FitYou: Integrating Health Profiles to Real-Time Contextual Suggestion

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ABSTRACT
Obesity and its associated health consequences such as high blood pressure and cardiac disease affect a significant proportion of the world’s population. At the same time, the popularity of location-based services (LBS) and recommender systems is continually increasing with improvements in mobile technology. We observe that the health domain lacks a suggestion system that focuses on healthy lifestyle choices. We introduce the mobile application FitYou, which dynamically generates recommendations according to the user’s current location and health condition as a real-time LBS. It utilizes preferences determined from user history and health information from a biometric profile. The system was developed upon a top performing contextual suggestion system in both TREC 2012 and 2013 Contextual Suggestion Tracks.

1. INTRODUCTION
A 2010 U.S. National survey found that more than one-third of U.S. adults were obese.1 Obesity greatly increases the risk of diabetes, heart disease, and strokes. In addition, the National Institutes of Health estimates obesity will cause approximately 500,000 additional cases of cancer by 2030 given the current obesity trends.2 There has never been a more important time for people to incorporate healthier dining options and some form of physical activity.

The Text REtrieval Conference (TREC) 2012-2013 Contextual Suggestion Tracks have identified technologies to retrieve and suggest venues to visit at a user’s current location according to the user’s rated preferences of past venues, current location’s time, season, traffic, and temperature [2]. More general location-based recommender systems primarily use population interests, user interests, and friends’ interests but often fail to address a health component. In FitYou, we add a health dimension on top of our TREC system and demonstrate the effectiveness of our system on the Foursquare platform as a real-time LBS.

Some health domain LBS can find health care providers [1], but no system has yet accounted for the need to help people live healthier lifestyles. We propose that healthy, personalized contextual suggestions can be suggested by considering their medical history and future health goals. By integrating users’ health needs and their preferences, suggestions can be further personalized to help users live healthier and happier. Although users can consult with a nutritionist or physician, a specialist may not always be readily available. Thus, it is important to have technology that can generate personalized suggestions whenever necessary.

We separately suggest venues for dining and performing physical activity that burns at least 150 cal/hour. We selected 13 cuisine types3 to make dining suggestions and prepared a list of 45 activities4 with corresponding number of calories burned per hour as estimated for a 155 lb person.5

2. APPROACH
For testing purposes, we utilize interest profiles provided by TREC 2013 Contextual Suggestion Track and combine them with randomly sampled health profiles. First, we mapped each example venue to one of our categories. Past venues

1http://www.cdc.gov/nchs/data/databriefs/db82.pdf
2http://www.cancer.gov/cancertopics/factsheet/Risk/obesity
3Italian, Indian, Japanese, Chinese, American, Korean, French, Ethiopian, Vegetarian, Vegan, Seafood, Salad, Greek
4golf, walk, kayaking, softball, baseball, swimming, tennis, running, bicycling, football, basketball, soccer, outdoors & recreation, archery, badminton, ballet, ballroom dancing, bird watching, bowling, boxing, canoeing, rowing, cricket, croquet, skiing, diving, fencing, fishing, lacrosse, paddleball, polo, racquetball, skateboarding, rollerblading, table tennis, yoga, hiking, rock climbing, mountain climbing, snorkeling, ice skating, painting, billiards, shopping, museum
5www.nutristrategy.com/caloriesburned.htm
are rated by users on a five-level scale Interest score: -0.9 for strongly disinterested, -0.3 for disinterested, 0 for neutral, 0.3 for interested, and 0.9 for strongly interested.

Similar to [5], we employ state-of-the-art matrix factorization approach. We operate Singular Value Decomposition (SVD) over a user-category matrix $S_{u \times c}$. Each entry $S_{i,j}$ is estimated by $S_{i,j} = c_j u_i$ where $c_j$ presents category $j$ and $u_i$ presents user $i$. These vectors are estimated given the entries in $S_{u \times c}$. The value of $S_{i,j}$ in the matrix is determined by the user’s Interest as mentioned above. We calculate a user’s average interest score across all categories $\bar{y}_u$ and all users’ average interest score for a category $\bar{y}_{c,j}$:

$$\bar{y}_u = \frac{\sum_{i \in \mathtt{cat}} \text{interest}(u, c_j)}{|\mathtt{cat}|}$$

$$\bar{y}_{c,j} = \frac{\sum_{u \in \mathtt{users}} \text{interest}(u, c_j)}{|\mathtt{users}|}$$

One of the key factors in our success in TREC Contextual Suggestion evaluations [4] is our focus on satisfying users’ major interests. We classify a category as a major interest if a user’s score for the category is greater than the average of his score over all categories and if his score for the category is greater than the mean of all users for this category, that is, if $P_{\text{Interest}}(u|c_j) > \bar{y}_u$ and $P_{\text{Interest}}(u|c_j) > \bar{y}_{c,j}$.

### 2.1 Integrating Health Profile

The user health profile contains: age, gender, height, weight, neck, forearm, waist, hip, wrist, prevailing health conditions, and exercise preference (light, medium, or intense). In production, users will provide and update their health profile as needed. In order to experiment using the TREC dataset, we had to randomly sample health profiles. We assume health profiles and Interest are independent.

We next calculate biometrics using the health profile. Body mass index (BMI) is $\frac{703 \times \text{height}(\text{in})}{\text{weight}(\text{kg})^2}$ or $w(\text{kg})$. Body fat percentage (BFP) is $\frac{100 \times (w - (1.092 \times w + 64.42) - 4.53 \times \text{waist})}{\text{weight}}$ for male and $100 \times (w - (1.732 \times w + 8.987 + \frac{M}{11.14} - .157 \times \text{waist} - .249 \times \text{hip} + .434 \times \text{forearm})/w$ for female. Lastly, we provide a suggested weight using the J. D. Robinson formula: $52kg + 1.9kg$ per inch over 5 feet for male and $49kg + 1.7kg$ per inch over 5 feet for female [3], $w$ is weight and $h$ is height; other measures are circumferences of the body parts. Users can accept the suggested weight or manually set a target weight.

### 2.2 Activity Suggestion

Although calorie burning varies with body weight, the change is proportional for all activities. Considering the TREC dataset, we added a few activities which are not often associated with calorie burning such as shopping, museum, and outdoors and recreation, and estimated the calorie burning for venues of these types to be half that of walking.

When suggesting activity venues, we consider user interest, variety, and exercise intensity. Given the user’s current location, we issue separate queries for each activity type and collect the first fifty results. We determine each activity type’s score (ATS) by combining health and interest:

$$\text{ATS} = \frac{\text{CaloriesBurnedPerHour}}{1000} + (1 - \alpha)\text{Interest}$$

where we empirically set $\alpha = 0.4$ and Interest was the interest score. If the user has a health condition such as high blood pressure or cardiac disease, greater bias is given to burning calories and $\alpha = 0.6$. Calorie content is divided by 1000 so that it is similar in magnitude to Interest.

All activity types were sorted by their ATS. We first returned one venue corresponding to each major interest to increase the likelihood the user will find the first recommendations valuable. Next, we considered both major and non-major interests. One venue from the highest scoring activity was returned. After a venue of a given activity type was returned, the ATS score was discounted by 25% and the activity types are re-sorted. This ensures adequate variety in the recommendations. This process was continued until 50 recommendations were determined.

### 2.3 Dining Suggestion

We observe macronutrient information such as protein, fat, and carb content is not available for many restaurants; thus dining recommendations are optimized by considering calorie content. We estimated the typical calories in a meal for each cuisine type by randomly selecting several restaurants of each cuisine type that had calorie information available. We randomly selected entrees from each restaurant and computed the geometric mean for each cuisine type.

When recommending dining venues, we consider user interest, cuisine type variety, health conditions, and whether the user is trying to lose or gain weight. We determine each cuisine type’s score (CTS), which differs from ATS by introducing $\gamma = -1$ to penalize calories if the user needs to lose weight, else $\gamma = 1$. The dining suggestion process follows the same logic as for activity suggestions.

$$CTS = \gamma \alpha \frac{\text{CalPerMeal}}{1000} + (1 - \alpha)\text{Interest}$$

### 3. USER EXPERIENCE AND CONCLUSION

As obesity rates and their associated health concerns have prodigious effects upon a significant proportion of the world’s population, we determine a new type of contextual suggestion system should exist to help users live healthier lifestyles. FitYou, developed upon our system in the 2012 and 2013 TREC Contextual Suggestion Tracks, integrates health profile and preference history to generate personalized suggestions according to the user’s current location and its context.

Users have received high quality suggestions at different contexts ranging from Washington, DC to Vernon, CT. Based on initial user testing, we are confident that FitYou can supplement a physician’s advice to help health-conscious users improve their lives by suggesting healthy recommendations that they enjoy. For future work, we would like to implement further personalized dining recommendations as restaurant data becomes increasingly available.

### 4. REFERENCES


