Interactive Food Recommendation for Groups

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ABSTRACT

We present a prototype of a novel interactive food recommender for groups of users that supports groups in planning their meals through a conversational process based on critiquing. The system comprises two novel elements: a user interface and interaction design based on tagging and critiquing, and a utility function incorporating healthiness and diet compliance factors.

1. INTRODUCTION

Despite current technological progress, following a healthy diet is still a challenge. While there are numerous information resources such as books, websites, and mobile apps, finding a suitable meal plan is not easy, mainly due to the majority of resources being generic and non-personalized. As such, meals suggested by a diet may not appeal for users and they will not stick to the diet guidelines. Food recommender systems tackle this problem by generating personalized meal plans. They exploit food and recipe data, explicit and implicit food preferences (e.g., ratings and browsing behavior) to train predictive models and deliver personalized food recommendations to inform the meal plans [4].

Many of the existing works on food recommendations focused on individual users. However, in real-life scenarios the food is consumed by a group of people, e.g., family, friends, or school canteen. Moreover, it has been shown that small groups of close users, such as families, have a profound role and supportive effect on health promotion within the groups [1]. In this work we propose a novel interactive mechanism for food recommendation for groups. This elicits user preference for food through a conversational process incorporating rating and tagging [7]. The preferences are used to compute personalized predictions for individual users, which are aggregated into group-based recommendations [5]. The users can provide their critiques and refine the recommendations [2]. This approach has the potential to be effective for heterogeneous small groups, with members of different ages, having different tastes and preferences, e.g., families. Also, the interactive nature of the recommendations can potentially increase user engagement with the diet and make the recommender more enjoyable for users.

In summary, the contribution of this work is two-fold: (i) a novel interface design that applies interactive strategies, such as tagging and multi user critiquing, and (ii) a novel recommendation algorithm that generates a long term diet plan for users within the group.

2. APPROACH

One of the main considerations related to food recommendations refers to the recurrent nature of eating and food consumption. Indeed, people eat similar times a day and every day, and they plan their meals in a sequential manner. Although some works focused on sequential recommendations [5, 6], to the best of our knowledge none of them has been applied in the food domain. Likewise, the match of a recommended meal to a user cannot be measured on its own, but should rather be considered in the context of the entire meal plan, diet guidelines, and other nutritional factors. Here, we consider several factors that affect the overall meal utility function. For user u, the utility of meal m at time t is quantified by

$$util(u,t,m) \propto rat(u,m) + diet(plan(u,t_1,t_2),m) + health(m)$$

where $rat(u,m)$ denotes the rating of u for m, $plan(u,t_1,t_2)$ is the set of meals consumed by u in a recent time window $[t_1,t_2]$, $diet(plan,m)$ denotes the compliance of m to the diet constraints with respect to $plan$, and, finally, $health(m)$ denotes the health score associated with m.

Note that this computation disregards other factors that may affect $util(u,t,m)$. Among these are $cost(m)$ – the estimated cost of cooking m, $avail(u,m)$ – the availability of the ingredients of m to u, and $seq(plan,m)$ – the match of m to food consumption patterns observed in $plan$. At the current stage of our work, we focus primarily on rat, highlight $diet$ and $health$ as two influential factors, and leave the remaining factors for future research.

Once the utility of m is computed for every user $u \in g$ in the group g, predicted score for the entire group is quantified through aggregating the individual utility scores, as per $util(g,t,m) \propto \sum_{u \in g} util(u,t,m)$ [5].

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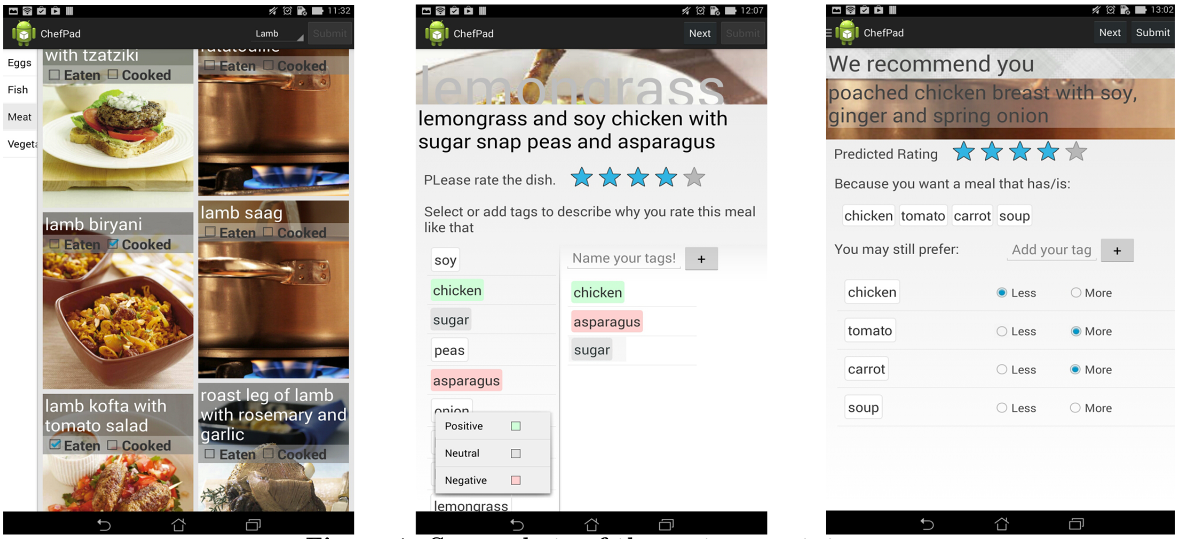

Figure 1: Screenshots of the system prototype

3. PROTOTYPE

We are developing an Android prototype food recommender for groups that is depicted in Figure 1. We will briefly present the interfaces and the envisaged interactions.

In the preference elicitation phase, we ask users to specify which meals they have ever eaten or cooked (see Figure 1-left). This is done by presenting a tree of meals, e.g., pasta → spaghetti → spaghetti bolognese. Users can navigate the tree and mark familiar meals. Next, users are asked to rate and tag meals selected from: (1) familiar meals marked by the user, (2) meals selected by an active learner [3], and (3) set of popular meals. The rating interface uses a 5-star Likert scale (see Figure 1-middle). In addition, the users can explain their ratings with tags extracted from the recipes and online resources. The tags can be meal characteristics, recipe ingredients, or free user feedback [7]. Users can select the suggested tags, add their own tags, and associate positive or negative attitude with the selected tags.

Given the rating and tagging input, we populate the $item \times tag$ matrix and incorporate the attitude into the matrix. Then, an extended matrix factorization algorithm (with content and tag features) is run to compute the predicted rating $rat(u, m)$. The computation of $diet(plan, m)$ and $health(m)$, as well as of other factors affecting $util(u, t, m)$, depends on the constraints of the user's diet and nutritional considerations and is left beyond the scope of this paper.

Apart from the individual rating and tagging elicitation, we also use group-based preference elicitation, in which we differentiate the role of the group leader, called the *cook*. Based on the tags and ratings of all the group members, the system delivers to the cook the meal recommendation using the group utility score (Figure 1-right). The cook can either accept the recommendation, reject it outright (e.g., due to unavailability of ingredients), or criticize it using the tags (e.g., "less spicy"). Similarly, each group member can criticize the meal accepted by the cook through a series of interactions with the recommender. The system then aggregates individual critiques into a compound critique by applying a voting mechanism and resolving possible conflicts, and recommends alternative meals [2]. The critiquing cycle continues until all the group members accept the recommendation.

4. DISCUSSION AND FUTURE WORK

In this paper, we have presented the prototype of an interactive food recommender for groups. It features a novel utility function, a tag- and rating-based preference elicitation interface, group recommendation aggregation, and critique-based conversational recommendations.

We are now implementing the proposed system and working on the user study design. In the future, we plan to apply a mechanism that considers the role of users in the group when aggregating recommendations. This is due to the higher impact of the preferences of dominant users (e.g., mother in the family) on the decisions of other group members (e.g., kids). We also plan to weigh differently the predictive rating and critiques of the group members. A group member with strict diet constraints like diabetes, may can be assigned a higher importance than other members.

5. REFERENCES

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