# The Automation of the Softer Side of Smart City: A Socio-Semantic Roadmap

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**Abstract –**

**We present a roadmap for guiding public officials on establishing platforms for citizen empowerment in the smart city. The proposed roadmap is not a technical architecture. Rather, a set of paradigms, guidelines and references to advanced technology approaches that can support building a technical architecture. We start from the perspective that the smart city architecture is not a venue for services, but a domain of innovation. We advocate encouraging citizen science to co-create new solutions—in contrast to engaging them to inform them or to evaluate solutions developed by professionals. We advocate giving equal attention to structured and unstructured data analysis. We also encourage the adoption of adaptable data orchestration tools to help navigate and organize the complexity of city data. Finally, we provide an outlook on the future trends (such as Blockchain and cognitive computing) in urban systems decision making.**

**Keywords –**

**Smart city; Citizen science; Socio-semantic analysis**

## 1 Introduction

Traditionally, cities take a *control-room approach, to* centrally manage and optimize urban systems. The target is to develop and use technical operational policies that can make cities more sustainable, efficient, comfortable and enjoyable (de Waal & Dignum 2017). This is a *service-user model*, where citizens are considered as subjects, or, at best, customers. However, the concept of e-citizen is far more transformative. First, a smart city effectively tracks and is highly responsive to its citizens' opinions, behavior and objectives. Support for behavior changes can be the most valuable resource for meeting the challenges of climate change and sustainability. This is because there is a limit to the extent of possible efficiency gains that smarter hardware can achieve. In contrast, a limited savings in energy at the individual level, if adopted by the crowds, will provide effective and lasting impact. Engaging citizens can help find the best approaches to support such behaviour change. For example, what incentives can be offered to citizens to encourage the use of public transit, what new technologies or motivations for energy saving can be implemented.

Second, and more importantly, we should move citizens from a reactive role of service-recipients to co-creator of policies. In post-modernist planning theories, knowledge is distributed with citizens possessing equally valid knowledge to that of professionals. The role of planners is not to decide, but rather to seek and actualize multiple knowledge(s) to support transformative decision making. Collaborative planning approaches span four major categories (Linnenluecke et al. 2017): predictive (using forecasting); adaptive (adjusting to changing conditions); visionary (generating alternatives); and transformative planning (co-creation of solutions). Transformative planning is not limited to the idea of co-creation and harnessing community knowledge. It aims to empower communities, promote social learning/ innovation and foster behavior change.

We aim to provide a high-level map for 1) the issues that should be considered in developing a socially-savvy e-city platform, and 2) illustrate the value, relevance and interactions between available enabling technologies. It is expected that a city manager or a director of capital projects will use the map as a benchmark or a starting point for scoping an actionable policy for engaging citizens, collating their input and supporting their collective deliberations and innovation.

We present here a set of requirements and an initial architecture for augmenting sensor data about the physical city systems with that of people: their views, needs, ideas. The objective is to establish a repository of data for the access, use and analytics of (unstructured) data in the context of smart city.

## 2 The Smart City

The complexity of the fusion of data about the physical systems (attributes of the infrastructure) with that of its citizen (input, views, ideas) is not limited to computational issues, but, more fundamentally, to the very definition of a smart city. Pardo and Nam (2011) view a smart city from three perspectives: i) a mandatory technological perspective with a general reference to smart hardware and information technology tools.; ii) citizen creativity perspective that considers the role of citizens in using and generating smart city data; and iii) an institutional dimension that refers to cooperation of societal institutions with governments to co-develop policies and decisions. These three perspectives corresponds to the terms Digital City, Knowledge City and Smart Community, respectively.

In a departure from the control-room approach, citizens and civic organizations are empowered to use digital technologies to create solution to advance city systems. They not only have the right to a share of decision making powers, but also an equal right to being the source of knowledge and innovation—technical and otherwise. Examples of this approach has inspired several new applications and concepts: citizen sensor networks, DIY-citizenship (Ratto and Boler 2014), tactical urbanism (Lydon and Garcia 2015) or hackable city-making (de Waal et al. 2017). Such state-of-the-art practices use interactive citizen science for pooling citizen knowledge across all phases of city management including data collection, selecting amongst proposed alternatives, definition of the problems to consider, generating solutions, initiation of decision making, and monitoring actual implementations. This infuses more democracy into decision making, harness social innovation and allow citizens to act as agents of change.

In fact cities of the future are described to be "*territories with high capability for learning and innovation, which is built-in the creativity of their population, their institutions of knowledge creation, and their digital infrastructure for communication and knowledge management*" (Komninos 2006). The co-creation of knowledge by citizens and institutions is in fact "*continuous creation, sharing, evaluation, renewal and update of knowledge*" (Ergazakis 2004).

### 2.1 Collaborative Social Innovation

Several recent initiatives showcase that a paradigm shift towards citizen science in urban areas is viable and valuable—for example, Hackerspace (with 1330+ physical sites); include Network of 'Science Shops': scientific research in cooperation with citizens and local and national civil society organizations; DESIS-network: over 30 design labs supporting 'social innovation towards sustainability'; Global Ecovillage Network: network of 500 ecovillages; and Transition Towns: 450 grassroots community initiatives working on "local resilience". These advocate using sensing tools to enhance perception of environmental conditions (ex, Extreme Citizen Science); diffusion of solution and implementation tools (ex. Citizen Cyberlab); creating new sets of data (ex. Mapping for Change); provide open access to data (ex. DataShare); collection of idea (ex. IdeaConnection); taking collective actions (ex. Hacking the City). These efforts entwine electronics, media and humans, into co-agents in data and knowledge-production and decision-taking (Parikka, 2011).

### 2.2 Data Challenges for the Smart City

Smart city data is categorized into structured and unstructured data. Structured data follows a formal pre-defined data model and typically relates to physical and technology data—for example sensor and camera data or vehicle location. Unstructured data does not adhere to specific models. Unstructured data such as social media and popular media contents or citizen reviews is a fundamental input to any socio-technical analysis of smart city systems. This makes unstructured data more essential to citizen science, because it helps in understanding user needs and in customizing data delivery to them. For example, structured data can be used to define patterns of use of autonomous vehicles (AV) to support predicting traffic volumes or to correlate electric vehicles travel patterns to determine best location for electric charging stations. Unstructured data can be used to represent citizen willingness to support efficient mobility and energy usage; best means to operate an AV system or fix a broken pipe.

In general, one of the main challenges for serving data to citizens is the manipulation of data (especially the unstructured), due to the following challenges:

<u>Complexity</u>: The complexity of issues to consider in any urban decision is increasing. For example, Lambert et al. (2011) developed a model to prioritize major civil infrastructures projects. It included the following fourteen indicators: create employment, reduce poverty, improve connectivity and accessibility, increase industrial/agricultural capacity, improve public services and utilities, reduce corruption/improve governance, increase private investment, improve education and health, improve emergency preparedness, improve refugee management, preserve religious and cultural heritage, improve media and information technology, increase women's participation and improve environmental and natural resource management.

<u>Multidisciplinary analysis</u>: In addition to complexity, the issues are multidisciplinary. For example, considering the scope of assessment knowledge, Kabir and Khan (2013) enumerated 300 different possible issues for analysis. They span seven classes (each class is

followed by the number of related issues): hydrological resource systems (68), potable and wastewater (54), transportation (56), bridges (58), buildings (33), underground infrastructures (11) and urban systems (21).

Subjectivity: many of these issues are quite subjective in nature. To help quantify the assessment, a variety of quantification approaches have been developed (Hoogmartens et al. 2014), including life cycle analysis (LCA), life cycle costing (LCC) and cost–benefit analysis (CBA). Domain-specific methods were further explored, including environmental LCA (eLCA), social LCA (sLCA), financial LCC (fLCC), environmental LCC (eLCC), full environmental LCC (feLCC), societal LCC (sLCC), financial CBA (fCBA), environmental CBA (eCBA) and social CBA (sCBA).

## 3 The Proposed Architecture: Overview

The proposed roadmap aims to maximize the contribution of smart city systems (hardware and data) to empower citizens to lead innovation and knowledge generation within the city. The focus is on the know-how dimensions, which spans the creation of platforms to enable data management, processing, protection, visualization and analytics. It is out of scope for this roadmap to consider the know-why dimension, which models and understands the externalities that impact the development and effective management of smart city, including economic, legal, political, social and ethical issues. Also out of scope is the know-what dimensions which focuses on developing policies to create technical and process-based standards, and skill development and training (Cuquet et al 2017).

A high-level map that describes the main elements relevant to a typical smart city architecture is shown in Figure 1. Raw active data is ingested, curated and archived in long-term storage. Then data is catalogued and metadata and context information are extracted and used to tag/ annotate data. This enables searching through the "data lake." This workflow can be divided into detailed lower-level workflows that span each step; for example data upload and ingestion requires its own sub-workflow and User Interface.

The main pillars in the proposed map are as follows:

- The acquisition and ingestion of intrinsic data. Securing access to diversified and easy to use data. That is, the data has a higher value if it can be fused with other relevant data.
- Computational services. Much like an API or an "app store", this pillar offers citizens services to process data. Here, we assume that a citizen or a decision maker is using such data to create new products or conduct certain analyses.
- Modeling Pillar. Much like IFC (industry foundation classes), we need formalized models of data: rules that describe their behaviors, and basic relationships between datasets. How does the available data cohere to each other and how does the data relate to typical city analyses. Such conceptual models of data will require technical expertise, which is not easily available to citizens. For example, creating a bridge between IoT raw data and BIM-based software will enable users to access and develop a large number of applications without having to manipulate the technical architectures of this data (such as understanding IFC). Still, a savvy user can use the bridge to generate higher order models—without worrying about interoperability between the two data models.

## 4 Pillar 1: Data Acquisition

We identify below a set of challenges for acquiring smart city data and suggestions for possible solutions based on recent advances in data management approaches.

### 4.1 Data Heterogeneity

Establishing meaningful data from a multitude of structured and unstructured data will remain a challenge. For example, how to make sense and integrate CCTV data, with sensor data with citizen data. While ontologies can be very effective in handling this, their static nature will limit their ability to be exhaustive. Different types of tools were proposed to solve this problem:

Fact-finding platforms such as YAGO2 contains 350, 000 classes, 10 million entities and 120 million facts extracted automatically from online sources, with an accuracy of 95% (Hoffart et al. 2013).

Linked data and distributed stream computing help manage the high-variety and high-volume data within high-velocity activities (Hasan and Curry 2014). The combination of linked data tools and stream computing tools with machine learning tools will facilitate the semantic coupling of know-how knowledge with real time data. This creates a realm of self-improving data models and associated learning/analytics needed to support spot decision making (Curry et al. 2013).

Edge computing: Decision-embedded analytics that have real-time access to big data will facilitate in-network and in-field analytics (called edge-computing). In conjunction with enterprise-level analytics, these tools are poised to create higher levels of customization (for example, which driverless car is best choice for each commuter), real-time operational (what are the best evacuation routes for each commuter in the case of emergency), and even new business models (for example, carbon tax refunds based on usage of energy within/outside home)

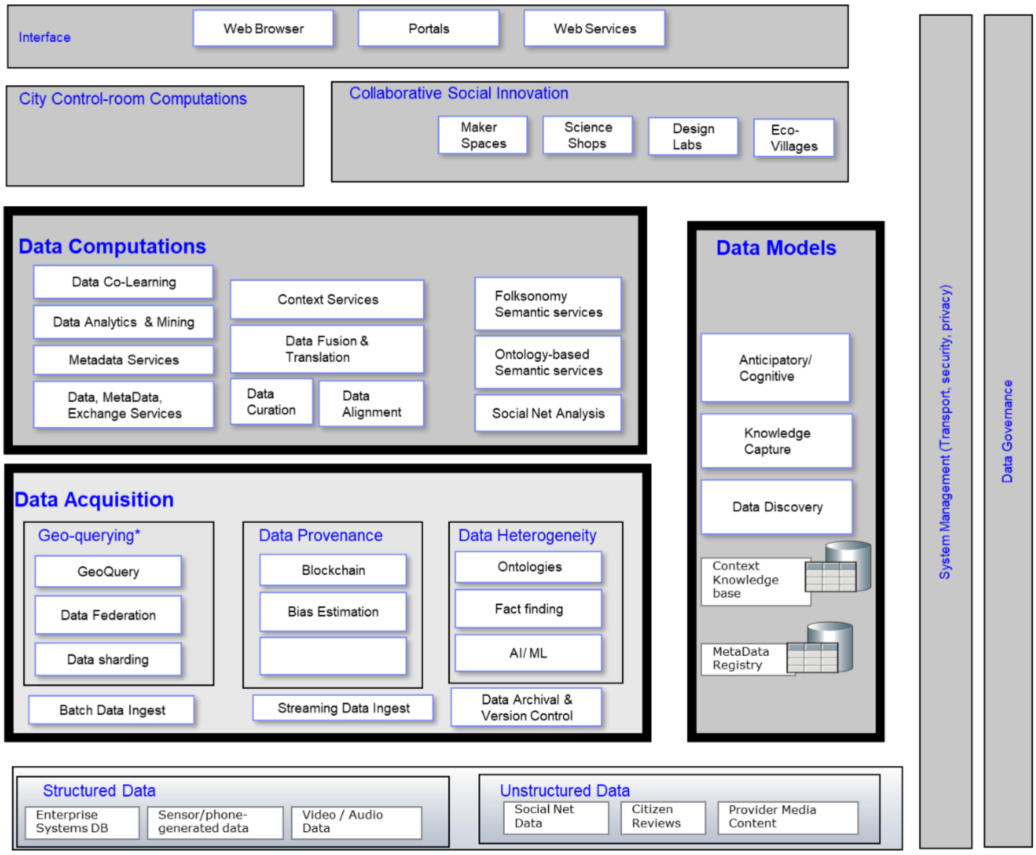


Figure 1. Overview of the proposed roadmap

## 4.2 High-Performance Data Access

Access can be provided by customizable and intelligent sharding of the data streams based on application and infrastructure requirements. Technologies such as Apache Kafka already provides an ability to shard relative to the memory capacity of the system conducting the analysis. Two of the key challenges that must be addressed by any smart city architecture are contextualization and federation.

The architecture needs to enable and include a process of contextual sharding. A set of intelligent mechanisms at the network edge are required to understand specific applications. This ranges from understanding their data structures to identifying access rights to specific users.

Another challenge is data federation. How to accommodate data query and retrieval functionality from multiple individual platforms. MicroELement (MEL) is a simplified software used to describe a basic IoT computation (Ranjan et al. 2018):

1. MicroServices: functionalities deployed/migrated across different infrastructures (e.g., Docker) available across Cloud, Edge, and Things layers;
2. MicroData: contextual information about i) devices, protocols for collecting and sharing data, ii) the specific type of data (e.g., temperature, vibration, pollution) it needs to process, and iii) data management steps, such as storage and access rules.
3. MicroComputing: executing analysis tasks based on historic and real-time data through tools such as NoSQL, stream processing, batch processing, etc.);
4. MicroActuator: interfaces with actuator devices for changing or controlling object states in the IoT.

MEL will need to expose a uniform programmatic interface (APIs) to models and analytics, hence, reducing the barriers to data ingestion. The new federated API suite may utilize the Apache Spark SQL API to benefit from its existing interoperability features, in addition to other Apache libraries such as Samza and Kafka. The API must be lightweight, and enable integration with services supported by other vendors.

## 4.3 Data Provenance

Traditional data provenance techniques require collection and transmission of large data volumes, which is impractical for IoT applications that warrant sub-second decision making and data processing latency. Hence, new techniques are required which can reduce and enhance the efficiency of provenance and metadata collection, recording, and transmission. Understanding how provenance relationships can be derived from IoT data processing activities is a challenge, as precedence relationships identifying which output was a consequence of an inputs may be difficult to establish.

One possible opportunity is to develop IoT data provenance technique based on Blockchain's Distributed Ledger Technology (DLT) to record lifecycle activities on data as it travels through the IoT ecosystem. Another hard challenge to solve will be to develop provenance techniques than can verify complying with data privacy regulation such as GDPR (Berberich & Steiner 2016). Undertaking GDPR compliance for statically held data (e.g. user information) can be easier to manage, however extending this to a dynamic data stream (which may be context dependent) remains a challenge. Another challenge is when IoT deployments involve more than one vendor. Finally, the authenticity of data and protecting it against organized campaigns is important. The roadmap recommends investing in technology to detect and eliminate misinformation and bias (amplified through the viral nature of social media) using algorithms like WSARE (What's Strange About Recent Events) and platforms such as SwiftRiver (Yu et al. 2016).

### 4.4 Access Control

It is important to identify application actors: Information flows between actors is modelled as message passing. Such messages are to be stated explicitly along with identification of the content of such messages. This makes it possible to discover which actors have access to information items necessary for answering provenance use case questions.

Of equal important is to map out actor interactions. This is a network of data items, users with access to them, and platform components processing them.

Finally, identify knowledgeable actors. Any actor that has access to an information item is known as a knowledgeable actor. The team will associate every information item (within a use case) with an actor. For each, the necessary provenance functionality is to be set. When an information has not been exposed in the interactions between actors through message exchanges, use cases (in data management system) must be revised.

### 4.5 Geo-Distributed Cross-Querying

In smart city applications, there is a need to curate data based on its geo-location. The challenge is to design multi-query planning algorithms that can not only map queries to different parts of an IoT infrastructure but also map that to the requirements of data analytics applications. The algorithms are required to also optimize end-to-end QoS associated with the query plan, to improve resource utility and meet users' SLAs. Existing geo-distributed querying systems were designed for managing only static data. They neither consider heterogeneous processing infrastructure, nor execute queries using standard heterogeneous models (e.g., stream processing, NoSQL, SQL, batch processing).

Event Processing Language (EPL) can enhance the performance of existing geo-distributed querying systems, EPL can limit the query data size to guarantee real-time processing. Hence, EPL has been used in majority of stream process platform such as Apache Spark, Kafka, Flink and Esper. Similar to SQL, however, one of the core limitations of EPL-based querying approaches is that they cannot handle heterogeneous data stored across multiple types of storage platforms and/or programmed using multiple types of storage and analytics programming models.

A more dynamic approach is to find data linkage through bottom-up discovery of association patterns. New tools such as blockmodeling (part of network analysis techniques) allow a platform to detect data clusters. Studying the patterns of repeated clusters can help discover and designate a set of data templates: a set of typical heterogeneous data that can be seen as complementary. This can span both the semantic and structured data. Machine learning approaches can also be very effective in this regard.

## 5 Pillar 2: Computation and Generation of New Knowledge

The computation pillar aims to create a bottom-up environment to foster collaborative analysis and re-mixing of data through collaboration between citizen scientists. This pillar spans the following features.

- Data representation: Structure and represent the data to facilitate multiple modalities (i.e. different models of data logic), exploiting the redundancy of different data sources.
- Data translation: Interpret data from one modality to another, i.e., a translator allows the modalities to interact with each other for enabling data exchange.
- Data alignment: bridges among modalities.
- Data fusion: integrate data from different domains
- Data co-learning: transfer modality knowledge between users.

The following are some relevant approaches to support bottom-up analyses of city systems:

### 5.1 Citizen Sensor Networks

Scientists and engineers are already providing interactive cloud-based models to help users (with limited or no technical background) to learn, conduct or study the use of some of these assessment methods. This can cover purely technical issues such as environmental modelling; visualization systems through interactive 3D modelling and GIS maps; and even tools to help connect mental models with quantitative system dynamics (Voinov et al. 2016). Examples includes (Evers al. 2016): stakeholder participation in developing an agent based model to profile social values; and modelling through role playing games (Haase et al. 2013); enhance acceptability of environmental models (Wassen et al., 2011); and environmental models validation (Newig et al., 2008). Kishita et al. (2016) developed a review of scenario generation for sustainability analysis, which is very relevant to supporting citizen science.

### 5.2 Gaming

Gaming has been used to help in recruiting and sustaining participants. Evolving as a venue for interactive co-creation, games galvanize partnerships and provide opportunities for peer-to-peer learning. They are also some of the best tools to study "choice molecules" (action-outcome combinations) especially when non-linearities make it hard to communicate system features and reactions in conventional learning and dialogue processes (de Suarez et al. 2012).

Cases for the use of games in co-creating and studying alternative futures include, for example, the game "Paying for Predictions". It helps in risk assessment in relation to resource shortages and disaster management in light of climate change. "Ready!" is a game that uses narrative to help identify solutions to environmental problems. The Rockefeller "Resilience game" addresses the disconnection between decisions and actions: government or communities not following options selected. The game "Before the Storm" generates decisions as players think through the various options that may be available to them when a particular disaster strikes. "Upstream, Downstream" game promotes consensus building and social learning through providing players with the ability to assign risks based on individual views. Through repeated reviews by all, a better collective understanding of risk can emerge. The game "Dissolving Disasters" considers choices in the context of changing probability of, say, rainfall. It is designed to rush players into decision making. Later, players are given time to reflect on the problem, and, more importantly, the decision making process.

### 5.3 Application Orchestration

An IoT application is typically expressed as a collection of multiple self-contained data analysis activities (e.g., MEL). These activities are orchestrated to execute in a specific order with specific rules that respond to user requirements. To realize a dynamic environment for citizens to collaborate on creating new knowledge, there is a need for platforms that can enable application orchestration, including the following:

- Choosing storage and analytics programming models (e.g., stream processing, batch processing, NoSQL) and data analysis algorithms to seamlessly execute in highly distributed and heterogeneous IoT;
- Dynamically detecting faults across multiple parts of the IoT infrastructure;
- Dynamically managing data, and software available in "Things, Edge and Cloud" layers driven by IoT.

## 6 Pillar 3: Modelling

Established models (such as IFC, for example) add context and structure to data. Such models represent the best means by which technical experts can communicate their knowledge to citizens in an indirect way. Because such models are limited to the data level, they allow users to benefit from the basic rules embedded in the data model, but, at the same time, they do not mandate specific analysis approach on the users. They act as connectors and check-system on data. This is similar to the IFC-BIM relationship. Users can be very innovative in their programming of BIM without worrying about the basics of data structures (they are served through IFC)

Using flexible data structures foster social learning. The proposed roadmap advocate balancing the top-down approach of data standards with a bottom-up discovery means. For example, the roadmap advocate using ontologies (formalized and programmed conceptual model) and, at the same time, using folksonomies (ad hoc, bottom-up and loose model of concepts).

On the long term, lifelong Machine Learning is a central paradigm in smart city systems. How to discover knowledge based on smart search, conduct intelligent analysis, and constantly re-train algorithms based on newly found knowledge. Recent trends in Transfer Learning and multitask learning are task-specific and domain-agnostic (Liu 2017). Such smartness is rooted and supported by the surge in synthesis research and the advancement of knowledge capture and representation tools. Synthesis is a type of inferential reasoning that recursively integrates inductive thinking (combine observations into a larger model) with deductive analysis (examining the consistency of a general model to real cases). Emphasis in recent years is focused on automating the inductive part given the mushrooming number of models in all domains.

### 6.1 Knowledge Capturing and Representation

Thanks to amazing advancement in semantic systems/ algorithms, the field of knowledge acquisition and representation has evolved into extensive and efficient levels. Probase (and its successor Microsoft

Concept Graph) is a probabilistic taxonomy (with 5.4 million concepts) that constantly assesses the typicality of knowledge using probabilities, which in turn is used to support probabilistic reasoning (Zang et al. 2013). YAGO2 is an informatics ontology based on WordNet and Wikipedia YAGO2 contains 10 million entities and 120 million facts, which were extracted automatically from Wikipedia, GeoNames, and WordNet. YAGO2 stores extraction rules in text files, which allows easy extension without changing source code. Human assessment of facts in YAGO2, showed that it achieved an accuracy of 95% (Hoffart et al. 2013). Freebase was a scalable graph database used to structure general human knowledge. The data in Freebase could be collaboratively created, structured, and maintained by people and software. Freebase provided automatic suggestion to help the user enter new knowledge. It was replaced by Googl's Knowledge Graph, which contains 70 billion facts!

Open Information Extraction (OPEN IE) is a protocol for extracting a large number of relations from arbitrary text on the Web without specifying the targets to be extracted (Fader et al. 2011). KnowItAll is a scalable and domain-independent system that uses OPEN IE for extracting facts from the Web in an unsupervised manner. It ran for four days on a single machine and extracted over 50 000 facts (Etzioni et al. 2004).

### 6.2 Cognitive and Anticipatory Computing

One of the most promising technologies in citizen science is cognitive computing. It refers to computers learning how to complete tasks traditionally done by humans. The focus is on finding patterns in data, carrying out tests to evaluate the data validity. A key technology in this regards is natural language generation (NLG). NLG is not like traditional natural language process (NLP) systems. NLG tools are able to transform unstructured data into readable summaries with synthesis of key takeaways. Advanced NLG offers traceability: why the system chose to communicate in a particular manner. Bots (a short name for software robots) are used for live chat with customers. Story Engine is a program that can read through unstructured data and summarize conversations, including the ideas discussed, the frequency of the communication and the mood of the speakers. Interestingly, some newspapers are starting to use some of these Bots to summarize sport events based on transcripts of commentators' speech.

The next frontier is anticipatory/assistive computing. In this regards, the computer moves from reacting to explicit commands into understanding implicit queries and anticipating questions and actions. Bot help search engines exploit big data analytics to infer similar/related strings of searches/questioning by other users (Reed et al. 2012). They exploit advances in inductive (logic) programming, which is predicated on finding solutions to problems/queries in the same manner humans would do through predicting next steps and inductively collating related facts from the web. Some of the most successful and sophisticated examples of Bots that deploy cognitive and anticipatory computing include Apple's Siri, Amazon's Alexa, Microsoft's Cortana, and Google's Google Home and Facebook Messenger. These and IBM's Watson apply deep learning for superior knowledge acquisition and representation. .

## 7 Discussion

Our aim here was not to build a technical architecture for smart city and citizen science applications. Rather, collate and organize relevant paradigms, governance issues and analysis approaches into a roadmap that can guide cities in developing the technical architecture. We advocated that smart city architecture has to balance the use of structured and unstructured data. They also have to be able to provide processed data and means to process data. A user, based on their technical agency can have the choice of using either approach. One of the main technical roles for a smart city architecture is in providing computational services (apps) that enables users to mix and match data analyses to produce new original contribution. Another significant contribution is to provide users with basic models that can create minimal and meaningful structure to data. This can include data models and ontologies or folksonomies.

The proposed architecture places special attention to machine learning and cognitive computing. These are very promising approaches in enabling smarter and easier analyses and, at the same time, customize the access, delivery and usage of data (including BigData) to user profiles.

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