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Recommender systems for smart cities

Lara Quijano-Sánchez*

Escuela Politécnica Superior, Universidad Autónoma de Madrid
UC3M-BS Institute of Financial Big Data, Universidad Carlos III de Madrid

Iván Cantador

Escuela Politécnica Superior, Universidad Autónoma de Madrid

María E. Cortés-Cediel, Olga Gil

Facultad de Ciencias Políticas y Sociología, Universidad Complutense de Madrid

Abstract

Among other conceptualizations, smart cities have been defined as functional urban areas articulated by the use of Information and Communication Technologies (ICT) and modern infrastructures to face city problems in efficient and sustainable ways. Within ICT, recommender systems are strong tools that filter relevant information, upgrading the relations between stakeholders in the polity and civil society, and assisting in decision making tasks through technological platforms. There are scientific articles covering recommendation approaches in smart city applications, and there are recommendation solutions implemented in real world smart city initiatives. However, to the best of our knowledge, there is not a comprehensive review of the state of the art on recommender systems for smart cities. For this reason, in this paper we present a taxonomy of smart city features, dimensions, actions and goals, and, according to these variables, we survey the existing literature on recommender systems. As a result of our survey, we do not only identify and analyze main research trends, but also show current opportunities and challenges where personalized recommendations could be exploited as solutions for citizens, firms and public administrations.

Keywords: Recommender Systems, Smart Cities, Urban Computing, Smart Sensors, Internet of Things, Open Data

1. Introduction

Smart city's definition was first issued in the 1990's decade, referring to the use of Information and Communications Technologies (ICT) and modern infrastructures within cities (Albino et al., 2015). Since then, the idea of smart city has been evolving, and nowadays is a fuzzy concept (Albino et al., 2015; Caragliu et al., 2011). The research literature is divided according to the method followed to identify the aspects a city must have in order to be considered smart (Alawadhi et al., 2012; Cortés-Cediel et al., 2019). Some authors have emphasized the importance of technological infrastructures, and have conceptualized a smart city as a functional urban area articulated by ICT, without which it is not possible to manage city services in efficient and sustainable ways (Anavitarte and Tratz-Ryan, 2010; Washburn et al., 2010). Hence, for example, Harrison et al. (2010) indicated that an intelligent, instrumental and interconnected city is possible through the integration of data obtained from sensors, physical devices, software applications, personal cameras, the web, smartphones and similar devices. Other authors, in contrast, have claimed that the notion of smart city is no longer solely related to the existence of technological city infrastructures, but to other types of infrastructures such as human and business ones, associating the idea of social capital and its relations within

*Corresponding author

Email addresses: lara.quijano@uam.es (Lara Quijano-Sánchez), ivan.cantador@uam.es (Iván Cantador), mcorte04@ucm.es (María E. Cortés-Cediel), olgagil@ucm.es (Olga Gil)

the urban environment (Albino et al., 2015). Hence, we can consider that smart cities use technology and human and business networks with the aim of improving economic and political efficiency, and are oriented to cultural, social and urban development (Hollands, 2008; Caragliu et al., 2011; Alkandari et al., 2012; Cortés-Cediel et al., 2019).

In the last two decades, smart city initiatives, conceived as a way to achieve a more sustainable development in urban environments (Alawadhi et al., 2012), have been progressively adopted to mitigate city problems mainly derived from the rapid growth of urban population and the uncontrolled urbanization (Chourabi et al., 2012). As pointed out by Gil-García et al. (2013), the poor management of resources leads cities to experience air pollution and major mobility difficulties, as well as high unemployment rates and unsafe environments due to the increase of criminal activities. In this context, aiming to improve aspects such as the citizens' quality of life and empowerment, a smart city is conceptualized as a scenario where the citizen is the center of all the services and initiatives that take place in the city, and where the use of technology plays a very important role.

The increasing development of smart city initiatives has been motivated by both the omnipresent use of ubiquitous computing and mobile solutions, and the significant recent advances in technological infrastructures, such as the development of low-cost sensors, the miniaturization of electronics and the advances in wireless communications (Salim and Haque, 2015). In particular, smart cities are equipped with different computing devices ranging from sensors embedded in everyday objects to smartphones, which collect information in real time from both the city and the citizens, and which are interconnected via internet enabling them to send and receive data. This phenomenon, so-called Internet of Things (IoT), is considered a core element in the implementation of smart city technological applications. In this scenario, another fundamental pillar of smart cities is Open Data, since it facilitates the development of public services applicable to all areas, such as business and public governance itself (Murgante and Borruso, 2015).

Critics have claimed that too often the design of online public services has been focused on the technological possibilities instead of the users' needs, and thus have called for more user-centered services (Verdegem and Verleye, 2009). Addressing this issue, progress has to be made on the development of personalized approaches that not only improve the effectiveness and efficiency of the services, but also increases the users' satisfaction and engagement (Dawes, 2008). In addition, the overwhelming amount of data and services also requires the implementation of information filtering approaches aimed to address the existing problems in a city, targeting its variety of stakeholders. It is in these contexts where recommender systems have challenging opportunities (Cortés-Cediel et al., 2017). In particular, within smart cities, recommender systems can be used to upgrade the relations between stakeholders, e.g., governments and the civil society, and assist in decision making tasks in the city through technological platforms.

There are scientific articles covering recommendation approaches in smart city applications, and there are also recommendation solutions implemented in real world smart city initiatives. However, to the best of our knowledge, there is not a comprehensive review of the research literature on that topic. Motivated by this fact, in this paper we provide a survey of the state of the art on recommender systems for smart cities. We first compile a number of smart city features, and present a taxonomy of smart city dimensions –namely smart economy, smart environment, smart mobility, smart governance, smart living and smart people–, actions and goals. Then, according to such features and taxonomy, we describe, characterize and compare recommender systems that have been proposed in the literature. From the conducted survey, we do not only identify and analyze research trends, but also show current research opportunities and challenges where personalized recommendations could be provided as solutions for citizens, firms and public administrations.

The remainder of the paper is structured as follows. In Section 2, we present an overview of recommender systems. In Section 3, we introduce the research methodology followed to identify and select the surveyed papers. In Section 4, we gather smart city definitions given in the literature, we explain the dimensions in which smart city initiatives are commonly classified, we describe their principal actions and goals, and we analyze the presence of the recommender systems reviewed in those categories. Next, in Section 5, we conduct a comparative analysis of the reviewed papers. Lastly, in Section 6, we end with some conclusions and future research directions.

2. Recommender systems

Recommender systems are information filtering systems designed to ease decision-making in domains and applications where there are many options to choose from. We refer the reader to (Adomavicius and Tuzhilin, 2005) for a comprehensive overview and (Ricci et al., 2015) for detailed explanations on research issues of recommender systems. Differently to search engines where a user has to specify her needs and interests in the form of a query, recommender systems are proactive in suggesting items of potential relevance for the user, according to personal data and preferences previously recorded in a profile.

The recommendation problem has mainly three tasks, namely, 1) collecting information about users; 2) learning from collected information and predicting users' preferences for unknown items; and 3) applying a function or building a model that selects (and ranks) the items that are more likely to be preferred by users.

In the next sections, we provide descriptions of the above tasks, and explain concepts and issues about recommender systems that will be considered in this paper.

2.1. Data collection and profiling

In order to provide personalized suggestions, recommender systems make use of past choices and preferences to reflect the users' tastes and interests. This information can be either explicitly provided or implicitly inferred.

Explicit feedback alludes to direct preference statements made by users about items they know. This knowledge is usually stored as *ratings* or as unary/binary values. Numeric ratings are used to range several (dis)like degrees and allow ranking items accordingly, whereas binary ratings are a simplified form of explicit preferences with which the users only acknowledge their positive or negative opinions about items. Besides, being the simplest form of explicit preferences, unary ratings reflect the users' affinity for a particular item; in this case, dislike preferences are omitted. Explicit feedback allows for a precise control on what the system knows about the users' preferences, but requires time and effort from users. Moreover, when including explicit interactions in real-world applications, there is a risk of biases in rating distributions and thus in item relevance predictions, as users may tend to rate only what they like (Zhao et al., 2018).

Implicit feedback, on the other hand, refers to user preferences that are inferred from user interactions with the system and/or the environment. This form of preferences can be obtained by recording search queries, product purchases, and mouse actions, among others. While it allows capturing abundant information about users, it tends to obtain information that is more noisy and may be biased to positive preferences (Zhao et al., 2018). A special type of implicit feedback in recommender systems is composed of data generated by mining personal opinions and contents freely available on social media resources such as social network profiles, textual reviews, blogs and forums (Anandhan et al., 2018).

In addition to explicit and implicit user preferences, there are **other features** that can be used to model users such as demographic data, personality traits, emotional states or trust relationships.

Furthermore, when designing a recommender system, the items to recommend also have to be profiled in some way. Again, there are several techniques –either explicit or implicit– to describe the items. Hence, profiles can be built with keywords, descriptions, attributes, properties, and latent features, i.e., features computed from observed features using matrix factorization, among others.

2.2. Types of recommender systems

Recommender systems can be classified according to different principles depending on the task they are focused in –i.e., predicting item ratings and ranking item sets–, the approach to extract user preferences –i.e., implicit or explicit–, and the recommendation dynamics they follow –e.g., single-shot or unique answer and conversational or iterative approaches.

In the literature, nonetheless, two main categories of recommender systems are usually considered, based on the way recommendations are generated: 1) **content-based** (CB) systems, which recommend items similar to those liked in the past (Lops et al., 2011), and 2) **collaborative filtering** (CF) systems (Ekstrand et al., 2011), which suggest to users items preferred by 'similar' people. In general, the former makes use of item similarities based on textual representations, whereas the later exploits rating patterns. Also, for each of the above categories, recommender systems can be placed by the algorithmic approach they use. In this sense, there are again two main types: 1) **heuristic-based**, which estimate the relevance of items through mathematical formulas and 2) **model-based**, which predict the relevance of items through machine learning techniques.

Recommendation approaches have different strengths and weaknesses. Some of the most common weaknesses are: the *rating sparsity problem*, which alludes to the fact that the ratings available are very small, and the *cold-start problem*, which occurs when the system does not have sufficient information about a (new) user to whom provide personalized recommendations (Schein et al., 2002).

2.2.1. Content-based recommenders

They use textual descriptions and/or additional content information –such as keywords, metadata, semantic annotations, and social tags–, to represent users and items, and suggest items whose profiles are more similar to the target user's requirements (Lops et al., 2011). Modeling item profiles so that they are available for automatic analysis is one of the main issues in this type of systems. In this context, it has to be noted that item descriptions may be obtained from contents in social media (e.g., reviews in e-commerce sites, posts in social networks, and blogs) that have to be processed accordingly.

A representative example of *heuristic-based* CB approaches is the Vector Space Model (VSM) for ad hoc document filtering, which converts document texts into vectors, and computes how closely/related documents are through a vector similarity function, such as Cosine or Jaccard. *Model-based* CB approaches are for example based on Bayesian models, which are intended to classify items as relevant or non-relevant (Pazzani and Billsus, 1997).

Cased-based recommenders are a particular type of CB filtering where recommended items are past recommendation cases similar to those the target user is currently interested in (Bridge et al., 2005). Furthermore, *ontology-based* recommenders are a specific type of *semantic-based* recommenders that model domain concepts and their relationships enhancing the computation of semantic similarities between items (Middleton et al., 2004).

2.2.2. Collaborative recommenders

They rely on the ratings already assigned by users to existing items (Ekstrand et al., 2011). Based on rating patterns or latent factors, these systems suggest to the target user items preferred by people with similar tastes and interests.

The most popular example of CF is the k–Nearest Neighbors (kNN) algorithm, a *heuristic-based* approach that makes use of mathematical formulas aimed to predict ratings by referring to the k-users' rating profiles more similar to those of the target user's (*user-based*), or to the k-items whose rating profiles are most similar to a queried item (*item-based*). Neighborhood methods vary considerably in how they compute user/item similarities and how they aggregate the rating profiles of most similar users/items. Specific examples of similarity measures are *Pearson correlation* (Herlocker et al., 2000), *Mean-Squared-Difference* (Herlocker et al., 2002), and *Vector cosine* (Pham et al., 2011).

On the other hand, examples of CF recommenders following *model-based* approaches, which build rating prediction models from training data by optimizing certain error or loss function, include artificial neural networks (Salakhutdinov et al., 2007), *cluster-based* methods (Ungar and Foster, 1998), and latent factor or Matrix Factorization (MF) models (Koren et al., 2009), among others.

2.2.3. Other types of recommenders

There are other types of recommenders aimed to address specific issues. This is the case of *context-aware* recommendation methods, which consider users' context (e.g., location, time, climate, etc) to enrich personalized recommendations (Adomavicius and Tuzhilin, 2015); *social-based* recommendation methods, which analyze users' social networks and their connections to recommend items that friends or other trusted users like (Quijano-Sánchez et al., 2013); *knowledge-based* recommendation methods, which keep a functional knowledge base that portraits how a specific item meets the needs of a particular user (Lu et al., 2015); and *demographic-based* recommendation methods, which rely on demographic data as an indicator of closeness between people (Al-Shamri, 2016).

Aiming to avoid specific limitations or problems of each recommendation approach, *hybrid* recommender systems combine two or more methods of different types (Burke, 2002).

2.3. Evaluation of recommender systems

Being still an active research topic, evaluation in recommender systems mainly requires three aspects to benchmark, namely the environmental setting, the testing data preparation, and the quantitative comparison between the recommendations (Gunawardana and Shani, 2015).

2.3.1. Online evaluation of recommender systems

When a recommender system is deployed in a real platform or environment, it can be evaluated with end users, who receive and thus test recommendations online and in real time. The conducted experiments can then be focused on analyzing the users' behaviour in reaction to the recommendations they receive. For such purpose, a commonly followed evaluation methodology is the well known **A/B testing** technique (Kohavi et al., 2009), where some users are assisted by a system A while others use a system B. Afterwards, stored user feedback is analyzed offline comparing the two systems according to certain metric.

The metrics in online evaluations may measure aspects related to the users (e.g., recommendation accuracy, and click-trough-rate), the vendor (e.g., catalog coverage, and revenue and churn rates) or even technical aspects of the system (e.g., CPU load, and scalability).

2.3.2. User studies to evaluate recommender systems

If there is not a deployed platform or environment where evaluations at large scale can be done, recommender systems may still be evaluated with users. In this case, a prototype system is usually tested in a controlled setting, where a limited number of people participate in what is called a user study (Knijnenburg and Willemsen, 2015).

This type of experiments require recruiting people willing to participate, for which **crowdsourcing** solutions are usually adopted. User studies can also follow a methodology based on A/B testing. However, in many cases, they are oriented to or complemented with user questionnaires, where participants express personal satisfaction or other subjective opinions about certain characteristics of the system, such as usability, serendipity and explainability. Besides these aspects, offline metrics about rating prediction accuracy and recommendation ranking quality could be also computed and analyzed. We overview some of these metrics next.

2.3.3. Offline evaluation of recommender systems

It is the most popular and cheapest approach. It is usually conducted on standard **datasets**, such as those provided by the Minnesota GroupLens group[1]. These datasets have relatively large amounts of real user feedback that were generated in a deployed system during certain period of time and are publicly available for research purposes. The provided data is acknowledged as the ground truth with which recommendation methods should be empirically compared.

With respect to offline metrics, we first have to distinguish between two types of accuracy metrics. Firstly, there are metrics proposed to measure the error made in the *rating prediction task*. Examples of these metrics, which nowadays are in disuse in the recommender systems area, are the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE). Secondly, there are metrics aimed to measure the ranking/order accuracy in the *top-N recommendation task*. Examples of these metrics are Precision, Recall, Mean Reciprocal Rank (MRR), and normalized Discounted Cumulative Gain (nDCG). Moreover, in addition to accuracy, other quality measures are commonly considered such as diversity or novelty (Gunawardana and Shani, 2015).

For particular domains where no datasets have been published, researchers may conduct simulations and artificially generate synthetic datasets. In these cases, they are not able to evaluate recommendation accuracy, but other aspects such as item catalog coverage, recommendation diversity, and system scalability.

3. Survey methodology and scope

In this work, we survey the state of the art on recommender systems aimed to address problems and challenges of smart cities. To collect the surveyed papers we first launched a formal query to the ISI Web of Knowledge[2] (WOK) and Elsevier Scopus[3] digital libraries, which index publications of major journals and conferences in a variety of academic disciplines. For both databases, the query was defined as the intersection between two specific queries: retrieving papers about recommender systems, and retrieving papers about smart cities.

More specifically, the first query was defined to retrieve those papers whose title or abstract contains any of the following keywords (enumerated by means of the OR Boolean operator): `recommender*`, `recommendation system*`, `recommendation service*`, `recommendation approach*`, `recommendation model*`, `recommendation method*`, `recommendation algorithm*`, `recommendation application*`, `recommendation engine*`,

[1] `https://grouplens.org/datasets`
[2] `https://www.webofknowledge.com`
[3] `https://www.scopus.com`

`recommendation framework*`, and `collaborative filtering`, where the asterisk `*` refers to the regular expression symbol that can be replaced by none or any combination of characters; Similarly, the second query was defined to retrieve those papers whose title or abstract contains any of the following keywords: `smart cit*`, `smart building*`, `smart home*`, `urban computing`, `internet of things`, `iot`, `smart economy`, `smart environment`, `smart mobility`, `smart governance`, `smart living`, and `smart people`.

The selection of the above keywords was done carefully in order to perform a query that retrieves the maximum number of relevant papers, and the minimum number of non relevant papers. For instance, the keyword `recommendation*` was discarded since it has associated a large number of papers related to recommendation guidelines instead of recommender systems. In this context, although our survey targets smart city applications, we also wanted to consider recommendation solutions for smart homes and smart buildings that may have a significant impact at city level. For this reason, we also included keywords for such concepts in the query. Moreover, we note that in addition to Internet of Things keywords, we also tested keywords related smart/intelligent sensors, but finally rejected them since the papers retrieved were out of the scope of our survey. We also launched queries including keywords related to digital cities and intelligent cities (Hollands, 2008; Komninos, 2009), but the few papers retrieved did not align with our study goals. Lastly, we note that recommender systems have been proposed in the area of urban computing (Zheng et al., 2014; Zheng, 2019), so we included it as a keyword in the query. We are aware, nonetheless, that we may be omitting relevant papers which were not presented in the context of smart cities. For a survey of these potential cases, mostly location-based recommender systems, the reader is referred to (Bao et al., 2015).

Furthermore, there exist relevant papers about Decision Support Systems for smart city applications that have certain recommendation component or functionality. We decided to filter them out since we understand their main focus was not in the recommendation approaches, as they did not contain any of our title and abstract keywords.

Executing the queries in March 2019, and considering only papers written in English, the number of initially retrieved documents were 287 and 369 from WOK and Scopus respectively. Merging both lists of results, we obtained a final set of 514 unique papers, dating from 2000 to 2019.

Afterwards, we manually inspected all the above papers, accepting for analysis those papers about (personalized) recommendations: aiming to address needs, problems or goals of a city, exploiting sensor or open data from a city, or mining sensor data or user generated contents in smart homes and smart buildings that may have an impact at city level.

Besides these constraints, we removed papers when the mentioned or proposed recommendation approaches were not described (with enough detail), and we imposed specific constraints to accept or reject papers for each of the smart dimensions. In Section 4, we shall explain these particular constraints. With all the above, we finally selected 94 papers for analysis and comparison. We note that when designing the conducted survey, we had to choose between performing a detailed review of a limited number of mature works –e.g., those works that present a system implementation and/or an exhaustive evaluation–, or a broad review of works presenting general issues and trends where any smart city-related topic had been addressed by means of a recommender system. Considering the seminal status of many of the compiled works, we focused on the latter option. Hence, with the goal of providing an entry point to the area, we covered the literature over all the smart city dimensions, thus helping to understand and identify which aspects and topics have attracted more attention and which ones have been relatively overlooked.

4. Recommender systems and smart cities

Nowadays, there is a general consensus about the existence of a number of relevant dimensions where smart city initiatives can be categorized. Among the many definitions, Giffinger et al. (2007) proposed six dimensions, which have been chosen as the theoretical framework for this survey. The dimensions, identified from factors appearing in numerous smart city initiatives, are: *smart economy*, *smart environment*, *smart mobility*, *smart governance*, *smart living*, and *smart people*. In the next subsections, we describe these dimensions and highlight the presence of the surveyed recommender systems in them. We shall conduct a comparative analysis of such papers and approaches in Section 5. For each smart city dimension, the analyzed recommender systems are grouped by their addressed smart city actions and goals. An *action* refers to a major initiative aimed to address a city issue or problem (e.g., *traffic management* in the mobility dimension), whereas *goals* are particular objectives that are established to fulfill a given action (e.g., *reducing traffic congestion*, *optimizing parking*, and *increasing driving safety* for the *traffic management* action).

4.1. Smart economy

In this dimension, smart solutions are aimed to stimulate economic growth through diverse actions that seek to promote flexibility in the labor market, productivity and transformation capacity, among others (Giffinger et al., 2007). The economic growth goals pursued in this dimension are mainly achieved by means of innovation mechanisms or ecosystems that are generated as different technological, human or economic infrastructures (Komninos, 2009). In particular, favoring the **creation of entrepreneurial environments**, these innovation infrastructures lead to the advent of new forms of collaboration between local authorities, businesses, research institutes and universities (Komninos et al., 2013). To foster these innovation environments, specific public policies are necessary. As Camagni et al. (1998) indicated, these policies should increase the innovation capabilities of the city and encourage local expertise in aspects such as knowledge production and use. In this sense, some key goals are **promoting local businesses**, **improving economic productivity** and **supporting business and commerce networks**. In addition to the previous actions, there are other smart economy initiatives aimed to provide flexibility in the labour market such as those focused on **facilitating access to the labour market**, **reducing unemployment** or **developing technological advances that enhance work flexibility**.

4.1.1. Recommender systems and smart economy

The surveyed papers that belong to the smart economy dimension have three main goals, namely promoting local businesses, improving economic productivity, and supporting business and commerce networks in a city. We do not consider papers presenting e-commerce recommender systems and papers about decision support systems aimed to improve a company productivity. These cases are focused on interests and needs of particular businesses and not on those of citizens, government actors or local businesses of a city.

Promoting local businesses. Regarding the development of a city economy by promoting local businesses, Ahrary et al. (2014) proposed a system that coordinates stakeholders, communicates and produces automatic inventory updates, provides citizens with healthy food recommendations, and suggests restaurants healthy menus based on local farmers' stock, whereas Tu et al. (2016) presented a system aimed to improve local stores advertising effectiveness in digital signage deployed in urban spaces. In the context of government-to-business (G2B) services, where recommender systems can inform companies about events that concern both their businesses and government agencies, Guo and Lu (2007) presented a system that suggests suitable exhibitions to individual businesses.

Improving economic productivity. In a situation of increasing delivery demand, with the goals of reducing traffic queues, optimizing carriers time, and reducing traveling costs, Wang et al. (2015) proposed a last mile logistics collaborative platform aimed to improve efficiency by consolidating delivery demands, and reducing the number of needed trucks. More recently, Wang et al. (2018) presented TaxiRec, a system that evaluates and recommends road clusters with potentially high number of passengers. In the G2B services context, Lu et al. (2009) investigated recommendation methods to support Australian government agencies in the provision of personalized business partner matching.

Supporting business and commerce networks. In future business and commerce networks of smart cities, filtering and recommending IoT services may represent crucial functionalities. Examples of service recommender systems are found in (Mashal et al., 2016; Zhou et al., 2017; Comi and Rosaci, 2017).

4.2. Smart environment

The smart environment dimension covers initiatives aimed at **increasing energy efficiency** in urban elements such as homes and buildings, both in new constructions and in the remodeling and refurbishment of old urban elements by incorporating technologies making them sustainable. In addition to increasing energy efficiency, smart environment also includes actions focused on **managing the environmental resources** of a city –such as water, air quality, waste and food– in a sustainable way (Giffinger et al., 2007). In this context, some main goals are protecting the natural resources and reducing the pollution levels. As an example, there are smart environment initiatives that materialize the above objectives though actions like the integration of renewable energy in the city. Other actions in the dimension are aimed at **involving different stakeholders in sustainable actions**, transforming society's behavior in environmental issues. For example, actions such as policies and systems that involve people in energy saving and natural resource care seek to model the society towards more awareness and sustainable relationships with the environment.

4.2.1. *Recommender systems and smart environment*

The surveyed papers that belong to this dimension consider approaches aimed to increase energy efficiency and enhance environmental resource management.

Increasing energy efficiency and enhancing environmental resource management. In the literature, several authors have addressed the use of recommender systems for energy efficiency purposes. In the context of **smart homes** and with the aim to save resources (mainly energy) and reduce consumption, we refer the reader to (Shah et al., 2010; González Alonso et al., 2011; Bhattacharjee et al., 2014; Zehnder et al., 2015; Streltov and Bogdan, 2015; Palaiokrassas et al., 2017; Ayres et al., 2018; Schweizer et al., 2015; Chen et al., 2016; García et al., 2017; Teoca and Ciuciu, 2017; Nakamura et al., 2016; Matsui, 2018; Li et al., 2013). Similarly, but in the context of **smart buildings**, we found (Fotopoulou et al., 2017; Pinto et al., 2019) as relevant papers. On a different matter, in order to stimulate **sustainability of the environment** and the economy, Kolstad et al. (2017, 2018) presented a smart closet prototype that recommends what to donate or recycle.

4.3. *Smart mobility*

In a city there are a number of problems related to mobility. Benevolo et al. (2016) pointed out that there are, on the one hand, public mobility problems and, on the other hand, business and commercial mobility problems. According to these authors, the former are related to public transport, whereas the latter are fundamentally logistic difficulties. One of the main objectives that are addressed in the context of mobility in a smart city is the **enhancement of the traffic management**. Smart solutions are oriented to innovative a sustainable mobility supported by the use of ICT, and aim to solve problems such as traffic congestion, parking management and driving safety. For such purposes, sensors located in the city allow deploying systems that collect data and monitor the city traffic in real time. A second type of smart mobility actions are aimed at **promoting the use of public transport** and **promoting non-motorized and clean mobility options**, with the goal of encouraging citizens to use more sustainable ways of transportation. In this context, actions such as promoting the use of public transport, raising support for clean energy vehicles and adapting streets and roads to facilitate walking and cycling mobility options can be found. Finally, other representative examples of smart mobility actions are those devised to **support physical accessibility** and **improve logistics** in the city. For instance, in the context of good transportation in the city, some main actions are those that allow for the trackability and traceability of the goods transported by trucks.

4.3.1. *Recommender systems and smart mobility*

The surveyed recommendation approaches belonging to the smart mobility dimension aim to enhance the vehicle traffic management, support emergency attendance, and promote the use of public transport and non-motorized/clean mobility options. These approaches tend to decrease pollution and consequently the negative impact on environment and human health.

Enhancing the traffic management. In the context of reducing **traffic congestion**, we find (Horng, 2014) and (Karatzoglou et al., 2017), which recommend whether a given vehicle should change routes or not, aiming to minimize the possibility of congestion in an entire urban area, and (Kong et al., 2018) and (Nayak and Narvekar, 2017), whose recommender system analyzes traffic flow data guiding users to reach a location and helping resource management such as time or fuel. Addressing **parking management** problems, Horng (2015, 2014); Yavari et al. (2016); Hassani et al. (2018); Gang (2018) provide parking spaces recommendations. A third intelligent traffic management application of recommender systems corresponds to **driving safety** where Outay et al. (2017) system alerts drivers and recommends proper speeds for vehicles approaching dangerous or risky situations and zones, such as those with low visibility conditions or adverse weather conditions.

Supporting emergency attendance. A relevant smart mobility goal for which recommendation solutions have been proposed is to aid citizens in emergencies. Examples are (Lujak and Ossowski, 2015), which presented a system to manage mobility in **conglomerations**, and (Salis et al., 2018), which supports travelers in airports Salis et al. (2018). In the context of managing **evacuations**, we find (Lujak et al., 2017; Krytska et al., 2017; Yamamoto and Fujita, 2017).

Promoting the use of public transport. In this context, Handte et al. (2016) motivate the usage of public transport by enhancing user experience, while Concepción-Sánchez et al. (2017) try to blur impediments between elderly people and public transport.

Promoting non-motorized and clean mobility options. Addressing this issue, Torres et al. (2015) and Kuhail et al. (2018) focused on recommending **cycling facilities**. Also, given the increasing number of private vehicles that lead to traffic jams, incidents and pollution, D'Andrea et al. (2016) and Toader et al. (2017) proposed a **vehicle sharing** recommender system that suggests to users who to travel with. On the other hand, the works in (Devigili et al., 2013; Di Martino and Rossi, 2016) propose **multimodal transport** recommendations aiming at reducing traffic and consequently pollution, stress and accidents. Finally, Agrawal et al. (2018) and Yuan et al. (2013) presented algorithms that recommend optimal taxi parking and finding locations to reduce traffic and increase energy saving.

4.4. Smart governance

A primary application of smart city actions in the government dimension is **increasing efficiency in municipal management** by means of ICT. Governments may aim to provide services between departments facing the complicated issue of integrating and interconnecting services to guarantee the interoperability between the different levels of administration (Nam and Pardo, 2011). Smart applications addressing these problems are developed to provide advanced online public services (e.g., e-government and e-administration services), integrate and interconnect services, and improve management, regulation and provision of services. Another goal in government management is the **provision of transparency and accountability** (Johannessen and Berntzen, 2018). In particular, *Open Government* is established as a governing doctrine that aims to allow citizens collaborating in the creation and improvement of public services and in the strengthening of government transparency and accountability. An additional aspect of smart governance is **access to information**. In smart cities, *Open Data* represents an initiative for which data generated in any of the smart city dimensions is freely available to everyone who wants to use it. Open data allows improving various facets of public life like citizens' involvement, confidence in governments, the averting of corruption, and informed decision-making on the basis of access to public information (Hivon and Titah, 2017). Objectives are also pursued to **promote citizens in decision making** within public policy processes in a city. In fact, policy making in a smart city is no longer seen as a top-down process, but rather as a negotiation among many stakeholders (Bovaird, 2007). The smart governance dimension includes those actions that promote governance systems in the city that are characterized for being collaborative and participative models (Bolívar, 2018). Thus, the interaction between the different stakeholders guarantees not only that citizens can formulate complaints and suggestions, but also participate in the co-creation of public services and political strategies (Giffinger et al., 2007).

4.4.1. Recommender systems and smart governance

The recommendation approaches identified in this dimension aim to increase efficiency in municipal management, and promote citizen participation and inclusion. Note that we may find more recommendation solutions in research works that are not contextualized in the smart governance domain, but in related areas such as electronic/digital governance, government and democracy.

Increasing efficiency in municipal management. Aiming to improve the efficiency in municipal management, Eirinaki et al. (2018) addressed a two-fold city issue: on the one hand, the difficulty of obtaining, understanding and properly using **building permits** for citizens that need to make changes in their properties; on the other hand, at the city government side, the slow workflow and lack of coordination between departments. In the government-to-citizen (G2C) services context, personalized recommender systems have been proposed that suggest **government electronic notifications and services** to citizens (Janssen et al., 2003; De Meo et al., 2005; Martín-Guerrero et al., 2006; Baldassarre et al., 2013; Ayachi et al., 2016). For example, Sabucedo et al. (2012) presented a recommender system that assists citizens in the the discovery of Public Administration services, such as address changes, transport discounts, grant requests, and university enrollments.

Promoting citizen participation and inclusion. Government-to-citizen e-services can be ranked according to the interaction extent between the government and the citizens and to their goal, e.g. informing, consulting or co-participating. At the (electronic) consultation level, the government provides online consultation tools in which citizens are presented with choices about public policies, and where they deliberate in real time, as well as access to archived recordings of past meetings. With such tools, citizens are encouraged to contribute in public consultations. In this context, Terán and Meier (2010) and Dyczkowski and Stachowiak (2012) present recommendation solutions that assist voters in decision making by presenting candidates with similar political views. At the (electronic) participation level, the government offers online participation tools in which citizens propose, discuss and vote for projects and initiatives aimed to address a variety of issues and problems of a city, such as economic development, health care, education, culture, public safety, social rights, urban mobility, public transport, energy and environment. In these tools, recommender systems help citizens to find relevant proposals, individuals, associations and discussions, based on personal preferences explicitly stated by means of votes, or implicitly expressed in online comments and social links. In this context, we found (Nelimarkka et al., 2014; Cantador et al., 2017, 2018) as relevant papers.

4.5. Smart living

The smart living dimension comprises aspects relevant to the quality of life in the city. These aspects do not only include those related to issues such as health, housing, education, security and social cohesion, but also others such as culture, leisure and tourism in a city (Giffinger et al., 2007). Due to the importance of ICT in smart cities, one of the main goals in the smart living dimension is the provision of **technology access and support**. The creation of urban labs, media labs, and smart city centers are frequent, so that users can not only overcome technological barriers, but also create and participate in environments where different stakeholders collaborate to generate valuable outcomes for the city. Other principal actions are aimed to improve the **social inclusion** of citizens. Hence, there are actions that seek to reduce levels of poverty, give specific aid to families and children, provide particular services to immigrants, enhance gender inclusion and women support, and facilitate the labor of NGOs and volunteering among others. Smart living is also related to **healthcare measures**. In this context, we can find actions to promote a healthy lifestyle and well-being, support disease prevention, improve healthcare systems and provide health information and education. Other key actions focus on **education**. Initiatives to improve the quality and access to the education systems are representative examples on this matter. Increasing **urban security** –e.g., through actions to avoid and manage crime and vandalism in the city–, and addressing **housing** problems –e.g., by ensuring minimal housing quality standards and facilitating house buying and renting–, are other examples of smart living goals. Furthermore, in this dimension, we can find actions that enhance **tourism** services in the city. On the one hand, there are actions aimed to protect and promote the city cultural heritage. On the other hand, there are actions to reduce negative impacts derived from tourism. Finally, there are smart initiatives targeted to **culture and leisure** services, such as culture and leisure information via internet, on-line tickets and reservations, and local cultural programs.

4.5.1. Recommender systems and smart living

The surveyed papers on recommender systems for smart living address the following goals: providing accessibility facilities, supporting healthcare measures and enhancing tourism services. In this context, we discard approaches that provide leisure recommendations; the research literature on leisure domains (e.g., movies, music and books recommendations) is extensive and out of the scope of smart cities. Similarly, we also discard approaches that suggest daily activities in smart homes, such as cleaning the oven, switching off the television, and making the shopping list, if they do not care about people with certain difficulties and needs; we understand these recommendations do not have a significant impact on city issues. Moreover, we also omit the numerous approaches on domains such as e-learning, e-health and e-tourism that target individual users or groups of users, without focusing on the citizens as a whole or taking city needs and goals into account.

Providing accessibility facilities. An important aspect of smart city services is to provide technologies that enable accessibility to people with disabilities. In this domain, Gómez-Martínez et al. (2015) presented a system that helps disable people to install Assistive Software (AS) in devices/controllers, and Guo et al. (2017) presented a system that provides recommendations of alternative services when the required ones are unavailable. Differently, to enable accessibility facilities in smart homes, the works (Hussein et al., 2015; Sohn et al., 2013; Oyeleke et al., 2018) proposed systems to aid elderly people, persons diagnosed of mild cognitive impairment or Alzheimer's in performing safely their daily activities.

Assisting mobility. To adapt route planning recommendations to people with disabilities, Barczyszyn et al. (2018) presented a participatory sensing system that personalizes routes for people in wheelchairs and reports issues for improvement to the department of city planning.

Supporting healthcare measures. Recommender systems have also been proposed to promote **healthy lifestyle and well-being**. Lemlouma and Chalouf (2012) proposed a system that provides personalized recommendations of media and different alerts for elderly and dependent people. Vavilov et al. (2014) proposed a system that suggests healthier habits to prevent sedentariness. Claiming that promoting healthier habits for citizens supposes in the midterm a reduction of healthcare system costs, Casino et al. (2015, 2017, 2018) presented a system that recommends routes to develop physical activities that better fit the users' capacities. Also with the goal of improving lifestyle, but also reducing chronic diseases and medical expenses, Asthana et al. (2017) proposed to improve life conditions by predicting a user's most probable diseases and recommending which measurements should be taken and which existing wearable technologies can help monitor them. In the context of **disease prevention**, Benyahia et al. (2012) and Kim and Chung (2017) presented a system to alert and recommend medical consulting. Aiming to increase the performance of chronic **healhtcare systems**, by effectively overcoming the load of patients in hospitals, and helping medical staff to automatically retrieve patient information for diagnoses, Ali et al. (2018) described a software platform with a recommender that provides diabetes patients with personalized diets consisting of specific foods and drugs. Enhancing the **access to healthcare services**, Narducci et al. (2015, 2017) and Jung et al. (2018) proposed to improve health assistance by recommending the best doctor or hospital for a given disease. Finally, recommendation solutions have been devoted for the provision of **health-related information**. Addressing the risk of wrongly mixing medicines between them or with food, which may lead to intoxication or death, Roitman et al. (2010) proposed a system that gives up-date-recommendations of what not to mix depending on the patient's current prescriptions.

Increasing urban security. Addressing the challenge of crime prosecution in a city, Gómez et al. (2015) presented a data streaming mobile application that provides citizens with protection and monitors risk and privacy issues. In particular, the system provides fast outcomes through police patrols attributed to specific locations, and generates personalized recommendations of safest places to visitors.

Enhancing tourism services. With the aim of enhancing the dissemination and protection of the **cultural heritage** of a city, as part of a smart tourism application, the reader is referred to (Barile et al., 2014; Cha et al., 2016; Massimo, 2018; Amato et al., 2012; García et al., 2018). Large amounts of tourists in few city areas may cause **mobility problems**, such as traffic congestion, and an unbalanced economy or discordance between tourists and residents. Therefore, a key point in smart tourist trip planning applications should be to coordinate multitudes as proposed in (Mrazovic et al., 2017).

4.6. Smart people

The smart people dimension includes relevant aspects of the society in a smart city. This dimension puts the focus on the state of the social and human capital of the city, by means of initiatives that pursuit social cohesion, integration of individuals, and citizen participation in public life (Giffinger et al., 2007). Actions are then configured according to community characteristics that show different levels of identity, integration and cohesion, and are measured through indicators such as the individuals' level of qualification, ethnic plurality, creativity and participation. In this context, major objectives of smart people actions are **supporting community building and urban life management** and **encouraging citizen participation** in public life through the use of ICT (Effing and Groot, 2016). Through online social networks and ad hoc web platforms, the community creates collective awareness, and is able to participate in an organized way. In fact, bottom-up initiatives can be generated and promoted by citizens and groups, and not only by governments. There are other actions aimed at **promoting an inclusive society**. Some of them offer opportunities to individuals through training in different subjects with the goal of reducing the educational gap and increasing the level of qualification. Examples of these actions are digital education and long-life learning, creative networks and community and urban life information spread and sharing. Others promote integration and social cohesion among individuals, especially in less favored groups. Examples of these actions are those initiatives and policies oriented to employment, cultural pluralism, and poverty. Actions that pursue social awareness, activism and human rights are also conducted.

4.6.1. Recommender systems and smart people

The recommender systems belonging to the smart people dimension found in the literature aim at supporting community building and urban life management, as well as promoting a participatory society. We are aware that other recommendation approaches may appear in papers on related topics such as citizen participation in social media, and ICT solutions that promote civil creativity and inclusive societies, among others.

Promoting creativity. Evidence shows that promoting creative processes is both beneficial to a city's community and economic outcomes. Supported by this fact, Casadevall et al. (2018) presented a prototype system that employs social network analysis to recommend interdisciplinary co-working spaces promoting environments that have less homophily and are beneficial for innovation.

Supporting community building and urban life management. With the goal of enabling urban residents to better enjoy community life, He et al. (2017) developed a participatory sensing application, whereas Kinawy et al. (2018) proposed a system to share community project information with citizens.

Promoting a participatory society. Related to the enhancement of **citizen-government communication**, we find works such as (Kavanaugh et al., 2014), which facilitates citizens' discussion and interaction by recommending information from social media and news providers, and (Gampert, 2015), which proposed a mobile citizen cooperation application for reporting urban problems. Rather than targeting citizens, Marsal-Llacuna and De la Rosa-Esteva (2013) proposed a recommendation model that mining **citizen opinions** assist planners in the design of urban plans.

5. Analyzing the state of the art in recommender systems for smart cities

In this section, we first analyze discerning features of the surveyed papers, and then compare such papers in order to identify major trends and open research issues in the literature on recommender systems for smart cities.

5.1. Analyzed features

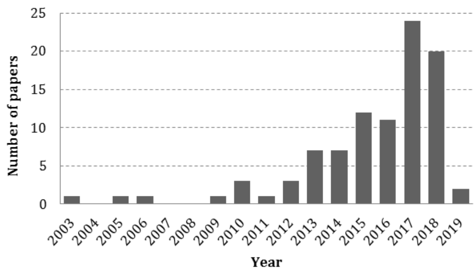
In our analysis, we consider three types of features to be compared among the surveyed research works. The first type refers to contextual features related to the location and time of the proposed recommendation solutions. More specifically, we analyze the:

- *Year*, i.e., the year of publication or if exists the year of the smart city project/initiative.
- *City*.
- *Country*.
- *Continent*.
- *City population* (not given in the papers).

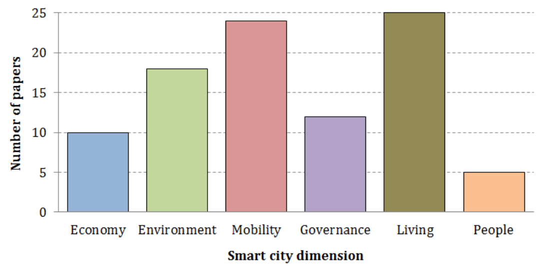
We note that not all the analyzed recommendation approaches have been implemented in deployed systems, but are proposals or algorithms open to future development.

The second type of analyzed features refers to those related to the **smart city** dimensions, goals and data sources addressed by the surveyed recommender systems, namely:

- *Smart city dimension*, e.g., smart mobility.
- *Smart city action*, e.g., traffic management, emergency attendance, public transport, and non-motorized/clean mobility options for the *smart mobility* dimension.



1.a. Publication year distribution of surveyed papers



1.b. Smart city dimension distribution in surveyed papers

- *Smart city goal*, e.g., reducing traffic congestion, optimizing parking, and increasing driving safety for the *traffic management* action.
- *Application scope*, e.g. recommendations focused on or with impact at city, building, home and user levels.
- *Data source*, e.g., city sensors, IoT devices, web services, open data, and social media.

Lastly, the third type is associated to features representing issues and characteristics of each **recommender system**, on the user modeling, recommendation generation and evaluation tasks:

- *Target users*, which could be any city stakeholder (e.g., citizens, governments and businesses), and its corresponding roles (e.g., residents and tourists for citizens, government managers and public policy makers for government).
- *Recommended items*, which differ depending on the addressed smart city actions and goals.
- *User preferences*, which may be explicit or implicit, and may be of different forms: numeric ratings, *likes*, social tags, reviews, micro-blogging messages, social network posts, and interaction logs, among others.
- *Knowledge representation* of users, items and other involved domain entities, e.g., vector-, taxonomy- and ontology-based profiles.
- *Recommendation method*, described in terms of the type of recommendations (e.g., content-based, collaborative, hybrid, context-aware and social recommendations) and the type of algorithm (e.g., heuristic vs. model-based algorithms).
- *Implementation level* of the recommendation proposal, namely proposal, algorithm, prototype and deployed system.
- *Evaluation type*, e.g., simulation, offline experiment, user study, and real-life evaluation.
- *Evaluation metric*, which could be focused on the rating prediction accuracy (e.g., MAE and RMSE), ranking quality (e.g., precision and recall), recommendation diversity, and system efficiency and scalability, among others.
- *Public dataset*, if available.

5.2. Analysis based on context features

In our analysis, we first consider contextual features that are independent of the addressed smart city goals and recommendation solutions. In particular, we analyze the **publication years** of the surveyed papers, aiming to get insights about the current relevance that smart city recommender systems have. In Figure 1.a, we show the distribution of papers published per year. It can be seen that since 2011 there has been a growing tendency, and in 2017 and 2018 the number of papers is more than the double than in previous years. In the light of these data, we claim that smart city recommenders represent a recent and promising research topic. This fact and the reasonable number of papers

continent	*country*	*city*	*population*	*reference*	*dimension*
Asia	China	Beijing	21.822M	Yuan et al. (2013)	Mobility
		Nanjing	8.335M	Wang et al. (2018)	Economy
		Taipei	2.674M	Tu et al. (2016)	Economy
		Wenzhou	3.039M	He et al. (2017)	People
	Japan	Chiba	6.148M	Matsui (2018)	Environment
		Kawasaki	1.496M	Nakamura et al. (2016)	Environment
		Shizuoka	3.751M	Matsui (2018)	Environment
		Tokyo	9.273M	Matsui (2018)	Environment
		Yokohama	3.725M	Yamamoto and Fujita (2017)	Mobility
	South Korea	-	-	Jung et al. (2018)	Living
Europe	Italy	Alpine towns	-	Massimo (2018)	Living
		Italian towns	-	De Meo et al. (2005)	Governance
			-	Baldassarre et al. (2013)	Governance
		Naples	967.1K	Barile et al. (2014)	Living
		Pisa	90.5K	D'Andrea et al. (2016)	Mobility
	Spain	Barcelona	1.620M	Mrazovic et al. (2017)	Living
		Catalonia	-	Casino et al. (2018)	Living
		Galician towns	-	Sabucedo et al. (2012)	Governance
		Madrid	3.166M	Handte et al. (2016)	Mobility
				Cantador et al. (2017)	Governance
		Valencia	790.2K	Martín-Guerrero et al. (2006)	Governance
				Gómez-Martínez et al. (2015)	Living
	The Netherlands	Dutch towns	>100K	Janssen et al. (2003)	Governance
	Rumania	Cluj-Napoca	321.7K	Teoca and Ciuciu (2017)	Environment
North America	Canada	Toronto	2.732M	Kinawy et al. (2018)	People
	United States	Cambridge	113.6K	Cantador et al. (2018)	Governance
		Miami	463.3K	Cantador et al. (2018)	Governance
		New York City	8.623M	Eirinaki et al. (2018)	Governance
				Cantador et al. (2018)	Governance
South America	Brazil	Curitiba	1.765M	Barczyszyn et al. (2018)	Living
	Chile	Santiago	5.614M	Torres et al. (2015)	Mobility
	Colombia	Cartagena	971.5K	García et al. (2018)	Living
		Montelíbano	59.7K	Gómez et al. (2015)	Living
Oceania	Australia	-	-	Lu et al. (2009)	Economy
		-	-	Li et al. (2013)	Environment

Table 1: Continents, countries and cities where the recommender systems of the surveyed papers were evaluated.

on each smart city dimension, make worthwhile the characterization, categorization and comparison of the literature presented in this manuscript.

After analyzing *when* the surveyed smart city recommenders have been published, we focus on *where* they have been implemented. Hence, in Table 1, we show the **cities, with their respective countries and continents**, where surveyed recommender systems have been deployed. The first observation we can make from the table is that the number of papers presenting a real system implementation in a smart city initiative is very small; specifically, only 31 out of the 94 papers analyzed. From them, 45% are smart city projects in European cities, followed by 26% which where developed in Asian cities. It has to be highlighted that in the table there are no African or Third World cities, which may benefit, for example, from recommendation approaches in actions like natural resource management, economy productivity, and healthcare measures. It is also noteworthy that only 13 countries appear in the research literature, being Spain and Italy the countries that host more initiatives. Moreover, most of the reported cities do have large populations. In this sense, well-known, popular smart cities are missing. Largely populated smart cities, such as Singapore, New Delhi, Santiago de Chile, and Monterrey, would benefit from recommender systems helping on actions like energy efficiency, traffic management, and emergency attendance. In fact, we note that the list of cities in Table 1 does not match with those of the IESE Cities in Motion Index (CIMI)[4], which ranks the World smartest cities. This may signal that important personalized recommendation solutions in smart city initiatives that actually exist are not reported in the research literature.

Finally, regarding the **smart city dimensions** addressed in the listed papers, we can observe that those focused on *smart governance* seem to stand out, whereas the remainder evenly address the other dimensions. We presume that one of the main reasons of this situation is that recommender systems aimed to address governance goals are easier to set up, as they mainly require a web platform, while recommendation approaches on the other dimensions require sensors, devices and specific technologies utilized by users and integrated into city infrastructures, which are much more costly and thus more difficult to put into production.

[4] `https://www.ieseinsight.com/doc.aspx?id=2124`

5.3. Analysis based on smart city features

The second set of properties to consider in our analysis is composed of those features related with smart city aspects. Tables 2, 3 and 4 summarize the analyzed paper characteristics regarding smart cities actions, scope, data sources used, target users and recommended items. To better identify commonalities and differences, the tables are organized in subtables that group surveyed papers by dimension. Each subtable is divided according to the smart city action performed by the referred systems. Divergences are further stressed by grouping in each action those papers that address the same smart city goal. Next, Figure 1.b shows the distribution of **smart city dimensions** addressed by the recommender systems presented in the literature. It can be seen that 26% of the papers are focused on *smart mobility* actions and another 26% on *smart living* actions. *Smart environment*, *smart governance* and *smart economy* represent 19%, 13% and 11% of the reviewed papers, respectively, and only 5% are related with *smart people* goals. We point out that recommender systems in *smart living* encompasses a number of heterogeneous goals, where those focused on tourism and health actions are among the most popular ones. On the contrary, recommenders for *smart people* actions are barely investigated, which calls for future research.

Regarding specific **smart city actions and goals**, as it can be seen in Tables 2, 3 and 4, the most addressed actions are in energy efficiency, healthcare measures and traffic management. Moreover, as trending goals, saving energy in smart homes in *smart environment* stands out among all. Far below, notifying government e-services in *smart governance*, promoting healthy lifestyle and city cultural heritage in *smart living* and optimizing parking space usage in *smart mobility* follow the previous one in popularity goals. We point the reader to the last column of the tables, where the recommended items of the papers associated to each goal can be used to further assess the commonalities and differences between them. For instance, it can be seen that regarding energy efficiency, the majority of approaches recommend energy saving actions or plans. Only (Palaiokrassas et al., 2017) and Chen et al. (2016) tackle the problem from a different angle by means of approaches that recommend heating services and sensors to (de)activate respectively

Comparing the smart city actions and goals presented in Section 4 with those addressed in the recommender systems literature (Tables 2, 3 and 4), we observe that there are several areas where recommendation solutions have not been reported (and maybe applied) yet. Grouped by smart dimension, some of these areas are the following:

- In *smart economy*: creating entrepreneurial environments, facilitating the access to labour market, reducing unemployment, and developing technological advances that enhance work flexibility.
- In *smart environment*: involving different stakeholders (i.e., not only citizens) in sustainable actions.
- In *smart mobility*: supporting physical accessibility and improving logistics in a city.
- In *smart governance*: providing transparency and accountability, and improving access to government information.
- In *smart living*: providing technology access and support, enhancing social inclusion, urban security, and education, and addressing housing problems.
- In *smart people*: promoting an inclusive society.

In our humble opinion, these missing areas represent potential applications of interest for recommender system researchers. For instance, *smart economy* focuses on business innovation mechanisms and environments, which not only need to be supported by public policies, but also to encourage local expertise. Networking and sharing knowledge recommender systems could be designed as optimization schedulers that help on the coordination and collaboration among local business. In *smart environment*, recommender systems for natural resource care are very scarce in the literature. In fact, in our survey, there is no recommender aimed at rising awareness or creating sustainable relationships with the environment, e.g., by means of recycling recommendations. On the other hand, related to energy efficiency, saving energy at homes is shown as one of the main addressed goals. However, there is work that could be done, for instance, on providing recommendations for remodeling and refurbished old urban elements. Regarding *smart mobility*, we could expect more recommendation solutions focused on the efficient management of freight transport and logistics. As mentioned in Section 4, this goal diverts in the avoidance of traffic and pollution problems. In this dimension, we also miss recommendation approaches to help on physical accessibility issues,

Smart economy								
smart city action/goal	*#papers*	*%category*	*%total*	*reference*	*scope*	*data sources*	*target users*	*recommended items*
Local businesses	**3**	**30%**	**3%**					
Supporting business coordination	1	10%	1%	Ahrary et al. (2014)	c	IOT	C:consumers, B:owners	food to offer or consume
Improving business advertising	1	10%	1%	Tu et al. (2016)	c	SEN, IOT	C:consumers	products of interest
Informing about business events	1	10%	1%	Guo and Lu (2007)	c	WP	B:companies	companies
Economy productivity	**4**	**40%**	**4%**					
Improving logistics and transport	3	30%	3%	Wang et al. (2015)	c	DB	B:shippers/carriers	places to deliver packages
				Wang et al. (2018)	c	GPS	B:taxi drivers	road clusters
				Yuan et al. (2013)	c	GPS	B:taxi drivers, C:taxi passengers	parking areas
Providing business partner matching	1	10%	1%	Lu et al. (2009)	c	WP	B:companies	companies
Businesses and commerce networks	**3**	**30%**	**3%**					
Informing about (IoT) services	3	30%	3%	Mashal et al. (2016)	h, b, c	IOT, SEN	C:consumers	IoT services
				Zhou et al. (2017)	h, b, c	IOT, SEN	C:consumers	IoT services
				Comi and Rosaci (2017)	h, b, c	-	C:consumers	IoT services

Smart environment								
smart city action/goal	*#papers*	*%category*	*%total*	*reference*	*scope*	*data source*	*target users*	*recommended items*
Energy efficiency	**15**	**83%**	**16%**					
Saving energy in smart homes	13	72%	14%	Shah et al. (2010)	h	SEN	C:home inhabitants	energy saving plans
				González Alonso et al. (2011)	h	IOT	C:home inhabitants	energy saving actions
				Bhattacharjee et al. (2014)	h	SEN	C:home inhabitants	energy quality displays
				Zehnder et al. (2015)	h	SEN	C:home inhabitants	energy saving actions
				Streltov and Bogdan (2015)	h	IOT	C:home inhabitants	energy saving actions
				Palaiokrassas et al. (2017)	h	SEN, QNR	C:home inhabitants	heating services
				Schweizer et al. (2015)	h	SEN	C:home inhabitants	energy saving actions
				Chen et al. (2016)	h	SEN	C:home inhabitants	sensors to (de)activate
				García et al. (2017)	h	SEN	C:home inhabitants	energy saving actions
				Teoca and Ciuciu (2017)	h	SEN	C:home inhabitants	energy saving actions
				Nakamura et al. (2016)	h	SEN, EK	C:home inhabitants	energy saving plans
				Matsui (2018)	h	SEN, QNR	C:home inhabitants	energy saving actions
				Ayres et al. (2018)	h	WS, DB, SEN	C:home inhabitants	energy saving actions
Saving energy in smart buildings	2	11%	2%	Fotopoulou et al. (2017)	b	SEN, IOT, EK	C	energy saving actions
				Pinto et al. (2019)	b	SEN, DB	C	energy saving actions
Environmental resource management	**3**	**17%**	**3%**					
Optimizing water consumption	1	6%	1%	Li et al. (2013)	b	SEN, OD	C:farmers	irrigation actions
Increasing recycling	2	11%	2%	Kolstad et al. (2017)	u	IOT, DB	C	clothes to recycle
				Kolstad et al. (2018)	u	IOT, DB	C	clothes to recycle

Table 2: Smart city features of the surveyed papers in smart economy (10 papers) and smart environment (18 papers). Abbreviations used in the table stand for scope: u (user), h (home), c (city), b (building); data sources: SEN (sensors), GPS, IOT (Internet of Things devices), WS (web services), WS (web platforms), OD (open data), DB (databases), QNR (questionnaires), SM (social media), EK (expert knowledge); target users: C (citizens), B (businesses), G (governments)

Smart mobility

smart city action/goal	*#papers*	*%category*	*%total*	*reference*	*scope*	*data sources*	*target users*	*recommended items*
Traffic management	**10**	**42%**	**11%**					
Reducing traffic congestion	4	18%	4%	Horng (2014)	c	SEN	C: drivers	driving routes
				Karatzoglou et al. (2017)	u	IOT, SEN	C: drivers	predict movement behaviour
				Kong et al. (2018)	u, c	IOT, SEN	C: drivers	road planning
				Nayak and Narvekar (2017)	u	IOT, DB	C: drivers	route to destination
Optimizing parking space usage	5	21%	5%	Horng (2015)	c	IOT, SEN	C: drivers	driving routes near parking
				Yavari et al. (2016)	u, c	IOT, SEN, DB	C: drivers	where to park
				Hassani et al. (2018)	u, c	IOT	C: drivers	parking spaces
				Gang (2018)	u, c	IOT, SEN	C: drivers	parking spaces
				Rizvi et al. (2019)	u, c	IOT, DB, SEN	C: drivers	parking spaces
Increasing driving safety	1	4%	1%	Outay et al. (2017)	c	IOT, SEN	C: drivers	car speed change directives
Emergency attendance	**5**	**21%**	**5%**					
Supporting conglomeration management	2	8%	2%	Lujak and Ossowski (2015)	u	SEN	C	safe routes
				Salis et al. (2018)	u	IOT	C: disable travelers	pois in airports
Supporting evacuation management	3	13%	3%	Lujak et al. (2017)	u	SEN	C	escape routes
				Krytska et al. (2017)	u	IOT	C	safe routes
				Yamamoto and Fujita (2017)*	u	SM	C	POIS, routes
Use of public transport	**3**	**13%**	**3%**					
Optimizing public transport usage	3	13%	3%	Handte et al. (2016)	u	IOT, SEN	C: travelers	best least crowded route
				Concepción-Sánchez et al. (2017)	u	IOT, SEN	C: travelers	best route
				Agrawal et al. (2018)	u,c	IOT	C: travelers, B: taxi-drivers	taxis
Use of non-motorized and clean mobility options	**6**	**25%**	**6%**					
Supporting cycling facilities	2	8%	2%	Torres et al. (2015)	u, c	IOT	C: cyclists	biking routes
				Kuhail et al. (2018)	u, c	SEN	C: travelers	active transportation
Supporting vehicle sharing	2	8%	2%	D'Andrea et al. (2016)	u	DB	C: drivers	routes to share
				Toader et al. (2017)	u	SEN	C: drivers	who to travel with
Supporting multimodal transport	2	8%	2%	Devigili et al. (2013)	u	IOT	C: travelers	best travel option
				Di Martino and Rossi (2016)	u, c	IOT, SEN, DB	C: drivers	best route, parking

Smart people

smart city action/goal	*#papers*	*%category*	*%total*	*reference*	*scope*	*data sources*	*target users*	*recommended items*
Creativity	**1**	**20%**	**1%**					
Promoting creative networks	1	20%	1%	Casadevall et al. (2018)	u	SM	C: workers	local working spaces
Community building and urban life management	**2**	**40%**	**2%**					
Promoting community life	2	40%	2%	He et al. (2017)	u	IOT	C	picture tags
				Kinawy et al. (2018)	u, c	DB, WS	C	projects of interest
Participatory society	**2**	**40%**	**2%**					
Supporting C2G communication	2	40%	2%	Kavanaugh et al. (2014)	c	SM	C: policy making contributors	local events and news
				Marsal-Llacuna and De la Rosa-Esteva (2013)	c	SM	G: policy decision makers	urban planning actions

Table 3: Smart city features of the surveyed papers in smart mobility (24 papers) and smart people (5 papers). Abbreviations used in the table stand for scope: u (user), h (home), c (city), b (building); data sources: SEN (sensors), GPS, IOT (Internet of Things devices), WS (web services), WS (web platforms), OD (open data), DB (databases), QNR (questionnaires), SM (social media), EK (expert knowledge); target users: C (citizens), B (businesses), G (governments)

smart city action/goal	#papers	%category	%total	reference	scope	data sources	target users	recommended items
Smart living								
Accessibility facilities	**5**	**21%**	**5%**					
Assisting with software applications	2	8%	2%	Gómez-Martínez et al. (2015)	u	EK, DB	C: disable	software
				Guo et al. (2017)	u	IOT, SEN	C: home inhabitants	home services
Assisting mobility	1	4%	1%	Barczyszyn et al. (2018)	u, c	IOT, SEN	C: disable travelers	routes
Assisting with smart home devices	2	8%	2%	Hussein et al. (2015)	h	IOT, SEN	C: home inhabitants	quotidian tasks
				Sohn et al. (2013)	u	IOT, SEN	C: disable	settings of home devices
				Oyeleke et al. (2018)	u	SEN	C: disable	quotidian tasks
Healthcare measures	**13**	**54%**	**14%**					
Promoting healthy lifestyle	5	21%	5%	Lemlouma and Chalouf (2012)	h	SEN	C: home inhabitants	media consumption directives
				Vavilov et al. (2014)	u	SEN	C	healthier habits
				Casino et al. (2015)	u	IOT, SEN	C	routes to walk, run
				Casino et al. (2017)	u	IOT, SEN	C	routes to walk, run
				Casino et al. (2018)	u	IOT, SEN	C	routes to walk, run
Supporting medical surveillance	1	4%	1%	Asthana et al. (2017)*	u	IOT, SEN	C	health controllers
Supporting disease prevention	2	8%	2%	Benyahia et al. (2012)	u	SEN	C: patients	seek doctor
				Kim and Chung (2017)	u	WS	C: patients	seek treatment
Improving healthcare system	1	4%	1%	Ali et al. (2018)	u	IOT, SEN	C: diabetes patients	food/diets
Supporting healthcare service access	3	13%	3%	Narducci et al. (2015)	u	SM	C: patients	doctors/hospitals
				Narducci et al. (2017)	u	SM	C: patients	doctors/hospitals
				Jung et al. (2018)	c	GPS	C: patients	hospitals/clinics
Providing health-related information	1	4%	1%	Roitman et al. (2010)	u	DB, WS	C: patients	seek treatment
Urban security	**1**	**4%**	**1%**					
Supporting safe places identification	1	4%	1%	Gómez et al. (2015)	c	GPS, SEN	C: visitors, police	safest places
Tourism services	**5**	**21%**	**5%**					
Promoting city cultural heritage	4	17%	4%	Barile et al. (2014)	u	SEN, SM	C: tourists	POIS
				Cha et al. (2016)	c	IOT, GPS	C: tourists	POIS
				Massimo (2018)	c	IOT, SEN	C:tourists/visitors	POIS
				García et al. (2018)	c	WS	C: tourists/visitors	routes, cultural info
Reducing tourism negative impacts	1	4%	1%	Mrazovic et al. (2017)	u, c	OD, SEN IOT, QNR	C: tourists, G	routes, POIS

smart city action/goal	#papers	%category	%total	reference	scope	data sources	target users	recommended items
Smart governance								
Efficiency in municipal management	**7**	**58%**	**7%**					
Informing about building permits	1	8%	1%	Eirinaki et al. (2018)	u, c	OD	C, G	building permits
Notifying government e-services	6	50%	6%	Janssen et al. (2003)	c	WS	C: e-gov service consumers	government services
				De Meo et al. (2005)	c	WS	C: e-gov service consumers	government services
				Martín-Guerrero et al. (2006)	c	WS	C: e-gov service consumers	government services
				Sabucedo et al. (2012)	c	WS	C: e-gov service consumers	government services
				Baldassarre et al. (2013)	c	WS	C: e-gov service consumers	government services
				Ayachi et al. (2016)	c	WP, SM	C: e-gov service consumers	government services
Citizen participation and inclusion	**5**	**42%**	**5%**					
Enhancing e-voting	2	17%	2%	Terán and Meier (2010)	c	QNR	C: voters	political candidates
				Dyczkowski and Stachowiak (2012)	c	QNR	C: voters	political candidates
Enhancing e-participation	3	25%	3%	Nelimarkka et al. (2014)	c	SM	C: policy making contributors	citizen proposals
				Cantador et al. (2017)	c	SM	C: policy making contributors	citizen proposals
				Cantador et al. (2018)	c	SM	C: policy making contributors	citizen proposals

Table 4: Smart city features of the surveyed papers in smart living (24 papers) and smart governance (12 papers). Abbreviations used in the table stand for scope: u (user), h (home), c (city), b (building); data sources: SEN (sensors), GPS, IOT (Internet of Things devices), WS (web services), WS (web platforms), OD (open data), DB (databases), QNR (questionnaires), SM (social media), EK (expert knowledge); target users: C (citizens), B (businesses), G (governments)

which represent a major mobility goal for large cities. As for the *smart governance* dimension, our survey does not include recommenders that empower transparency and accountability of local governments. Recommender systems that facilitate the access to government information could enhance trust in governments and help on the prevention of political corruption. With respect to *smart living*, we identify diverse applications areas of potential interest. For instance, in actions taken to improve social inclusion, recommendation goals could be centered in reducing the level of poverty, giving specific aid to families and children, providing particular information services to immigrants, and enhancing gender inclusion and women support campaigns. Surprisingly, although there are many recommenders in the e-learning literature –which are out of the scope of this paper–, we did not find recommender systems aimed to improve the quality and access to education in the context of smart cities. Recommender systems on urban security are also absent in the revised work. In this context, although there is ample room for further research in recommender systems to support predictive policing, it is important to note that there are related decision support systems (e.g., Camacho-Collados and Liberatore (2015)), which have been left out of this survey.

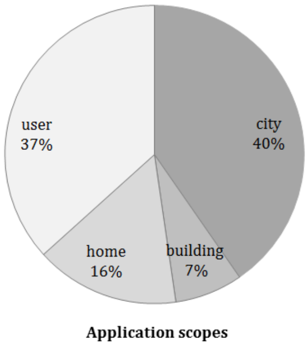
When we analyze this data we observe a relation between the percentage of public policies in a certain dimension with the number of papers addressing a particular question. We can also observe that policies and actions that are implemented at the microlevel, such as smart living, receive both more action and attention, while those systems targeting a wide area of population -environment, related to the economy, and people that is related to the previous both-are areas more difficult to target and under researched, comparatively. The reason as to why there are some topics that seem to have attracted less attention while others have been studied more, may lay on different barriers such as data availability, technological challenges or money needed to implement the proposal. Nevertheless given the seminal status of many of the surveyed works and the increasing publication rate we believe that there is still a lot of work to be done specially related to implementing systems that end up being broadly used within a city.

Also, historically, culture and leisure have been core domains for the recommender system research community. Although there are hundreds of systems that suggest leisure activities, approaches that promote leisure information taking into account not only personal user preferences but also city needs and POI occupation levels should be investigated. Finally, research work centered in city housing problems is also missing. Recommender systems helping on ensuring minimal housing quality standards and facilitating house buying or renting, would be, in our opinion, relevant contributions. Last but not least, *smart people* centered recommender systems should also focus on promoting integration and social cohesion among individuals, i.e., building an inclusive society, by strengthening collective awareness and networking, especially in less favored groups.

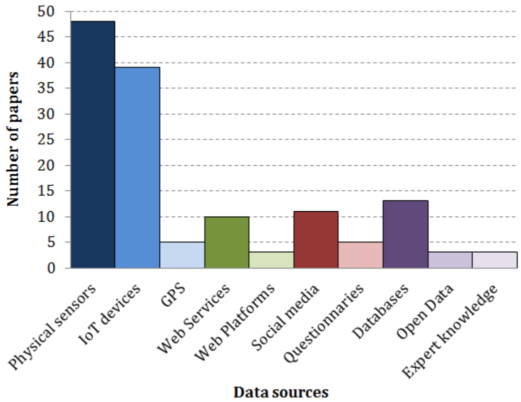
Figure 2.a shows the distribution of the **application scopes** targeted by the surveyed recommender systems. It can be seen that most papers present recommendation approaches that are applied at city level (40%) or provide personalized suggestions to particular users (37%). Only 7% and 16% of the papers report recommendation solutions designed for buildings and homes, respectively. Based on these data, it is important to note that many recommender systems for smart cities consider a formulation of the recommendation problem distinct to the classic one Adomavicius and Tuzhilin (2015), where the goal is to find relevant items for a target user according to personal preferences (and/or contextual conditions). For smart city actions and goals, in addition to user preferences –i.e., tastes, interests and needs– and context factors, recommender systems also consider city, building and home problems, requirements, constraints and data.

Continuing the analysis based on smart city features, Figure 2.b shows the distribution of the different **data sources** exploited by the surveyed recommender systems. Most of them make use of physical and GPS sensors and IoT devices located along the city, integrated into buildings and homes, and carried or managed by users. This was expected since both data sources are common, appropriate tools for obtaining information about users and their context without the need of explicit requests. As explained in Section 1, it was the appearance and widespread of these data sources and technologies what triggered the boom of smart cities.

The use of data from web services/platforms and social media, on the other hand, appear in the literature in a moderate extent. We believe this use should be much greater according to the large amounts of content generated by users (citizens) in such systems. In fact, subjective opinions and real-time information appearing in social networks have widely attracted the attention of academia and industry in the context of recommender systems for other domains. Definitely, particular actions and goals of smart city recommender systems, like those appearing in smart governance Cortés-Cediel et al. (2017), could be addressed by exploiting the above types of data. Hence, in addition to sensor and IoT data, user contents generated in social media and digital platforms, such as e-administration services and e-participation portals, should be much more considered for recommendation purposes in smart city projects. More-



2.a. Distribution of the application scopes targeted by the surveyed recommender systems



2.b. Distribution of the data sources exploited by the surveyed recommender systems

over, when there is a need for explicit feedback, the main channels are web services/platforms and questionnaires, representing 16% of the reported data sources.

On a different matter, databases appear in 14% of the surveyed papers, which differ from other domains where recommender systems are in general built upon user rating and item attribute databases. What is even more surprising is the very low (3%) use of Open Data.

Due to the promotion of Open Government initiatives, the availability of these data is increasing everyday, and their use in recommender systems is envisioned as a promising research direction. Going beyond providing transparency and accountability, Open Data will allow in-depth analysis of existing problems in the cities, and lead to smarter solutions and decision making tasks of all city stakeholders.

5.4. Analysis based on recommender system features

After considering context and smart city issues, the third and final part of our analysis, is based on features of the surveyed recommendation approaches. Tables 5, 6 and 7 analyze paper characteristics regarding the recommender type, user preferences, exploited data, and implementation level. To better identify commonalities and differences, tables are again organized in subtables that group papers by dimension. Also, each subtable groups papers by common smart city action and smart city goal, further stressing differences between papers. As it can be seen, there are no clear trends among these divisions. Thus in the following we summarize observations across all dimensions. We start with the **target users** who receive generated recommendations. In particular, we note that 87% of the analyzed systems are targeted to citizens. Only 10% of the papers considered business actors as target users, and the percentage goes down to 3% for systems aimed to assist government stakeholders. In more detail, Figure 3 shows particular roles of the above recommendation targets, being home inhabitants, drivers, medical patients, and tourists the most popular citizen roles, and taxi drivers the predominant business actors. In this context, we believe that recommendation solutions aimed to increase business productivity, reduce production costs, and enhance companies networking, communication and collaboration, will be major challenges for researchers and practitioners. Note that we do not mention recommender systems aimed to promote costumer fidelity and engagement, since they are extensively investigated in the e-commerce domain. Furthermore, we also believe that research work will be done on recommendation solutions for government actors, especially aimed to assist policy decision making and improve government agents communication.

While in the previous section (Figure 22.b. and Tables 2, 3 and 4) we analyzed the source of the data used in each of the surveyed papers –i.e., sensors, GPS, IoT devices, web services, web platforms, open data, databases, questionnaires, social media, and expert knowledge–, we now dissect the different types of data used to model both users and their context, such as user personal and demographic data, comments, system usage and item consumption records, climatic conditions, and domain knowledge, among others. With respect to the considered **user profiles** (see Tables 5, 6 and 7), in 62% of the revised papers, user preferences are requested explicitly while 39% implicitly. Figure 4.a

smart city action/goal	reference	recommender	user preferences	exploited data	impl. level
Smart economy					
Local businesses					
Supporting business coordination	Ahrary et al. (2014)	-	-	stockage data	p
Improving business advertising	Tu et al. (2016)	H: hyb (cf, cb, ctx)	I: facial expressions	product taxonomy, his	s
Informing about business events	Guo and Lu (2007)	H: hyb (cf, cb)	E: rat	db	a
Economy productivity					
Improving logistics and transport	Wang et al. (2015)	-	E	general goods info, o.d.	p
	Wang et al. (2018)	M: nn, cl	I: taxi location	l, road features	s
	Yuan et al. (2013)	M: cla	I: taxi location	l, parking features	p
Providing business partner matching	Lu et al. (2009)	H: hyb (cf-fz, cb)	E: rat	db	a
Businesses and commerce networks					
Informing about (IoT) services	Mashal et al. (2016)	H: hyb (cf, pop)	I: services consumption	service-object graph	a
	Zhou et al. (2017)ˆ	M: mab.a (ctx, cf, sb)	I: sensors, E: soc	ctx, sn	s
	Comi and Rosaci (2017)	H: cb, cf-trust	E: rat, soc	trust, service features	p

smart city action/goal	reference	recommender	user preferences	exploited data	impl. level
Smart environment					
Energy efficiency					
Saving energy in smart homes	Shah et al. (2010)	H: o, rb	I: e.c., E: rat	h.d	p
	González Alonso et al. (2011)	-	I: e.c.	h.d.	p
	Bhattacharjee et al. (2014)	H: cla	I: e.c.	h.d	s, p
	Zehnder et al. (2015)	H: rb, fsm	I: e.c.	h.d., house map	s
	Streltov and Bogdan (2015)	M: cf, cl	I: e.c.	devices info	p
	Palaiokrassas et al. (2017)*ˆ	H: cb (cosine, euclidian)	E: rat	-	s
	Schweizer et al. (2015)*	H: rb	I	h.d	s
	Chen et al. (2016)	H: hyb (cf,cb,ctx)	I	h.d., w.d.	s
	García et al. (2017)	M: nn, ma	I: e.c.	c.c., h.d., ctx, l	s
	Teoca and Ciuciu (2017)	H: cb, o	E: rat, p.d.	h.d.	pt
	Nakamura et al. (2016)	H: rb, ps	I: e.c.	h.d., e.k.	pt
	Matsui (2018)	M: cl, ps	E: rat	h.d., c.c., ctx	s
	Ayres et al. (2018)	M: dt, rb, nb, knn	E: p.d, I: e.c.	h.d.	p
Saving energy in smart buildings	Fotopoulou et al. (2017)	H: rb	E: rat, p.d.	e.k., c.c., ctx	p
	Pinto et al. (2019)	M: knn, svm, rb, ma	I: e.c., E: cr	c.c., ctx	p
Environmental resource management					
Optimizing water consumption	Li et al. (2013)*ˆ	H: cb	-	c.c., water availabilty	s
Increasing recycling	Kolstad et al. (2017)	H: cb, cf	I: his, E: rat	c.c., db	pt
	Kolstad et al. (2018)ˆ	H: cb	I: his, E: rat	c.c., db	s

Table 5: Recommender system features of the surveyed papers in smart economy and smart environment. Abbreviations used in the table stand for recommender: Model (M), Heuristic (H), algorithm (a), classifiers (cla), clustering (cl), collaborative filtering (cf), content based (cb), context based (ctx), decision tree (dt), finite states machines/stochastic learning automata (fsm), fuzzy logic (fz), graph algorithm (ga), hybrid (hyb), inverse reinforcement learning (irl), knowledge based (kb), k-nearest neighbours (knn), location aware (la), markov chains (mc), multi-armed bandit algorithm (mab.a), multi agent system (ma), matrix factorization (mf), naive bayes (nb), neural networks (nn), ontologies (o), optimization model (op), prefixed sentences (ps), popularity (pop), rule-based (rb), semantic similarities (sem), social based (sb), swarm algorithm (sa), support vector machine (svm), tag based (tag); user preferences: explicit (E), implicit (I), users' comments (com), consumption records (cr), user's energy consumption (e.c.), users' history of usage with the system (his), user's origin and destination (o.d.), personal data (p.d.), users' profiles with preferences via some type of ratings (rat), users' requirements (req), user's satisfaction levels (sat), semantic annotations (sem), users' social relationships (soc), social tags (tag), user's sequences of visit actions (vis); exploited data: business process models (bu), cameras (cam), climatic conditions (c.c.), users' context (ctx), product database (db), demographic data (d), expert knowledge info (e.k.), home devices usage reports (h.d.), sensors to locate users (l), medical records (m.r.), citizens' and political candidates' profiles (pro), participatory sensing (p.s.), service registry (reg), users' social network (sn), vehicle-to-infrastructure sensor data (v.t.i.), vehicle-to-vehicle sensor data (v.t.v.), body signal data from wearable devices (w.d.); implementation level: proposal (p), system (s), prototype (pt), algorithm (a).

		Smart mobility			
smart city action/goal	*reference*	*recommender*	*user preferences*	*exploited data*	*impl. level*
Traffic management					
Reducing traffic congestion	Horng (2014)	H: rb	E: o.d.	l, v.t.i.	a
	Karatzoglou et al. (2017)^	M: cf	E: record activities	l	p
	Kong et al. (2018)*	M: nn	-	v.t.i.	s
	Nayak and Narvekar (2017)	H: ga (A*)	E: o.d.	l, maps, statistics	p
Optimizing parking space usage	Horng (2015)	H: rb, M: nn, sa	E: o.d.	l, v.t.i., parking sensor	a
	Yavari et al. (2016)*^	M: cf, sem	E: rat, p.d.	l, v.t.i., p.s.	s
	Hassani et al. (2018)*	H: o, a	E: rat	v.t.i., c.c., maps, db	s
	Gang (2018)	H: ga (A*)	E: rat, o.d.	l, v.t.i.	a
	Rizvi et al. (2019)	H: ma, fsm	E: rat, o.d.	l, v.t.i., db, cam	a
Increasing driving safety	Outay et al. (2017)	H: kb, rb	-	v.t.i., v.t.v.	p
Emergency attendance					
Supporting conglomeration management	Lujak and Ossowski (2015)	M: ma, H: ga	E: o.d.	l, maps, cameras	s
	Salis et al. (2018)	M: ma, cf, nn, mf	E, I: rat	l, db	p
Supporting evacuation management	Lujak et al. (2017)	M: ma, H: ga	E: rat	c.c., l, ctx	pt
	Krytska et al. (2017)	H: multilayer grid, a	-	c.c., l, ctx, maps	pt
	Yamamoto and Fujita (2017)*	H: mc, cb	his E: rat, p.d.	l	p
Use of public transport					
Optimizing public transport usage	Handte et al. (2016)*	H: ga (A*)	E: o.d.	maps, db, v.t.i., l	s
	Concepción-Sánchez et al. (2017)	H: ga (Dijkstra), fz	E: o.d.	l	p
	Agrawal et al. (2018)^	M: fsm, ga, cl	E: o.d.	l, v.t.i.	a
Use of non-motorized and clean mobility options					
Supporting cycling facilities	Torres et al. (2015)*	H: ga (A*, Dijkstra)	I: his, E: o.d.	l, maps, statistics	s
	Kuhail et al. (2018)	H: ga (Dijkstra), cb	I: his, E: o.d., rat, sat	ctx, maps	s
Supporting vehicle sharing	D'Andrea et al. (2016)	H: fz, ga	E: o.d.	map	p
	Toader et al. (2017)^	H: ga, time series	E: rat	v.t.i., ctx, l	p
Supporting multimodal transport	Devigili et al. (2013)	-	E: rat	v.t.i., l, ctx, c.c., cam	p
	Di Martino and Rossi (2016)	M: ma	E: rat	l, maps, db	p
		Smart people			
smart city action/goal	*reference*	*scope*	*user preferences*	*exploited data*	*impl. level*
Creativity					
Promoting creative networks	Casadevall et al. (2018)	H: a	E: rat	sn	pt
Community building and urban life management					
Promoting community life	He et al. (2017)	H: cf	I: his	l, ctx, db, tags	s
	Kinawy et al. (2018)	H: cf	E: rat	tags	pt
Participatory society					
Supporting C2G communication	Kavanaugh et al. (2014)*	-	E: rat, I: soc, his	access logs, tags	s
	Marsal-Llacuna and De la Rosa-Esteva (2013)	H: hyb (cf, cb)	E: sat, I	comments	p

Table 6: Recommender system features of the surveyed papers in smart mobility and smart people. Abbreviations used in the table stand for recommender: Model (M), Heuristic (H), algorithm (a), classifiers (cla), clustering (cl), collaborative filtering (cf), content based (cb), context based (ctx), decision tree (dt), finite states machines/stochastic learning automata (fsm), fuzzy logic (fz), graph algorithm (ga), hybrid (hyb), inverse reinforcement learning (irl), knowledge based (kb), k-nearest neighbours (knn), location aware (la), markov chains (mc), multi-armed bandit algorithm (mab.a), multi agent system (ma), matrix factorization (mf), naive bayes (nb), neural networks (nn), ontologies (o), optimization model (op), prefixed sentences (ps), popularity (pop), rule-based (rb), semantic similarities (sem), social based (sb), swarm algorithm (sa), support vector machine (svm), tag based (tag); user preferences: explicit (E), implicit (I), users' comments (com), consumption records (cr), user's energy consumption (e.c.), users' history of usage with the system (his), user's origin and destination (o.d.), personal data (p.d.), users' profiles with preferences via some type of ratings (rat), users' requirements (req), user's satisfaction levels (sat), semantic annotations (sem), users' social relationships (soc), social tags (tag), user's sequences of visit actions (vis); exploited data: business process models (bu), cameras (cam), climatic conditions (c.c.), users' context (ctx), product database (db), demographic data (d), expert knowledge info (e.k.), home devices usage reports (h.d.), sensors to locate users (l), medical records (m.r.), citizens' and political candidates' profiles (pro), participatory sensing (p.s.), service registry (reg), users' social network (sn), vehicle-to-infrastructure sensor data (v.t.i.), vehicle-to-vehicle sensor data (v.t.v.), body signal data from wearable devices (w.d.); implementation level: proposal (p), system (s), prototype (pt), algorithm (a).

smart city action/goal	reference	scope	user preferences	exploited data	impl. level
Smart living					
Accessibility facilities					
Assisting with software applications	Gómez-Martínez et al. (2015)*	H: cb, o	E: rat, I: his	db, e.k.	s
	Guo et al. (2017)^	H: cf	I: his	h.d.	s
Assisting mobility	Barczyszyn et al. (2018)	M: ga	E: o.d., rat	maps, ps, l	pt
Assisting with smart home devices	Hussein et al. (2015)	H: rb, o	I: his	l, ctx	a
	Sohn et al. (2013)	H: o	I: his	h.d., c.c.,	pt
	Oyeleke et al. (2018)	M: fsm	I: req	e.k., ctx	p
Healthcare measures					
Promoting healthy lifestyle	Lemlouma and Chalouf (2012)	H: rb	I: his, E: rat	d	pt
	Vavilov et al. (2014)	H: a	I: his	-	a
	Casino et al. (2015)	H: cf, ctx	E: rat, p.d.	p.s., ctx	p
	Casino et al. (2017)	H: cf, ctx	E: rat, p.d.	p.s., ctx	pt
	Casino et al. (2018)	H: cf, ctx	E: rat, p.d.	p.s., ctx	pt
Supporting medical surveillance	Asthana et al. (2017)	M: op, cla	I	m.r., w.d., d, db	s
Supporting disease prevention	Benyahia et al. (2012)	H: o, rb	I	w.d., m.r., e.k.	p
	Kim and Chung (2017)	H: cf	E: rat	e.k.	p
Improving healthcare system	Ali et al. (2018)	H: fz, rb	I, E: p.d.	w.d., m.r., db	pt
Supporting healthcare service access	Narducci et al. (2015)	H: cf	E: p.d.	m.r.	s
	Narducci et al. (2017)	H: cf, sb	E: p.d., soc	m.r.	p
	Jung et al. (2018)	-	E: rat	m.r., l, db, e.k	pt
Providing health-related information	Roitman et al. (2010)	H: cf	E	m.r, db	p
Urban security					
Supporting safe places identification	Gómez et al. (2015)	H: hyb (cf, ctx)	E: rat	l, ctx	s
Tourism services					
Promoting city cultural heritage	Barile et al. (2014)	H: cf	I: rat, soc	l	s
	Cha et al. (2016)	M: cl, cf	I	l, ctx	pt
	Massimo (2018)	H: cf, irl	I: vis	db	p
	García et al. (2018)*	H: cf	E: rat, p.d., soc	db, l, d	s
Reducing tourism negative impacts	Mrazovic et al. (2017)*^	H: op, ga	E: rat	db, e.k.	s
Smart governance					
smart city action/goal	*reference*	*recommender*	*user preferences*	*exploited data*	*impl. level*
Efficiency in municipal management					
Informing about building permits	Eirinaki et al. (2018)*^	H: cf	I: his, E: rat	city permits	s
Notifying government e-services	Janssen et al. (2003)	-	E: req	bu	p
	De Meo et al. (2005)	H: cb	E: rat, req	db	pt
	Martín-Guerrero et al. (2006)	H, M: cf, cl	I: his	db	a
	Sabucedo et al. (2012)	H: hyb (cf, cb, pop), tag	I: cr, tags	-	a
	Baldassarre et al. (2013)	H: cb	E: p.d. ctx, req	bd	s
	Ayachi et al. (2016)	H: cf, cb, ctx	E: p.d. ctx, req	reg	p
Citizen participation and inclusion					
Enhancing e-voting	Terán and Meier (2010)	M: fz, cl	E: rat	pro	a
	Dyczkowski and Stachowiak (2012)	H: fz	E	pro	pt
Enhancing e-participation	Nelimarkka et al. (2014)	M: cb	E: rat com	-	a
	Cantador et al. (2017)^	H: hyb (cf, cb)	E: rat, I: tag	-	a
	Cantador et al. (2018)^	H: hyb (cf, cb, la)	E: rat, I: l, sem	-	a

Table 7: Recommender system features of the surveyed papers in smart living and smart governance. Abbreviations used in the table stand for recommender: Model (M), Heuristic (H), algorithm (a), classifiers (cla), clustering (cl), collaborative filtering (cf), content based (cb), context based (ctx), finite states machines/stochastic learning automata (fsm), fuzzy logic (fz), graph algorithm (ga), hybrid (hyb), inverse reinforcement learning (irl), location aware (la), ontologies (o), optimization model (op), prefixed sentences (ps), popularity (pop), rule-based (rb), semantic similarities (sem), social based (sb), tag based (tag); User preferences: explicit (E), implicit (I), users' comments (com), consumption records (cr), users' history of usage with the system (his), user's origin and destination (o.d.), personal data (p.d.), users' profiles with preferences via some type of ratings (rat), users' requirements (req), semantic annotations (sem), users' social relationships (soc), social tags (tag), user's sequences of visit actions (vis); Exploited data: business process models (bu), climatic conditions (c.c.), users' context (ctx), product database (db), demographic data (d), expert knowledge info (e.k.), home devices usage reports (h.d.), sensors to locate users (l), medical records (m.r.), citizens' and political candidates' profiles (pro), participatory sensing (p.s.), service registry (reg), body signal data from wearable devices (w.d.); Implementation level: proposal (p), system (s), prototype (pt), algorithm (a).

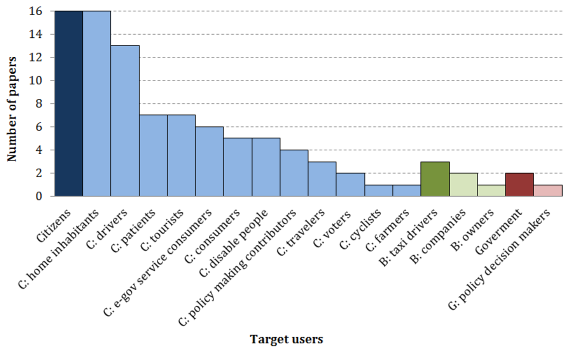
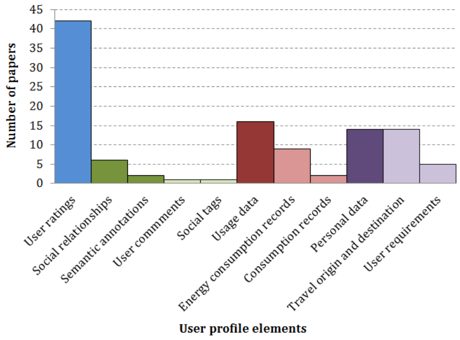
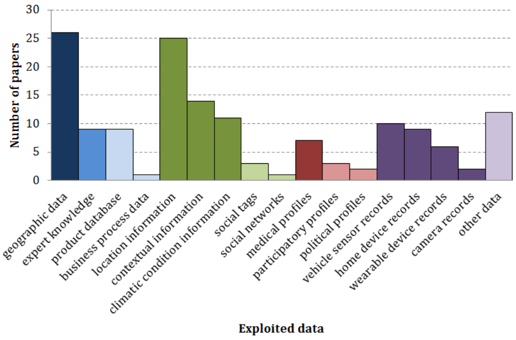


Figure 3: Target users of the surveyed recommender systems



4.a. User profile elements in the surveyed recommender systems



4.b. Exploited data by the surveyed recommender systems

As previously mentioned, additional knowledge used by recommender systems appear in different forms of **exploited data** (see Figure 4.b). Most systems make use of geographic data and user context information, especially location-based. We notice a lack of usage of information regarding user comments, social tags, and semantic annotations, since they represent data than can be relatively easy to obtain, due to their massive presence in social media. We thus point to future research towards further exploiting this possibility, as it could add valuable implicit data that would help on enhancing recommendations without bothering users by explicit preference requests. The exploitation of home and wearable device data could also represent challenging issues thanks to the growing use of such devices. Other types of data, in contrast, seem more difficult to gain popularity, due to privacy and security constraints. This is the case of social network, trust, participatory and political profiles.

shows the distribution of user profile elements utilized across the papers. User preferences expressed via some type of ratings are the most common element, followed by system usage, user personal data and travel origin and destination requirements.

As for the followed **recommendation methods**, heuristic-based recommendations are clearly dominant, representing 71% of the surveyed papers, against the 23% of the papers that present model-based recommendation approaches. Concerning the **recommendation strategies**, Figure 5 shows their distribution in the papers. The majority of the approaches are collaborative filtering and content-based, representing 35% and 22% of the surveyed papers respectively. However, as it can be seen in Tables 5, 6 and 7, in most papers, several recommendation strategies are performed following some hybridization technique. More specifically, we distinguish between three cases: 1) those that have several stages and modules, and perform certain strategy for each of them, e.g., using ontologies for structuring data first and a rule-based recommender later; 2) those that present a recommender implementing several strategies that complement each other, e.g., a content-based collaborative filtering system; and 3) those that use different approaches to test which one works better. In this context, we envision the development of recent matrix factorization and deep learning models as promising recommendation approaches to deal with the vast amounts of data managed at city scale.

Lastly, as shown in Figure 6.a, it is important to note that regarding the **implementation levels**, only 34% of

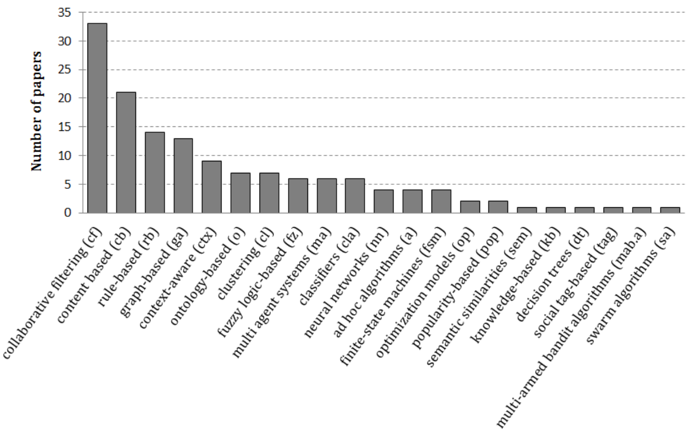


Figure 5: Recommendation approaches followed in the surveyed papers

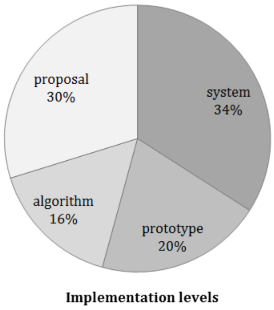
the papers present recommenders deployed in real systems and, more remarkably, 30% describe proposals of recommendation approaches. In the rest of the papers, we find prototype systems (20%) and algorithms/methods (16%). According to these facts, we confirm that recommender systems for smart cities are still in their infancy, and can evolve significantly and fast by taking into account proposed recommendation solutions on other domains and applications. We note that out of the 34% papers that do present recommenders deployed in real systems, just 15 cite the recommendation technologies/tools/frameworks used. Most of the works present own developments and do not use existing software libraries popular in the recommender system field. Those that do reflect this information (highlighted in the Tables 5, 6 and 7 with a *) have no common patterns. Thus, we believe that this is a research issue that should be addressed.

With respect to recommendation evaluation, Figure 6.b shows the distribution of the **types of evaluations** conducted in the surveyed papers: 38% of such papers do not present any evaluation at all, which makes sense given that 30% of the papers depict proposals that were not implemented; 19% describe simulations based on synthetic data; and the reminder papers report user studies (17%) and offline experiments (17%) –which is also in accordance with the implementation level of the approaches–, 20% prototypes and 16% algorithms/methods. Only 11% of the papers present real life experiments. All the evaluated studies claim the provision of a service that has facilitated, improved or fastened decisions that otherwise would have been difficult or impossible to reach. However, their testing is limited to a small number of users, instead of reporting results from systems widely and publicly used inside a city. Bearing in mind all these issues, we believe that strong effort has to be done to generate **public datasets** with which experimenting on smart city problems and challenges. We note that only 16% of the papers with some kind of evaluation provide/use a public dataset. To address this situation, as stated before, social media and Open Data may be key data sources. In order to support future investigation, papers that use or report the existence of public available datasets have been highlighted with ˆ in Tables 5, 6 and 7).

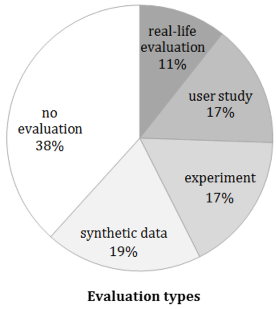
In terms of the computed **evaluation metrics**, the majority (44%) of the papers presenting certain evaluation make use of ranking quality metrics, mainly precision and recall. The next most popular metrics are MAE and RMSE –which measure rating prediction errors and are reported in 18% of the cases–, and user satisfaction, representing another 18%. System response time is considered in 8% of the cases, whereas system effectiveness is analyzed in 6% of the evaluations. The rest of the used metrics are related to a variety of task dependent issues, such as time saved by users, energy consumption reduction and traffic congestion avoidance.

6. Conclusions

In this paper we have surveyed the research literature on recommender systems for smart cities, presenting a characterization, categorization and comparative analysis of published papers. We have analyzed a total of 94 journal and conference papers proposing recommendation approaches aimed to address major actions and goals in six well-known smart city dimensions, namely smart economy, smart environment, smart mobility, smart governance, smart



6.a. Implementation level of the surveyed recommender systems



6.b. Types of evaluations conducted in the surveyed papers

living, and smart people.

The majority of the surveyed work has been published since 2011, and the number of papers per year has been increasing and has doubled in 2017 and 2018. This recent and growing tendency suggests that smart city recommenders represent a novel and promising research topic. In this context, our survey serves as a comprehensive framework for researchers and practitioners, and stands the basis for future developments.

For each work, we have considered features related to smart city issues, such as actions and goals, application scopes (i.e., at city, building, home and user levels), and exploited data sources (e.g., city sensors, IoT devices, web services, open data, and social media). We have also considered features associated to the recommendation approaches, such as target users (e.g., citizens, governments and businesses), recommended items, user preferences, knowledge representations, recommendation methods, implementation levels, and evaluation types and metrics. Comparing the papers according to all the above metrics, we have identified both the most addressed smart city problems and followed recommendation approaches, and issues open for investigation.

In particular, our study has revealed that the main smart city actions for which recommender systems have been proposed are energy efficiency, healthcare measures and traffic management. And more specifically, it has shown that the most popular smart city goals addressed by recommender systems are saving energy in smart homes, notifying government e-services, promoting a healthy lifestyle, optimizing parking space usage, promoting a city's cultural heritage and reducing traffic congestion.

Proposed recommendation approaches mainly use data extracted from sensors and IoT devices, and are applied at city and user levels. Thus, location and other contextual information are predominant in the surveyed papers. Besides explicit ratings –commonly used by collaborative filtering approaches–, item usage and consumption data (considered as implicit feedback) are the most frequent forms of user preferences. In this sense, we observe that exploiting user reviews, contents generated in social media, Open Data, and participatory sensing data have been barely exploited, but represent data sources of high potential for recommendation applications in the context of smart city initiatives.

In addition to exploiting these data sources, we also envision some open, challenging tasks for smart city recommender systems. Among others, we identify the following relevant goals to address through recommendation solutions: promoting recycling and sustainable actions, supporting logistics, facilitating flexibility in the labour market, providing government transparency and accountability, and promoting an inclusive society.

Similarly, the majority of the published recommenders have been targeted to citizens, playing a variety of roles –such as home inhabitants, drivers, hospital patients, tourists, and policy making contributors. A few approaches have been proposed to assist companies, and even less have been aimed to help government stakeholders. However, business and government actors are usually involved in city decision making tasks and, in our humble opinion, could benefit much more from recommender systems in order to find relevant information for the above tasks.

A trend in science is to study and address problems by analyzing and exploiting large datasets, and recommender systems for smart cities is not an exception to that. We have suggested future work on the basis of categories less studied so far, but there are also other very important aspects to consider, such as the need to merge recommender systems with social incentives, which is an interesting research issue for applications in certain areas, e.g., public administration and politics.

Regarding the developed recommendation methods, we have shown that the great majority (around 70%) of the surveyed approaches are based on heuristics, being collaborative filtering the most popular technique. In the recommender systems field, however, there has been a consolidation of matrix factorization and deep learning models as the best performing approaches in many domains. We believe that these model-based methods may have an important impact in smart city initiatives, especially due to the huge amounts of sensor data generated at city scale in many applications. With this respect, we also miss more work on context-aware and social-based recommendation approaches, considering the relevance that IoT devices and social media already have in the citizens' daily life.

Lastly, we note that only 30% of the surveyed papers present recommendation approaches actually deployed in real platforms. The remainder are prototypes, algorithms, or even proposals. For this reason, the literature on smart city recommenders does not report remarkable evaluations. In fact, only 11% of the works conducted real life experiments, which is in line with the very low percentage (16% approximately) of studies that made use of public datasets. Our survey has shown that there is much to be done in order to contribute positively to modern societies and smart cities, providing a number of heterogeneous, challenging scenarios for recommender systems. In this context, we recall the attention at the work done in the urban computing area, where data sources and applications potentially related to recommendation tasks and solutions have been well established (Zheng et al., 2014; Zheng, 2019).

7. Acknowledgments

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