Making Smart Cities *Smarter*
Using Artificial Intelligence Techniques for Smarter Mobility

Javier Vázquez-Salceda, Sergio Alvarez-Napagao, Arturo Tejeda-Gómez, Luis Oliva,
Dario Garcia-Gasulla, Ignasi Gómez-Sebastià and Victor Codina
Universitat Politècnica de Catalunya-BarcelonaTech, Barcelona, Spain
{jvazquez, salvarez, jatejeda, loliva, dariog, igomez, vcodina}@lsi.upc.edu

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Abstract: The term *Smart City* is tipically applied to urban and metropolitan areas where Information and Communication Technologies provide ways to enable social, cultural and urban development, improving social and political capacities and/or efficiency. In this paper we will show the potential of Artificial Intelligence techniques for augmenting ICT solutions to both increase the cities competiveness but also the active participation of citizens in those processes, making Smart Cities *smarter*. As example we will describe the usage of Artificial Intellgence techniques to provide Smart Mobility in the context of the SUPERHUB Project.

1 INTRODUCTION

The term *Smart City* is a broad term that refers to the *smart* management of the cities socio-economic and environmental capital through the use of Information and Communication Technologies. These technological solutions are said to be *smart* as they provide ways to enable social, cultural and urban development, improving social and political capacities and/or efficiency. But sometimes there is some abuse on the term, converting any technological solution that eases information gathering, analysis, management or sharing as a Smart City solution, without careful analysis of its real impact on the cities efficiency or capacity, and on the users empowerment.

Mobility is one of the main challenges for urban planners in the cities. Even with the constant technological progress, it is still difficult for policy makers and transport operators to 1) know the state of the city in (near) real-time, and 2) achieve proximity with the end-user of such city services, especially with regards to communicating with the citizen and receiving proper feedback. Many Smart City solutions for mobility have focused on empowering the user with the ability to decide the best way to move through the urban or metropolitan transport network, by creating *journey planners*. But most of the existing journey planners only provide a few options to let users customize, to some extent, how the journey should look like. The reality, however, is more nuanced – different users might prefer different routes and/or combinations of modes and these may, in addition, depend on the users context (e.g. a shopping trip, travelling with small children or going back home) as well as on the environmental context: weather, traffic, crowdedness, events. Specifying all of the circumstances affecting what the user perceives as the ideal plan, however, would be overwhelming. The use of personalization in the field of journey planning is mainly focused on tourism (Ricci, 2002), although there are other domains where routes are also recommended, e.g., for sporting/leisure purposes (Diaspero et al., 2011; Knoch et al., 2012). For instance, (Diaspero et al., 2011) produces journey hiking walkways according to a set of milestones or personalize journey plans by choosing from pre-defined routes which better fit users preferences. Afterwards, the selected routes are enhanced by means of adding Points Of Interest (POI) -relevant geographical features that may be relevant to the user. In general, these approaches can be considered as aimed at providing journey plans to users on closed domains where the set of potential journey plans is already defined, and those plans are built based on a recommended set of POIs (e.g., touristic routes), meaning that first the POIs are obtained and routes designed to visit them. Other approaches try to overcome this closed domain constraint. While some solutions successfully generate this kind of routes, they do not incorporate users preferences or just a small set of generic preferences are taken into account (e.g., departure time or cost) (McGinty and Smyth, 2003).

Another aspect that is overlooked in many ICT solutions for Smart Mobility is the role citizens can play to perceive and build an up-to-date model of the city status. Thanks to smartphones, users that move in a city can potentially generate automatic data that may be hard to obtain otherwise: location, movement flow, average trip times, and so on. Moreover, network problems and incidents that affect mobility services are often documented by users in Social Networks at the same time or, in some cases, even before those are detected by the mobility operators. This phenomenon has been referred to as *humans as sensors* (Srivastava et al., 2011). Sensing the city through mobile humans potentially provides sensor coverage where events are taking place, and takes advantage of the citizen's capacity to analize the situation and evaluate its impact at the individual and even the collective level. Some proposals have recently appeared to exploit data generated by users to sense the cities' status, either from the individual sensoring perspective, closer to multi-agent based systems (Ellul et al., 2013) or from big data techniques applied to social network streams by combining statistical analysis with semantic interpretation (Gabrielli et al., 2013). However, such proposals work at a granularity level that is either too high or too low: in the former approach there is, in principle, no centralised mechanism to maintain global aggregations; in the latter, systems do not take advantage of the end-user terminals and their potential dispersion in time and space. In this paper we present a system that can work at both levels, leveraging global aggregations with local awareness to have the best possible picture of the context of the city whenever possible.

In this paper we will present some of the results of the EU SUPERHUB project(Carreras et al., 2012), describing how, by the usage of some Artificial Intelligence techniques (knowledge representation, machine learning, natural language processing, sentiment analysis, semantic inference, information diffusion models and knowledge mining techniques), interactions of users in certain social networks -i.e.: Twitter and Foursquare- are combined with knowledge of the city, city events calendars and geospatial data to learn local behavioural patterns in the city, capture those deviations that may reflect events that affect mobility in the city and then provide better travel recommendations, taking advantage of a richer city model and a more accurate user profiling.

2 THE CASE OF SUPERHUB

SUPERHUB (Carreras et al., 2012) is a project co-funded by the European Commission that aims at realizing a new services mobility framework supporting an integrated and eco-efficient use of multi-modal mobility systems in an urban setting. The main goal of the project is to provide an open platform able to consider in real time various mobility offers and to provide a set of mobility services able to address user needs, promote user participation, and foster environmental friendly and energy-efficient behavioural changes.

To achieve this SUPERHUB is developing:

1. a persuasive engine based on captology principles to facilitate the voluntary adoption of environmentally-friendly multi-mobility habits,
2. novel methods and tools for real-time reasoning on large data streams coming from heterogeneous sources,
3. new algorithms and protocols for inferring traffic conditions from mobile users by coupling data from mobile operator networks with information coming from both GPS based mobile phones and social network streams,
4. mechanisms for dynamic matchmaking of resources, and
5. a journey planner with the goal of best fulfilling user mobility needs and preferences while minimizing negative environmental impact.

The concept of the project builds on the notion that citizens are not just mere users of mobility services, but represent an active component and a resource for policy-makers willing to improve sustainable mobility in smart cities. In SUPERHUB, users play an active, consumer and producer role (prosumer), acting, on the one hand, as providers of mobility offers, such as in car-pooling negotiations, and on the other hand, as consumers of mobility resources, such as taking the bus, using a public parking, or renting a bike).

The SUPERHUB travel planner employs the state of the art user modelling and recommender systems techniques – by observing the past users' choices and the context in which these choices were made, SUPERHUB gradually learns the model that accurately reflects the multifaceted nature of each users preferences and constraints. During a journey plan search, the user model is used, in addition to the automatically acquired contextual information, to guide the search process in order to provide highly-tailored journey plan recommendations that best reflect the unique needs and situational context of each user. Technically, the personalization process relies on a mixture of contextual content-based filtering plus the use of semantics applied to contextual data, thus being able to assess different contexts, even if these have not been experienced by the user yet.

In addition, journey plans are further personalized by means of opportunistic recommendation. The SUPERHUB opportunistic recommender enhances journey plans by adding points of interest that might be interesting for the user during the journey. For example, if the user is going back home and she has to wait to take the train, the recommender may suggest having a coffee or doing some small shopping. In some circumstances, the recommender may even suggest alternative destinations (e.g. a different cinema or supermarket) if the original destination is difficult to reach in a current traffic.

2.1 From City Sensing to City Interpretation

In a real-world setting, the SUPERHUB journey planner has to be ready to receive high amounts of journey plan requests and deliver multimodal recommendations that best fit a wide range of criteria, including the user preferences. However, the evaluation of such criteria is continuously dependent on factors that occur in the external world, what we call the context of the request. But the context, given the same external conditions, is always city-dependent. For instance, a request for a journey plan made in January in a day that it is snowing defines different contexts if the user is in Helsinky (where snowing is considered a normal situation and public transport is prepared) or if the user is in Barcelona (where snowing is considered an extraordinary case that has numerous, unpredictable consequences on the transport networks). Therefore, weather sensor data may be useful to detect a context, but not sufficient by itself.

Another issue is aggregating heterogeneous situational data in a common model when such data is specified at different levels of abstraction. For instance, a subset of the SUPERHUB sensor adaptors belong to the field of web-based social networks, with content typically expressed in plain text. Some intermediate steps (based in Natural Language Processing (NLP) semantic extraction techniques) must be followed in order to extract a structured concept representation of the meaning of the raw data. More generally, data has to be normalised, so that values used in the representation of the data belong to the same abstract data type ranges; and aggregated, so that data that comes from potentially unreliable sources can be contrasted and therefore reinforced or discarded. Expert knowledge in the form of input models, such as the model of the city, designed by mobility experts, is converted into rules that will be used to infer a first abstraction of knowledge.

Both data homogeneisation and the inference of the state of mobility in a city are made by the Semantic Interpreter. We take advantage of state-of-the-art semantic interpretation techniques in order to infer knowledge from both situational and historical data. Via the Semantic Interpreter, raw data is filtered, normalised and interpreted into high-level concepts. Such concepts can be merged and analysed to generate derivative concepts that are not explicit in the sensor data but implicit in the aggregation of large instances of it. The analysis relies in applying expert knowledge and information about the city and is based in semantic methods rather than statistical ones. The obtained knowledge can be then applied by other SUPERHUB components for several diverse purposes, such as managing mobility high-level contexts to generate more fine-grained user models, or being able to understand normality with respect to policy fulfillment and thus derive and predict unexpected situations.

2.2 Inferring City Context from Social Networks

In SUPERHUB, situational data is retrieved not only from sensors such as weather or traffic sensors, but also from the social networks. Twitter (microblogging), Instagram (microblogging) and Foursquare (location-based) data are combined in order to automatically model the normal situations in the city and detect abnormal ones. Based on user's geolocated posts, the Semantic Interpreter is able to identify: which are the main points of interests, how the people move along the city on their daily basis or before/after an event occurs (trajectories), and specific mobility user profiles (e.g. tourists). Besides that, other data sources are cross referenced with social networks data in order to filter noisy information, provide reliability and add explanations about events and validate the results of the detection system.

In the case of tweets, text content related to mobility concepts are aggregated and analysed in time windows in order to find located trends (Weng and Lee, 2011). In information diffusion, reliability of data obtained is a big concern, and our solution is to filter bots and spammers by analysing the topology of the individual social networks of the users (Boccaletti et al., 2006), and by calculating their influence on other users (Gomez et al., 2012). The Foursquare API adds to the reliability score of the aggregated data by contrasting the detected trends against area-based collections of check-ins in the same time windows.

One interesting usage of social network data is for the detection of disruptive (un-expected) events. Disruptive events and incidents in the mobility city field are abnormal situations that have a negative impact on the city mobility, for instance: traffic or metro service. In order to maintain a reliable mobility city behaviour, it is necessary to detect and predict these kind of events. Basically, a normal situation in the city can be modelled under a spatio-temporal context; which can be defined as any information that characterize a situation. It means that a day of a week, weather conditions, city zone (geolocation) and the type of road could be part of this context. For instance: traffic could be different on Monday at 7:00 am compared to Saturday at the same time; between two different weather conditions (rainy or sunny); or the type of road (highway or boulevard). However, to monitor an entire city with several type of sensors for discovering disruptive events and incidents may not be affordable. Alternatively, a *human as a sensor* approach brings a new opportunity to minimize the cost and reveal information that cannot be extracted directly from others sensors. Users can inform and provide context about events having real impact on them in real-time. The identification of recurrent events allow the classification of what is normal and what it is not.

2.3 Context-aware Travel Recommendendation

SUPERHUB aims to generate journey plans taking into consideration both a rich user behavioural model and an up-to-date context model. Users select a destination and plans are designed accordingly, using different modes of transport, including carpooling. The Intelligent Mobility Recommender is composed by three main components: the IMR Manager, which manages mobility requests and keeps user behavioural profiles; the Journey Plan Recommender (JPR), which incorporates the user preference to support journey plan design; and the Opportunistic Recommender (OR), which provides opportunistic recommendations.

In SUPERHUB, Journey Plans are dynamically generated by the JPR with regards to different criteria (among them the user preference). The generation of Journey Plans is done iteratively, searching for suitable Journey Legs and using critics to reduce search space. Finally, once the set of Journey Plans have been found, the OR selects POIs along the route that may be appealing and may represent opportunities for the user to improve his experience. Semantic relations and interpretations of items are used to enhance the OR results, to obtain semantically similar POIs which are described in SUPERHUB's City Model. Then, the selected POIs are added to the Journey Plan to enhance it. Given that the domain of POIs is not as large as Journey Plans it is feasible to consider collaborative-filtering approach, which has proven to be effective and requires less information about items (venues in this case). Nevertheless, collaborative-filtering can suffer from data sparsity, thus we use Matrix Factorization to find latent factors and reduce sparsity.

Both the IPR and OR recommenders contribute to build and maintain a user model and make use of contextual data to perform context-aware recommendations. When context matters, as is the case of mobility domain (e.g., when it is raining people prefer to avoid walking or riding a bike), it is sensible to use a user model that has been learnt with feedback acquired in the same context as the target user because only that feedback is relevant for the prediction. This allows improving results and dynamically adapt to the real situation in the city and to user's needs, goals and current context (e.g., in a rush, going to work, with children). Both recommenders use context to pre-filter the learned user models and exploit contextual user models which are built taking into account the contextual information obtained from situational data.

Both approaches, using contextual information and semantics, provide novelty to the state of the art beyond the use of recommenders in the mobility domain. The closest approach to ours is the one by (Diaspero et al., 2011) which incorporates the user preference to support journey plan design. SUPERHUB differs from that approach that routes are not taken from a pre-defined set, but are dynamically generated according to contextual situation in the city. Thus, (Diaspero et al., 2011) adds a set of POIs to enhance the routes which is similar to SUPERHUB's approach for opportunistic recommendation, although it does not take into consideration contextual information.

3 CONCLUSIONS

In this paper we have outlined the usage of a combination of Artificial Intelligence techniques (knowledge engineering, machine learning, sentiment analysis, semantic inference, information diffusion) to enhance mobility in the cities, by empowering users not only with means to plan their routes through the transport network smartly but also to act as sources of event information that can help build a better snapshot of the city status. On one hand SUPERHUB's Semantic Interpreter receives interactions of users in certain social networks and combines them with city-specific knowledge, city events calendars and geospatial data. Data is analysed in two stages, on-line and off-line, in order to learn behavioural patterns and capture those deviations that may reflect events that affect urban mobility. On the other hand SUPERHUB's Intelligent Mobility Recommender, by having a strong focus on the use of semantically-enhanced contextual information, provides better route recommendations more suitable for the current user needs and situation.

The Semantic Interpreter is currently running and producing results for Barcelona, Milan and Helsinki, the three trials cities for the SUPERHUB project evaluation. Depending on the periodicity of the aggregation set in the configuration of the Semantic Interpreter instance, the delay between the start of the event in the city and the instant at which it is detected by the SUPERHUB platform may vary, but we have empirically proven it can be as low as 5 minutes. Early versions of the Intelligent Mobility Recommender have been tested with real users in the three cities, and the final version will be tested and validated in the third quarter of 2014.

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