Towards a Platform for Urban Data Management, Integration and Processing

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Keywords: Smart City, Iot, Urban Data Streams, Semantic Interoperability, Edge Computing, Urban Data Analytics.

Abstract: Smart city infrastructure includes deployment of a variety of sensors and provision of open data platforms and applications that can help improve the quality of life of the citizens. The large volumes of data generated by sensors and various Internet of Things (IoT) devices need to be harnessed to help smart city applications make informed decisions on the fly. Also, efficient management of smart city components relies on the ability to federate their data, locally process urban data streams, and utilize big data analytics to harness their governance. Data interoperability and integration is one of the most challenging problems facing smart cities today. Successful data integration is one of the keys to improved services and governance. This paper describes the architectural design of a framework that aims to deal with the integration of data across the various systems of the city, urban data analytics, and creation of value-added services. The framework relies on recent technologies for data processing including IoT, edge computing, cloud computing, data analytics, and semantic integration.

1 INTRODUCTION

Over the last few decades, cities are experiencing tremendous pressure due to migration waves and urban growth. Their infrastructures need to cope with growing demand for the supply of energy, water, transportation, and healthcare services. City stakeholders are using digital technologies to reduce costs, improve the quality of services delivered to citizens, balance budgets, and enhance the efficiency of various city systems. However, the lack of integration of data generated by the diverse city components and systems results in making city utilities and services operate sub-optimally, limiting the creation of value-added services, increasing transport costs, etc. Recent digital technologies offer new opportunities to mitigate these impacts and transform cities into smart cities through smart and innovative planning, management, and operation.

Managing a smart city holistically and harnessing its governance are becoming essential to federate its data, locally process data streams generated by various IoT devices and sensors, and utilize big data analytics (Khan, 2015) (Ojo, 2015). An integrated data perspective can benefit smart cities using big data collection, integration, processing, and sharing through cloud-based services. Nevertheless, such data integration and utilization necessitate suitable software technologies to collect, store, analyze and visualize enormous amounts of data from the city ecosystem.

Data interoperability and integration are two of the most challenging issues facing smart cities today (Trilles, 2016) (Gyrard, 2016). Indeed, to enable the efficient governance of smart cities and to create value-added services that enhance the lives of citizens, smart city stakeholders have to interpret many types of information from a variety of sources including water consumption, road traffic, energy consumption, healthcare services, and many others. Unfortunately, they are not currently able to efficiently harness that information because of the massive amounts of generated data, data heterogeneity across the city systems, and the lack of a common data model and ontology. Successful data integration is one of the keys to improved services and governance (An, 2016) (Luciano, 2014). It will allow for analyses of economic activity, resource consumption, mobility patterns, and public health, which will guide the city development.

This work describes the architectural design of a framework able to deal with the integration of data

Badidi, E. and Maheswaran, M.
Towards a Platform for Urban Data Management, Integration and Processing.
DOI: 10.5220/0006789602990306
In *Proceedings of the 3rd International Conference on Internet of Things, Big Data and Security (IoTBDS 2018)*, pages 299-306
ISBN: 978-989-758-296-7

across the various systems of the city, urban data analytics, and creation of value-added services. The framework relies on recent technologies for data processing including IoT, edge computing, cloud computing, data analytics, and semantic integration. The framework aims at allowing smart city stakeholders to connect, manage, process and analyze data from thousands of IoT devices and sensors at the edge of their networks. It will mainly allow to:

- collect data from thousands of IoT devices,
- normalize the integration of IoT devices within the smart city,
- perform real-time big data analytics on IoT streams and events, and
- extend smart city applications and processes with IoT data seamlessly.

The remainder of this paper is organized as follows. Section 2 provides background information on urban data streams and describes the challenges of urban data streams processing. Section 3 provides an overview of some of the techniques used for data integration. Section 4 describes the conceptual architecture of our proposed framework for urban data integration. Section 5 discusses challenges and concerns of urban data integration. Finally, Section 6 concludes the paper.

2 URBAN DATA STREAMS

In a smart city context, systems are equipped to work with real-time data from sensors, electric and water meters, or other devices used to assure the functions of the city. Sensors usually convey information about real-world phenomena, generally ranging from direct measurements such as temperature or pressure to user observations like water leaking. Sensors include not only hardware sensors but also people. The concept of people as sensors refers to users providing direct input via social networks or dedicated end-user interfaces (Doran, 2013).

Urban data streams come from a variety of IoT devices and sensors that monitor and report on:

- Weather conditions as they relate to traffic jams and accidents so that alerts and warning systems are activated.
- Parking space availability so that drivers avoid the lengthy searches for open spaces.
- The structural integrity of bridges, historical monuments, and buildings when it comes to the impact that weather conditions and vibrations have on the structure's safety.
- Trash levels in waste containers to optimize trash collection routes.
- Night activity and traffic so that adaptive smart lighting lights streets, sidewalks, and roads in an energy efficient manner.

Over the last few years, the European Union has been encouraging its member states to develop smart cities and allocated 365 million euros for this initiative. Amsterdam, Barcelona, and many other cities are leading the smart city development effort.

Copenhagen, which aims to be the world's best city for cyclists, has started monitoring the city's bike traffic in real time by deploying sensors throughout several parts of the city. These sensors provide valuable data helping improve bike routes in the city as at least 50% of the city's residents commute to their workplaces or educational institutions by bike every day (Wired.com, 2015).

London started installing smart parking sensors that would allow drivers using a map to view a real-time map of parking spaces and to quickly locate parking spaces and remove the need for lengthy searches for an open spot. Londoners hope that this system would alleviate urban traffic congestion and cut down on carbon emissions. Other cities around the world are also trying out deploying smart parking systems in an attempt to improve the everyday life of their citizens (Computing, 2014).

Furthermore, many cities are using cutting-edge IoT solutions to implement intelligent adaptive street lighting systems. These systems can help cities create safer urban environments and at the same time save energy and protect the environment. They light up when human activity is detected and dim down to reduce costs when streets are empty. For example, San Diego city has recently started a $30 million Smart City IoT platform project in what represents the world's massive Smart City IoT platform deployment. The platform will add nearly 3,200 intelligent IoT nodes to the current street lighting infrastructure to collect real-time sensor data across the city (Diginomica.com, 2017). The collected data can be used to optimize municipal systems, increase safety, guide fire and police to accident or emergency scenes as well as develop smart apps that, can, for instance, direct drivers to available parking spaces.

Several efforts investigated the realization of smart cities through the IoT, often considered as the principal technological enabler. Jin et al. (Jin, 2014) introduced IoT for smart cities from three different perspectives: network-centric IoT, cloud-centric IoT, and data-centric IoT. The data-centric IoT perspective includes data collection, data processing, data storage, and data visualization. Zanella et al. (Zanella, 2014) provided a survey of the enabling technologies, protocols, and architecture for an urban IoT, i.e., a communication infrastructure that aims to provide simple, unified, and cost-effective access to a variety of public services.

One of the challenging issues of current urban deployments is the non-interoperability of the diverse and heterogeneous devices and technologies used in the city (Trilles, 2016) (Gyrard, 2016). These devices generate different types of data conveyed to a control center for storage and processing. Zanella et al. described the Web-service approach for IoT service architecture and explained its benefits for implementing interoperable services. International standardization bodies such as IETF, ETSI, and W3C, among others, are also promoting this approach.

3 DATA INTEGRATION TECHNIQUES

Efficient utilization of data from disparate sources requires understanding the database schema of each data source and devising a translation mechanism to permit data exchange. The literature on data integration identifies six main techniques: data consolidation, data federation, data propagation, utilization of the Extensible Markup Language (XML) and the JavaScript Object Notation (JSON) as standard formats for the exchange and storage of data, development of controlled vocabularies, and mashups.

Data consolidation refers to the collection of data from multiple sources and its integration into a single persistent data store (see fig. 1). It allows to cope with data duplication and reduce the costs associated with the reliance on multiple data management points and databases. It will enable organizations to do reporting and efficient data analysis as in data warehousing. The data store can act as a data source for downstream applications as in an operational database system. Since data originates from multiple data sources, there is always a delay between the time data is generated or updated in a data source and the time those changes appear in the data store. Depending on the underlying communication infrastructure and the nature and size of updated data, this delay might range from a few seconds to several days (Loshin, 2009) (Levin, 2004).

Data federation represents an alternative model for data storage and usage by organizations. Data federation technology refers to software resources that provide users with a single logical view to present and access data stored throughout one or more data sources. This technique is also known as data virtualization technology. When the data sources are traditional databases, data federation leverages the native data management and search capabilities of individual source databases and creates a single, unified, logical view of the federated databases (Haas, 2002). Business applications are presented with a combined data schema even though the source database schemas are distributed across many federated databases (see fig. 2). When a business application issues a request against this logical view, the data federation engine retrieves data from the appropriate data source, adapts it to match the virtual view, and sends the results to the requesting business application (Loshin, 2009) (Barnaghi, 2015) (Haas, 2002).

Data propagation denotes the movement of data from one or multiple data sources to target locations. Data propagation systems usually push data to target locations. Most often, they are event-driven, and data propagation is performed according to propagation rules (see fig. 3). Data updates in a source system may be propagated to the target system synchronously or asynchronously (Loshin, 2009). Propagation ensures the delivery of data to the target system irrespective of the type of synchronization used. This data delivery guarantee is a key distinctive feature of data propagation. For instance, in data warehouses and operational data stores based systems, updates involve moving large volumes of data from one system to another. Data movement is carried out in batches to avoid impacting the performance of the operations on the data warehouse.

XML is a markup language that facilitates sharing of data across heterogeneous computing systems (Bertino, 2001). Many databases, software applications, and tools are XML-compliant. XML facilitates data integration and application interoperability by adopting standards for representing certain types of data.

JSON is an open-standard file format that uses text to transmit data objects consisting of attribute–value pairs and array data types. It is a language–independent and light-weight data-interchange format, which is easy for humans to read and write and easy for machines to generate and parse. JSON is more and more becoming the preferred format for data exchange and integration using RESTful Web services.

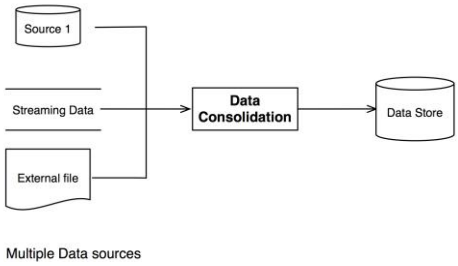

Figure 1: Consolidation of data from multiple sources.

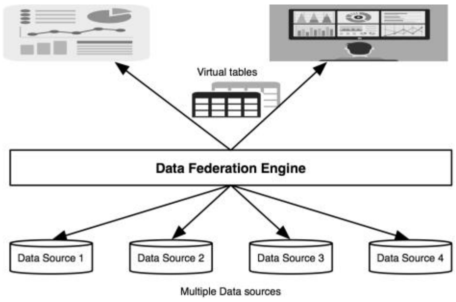

Figure 2: Federation of Data from Multiple Sources.

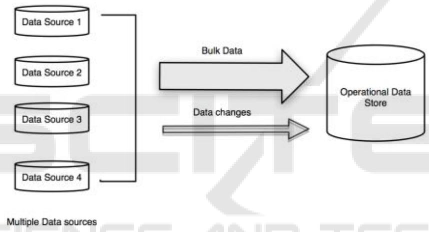

Figure 3: Data propagation from data sources to operational data store.

Controlled vocabularies offer a form of data integration by enforcing naming conventions for data elements that ultimately appear in databases. One example of a controlled vocabulary is an ontology developed in the context of a smart city (Nemirovski, 2013). The ontology acts as a mediator for distinct schemas of individual data sources and as a reference schema for federated data queries. Also, researchers at the DISIT Lab at the University of Florence (http://www.disit.org) have created an ontology for a smart city, which integrates regulatory elements, sensors, points of interests, people, etc. and is used in other smart city projects (DISIT Lab, 2015).

A ***Mashup*** is a technique for building new Web applications that combine data from multiple sources to create an integrated experience. Mashup applications can be constructed using widgets, open APIs, Web services, and data sources. An example of mashups developed in the case of smart cities is FixMyCity (Fraunhofer, 2012), a government mashup that allows citizens to contact the appropriate person in a local administration quickly to report damages in public spaces.

4 ARCHITECTURE OVERVIEW

Figure 4 depicts our proposed architecture to address the data integration and processing issues in smart cities.

4.1 Infrastructure Layer

This layer is made up of various smart city data sources such as smart IoT devices, traditional databases, Web servers, and edge servers. An IoT device detects some input from its surrounding environment and responds to it. The particular input could be light, motion, speed, vibration, pressure, water level, heat, or any other environmental phenomenon. The device reading is then converted into a human-readable form or sent over a network to a gateway for further processing. An IoT device, with typically an IP address, can connect to a network to exchange data. Smart IoT devices enable automating operations of a city by collecting data on various physical assets (equipment, vehicles, buildings, facilities, etc.) to monitor their behavior and status, and using collected data to optimize resources and processes. IoT devices and actuators, which do not have operating systems, connect to edge devices or edge gateways using Wi-Fi or Ethernet connections of a Local Area Network (LAN) or using Bluetooth, ZigBee, and Ultra-Wide-band (UWB) of Personal Area Network (PAN).

The realization of smart energy, smart transport, smart health, smart agriculture, etc. will be permitted by IoT technologies, which require the deployment of a vast number of IoT devices and sensors. Web servers' logs also represent an essential data source for the various city systems. Log streaming permits troubleshooting connectivity problems and diagnosing the causes of service disruptions. Also, clickstream analysis can be used to assess the effectiveness of providing online city services.

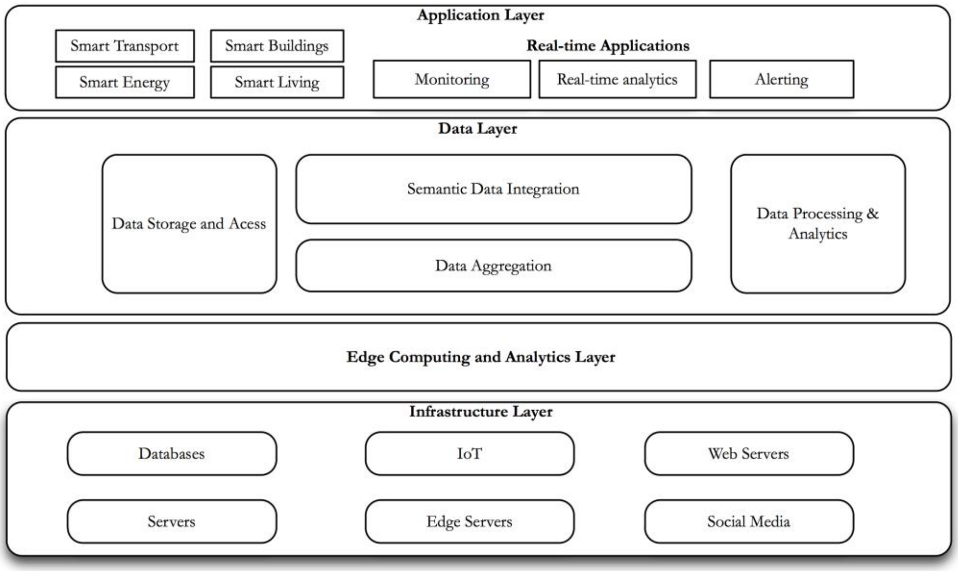

Figure 4: Architecture for Smart City Data Integration.

4.2 Edge Computing Layer

As sensors and IoT smart objects generate massive amounts of data, traditional data management systems and practices will no longer be sufficient to take full advantage of the IoT. The fundamental idea behind Edge Computing (EC) is to place storage and computation resources at the network edge, in the proximity of the data generation location. IDC predicted that: "*By 2019, at least 40% of IoT-created data will be stored, processed, analyzed, and acted upon close to, or at the edge of, the network*" (IDC.com, 2017). Thus, the processing of urban data streams can be pushed from the cloud to the edge. EC reduces traffic bottleneck towards the core network by processing the data locally and expediting data streams by using various techniques (i.e., caching and compression). Besides, it helps to shorten end-to-end latency, enabling the offload of heavy computation load from power constrained user equipment to the edge. This can be very beneficial when IoT devices are deployed on remote locations suffering from poor network coverage or when stakeholders aim to reduce the costs of expensive cellular connectivity technologies.

Edge devices, which are often battery-powered, run complete operating systems such as Linux, Android, or iOS. They process raw data they receive from IoT devices and sensors, and they send commands to actuators. They are connected to the data layer directly or through edge gateways. Edge gateways also run complete operating systems and have unrestricted power supply, more CPU power, memory, and storage. They can aggregate data and support analytics at the edge of the network, and they act as intermediaries between the data layer and the edge devices.

Both edge gateways and devices forward selected raw or pre-processed IoT datasets to the data layer services, like storage services, machine learning or analytics services, and they symmetrically receive commands from the above layers, like configurations or data queries.

Centralized databases are indispensable for carrying out the various operations of the smart city systems. Nevertheless, as the data incessantly spreads from sensors and IoT devices at the edge, central databases only need to cope with data inflow at a more controlled rate for instance once per minute. Using edge servers, which typically have limited computing and storage capacities, permits conveying data in real-time and receiving instructions in a timely fashion. Data streams can be aggregated and merged at the edge and then transported to the central databases as averages of sensed data over well-controlled periods of time (see figure 5). Thus, moving data management partially from primary databases towards the edge of the network is crucial for coping with real-time data feeds.

4.3 Data Layer

This layer is in charge of storing and providing access to data, obtained from the infrastructure, and processing and analyzing data that other layers can use to generate valuable insights.

4.3.1 Data Storage and Access

The resources across a smart city infrastructure together with people’s wearable devices and smartphones incessantly generate vast amounts of data in structured and unstructured formats. IoT devices and sensors monitor in real-time the operations of many city systems such as transportation, water, and energy systems. Furthermore, social media networks such as Twitter, Google+, and Facebook, often considered as social sensors, represent a new source of real-time data.

The data layer allows city stakeholders to store and access these large urban datasets using conventional and modern management tools. Over the last few years, Data-as-a-Service (DaaS) emerged as a new delivery model for data storage and provisioning wherein data are provided on-demand to the consumer regardless of their geographic locations (Olson, 2009). This delivery model relies on the service-oriented architecture (SOA) and advocates the view that data management can be done in a centralized place where datasets are cleansed, aggregated, and enriched to be accessed by different applications or users irrespective of their location or network.

4.3.2 Data Aggregation

Data aggregation typically deals with large volumes of data to reduce the size of raw sensory measurements (Jugel, 2014). It allows reducing the communication overhead and helps to perform more advanced tasks in large-scale systems such as clustering or event detection. To efficiently access and use sensory data, semantic representation of the aggregations and abstractions are crucial to providing machine interpretable observations for higher-level interpretations of the real-world context (Jugel, 2014).

Data aggregation is common in many applications. For example, in the healthcare industry, to meticulously analyze the situation of a patient, it is necessary to aggregate data from various IoT-based healthcare service providers that collect data of that patient using multiple sensors. Fig. 5 depicts the aggregation of data from one or several data streams.

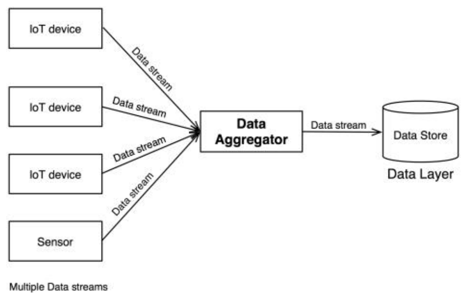

Figure 5: Aggregation of data from one or multiple data streams.

4.3.3 Data Semantic Integration and Interoperability

The IEEE defines interoperability as: "*The ability of two or more systems or components to exchange information and to use the information that has been exchanged*" (IEEE, 1990).

If two or several systems can communicate and exchange data, they are demonstrating syntactic interoperability. Specified communication protocols and data formats are essential for successful data exchange. XML or SQL standards provide syntactic interoperability. Syntactical interoperability is a requirement for any efforts of additional interoperability. Beyond the ability of two or several systems to exchange information, semantic interoperability means the ability to interpret the data exchanged meaningfully and accurately to produce useful results as defined by the end users of both systems. Semantic interoperability requires that both sides agree on a mutual information exchange reference model.

In smart cities, achieving semantic interoperability is a more critical and difficult task given the complexity of the city ecosystem (Ramparany, 2016) (Psyllidis, 2015) where government entities and private businesses often use different terminologies. Therefore, a semantic data model should be developed to standardize terms and descriptors whose meanings are defined. Concerning this issue at the sensor level, the W3C incubator group created the Semantic Sensor Network (SSN) ontology (Compton, 2012).

4.3.4 Data Processing and Analytics

In addition to providing efficient storage and access to data, the data layer allows city stakeholders to efficiently transform, and analyze these vast urban data streams so that applications of the smart city can use it to generate valuable insights. The real value of such integrated data will be gained by acquiring new knowledge through the utilization of data analytics using a variety of data mining, machine learning, and statistical methods. A growing set of reputable open source and commercial solutions is available for data streams processing. This set includes: Apache Kafka (http://kafka.apache.org), Apache Storm (http://storm.apache.org), Apache Samza (http://samza. apache.org), Google Cloud Dataflow (https://cloud. google.com/ dataflow), and Amazon Elastic MapReduce (https://aws. amazon.com/elasticmapreduce). These solutions allow processing both streaming and historical data, which is a vital aspect of current smart cities.

For instance, by using Apache Kafka together with Apache Storm, Apache HBase and Apache Spark, real-time (or near real-time) data streams can be processed efficiently. Deployed as a cluster on multiple servers, Kafka handles its entire publish and subscribe messaging system with the help of its four APIs, namely, producer API, consumer API, streams API and connector API.

4.4 Application Layer

The application layer provides a comprehensive set of methodologies and tools for efficient design, development, distribution, and operation of smart city applications and services. The Service Oriented Architecture (SOA) embodied by Web services has emerged as a fundamental technology for providing services over the Web. Web services are interoperable across platforms and neutral to languages, which makes them suitable for access from heterogeneous environments. Web services technology has all the potential to be a significant component in the integration endeavor because it provides a higher layer of abstraction that hides implementation details from applications.

In this work, we consider the service-orientation as the major design principle for the interoperability foundation for smart city systems facilitating the ground for the support of security assurance, semantic layer, IoT integration, business process management capabilities, and a multimodal portal with mobile device support. Service orientation will be the basis for the development of a Smart City Service Bus (SCSB). The SCSB will be the backbone of services from the different government agencies and private businesses. It will enable creating new value-added services and deliver updated information at all times to city stakeholders, citizens, and businesses.

5 URBAN DATA INTEGRATION CHALLENGES

Data integration and semantic interoperability involve continuous change management and a tedious engineering effort. It is a long-term effort that requires the organization of processes for consensus-building and cooperation among all players involved.

The following factors might impact the success of the data integration endeavor:

- Security and privacy issues (Privacy of personal data, high cost of security applications and solutions, threats from hackers and intruders, etc.)
- Resistance to sharing data or lack of interest in data integration by some city entities.
- Lack of alignment of organizational goals and the high cost of IT professionals skillful in data integration.
- Required effort to coordinate data resources that have conflicting conceptualizations and representations, which makes the smart city data integration endeavor harder.
- The lack of standards for data integration. Standardization would significantly alleviate the above challenges. Standards take too much time before being approved and implemented.

As we mentioned earlier, already many smart city initiatives are underway based on the integration of data obtained from multiple stakeholders. It remains to be seen to what extent such efforts can deliver promised intelligent services.

6 CONCLUSIONS

Creation of value-added services and single-entry point of services for city citizens involves the integration of data from several governments and private entities. IoT technologies, semantic interoperability, service orientation, edge computing, and cloud computing will play a primary role in the achievement of the smart city goals. A clear understanding of the requirements of citizens and smart city governance goals could reveal the integration tasks to undertake by the various city stakeholders and the challenges that have to be faced. A conceptual data integrative framework is here proposed to cope with the heterogeneity of systems at different levels including data models, data semantics, service implementation, and interfaces. Edge computing, semantic interoperability, service orientation, and cloud-based data analytics are the cornerstones of the proposed framework.

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