and tools from data science, including data mining, more efficient data management, and machine learning algorithms such as k-means clustering, logistic regression, and predictive modelling. While these topics are not mundane, training to the state of the agencies puts the focus on how and when these tools should be applied, rather than their derivation or mathematical construct.

Correlation vs causation: The discussion of big data has often turned to the tension between correlation and causation [1]. In many applications of big data analytics—search engine optimization and predictive online shopping, for instance—causal inference is not needed to achieve an optimal outcome. Likewise, a theoretical framework is not necessary to recommend what book to buy, based on previous purchasing habits—applying theories of human behavior often do not improve the results beyond simple predictive analytics. The case of cities is more nuanced and complex. Understanding the cause of a particular problem is vital to the effective implementation of a solution. In addition, the stakes are much higher, as blind devotion to goodness-of-fit measures may cause the urban data scientist to miss a critical weakness of an analytical solution, or, as significantly, may reinforce bias in outcomes based on the underlying data or model assumptions [10].

Urban data vs urban problems: In the vein of the above, there is a tension between where the focus of urban informatics should lie. For some, particularly from the computer sciences, the emphasis naturally falls to the data. The problems, in this case, revolve around computing—new ways to visualize large data sets, algorithms to query data sets more efficiently, computational methods to reduce error caused by over-fitting, etc. Success, then, is measured in these terms. On the other hand, many see the field, particularly those from social science and engineering backgrounds, as needing to focus on the problems defined by urban operational, infrastructural, or planning challenges.

Social sciences vs data sciences: There is also the question of which direction to lean or from what discipline to start—toward a computational social science or an applied data science. The distinction here reflects multiple aspects of urban science—to focus on urban data and the challenges of extracting insight from data, or to focus on an understanding of policy and the causes of urban problems, using a data-driven approach to enhancing the efficacy of potential solutions.

Ultimately, the disciplinary foundation for urban informatics rests with the resolution of the tensions described, and the institutional context for this type of research within a particular academic

environment. The choice is not insignificant, as it will constrain the nature of problems emphasized, the analytical tools employed, and the types of solutions proposed. For instance, establishing urban informatics research in a civil engineering department will tend to push the focus of the research to physical infrastructure and optimization problems, using modelling tools from systems analysis. Situating this research in a school of public policy will lead to a greater emphasis on policy and planning problems and recommendations to address them. Here, however, the analytical tools may be more consistent with traditional econometric and spatial analyses found in quantitative social science research.

4 CONCLUSIONS AND FUTURE DIRECTIONS

The interest in data-driven city governance and the growth of urban-focused data science and analytics programs can be expected to continue. The need for such skills in city government, and in private and non-profit organizations that work with cities, is accelerating as outmoded information technology and data management infrastructure and new performance management and data-driven service delivery approaches are replacing legacy processes. The rapid proliferation of the deployment of urban sensors and internet-of-things devices will further reinforce the need for technology- and analytics-focused city leaders.

There are, of course, limitations to the application of urban informatics to city operations and planning. Availability of the “right” data for a given problem will continue to be a challenge, as city agencies remain siloed with respect to data infrastructure and operations. In addition, novel sensing technologies and the ubiquity of more traditional methods (CCTV) have yet to scale, and therefore the application of such derived data remain largely exploratory. Similarly, the widespread interest in the use of social media to understand urban function has revealed promising insights, but the representativeness and other biases in these data must be more fully considered before they can be used for real-world decision-making. The computing challenges are solvable; the real uncertainty lies with how to integrate data-driven processes into public sector management, and, more significantly, urban decision-making processes.

As stresses on urban infrastructure build, and demands for social and operational services increase, cities need to find ways to more efficiently and effectively extract value from existing investments and develop new innovations to meet changing needs of citizens. Data-driven approaches, and the application of widely-used and novel sensing and communication technologies, have shown promise in improving decision-making and positively impact quality-of-life. This paper identified three primary infrastructural constraints to the widespread adoption of data-driven decision-making processes in cities, and outlined the tensions in training future city leaders. The presented framework provides the basis for the continued evolution and definition of the urban informatics field. Establishing core competencies and skills needed to extract actionable insight from data will be the starting point for more significant shifts in urban governance and the methods used to address persistent operational, policy, and planning challenges.

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