Context In Recommender Systems

Tutorial (half-day) Proposal by Yong Zheng
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Abstract

Recommender system (RS) is a popular personalization system recommending appropriate items to the end users. It has been widely used in different domains and applications, such as Amazon.com, Netflix, Pandora, Facebook and Twitter, etc. During the past decades, ther are many novel RS emerged, such as social RS, group RS, and context-aware RS. Context-aware recommender system (CARS) is one RS trying to adapt their recommendations to users' specific contextual situations, since users usually make different decisions in different situations. For example, users may choose a romantic movie to watch with partner, but probably a cartoon if he or she is going to watch it with kids. Companion, either partner or kid, in this example, is one influential context factor. Other examples of the contexts could be time, location, weather, and so forth. Due to that users' preferences and decisions vary from situations to situations, it is necessary to take context into consideration when providing recommendations to the end users.

There are two typical recommendation tasks involved when context is taken into account: one is context-aware recommendation (CAR) and another one is context recommendation (CR). The topics in CAR are focused on how to build context-aware recommendation algorithms to recommend items to users in a specific situations. For example, which restaurant I should choose if I am going to have a formal business dinner with a company director. By contrast, context recommendation is a novel research direction emerged in recent years, where it aims to suggest appropriate contexts for the users to consume the item. For example, which could be the best contexts for me to watch the movie "Titanic"? Potential answers could be seeing it in a theater with your partner at weekend.

In this half-day tutorial, a comprehensive of the overview on the two tasks – CAR and CR, will be introduced to the audience. More specifically, what is context and how to build context-aware recommender systems will be introduced at the beginning. Various CARS algorithms will be further discussed and an open-source context-aware recommendation library, CARSKit, will be shown to the audience with the specific instructions on how to build an devaluate CARS algorithms by using this toolkit. Furthermore, the remaining time will be spent on the introduction of context recommendation and its solutions, as well as challenges.

1 Introduction and Motivations

Context-aware recommender systems (CARS) have been demonstrated to be able to improve the performance of recommendation in many recommendation tasks, such as travel accommodation [1], food menus [2], and movie recommendation [3]. Traditional recommendation problem can be modeled as a two-dimensional (2D) prediction – R: $Users \times Items \rightarrow Ratings$, where the recommender system's task is to predict that user's rating for that item. Context-aware recommender systems try to additionally incorporate contexts to estimate user preferences, which turns the prediction into a "*multidimensional*" rating function – R: *Users* $\times$ *Items* $\times$ *Contexts* $\rightarrow$ *Ratings* [4], where context is defined as "any information that can be used to characterize the situation of an entity" [5].

1.1 Motivation Behind The Topic

Context plays an important role in recommender systems, since users' preferences and decisions are always changing from contexts to contexts. For example, you may choose a fast food store for food if you just need a *quick lunch*; otherwise, you may choose a formal restaurant if you would like to have a *business dinner*. Also, you may choose romantic movie "Titanic" to watch *with partner*, rather than "Kung Fu Panda" if you are going to watch the movie *with kids*.

It is not only useful in research, but also meaningful in real practice. People may need to understand their patterns on behaviors from the perspective of contexts. And recommender system itself would like to adapt to users' preferences on different contextual situations, in order to better serve the peoples; dynamic requirements at the right time and right place.

1.2 Audience Interests

Recommender system is well-known as an applied science, where multi-disciplines are involved, such as artificial intelligence, data mining and machine learning, information retrieval and extraction, Web technologies and social media, as well as mobile computing and e-learning, and so on. The applications of recommender systems are well-familiar by the audience, since it is a highly applied system in real practice, such as the e-commerce website like Amazon.com, eBay, music areas like Pandora and Spotify, tourism applications like tripadvisor and expedia, etc. In addition, the notion of "context" raises research attentions in recent years too, not only in ubiquitous computing, but also in information retrievals and computational advertising. It is a good chance to have such a tutorial to attract different audiences from multi-discipline or research areas to join together, where it fully takes advantage of the ACM SAC conference, since this is already a multi-discipline symposiums with the support of various research and technical communities.

2 Outline and Objectives

A half-day tutorial (i.e., 3 hours) can be organized as follows:

- Intro: Recommendation Systems and Applications (10 minutes)
- Context-aware Recommender Systems [4] (1.5 hour in total)
  - Context Definition and Identification [6] (10 minutes)
  - Context-aware Recommendation Architectures and Algorithms [7, 8, 9, 10] * (1 hour)
  - CARSKit: An Open-source Context-aware Recommendation Library [11] (20 minutes)
- Context Recommendation or Suggestion [12] (1 hour in total)
  - Context-aware Recommendation v.s. Context Suggestion (10 minutes)
  - Tasks and Applications in Context Suggestion [13] (10 minutes)

*There are many more references in this section which we did not list here.

  - Solutions and Challenges [12, 13] (40 minutes)

- Summary and Discussions: Opportunities and Challenges (10 minutes)
- Q&A (10 minutes)

The objective is to let the audience clearly know the role of context in recommender systems, and how to perform the context-aware recommendation and context suggestion tasks by providing easy-understanding introductions and examples, as well as specific introductions on the solutions or algorithms developed in the past decade. Also, CARSKit, as an open-source context-aware recommendation library will be shown to the audience to let them learn how to use such toolkit to build and evaluate the popular algorithms for context-aware recommendation. In terms of the context suggestion, it is still a brand new and novel research area. We'd like to leave more discussions on the solutions and challenges to achieve communications among different research communities.

3 Requirements

There are no specific requirements or prerequisites for the audience, since the topic of recommender systems is a pretty popular and well-known area. It is highly developed and applied in real practice, and almost everybody has used such kind of systems in their life. For the technical pieces, the talk will give real-world data set and applications to let the audience fully understand what's going on in order to let them easily follow the topics. Similarly, there are no special equipments required, where I will take my own laptops for presentations and for the demo purposes.

References

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