

Context Suggestion: Solutions and Challenges

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Abstract—Recommender systems (RS) have been popular for decades and many novel types of RS have been proposed and developed, such as context-aware recommender systems (CARS) which additionally take contexts (e.g., time, location, occasion, etc) into consideration to further assist users’ decision makings. Meantime, the emergence of CARS also brings new recommendation opportunities, such as context suggestion which recommends a list of appropriate contextual situations for the users to consume the items. In this paper, we discuss the latest progress in this research direction, including potential recommendation opportunities, the existing real-world applications, as well as its relevant solutions and challenges.

I. MOTIVATIONS AND RELATED WORK

Recommender systems (RS) have been successfully applied to various applications and domains, such as e-commerce (e.g., Amazon and eBay), social networks (e.g., Facebook and Twitter), and streaming media (e.g., Pandora and Netflix), etc. Context-aware recommender system (CARS) [1], as a novel type of RS, is able to additionally take contexts into consideration and adapt to users’ preferences in different situations. For example, a user may choose different types of movies to watch if the companion is *kid* rather than *partner*. And, you may select a formal restaurant for *business dinner* rather than a fast food store for *quick lunch*. Here, *companion* and *occasion* are deemed as influential contexts in the movie and restaurant domain correspondingly. Researchers believe that recommendations cannot stand alone without considering contexts, since users’ preferences are always changing from contexts to contexts.

During the past decade, several context-aware recommendation algorithms have been proposed and some of them have been put into practice, such as South Tyrol Suggests¹ which is a tourism app providing context-aware suggestions for attractions, events, public services, restaurants. In addition, the emergence of CARS also brings new recommendation opportunities, such as *context recommendation* or *context suggestion*. The first attempt was made by Baltrunas *et al.* [2], where they tried to predict the best contexts for users to listen to music. They proposed different K-nearest neighbor classifiers to predict the context labels. Later on we further explored comprehensive multi-label classification techniques to assist personalized context suggestions [4]. In this paper, we introduce the potential recommendation tasks and existing real-world applications in context suggestion, and finally discuss feasible solutions as well as remaining challenges.

¹STS, <https://play.google.com/store/apps/details?id=it.unibz.sts.android>

II. RECOMMENDATION TASK AND APPLICATIONS

The main difference between traditional item recommendation and context recommendation can be depicted by the different inputs and outputs which can be shown in Table I.

TABLE I: Comparison of Item & Context Recommendation

		Inputs	Outputs
Item Recommendation		user [, contents, context]	a list of items
Context Recommendation	Context Suggestion	user	a list of contexts
		item	a list of contexts
	user, item	a list of contexts	
	Bundle Suggestion	user	items + contexts
		item	users + contexts
user, item		contexts + items	
Rich Suggestion	user, item	contexts + users	

In traditional RS and even CARS, it is typically a task of item recommendation – suggesting a list of appropriate items (users are considered as “items” in social RS) to a specific user, where contents (e.g., gender, age, etc) and contexts (e.g., time, location, etc) may be considered as additional inputs.

By contrast, context recommender is a novel recommender system which aims to suggest a list of appropriate contexts for the end users in order to maximize the overall experience on consuming the items (e.g., listening to a song). More specifically, it can be divided into three categories: *context suggestion*, *bundle suggestion* and *rich suggestion*.

Basic functions are embedded in context suggestion, while the output is simply a list of appropriate contexts, but the inputs could be a single user or item, or a pair of user and item. For example, it may suggest appropriate time (e.g., day, season) for a user to go vacation; or, it could suggest the best season for tourists to visit Hawaii, in which case the user or the item (i.e., Hawaii) is the single input. In addition, the suggestions could also be customized for a user to go to a specific destination, where the pair of user and item is considered as the input. Previous work [4] has demonstrated that personalization is required even if the input is a single user or item, e.g., *Titanic* is a romantic movie, the appropriate *companion* may be partners from common sense; but actually it varies from user to user.

Bundle suggestion provides a finer-grained way to recommend a combination of appropriate contexts together with a list of users or items. For example, the system may recommend the user to listen to a list of *songs* at *workout* time. In this case, it suggests an activity, *workout*, as well as a personalized playlist appropriate for this user. Similarly, the system may also suggest a list of users (whom) and time (when) for a company to send emails to for marketing purpose.

The recommendations could also be collaborative, which enables rich suggestions, e.g., a user is browsing a book at Amazon.com, the system may suggest the appropriate occasion (e.g., Mother’s Day) for users to gift this book. Meantime, the

system can also provide book recommendations which were gifted by other users in the same occasion.

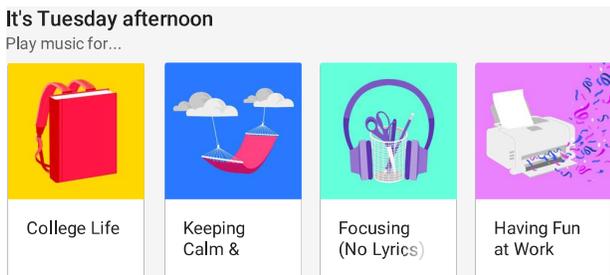


Fig. 1: Occasions suggested by Google Music

Recently, Google released “Browse” functions on Google Music and Youtube channels so that users can view recommendations by browsing specific content categories (e.g., music genre) and context categories (e.g., mood, activity). The “Listen Now” page on Google Music (shown in Figure 1) is able to suggest a list of contexts, where users will get a list of personalized playlists by clicking one of those suggestions. The suggested contexts will dynamically change during a day, and it could be personalized for each user.

III. SOLUTIONS AND CHALLENGES

Our previous work [4] has pointed out two categories of potential solutions: one is *direct context prediction* which views each context condition as a label and try to predict the appropriate labels to be suggested. Multilabel classification is the principal technique as the solution, and we have explored it in [4]. Another solution is named as *indirect context recommendation*, where users’ preferences on contexts can be inferred by context-aware recommendation algorithms, especially the ones exploring the dependencies between contexts and the other dimensions (e.g., users or items).

In this paper, we take one of context-aware recommendation algorithms – user splitting [3] for example, to explore its feasibility as a solution. User splitting is trying to split each user to two new ones by exploring user’s ratings in two associated binary contextual conditions. For example, a t-test can be performed on user’s two rating lists based on “weekend” and “Non-weekend” (this may include multiple situations, such as “weekday”, “holiday”, etc). The context condition (i.e., “weekend”) can be used to split a user if the t-test result is statistically significant, which implies that this user has significant different preferences or attitudes in those two situations – “weekend” and “Non-weekend”.

A sample of user splitting results on LDOS-CoMoDa data set² can be shown in Table II. The table describes four possible and significant splits by different contextual conditions. Take the first row for example, it tells that user u_1 can be split by “time = weekend”, where user’s average rating in “weekend” is 4.2, and this rating is generally 1.9363 higher than user’s average rating in the situation “Non-weekend”. The column t-value tells how good the choice is – the larger t-value is, user’ rating difference in this binary context condition is larger. In this case, we can provide a ranked list of appropriate context labels to each user by looking at the splitting results, especially

the mean rating and mean rating difference. In case that no significant splits found for a user, the suggestions can be inferred from the user neighborhood who have similar tastes with this user.

The splitting approach introduced above takes advantage of dependent rating deviations, while other deviation-based context-aware recommendation algorithms (e.g., CSLIM [5], [6]) can also be applied in the same way for context suggestion. However, they only suggest a single context each time and cannot infer how good it is for a set of combinations.

TABLE II: A Ranked Contextual Conditions in User Splitting

User	Split	MeanRatingDiff	MeanRating	t-value
u_1	time: weekend	1.9363	4.2	5.852
u_1	with: girlfriend	1.0833	3.68	4.204
u_1	mood: positive	0.9830	3.89	3.022
u_1	mood: negative	-0.3409	2.68	2.899

The main challenge in context suggestion is the evaluation. For example, a user may give a high rating in context {“time = weekend”, “with = girlfriend”}, but he may only care that the companion is girlfriend or not, whenever they watched the movie. In this case, A/B test or user centric evaluation is required for accurate evaluations.

IV. CONCLUSIONS AND FUTURE WORK

In this paper, we discuss context suggestion, where the recommendation tasks and existing real-world applications are formally introduced, as well as its relevant solutions and challenges. Specifically, we introduce how to suggest contexts by deviation-based context recommendation algorithms, such as user splitting. Besides, similarity-based recommendation algorithms [7] could be another solution to further explore the correlation between contexts, which we will explore in future. Also, we’d like to empirically compare the performance of context suggestion between indirect context recommendation and direct context prediction in our future work. Context suggestion is still a novel and open area, we’d like to welcome different communities (e.g. AI, data mining and machine learning, etc) to solve this problem, especially when it comes to the label ranking and evaluation challenges.

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²LDOS-CoMoDa movie rating data, www.ldos.si/comoda.html