Handling the complexity of personalised dietary guidance

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1. Introduction

A balanced diet is an essential element of a healthy lifestyle [1]. Following such a diet requires consumers to make sensible decisions on the food they purchase and consume. However, these choices are very complex. This paper presents a framework that decomposes the decision making process into manageable elements, ready for use as a generic 'engine' in digital dietary guidance systems.

In the area of nutrition and health, hypes come and go. Consumers face continually changing and contradicting statements about the impact of food on health. At the same time, thousands of apps and websites claim to provide dietary advice, increasingly relying on smart sensors [2]. However, their scientific basis is often lacking, and the limitations on their applicability unknown.

The problem is that the decision on what to eat depends on many individual and situational factors, including personal health, lifestyle, preferences, habits, eating moment, cultural factors, etc. Consumers and even dieticians cannot oversee and handle all the data and knowledge that is required in each case.

A common approach in dietary apps is to generate a general dietary advice based on limited information from the user, leaving the user puzzled about whether it is actually good for him. Other apps suggest healthy alternatives for specific products. These applications directly translate input data into an advice, using generally accepted guidelines. This limits their scalability, flexibility and transparency, plus optimising one product doesn't give a balanced diet.

2. Approach

We present a structured and traceable approach to creating personalised dietary advice. The first step is to distinguish between *form* and *content*. In terms of *content*, we define the following personal data:

- Health parameters, e.g., body mass index, cholesterol HDL, specific health risks.
- Products or ingredients to be selected, e.g., a shopping list, a selected recipe.
- Preferences and conditions, e.g., vegetarian, allergies.
- Situational context, e.g., lunch or dinner, special occasions.
- Typical food intake for some period of time, e.g., obtained from a nutritional diary.

In many cases, not all input data will be available. Food intake, for example, is notably difficult to measure. In our framework we develop ways to approximate input data, e.g. using group data to approximate individual data.

We aim to change specific aspects of dietary habits by giving suggestions at a decision making moment. For the advice engine we propose the following outputs:

- Changed portion sizes of items in one's diet.
- Products or ingredients that replace items in a diet, and have better nutritional values.
- Products or ingredients outside one's regular intake, in order to get a more balanced diet.

Now, given a set of input data, we infer the advice outputs by applying several knowledge sources, such as the following.

- Food-health impact relations.
- General product and product class replacement rules.
- Product properties: nutritional values, preference properties, context properties, etc.
- Nutritional value indicator, weighing the importance of multiple nutrition parameters for the individual.

By defining these independent knowledge sources, a flexible and scalable architecture is created. The knowledge sources can continuously be updated and extended, but they can also be simplified if needed. The methods that generate a specific advice from these sources are themselves generic and hence reusable. Moreover, each knowledge source has its own provenance information, making it traceable.

3. Concluding remarks

We have created the overall framework for a personalised dietary advice system and identified required knowledge sources. We are evaluating our approach by discussing use cases with several dietary experts. This will be followed by the implementation of our framework in intervention studies (field labs) with consumers.

One challenge is to discover the assumptions that dieticians use in practice. How do they decide which effect is considered dominant for an individual – e.g. should they concentrate on reducing fat or sugar? Automated approaches need to make such decisions explicit in order to be reliable.

References

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