Decision Support using Linked, Social, and Sensor Data

Research-in-Progress

David N. Crowley[1,2]
DERI, NUI Galway[1]
david.crowley@deri.org

Maciej Dabrowski[1]
DERI, NUI Galway[1]
maciej.dabrowski@deri.org

John G. Breslin[1,2]
Electrical & Electronic Engineering, NUI Galway[2]
john.breslin@nuigalway.ie

ABSTRACT

The explosion of social and sensor data available on the Web provides both challenges and opportunities for their exploitation in contemporary decision support systems. In this paper, we propose a framework for aggregating and linking heterogeneous data from various sources and transforming them to Linked Data. This allows reuse and integration of the produced data with other data resources enabling spatial business intelligence for various domain-specific applications. Our framework can be easily applied to aggregate and interlink data from various types of sources: legacy systems, citizen sensor data, sensor data, and open web data. This paper outlines a number of possible applications of the framework and discusses in detail an example use case where the proposed methodology facilitates identification of business opportunities in London City through analysis of various information facets including property pricing, population spending, sensor, and social data.

Keywords (Required)

Decision Support Systems, Linked Data, Citizen Sensing, Spatial Business Intelligence.

INTRODUCTION

The use of smartphones and other mobile devices led to exponential growth of various types of available user-generated data, also referred to as User Generated Content (UGC) (Wunsch-Vincent and Vickery, 2007) and published through numerous social platforms such as Facebook[1], Twitter[2], or Foursquare[3]. Availability of such rich, cross-domain data creates a need for a new type of decision support tools that offer business intelligence capabilities exploiting UGC and location of the users to provide information that is much more complete for decision makers in various domains. At the same time, a large volume of structured, interlinked data is openly available in the form of Linked Data (see Figure 1 – Linked Open Data Cloud) (Heath, Bizer, 2011). The usage of such data requires novel methodologies and robust tools for linking and analysis of large datasets both on the Web and within organizations. Recent studies (Chen, Chiang, and Storey, 2012) explore the challenges for supporting decisions with large, location-aware data from various sources and domains. In this paper, we address this challenge, discuss a framework for combining social, open, and legacy data with physical sensors using linked data principles, and examine use cases where the linked data cloud is highly relevant for decision support, both for businesses and government.

In the past ten years, we have seen the growth of online social networks and an explosion of UGC on the Web, in particular published from mobile devices. For example, a popular microblogging platform Twitter was founded in 2006 with an extremely fast growing user base with 175 million users[4] by October 2010 and about 340m posts processed per day as of March 2012 with 140m active users[5]. The ease of posting to services like Twitter while attaching data such as pictures, videos, and links significantly contributes to the growth in the volume of UGC.

---

[1] http://facebook.com/

[2] http://twitter.com/

[3] http://foursquare.com/

[4] http://www.pcmag.com/article2/0,2817,2371826,00.asp

[5] http://blog.twitter.com/2012/03/twitter-turns-six.html

With the growth of ownership of smart mobile devices that often include a multitude of sensors like GPS, applications that build upon these sensors have become commonplace. In the U.S.A., ownership of smartphones is at 45% of adults according to PEW Research Center (Smith, 2012) and 50.5% according to Nielsen[6]. Mobile devices offer location services through both GPS and coarse-grained location from cell masts or wireless networks. As of February 2012, 74% of smartphone owners use their phone to access location-based information (up from 55% in May 2011). At the same time, only 18% of smartphone users use location-sharing services like Foursquare to share their locations with their friends (Zickuhr, 2012). In the case of Twitter, only ~1.5% posts contain geolocation information as Twitter's post geolocation is disabled by default (opt-in policy). Nevertheless, research on retrieving user location from social media content (Kinsella, Murdock, O' Hare, 2011; Cheng, Caverlee, and Lee, 2010) has demonstrated that "hidden in most data is a geographical component that can be tied to a place: an address, postal code, global positioning system location, (…) region or country" (Business Objects, 1998). This geographical component can be viewed as a valuable common factor that, together with linked data from different sources, supports spatial business intelligence and decision support.

The contributions of this research in progress paper are twofold. First, we acknowledge the need for decision support tools that aggregate heterogeneous data from various sources. We argue that the use of Semantic Web technologies and Linked Data can facilitate the integration of sensor, social media, and open (linked) data improving spatial business intelligence and decision support. Secondly, we propose a generic framework for aggregating and linking heterogeneous data from various sources and transforming them to Linked Data building upon existing W3C standards (e.g. Resource Description Framework[7]). This allows reuse and integration of the produced data with other data resources (including social media and sensors) enabling spatial business intelligence for various domain-specific applications. Our framework can be easily applied to aggregate and interlink data from various types of sources: legacy systems, citizen sensor data, sensor data, and open web data. In the next sections, we review the relevant literature on citizen sensing and linked data. We follow up with an overview of the proposed framework, discuss present possible applications of the framework, and consider in detail an example use case where the proposed methodology facilitates identification of best location for a business in London area.

BACKGROUND

Business intelligence technologies provide historical, current, and predictive views of business operations, among other including reporting, analytics, or predictive analytics. Business Intelligence applications typically use data gathered from a data warehouse, yet "the cost of deploying a large data warehouse to support a BI system is still high for many organizations" (Lawton, 2006). (Chung, Wingyan, and Tzu-Liang Bill Tseng (2010) argue that UGC, such as online product reviews or microblog posts, is a valuable source of data for BI applications. Cao and colleagues (Cao, Meihong, and Xiangjiu Shen, 2012) support this view and in their recent study show that information integrated from multiple sources can be efficiently used by decision makers at various levels. Nevertheless, based on a comprehensive review of literature and a set of interviews, Blomqvist (2012) argued that although the need for information integration exists, the solution to the integration problem does not exist in contemporary systems. Further, many BI systems fail to incorporate sufficiently external data sources such as Web data or user-generated content. Unfortunately, the use of Semantic Web technologies, considered a cornerstone for the Linked Data Cloud, in developing Decision Support Systems (DSS) is very limited. Through interlinking of data with metadata, provenance, and with the Linked Data Cloud we can create better data warehousing approaches and allow for creation of better decision support tools (Watson and Wixom, 2007). In this section, we provide an overview of most notable applications of these technologies in BI and outline major challenges for integration of social, open and sensor data, focusing on citizen sensors and linked data.

Citizens as Sensors

Goodchild discusses citizen sensing in the field of Volunteered Geographic Information (VGI) and sees citizens as a network of human sensors with over "6 billion components, each an intelligent synthesizer and interpreter of local information. One can see VGI as an effective use of this network, enabled by Web 2.0 and the technology of broadband communication" (Goodchild, 2007). Sheth defines the role of these citizen sensors as "humans as citizens on the ubiquitous Web, acting as sensors and sharing their observations and views using mobile devices and Web 2.0 services" (Sheth, 2009). Citizen sensors are very capable of providing quality information, for example, OpenStreetMap project created maps with large volumes of geographic data that were entirely produced by volunteers (Goodchild, 2013). These user-generated maps have been described as a significant step towards the use of UGC in GIS (Boulos, 2005). Further, social platforms such as Twitter allow for both non-human sensors and humans carrying smartphones to directly post time, date, and location-stamped sensor

[6] http://blog.nielsen.com/nielsenwire/online_mobile/who-owns-smartphones-in-the-us/

[7] http://www.w3.org/TR/REC-rdf-syntax/

readings to Twitter, and consume tweets relating to the physical world. In this context, accuracy of location services is of utmost importance especially in applications and environments, where GPS is not at its most accurate. Although a potential issue for some specific cases, fairly accurate (e.g. within 10m+ range) localization is enough for most applications. In our use case (Section Use Case), this coarse-grained location in urban areas where there is cell mast coverage and Wi-Fi networks would be sufficient to allow decision makers to get timely, appropriate, and relevant information. Companies like Foursquare already utilize coarse location for their check-in system, as users of smartphones do not generally have GPS service activated.

In Sheth's citizen sensing, the people themselves can be seen as acting in a similar manner to physical sensors, but what is being sensed must typically be derived from the texts of their status updates, photo or microposts. Citizen sensing and crowdsourcing have been applied to a large number of use cases as described in (Boulos, Resch, Crowley, Breslin, Sohn, Burtner, Pike, Jezierski, and Chuang, 2011). Various studies (Crowley, Passant and Breslin, 2011; Demirbas, Bayir, Akcora, Yilmaz and Ferhatosmanoglu, 2010) examined forms of “sensor tweeting standard” and tweet metadata. The embedding of metadata into these short messages is important due to the casual nature of the language used on Twitter where words and phrases are often abbreviated similar to Short Message Service (SMS) style messages. Citizen sensors can be characterized as proactive (human) sensors that have the ability to share information through mobile devices on social media sites; this combined with the humans’ background knowledge, experience, and perception transforms any device-holder in a potential proactive intelligent sensor. In contrast, passive sensors collect data without any active participation like for example a traffic monitoring system or a travel card system that stores trip data (Villatoro and Nin, 2013). Yet, the real value (and challenge) lays in analysis of these diverse data streams, in particular combined with the Linked Data Cloud.

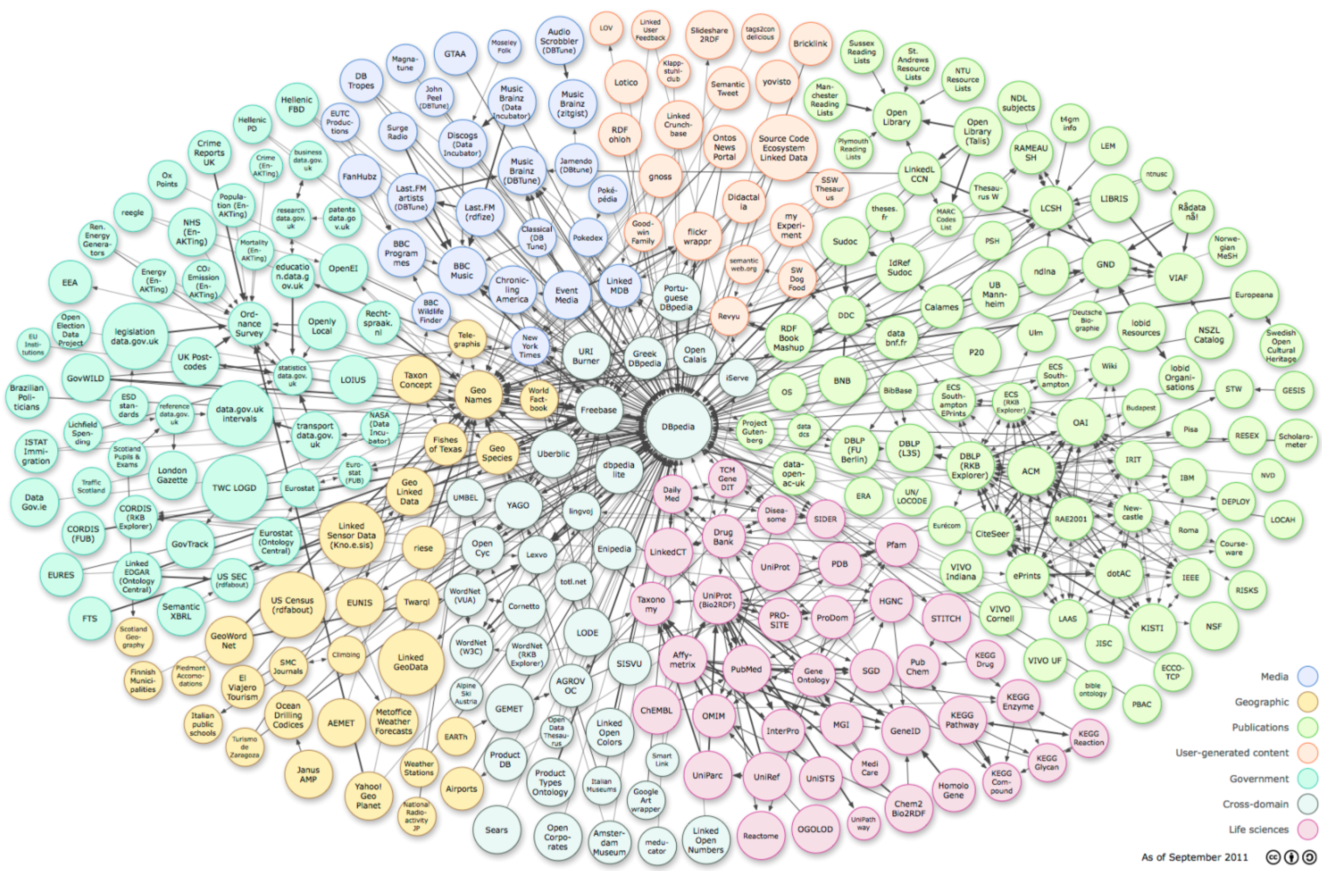


Figure 1 - Linked Open Data Cloud diagram, by Richard Cyganiak and Anja Jentzsch. http://lod-cloud.net

Linked Data Cloud

Linked Data provides a publishing paradigm in which not only documents, but also data, can be a first class citizen of the Web, thereby enabling the extension of the Web with a global data space based on open standards - the Web of Data (Heath, Bizer, 2011). Linked data leverages the existing open protocols and standards from the World Wide Web Consortium (W3C) and the existing architecture of the World Wide Web for sharing structured data on the web. As part of the Open Data movement many organizations, governments, and scientific communities are actively publishing data on the web as Linked Data (Heath, Bizer, Berners-Lee, 2009). The advantage of Linked Data can be seen as the rise in value of your information by linking to other datasets and resources (Berners-Lee, 2006). Linked Data allows data to become a first class citizen of the Web and the system described later utilizes these principles to enable social and sensor web data to become part of this Web of Data. Figure 1 shows published datasets in Linked Data format and clusters the datasets by category, like media, geographic, government, cross-domain, and life sciences.

The aggregation of citizen sensing data and Linked Data Cloud poses a number of challenges for data integration, linking and usage for spatial business intelligence and decision support. In the next section, we discuss a framework that by leveraging the power of Semantic Web technologies enables the aggregation and linking of heterogeneous sources of data and their use in various decision support applications, enabling key business intelligence functions, including interactive information dashboards and location intelligence.

LINKED SENSOR FRAMEWORK

In this section, we present the architecture of a framework (see Figure 2) that aggregates and interlinks data from heterogeneous sources (e.g. citizen sensors, legacy information systems) and provides decision support capabilities in various domain and context-specific applications. **Citizens** generate large volumes of highly valuable, geolocated data through their use of social platforms and mobile devices. In particular, the available types of **data sources** include social and sensor data, open data available on the Web, as well as enterprise information systems (i.e. data warehouses) that are crucial for enterprise BI applications. This data from different, heterogeneous sources are processed by linked data wrappers (open data or social data) and Linked Sensor Middleware (LSM) (as discussed in the next section), converted to a suitable format (e.g. RDF) and linked to other existing datasets in the **Linked Data Cloud**. Various domain-specific data analytics and decision support **applications**, both in enterprise and citizen context, can be created that exploit this aggregated data and enable more informed decisions. For example, by using census, social, and sensor data, companies can investigate market size and customer tastes in a given area to justify the decision about launching a new business initiative (e.g. new pharmacy). At the same time, various citizen-centric applications are possible, such as local government involving citizens in a given area to provide opinions and crowdsource solutions to specific problems (e.g. decisions on public transport, schools in the area etc.). In the next paragraphs, we discuss in more detail the components of the Linked Sensor Framework outlined previously.

Data Sources

Building sensor networks in urban environments can be problematic as cost of sensor nodes, their distribution, and creation of dense networks is often not viable due to geographical and monetary issues (Welsh, 2010). *Citizen sensing data* can augment physical sensor data and create denser networks that provide a clearer picture of a given environment. Citizen sensor data from social platforms is often available to external systems through APIs. Twitter due to its relatively open API and its binary user privacy features (user's account is either open or closed) is the platform that this work will concentrate on but platforms such as Facebook, Flickr, and Google+ could also be integrated. On the technical level, developers can access Twitter data stream in three modes: firehose, gardenhose, and spritzer that provide 100%, 10%, and 1% of user posts respectively. Twarql (Mendes, Passant, Kapanipathi, Sheth, 2010) uses information extraction techniques to extract entities (including hashtags) from the tweets, converts the tweets into RDF, and publishes them as Linked Data. By converting tweet content into RDF it is also possible to link the entities extracted (for example #Obama) to concepts on the Linked Open Data Cloud from sources such as DBPedia (a structured data version of Wikipedia), technology pipelines such as the examples given here allow for the aggregation of social sources with the Linked Data Cloud.

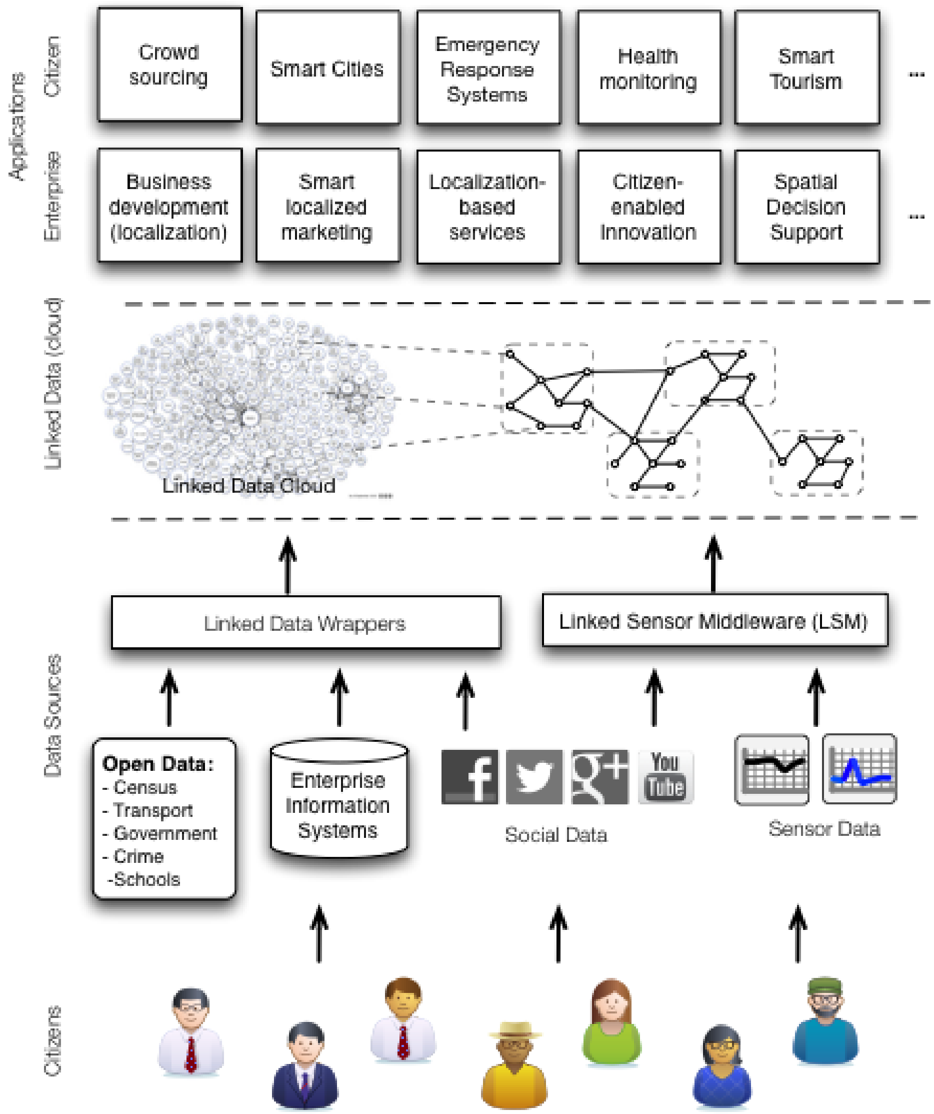


Figure 2 An overview of the Linked Sensor Framework.

Fusion of this *physical sensor* and *citizen sensing* data (Liu, Chu, and Tsai, 2012) has been examined as a method for disaster surveillance for when physical sensors are unavailable or incapable of supplying adequate data. Sensor data can be represented in many formats like SensorML, Observations, and Measurements (OM) from the Open Geospatial Consortium (OGC), and more recently the W3C Semantic Sensor Network (SSN) ontology. The SSN ontology merges the concepts from SensorML (sensor focused), the OGC OM (observation focused), and system models. The SSN ontology is used in the Linked Stream Middleware system described in the next section, as it is very flexible in representing a sensor. It develops a general representation of sensors and relies on upper-level ontologies to define the domain, and an operation model that describes the implementation of the measurement. The representation of a sensor in the ontology links together what it measures (the domain), the physical sensor (the grounding) and its functions and processing (the models) (Compton, Barnaghi, Bermudez, García-Castro, Corcho, Cox, Graybeal, Hauswirth, Henson, Herzog, Huang, Janowicz, Kelsey, Le Phuoc, Lefort, Leggieri, Neuhaus, Nikolov, Page, Passant, Sheth, Taylor, 2012). Studies in the area of citizen sensing leveraged the capabilities of the SSN ontology to model sensors on mobile devices for rural transportation projects (Corsar, Edwards, Velaga, Nelson, and Pan, 2011) and in emergency reporting applications using social media (Crowley et al, 2011).

With the current push in many countries (for example U.S.A., United Kingdom, Ireland, Australia and New Zealand) for transparent government, publishing open data is becoming a standard practice. This data is often in data dumps or in spreadsheet style formats but conversion to RDF and linking to the Linked Data Cloud is quite common and some datasets from this data already exist (data.gov.uk datasets).

Linked Sensor Middleware

Linked Stream Middleware (LSM)[8] a platform developed at Digital Enterprise Research Institute (DERI)[9] aggregates live real world sensed data and uses semantic web technologies to produce linked data and make it available to other tools. It is an example of a large-scale sensor platform that through combining with citizen sensing data can provide an insight into many application areas like smart cities or city planning. A sample LSM deployment is available at http://lsm.deri.ie/ that currently displays data from over 100,000 sensors around the world including flight status, weather, trains/buses arriving times, street cameras, sea level monitors etc. The interface uses a map overlay (see Figure 4) to display the sensor information. The data produced by a particular source is available and downloadable in RDF format (Le-Phuoc, Quoc, Parreira, and Hauswirth, 2011). The LSM architecture, as shown in Figure 3, is divided into four layers, the Data Acquisition Layer which provides three wrapper types. Physical wrappers designed for collecting sensor data from physical devices and Linked Data wrappers that expose relational database sensor data into RDF. Mediate wrappers allow for collection of data from other sensor middleware like Global Sensor Networks (GSN)[10], Cosm[11], and the sensor gateway/web services from National Oceanic and Atmospheric Administration (NOAA)[12]. The Linked Data Layer allows access to the Linked Sensor Data created by the wrappers and links to the Linked Data Cloud (a subset of the Linked Open Data Cloud as shown in Figure 1). The Data Access Layer provides two query processors a Linked Data query processor and the Continuous Query Evaluation over Linked Streams (CQELS) engine and exposes the data for end-users or machine-users. The fourth layer, the Application layer offers a SPARQL[13] (an RDF query language) endpoint, a mash-up composer, linked sensor explorer, and streaming channels (Le-Phuoc, Dao-Tran, Parreira, and Hauswirth, 2011).

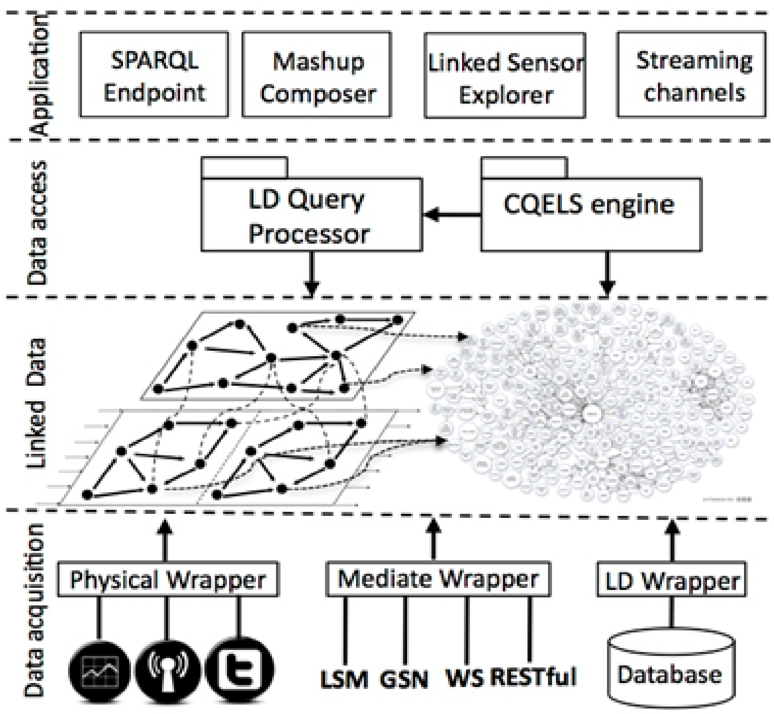


Figure 3 Linked Sensor Middleware overview, following (Le-Phuoc, Dao-Tran, Parreira, and Hauswirth, 2011).

[8] http://code.google.com/p/deri-lsm/

[9] http://www.deri.ie

[10] http://sourceforge.net/apps/trac/gsn/

[11] http://cosm.com/

[12] http://www.noaa.gov/

[13] http://www.w3.org/TR/rdf-sparql-query

The LSM system is of importance in the area of decision support as it implements a scalable architecture applicable for large-scale projects. Scalability and reliability are important factors when designing any system; but when collecting real-time stream data (i.e. from Twitter feeds or sensor feeds) then uptime and scaling of a system is critical to process the data in real time. Transforming the sensor data into a standard format like RDF also allows for standard sensor descriptions using the SSN ontology as described earlier. By implementing LSM with Linked Data principles, it allows easier integration of citizen sensing data, interlinking between sensor data and citizen data, and allowing interconnection with other Linked Data sources (i.e. government open data).

USE CASE: IDENTIFY BEST LOCATION FOR A NEW VENTURE

The methodology described in the previous section can be applied to decision problems in various domains. Due to space limitations, we focus on one use case that is identification of business opportunities in a given area. The decision about the location for a new venture (e.g. coffee shop) is vital for increasing the chances of a success, yet very difficult. Our approach enables aggregation of various sources of data (see Table 1) to enable comprehensive analysis and minimize decision risk.

Goal Find best location for the new business (coffee shop) in London given estimated market size, spending, crime levels, social tastes/moods, and property prices together with sensor data.	
Social data	• Twitter[14] – micro blog posts with localization indicate interests and mood. • Flickr[15] – pictures of relevant neighborhoods and properties. • Foursquare[16] – check-ins to similar businesses in the area of interest.
Sensor data	• Traffic density (Oyster cards)
Open data	• Recent property transaction data[17] • Public transport timetables[18] • Job density[19] • Census data • Area maps (available through http://maps.google.com/)
Legacy data	• News articles

Table 1 Example data sources utilized in the decision making process.

There are a number of factors crucial for making a good business decision. In our use case, we identify potentially interesting locations for a coffee shop in London taking into account number of potential customers estimated using census (population density), social media (check-ins, activity), open data (job density), and sensor data (traffic volume and oyster card usage). The location for the use case was selected based on 655 available open datasets for the area of London[20]. Potentially interesting areas can then be evaluated on multiple criteria including property price (Fig 4a) and crime levels (see Fig 4b), as well as topics and opinions expressed by people in the area through social media and local news sources. Concrete buildings and/or premises can be initially assessed using their current market price and recent pictures collected by traffic sensors and cameras (see Fig 4c) as well as by citizen sensors through services such as Flickr (see Fig 4d). The aggregated localized data can be overlaid on maps and combined based on user preference to interactively support decisions. For example, an investor that attempts to find the best location for his new coffee shop in London can analyze a wide range of factors that is impossible to analyze using current business intelligence tools. Such comprehensive analysis may lead him to different

[14] http://twitter.com/

[15] http://flickr.com/

[16] http://foursquare.com/

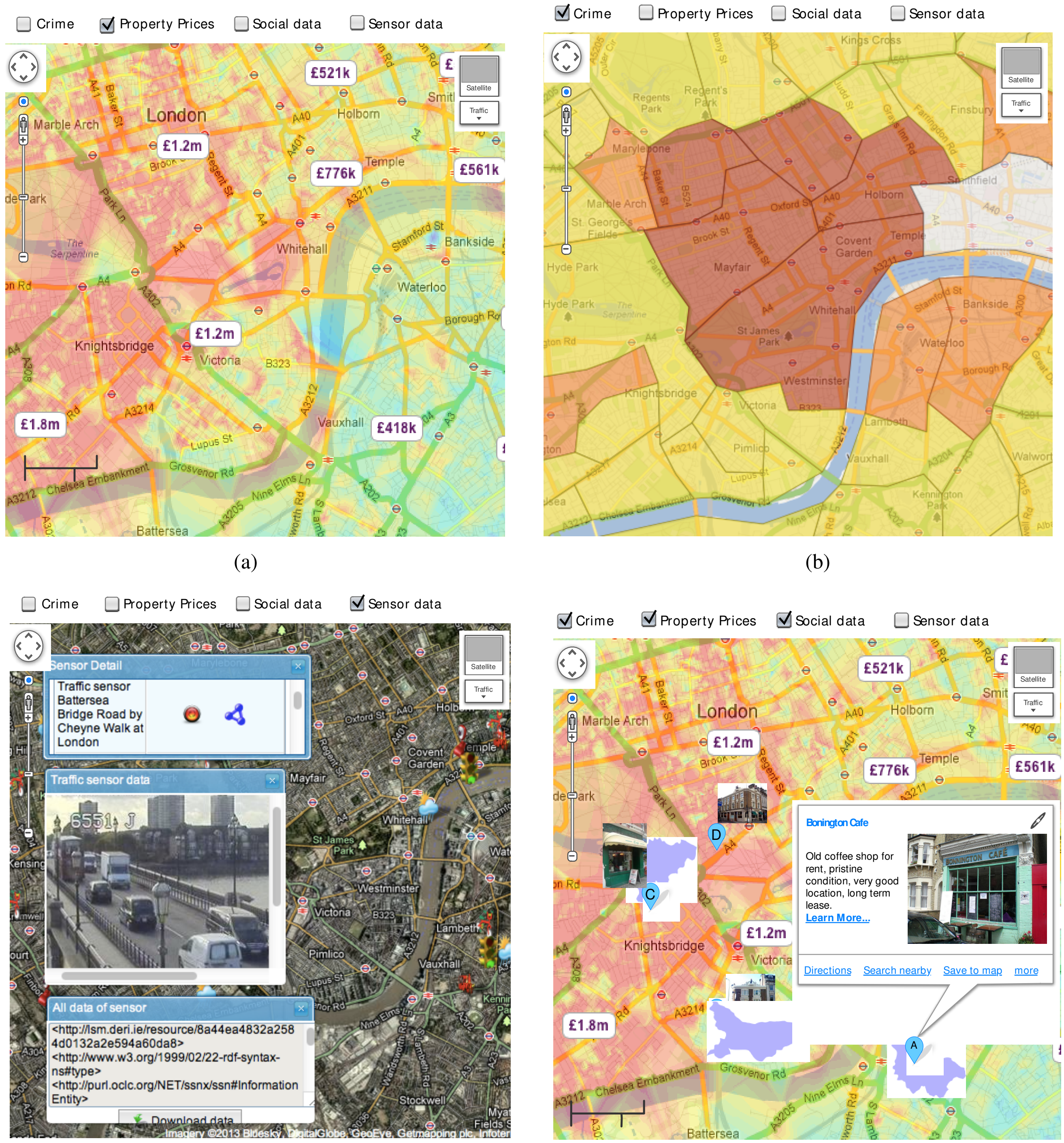
[17] http://www.landregistry.gov.uk/professional/market-trend-data/public-data/transaction-data

[18] http://data.gov.uk/dataset/nptdr

[19] http://data.london.gov.uk/datastore/package/jobs-and-job-density-borough

[20] http://data.gov.uk/data/search?ext_bbox=-0.52,51.24,0.33,51.72

investment decision and not only affect revenue but also propel local growth. It is worth mentioning that in our use case we used just a small set of dataset that we found relevant. The data included in the analysis can be selected based on interest and requirements for specific applications and contexts (for example traffic density and public transport timetable for transport-related decisions).



(a) (b)

(c) (d)

Figure 4 Spatial Business Intelligence platform using Linked, Social and Sensor data. (a) Property prices, (b) crime data, (c) sensor data view using lsm.deri.ie, (d) complete view with images, property prices and suggested areas (blue).

Other Applications

The methodology we discuss here can be applied to a variety of use cases and adapted to accommodate very diverse data sources. Other possible applications may include decision support systems for emergency response, smart cities and tourism or spatial crowdsourcing (see Figure 2 for more examples). Crowdsourcing is a recently popular approach often defined as "a type of participative online activity in which an individual, an institution, a non-profit organization, or company proposes to a group of individuals of varying knowledge, heterogeneity, and number, via a flexible open call, the voluntary undertaking of a task." (Estellés-Arolas and González-Ladrón-de-Guevara, 2012). Many commercial crowdsourcing platforms such as InnoCentive[21] or Daily Crowdsource[22] enable generation of novel ideas and promote innovation among citizens. Crowdsourcing is also used in solving government challenges[23] and aids in policy making through citizen participation, location-based surveys and can provide valuable opinions on new developments or new traffic layouts. Our framework supports spatial crowdsourcing, among other applications, through integration of UGC (opinions, social media data, surveys) with sensor data and other sources, allowing for example, collection of opinions, sentiment and ideas from particular area of London about best dates for closure of a given subway station for maintenance, or changes in public transport timetables. Other applications include mobile social reporting, where citizens can report issues within their locality or issues they experience while traveling i.e. in their local commercial area (Crowley, Corcoran, Young, and Breslin, 2012).

CONCLUSIONS

In this paper, we proposed a framework for aggregating and linking heterogeneous data from various sources and transforming them to Linked Data building upon existing W3C standards. This allows reuse and integration of the produced data with other data resources enabling spatial business intelligence for various domain-specific applications. Our framework can be easily applied to aggregate and interlink data from various types of sources: legacy systems, citizen sensor data, sensor data, and open web data. This paper outlines a number of possible applications of the framework and discusses in detail an example use case where the proposed methodology facilitates identification of business opportunities in London City through analysis of various information facets including property pricing, population spending, sensor, and social data. We show how existing components such as Linked Sensor Middleware (http://lsm.deri.ie/) can be integrated with our framework providing access to 100s of thousands of available sensors in a selected location around the World.

ACKNOWLEDGEMENTS

The work presented in this paper is funded in part by Science Foundation Ireland under grant number SFI/08/CE/I1380 (Líon 2)

REFERENCES

1. Berners-Lee, T. (2006). Linked data-design issues.
2. Bizer, C., Heath, T., & Berners-Lee, T. (2009). Linked data-the story so far. *International Journal on Semantic Web and Information Systems (IJSWIS)*,*5*(3), 1-22.
3. Blomqvist, Eva. "The use of Semantic Web technologies for decision support–a survey." Semantic Web Journal, 2012.
4. Boulos, M. N. K., Resch, B., Crowley, D. N., Breslin, J. G., Sohn, G., Burtner, R., Pike, W. A.,Jezierski, E., & Chuang, K. Y. S. (2011). Crowdsourcing, citizen sensing and sensor web technologies for public and environmental health surveillance and crisis management: trends, OGC standards and application examples. *International journal of health geographics*, *10*(1), 67.
5. Cao, Meihong, and Xiangjiu Shen. "The business intelligence-based integrated information management system in the road transport research." *Information Management, Innovation Management and Industrial Engineering (ICIII), 2012 International Conference on*. Vol. 1. IEEE, 2012.
6. Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: from big data to big impact. *MIS Quarterly*, *36*(4), 1165-1188.

[21] http://www.innocentive.com

[22] http://dailycrowdsource.com

[23] http://challenge.gov

7. Cheng, Z., Caverlee, J., & Lee, K. (2010). You are where you tweet: a content-based approach to geo-locating twitter users. In *Proceedings of the 19th ACM international conference on Information and knowledge management*(pp. 759-768). ACM.
8. Chung, Wingyan, and Tzu-Liang Bill Tseng. "Extracting business intelligence from online product reviews: An experiment of automatic rule-induction." (2010).
9. Compton, M., Barnaghi, P., Bermudez, L., Garcia-Castro, R., Corcho, O., Cox, S., Graybeal, J., Hauswirth, M., Henson, C., Herzog, A., Huang, V., Janowicz, K., Kelsey, D. W., Le Phuoc, D., Lefort, L., Leggieri, M., Neuhaus, H., Nikolov, A., Page, K., Passant, A., Sheth, A., & Taylor, K. (2012). The SSN ontology of the W3C semantic sensor network incubator group. *Web Semantics: Science, Services and Agents on the World Wide Web*.
10. Corsar, D., Edwards, P., Velaga, N., Nelson, J., & Pan, J. (2011). Short Paper: Addressing the Challenges of Semantic Citizen-Sensing. In *4th International Workshop on Semantic Sensor Networks, CEUR-WS* (pp. 90-95).
11. Crowley, D. N., Passant, A., & Breslin, J. G. Short Paper: Annotating Microblog Posts with Sensor Data for Emergency Reporting Applications. In *Proceedings of the 4th International Workshop on Semantic Sensor Networks 2011 (SSN11), a workshop of the 10th International Semantic Web Conference-ISWC 2011: 23-27 October 2011; Bonn, Germany* (pp. 84-89).
12. Crowley, D. N., Corcoran, P., Young, K., & Breslin, J. G. (2012, September). Gamification of citizen sensing through mobile social reporting. In Games Innovation Conference (IGIC), 2012 IEEE International. IEEE.
13. Demirbas, M., Bayir, M. A., Akcora, C. G., Yilmaz, Y. S., & Ferhatosmanoglu, H. (2010, June). Crowd-sourced sensing and collaboration using twitter. In *World of Wireless Mobile and Multimedia Networks (WoWMoM), 2010 IEEE International Symposium on a* (pp. 1-9). IEEE.
14. Estellés-Arolas, Enrique and González-Ladrón-de-Guevara, Fernando (2012), "Towards an Integrated Crowdsourcing Definition", *Journal of Information Science* 38(2): 189–200
15. Goodchild, M. F. (2013). Unforeseen at GISRUK '93. *Transactions in GIS*.
16. Goodchild, M. F. (2007). Citizens as sensors: the world of volunteered geography. *GeoJournal*, *69*(4), 211-221.
17. Heath, T., & Bizer, C. (2011). Linked data: Evolving the web into a global data space. *Synthesis Lectures on the Semantic Web: Theory and Technology*,*1*(1), 1-136.
18. Kinsella, S., Murdock, V., & O'Hare, N. (2011). I'm eating a sandwich in Glasgow: modeling locations with tweets. In *Proceedings of the 3rd international workshop on Search and mining user-generated contents* (pp. 61-68). ACM.
19. Lawton, George. "Making business intelligence more useful." *Computer* 39.9 (2006): 14-16.
20. Le-Phuoc, D., Quoc, H. N. M., Parreira, J. X., & Hauswirth, M. (2011). The linked sensor middleware–connecting the real world and the semantic web.*Proceedings of the Semantic Web Challenge*.
21. Le-Phuoc, D., Dao-Tran, M.,Parreira, J.X., & Hauswirth, M. (2011). A native and adaptive approach for unified processing of linked streams and linked data. *The Semantic Web–ISWC 2011*, 370-388.
22. Liu, J. W. S., Chu, E. T. H., & Tsai, P. H. (2012). Fusing human sensor and physical sensor data. In *Service-Oriented Computing and Applications (SOCA), 2012 5th IEEE International Conference on* (pp. 1-5). IEEE.
23. Mendes, P. N., Passant, A., Kapanipathi, P., & Sheth, A. P. (2010, August). Linked open social signals. In *Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010 IEEE/WIC/ACM International Conference on* (Vol. 1, pp. 224-231). IEEE.
24. Rosi, A., Mamei, M., Zambonelli, F., Dobson, S., Stevenson, G., & Ye, J. (2011). Social sensors and pervasive services: Approaches and perspectives. In *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2011 IEEE International Conference on* (pp. 525-530). IEEE.
25. Sheth, A. (2009). Citizen sensing, social signals, and enriching human experience. *Internet Computing, IEEE*, *13*(4), 87-92.
26. Sheth, A., Henson, C., & Sahoo, S. S. (2008). Semantic sensor web. *Internet Computing, IEEE*, *12*(4), 78-83.
27. Smith, A. (2012). 46% of American adults are smartphone owners. Pew Internet & American Life Project.

28. Villatoro, D., & Nin, J. (2013). Citizens Sensor Networks. In *Citizen in Sensor Networks* (pp. 1-5). Springer Berlin Heidelberg.

29. Watson, H. J., & Wixom, B. H. (2007). The current state of business intelligence. Computer, 40(9), 96-99.

30. Welsh, M. (2010). Sensor networks for the sciences. *Communications of the ACM*, *53*(11), 36-39.

31. Wunsch-Vincent, S., and G. Vickery. "Participative Web: User-Generated Content. Organisation for Economic Co-operation and Development." (2007).

32. Yerva, S. R., Jeung, H., & Aberer, K. (2012). Cloud based social and sensor data fusion. In *Information Fusion (FUSION), 2012 15th International Conference on* (pp. 2494-2501). IEEE. Business Objects (1998). Business Objects and ESRI Announce Strategic Partnership Press Release.

33. Zickuhr, K. (2012). Three-quarters of smartphone owners use location-based services. *Retrieved August*, *15*, 2012.