

Promoting Healthy Food Choices Online: A Case for Multi-List Recommender Systems

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Abstract

Many food choices are made online. Interactive, personalized interfaces, such as recommender systems, can help users to find new products to eat or recipes to cook, but they tend to promote unhealthy alternatives. In this position paper, we argue that better algorithms are not the *only* way forward. We blend algorithms and user interface design to present a multi-list recommender interface that presents multiple lists of personalized items in a single interface, where each list is optimized for a specific feature (e.g., ‘less fat’). We argue how multi-list recommenders can be used to support healthier food choices.

Keywords

Recommender Systems, Food, Digital Health, Interfaces, Algorithms

1. Introduction

Recipe websites have become increasingly popular. This has spurred the development of food recommender systems, which help users to navigate the thousands of recipes found online, by presenting personalized content [1]. However, online users struggle to identify healthy recipes, due to a lack of knowledge and misleading cues, and because popular recipes tend to be unhealthy [1].

An increasing number of algorithmic approaches to personalization have surfaced [2]. For example, recommender systems present food (e.g., meal plans) that is similar to what a user liked in the past [1]. Yet, there has been little attention for health [1, 3]. It has been shown that computing similarity between recipes (cf. [2]) is not enough to shift preferences towards health-related behaviors [3, 4]. In fact, it is suggested that suitable recommendations for one’s current preferences could even be counterproductive [5, 6, 7], especially if one’s current lifestyle is rather unhealthy [3].

Most users stick to familiar recipes [8]. For example, in the context of sustainability, users might swap their hamburger’s beef-based patty for a plant-based one, relying on familiar substitutes. Although this is consistent with recommendation strategies on recipe websites, which typically present a ‘more like this’ set of recommendations alongside each recipe [2], such similar recommendations are unlikely to produce healthy recommendations.

In this position paper, we argue that personalization approaches should go beyond only changing *what* is recommended, by also focusing on the decision context: *how*

content is recommended (cf. [9]). We propose a multi-list recommender interface to support healthy food choices, based on the UI of Netflix [10]. This interface combines different ‘single lists’ of algorithms that use a specific optimization (e.g., ‘Drama movies’ or ‘Because you watched Frozen’) to come up with a new subset of similar recommendations, which are combined into a comprehensive multi-list UI. We describe how this can be applied in the food domain to promote healthier alternatives, taking as a starting point an interface that suggests alternatives for a recipe that a user had searched for, either through a look-up task or implicitly in an exploratory search.

2. Case: Multi-list Recommenders

Most recommender systems optimize their content to be similar towards a user’s past preferences. Algorithmically speaking, this leads to “more like this” recommendations [1]. For example, in the food domain, if a user has bookmarked several recipes that contain potatoes, then a recommender system will present more potato-based recipes. The downside of this approach is that if a user is currently unhealthy, she is reinforced into her current preferences through more unhealthy content [3, 4].

A few solutions have been proposed to alleviate this. For example, imposing health constraints on the algorithm might boost the healthiness of chosen items [11], but this might leave users dissatisfied if they have no healthy eating goals. Moreover, one could show a much larger list of recommendations, but this will lead to a sharp increase in choice difficulty, or choice overload, when not explained properly to a user [12].

We argue that a multi-list recommender system can overcome algorithmic biases towards unhealthy foods and mitigate choice overload. It comprises novel algorithmic and interface components. In terms of content,

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a multi-list recommender uses multiple algorithms that each retrieve similar content, but differ in terms of what specific attributes are optimized for. For example, similarity could be computed across multiple attributes (e.g., ingredients, nutrients) to optimize utility (cf. [13]), of which the importance weights can be adapted in line with a user’s goals (e.g., putting more weight on calorie content for users who wish to lose weight). In terms of the interface, the most important contribution is to highlight the differences between the different ‘single lists’, by explaining them to the user. For example, by highlighting the similarity of new recommendations with items liked in the past [10] or by emphasizing health benefits in a food recommender system [6].

A recommender study on computers shows how this can be achieved, by using a ‘critiquing’ approach [14]. The recommender system would present an initial item that fits a user’s past preferences, for which alternatives are presented underneath it across various attribute categories, such as ‘Cheaper and Heavier’ or ‘Higher Processor Speed, but More Expensive’. This way, each additional attribute category forms a new list of similar recommendations, which are diversified based on different attributes, as well as explained clearly to a user.

An example of a multi-list recommender interface is depicted in Figure 1. A reference recipe is depicted at the top, which a user may have searched for earlier. To explore alternatives, similar item recommendations are presented underneath it, in separate ‘single lists’, where each list is optimized towards a certain attribute. In our example, the first row optimizes for similarity with the reference recipe, explained as “Recipes that contain similar ingredients”. This could be achieved by using similarity functions and metrics, such as cosine similarity and RMSE [2]. In contrast, the second row focuses on ‘Similar recipes with less fat’, which could be achieved by either putting more attribute weight on a recipe’s fat content or determining the top-100 similar recipes and subsequently re-ranking that list on fat content. This way, multi-list recommender interfaces can be used to support a variety of user goals, recommending recipes that people like, yet supporting variations that some users might find particularly interesting.

2.1. Directions for Future Research

The effectiveness of multi-list recommenders to support changes in user preferences and behavior has yet to be tested. The food domain is an excellent starting point, for multi-list interfaces provide algorithmic diversity that is needed to improve current unhealthy approaches in food recommenders [3, 4]. We propose two lines of research to examine visual UI design in recommender systems. First, different list representations (i.e., single list vs multi-lists) should be compared in terms of choice behavior

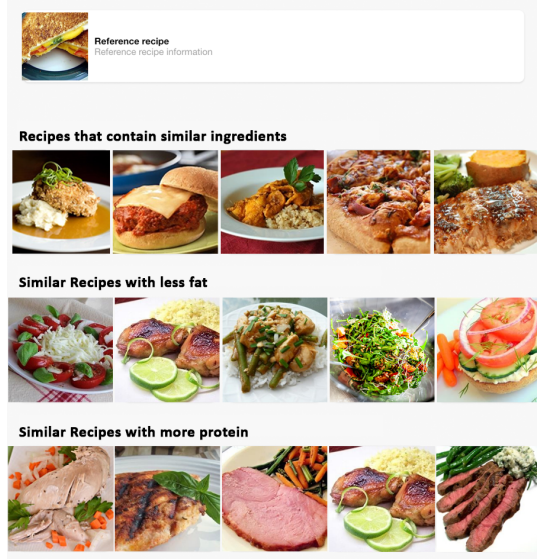


Figure 1: Example of a multi-list food recommender system. Depicted at the top is a recipe that a user may have searched for (i.e., reference recipe). Based on that recipe, the recommender presents three (or more) ‘single lists’ of personalized recipes that optimize for a specific attribute: ‘less fat’ and ‘more protein’. Depicted here are only recipe photos, but also more information could be shown, e.g., names, ingredients.

and user evaluation, for it is currently unclear to what extent they are effective [10]. For example, does a multi-list representation reduce choice overload? Second, we propose to investigate what types of explanatory labels in a multi-list representation are the most persuasive to shift a user’s food preferences. For example, should they highlight health prevention (‘Similar, but less fat’), or health promotion attributes (‘Similar, but more fiber’)?

Another interesting avenue of research is the use of visual cues, which can affect consumer preferences for food selection [15, 16]. For one, product packaging color may be adapted to invoke certain emotions in supermarkets [16]. In an online context, recipe websites could exploit findings that recipes tend to be rated more favorably if they are accompanied by visually attractive photos [15].

Above all, we argue to evaluate multi-list recommender systems through a user-centric approach (cf. [17]). Not only should be examined what recipe is chosen, but also how users perceive and evaluate a multi-list recommender interface, for instance, compared to a single list approach. An important measure would be the perceived choice difficulty (cf. [12]), since it is currently unclear whether presenting many sub-lists (5+) is possible without affecting user satisfaction. Moreover, it would be interesting to examine which types of ‘single lists’ are the most effective in supporting health food choices, which could be a interdisciplinary field of study

between computer science and nutrition science. In doing so, it would be important to striking the right balance between algorithmic accuracy (i.e., reducing RMSE) and interface design (e.g., nudges).

3. Conclusion

We have proposed how healthy food choices could be supported by combining adaptations in the presented content (i.e., algorithms) and the decision context (i.e., the interface), in a new approach. We have argued how to enable users to find and to select healthy content in a recommender system. Fundamental to our approach is that users are still given the freedom to choose what they want, in line with research on nudging [9], but that the use of the interface would not trigger choice overload or increase choice difficulty [12].

For future research, we stress that interfaces and algorithms are not two mutually exclusive categories of research. Our multi-list recommender systems case nicely illustrates how ‘similar content’ and ‘healthy content’ can go hand in hand, by pointing out what each single list of recommendations represents. We expect that diversifying the different types of recommendations presented, rather than only focusing on algorithmic optimization will be more effective in supporting healthy eating habits. For instance, should these lists always be fully personalized, or can they be less personalized in terms of past preferences and optimized to a user’s eating goals?

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