A Baysian Approach to Collaborative Dish Selection

Team 10

Introduction

As anyone who has ever planned a catered event can attest, attempting to satisfy the various palates, dietary requirements and tastes of a group of diners can be a daunting task. This is particularly true given the exponential number of dishes which can be created from a small number of ingredients, as well has hard constraints such as allergies and religious beliefs. Many professional catering services handle this problem by allowing guests to select from a very limited menu. We propose to develop a dish recommendation system based on Bayesian Networks modeling user preferences and which proposes meals that most likely match the varied tastes of the customers, using a limited set of ingredients. This type of expert system would be of great use to a catering service or restaurant which needs to rapdily decide on a small number of dishes which would be acceptable for a large dinner party, given diverse requirements and preferences.

Related Work

Boekel and Corney propose using Bayesian Networks to model consumer needs in food production chains [5] [1]. Janzen and Xiang propose an intelligent refrigerator capable of generating meal plans based on inventory and past food choices [2]. Baysian networks have also been applied to recommendation systems before in on-line social networks [4] making predictions of the form "if you bought those items what is the probability you would like to buy that". We suggest that these approaches are limited in that they only consider the preferences of a single (or supposed 'typical') user rather than a group.

Proposed Approach

The approached problem is to pick a single meal which best meets the requirements and tastes of different people dining together.

First, we will accumulate a diverse collection of sample recipes using the open source AnyMeal application to convert freely available MealMaster format (flat file) recipes to XML format for input into the Java Bayesian network / optimization application we propose.

Next, we will gather data representing several diners' preference for approximately 20 meals using a simple survey of the type 'rate on a scale of 1 to 10, 10 being favorite and 1 being least favorite'. A value of 0 for a given dish will be taken to mean that one or more ingredients trigger and allergy or violate a religous constraint, and the diner cannot consume the dish.

We will model each individual user's preferences and needs as a Bayesian network, which means a set of independence and conditional independence relationships between variables [3]. Our model consists of 4 layers, each modeling a different aspect of taste and needs. In the first layer

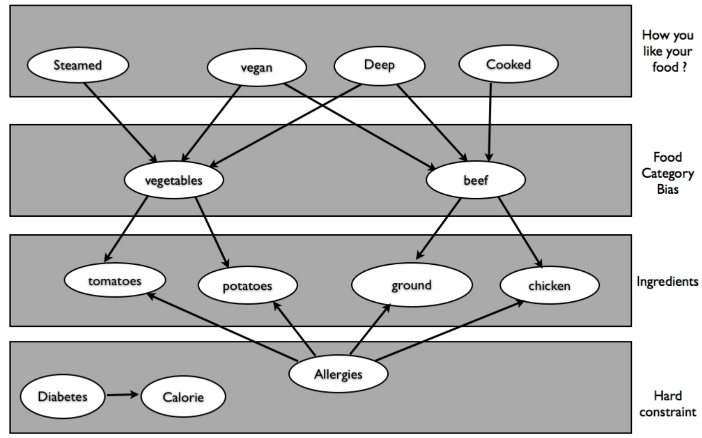

Figure 1. Our Baysian net modeling user preferences

we capture general meal preferences, like being vegetarian or not liking your food steamed. The second layer models a general preference towards different food categories like vegetables or beef. As one can see, the food categories are dependent on the general meal preference. For example being vegetarian will exclude beef and will support vegetables. The third category models different ingredients. Each ingredient is conditioned by the food category it belongs to. In the last layer we have hard constraints like allergies (that will exclude a particular ingredient) or the overall calorie content of the meal given someone suffers from diabetes. The overall net is shown in Figure 1. Given a recipe with a list of ingredients $I = i_1, ..., i_n$ and a Bayesian network capturing user preferences we can calculate the probability of users liking the dish as $P(i_1 \wedge i_2 \wedge ... \wedge i_n) = \Pi_{i=1}^{n} p(i_i \mid parents(i_i))$ [3].

In order to estimate the model parameters, the system will be trained with statistics about taste and preferences given a set of dishes with ratings from multiple users. From that information we can directly calculate the probabilities for the ingredients.

When learning the rest of the variables (that are not observed and therefore hidden / latent) we will use Expectation Maximization [3].

Evaluation

The application model will be trained using a sparse subset (25-50%) of the survey data and the optimization problem soled for the inferred constraints. Next, we will calculate the correlation between the application's ranking of all dishes and the actual ranking as determined by the user surveys. We suggest that a high degree of correlation indicates that the system has the potential to accurately appraise constrained group food preferences for dishes which are not part of the survey, given sufficiently detailed recipe information.

References

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