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he amount of data produced and communicated over the Internet and the Web is rapidly increasing. Every day, around 20 quintillion (10<sup>18</sup>) bytes of data are produced (www-01.ibm.com/software/data/bigdata). This data includes textual content (unstructured, semistructured, and structured)

to multimedia content (images, video, and audio) on a variety of platforms (enterprise, social media, and sensors). One of the fastestgrowing types of data relates to physical observations, measurements, and occurrences in the real world. The growth of physical world data collection and communication is supported by low-cost sensor devices, such as wireless sensor nodes that can be deployed in different environments, smartphones, and other network-enabled appliances. This trend will only accelerate, as it's estimated that by 2020 more than 50 billion devices will be connected to the Internet (http://share.cisco. com/internet-of-things.html) Extending the current Internet and providing connections and communication between physical objects and devices, or "things," is described under the general term of *Internet of Things* (IoT). Another oftenused term is *Internet of Everything* (IOE), which recognizes the key role of people or citizen sensing, such as through social media, to complement physical sensing implied by IoT. Integrating the real-world data into the Web and providing Web-based interactions with the IoT resources is also often discussed under the umbrella term of *Web of Things* (WoT). Data collected by different sensors and devices have various types (such

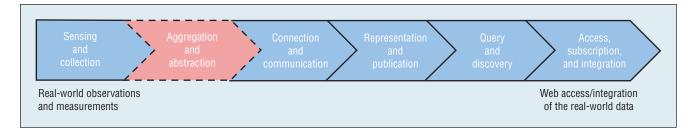


Figure 1. The data production and access chain. The real-world observation and measurement data are processed and refined and/or transformed to low-level abstractions or aggregated data. Different communication, representation, publication, subscription, query, and discovery methods are then required to provide higher-level access to these data.

as temperature, light, sound, and video) and are inherently diverse (the quality and validity of data can vary with different devices through time; data is also mostly location- and time-dependent).1 WoT resources can be ubiquitous and are often constrained in terms of power, memory, processing, and communication capabilities. The heterogeneity, ubiquity, and dynamic nature of the resources and devices, and the wide range of data, make discovering, accessing, processing, integrating, and interpreting the physical world data on the Web a challenging task.

The WoT data, however, isn't limited to only sensor device data. Webresident data and knowledge (such as Wikipedia or Linked Open Data) and information exchanged over social media and user-submitted physical world observations and measurements make up a rich cyber component. Integration of physical, cyber, and social resources enables developing applications and services that can incorporate situation and contextawareness into the decision-making mechanisms, and can create smarter applications and enhanced services (http://wiki.knoesis.org/index.php/ Smart Data).2,3

WoT data is a type of Big Data that is not only large in scale and volume, but also continuous, with rich spatiotemporal dependency. The resources that produce the data often operate in dynamic and volatile environments, or can collect and communicate the data on an ad hoc basis. The dynamicity of the environment and data providers make efficient use of the WoT data on a global scale a challenging task. Figure 1 shows the access and process chain of physicalworld data. The data are produced and collected using machine sensors, human sensing, smartphones, and other devices. The data can be aggregated and summarized, or they can be processed and transformed to higherlevel abstract descriptions of situations and events. The collected dataraw, and at times aggregated, and/or abstracted-are communicated over networks. The data can be published and stored temporarily or they can be added to repositories, and the publication interfaces can provide a metadata-enriched representation of the data. The query and discovery services can support search processes for finding the data in large-scale distributed environments. Data aggregation and summarization can also occur at later stages by combining data from different sources and various types. The aggregation and summarization highlight the role and importance of creating knowledge from raw data.

The most exciting outcome of addressing WoT Big Data is the new class of applications—for example, applications that make individualized traffic prediction and health outcomes, or more refined approaches to energy and sustainability challenges.

#### **Sensing and Data Collection**

Sensor devices, smartphones, social media, and citizen-sensing resources

are some of the key sources for producing and collecting physical-world data that can be communicated, integrated, and accessed on the Web. These resources can produce large volumes of data in which the quality of the data can also vary over time. The data can be represented as numerical measurement values or as symbolic descriptions of occurrences in the physical world. Determining the quality, validity, and trust of data are among the key issues in Big Data collections from the physical world, especially in use-case scenarios where the data is made available by a large number of different (and sometimes unknown) providers. As the physicalworld data can be related to the environment, people, and events, privacy and security are always key concerns. When the scale of the data and the number of different parties that can access and process the data increase, dealing with these issues becomes more challenging. For example, in a smart city environment where the sensory devices collect data related to citizen activities, and multiple agencies can access these data, ownership, duration of storage, and types of use can raise significant privacy and security concerns.

#### Connection and Communication

The WoT resources, especially those provided by wireless sensor devices and smartphones, have various connection interfaces and are often limited in their power and processing capabilities. It would be unrealistic to assume that all the devices will be open and available to all the requests coming from various sources on the Web. However, there's still a need for addressing and naming mechanisms to provide a means of identifying the data items and making them traceable (if required).

The large number of sensory devices, and large volumes of observation and measurement data, will require bandwidth and reliable QoS solutions to effectively communicate these data. Different strategies, depending on the application and capabilities, are required for in-network processing, connection, and middleware solutions, as well as short-term versus long-term storage requirements and design. The preprocessing of data-that is, aggregation, summarization, and/or abstraction-can help deal with the deluge of data at the source level. Instead of surging all the raw data from sensory devices into the networks, this would allow the devices to send only higher granularity information, or digests of the data, which can be utilized in higher-level applications and services. Real-time access and missioncritical applications in scenarios such as disaster monitoring and control also require efficient communication of timely data into the processing of application and services from a large number of distributed sources.

#### Representation and Publication

Different data publishers have various ways of publishing and reporting data, and providing access to sensory data streams. Sensory data can be transient or it can be published and stored in repositories for longterm access and use. As the size and diversity of multimodal physicalworld data increases, publication and representation of the data in a way that makes discovery and access more flexible and scalable becomes a challenge. In recent years, there have been several efforts focusing on adding enriched metadata to enhance semantic interoperability and to provide machine-readable (and potentially machine-interpretable) descriptions of sensory data-a notable example is the World Wide Web (W3C) Incubator Group on Semantic Sensor Networks.<sup>4,5</sup> Several other models and semantic annotation frameworks have also been proposed for physical-world data publication and representation.<sup>6</sup> An important work in progress related to the representation and publication of heterogeneous physical-world data includes how to automate semantic annotations, interpretation, mapping, and mediation between different schema models, and efficiently balancing between expressability and complexity of descriptions.

#### **Query and Discovery**

The query and discovery of physicalworld data are often based on type, time, location, and the entity of interest. However, in large-scale dynamic and distributed environments, defining the region and location of requested data, indexing and querying of distributed data, and/or services and data provider sources isn't easy. Current solutions are highly effective in processing and interpreting textual and audio-visual data. However, large-scale distributed data streams that provide numerical location and time-dependent data of varying quality related to physical-world phenomena and discovery scenarios where the data is location and time-dependent, and varies in quality, requires a different set of solutions. In principle, we still don't have fully matured search engines, similar to those on the Web, which can provide for query, indexing, discovery, and resolving real-time numerical and descriptive sensory measurements and observations.

To better manage the tasks of publishing, sharing, analysing, and understanding streaming data, researchers are adapting and extending Semantic Web technologies. In particular, there are several efforts towards the extension of SPARQL for streaming data processing of semantically annotated data.<sup>7,8</sup> By extending query languages to allow continuous queries over semantically annotated data, WoT applications will more easily integrate various streams of realworld data with background domain knowledge available on the Web as Linked Open Data.

# Access, Subscription, and Integration

Physical-world data often require processing, analysis, and interpretation in relation to other existing data on the Web. The WoT data are usually more meaningful when they aren't combined with metadata (for example, what the data refers to, and the location and time that data are captured) and are further enhanced by combining different sources or types of data to create composite and complex data types that describe a physical-world phenomena or an occurrence/event related to a "thing." Providing an automated integration and combination of data requires cooperation between various data providers that sense, measure, capture, and communicate the data. It will also require flexible solutions to define composite data types, to select the resources that provide the required data, and to synchronize the process. The data-access scenarios can also be longer-term and continuous. In the latter case, efficient mechanisms are required to coordinate and orchestrate subscriptions to several resources for consumers and to support mobility, access continuity, and context-aware, energy-efficient data access and subscription to the resources.

#### From Data to Knowledge (Aggregation and Abstraction)

WoT data are not only voluminous; they're also continuous, streaming, real-time, dynamic, and volatile. Consequently, Big Data analytics for distributed processing of large-scale data (such as Hadoop) and programming models that allow automatic parallelization of the execution of tasks (such as MapReduce)9 won't be effective or adequate. In addition, creating human-understandable and/ or machine-readable information from raw observation and measurement data and providing real-time processing and response mechanisms are also important. The distribution and efficient scalable processing of data in WoT, in addition to enhanced data publication and dissemination, will be dependent on effective mechanisms for in-network processing, aggregation, and summarization. Creating abstractions from data, or patterns of data, that can provide an aggregated view on the data will be useful. This will require using domain-specific background knowledge to extract meaningful information and actionable knowledge from the WoT data.10

WoT resources are often dynamic; they can join a network, but might later become unavailable due to network or power outage, or the source providing them can move and join a different subnetwork. This will add to the challenges of discovery, integration, and exploitation of data in conventional systems.<sup>11</sup> Indexing and discovery of resources will require a set of mechanisms that can support mobility and dynamicity in real-time data and resource discovery, and can find the data by referring to their relations to objects and entities in the physical world. Unlike Internet search engines that rely on indexing existing data, the publication and integration of data in the WoT can't be separated from data discovery and search. Internet search engines discover available data, whereas WoT data aren't usually available at the time of query, and so discovery and search mechanisms would need to obtain such data from suitable resources.

The quality and form of resources is another major challenge. For example, during the Fukushima disaster, when people started publishing radiation data, different users provided a wide variety of inconsistent data for similar or nearby locations.<sup>12</sup> Inconsistency can be due to a number of factors, such as errors in reading and reporting, the use of different and uncalibrated devices, or different processes of data collection. Discovery and search methods would therefore require learning, feedback, and profiling mechanisms for quality-based data queries.

In WoT, millions of devices and resources, including citizen sensors (humans reporting what they see or think using social media) participate in collecting and publishing data from the physical world. Going beyond device and resource connectivity on a large scale, we'll need data and semantic connectivity among resources and consumers for supporting the effective use of networks of the future. With the huge diversity and volumes of data expected in the near future, connectivity at the information level becomes more important than connectivity at the network level to facilitate effective interpretation

and extraction of knowledge (that is, abstraction) from the WoT Big Data.

Developing scalable and flexible analysis and processing modelsand learning mechanisms-that can interpret large volumes of dynamic data of diverse quality requires coordination and collaboration between different methods and solutions. This includes different methods and solutions to preprocess the raw sensory data (for example, aggregation, summarization, and filtering mechanisms), various metadata and annotation models and techniques (such as data representation frameworks and languages), data abstraction and pattern recognition methods, and semantic interpretation and online analytical processing methods. This will provide a value chain for the raw sensory data from various sources to be processed, integrated, and interpreted, thus transformed into actionable information, insight, and knowledge that leads to improved decisions and human experience. Figure 2 demonstrates different steps that can be envisaged for efficient processing and for making use of WoT data.

#### In This Issue

We received 27 submissions for this special issue and identified two that meet high-quality standards. These articles demonstrate how the WoT data can be used to monitor and interact with resources in the physical environment.

In "Farming the Web of Things," Kerry Taylor and her colleagues describe how sensor data can be used to monitor a smart farm in New South Wales, Australia. In the Smart Farm application, a set of environmentalmonitoring sensors are deployed to provide (near) real-time information related to different situations on a farm. The authors use linked-data

### GUEST EDITORS' INTRODUCTION

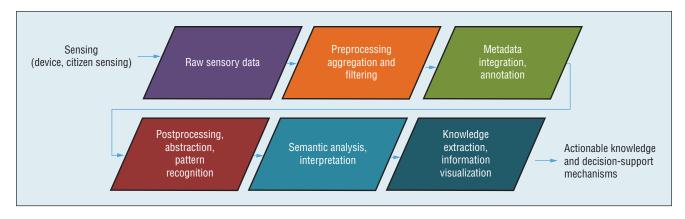


Figure 2. The process chain for physical-world data on the Web. The raw sensor data needs to be filtered, preprocessed, and/ or aggregated. The aggregated and preprocessed data and their associated metadata are then used to create abstractions or pattern representations. The semantic analysis and interpretation methods, with the help of domain knowledge, then allows extracting situation intelligence and actionable knowledge that can be used in higher-level service and applications.

representations of the observation data. Their proposed framework uses real-time data analysis techniques for event processing and creates semantic event descriptions that are processed to generate alerts. The article then discusses the business challenges, barriers, and drivers in using WoT technologies and sensor data in a smart-farm environment.

Then, in "Human Attention-Inspired Resource Allocation for Heterogeneous Sensors in WoT," Huansheng Ning and his colleagues describe a new technique for resource allocation in WoT applications. The article discusses adapting different human attention models—including sustained attention, selective attention, and divided attention—and describes a resources-allocation model that uses prior and posterior attention data to dynamically allocate resources for a WoT application.

Cost-efficient, network-enabled devices facilitate machine-tohuman and machine-to-machine communication of physical world data and its integration into the Web. Social media platforms also facilitate publication and access to this data. The size and diversity of the generated data is growing at an extraordinary pace. The dynamicity, volatility, and ad hoc nature of most of the underlying networks and resources that produce physical world observation and measurement data introduce additional challenges for processing and utilization of Big Data. The physical world is also often related to people and their surroundings, so ethical issues and privacy and security concerns always remain at the heart of WoT systems and applications. The limitations and status of energy- and resourceconstrained devices and networks, and the ability to effectively publish, discover, and access the data in large-scale distributed environments, have a direct impact on systems' performance that use this data. Semantic enhancements and metadata are also important to make the physical world data interoperable and interpretable by the automated software tools and services. To keep development apace for WoT systems, it's essential to provide efficient and scalable solutions for annotating physical-world data-and offer solutions that can provide high performance and sometimes (near) realtime analytics.

Today, WoT is a driving force to generate, access, and integrate data from physical, cyber, and social sources. The ability to develop solutions that can effectively analyze and interpret physical-world data requires collection and integration of data from various sources. The ability to analyze and interpret this data to create meaningful insights, extract knowledge, and create situational awareness is crucial to fulfilling the future potential of big WoT data.

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