CSE 6242 – Data and Visual Analytics, Team 15

SMART MEAL PLANNER

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INTRODUCTION

Current recipe websites allow people to search for recipes online but offer little in terms of recommendation. Some only recommend the newest or top recipes to all users while others recommend similar dishes to the recipe being viewed. For people who have a busy lifestyle, cooking without prior planning is a difficult job. For example, one is constrained by the ingredients they have at the moment. Moreover, given the lack of time, they are likely to stick to recipes they are familiar with. Further, such haphazard activity can lead to not meeting recommended daily nutritional intakes [HQ2].

As a core activity of life, we believe cooking should be a more fun experience. A successful solution should take into consideration what users like and recommend recipes that are delightful and help maintain a balanced diet while trying to keep daily effort low [HQ4].

PROBLEM DEFINITION

We created a web app to recommend a week's worth of recipes at a time. This app will allow the user to select a set of favorite recipes initially. Based on the selection, it will generate a personalized meal plan for the week that satisfies the nutritional requirements of the user. It will also generate a grocery shopping list for the week [HQ1].

SURVEY

We explored different studies that clustered users and recipes based on their similarities [1]. Identifying key features of clusters and manually labelling features based on those can lead to users being more trusting of the recommending systems more. [2]. By tracking usage history in the app that notes what users modified or actually had in their plan, we can analyze users' past behaviors [3 – 6]. For the recommendations itself, there are several algorithms that can be potential candidates: from regular collaborative filtering and content-based filtering algorithms [7, 8], to various group collaborative filtering systems. Recipe and food consumption are group activities, with members of a family usually preparing and having at least some meals together. For such scenarios, the system should take into account each family member's preference and try to satisfy them to the maximal extent [9].

Also of consideration is ingredients. Foods which contain disliked ingredients, but in small quantity may be acceptable if other preferred ingredients are in large quantity [10]. Techniques are also need to deal with recipes or ingredients may be quite the same but have different name variations [11], with some variations being more appealing ("kid-friendly") [12].

One of the focuses of this app is to let users discover new recipes which they might potentially like. While most works focus on similarity between recipes [13], we flip this for the use case of suggesting dissimilar recipes over the course of the week.

Our intended users for this app are those constrained by the time they have or the amount they can spend. While there is not much previous work on costs, some studies have explored quantitatively measuring the easiness of a recipe [14].

Having recipes recommended based on nutrition or healthy food choices is increasingly getting more public attention [15]. Perhaps of even more importance is to suggest recipes that cater to specific medical conditions [16]. Building on [16] which clusters food into normal and avoidable for patients with diabetes, we intend to incorporate specific requirements that users' may have (e.g. medical conditions, allergens, whatever reason to avoid particular foods). For medical conditions, one way could be to use natural language to map health issues to nutrients [17, 18].

METHOD

We obtained 30000 recipes from Yummly using an API. We cleaned this data (containing recipe titles and ingredients) to separate the ingredients and quantities and stored this information on a MongoDB server on our backend.

Pre-computation

We converted recipes into Boolean vectors having one entry per unique ingredient. Only those ingredients that appear more than once have been retained for this step. Using the following formula, we calculated the pairwise cosine similarity storing only non-zero similarity scores.

$$\text{similarity} = \cos\theta = \frac{\boldsymbol{A}.\boldsymbol{B}}{|\boldsymbol{A}||\boldsymbol{B}|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Based on the ingredient, we clustered the recipes into 200 clusters.

Recommendation Algorithm

For each recipe in our database, we find the maximum similarity to a recipe in the set of favorites picked by the user. The scores obtained are sorted and the top one thousand recipes are stored to limit computation time. A modified version of 3SUM is run to get all possible sets of three recipes that add up to satisfy the daily recommended nutritional intake for the specific user. These sets are then intersected to get valid day combinations for the thousand recipes. After sorting in them in decreasing order of the recipe scores (sum of the set), we greedily pick the top seven scoring days that do not overlap in the clusters determined previously. That is, keeping a set of selected clusters and working through each day in the list of days for the week, we map each recipe in the list to its precomputed cluster. If the day clusters and the selected clusters do not intersect, we add each cluster for that day into the selected cluster set. Once the day is assigned, it is removed from the list and this process is repeated until all seven days are assigned (Figure 1).

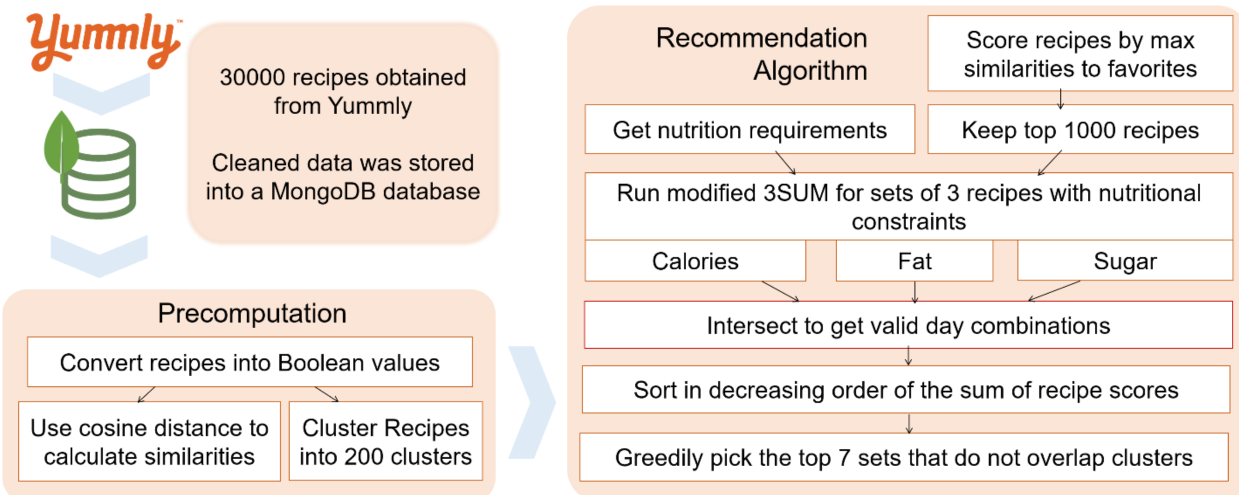

Figure 1: The Recommendation Algorithm

Intuition

What's novel about our approach is the use of 3SUM to determine valid combination of recipes according to nutritional values and modifying it to allow for a range of values instead of just one. While clustering is typically used to suggest similar items, we flip the use of it to recommend combinations with a variety of cuisines while still accounting for the user's preference and nutrition constraints (Figure 2) [HQ3].

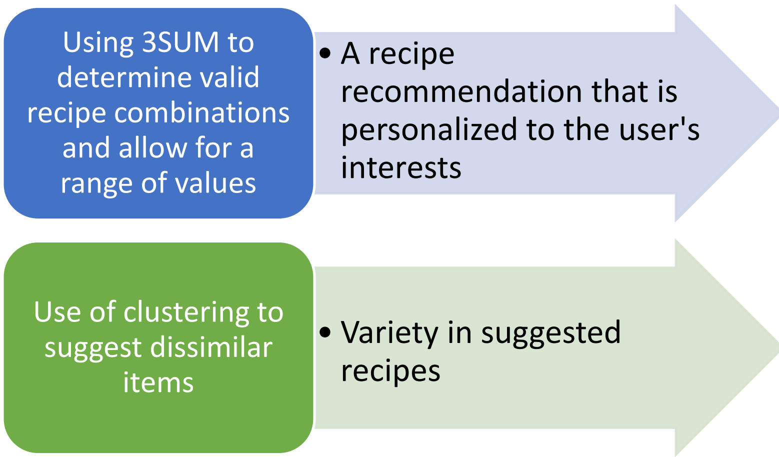

Figure 2: Innovation

Presentation and Visualization

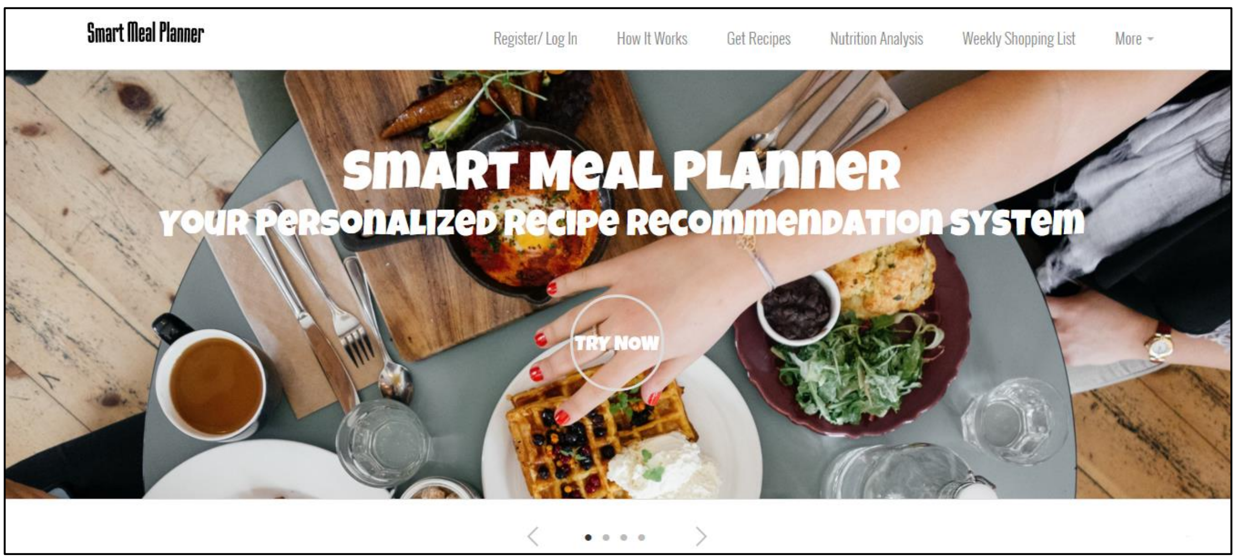

Figure 3: The Home page of the app

We implemented a web app using Express, a framework for Node.JS to power the backend and MongoDB to store the data. The client interacts with the server using RESTful APIs. The app can be viewed at this URL: http://52.91.113.244/project/main_frame.php

The home page advertises the features the app (Figure 3). Upon user registration and login, a short form is presented to understand user preferences (Figure 4). Age and weight are requested to compute the user's nutritional needs.

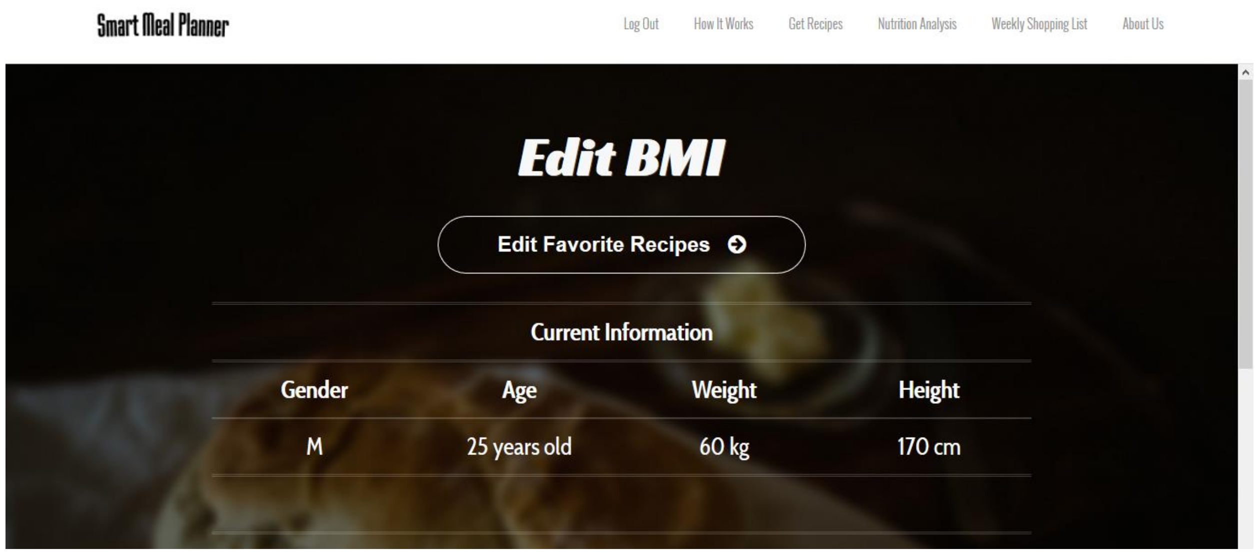

Figure 4: A form to understand the user's nutritional requirements and seed the initial recommendations.

Once the algorithm analyzes the data provided with the recommendation algorithm described above, the weekly meal plan is presented (Figure 5) along with a shopping list with the required grocery items for cooking all the recipes suggested in the meal plan.

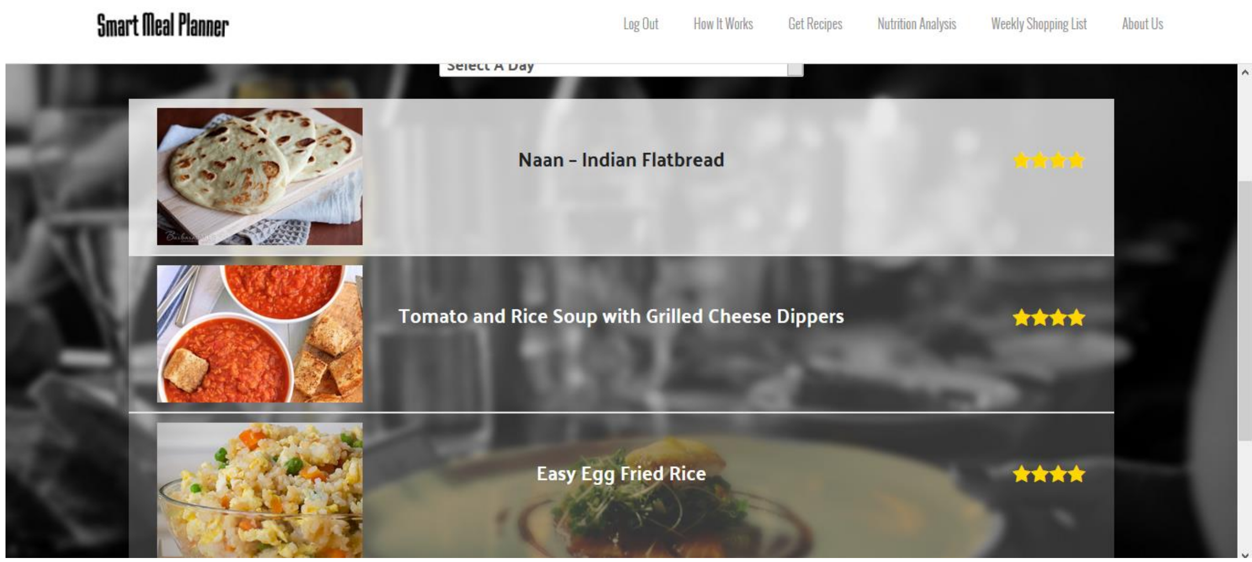

Figure 5: The meal plan with the recommended recipes

The meal plan suggested by the app is editable by the user. When a user clicks on a recipe in the recommended list, they will be presented with a force directed graph of alternatives where each node is a recipe sized according to the recommendation score and each edge is proportional to the similarity between those two recipes. Clicking on a recipe in the graph will show a bar graph comparison of the recipe selected and the original recipe recommended. If desired, the user can then swap to this new recipe (Figure 6).

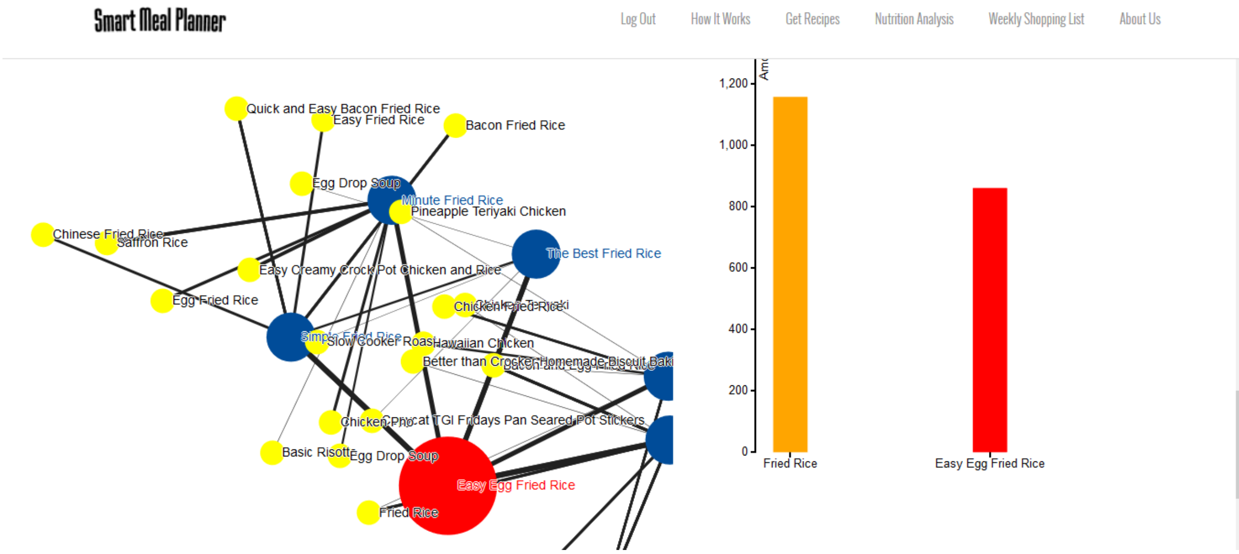

Figure 6 : A force graph to change the recommended recipe. The bar chart on the right compares the two recipes by a nutrition metric.

One of the promises of the app is to suggest not only recipes of diverse tastes but also ensure the nutritional requirements are met to maintain a well-balanced diet. We achieve this by presenting the user with a comprehensive view of the nutritional information of the suggested meal plan aggregating by recipes / day / week (Figure 7).

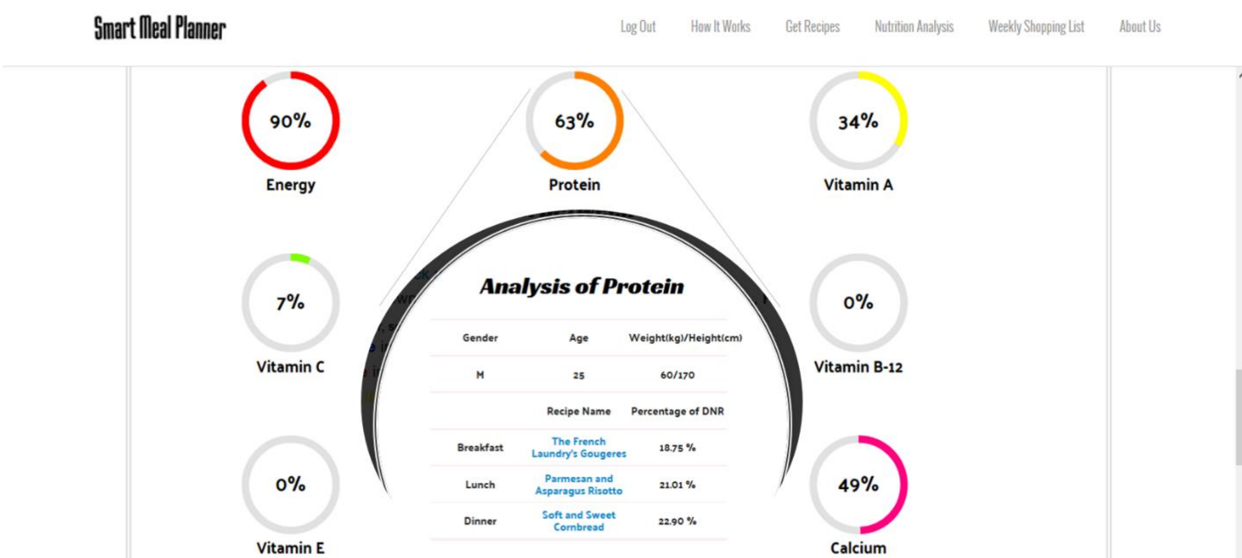

Figure 7: Nutritional Analysis – Day View

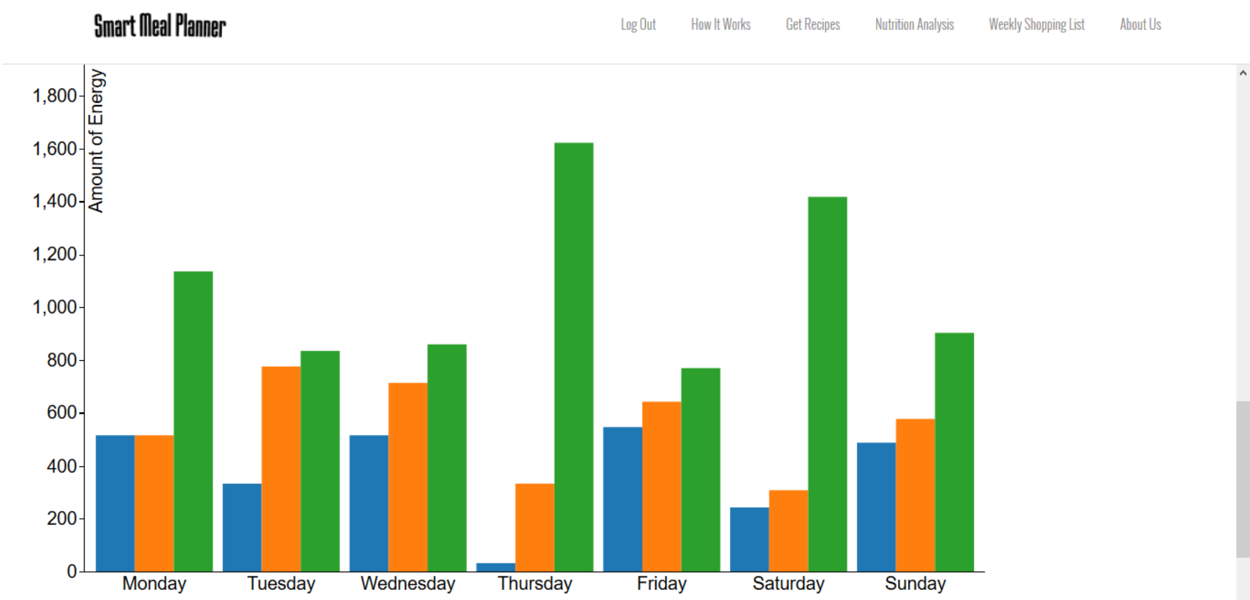

Figure 8 : Nutritional Analysis - Week View

EVALUATION

We started building the app with the goal to suggest diverse yet interesting recipes while trying to keep the meal plan economical and nutritional. After seven weeks of development [HQ8], we conducted a two-phase survey (Figure 9) to evaluate the effectiveness of our application [HQ9]. Since our target users are budget-minded students or professionals with a busy lifestyle [HQ4], we sent out the survey to the students in this class. The first survey gauges people's cooking styles. To incentivize participation we offered a $5 Starbucks gift card randomly awarded to one participant. Totally 14 people participated in the study. As shown in Figure 9, almost universally, participants said they are often pressed for time and spend less than an hour every day on cooking. About 30% of the people go grocery shopping based on need with no pre-set schedule; something we would like our app to help change (planning groceries ahead of time and avoid running out of ingredients).

The second survey explains participants how they can generate the meal plan from the app and asks to compare the suggested meal plan against the top recommended recipes from Yummly. This survey takes about 15-20 minutes for a person to complete. (About 10-15 minutes to use the app and get a recommendation and 5-10 minutes for the survey). 6 people participated in this survey. Yummly was preferred over our custom recommendation for the variety of recipes suggested, but participants liked our recommendations in terms of what they actually would prefer to eat and follow. Universally, participants believe our meal plan would cost less if followed through.

Most participants found the force graph to change recommendations useful but about half of them found it unclear to use. Participants were divided on the effectiveness and usefulness of the nutrition charts.

SURVEY 1 – Understanding Cooking Styles

Number of participants : 14

Participant demographics:
42.9% (**6**) Female, 57.1% (**8**) Male

Age groups: **20 – 25:** 8; **26 – 30 :** 5; **31 – 35 :** 1

Time I typically spend on cooking in a day:
< 30 min : 21.4%
30 min – 1 h : 71.4%
1 h – 2 h : 7.1%

I go grocery shopping:
Once a week : 57.1%
Once a month : 14.3%
No set time : 28.6%

I prefer cooking over eating out: 64.2% in favor

I care about the nutrition content in my food: 71.2% in favor

I am often pressed for time: 92.9% in favor

I often lookup recipes online: 49.9% in favor

I narrow down to my desire recipe by:
Searching for the recipe : 83.3%
Recommend recipes / other means : 16.7%

Features important to me in a recipe recommendation app (Multiple answers):
Discovering New Recipes : 78.6%
Time saved due to the app : 71.4%
Similarity to the recipes I like : 64.3%
Nutritionally balanced: 57.1%

SURVEY 2 –
Comparing Yummly and Smart Meal Planner (SMP) and Evaluating SMP

Number of participants : 6

Which menu would you be more likely to follow for one week?
Yummly : 33.3%, SMP : 66.7%

Which menu is more suited to your personal tastes?
Yummly : 0%, SMP : 100%

Which menu has better variety?
Yummly : 50%, SMP : 16.7%. No preference : 33.3%

Which menu would you expect to cost more?
Yummly : 100%, SMP : 0%

Which menu would you expect to be more nutritionally balanced?
Yummly : 16.7%, SMP : 33.3%, No preference : 50%

What factors do you prefer about SMP (Multiple Answers)?
Variety : 60%, Taste: 40%, Nutrition : 20%, None : 20%, Cost : 0%, Time : 0%, Other : 0%

What factors do you prefer about SMP (Multiple Answers)?
Time : 83.3%, Taste : 66.7%, Variety : 50%, Cost : 50%, Nutrition : 16.7%, Other : 16.7%, None : 0%

How likely would you be to use SMP on a regular basis if available?
Likely : 83.3%, Undecided: 16.7%

Were the nutrition visualizations clear and useful?
The visualizations were clear and useful : 33.3%
The visualizations were clear but not useful : 16.7%
The visualizations were confusing or unclear : 33.3%
The visualizations were unclear but could have been useful : 16.7%

Was the recipe replacement graph clear and useful?
The graph was clear and useful : 33.3%
The graph was clear but not useful : 0%
The graph was confusing or unclear : 16.7%
The graph was unclear but could have been useful : 50%

Figure 9: The two surveys administered to evaluate the app

DISCUSSION AND CONCLUSION

The survey shows a strong interest for a recipe recommendation app that is personalized to individual preferences [HQ5]. Much of the criticism was on the user experience/interface, such as too much explanatory text preceding the nutrition visualization charts and navigational difficulties between different sections. However, the charts themselves were rated useful. This can be addressed in further iterations by tweaking the interface.

Currently we compute similarities of the user's favorites to the 30000 recipes stored on the server and only retain the top thousand scores. Eventually with a wider usage and access to more storage capacity, we should be able to store all the similarity scores. More powerful and distributed compute power would also be needed if we plan to scale it for general public use to reduce the computation time to generate meal plans [HQ7].

Due to the nature of data obtained from Yummly, we clustered recipes by their ingredients. While this technique works great in finding similar cuisines to the user's choices, sometimes the recommended meal may be unsuitable for the time of the day (for example, recommending a light breakfast item for lunch) [HQ6]. This can be fixed by tagging each recipe into the appropriate meal category.

Overall, we have demonstrated the appeal for recommendation algorithms as a proof-of-concept in the context of planning meals.

REFERENCES

[HQ1 - 9] Heilmeier Questions.
http://poloclub.gatech.edu/cse6242/2015fall/project.html#proposal

[1] Svensson, M., Hook, K., and Coster, R. Designing and evaluating Kalas: A social navigation system for food recipes. ACM Transactions on Computer-Human Interaction (TOCHI) 12, 3 (2005), 374–400.

[2] Svensson, M., Laaksolahti, J., Waern, A., Höök, K. A recipe based on-line food store. (2000).

[3] Forbes, P., and Zhu, M. Content-boosted matrix factorization for recommender systems: Experiments with recipe recommendation. Proceedings of Recommender Systems (2011).

[4] Ueda, M., Takahata, M., and Nakajima, S. User's food preference extraction for personalized cooking recipe recommendation. Proc. of the Second Workshop on Semantic Personalized Information Management: Retrieval and Recommendation (2011).

[5] Teng, C.-Y., Lin, Y.-R. & Adamic, L. A. Recipe recommendation using ingredient networks. (2011).

[6] Mayumi Ueda, Syungo Asanuma, Yusuke Miyawaki, and Shinsuke Nakajima, "Recipe Recommendation Method by Considering the User's Preference and Ingredient Quantity of Target Recipe," Proceedings of the International MultiConference of Engineers and Computer Scientists 2014 Vol I, IMECS 2014, March 12 - 14, 2014.

[7] Jill Freyne, Shlomo Berkovsky, and Gregory Smith. 2011. Recipe recommendation: accuracy and reasoning. In Proceedings of the 19th international conference on User modeling, adaption, and personalization (UMAP'11), Springer-Verlag, Berlin, Heidelberg, 99-110.

[8] Leskovec, J., Rajaraman, A., Ullman, J. Mining of massive datasets: Chapter 9. (2014).

[9] Shlomo Berkovsky and Jill Freyne. 2010. Group-based recipe recommendations: analysis of data aggregation strategies. InProceedings of the fourth ACM conference on Recommender systems (RecSys '10). ACM, New York, NY, USA, 111-118.

[10] Ueda, Mayumi, and Shinsuke Nakajima. 2015. "Cooking Recipe Recommendation Method Focusing on the Relationship Between User Preference and Ingredient Quantity." Transactions On Engineering Technologies (9789401795876) 385. Publisher Provided Full Text Searching File, EBSCOhost (accessed September 30, 2015).

[11] Harvey, M., Ludwig, B., & Elsweiler, D. (2012). Learning user tastes: a first step to generating healthy meal plans?. In First International Workshop on Recommendation Technologies for Lifestyle Change (LIFESTYLE 2012) (p. 18).

[12] Tachibana, A., Wakamiya, S., Nanba, H., Sumiya, K. Extraction of naming concepts based on modifiers in recipe titles. (2014).

[13] Wang, L., Li, Q., Li, N., Dong, G., and Yang, Y. Substructure similarity measurement in Chinese recipes. In WWW, ACM (2008), 979–988.

[14] Asami Yajima and Ichiro Kobayashi. 2009. "Easy Cooking Recipe Recommendation Considering User's Conditions. In Proceedings of the 2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology - Volume 03 (WI-IAT '09), Vol. 3. IEEE Computer Society, Washington, DC, USA, 13-16.

[15] Muller, M., Harvey, M., Elsweiler, D., & Mika, S. (2012, May). Ingredient matching to determine the nutritional properties of internet-sourced recipes. In Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2012 6th International Conference on (pp. 73-80). IEEE.

[16] . Phanich, M.; Pholkul, P.; Phimoltares, S., "Food Recommendation System Using Clustering Analysis for Diabetic Patients," in Information Science and Applications (ICISA), 2010 International Conference on, vol., no., pp.1-8, 21-23 April 2010.

[17] Tsuguya Ueta, Masashi Iwakami, and Takayuki Ito. 2011. Implementation of a Goal-Oriented Recipe Recommendation System Providing Nutrition Information. In Proceedings of the 2011 International Conference on Technologies and Applications of Artificial Intelligence (TAAI '11). IEEE Computer Society, Washington, DC, USA, 183-188.

[18] Y-H Ting, Q Zhao, and R-C Chen, “Dietary Recommendation Based on Recipe Ontology, ” 2014 IEEE 6th International Conference on Awareness Science and Technology (iCAST), pp. 1-6, 2014.

DISTRIBUTION OF TEAM MEMBER EFFORT

All team members contribute similar amount of effort.