ABSTRACT

Recommenders are systems that employ some knowledge on items and user preferences, along with sophisticated algorithms to provide personalised content and services. They have been around to tackle the information overload and personalisation demand in today’s always-connected world. This technology appeared in the cultural heritage domain relatively recently, but the bibliography is already rich, as cultural tourism plays an important role for regional economies. From the technical perspective, different approaches, like collaborative filtering, content-based, knowledge-based and hybrid approaches, have been adopted. From the intuition perspective, the approaches are influenced by current conceptualisation and specific application domains and demands. The museum has been one of the main target applications, either as a part of visit support or in the context of cultural tourism initiatives. This article presents a review of the domain and draws a generic blueprint for the end-to-end development of a recommender for cultural tourism that outperforms a baseline popularity-based approach.

KEYWORDS
Artificial Intelligence, Cultural Heritage, Cultural Tourism, Machine Learning, Museum Guide, Recommender, User Modelling, User Satisfaction

INTRODUCTION

It was in the late 20th century that the flourishing of a particular domain of narrow artificial intelligence applications took place, the recommenders. Recommenders are systems with a usually complete knowledge of a set of items and a usually incomplete knowledge of user preferences on those items, in order to provide recommendations for interactions with unseen items, by targeting the maximisation of user satisfaction. The generated recommendations can be of any form of suggestion for any kind of interaction or engagement, depending on the context, and may include buying options, music or movie suggestions, path following and time allocation. In either case recommenders cannot be generic and are typically adapted to perform efficiently for particular cases. The main goal of recommenders is to generate personalised recommendations as an effective solution to the pervasive problem of information overload, and is compliant with a particular user group and context (educational,

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recreational, location-based, time-dependent) (Adomavicius & Tuzhilin, 2005; Aggarwal, 2016a; Asanov, 2011; Melville & Sindhwani, 2011). It should be noted that recommenders draw their theoretical background on various domains including approximation theory, information retrieval, forecasting, management, cognitive science and consumer modelling (Adomavicius & Tuzhilin, 2005). Online advertisement is one sector in which recommenders thrive and thus are extensively studied as an interesting machine learning application in information technology (Goodfellow, Bengio, Courville, & Bengio, 2016).

Apparently, recommenders rely on all available data, which may include contextual assumptions and information, user demographics and assumptions, features of the item, and ratings assigned to the items by the users. Those available data may often be unreliable, as data for the users may be missing or be inaccurate, the user profile models may be inaccurate, the ratings for the items are extremely rare and context modelling may be considered static in situations that it is highly dynamic and possibly biased. The item ratings, which are the most direct form of information connecting user preferences to items, are so scarce that the typically used ratings matrix representation is around 99% sparse. The ratings matrix is a mathematical construct that is persistent in many technical approaches and particularly those based on what is called the collaborative filtering, an approach of predicting item ratings using a cost function optimisation as a form of a multi-dimensional regression. As the ratings matrix is highly sparse there is a major challenge in identifying such this super-surface. Another significant challenge for recommenders is the cold-start problem, the inability to generate accurate recommendations for new users, which is usually approached as a user modelling problem. Other challenges for recommenders include fraud and attacks, which are interesting and specific forms of malicious manipulation of the recommender to generate biased recommendations (Aggarwal, 2016b; Burke, Mobasher, Bhaumik, & Williams, 2005; Lam & Riedl, 2004; Melville, Mooney, & Nagarajan, 2002; Melville & Sindhwani, 2011; Schein, Popescul, Ungar, & Pennock, 2002; Su & Khoshgoftaar, 2009).

Typically, in recommenders there is a baseline system, which is no other than a recommender that assumes a gaussian model and provides its recommendations based purely on the popularity of the items. In this approach items are being ranked following a decreasing order of popularity that is estimated using statistical data. Using this list, the top ranked items are those that are recommended first. Regardless the simplicity of this model, the results are usually accurate (or at least valid). As a matter of fact, the results are so valid that any new recommender has to win the popularity-based recommender in the application at hand.

A literature review of the advancements in recommenders reveals a plethora of works in various domains since the 1990s. This review is beyond the scope of this paper and the interested reader is advised to delve into highly cited works in established scientific journals and conferences (Adomavicius & Tuzhilin, 2005; Aggarwal, 2016a; Anand & Mobasher, 2005; Bobadilla, Ortega, Hernando, & Gutiérrez, 2013; Goldberg, Nichols, Oki, & Terry, 1992; Good et al., 1999; Iaquinta, de Gemmis, Lops, Semeraro, & Molino, 2010; Jannach, Zanker, Felfernig, & Friedrich, 2011; Kabassi, 2010; Kaminskas & Ricci, 2012; Konstan, 2004; Lü et al., 2012; Resnick, Iacovou, Suchak, Bergstrom, & Riedl, 1994; Ricci, Rokach, Shapira, & Kantor, 2011).

This paper presents a review of recent advancements in recommenders for cultural heritage applications and a blueprint for the creation of an end-to-end recommender for cultural tourism based on three pillars outlined in recently published works: (a) a novel user satisfaction modelling (Pavlidis, 2018c); (b) the identification of the role of recommenders in cultural heritage (Pavlidis, 2018b); and (c) the way forward (Pavlidis, 2018a). In the presentation that follows, the terms visitor and user, and also the terms exhibit and item are being used interchangeably to denote the generalisation that may be attained from a visit to a museum and the appreciation of exhibits or to a cultural tourism activity that involves a user interacting with cultural items.
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