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Urban Operating Systems

Producing the Computational City

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6 Prediction: The City as a Calculative Machine

At its core, our idea allows us to anticipate and get ahead of problems before they begin, helping us to be a more effective, smarter government. This platform has the potential to fundamentally change the way cities operate. With data, we are building a new path for all cities in the 21st century.

—Rahm Emanuel, mayor of Chicago 2011–2019 (City of Chicago 2013)

In 2013, Chicago's SmartData Platform was selected by Bloomberg Philanthropies as one of five winners in its first Mayor's Challenge. Developed by the municipality as the world's first citywide, real-time analytics platform, the SmartData Platform was designed as an open software tool for use in any city whose administration wanted to use a combination of data and predictive analytics for decision-making. Rahm Emanuel, Chicago's mayor, believed the platform would transform how cities operate by giving them the capacity to make use of millions of pieces of data: "Residents will see services delivered earlier. They will see more targeted responses that will address a wide range of urban issues—from managing weather emergencies to scaling back traffic accidents" (City of Chicago 2013). Michael R. Bloomberg, then mayor of New York City, lauded the project: "Chicago's predictive analytics platform will help the Windy City—and other cities—harness the power of data. . . . [It] tackles an issue of growing importance for cities and companies alike" (City of Chicago 2013).

Both Emanuel and Bloomberg point to the significant impact that predictive logics can have on cities. In our view, their importance lies not so much in their ability to solve urban problems, but rather in the way that they advance a new epistemology of the urban, one characterized by the

coming together of mathematics, time, and space. With predictive analytics, the data-driven city is reconceptualized as a calculative machine. This is a step change from the datafication logic examined in chapter 3, where transparency (e.g., open data platforms), visibility (e.g., data visualizations), and ease of use (e.g., the various interventions by civic hackers) were arguably the main drivers for the digitalization of the urban. By contrast, prediction involves a more explicit desire to rework both time and space in the city through calculation. Under this logic, *space in a calculative form* (specifically, as a numeric set of coordinate points) becomes the common denominator for all urban transactions. This translation of space into numeric common denominators is precisely what enables interoperability across urban domains and the possibility of calculating the urban across time—that is, predicting the city.

The very attempt at prediction involves rethinking how we come to know and engage with urban futures. It operationalizes a foreshortened temporal horizon, pushing decision-making away from the long term and strategic and toward the immediate and responsive. Engaging with prediction is fundamentally *preemptive* rather than preventive; it deems considering an “array of *possible* projected futures” and an incorporation of “the very unknowability and profound uncertainty of the future into *imminent* decision” (Amoore 2013, 9; our emphasis). The implication of this is that the future is not to be known and governed only through a long-term extrapolation of past statistical data (a common feature of planning), but also through working with uncertainty via short-term time frames that prioritize the immediate. Within predictive computational logics, rolled out in the context of big data (Aradau and Blanke 2017), what is at stake is not so much the strategic horizon of the future needed for city planning, but rather near-real-time decision-making. As such, urban prediction operates through the microhorizon of the future needed for urban operationalization. In this chapter, we will examine attempts to predict the city through calculative processes and the way these operate via a close coupling of time and space—more specifically, through the coming together of time sequences with a detailed fragmentation and parceling of space. The experience of Chicago points to an epistemology of the urban wherein calculation and the use of mathematical tools are the driving forces—an urban capacity constituted through a specific computational product.

A Short Genealogy of Prediction

As with many other computer applications, the history of predictive analytics is intertwined with both the history of military applications and that of cybernetics. Within cybernetics, established in the late 1940s by Norbert Wiener following years of experience working on anti-aircraft control systems, flows of information and flows of matter are conceptualized in identical statistical terms. Both are seen as “behaviours or events” that are “subject to predictive analysis” (Hookway 2014, 95). From the perspective of military defense, prediction is the key capability underpinning anti-aircraft warfare—an essential calculation required for reaching a target that is moving over time. By its very nature, this is a time-dependent calculation, with very short temporalities attached to it. One of its earliest applications was the Kerrison Predictor, an automated anti-aircraft targeting system based on an electromechanical analogue computer designed in the late 1930s at the UK’s Admiralty Research Laboratory. This was followed in 1946 by the legendary Electronic Numerical Integrator and Computer (ENIAC), developed by the University of Pennsylvania for the US Army Ordnance Corps. Built to calculate artillery-firing tables, ENIAC was one of the earliest applications of digital computing (Atomic Heritage Foundation 2014; Haigh, Priestley, and Rope 2016). Both predictive analytics and the computers that were calculating them played a key role in the prediction of nuclear chain reactions within the Manhattan Project, the World War II research initiative leading to the first nuclear weapons.

Over time, the targeting capabilities offered by computerized prediction extended beyond military uses. From the 1960s onward, corporations and research institutions began the era of commercial predictive analytics, with applications including forecasting the weather, solving the “shortest-path problem” to improve air travel and logistics, and applying predictive modeling to credit-risk decisions.¹ Set within a context of evidence-based decision-making, data within predictive analytics came to matter in relation to decisions. Computer scientists and corporate leaders began to see predictive analytics as part of a wider movement to transform fleeting forms of decision-making into systematic and process-driven acts via “digital things that we can describe, store, evaluate, compare, automate, and modify at the speed required by modern business” (Taylor 2011, xvii). In retail, a technological confluence of prediction and big data was used by

large supermarket and retail chains for targeting offers, managing inventories, and modeling trends in customer behavior—a process referred to in the industry as extracting business value from the data, drawing on the collection of data on customers' consumption patterns via loyalty schemes (Hirst 2008; Swamy 2011).

What is at stake in predictive analytics is the spectrum of possible relationships (i.e., the associations), rather than a direct causality between them—and the implications for decision-making attached to this ontology of association (cf. Amoore 2011). In contrast to *descriptive analytics* (which refers to linear calculations based on historical data) and *prescriptive analytics* (aimed at evaluating new ways of operating and achieving business objectives), *predictive analytics* is concerned with what-ifs, transcending both data and probabilistic future trends (Evans and Lindner 2012; Haas et al. 2011). In the process, the role of data itself is reimaged. As IBM researchers Haas et al. (2011, 1486–1487) explain, the statistical “focus on data is much too narrow and must be expanded dramatically. . . . By definition, data reflects facts or assertions of facts that are already in existence. . . . Data just lies passively. . . . But data alone—even with very powerful descriptive analytics—tells us about the world as it is, and was, but cannot tell us much about the world as it might be.” Data within predictive analysis thus is proactive and nonlinear; it plays a key role in navigating a world of possibilities and uncertainties in order to access the as yet unmade future.

In the context of predictive analytics, data goes through a process of discovery, standardization, and aggregation in order to enable anticipatory decision-making.² Applications use a variety of statistical and analytical techniques to model future events or behaviors, from forms of regression modeling to more advanced models using neural networks and nonlinear statistical modeling (Nyce 2007). The attraction of these techniques includes the speed with which they can process huge volumes of data, their potential to produce more consistent and reliable forecasts than humans, and their ability to identify hidden trends and relationships (Finlay 2014; Nyce 2007). The critical issues, from our perspective, lie in the translation of these techniques into the urban context. What are the consequences of utilizing a targeted form of calculative decision-making, based on preemptive and anticipatory modes of knowing? How is a data-driven reconfiguration of time-space likely to affect the way we understand the urban, the planning process, and its temporalities? Can this new logic be applied to

any domain of urban life and infrastructure, or does the predictive logic of decision-making have limitations that restrict its use to specific domains? In this chapter, we will attempt to answer these questions, drawing on empirical fieldwork that we conducted in Chicago, a world-leading site for the application of predictive analytics to city management.

Predicting the City

Predictive analytic tools underpin a change in decision-making processes, arguably positioning algorithmic decision-making and mathematical thinking as the new shape of evidence-based policy in the city. Those developing predictive tools for cities argue, that this is allowing cities to move “from a reactive mode of operation based on gut instincts to a proactive mode of operation based on mathematical models” (Appel et al. 2014, 172). Indeed, city administrators and urban practitioners are increasingly turning to techniques based on algorithms and artificial intelligence as ideal tools for knowing and intervening in the city, in part “because they are able to process huge amount[s] of uncertain, imprecise and incomplete data, and to find approximate solutions for problems that, otherwise, would be intractable” (Salcedo-Sanz et al. 2014, 243). Fueled by this desire to model all things urban using algorithms, the city and its infrastructures are increasingly becoming privileged sites for the application of, and experimentation with, forms of prediction. One of the earliest applications of predictive analytics in cities was traffic modeling, mobilizing a mathematical understanding of urban circulation (Microsoft 2011; Min, Wynter and Amemiya 2007). Increasingly, predictive analytics play an essential role within utility services. In the case of water and energy, for example, the rollout of smart electricity and water meters has incentivized the development of predictive models to forecast short-term demand for these services (e.g., Candelieri and Archetti 2014). But the use of predictive analytics in the city stretches well beyond infrastructures: in the City of Syracuse, New York, for example, IBM researchers working in collaboration with the municipality have developed tools to predict and preempt property vacancies (Appel et al. 2014), generating within the municipality a set of capabilities for the calculation of space across time, in effect allowing them to target the sites and mechanisms of both urban decline and vitality. Decisions based on prediction thus intervene in urban sites, preempting one series of futures and

enacting another (cf. De Goede and Randalls 2009). However, this highly targeted approach to city-making has not been mobilized evenly across urban domains.

For over twenty years, city administrations and police forces have used predictive decision-making to fight crime and track “abnormal” patterns of behavior. Within a “globalizing and urbanizing ‘battlespace,’” both at home and in hostile cities (Crang and Graham 2007, 803), prediction as a form of anticipatory seeing has played a critical role in the *making* of urban targets. Perhaps the most common predictive analytics application in cities, particularly in the United States, has been crime forecasting, through what is known as predictive policing. Software packages such as HunchLab and PredPol are marketed to local authorities to enable them to identify “where and when crime is most likely to occur enabling [cities and municipalities] to effectively allocate . . . resources and prevent crime” (PredPol, n.d., “Overview”). As with the logic of datafication discussed in chapter 3, the technology’s wide market appeal lies in its claim to use empirical data objectively, in a way that is arguably “free from human biases or inefficiencies” (Ferguson 2017, 1114). PredPol, originally developed through a collaboration between the Los Angeles Police Department and UCLA, combines algorithmic calculations, historical event datasets, and machine learning to predict crimes, prepare heat maps, and recommend areas for patrol. “Predictions are displayed as red boxes on a web interface via Google Maps. Each box is a 150 ×150-meter square . . . [and the boxes] represent the highest-risk areas for each day” (PredPol, n.d., “Predictive Policing”). Prediction of this type inevitably alters a future that is yet to come. It brings into being a specific reality of policing: targeting and deterrence. According to a police officer in Los Angeles whose words are cited by PredPol as part of the company’s marketing material: “We told [officers] to go into the boxes. . . . They may stay there for just 15 minutes to a half-hour and let people see them walking around the area. . . . Would-be offenders see the police activity and are deterred from committing a crime there” (PredPol, n.d., “Predictive Policing”). As early as 2013, over 150 police departments in the United States were reportedly using predictive policing (Bond-Graham and Winston 2013), including initiatives in Santa Cruz, California; Seattle, Washington; Atlanta, Georgia; Memphis, Tennessee; and Chicago, Illinois. Software companies like PredPol now claim a proven track record of crime reduction.³

Critiques of predictive policing abound. The industry claims not to use personal information about individuals or groups of individuals, thus “eliminating any personal liberties and profiling concerns” (PredPol, n.d., “Proven Crime Reduction Results”). Civil rights activists disagree, arguing that predictive policing results in targeting not only high-risk zones but also high-risk individuals (Townsend 2015; Ferguson 2017; Selbst 2017). Critical geographers accuse the technology of racial bias, arguing that it refreshes and extends preexisting modes of racialized police profiling (Jefferson 2018). For Jefferson, whose research focuses on Chicago,

predictive crime mapping further entrenches and legitimizes racialized policing as it (1) rearticulates police data sets as scientifically valid and (2) correlates those data with other geocoded information to create new rationalizations for controlling racialized districts through differential policing practices . . . the Chicago case illustrates that predictive crime mapping does not incur more precise applications of police force but rather legitimizes the widespread criminalization of racialized districts . . . Precrime maps garb the epistemologies of racialized policing in a scientific veneer, by mobilizing the language of spatial statistical analysis and data analytics to bolster city officials’ rationale for using differential police surveillance and control in Black Belt and latinx districts. (Jefferson 2018, 1, 11)

As in many other cities, the history of predictive analytics in Chicago began with its police department (the Chicago Police Department, or CPD). Since the late 1980s, the CPD has been innovating with forms of matching computerized mapping and crime data for the purpose of devising strategies to respond to crime (Maltz, Gordon, and Friedman 2000). In 1995, the CPD implemented a system for displaying crime data known as the Information Collection for Automated Mapping (ICAM). ICAM was a user-friendly system running on Microsoft’s Windows 95 and MapInfo 2.0 software that enabled police officers to print maps and tables showing the most frequently reported offences in a specific area of the city (e.g., police districts, sectors, and beats; O’Neil 2011; Rich 1996). The system has been “celebrated by officials for pinpointing hot spots of criminal activity at unprecedentedly spatial resolutions” (Jefferson 2018, 5). In the early 2000s, ICAM gave way to the Citizen and Law Enforcement Analysis and Reporting (CLEAR) system. Developed in partnership with the Oracle Corporation, CLEAR consists of a large GIS database of crime reports and offender records, among other data (Government Innovators Network, n.d.; Skogan et al. 2003). CLEAR now provides the data-driven foundations for a range of policing functions within the city.

In 2010, the CPD launched its Predictive Analytics Group, under the leadership of Brett Goldstein, a graduate of the University of Chicago's Graduate School for Computer Science. Goldstein joined the CPD in the mid-2000s and, after a period working on the beat, he started to combine his computer science knowledge with policing. Working on the streets of Chicago led him to ask questions about how he could “‘design a computer model that could replicate’ an officer’s intuition” (Flock 2011; see also Howard 2015). Shortly after, his experience in dealing with data and databases and developing a predictive analytics strategy for the CDP propelled him to city hall. In 2011, Goldstein was appointed by the recently elected mayor, Rahm Emanuel, as the city’s first chief data officer (CDO), after which he became the city’s chief information officer (CIO), and then the commissioner of the city’s Department of Innovation and Technology (DoIT).⁴ Goldstein’s progression through these newly created roles suggests the increasing importance accorded by Chicago’s city administrators to his data-driven work.

Calculating Chicago: Operationalizing Urban Sciences

“We have a history in Chicago of operationalizing urban sciences,” one of Goldstein’s successors in the role of city CIO tells us in an interview. For over one hundred years, Chicago has been a hotspot of theoretical and applied urban knowledge. From the times of Jane Addams at Hull House (1889–1963) through the Chicago School of Urban Sociology (broadly speaking, 1920s–1960s), Chicago has been an object of study for the contemporary urban condition as well as an urban laboratory to test emerging ideas about the city. Here, scholarly knowledge about the urban has found routes into social reform, while also shaping how the very idea of the city—as a spatial abstraction of global purchase—is imagined and dealt with.

As smart city narratives began to dominate the world of urban planning, academic institutions in the vicinity, such as the University of Chicago, the University of Illinois, and Northwestern University, started offering graduate programs and postgraduate degrees on the application of computational analysis to urban planning.⁵ Working in parallel with research centers such as the Urban Center for Computation and Data (University of Chicago/Argonne National Laboratory), the Center for Data Science and Public Policy (University of Chicago/Carnegie Mellon University), and the

Mansueto Institute for Urban Innovation (University of Chicago), these scholarly initiatives sought to mobilize ICT knowledge, data, and computer science to inform day-to-day decision-making in the city and to advance sustainable modes of urbanization. Brett Goldstein, a computer science graduate from the University of Chicago, is both a product and a developer of this landscape and a key figure in the application of predictive analytics to Chicago itself. At the start of his career, a key question for Goldstein was how to predict crime using not just data from past criminal events, but other information—such as 911 calls (the North American phone number set aside for accessing emergency services). He believed in the interoperability of urban processes across temporal and spatial sequences and, through that, in the possibility of identifying patterns that cut across different domains. In practice, this led to the somewhat counterintuitive claim that you did not need direct knowledge about crime in order to predict it. As Goldstein explained to us, “You’ll talk to lots of other people in the field who will say ‘you need to understand the subject matter and you need to sit down and hear people’s stories’ and all of these things—that wasn’t me.” In removing the need for sector-based expertise in order to achieve meaningful insights, Goldstein was going against established ideas about how urban processes operate and how knowledge about them should be accessed.

In the resulting urban computational system, prediction is not bounded by epistemic disciplines: it emerges from the calculative coming together of space and time, creating patterns that transcend any specific domain. Taking inspiration from epidemiology, by 2010 Goldstein had rolled out a system that predicted “when and where people would get shot or killed.” Critical to this was the ability to predict through proxies, avoiding crime data. “I believed in sort of the purity of the math behind it,” explained Goldstein, “where . . . there are polygons, there are vectors, there are segments, and if you understand the interoperability in the temporal spatial sequencing of the events, you’re able to really apply prediction.” Under this model, bounded disciplinary and professional knowledges no longer matter because the model uses indirect data. Its primary skillset is mathematical.

WindyGrid: An Emerging Bricolage of Hybrid Informational Ecologies

After he was appointed Chicago’s first chief data officer, Goldstein took the knowledge he had developed in the police department to city hall. He set out

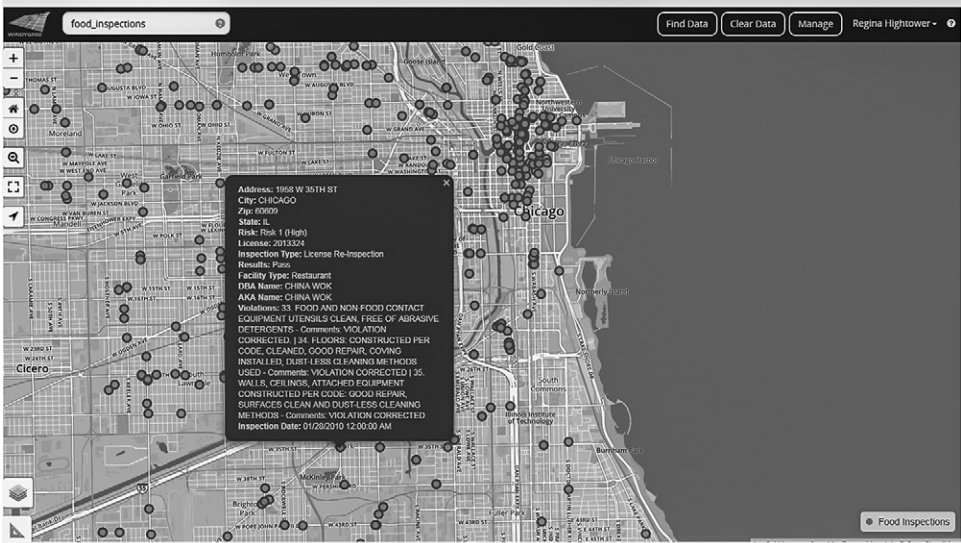


Figure 6.1

Screen capture of Chicago's WindyGrid interface, following a user query on food inspections. Taken from the WindyGrid online manual. *Source:* City of Chicago (<https://webapps1.chicago.gov/windygrid/>). Creative Commons Attribution-ShareAlike 4.0 International.

to develop WindyGrid, a computer application aimed at situational awareness and incident monitoring in real time. It combined GIS mapping, the city's key databases (e.g., 911 and 311 call records, building information, licenses and permits, etc.), social media feeds (e.g., Twitter), and a range of other software tools (Thornton 2013). WindyGrid (figure 6.1) was initially developed for the Chicago 2012 NATO Summit and more recently reconfigured as an open-source package by the name of OpenGrid (City of Chicago 2015; Thornton 2016). Discussing the early days of the platform, Goldstein recalls: "My responsibility was to ensure that we could determine what went on at any given place and at any given time during NATO. With a new Mayor, large-scale event, 'Black Block' [*sic*]⁶ expected and various threats coming in, this was very important" (Goldstein 2015, 7). As Goldstein explained:

WindyGrid consumes all of the spatial data available, lifting information from the base and creating a so-called "large spatial index." In any given area, it became possible to find responses to queries as diverse as the number of police cars active, the sources of the Tweets being sent out, the identities of those using 911, etc.

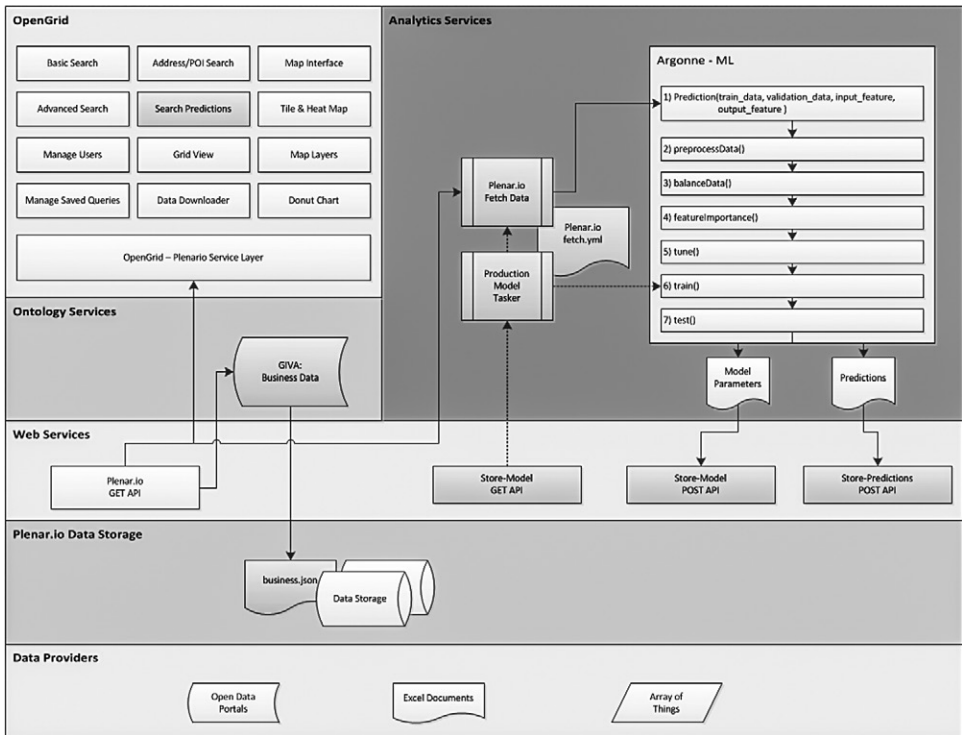


Figure 6.2

Information architecture diagram of Chicago's SmartData Platform. *Source:* City of Chicago/Smart Chicago Collaborative (via GitHub: <https://chicago.github.io/smart-data-platform/>).

and making the needed predictions, for instance, on where rats would likely to be seen or where an outbreak might occur. All of this was achieved using open resources and entailed extraordinarily low costs. It is a system in which we take great pride. (Goldstein 2015, 7–8)

Critically, WindyGrid allows access to the city's predictive analytics application, Chicago's SmartData Platform.⁷ Like many other digital platforms, Chicago's SmartData Platform was developed in collaborative ways using GitHub.⁸ The SmartData Platform is described as a user-friendly system that “helps automate predictive analytics for use within cities and display it without requiring a background in data science or statistics” (City of Chicago 2017). Within GitHub, the application is illustrated with an image that is not unlike the various graphic illustrations discussed in chapter

2. It shows a novel bricolage of hybrid informational ecologies working together to form a type of Urban OS (figure 6.2). The platform “grabs data from multiple city systems which allows users to explore in a single map and provides predictions to help cities operate efficiently and *proactively*” (City of Chicago, n.d.; our emphasis). Indeed, proactivity is a theme in wider journalistic coverage of the system: “The intention is that the Smart-Data platform will shift city management away from a reactive model towards a proactive approach. The predictive power of the tool resides in its ability to analyze relationships in the data at a speed and on a scale not previously possible, helping Chicago to optimize services of all kinds” (Garnier 2014).

Rats! Mobilizing Predictive Analytics in City Hall

The use of predictive analytics in urban settings illustrates a fundamental tension in the mobilization of computational devices and logics for city-making: a contrast between claims of fundamental change and a range of remarkably consistent processes that rather than being transformative reproduce forms of sociospatial targeting and well-established logics of control in search of efficiency. As the quote from Chicago’s mayor at the start of this chapter illustrates, the use of predictive analytics is seen by many as a transformative new path for cities. Yet for those who are involved in mobilizing predictive analytics at the street level, this is about operational efficiency. As a former chief data officer of Chicago noted: “When the mayor was elected the first time [in 2011], part of his election strategy was around being data driven. . . . When you translate that into operations, that pretty much means applying data to become more predictive in city services, and you can sort of apply that to almost any city service. . . . Our focus is on how can we drive day-to-day decisions that either improve the quality of life for residents or improve the efficiency of city operations.”

Predictive analytics’ entrance into City Hall (i.e., beyond the police department) evidences how this computational logic is not about structural transformation but about enabling the city’s everyday. The initial uses of the predictive analytics applications developed by Chicago’s Department of Innovation and Technology (DoIT) have centered on mundane processes: food safety violations, lead poisoning, the identification of black markets for cigarettes, and rat infestations (City of Chicago 2018). Working together with the Department of Public Health, for example, DoIT identified nine

variables associated with food safety violations (including previous violations, nearby sanitary complaints, and length of time since last inspection) and produced an algorithm that generated a list of restaurants likely to breach safety standards in the near future. This work changed the order in which inspectors carry out restaurant visits, targeting those flagged by the algorithm. Media reports state that the prediction “found violations 7.5 days earlier, on average, than the inspectors operating as usual did” (Spector 2016). The work on lead poisoning is also about targeting, with the Department of Public Health, DoIT, and the University of Chicago’s Center for Data Science and Public Policy working together on the identification of homes where children and pregnant women were at risk of being poisoned by lead paint (City of Chicago 2018).

An algorithm for predicting rat infestations, developed by DoIT in collaboration with the Event and Pattern Detection Laboratory (EPD Lab) at Carnegie Mellon University, uses thirty-one different variables to predict where rodents will appear. The data used comes primarily from citizen reports to 311 City Services (the city’s telephone-based system for nonemergency requests) and includes things like the accumulation of garbage and broken water pipes. As the CDO behind the application explained: “Every single night we run that [data] through a series of algorithms to predict where we think rodents are going to be within the next seven days” (Chicago Architecture Center 2014). In an interview, he described how a combination of historic datasets and near-real-time events (311 calls) are a sound predictor of an increased number of rat-related calls: “We have a wealth of data from our 311 system. . . . We have about thirteen years of data in that system, so it’s a wealth of information about the city and we’ve used it through a lot of our analysis. . . . Almost through just playing with that, the data engineers detected certain patterns that seemed to indicate a relationship that to us looked like we would be able to predict that we were going to get a call about a rat infestation prior to the call coming in.”

This interviewee makes no claims about the algorithm replacing human knowledge. Rather, the city’s new predictive capabilities complement years of knowledge, experience, and intuition already present within city hall staff. When DoIT contacted the Department of Streets and Sanitation, the latter was initially skeptical about the ability of an algorithm to replace the accumulated understanding of the streets gathered by rat baiters over decades of work. However, the deputy commissioner of the Bureau of



Figure 6.3
 Baiting rats in Chicago. Photo courtesy of Leif Johnson.

Rodent Control was surprised by the accuracy of the system: “To me it works. . . . It helps us because we are getting ahead of an issue before it gets worse,” she explained. At the time of fieldwork, between twelve and sixteen crews of rat baiters were working in the city on a daily basis, one of which was dedicated to sites identified through predictive analytics. The deputy commissioner explained that she had noticed a reduction in 311 calls associated with rat problems and that she believes that this reduction is partly linked to the predictive analytics work. In the context of rat baiting, one of the most mundane operations of the city (figure 6.3), an emerging predictive knowledge uses correlational logics for targeting purposes, mobilizing mundane unknown futures into city-making. This is also, at times, a contingent knowledge, with the key markers of prediction often identified in rather serendipitous ways. Chance still plays a role.

The City as a Calculative Machine

The transmutation of the urban into a combination of data and mathematical equations opens a window into a different understanding of time-space

in the city, alongside interoperability across a range of urban domains. Despite claims about the transformative nature of Chicago's predictive analytics platform, what such systems do is often very mundane, concerned with everyday services (e.g., rodent control, environmental services) and the short-term temporalities associated with immediate events (e.g., knife crime, food safety violations). As a general rule, the sciences of prediction operate better in time intervals closer to the present, foregrounding short-term horizons. From meteorological to economic forecasts, the longer the time frame for the prediction, the greater the degree of variability, uncertainty, and error. Inevitably, rethinking time in the city through prediction locks the analyst into a short-term outlook. This, in practice, takes the form of operationalization and a focus on the immediate, affecting the system's ability to advance long-term perspectives and strategic transformation. A relevant consideration is that the logic behind the knowledge produced by prediction is not causative but correlative; it is a calculus that "does not seek a causal relationship between items of data, but works instead on and through the *relation* itself," based on "an unknown value that comes into view only through its association with other unknown values" (Amoore 2013, 59; original emphasis).

Urban predictive analytics systems, we argue, are marked by the calculative recombination of space and time. We discuss this through references to WindyGrid and the work of Chicago's first CDO, Brett Goldstein. There are five interrelated steps involved in operating the city as a calculative machine. The first is *a numeric and calculative understanding of space, alongside its recombination with time*. Data points (e.g., transactional databases) and polygons (e.g., spatial databases) allow for calculations (e.g., large-scale multivariate analysis). Space in a calculative form, via spatial coordinates within a GIS system, becomes the common denominator for all urban transactions, enabling interoperability across urban domains. It brings together the various databases of the city, mobilizing them toward a predictive system. In the words of Goldstein: "You have like a 911 system, a police [database], permits, licenses, you name it; and then maybe you have some sort of data warehouse or data-mart and you have all this data . . . you look at the rows of data and what's a common denominator through all these? Their coordinate systems . . . all the data pipes in and you build a massive spatial index."

In conjoining transactional urban data and the map, this way of engaging with GIS prioritizes the database over forms of representation (see

chapter 5). Jeremy Crampton has previously identified this in his analysis of the territorial politics of spatial calculation. Crampton builds on Foucault's (1970) *The Order of Things* and Heidegger's (1966) *Discourse on Thinking* to point to the dangers of this "machinization" of the state (see also Hacking 1990). For Crampton, the issue at stake is not only a way of knowing, but the extent to which this determines a way of being—where "to be, is to be calculable": "The danger is that we already approach the world in a predetermined, calculative manner; where to be, is to be calculable: 'This calculation is the mark of all thinking that plans and investigates. Such thinking remains calculation even if it neither works with numbers nor uses an adding machine or computer. Calculative thinking computes. It computes ever new, ever more promising and at the same time more economical possibilities' (Heidegger 1966, 46)" (Crampton 2011, 94).

Only types of spatial experience and relations that are amenable to calculation and can be captured within the fragmented logic of data (see chapter 3) can play a role in this emerging form of urban knowledge. The coming together of the algorithm (as a mathematical calculation) and space, in combination with sequential time variables, underpins the possibility of prediction. Predictive logics break time into a series of sequential units (T1, T2, T3, etc.) that function as small, knowable, and quantifiable increments in the condition of an unfolding event (the numeric distance between T1 and T2, between T2 and T3, between T3 and T4, etc.). As previously mentioned, the greater the timeframe, the greater the uncertainty: accurate prediction requires time to be controlled and maintained close to the original point of inception (T1), privileging short-term interventions and a focus on the immediate over long-term planning.

Second, urban prediction relies on *a conceptual fragmentation of the urban*—where both the space and time of the city enter the calculative system only through small and disaggregated units or discreet fragments (see chapters 2 and 4). Behind the possibility of calculating and predicting the city lies the idea of *microgeographies*. This type of spatial-numerical analysis, particularly popular within criminology, relies on fine-grained modeling and small scales (cf. Weisburd, Groff, and Yang 2012). Microgeographies are about mobilizing a grid-based understanding of the city as an aid to algorithms for the purpose of calculating urban events. In the case of Chicago, the idea of microgeographies leads to the very name of the original

predictive analytics tool, WindyGrid. *Windy* evokes the environmental conditions of Chicago (famously called the Windy City), while *grid* evokes the small-scale spatial abstraction required for predictive knowledge. The city is seen as a spatial abstraction in the form of a numeric grid where all events have coordinates associated with them.

The third consequence of the urban computational logic of prediction is that it effects *a transformation in the forms of knowledge (expertise)* that matter. With the city seen as a computational entity, mathematical expertise alongside technical GIS knowledge becomes a driving force behind emerging forms of urban knowledge. Once space and time have been fragmented into standardized units, the engine of knowledge production is the algorithm: “It’s a whole new way for a city to do things. . . . If you’re going to make a prediction in my grid, there’s some algorithm that drives it, there needs to be underlying mathematics that do it. . . . Algorithms are at the heart of it. . . . The brains are the algorithms. . . . And the brains do everything from offer up ideas to answer questions,” Goldstein tells us. “The math that drove the rats [analysis] was remarkably similar to the math that predicts the homicides . . . algorithmically.” For the predictive logic of urban computing, whether it is homicides or rats doesn’t matter. What matters is calculating a point within an adjacency matrix associated with a targeted behavior. For those involved in developing the prediction system, the different and multiple data sources involved provide an “enormous amount of ability to create equations for outcomes”—equations that can be repurposed across a range of urban domains in order to achieve different outcomes. Expertise on urban issues, while retained, is seen as a form of intuition that could and should be codified. Once nonurban experts achieve access to models underpinned by mathematics, they are in a position to become the new urban experts.

Fourth, urban prediction is about *targeting and microcustomization*. The analytically integrated city operates through a range of forms of targeting, originally derived from security domains (from military approaches to policing and criminology). Establishing an analogy with bodily disease, Goldstein suggests that prediction opens the possibility of “tailored” or targeted approaches: “15 or 20 years ago if you got cancer, how did we treat it? We treated the whole system, you would have blank radiation, you would have chemotherapy. Now it’s all about tailored focal treatment. It’s the

same thing in government . . . you have customized policy approaches.” Yet the specificity of this approach to the city has significant political and social implications. As Louise Amoore argues in her study of the role played by predictive algorithms in identifying potential terrorists at international border crossings, the computational logic of prediction allows the imposition of partial and fractured exceptions, creating “differential degrees of inclusion or exclusion” (Amoore 2013, 8). At the city level, such technology may be used to understand, control, and govern neighborhoods in differential ways, not only reproducing and entrenching the characteristics of particular urban spaces, but potentially discriminating against neighborhoods with “undesirable” profiles.

Finally, within this configuration of the urban, *the possibility of asking questions is subservient to the predictive system itself*. Predictive analytics promises to uncover meaningful relations that would otherwise remain hidden and unknown. The claim is that “advanced statistical data mining, and machine learning algorithms dig deeper to find patterns that traditional BI [business intelligence] tools may not reveal” (Gualtieri, Powers, and Brown 2013, 2).⁹ Yet this creates a domain that is explicitly *not* known, beyond that of straightforward uncertainty: the *causes* of patterns in the data may remain unknown, as only the correlation is seen. What precisely are the causal or associational relations that matter is, in view of the system, an unknown, and this influences how we pose questions to the system.¹⁰ In addition, the scope of questioning is narrowed by the form of operation of the system itself. As we argued in chapter 3, urban prediction relies on datafication—that is, the quantification of all urban processes. This remains its limit; anything that cannot be reduced to quantitative data is left out. For many of those who embrace urban prediction, the limit is data. In strategic terms, the main limitation of the system is seen as the city’s ability to quantify things—often overlooking an inquiry into who is asking questions to the system or what are the right questions to ask. As those behind WindyGrid themselves argue, within computational logic, such matters are of secondary importance: “Question-asking is a sexier part of the job but we still . . . it’s kind of like worrying about the paint on a house when you’re still building the foundation. If you don’t build a really smart and good foundation to your house, your house will fall down.” Data in the computational city is teleological: seen as the foundation for analytics, its assembly becomes a driver beyond and above its specific function.

Conclusions

Not every problem of the city can be solved through predictive analytics. We were reminded of this by the CDO of Chicago, who was acutely aware of the gap between the expectations created by the promise of urban predictive analytics and its potential to deliver results on the ground: “Every time we sit down with the mayor’s office to look at priorities, the first thing out of their mouth is “we need you guys to look at tree trimming.” And there is such a deep backlog [in tree trimming] that the only thing our data engineers could ever do was go out and help trim the trees! . . . They think predictive analytics is a bit of a panacea, [but] it doesn’t fix every kind of problem. So they’ll present us with something and when we explain that it’s not something that can be addressed by predictive analytics, it is a little bit hard to explain to them.”

This example perfectly illustrates the gap between the limitations of these methods and their perceived benefits: technology cannot yet perform all aspects of human labor and cannot therefore find creative solutions to problems caused by a lack of resources. There are multiple material issues that remain obdurately beyond technological solution: however accurately the computational logic of prediction may allow us to foresee events in the urban realm, it cannot produce the extra tree surgeons that the city needs! In practice, urban prediction is currently about creating opportunities for intervention at microtemporal scales that form part of wider efforts to operationalize the city. Additionally, however, computational prediction is reshaping expectations about how the city can and should function, reshaping the urban in its own image.

An important implication of urban prediction is that calculation becomes a dominant way of knowing and making the city. Prediction generates knowledge that can improve the short-term operational efficiency of an urban service, and in doing this it *tends to reproduce socio-economic conditions, rather than to transform them*. The limitations of a close temporal horizon effectively mean that the use of urban predictive analytics tends to reduce possibilities for significant structural change. It is not so much transformational as operational, with data-led mathematical expertise as an obligatory passage point in the production of knowledge about the city. Rather than responding to strategic priorities, the system itself searches for problems to be solved. This highly procedural way of knowing the city

privileges mathematical reasoning and computational expertise, and it attempts to provide a standardized way of knowing the future, to the exclusion of other forms of knowing, such as experience, deliberation, emotion, embodied encounter, and language. The holders of mathematical and computational expertise become critical to this new urban science, as they decide the means and rules (and at times purposes) by which these systems are used. This is a change that is advancing the emergence of a new class of urban actors.

As the computational logic of prediction operationalizes the city, it also advances a particularly powerful way of seeing the urban context, with significant effects not only on decision-making, but also on the horizon of possibilities. Prediction prioritizes short-term questions around efficiency and optimization, at the expense of long-term questions about strategic intent and politics. Its numeric and calculative way of encountering the urban through mathematical expertise reduces what is seen to what is standardizable within a dataset. Its tendency to produce solutions that are specifically targeted develops a microcustomized way of approaching the city, based on spatiotemporal fragmentation and spatial differentiation. The diverse and varied experience of human encounter in the public realm of the city, as well as insights from non-data-based experts, are largely ignored, as systems capture only events that can be reduced to standard units of time and space: neighborhood, street, polygon. The predictive city, endlessly analyzing itself through a closed loop of data flow, prediction, and action, is therefore at risk of entrenching spatial inequalities while it locks down possibilities for wider and more significant forms of structural transformation.