Preference-maximized Nutrition Planning by Relative Learning and Ranking

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Diet Management and Planning Service

- Good eating habits are important for maintaining a healthy life and preventing the lifestyle-related disease epidemic.
- With the number of people considered to be obese and having chronic disease rising across the world, the role of IT solution in diet management and planning has been receiving increased attention in recent years.
- A key factor toward a successful diet planning is the degree of personalization.
Diet Planning Problem

What is “Personalized” Diet Planning

A Conventional Perspective

- Finding a food combination that matches specific nutritional needs

An example

- Diet suggestion merely follow some general guidelines and are not intended for individuals

[US 2009/0234839 A1] Smart Sensor Based Environment for Optimizing a Selection of Meal Plans
A meal plan is a guide that provides information about how much and what kinds of food should be eaten and when.
For example, servers may store results of the latest medical studies indicating which foods are known to lower cholesterol, counteract the effects of high blood pressure, or provide an adequate amount of calories for an endurance athlete.
Diet Planning Problem

- **What is “Personalized” Diet Planning**
  - It is unlikely that an individual would accept the meal plan merely based on the nutrition supplements

- **A Revised Perspective**
  - Finding a food combination that matches Individual’s **NUTRITIONAL** needs and **PREFERENCE** about food

\[
\begin{align*}
\text{maximize} & \quad \sum_{i} x_i \cdot PF(f_i) \\
\text{subject to constraints} & \\
\end{align*}
\]

\[
\begin{bmatrix}
    f_1 \\
    \vdots \\
    f_n \\
\end{bmatrix} =
\begin{bmatrix}
    e_{11} & \cdots & e_{1m} \\
    \vdots & \ddots & \vdots \\
    e_{nm} & \cdots & e_{nn} \\
\end{bmatrix}
\]

\[
\sum_{i} x_i \cdot \sum_{j} e_{ij} - E_j \leq E_j + \theta_j
\]

\[
\sum_{i \in FC_k} x_i \leq 1
\]

\[
\sum_{i=1}^{n} p_i x_i \leq B
\]

**Quality of diet suggestion**

- **Level 1.** Rule-based Planning
- **Level 2.** Dynamic Nutritional Needs Planning
- **Level 3.** Preference-driven Planning

\(x_i\): the quantity of \(i\)-th food (i.e., decision variable)

\(PF(f_i)\): the score of user preference about \(i\)-th food

\(E_j\): the expected \(j\)-th nutrition element per day

\(\theta_j\): nutrition requirement buffer

\(FC_k\): the \(k\)-th food category

\(p_i\): the price of the \(i\)-th food and

\(B\): user’s budget for a meal
Previous Methods for Preference Extraction (1/3)

1. Questionnaire

- It asks a user a bunch of questions for investigating a user’s preference
- Exhaust users’ patience and easily bore them
- Oversimplify the user preference into a binary classification (e.g., “like” or “dislike”)
Previous Methods for Preference Extraction (2/3)

2. Explicit Rating

- It asks a user to explicitly rate the item in certain range (e.g., 1~10) to reveal individual’s preference
- Users’ preference are hard to be quantified
- Exhaust users’ patience and easily bore them
3. Statistical Inference

- It automatically infers a user’s preference by examining their past diet habits.

**Cold Start problem**

- It concerns the issue that the system cannot draw any inferences for users or items about which it has not yet gathered sufficient information.
- It is caused by the poverty of training data at the very start after system launching and often lead to an erroneous preference inference.

\[
g(\bar{x}) = \sum_{i=1}^{n} x_i [\alpha CF_i + (1 - \alpha) \frac{NC_i}{TNC}] \\
\]

where \( CF_i \) is the user’s preference about the \( i \)-th food, \( NC_i \) is the number of individuals who had consumed \( i \)-th food in the restaurant, and \( TNC \) is the total number of customers who had ever visited the restaurant. The rationale behind this objective function is to propose a diet in which the selection of individually and publicly preferred foods (e.g., signature dishes in a restaurant) is encouraged. Here \( \alpha \) can be used to control the tendency toward individual preference or public opinion.
Core idea (1/2)

- **k-comparative Food Annotation**
  - We observe that an individual’s preference can be represented more appropriately in a relative way instead of an explicit rating.
  - The proposed method merely requires users to select their most preferred food among \( k \) presented foods each time.
  - “Learn to rank” algorithm can then be employed to learn the preference ranking.

- Advantages
  - Saving food annotation time
  - The ability to capture user’s preference in a more precise manner

The parameter \( k \), which is configurable, is a trade-off between annotation time (i.e., user effort) and data collection efficiency.

(Training pairs steak>fish and steak>chicken if user select steak)
Core idea (2/2)

- Hierarchical Reasoning

- Be able to Infer a user’s preference on unknown foods without the need to ask a user to explicitly annotates them in advance

  - It breaks meal/dish/food into ingredient level and then integrates the impact of each element back to the upper level is adopted to accurately infer the unknown or un-annotated foods

**Hierarchical Reasoning**

**Food/Dish feature** $m = \{d_1, d_2, ..., d_{dim}\}$

- Binary feature to show the existence of a ingredient or cookery
  - $[0, 1, 0, 0, 1, 0, 1]$  

- Weighted-vector feature to show the proportion of an ingredient
  - $[0.1, 0.2, 0.5, 0, 0.25, 0.05]$
Hierarchical Preference Diagram

- An example of hierarchical preference diagram produced by hierarchical reasoning
  - To infer a user’s preference at any level
- Note that conventional methods have obstacle to produce the hierarchical preference diagram since they are unable to infer unknown or un-annotated recipe/food/ingredient.
If the user annotate food4 (i.e., simply click food4 on the UI) as his most preferred food among food 2, 4, and 6, the information conveyed from the 3-comparative annotation will be

food4 < food2
food4 < food6

(Training pairs)
Flowchart

1. System presents a user $k$ different foods for $k$-Comparative Annotation

2. Generate training pairs according to $k$-Comparative Annotation

3. Hierarchical Reasoning

4. Rank foods according to user's preference

5. Diet recommendation based on nutrition guideline and personal preference

Iterate to improve the reasoning accuracy
Ranking (1/2)

- Learning to rank

\[
\min \ V(\vec{w}, \vec{\xi}) = \frac{1}{2} \vec{w} \cdot \vec{w} + C \sum \xi_{i,j,k}
\]

subject to:

\[
\forall (f_i, f_j) \in r_1^* : \vec{w}\Phi(m_i) \geq \vec{w}\Phi(m_j) + 1 - \xi_{i,j,k}
\]

\[
\forall (f_i, f_j) \in r_n^* : \vec{w}\Phi(m_i) \geq \vec{w}\Phi(m_j) + 1 - \xi_{i,j,n}
\]

\[
\forall i \forall j \forall k : \xi_{i,j,k} \geq 0
\]

* can be solved using decomposition algorithms similar to those used in SVM.

- Normalized food preference score \( PF(f_i) = \frac{1}{z} \vec{w}\Phi(m_i) \)

- Food/Dish feature \( m = \{d_1, d_2, \ldots, d_{\text{dim}}\} \)
  - Binary feature to show the existence of a ingredient or cookery
    - [0, 1, 0, 0, 1, 0, 1]
  - Weighted-vector feature to show the proportion of an ingredient
    - [0.1, 0.2, 0.5, 0, 0.25, 0.05]
Ranking (2/2)

- Collaborative Filtering for fine-tuning the preference score
  - For finding the nearest neighbors or like-minded people, the Pearson Correlation is used to define the similarity between user u and v and defined as

\[
sim(u, v) = \frac{\sum_{i \in \{r_{ui}, r_{vi} \neq 0\}} (r_{ui} - \bar{r}_u)(r_{vi} - \bar{r}_v)}{\sqrt{\sum_{i \in \{r_{ui}, r_{vi} \neq 0\}} (r_{ui} - \bar{r}_u)^2 \sum_{i \in \{r_{ui}, r_{vi} \neq 0\}} (r_{vi} - \bar{r}_v)^2}}.
\]

- \( r_{ui} \) (\( r_{vi} \)) is the rating of \( i \)-th food given by user u (v)
- \( \bar{r}_u \) (\( \bar{r}_v \)) is the average rating of food for user u (v)

- Integration of rank score and collaborative filtering

\[
PF(f_i) = \alpha \left( \frac{1}{Z} \Phi(m_i) \right) + (1 - \alpha) \frac{\sum_{v \in N(u)} \sim(u, v) \cdot r_{vi}}{\sum_{v \in N(u)} |\sim(u, v)|}
\]
Nutrition Management Prototype

EasyDiet Android
Self-monitoring could be the single best behavior an individual can use to improve their health. Empirical studies repeatedly demonstrated that individuals often lose more weight and effectively keep away from chronic diseases.

**EasyDiet** for self diet management

As easy as the following steps: Search, Record, and Track.
Intelligent Input

1. Taking a picture on the menu

2. Smart Input by Recognition

<table>
<thead>
<tr>
<th>Food Name</th>
<th>Chocolate vanilla</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calories</td>
<td>400</td>
</tr>
<tr>
<td>Protein</td>
<td>7</td>
</tr>
<tr>
<td>Fat</td>
<td>9</td>
</tr>
<tr>
<td>Carbohydrate</td>
<td>65</td>
</tr>
</tbody>
</table>
Preference-maximized Nutrition Planning

Diet Suggestion

What-if Analysis

What if I want to eat a steak today!

Menu

1. 鮮奶牛肉
2. 黃豆燉排骨
3. 蔓越莓麻糬
4. 巧克力水果布丁

Nutrition Information:

卡路里: 911.0  蛋白質: 35.0  脂肪: 31.0  碳水: 148.0  鈉(mg): 1199.0  鈣(mg): 613.0
Conclusion

- In this paper, we have presented the $k$-comparative annotation and reasoning technique to alleviate the effort-intensive annotation, unreasonable preference quantification, and cold start problem in previous recommendation works.

- Based on these extracted food preference, a customized nutrition service can be provided, where the resulted diet planning can be more personalized and the health diet compliance can thus be further improved.
Thank you!