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Measuring Cities with Software-Defined Sensors

Charlie Catlett*, Pete Beckman, Nicola Ferrier, Howard Nusbaum, Michael E. Papka, Marc G. Berman, and Rajesh Sankaran

Abstract: The Chicago Array of Things (AoT) project, funded by the US National Science Foundation, created an experimental, urban-scale measurement capability to support diverse scientific studies. Initially conceived as a traditional sensor network, collaborations with many science communities guided the project to design a system that is remotely programmable to implement Artificial Intelligence (AI) within the devices—at the "edge" of the network—as a means for measuring urban factors that heretofore had only been possible with human observers, such as human behavior including social interaction. The concept of "software-defined sensors" emerged from these design discussions, opening new possibilities, such as stronger privacy protections and autonomous, adaptive measurements triggered by events or conditions. We provide examples of current and planned social and behavioral science investigations uniquely enabled by software-defined sensors as part of the SAGE project, an expanded follow-on effort that includes AoT.

Key words: sensors; edge computing; computer vision; urban science

1 Introduction: A New Approach to Measuring Cities

In 2012, the City of Chicago announced plans to replace 300 000 street lights with Light Emitting Diode (LED) systems, potentially with sensors and a wireless data network. To computer scientists developing experimental sensor networks, this seemed to be an opportunity to explore the potential for an urban-scale measurement system. What new science might be possible with hundreds or even thousands of devices deployed throughout a major city? What would scientists, policymakers, community groups, or individual residents want to measure? Would other capabilities be useful, such as beacons for precise positioning or to provide cryptographic tokens that would work with applications to validate the location of a device at a particular point in time or perhaps to design entirely new mobile services and applications? Could we get a sense for the volume and flow of people in public spaces by counting Bluetooth devices? How would such a system publish data in ways that would be useful not only to scientists but also to students, educators, city managers, residents, and businesses in the city? With these questions in mind, we organized a series of workshops[1] including both interdisciplinary and discipline-specific, asking a common set of questions. In these workshops and separate discussions, we engaged scientists as well as city planners and managers from multiple City of Chicago agencies and departments (transportation, parks, building and fleet management, public health, and information technology) and open data teams. Each workshop began with a question: "*if we could deploy*

• Charlie Catlett is with University of Illinois Discovery Partners Institute, Chicago, IL 60606, USA. E-mail: ccatlett@illinois.edu.
• Pete Beckman is with Northwestern University, Evanston, IL 60208, USA. E-mail: beckman@anl.gov.
• Nicola Ferrier, Howard Nusbaum, and Marc G. Berman are with University of Chicago, Chicago, IL 60637, USA. E-mail: nferrier@anl.gov; h-nusbaum@uchicago.edu; bermanm@uchicago.edu.
• Michael E. Papka is with Northern Illinois University, DeKalb, IL 60115, USA. E-mail: papka@anl.gov.
• Charlie Catlett, Pete Beckman, Nicola Ferrier, Michael E. Papka, and Rajesh Sankaran are also with Argonne National Laboratory. E-mail: rajesh@anl.gov.
∗ To whom correspondence should be addressed.
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some form of electronic device in hundreds of locations throughout Chicago, what would those devices do to help you answer the questions you are investigating?"

These and many other engagements identified two broad classes of measurement: traditional measurements (for which electronic sensors are available, such as temperature or light levels) and what we termed "*observations*". For traditional measurements, the workshops produced a list of several dozen sensors including air quality (gases, particulate matter), meteorology (temperature, humidity, and pressure), vibration, sound, and light. For observations, suggestions were based on measurements typically done infrequently by human observers, either systematically, such as counting vehicle or pedestrian traffic at intersections, or through ad hoc mechanisms, such as residents reporting street flooding.

What began as a sensor network project[2], then, evolved into an intelligent measurement project emphasizing new measurements that could be supported with edge computing, in turn requiring Artificial Intelligence (AI) and Machine Learning (ML) support, or "AI-at-the-Edge". In order to engage the broadest community of developers and experimenters, this meant using an open computing platform that would support current and envisioned AI/ML software frameworks used by those communities. The resulting system combines traditional sensors with measurements that are defined by the software interpreting those sensors (e.g., image processing with a camera). *We term this new type of measurement system a "software-defined" sensor*[3].

We named the project Array of Things[4] (AoT) combining the underlying technology approach, leveraging technology trends in embedded computers and wireless networks—or "Internet of Things (IoT)"—with the strategy of deploying many identical detectors aimed at the sky, as with an array telescope[5]. AoT comprises individual devices, or "nodes", focused on the city, which some have also described as a fitness tracker[6] for the city.

With systems deployed in over 130 locations throughout Chicago (Fig. 1) and smaller pilot deployments in other cities, AoT[7] and the underlying platform, called Waggle[8], have catalyzed partnerships between computer scientists (in particular, AI/ML and computer vision experts) and researchers and practitioners in fields ranging from transportation to social and behavioral sciences to civil and environmental engineering.

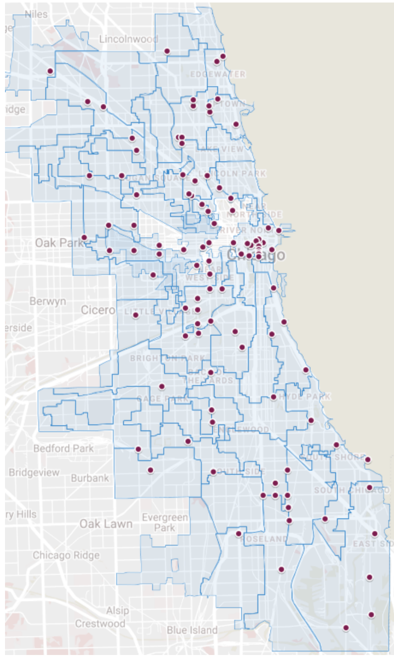

Fig. 1 Since 2016 over 250 AoT nodes have been installed, including upgrades to existing locations. Shown here are 130 nodes in Chicago as of 2020. Map created with Google Maps.

In this paper, we discuss early, emerging, and envisioned use of software-defined sensors providing measurements for social and behavioral science questions that were heretofore only possible with human observers. Moreover, by removing the limitations of human observation—chief among them is the need to sample rather than continuously measure—an even broader set of measurement opportunities can be envisioned, including measurements across much larger spatial and temporal scales. Indeed the advantage of software-defined sensors is that one need not define all possible measurements prior to building and installing devices. Section 2 discusses AoT in context of deploying an urban-scale intelligent measurement system, privacy and ethics considerations, and how these along with practical matters, such as installation, were coordinated. Section 3 introduces the concept of software-defined sensors, focusing on the application of software-defined sensors to understand urban activity patterns and support social and behavioral science investigations. Section 4 provides a brief overview of the underlying technology platform and the associated software and hardware architecture necessary to move from bespoke systems like AoT to a more general-purpose user-programmable experimental infrastructure. Finally, in Section 5, we conclude with directions of future work, including the current follow-on and expansion of the AoT project, *SAGE*: *A Software-Defined Sensor Network*[9], with examples of the potential for increased autonomy in software-defined sensors and for understanding, and ultimately improving urban life.

2 Array of Things: A Research Instrument in Public Way

Common sensor networks are relatively straightforward to build and scale, but the AoT user community needed both traditional sensor measurements and new types of measurements—*observations*—that would require edge computing capabilities. Sending images or video streams to a central server for analysis would have been cost-prohibitive for hundreds of locations, thus it was necessary to process images within the devices. Even if free network access was available, some scientists requested programmable devices that could process data and act on that data in some fashion—in near-real time. For instance, experiments with intelligent traffic controls coordinating with vehicles to make instantaneous decisions. These factors—cost and latency—ruled out doing all data processing on central servers.

With each science workshop, the number of traditional sensors accumulated, and atmospheric scientists (the first workshop we held) emphasized that a multi-sensor approach is essential given the need for the context of each measurement. For instance, interpreting a temperature reading requires knowing not just the sensor characteristics but how and where that measurement was taken. Was it under the shade of a building or an oak tree? In the middle of a concrete parking lot? Near a large body of water? Similarly, does an air pollutant measurement come from a sensor in a park? At a congested intersection? Near a factory? The need for context to each requested measurement was reinforced throughout our interactions with science communities, leading to a device design with several dozen sensors (Fig. 2).

Fig. 2 An AoT node. Computers, camera, and light (Ultraviolet (UV), Infrared (IR), and visible) sensors are in the blue enclosure; a cellular modem, camera, environmental (vibration, sound, magnetic field, temperature, relative humidity, and barometric pressure), and air quality (CO, NO_2, SO_2, PM2.5, and O_3) sensors are in the white enclosure.

2.1 Capability and scale

What scale would make sense for such an urban measurement system? Tens of devices? Hundreds? Thousands? Many traditional measurements, for instance air quality, were at the time primarily done regionally. In the area within roughly 50 miles of downtown Chicago, there are only two dozen regulatory air quality monitors, providing hourly readings for criteria air pollutants[10]. Yet we know that air pollution is highly variable over geography and time in urban areas[11], with significant impact to human health and behavior even on short timescales[12–14]. Hourly measurements representing hundreds of square kilometers, while valuable for many studies, do not offer the spatial or temporal resolution necessary to understand factors such as the impact of traffic on air quality in individual communities. Noise is another environmental factor that impacts human health and well being[15, 16], yet few cities have measurement systems providing noise levels at all, much less on a neighborhood scale. A notable exception is New York University (NYU)'s Sounds of New York City (SONYC[17]), which involves over 100 sound sensors in selected neighborhoods. Many cities, Chicago included, also have microphone-based systems that detect gunshots and use trilateration to locate the source of the sound, but these are special-purpose, closed systems that do not measure other sounds.

Equally important to the overall system architecture was the continuous improvement of low-cost components including sensors, processors, storage, and communications. We thus targeted a roughly 2-year life span for the systems, expecting to replace them with upgraded systems. Consequently, while the selection of particular sensors and other components was important, the more central objective was to develop the underlying software, protocols, management tools, data management and access capabilities, and device deployment partnerships and strategies, that could support multiple generations of devices[4].

2.2 Creating an urban-scale "laboratory"

Although AoT was primarily a technology prototyping effort to explore the feasibility of an urban-scale measurement instrument, embedding such a system in the public way required partnerships with local government and the residents of the city. We worked with Mayor Rahm Emanuel's office to include the concept of such an instrument in the city's 2013 Strategic Technology Plan[18, 19]. In addition to science and stakeholder partnerships, policies and governance structures were needed along with a feasible and affordable plan to install and communicate with hundreds of devices in the city. Devices had to be prototyped, stress-tested for outdoor harsh conditions, packaged, and mass-produced. The architecture had to be reasonably secure with respect to cyber (e.g., Internet-based) or physical threats. Mechanisms were also required to provide data to a diverse audience of scientists, policymakers, and residents. We briefly describe these topics below, and they are covered in much greater detail in Refs. [4, 8].

Placing scientific instruments—particularly those with cameras and microphones—in the public way required taking initiative to engage residents and community groups on issues such as privacy and governance. At the same time, a shared objective between the project team, the National Science Foundation (NSF) and the City of Chicago was to stimulate interest in science and technology among Chicago's youth. This suggested that the devices should be visually conspicuous, inviting curiosity or even engagement. To this end, the physical form and appearance of the nodes were explored with artists, designers, and behavioral and social scientists. Although some behavioral science research suggested that the appearance of the devices would have an impact on behavior[20], this was not an objective for the project. The goal of the bright and inviting design was to draw attention and ideally foster a sense of ownership by using the blue and red colors similar to Chicago's city flag[21]. To explore the design options, faculty members from the School of the Art Institute of Chicago created a special course for masters of fine arts students in fall 2013. Students developed multiple prototypes in and around the University of Chicago, leading to the design shown in Fig. 2[22].

To engage residents and community groups, we partnered with the Smart Chicago Collaborative[23], now part of the CityTech Collaborative[24]. Smart Chicago's mission is to engage residents, especially youth, to leverage technology to improve lives in Chicago. The Collaborative worked with our team and Chicago's Department of Innovation and Technology to organize a series of open public town halls in different Chicago neighborhoods where residents were briefed on the project and its objectives, with open discussion regarding their interests and concerns.

2.3 Ethics, privacy, and policy

Many private entities, such as businesses and even universities, have live cameras in and around their property, including those trained on public spaces (e.g., sidewalks in front of a café). Because AoT involved partnership with local government and installation of devices with cameras on public infrastructure, residents would understandably have concerns about potential government surveillance. Anticipating this, we begin the public dialog well in advance of deploying systems, presenting the concept to Chicago's civic data community at the weekly ChiHackNight[19, 25]. These weekly gatherings draw hundreds of people who are active in civic data analytics in support of open data and transparent government. The ensuing discussions, including both skeptical and supportive media coverage, helped to guide subsequent and ongoing public engagement activities.

At the time (2014), we found no examples of published privacy policies regarding public cameras. The prevailing view from ethics and privacy law experts, as well as the University of Chicago's Institutional Review Board (IRB) confirmed that there were no ethical or legal restrictions on capturing images in the public way given there is "no expectation of privacy". However, a central goal of the AoT project was to provide open data about the city for use by students, scientists, businesses, the city, and the general public. Thus we collaborated with Trusted CI, the NSF Cybersecurity Center of Excellence[26] to develop privacy and governance policies. With drafts in hand, we convened experts from academia, industry and government privacy law, and privacy advocacy groups including the Electronic Frontier Foundation (EFF) and American Civil Liberties Union (ACLU) to review and improve the policies. A subsequent series of public town halls, along with online feedback and discussion forums, were used to improve and finalize the AoT privacy policies and governing principles[27]. After a six-month public comment period, the policies as well as all questions and concerns with responses from the team, were published in early 2016, prior to the first installations.

Here, edge computing and software-defined sensing also provide a means for stronger privacy protections than traditional camera networks, which transmit and store all images, because all of the images are analyzed within the node and then deleted, in contrast to being sent to central servers for processing (and saving). Moreover, a list of all image and sound processing functions and associated research objectives are maintained at the AoT website, thus publishing the exhaustive list of what is done with images, rather than a list of prohibited uses (implying an infinite number of other potential uses). AoT nodes only save sample images—typically one every fifteen minutes—which are kept in a protected repository for research use only. Access to this library of images, necessary for training AI/ML algorithms, is provided to academic researchers under a data use agreement that defines the specific intended use and prohibits, for instance, publishing any images with visible identification, such as faces or license plates.

All of these training images are owned by the University of Chicago, and the nodes are managed and operated by the University of Chicago and Argonne National Laboratory. The City of Chicago provides power and installation services, but the city has no special access to the limited volume of training images, which are only available for scientific research within the data use agreement.

2.4 Practical matters

A common question early in the AoT project was "how will you decide where to place AoT nodes, with only a few hundred nodes and a city of nearly 600 square kilometers?" Through the policy discussions noted above, a rubric was developed for node placement, requiring three factors. Firstly, it is essential that residents are interested in an issue for which AoT devices can provide relevant data, such as air quality, traffic safety, or noise. Secondly, one or more scientists must be interested in using AoT data to study that issue. Thirdly, a representative from local government, such as a commissioner or department head, must share the interest in understanding and potentially acting on the insight from scientific analysis of AoT data. In some cases, the locations were suggested by scientists as illustrated by the line of nodes along the 18-mile shoreline of Lake Michigan in Fig. 1, which is intended to support the study of lake-effect on air quality and weather. In other cases, locations were requested by city officials. For example, Chicago's Vision Zero safety program[28] requested nodes in the forty intersections and corridors with the greatest number of traffic-related fatalities. In at least a half dozen instances, the requests came from residents or community groups (for example, a school crossing guard concerned about illegal heavy truck traffic).

Most nodes were installed by the Chicago Department Of Transportation (CDOT), and discussions regarding electrical safety and ease-of-installation began with CDOT electricians two years before the first installation. In addition to electrical safety reviews, this collaboration led to design changes to streamline installation in order to enable crews to swap (i.e., upgrade) units in under 15 min—roughly the time it takes to change holiday decorations.

The most common AoT installation is on a traffic signal light pole, roughly 8 m above the sidewalk, with the unit (and thus the downward-facing camera) facing the center of the intersection (see Fig. 3). In most cases, this provides a field of view covering the entire intersection including sidewalks and crosswalks. Additional partners also installed nodes, including Crown Castle Communications and ComEd/Exelon. AoT nodes have dedicated electrical circuits to reduce the possibility of being confused with operational traffic signal systems during routine city maintenance work. Though not legally required, AoT nodes were also tested for susceptibility to power surges and for radio frequency emissions to provide evidence (if requested) that the

Fig. 3 A typical view from an AoT camera showing object recognition results from edge software.

devices would not interfere with other services.

Corporate partners also participated in the project. Intel designed, developed, and prototyped the air quality sensor board; Cisco and Schneider Electric brought engineering insight into packaging electronics for outdoor installation; AT&T provided initial cellular data service; and Microsoft prototyped an education portal for students to analyze AoT data.

3 Software-Defined Sensors for Urban Social Sciences

AoT introduced new capabilities for measuring the urban environment, with rudimentary software-defined measurements, such as river water levels, cloud cover, or pedestrian and vehicle flows (e.g., Fig. 4). The AoT devices—still used today to develop such measurements—nonetheless have very limited edge compute capacity relative to what is available now, four years after the first units were built. AoT is now one of several measurement instruments, or observatories, participating in the NSF-funded *SAGE*: *A Software-Defined Sensor Network* project[29]. Below we discuss the SAGE project, the basics of software defined sensing, and applications in social and behavioral sciences.

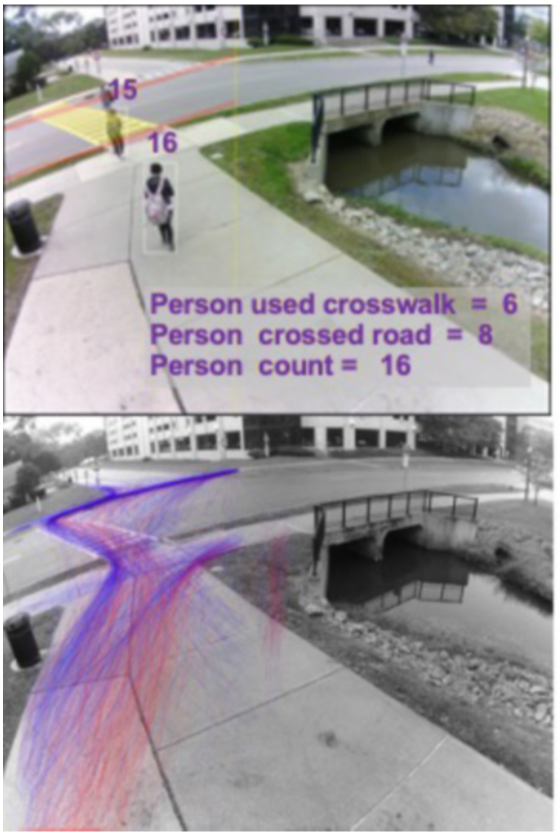

Fig. 4 Software-defined sensor to measure crosswalk usage. Images courtesy P. Bharti, D. Koop, and M. E. Papka, Northern Illinois University.

Fundamentally, AoT is a distributed system of independent computing and sensing devices with a central service (as detailed in Section 2) to publish measurements. Such a system allows for software-defined sensors—measurements defined by software running within the nodes based on analysis of data from the node's sensors, including cameras, microphones, etc. SAGE builds on lessons learned from AoT[7] to extend the Waggle platform in several directions. The first is a modular design to support independently developed (or purchased) sensor packages, commercially-packaged cameras, and edge processing functions. Thus, different projects can develop or purchase commercial sensor packages necessary for their investigations. The second involves extensions to the software infrastructure to enable scientists to develop, test, and deploy edge functions as discrete modules, similar to the virtual machines that can be developed, managed, and operated as units in cloud services, such as Amazon Web Services.

3.1 SAGE: Cyberinfrastructure for software-defined sensing

With today's edge computing power, scientists can design software-defined sensors ranging from image processing (e.g., count the number of people wearing face masks) to fully autonomous behaviors, such as to learn what are "typical" values for measurements and increase the sampling rate when atypical events or conditions are detected. For example, if the typical pedestrian count at 3 am is fewer than 5 people but 50 are detected, an autonomous software defined sensor could begin to analyze the aggregate movements of the crowd to determine the nature of the gathering.

For AoT, the significantly increased edge computing power of SAGE nodes will enable more nuanced measurements heretofore requiring trained human observers. These will in turn catalyze new research into human interactions in public spaces, such as not only the trajectories of people moving through a public square, but how those movements are influenced by other people and groups. Combining these visual analyses with sound analysis capabilities[30], researchers can begin to explore whether it is possible to determine stress, depression[31], fear, or social cohesion[32] from ambient measurements of human movement. For example, speed or gait measurements—extrapolating from nonhuman animal research[33–35] and also from research on the pace of life and movement in cities[36,37]—could be used to measure individual and group level factors (e.g., mood, stress, and neighborhood cohesion). Auditory data, such as the volume and pace of speech[38,39], as well as physical activity, exposure to human voice, ambient audio amplitude, phone usage, and location data[40], could also be used to further elucidate specific features of people in these spaces to predict their internal emotional states.

The central objective of the AoT and SAGE software-defined sensor work is to provide a platform with which scientists can define these and other new types of measurements about the urban or natural environment. For instance, new protocols, such as the Gehl Institute's Public Life Protocol[41] for measuring the use of public spaces, are ideal for implementing via software-defined sensors. The work of a computer science team at Northern Illinois University (NIU) shown in Fig. 4 demonstrates exactly the kind of software-defined measurements necessary for the Gehl Public Life Protocol. Similarly, these types of new measurements are needed in order to explore the impact that different urban and natural environments have on cognitive performance[42,43] or more generally how urban morphology affects human decision-making[44].

3.2 Observation with computer vision

Computer Vision (CV) systems seek to obtain high-level information from digital images or video. A computer vision technique may produce numerical or symbolic information, e.g., there are 6 cars, or, this is a coyote, not a dog. CV has been an active area for computer scientists since the 1960s, and includes tasks, such as object detection and recognition, event detection and recognition, motion tracking, and 3D scene reconstruction. Many techniques have been developed using geometry, physics, statistics, and signal processing (electrical engineering), but recent CV systems often rely heavily on ML. These ML-based approaches have outperformed earlier methods for many tasks, especially object/event detection and recognition. Object recognition or object classification is the task of identifying that the image contains a specific object (from a set of possible objects). Similarly, event recognition is applied to video to classify the video into one of a set of pre-specified activities (e.g., person is playing guitar, brushing teeth, etc.). Tracking involves locating the same object in a sequence of images (or video). While object recognition could be applied in every image of the sequence, more effort is involved to "connect" the object across images. For example, if two people cross by each other, simply recognizing that there are two people is not sufficient. Tracking algorithms typically also use various techniques to measure the similarity between objects across images in the sequence and assign unique IDs to objects, as is illustrated in Figs. 3 and 4, which shows the output of a tracking approach to record movements of pedestrians.

Computer vision techniques can thus be developed to address a large variety of applications. For example, object recognition could be used to recognize animals and measure occurrences of urban wildlife. AI-based methods in CV can also classify images along axes, such as natural-vs-built or ordered-vs-disordered (Fig. 5). CV might improve traffic control by adjusting traffic signal timing to improve flow. Likewise, CV methods could

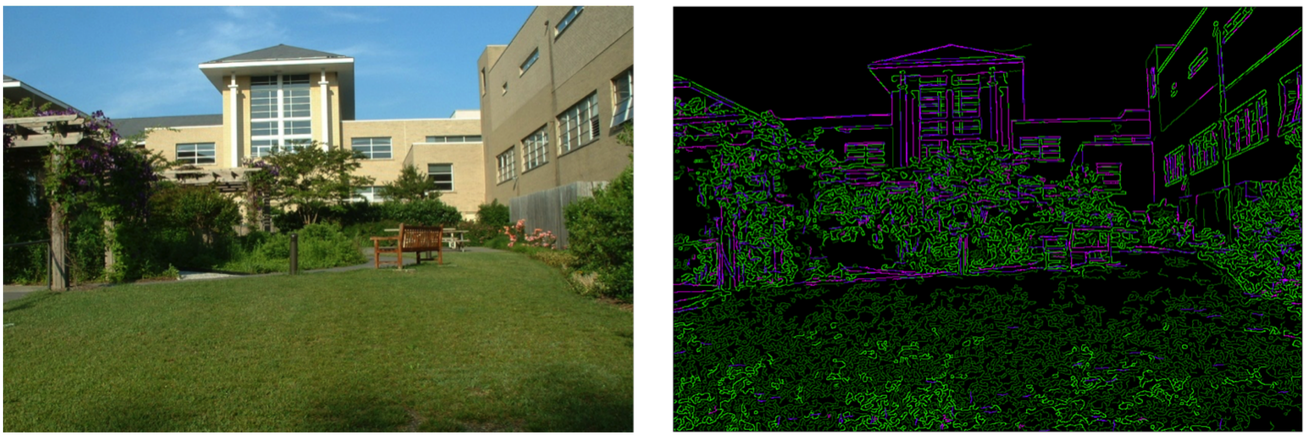

Fig. 5 Use of AI to extract straight edges (magenta) and curved edges (green) from scenes for characterization of different features of the scene (e.g., more ordered vs. more disordered[45–48] as well as providing privacy protection). Figures adapted from Ref. [49].

make it straightforward to understand, for instance, the impact of at-grade rail crossings on different types of roadway traffic. By recognizing and counting the number of types of vehicles (public transit, private, emergency, etc.) affected by an at-grade rail crossing, decisions can be made as to which crossing should be prioritized for replacement with under- or over-passes.

Pedestrians interact in a variety of ways that can be observed even from a distance. Observing pedestrians, isolating individual bodies in motion, and tracking this motion in space as just described can yield information about body velocity and acceleration, distribution of spatial distance among bodies, and collisions. These basic measures could be used, with an appropriate ground-truth database of motion-related to behavior, to infer social relationships among the bodies. For example, a group of bodies sharing velocity with a defined spatial distribution would constitute a group. Vectors for different groups that come together or have different trajectories could form an observational basis for inferring social relationships among groups. Similarly, two vectors for individuals coming together and stopping before collision could serve to make inferences about a social interaction between individuals. To the extent that the major axis of a body can be observed, some aspects of posture or body inclination can be classified and possibly serve as the basis for inferring more about the nature of the social interaction (see Fig. 6). Similarly, sound recording, if sufficient to capture speech envelope information of proximal pedestrians, could be used to model the prosodic aspects of pedestrian speech. Combined with spatial vector modeling of motion and body inclination, these observations could provide the first naturalistic measurements of real-life social interaction including the affective tone of the communication.

In principle, this information could be used as the basis for classifying the nature of the social interaction. Are groups or individuals that come together interacting in a positive or negative way? How does the frequency of such interactions vary with environmental, sociological, and cultural factors? Is it possible to predict an adverse or threatening interaction from the trajectory of motion of a group or person prior to the interaction? Does the prediction based on particular motion parameters change based on heat index, air quality, proximity of green space, Social-Economic Status (SES), neighborhood crime statistics, or population diversity? By observing pedestrian movement at street level, measuring sound

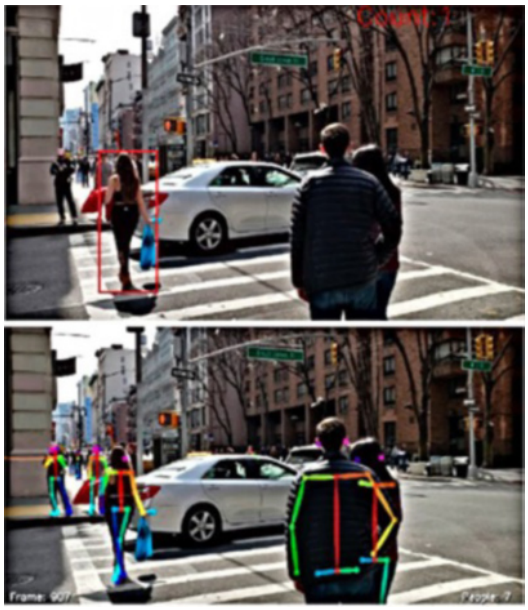

Fig. 6 Use of edge computing in Ref. [53] to detect a pedestrian crossing during a red-light (top) and analyze body language (bottom). Images courtesy of Potdar and Torrens, used with permission.

properties and spatializing those to particular pedestrians, and combining these visual observations with acoustic measurements, it is possible to address a large number of questions about social interaction including physical-social interaction within and between different social groups, such as race or SES, or amongst friends and strangers. Although previous research has used certain physical observations of individuals, such as gait, proximity, and speech envelope, as markers of social interaction, most of the prior work has taken place in laboratory settings. While individuals in these studies have been characterized by group membership (race, SES, age, etc.) or relationships among group constituents have been characterized (friends or strangers, same or different races, same or difference SES, etc.), SAGE software-defined sensing capabilities offer the possibility to make these observations in the wild, in natural environments, and at unprecedented scales, thereby increasing the power of data to address fundamental questions about behavior, mind, and society.

Observation of human location distributions has also been used as the basis for inferences about behavior, particularly in combination with other sources of data. For example, predictive policing[50] has used statistical distributions of crime locations and event data to predict crime hotspots. In other words, criminal behavior is predictable from past behavior-history data. But of course this only predicts behavior probability and collecting such statistics is coarsely limited to the grain of reporting. Using geotagged Twitter data can provide more specific location and movement information[51], but activities that are not fully Twitter-reportable (e.g., crime or just a chance social interaction) will not be observed. Direct street-level physical movement can augment such information and potentially provide, on the basis of observed movement trajectories information about the nature of the social interaction. Meng et al.[52] used ego-motion from body mounted cameras to show that physical body movements of different kinds have different spectra. Although the egocentric motions of looking and turning may not be easily detectable from a third-person camera observation, small steps, walking, and running have discernible spectra. This is clear evidence that SAGE should support recognition of aspects of motion trajectory and characteristics of movement from an analysis of the visual record. Further, Potdar and Torrens[53] showed that it is possible from a street-level third-person camera to determine aspects of pedestrian behavior, such as crossing a street at a red light (Fig. 6). While the kind of modeling of limbs that can be carried out shown in Fig. 6 from a street-level view is not possible from a bird's eye perspective above the street, other inferences can be made. Hands moving in front of the body, body changing orientation, and bending will be observable. From these images, it is possible to infer aspects of face-to-face social interaction when taken together with changes in movement allowing the possibility of classification as confrontation, greeting, or conversation.

4 Underlying Technology: Waggle Platform

Ultimately, all of these software-defined sensor applications require a robust, programmable platform installed outdoors. Here we describe the Waggle platform. Designing a device to support edge computation and associated challenges, such as packaging for severe weather conditions, increases device complexity and requirements for security and resilience. The edge computers must be well-secured and require a high level of resilience, with the ability to recover from common types of hardware and software failures without physical intervention as they are typically located beyond convenient reach on city poles and buildings. When the AoT project was conceived, no commercial devices provided the functionality defined by scientific input from an expanding science and education community[54]. A hardware/software platform was necessary to support edge computation, reliable data transmission, and protocols for keeping track of continual streams of sensor readings from hundreds of nodes. The Waggle platform that the team had begun to develop at Argonne National Laboratory provided a starting point.

We have elsewhere described the architecture and details of the Waggle platform[8], which employs special-purpose resilience and recovery hardware and software, foundational architecture features to minimize security vulnerabilities, and open protocols for communication, management, and data publication. Designed to support remote sensing, Waggle borrows its name from the elaborate dance that honeybees perform to communicate with the hive regarding the location of food sources[55]. Naturally then, the central servers that support AoT and SAGE nodes are collectively called Beehive.

4.1 Platform at the edge: What is a node

AoT nodes comprise both computing and sensing hardware, and are programmed to report all sensor values at specific intervals (typically 30 s), transmitting these to a central database (discussed below). Each node has sensor packages (see Fig. 2), communications (typically a cellular modem, though WiFi and other options have been used in other Waggle projects), and two fully programmable Linux computers. Because they are typically installed high on utility poles or in remote locations that make physical access impractical, Waggle nodes include multiple hardware and software components to enable recovery from common faults (e.g., a power or network outage) without human intervention.

One of the Linux computers functions as the "node controller", which performs system functions, such as data integrity checking, reading simple sensors, reporting data, and managing security and reliability. The node controller is only accessed by system support staff. The second Linux computer is used as an "edge processor", which runs user-provided software for analysis of images, sound, and other sensor data. Software running on the edge processor is reviewed to ensure its functionality aligns with its description and that it complies with privacy policies. This includes a specification of what data will be recorded and reported with other sensor data. User software running on the edge processor has no way to transmit data—it places data into a common data cache for the node controller to validate and transmit to the central database.

4.2 Waggle Beehive: Data and management

All AoT nodes (and Waggle nodes in other projects) regularly transmit sensor readings, data from software-defined sensors (e.g., the number of vehicles seen in the past reporting interval), and internal management data for system administration and troubleshooting. Three central services are collectively called "Beehive". A *registration* service manages node registration, secure credentials, and a database with node manifests (node-specific data, such as location, street address, and sensor hardware configuration). A *management* server maintains encrypted (node-initiated) connections to nodes along with information and tools for maintaining software updates and configuration data. The third service is a parallel *database* scalable to support thousands of concurrent node connections for reporting data. At each reporting interval, each node sends a set of sensor readings. After injection into appropriate databases, the sensor data are decoded, processed, and exported as comma-delimited text. Each line includes a node identifier, date and timestamp, metadata (such as the sensor board, firmware version, and exact part number of the sensor), and the raw data read from the sensor (typically a voltage or current level). Each line also includes the converted value of the raw reading in appropriate units, such as temperature, light levels, or sound pressure. With some sensors, this conversion is a simple mapping while others involve sensor-specific calculations, in some cases including data from other sensors. For instance, some gas sensors are temperature-sensitive or cross-sensitive to multiple gases, thus conversion requires temperature data and data from other sensors. For software-defined sensors, the metadata include information to enable data users to examine the software used to create the measurement.

The Beehive database does not provide access directly to external users, but rather uses a periodic data push to provide data through two public-facing services. First is a *data download* service. Every 24 h all data are exported to a bulk download server, where users can download bundles ranging from a single day to all data from the first installations in 2016. Downloads include instructions and additional information, such as where to find sensor data sheets and how to map a node identifier to a geographic location. Waggle supports multiple "projects" so that, for instance, the Chicago AoT nodes and associated data services are distinct from those associated with deployments in other cities or deployments by other scientific teams, such as environmental sensing projects. Secondly, Beehive supports the AoT Application Programming Interface (API)[56] by exporting data to a process that caches data and handles API calls in Amazon Web Services. With a latency of 3–5 min from measurement to availability (not real-time, yet relevant for questions about what is happening "at the moment"), the API supports mobile applications and integrating AoT data into other data systems.

4.3 Security

Primary node security risks identified through numerous security reviews are (1) service disruption and (2) the introduction of unauthorized functions, such as the use of the cameras and microphones for surveillance. These threats typically involve unauthorized access. To reduce the potential for unauthorized access, Waggle nodes have no software enabled to "listen" for, and thus respond to, any network connection requests (even from system administrators). This requires that the nodes operate autonomously, initiating an encrypted Internet connection back to the central servers to enable remote access for management functions discussed above.

5 Conclusion and Future Work

In discussions with social scientists seeking to understand cities, two challenges seem to recur. The first is that experiments in laboratory settings are very difficult to conduct "in the wild", that is, in natural urban settings. For instance, multiple studies show that people tend to sit near others who look like them[57], yet does this hold true with the movement of people in public spaces? Are such principles limited to seating in some contexts (e.g., a classroom) but not others (e.g., on public transit)? Physical distance and interpersonal movement have been used in relatively restricted settings as measures of social interaction and attitudes. Instrumenting public spaces with software-defined sensors opens the potential for testing these hypotheses in the real world, in natural human movement and interaction, and provides an important basic test of the interpretations of these findings. A second challenge identified is a paucity of opportunities for repeatable experiments, for instance to examine social interaction theories in similar public venues across cities of different populations and densities, cultures, climates, or topology.

To address the first of these challenges, a SAGE laboratory is being deployed at the University of Chicago in collaboration with its Environmental Neuroscience Laboratory[58]. In order to interpret pedestrian motion vectors, spatial distribution, postural inclination, and acoustic properties of vocal behavior including speech, it will be necessary to develop a database of defined measurements. Firstly, from large scale data collection with SAGE software-defined sensors, over a broad range of pedestrian behaviors and interactions at street level, after computing motion, spatial distribution, and acoustic properties, multivariate statistical classification of observations will yield sets of categories that can be reviewed by human researchers. Taking examples from each category, researchers can review and code these examples for inferred social behavior (commercial transaction, friendly greeting, threat, social affiliates walking together, etc.). The reliability of this coding, given software-defined observations, can be assessed over the database. It will be important to have raters come from diverse backgrounds and experiences to reduce bias in the labeling. In fact, similar assessments will need to be made on the initial training data to ensure that we obtain a representative sample of social interactions to avoid bias. Secondly, for a subset of locations with SAGE nodes installed, higher resolution instrumentation at ground level can produce a "ground-truth" database that can be used to validate the coding of the social interaction categories. The coding of the high resolution audio-video recordings at ground level can be registered against the coding of the software-defined observation data, making it possible to test the validity of the classifications against the ground-level data. This strategy is being used in an installation at Argonne National Laboratory to improve vehicle type recognition. Traditional training images for vehicle type are taken from ground-level rather than from 8 m above, thus images from both vantage points are used to improve the accuracy of vehicle recognition from such angles.

For the second challenge—repeatable experiments—the SAGE team is exploring the potential for a collaborative, multi-city instrument—a set of software-defined sensor deployments in common venues (e.g., a marketplace, public park, or rail station) across a diverse set of cities in order to support these types of investigations (Fig. 7).

Ultimately, software-defined sensing infrastructure, which SAGE is developing, allows for the creation of a new kind of social science laboratory. At any location, in any city, where SAGE nodes are installed, it will be possible to "stage" specific kinds of social interactions (with or without ground-level recording). Confederates, such as actors, can meet, travel in groups, or interact in various "staged" ways as another means of producing "ground-truth" data. These interactions, recorded in high-resolution and through SAGE nodes, can be coded as prototypes for categories of social interaction. Similarly, such a laboratory would allow researchers to set up experimental situations using human subjects who are not confederates, that is, participants who are not explicitly instructed to behave in particular ways, but who are participants in studies designed to elicit different kinds of behavior, such as helping, challenging, greeting, ignoring, etc. These participants would not know the purpose of their behavior when acting, but would be primed to act in a specific way by virtue of context or expectations. In this way, it will be possible to elicit more natural social interaction behavior than explicit instruction to actor-confederates to further validate the classification of social interactions. We have described the origins and development of software-defined measurement systems to support new, diverse scientific questions, focusing here on social and

Fig. 7 SAGE social and urban science partners are exploring a network of software-defined sensor deployments at common venues in diverse cities (for example, public parks in (left-to-right) New York City, Chicago, San Francisco). Images from Wikimedia Commons, used without modification[59].

behavioral sciences.

Fueled with significant advances in AI/ML hardware and software capabilities, the underlying objective of this work is to empower domain scientists to "define" the measurements they require. To this end, the SAGE project is focused on supporting teams of AI/ML and domain scientists developing their own software-defined functions, and on providing a general-purpose platform, Waggle, that allows such teams to focus on measurements required for scientific insights without first having to design and build bespoke instrumentation.

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Charlie Catlett is a senior research scientist at the University of Illinois Discovery Partners Institute. His research focus is currently on measuring and analyzing the dynamics of cities, building on 35 years of research in high-performance computing, Internet technologies, and distributed systems. He led the Array of Things project at Argonne National Laboratory and the University of Chicago. He was chief technology officer at the National Center for Supercomputing Applications during the creation of the Mosaic web browser and open web server infrastructure.

Pete Beckman is a senior computer scientist at Argonne National Laboratory and co-director of the Northwestern University–Argonne Institute for Science and Engineering. He leads the Sage project funded by the National Science Foundation to build a nationwide infrastructure for AI at the edge to support ecological research for the National Ecological Observatory Network and urban research for the Array of Things.

Nicola Ferrier is a senior computer scientist at Argonne National Laboratory. Her research interests include computer vision and artificial intelligence. Her projects include AI for edge computing, vision-based control of robots, computer vision for biology materials, and manufacturing. She was faculty at University of Wisconsin-Madison during 1995–2013. She received the PhD degree from Harvard University in 1992, followed by a postdoctoral fellowship at Oxford University.

Howard Nusbaum is the Stella M. Rowley Professor of Psychology at the University of Chicago. He has previously served as an associate editor of *Brain and Language* and *PLoS One* and on the John Templeton Foundation Board of Advisors and a division director for Behavioral and Cognitive Sciences at the NSF. His research interests include wise reasoning, language use, attention, learning, memory consolidation and sleep, working memory, understanding, affect, categorization, cognitive neuropharmacology, cognitive engineering, and human factors.

Michael E. Papka is a senior scientist at Argonne National Laboratory; the laboratory's Deputy Associate Laboratory Director for Computing, Environment, and Life Sciences; the director of the Argonne Leadership Computing Facility; and a Presidential Research, Scholarship, and Artistry Professor at Northern Illinois University. He specializes in the use of high-performance computing for scientific visualization and data analysis.

Marc G. Berman is an associate professor at the Department of Psychology, University of Chicago and a director of the Environmental Neuroscience Lab. He is involved in the University of Chicago Cognition, Social and Integrative Neuroscience programs. His research centers on understanding the relationship between individual psychological and neural processing and environmental factors.

Rajesh Sankaran received the PhD degree in electrical and computer engineering from Louisiana State University in 2011. He is a member of the technical staff at Argonne National Laboratory where he co-leads the Waggle Edge-Computing research program. His interests include edge computing, AI/ML, sensing, and distributed and embedded computing systems.