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The CitRec'17 workshop manifesto

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Recommender Systems for Citizens: The CitRec'17 Workshop Manifesto

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This manifesto summarises the outcomes of the 1st Workshop on Recommender Systems for Citizens (CitRec'17), held at the 11th ACM Conference on Recommender Systems, in August 2017 in Como, Italy. We discuss challenges and opportunities for the development of recommender systems for citizens, including: the clarification of the role of recommender systems for cities and citizens; in this context, the identification of classes of items to be recommended; the need for targeting and engaging the right population, involving the right stakeholders; and the existence of underlying ethical issues such as fairness and consensus. We further provide an action plan to bring forward the research and application of recommender systems for citizens.

CCS Concepts: • **Information systems → Information retrieval**; **Recommender systems**;

Additional Key Words and Phrases: Recommender Systems; Citizens; Smart Cities

1 INTRODUCTION

Recommender systems are playing a central role in a variety of domains. When restricted to applications in cities, and for citizens, a large body of literature could be found on Point-Of-Interest (POI) recommendation [16], tourist location recommendation [17], healthcare recommendation [4], and, orthogonally, spatio-temporal context-aware recommendation [9, 11]. However, existing works have primarily focused on single recommendation domains, and mostly from an algorithmic perspective. We advocate the importance of a social perspective that considers how to design recommender systems that best serve our society.

The first Workshop on Recommender Systems for Citizens (CitRec 2017), co-held with ACM RecSys 2017 in August 2017, Como, Italy, addresses the specific types of recommender systems that are owned by citizens, and are aimed at serving the society as a whole. As proposed and discussed in the workshop, we envision that recommender systems have the potential to expand their impact greatly, and play an important role in today's society, improving citizens' living experiences and the effectiveness of environmental uses.

To optimise the social effectiveness of recommendation systems in cities, a deep understanding of the interactions between citizens, between citizens and the environment, and between citizens and other urban stakeholders, such as public administrations and local businesses, is needed. Consider the example of a driving route recommender system. To optimally recommend driving routes to a community of citizens, the system should be able to understand how the effectiveness of recommendations is influenced by the environment (e.g., road conditions) and how the recommendations to different citizens affect each other (e.g., to avoid traffic congestion). Here is another example: a citizen proposal recommender system in an online participatory budgeting platform. To provide personalised recommendations of proposals, the systems should look beyond a target user's profile (i.e., interests, needs, demographic characteristics, and geographical constraints) and consider aspects such as the satisfaction of public budget allocation programs, and inclusion of certain population segments and city assets. These examples, among others, call for research on both algorithmic design for the recommendations to benefit the society as a whole, and incentive mechanisms to balance personal and societal, governmental and business interests. Given these distinct goals, recommender systems for citizens are faced with more social and computational challenges beyond the mentioned above.

At the same time, the emergence of social data, i.e., data generated by people during their societal activities, available through new sources (e.g., social media, mobile phones, sensor networks) bring great opportunities to the development of recommender systems for citizens. Social data contains a multitude of dimensions – such as the targeted urban population, the purpose of use, and the spatio-temporal context – which allow describing comprehensively citizens' behaviours and their relationships, and thus represent valuable sources of information to deploy recommender systems for citizens.

In addition to social data, Open Data provided by government agencies could also be exploited for recommendation purposes. Following machine readable formats, public linked and open data repositories contain valuable information at large scale about a wide array of topics in a city, such as health, education, energy, finance, and public safety. These data facilitate government transparency, accountability and public participation, and support technological innovation and economic growth by enabling third parties to develop new digital services. An example of this is the Data.gov initiative of the U.S. Government, whose datasets have already been used in a large number of applications [1].

For problems where social data and open data are scarce, or not available, crowdsourcing may provide an alternative source by engaging citizens to actively contribute their behavioural data to the system via effective incentive schemes.

The challenges and opportunities described above were extensively discussed at CitRec 2017, to drive the research of recommender systems for citizens. This manifesto summarises the outcomes of the workshop. We address a variety of audiences, and provide suggestions for future work that include: further clarification of the of recommendation systems in cities and for citizens; the

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[1] https://www.data.gov/applications

need and potential solutions for targeting and engaging the right population; identification of classes of items that are relevant for recommendation; involvement of the right stakeholders; consideration for important ethical issues such as fairness and inclusiveness; and the selection of application domains to first address in future investigations.

2 CHALLENGES AND OPPORTUNITIES

We identified the topic of *Recommender systems for citizens* (CitRec) to sit at the intersection between Citizen Science and recommender systems and Information technologies, while showing elements of novelty due to its original perspective. The technological elements at the core of CitRec make the research focus different from Citizen Science; at the same time, the new application domain (i.e., citizens) poses new challenges for the research on recommendation techniques. This section discusses potential challenges and opportunities for the development of recommender systems for citizens.

The Role of Recommender Systems. Recommender systems can play a multitude of roles for different stakeholders in cities.

From the perspective of citizens, personalisation and information filtering – the core properties of recommender systems – are also of value in recommender systems for citizens. From the point of view of governments, recommender systems can serve as a method to promote inclusion of citizens in urban development, e.g. to engage citizens in the process of policy making through, for instance, e-participation. Recommender systems for citizens can also play a moderation role. Considering the different and sometimes conflicting interests among different communities in a city, recommender systems should be able to strike a balance among them. Such a role is fundamental to promote fairness, as we will discuss later. If we consider different types of stakeholders, recommender systems for citizens are expected to play the role of lubricant that can improve the efficiency of communication among them.

As an additional requirement, the recommender system infrastructure should be part of the infrastructure that the city provides and, in many cases, it should disappear into the background.

What to Recommend.

What can be the object of recommendation in CitRec systems? Participants agreed that often, information needs can be fulfilled by a diverse set of objects, and that recommendation techniques can be applied to a very diverse set of items. Let us consider a set of examples. In collaborative environments [18] the tasks (contributions) are designated / recommended to target "workers" (volunteers/contributors). This scenario has many parallels with crowdsourcing platforms that are looking for a better matching between workers and tasks [5, 7] and for a better quality of their service [2]. Examples of such tasks / contributions to recommend may consist of trusty hosts as in case of Couchsurfing[2] or companions in personal security solutions such as Companion[3] or social tasks like cleaning the garbage in the streets, helping elderly people doing grocery shopping, etc. Another example of services that can be viewed as collective good to recommend has been demonstrated in the work of Cantador *et al.* [3] in which the authors present an study on recommending citizens' proposals on an e-participation platform that aim to address existing issues and problems in a city.

Moreover, the recommendation purposes may be manifold. Among other aspects, they could be defined in terms of the level of citizen involvement. The Ladder of Participation proposed by Arnstein [1] considers three main levels, namely information, consultation, and co-design and co-production levels. At the information level, recommender systems may be designed to keep users informed, e.g. by providing citizens with personalised suggestions of government services. At the consultation level, recommender systems may be aimed to promote user participation, e.g. by suggesting initiative proposals for the city. Finally, at the co-design and co-production level, recommender systems could facilitate collaborative processes, e.g. by suggesting pilot projects in living labs. In this context, for each particular purpose, the effectiveness of generated recommendations have to be evaluated with an appropriate methodology and metrics [10].

Targeting the Right Users. A characteristic goal of recommender systems for citizens is that generated recommendations have to serve the public good. Therefore, the main beneficiaries of such systems may be on the one hand a community or a society as a whole, and, on the other hand, municipality, local authorities, government, or local businesses. Sometimes recommendations might target certain citizen segments, characterised by particular demographic, socio-cultural and economic attributes.

The objective functions are thus more complex than in traditional recommendation scenarios. The benefit from a recommender system cannot be reduced to the profit of a single user, organization or holding, and does not necessarily have money value. In this context, the evaluation methodologies and metrics may also differ from traditional ones [10].

Engaging the Population. In his work *Politics* [4], Aristotle said: "...a state is not a mere society, having a common place, established for the prevention of mutual crime and for the sake of exchange. These are conditions without which a state cannot exist; but all of them together do not constitute a state, which is *a community* of families and aggregations of families *in well-being, for the sake of a perfect and self-sufficing life*... political society exists *for the sake of noble actions*, and not of mere companionship."

Nowadays, we can witness the growth of population's conscience and societal shift to well-being and exploration of oneself. Recent psychological studies [8, 13] have shown that people are more satisfied with their life if they embrace diverse *Orientations to Happiness*, namely Pleasure (*i.e.* maximisation of sensory pleasures), Meaning (*i.e.* living life of full potential and contributing for something bigger than oneself), and Engagement (*i.e.* full immersion in an activity, feeling of flow).

This is to say that social involvement becomes an important component of decision making process. The idea of meaning of one's actions that can be expressed by *"'what I'm doing matters to society"* encourages people to contribute to the collective good. We believe that this is one of the motivations behind taking part in non-profit collaboration projects such as Wikipedia, crowdfunding campaigns

[2] https://www.couchsurfing.com
[3] https://www.companionapp.io

[4] http://classics.mit.edu/Aristotle/politics.3.three.html

(*e.g.* KickStarter[5], GoFundMe[6]), signing petitions (*e.g.* Change.org), and crowdsourcing campaigns, especially mobile crowdsourcing campaigns [15]. In the context of CitRec systems, we argue that the driver for participation moves from profit to the collective good, engaging more active participants [12].

Alternative, one could envision a type of driver for population engagement to relates to education and awareness creation. One of the goals of CitRec is to raise social awareness and social engagement in a city life. Therefore, we believe that the core driver of a system may be educational with or without gamification component. Example of such initiatives is a SenCityVity project recently launched in Mexico [15].

Involving Stakeholders. Who is going to pay for CitRec systems development, deployment, and maintenance? That is a natural question, which hints different possible answers.

One of the possible solutions constitutes in moving within the CitRec systems the economical incentives needed for their operation. This could be intuitively explained as follows. The ultimate goal of cities is to provide services. To deliver a service costs money. A government needs to be able to show that this investment will help to deliver a better service that the service that is currently provided.

Recommendations generated from citizens' data may be targeted to, or may exploit, information from other stakeholders [6]. For instance, in the government side, we could consider different actors, such as politicians, government agencies, and public employees, whereas at the business sector, in addition to enterprises, we could focus on public providers or NGOs. Moreover, for a particular actor, recommender systems may distinguish between different roles [14]. Hence, for example, a citizen may act as a city resident, as a public service consumer, or as a tourist depending on the current context. In any of the these cases, recommendations may not be generated for an individual user, but may involve multiple users, e.g. particular population segments, social collectives and local associations.

Fairness and Consensus. There needs to be fair services to everyone: inclusiveness and elimination of biases. Fairness will be a bigger problem when applying recommender systems for citizens because there is no definition of what the greater social good is. The unclear definition of social good will potentially enlarge the issue of bias. To alleviate such a problem, perhaps a purpose of the system needs to be creating a consensus on what is social good.

3 LOOKING FORWARD

Following the identified challenges and opportunities, we outline an action plan that we believe will be beneficial to push forward the research and application of recommender systems for citizens. To further drive the discussion, we are interested in building a community where scientists from various expert domains and disciplines, practitioners, and enthusiasts can discuss with each other on relevant topics. As suggested by CitRec participants, we will then focus on choosing relevant problems to investigate scientific approaches to address the challenges in concrete contexts. Based on the problem, we could then engage stakeholders and carry out research projects to deepen and diversify the research and application. We hope that this work will create a virtuous circle that helps to reach our ultimate goal of developing a novel class of recommender systems that will benefit the whole society.

[5]https://www.kickstarter.com
[6]https://www.gofundme.com

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