# Sequences of Recommendations for Dynamic Groups: What is the Role of Context?

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## ABSTRACT

Recommendation algorithms have been investigated and employed by many important companies in the past years: some scenarios, such as the one where a system suggests the points of interest to tourists, well adapt to sequence of recommendations to (groups of) users. We envision that sequences can be useful whenever the group of users has a limited time interval to spend together, since they reduce the time wasted in selecting the best next activity.

In this paper, we investigate the role played by the context, i.e. the situation the group is currently experiencing, in the design of a system that recommends sequences of activities. We model the problem as a multi-objective optimization, where the satisfaction of the group is one of the functions to be optimized. In particular, we suppose that, in many cases, the dynamic evolution of the group can be the key contextual feature that has to be considered to produce better suggestions.

## CCS CONCEPTS

• **Information systems → Recommender systems**;

## KEYWORDS

Recommendation sequence, dynamic group, context

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## 1 INTRODUCTION

Nowadays users are more and more often choosing what interests them on-line in huge catalogues: prominent examples are the lists of available video-on-demand movies and series, songs, restaurants nearby the user, or the products that can be purchased in online stores. These long lists of choices, if not properly managed and personalized, risk to confuse users instead of being a precious resource. Recommender systems (see [3] for a survey) suggest items that match the tastes of users and have quickly become a fundamental technology, employed by many important companies such as Netflix, Amazon and Google. In all the scenarios where activities are inherently social (e.g. going to the cinema, eating out or visiting a city) recommendation systems provide suggestions for *groups* of users, which in the literature are classified either as persistent or ephemeral [5]. Persistent groups are those where members have a history of activities together and thus can be considered as a normal user, while ephemeral ones may be constituted by people who are together for the first time and consequently the group preferences must be computed on the basis of those who are known.

The online recommendation of the next activity, either for single users, or for groups, has been studied extensively [3] [5]: we refer to this type of recommendation as *myopic*, since it focuses mainly on one activity at a time. Instead the recommendation of a *sequence* of activities has received little attention. For instance, the literature considers some scenarios such as the set of points of interest for tourist [7], or the list of songs to listen [6]. In these contexts, planning ahead the recommendation of a whole sequence – given some constraints, such as the available time – provides more flexibility, and it gives the chance to find solutions that a myopic recommendation is not able to find. Nevertheless, most of the works for sequence recommendations focus on a single user (see [6] for a recent survey)

In this paper we consider the problem of recommending a sequence of activities to groups of users, either persistent or ephemeral. The resulting sequence could reduce the thinking time required by a myopic recommendation system – e.g., channel surfing that users typically perform to find something interesting to watch next. Recommending sequences can be useful whenever the group of users has a limited time interval to spend together, since a sequence decrease the time wasted in selecting the best next activity. In addition, we consider the role played by the *context*, i.e. the situation, the group is currently experiencing. It has been recognized that the notion of context influences the user preferences [2], which may vary with respect to the group current context.

Our approach is to model the construction of recommendation sequences as a multi-objective optimization problem, where the satisfaction of the group is one of the functions to be optimized and


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the group composition can vary over time. We propose to solve such problem by using the Multi-Objective Simulated Annealing (MOSA) optimization heuristic [4]. More specifically, we extend such approach with the notion of context. The novelty with respect to the state of the art (see [6]) is that time (a contextual feature) influences the group composition, thus the current context. We envision that, given the sequence recommendation problem, time has a great impact in the evolution of groups and has a central role in the optimization of user/group preferences.

The proposed approach is general enough to be applied to any activity, as formalized in Sect. 2. Due to the availability of a dataset related to the TV domain, for the first preliminary experiments we consider such a entertainment scenario (see Sect. 3). Our main contributions can be summarized as follows:

**Sequences are produced for groups evolving along with time.** We are interested in generating sequences of recommendations for people spending time together. The composition of the group, which can change over time, is a feature that influences the recommendations, since movies to be suggested to adults are not always proper for kids. We consider as contextual features the group composition (*adults with kids*, *adults*, *teens*, or *kids*) and the temporal information (*daytime* or *night*, and the day of the week), but the proposal can be easily extended by including other relevant features to describe the situations users experience in a given scenario. We say that a group has changed whenever its current composition changes, i.e. from *adults with kids* the group has evolved into *adults* (no matter the number of members): our recommendations are contextual, thus, a change in context determines a different policy in providing recommendations to the actual group. Note that the group evolution is natural along with time, indeed, a group can dynamically change its composition; thus, a contextual feature (in this case the time) can have an impact on another feature (the group composition). In order to optimize recommendation sequences for a group in a given time interval, it is necessary to investigate how time can influence the group composition.

**Constraints and objective functions are considered in exploring the problem.** As we will describe later, MOSA is a multi-objective optimization technique that can take into account various constraints to be satisfied and functions to be optimized: different alternatives can be considered in aggregating individual preferences to obtain the group recommendation. In our scenario, we will consider as constraint the maximum interval of time the group can spend together ($T_{\max}$) and the maximum available budget ($b_{\max}$). As functions to optimize we will consider: i) the minimization of the empty slot between two following movies; ii) the maximization of the portion of $T_{\max}$ covered by recommendations; iii) the minimization of the number of movies the group components has already watched in the past; iv) the maximization of the group satisfaction. Notice that the latter is influenced not only by the context, but also by the possible evolution of the group.

**Customized sequences of recommendation for groups.** We analyze different possibilities to aggregate individual preferences to generate group preferences. To compute the preferences of a group for a given movie we use the classical aggregation functions, i.e. the Average Preference or the Least-Misery Preference. However, the analysis of past evolutions of groups can allow us to predict the evolution of the current group over time, e.g. it is frequent that after 9 p.m the group changes from *adults with kids* to *adults*; in this case we try to maximize the satisfaction of kids inside the group in the early phase, since we know that with high probability the group will evolve into another with a different composition.

An important aspect to consider when designing a recommendation strategy is the efficiency in the online recommendation task, since recommendations must be generated at runtime, when specific (groups of) users require them. Thus, the pre-computation of the past group histories may help in reducing the time required to provide the recommendation.

*Running example.* We consider a dataset in the TV domain, with users watching TV programs possibly in groups and in different contexts. Contexts are identified by temporal information (*daytime* or *night*, and the day of the week) and the type of groups, i.e. the number and age of members. The dataset contains TV viewing information related to almost 8,000 users and 119 channels, broadcast both over the air and by satellite. The dataset is composed of an electronic program guide (EPG) containing the description of 21194 distinct programs (their genre is mentioned in the dataset), and a log containing both individual and group viewings performed by the users. The log contains approximately 5 million entries, among which we retained just the synthonizations longer than three minutes. Almost 1.5 million iewings involve more than one person together. Each log row specifies the identifier of the user and that of the program he/she watched, along with start time and end time.

From the analysis of the dataset we found out that: i) the average number of programs each user watches sequentially in a day is about 3; ii) in 80% of cases where there is a sequence of program viewings for a user in a day, the number of short viewings is greater than the number of long (full) viewings and in the 46% of such cases the number of short viewings is more than double than the number of full viewings; iv) in 32% of cases where there is a sequence of viewings for the same user in a specific day, there are at least two long viewings with short viewings in the middle.

The last analysis suggested us the importance of providing sequences of recommendations also in the TV domain, since it could reduce the channel surfing to find something interesting to watch next.

## 2 OUR OPTIMIZATION APPROACH

Figure 1 shows an overall picture of our approach (in the blue rectangles the steps performed at run-time): we collect the description of items in the considered scenario, e.g. different kind of entertainments, and the logs of past accesses both for users and groups. When a group is ephemeral, its preferences will be inferred starting from the components' preferences or by using the preferences of a similar (w.r.t. the context) group. The collected information about the past users/groups history, can be used to predict a group evolution with a certain probability.

The context is related to the group composition (*adults with kids*, *adults*, *teens*, or *kids*) and temporal information (*daytime* or *night*, and the day of the week), but it may include other features. Given a group in a certain context (the temporal information can be sensed, the group composition has to be declared) and the slot of time to spend together, our framework analyzes the preferences computed

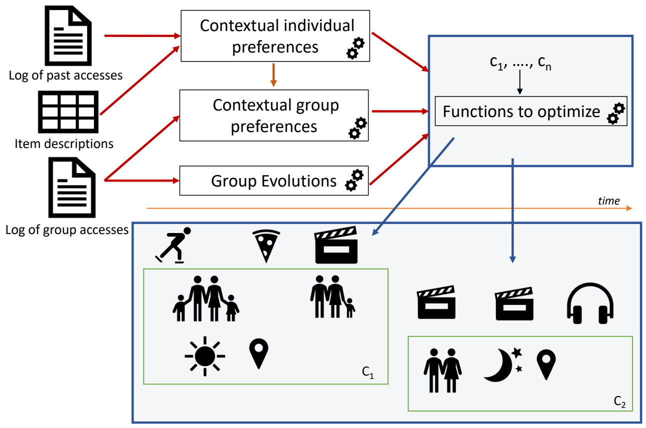


**Figure 1: Our approach: a high level vision**

off-line and determines a sequence of suggested entertainments. These sequences are affected also by the possible group evolution computed using the past known history. In particular, if the current group is a persistent one, its past history can be used to predict its evolution with an high degree of confidence; otherwise, we can use the past history of similar groups in order to make such prediction also in the case of an ephemeral group.

In the remainder of this section, we discuss how the problem can be formulated as an optimization problem (Sect. 2.1) and how a first solution can be found using the MOSA technique (Sect. 2.2).

## 2.1 Problem Formulation

This section provides a first formalization of the problem of suggesting a sequence of recommendations to dynamic groups.

*Definition 2.1 (Entertainment).* An entertainment $e$ is a leisure activity performed by a user or a group of users. It is characterized by several attributes, such as the duration $e.dur$, the start date and time $e.start$, the end date and time $e.end$, the genre $e.gen$, the suggested age $e.age$, and a cost $e.cost$.

Notice that for certain kinds of entertainments, such as TV shows, the duration is defined as $e.dur = e.end - e.start$, whereas for other kinds, such as POI visits, $e.dur$ may refer to the suggested time to spend, while $e.start$ and $e.end$ delimit the opening hours.

*Definition 2.2 (Experience).* An experience $\varepsilon$ is an ordered collection of entertainments, i.e. $\varepsilon = \langle e_1, \dots, e_n \rangle$, where $n$ indicates the number of entertainments contained in $\varepsilon$ ($|\varepsilon| = n$).

Given a predefined set of entertainments $O$, the set of all possible experiences, denoted by $\mathcal{E}$, contains all possible ordered combinations of entertainments in $O$, for any cardinality of $\varepsilon$.

Let $\varepsilon = \langle e_1, \dots, e_n \rangle$ be an experience, its overall duration $\delta(\varepsilon)$ is defined as $\delta(\varepsilon) = \sum_{i=1}^{n} e_i.dur$; while its overall cost $\gamma(\varepsilon)$ is defined as $\gamma(\varepsilon) = \sum_{i=1}^{n} e_i.cost$.

*Definition 2.3 (Dynamic Group).* Given a set of users $\mathcal{U}$, a dynamic group $g$ is a function that associate to each time instant $t$ a subset $\{u_1, \dots, u_n\} \subseteq \mathcal{U}$. Each (dynamic) group has associated a type $\overline{g}$, which is dynamic too, thus it depends on $t$.

The notion of group considered in this paper is a collection of users whose composition evolves with the time. Notice that, besides temporal information, we are interested in the group composition for determining the context (e.g., *adults with kids* or *adults*), not in the specific individual users that are currently inside the group.

*Definition 2.4 (Dynamic Context).* A dynamic context $c$ is characterized by the type of a dynamic group composition $\overline{g}$ (e.g. *adults*) and a temporal information $\tau$ (e.g. *daytime* or *night*, and the day of the week).

As previously discussed, the possible evolution about the group composition can be determined using the past collected history. Moreover, such evolution can be used to influence the computation of a group preferences in a given context.

*Definition 2.5 (Group Preference).* Let $c = \langle \overline{g}, \tau \rangle$ be a dynamic context of a group $g$, $e_j$ be an entertainment and $t_i$ a temporal instant. The function $\bar{p}(c, t_i, e_j)$ computes the preference of the group $g$ for the entertainment $e_j$ in the context $c$ considering its composition at the time $t_i$ and its possible evolution at time $t_{i+1}$.

Proposition 2.6. *Let $c = \langle \overline{g}, \tau \rangle$ be a dynamic context of a group $g$ and $t_i$ a time instant, such that $g(t_i) \cap g(t_{i+1}) \neq \emptyset$, and let $e_j$ be an entertainment. The weight of the users in $g(t_i) \setminus g(t_{i+1})$ is greater than the weight of the users in $g(t_i) \cap g(t_{i+1})$, during the computation of $\bar{p}(c, t_i, e_j)$.*

The rationale behind the above proposition is that the users that will leave the group have no chance to be satisfied in the future, while the users that remain the group can be satisfied also by the next suggestions.

*Definition 2.7 (Recommendation query).* A group of users looking for a recommendation submits a query $Q$ to the system containing the following information:

- the initial context $c_0$: it includes at least the group composition, the date and time at which the experience will start;
- the desired duration as an interval $(d_{\min}, d_{\max})$;
- the mandatory maximum duration $T_{\max}$;
- the mandatory maximum available budget $b_{\max}$;

Notice that, while the start time $t_0$, the maximum duration $T_{\max}$ and the maximum budget $b_{\max}$ are considered as mandatory constraints, the desired duration is intended as a desiderata: the recommended experiences can have an overall duration slightly different from, but very similar to, the desired one.

Among all possible sequences of entertainment that satisfy the given constraints, the exploration of the search space is guided by the value of the objective functions.

*Definition 2.8 (Objective functions).* Given a recommendation query $Q$, an experience $\varepsilon = \langle e_1, \dots e_n \rangle$ and a a dynamic context $c = \langle \overline{g}, \tau \rangle$, the considered objective functions to be minimized are:

- $$f_d(\varepsilon, c) = \begin{cases} w_a \cdot (d_{\min} - \delta(\varepsilon)) & \text{if } \delta(\varepsilon) < d_{\min} \\ w_b \cdot (\delta(\varepsilon) - d_{\max}) & \text{if } \delta(\varepsilon) > d_{\max} \\ d_{\max} - \delta(\varepsilon) & \text{otherwise} \end{cases}$$
  The function $f_d$ is the difference between the actual duration of the experience $\varepsilon$ and the desired duration, i.e. it is essentially as a measure of the empty slots. The two weights $w_a$ and $w_b$ can be used to consider less serious a duration less than the minimum desired one, w.r.t. a duration greater than the maximum desired one.

- $f_h(\varepsilon, c, t_i) = |\bigcup_{u_i \in g(t_i)} H(u_i) \cap \bigcup_{e_j \in \varepsilon} e_j|$
  The function $f_h$ counts of the number of movies already view by each components of the group, considering its past viewing. $H(u_i)$ is the past history of the user $u_i$, i.e. it is the set of entertainment performed by $u_i$ in the past. Function $f_h$ depends on the time instant $t_i$ in which it is computed.
- $f_s(\varepsilon, c, t_i) = n \cdot S - \sum_{i=1}^{n} \bar{p}(c, t_j, e_j)$
  The function $f_s$ minimizes the loss of preference, where $S$ is the possible maximum degree of satisfaction (preference) for an entertainment, $\bar{p}(c, t_j, e_j)$ as been defined in Def. 2.5.

The group recommendation problem can be formulated as an optimization problem:

$$\begin{aligned} \underset{\varepsilon}{\text{Minimize}} \quad & \langle f_d, f_n, f_s \rangle \\ \text{subject to} \quad & \delta(\varepsilon) < \text{TD}_{\max} \\ & \gamma(\varepsilon) < b_{\max} \end{aligned} \tag{1}$$

The three objective functions can be combined in a single function $\bar{f} : \mathcal{E} \rightarrow \mathbb{R}^3$ which, given an experience $\varepsilon \in \mathcal{E}$, returns a triple as value. It follows that it is possible to establish only a partial order between solutions. In particular, a *dominance* relation is defined between two solutions, represented as $s \prec s'$. We say that $s$ dominates $s'$ (denoted as $s \prec s'$), if and only if $s$ is better than $s'$ in at least one of the objective functions and equivalent in the other ones.

## 2.2 Proposed Solution

In the previous section we have defined the group recommendation problem as an optimization problem. However, finding an exact solution for Eq. 1 is computational expensive. For this reason, we need to apply some well known heuristics in order to produce a solution in a reasonable amount of time. Among all possible optimization heuristics, we choose to apply the Multi-Objective Simulated Annealing (MOSA) [8] technique. The rational behind this choice is twofold: (1) it has been demonstrated its ability to reach a global optimum if annealed sufficiently slow [1], while other solutions like the greedy algorithm, can suffer from the problem of getting stuck in local optima. (2) Rather than using a random artificial solution as starting point in the search space explorations, we can rely on the available historical data concerning the past experiences performed by the same group (if available) or by similar groups, in the given context.

The idea under the MOSA technique is that at each step of the procedure, the current solution $s_1$ is sightly modified in some way (perturbed) obtaining a new solution $s_2$, then $s_2$ is chosen in place of $s_1$ with a probability that depends on both the value of the objective functions and a global temperature parameter, which is progressively decreased during the execution, resembling what happen in physical annealing procedures. The mentioned perturbation operation is the way used to explore the solution space. In the considered problem, it may consist in the application of elementary changes to the current solution, such as such as the removal or addition of a single entertainment, the replacement of an entertainment with a new one, or the change in the order of the entertainments.

The result produced by the EMOSA algorithm, is a set of equally "good" suggestions, which can be proposed to the group as alternatives. A feedback about the actual choice performed by the group, can be used to better calibrate the algorithm for future queries.

# 3 EVALUATION

We have performed very preliminary experiments on our dataset. The group viewings were split into a training set, including the syntonizations between December 3rd, 2013 and February 15th, 2014 (1210316 entries), and a test set, containing the remaining ones (238748 entries) and used to asses the provided recommendations. From the training set we have learnt the contextual preferences (i.e. preferences correlated to temporal information) about the movie genre for both single users and groups. We have computed sequences of $n$ recommendations for all groups ($n$ depends on the duration of the time interval the members in the group spend together). The sequences were computed in two ways: 1) without predicting the group evolution along with time 2) by taking into account the information about the group evolution. We have evaluated the sequences on the test set and we have obtained the following results: without predicting the group evolution, the recall about the genre is 70% (i.e. the suggested sequence of genres in 70% of cases matches the genre of movies the group is watching together in the test), with the evolution prediction the recall is 85%. The benefit of the sequence recommendation should help the (group of) users to reduce the channel surfing time, that in our dataset was present in 32% of sequences of viewings.

# 4 CONCLUSIONS

We have presented a preliminary proposal on a multi-objective optimization algorithm for computing group recommendations: we envision that the role of evolving contexts along with time is central in the optimization problem. Our research agenda encompass the investigation of the different optimization criteria that can be included to produce better recommendations.

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