Q-Chef: A User Experience Based on AI Models of Curiosity

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1 Introduction

Diversification and change in a broad sense are largely positive and are proven to have many benefits in various domains. Q-Chef, short for curious sous-chef, looks at promoting this diversity in eating habits. The question becomes how can we elicit this change and furthermore how can we sustain in. Cognitive theories label curiosity as a possible driving agent in these behavioral changes [1]. Schmidhuber describes the key to designing a medium for curiosity as showing the user "non-trivial & novel & surprising data" [2]. Maximizing curiosity is a matter of increasing surprise in relation to an external goal; in our case, that goal is trying new foods. Maher introduces an adaptation of the Wundt curve emphasizing the lower and upper bounds of novel stimuli [3]. Understanding this spectrum of novelty for any given person requires a representation of their experience with the domain in question and a personalized model of that user's lower and upper bounds (see Fig 1).

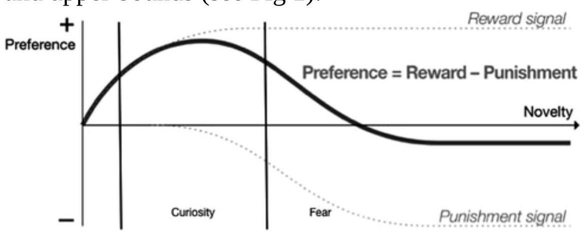

Fig 1. An adaptation of the Wundt curve as it relates to novelty depicting abstract lower and upper bounds of novel stimuli for some person

Q-Chef will use curiosity driven stimuli to promote users to try new foods and recipes with an overarching goal of dietary diversity. Personalized recipe systems have had moderate success in the past at promoting healthful choices. In these systems, past research shows that users want actionable advice and an enjoyable interface [4]. Our recipe suggestions become actionable when we give the user the drive to try them by being more curious. But unlike personalized recipe systems, Q-Chef doesn't recommend recipes based on closeness to user preference. Our model for Q-Chef has three elements: user preference and habit, a representation of that user's food curiosity, and a recipe recommender engine based on those models [5]. Recommendations are made on the upper bound of our model of that user's preference to novelty.

Q-Chef's innovative take on curiosity demonstrates the reach of computing into fields not typically thought of as numerical. Moreover, dietary diversity has a very practical social relevance to everyone.

2 Research Objectives

The research objectives for this project are a part of a larger project. Mainly, they are tools for further research on Q-Chef to be done. The objectives for developing a user experience based on AI models of curiosity are:

1. *To design and develop a model of personalized food curiosity.*

This model comes from data collected in a survey on familiarity and surprise with varying foods. Curiosity can be extracted from how likely someone is to seek out surprising stimuli. At the time of writing this paper we have results from 61 participants (32 males, 28 females, and 1 other). The survey was composed of a demographics, a food familiarity, a curiosity, and a results section [6]. This paper will only be analyzing responses from the third section on curiosity.

Each user's answers about a given recipe were given a category (0-4) based on their willingness to try a surprising food (2 being neutral). We model a user with a vector that has 10 elements, each element is the curiosity number (0-4) for one of the 10 curiosity questions. With those vectors a k-means clustering algorithm, where k=3, was used as a method of extracting three different types of people who took our survey. In Fig 2, the cluster centers are mapped on a

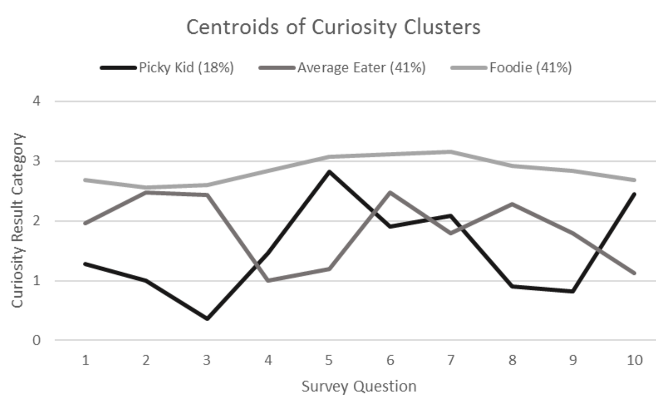

Fig 2. Line graph showing the vectors for 3 different types of users who took the Food Curious survey. The y-axis represents categories of curiosity.

line graph to show were that clusters preferences lie for each question. The labels *Picky Kid, Average Eater, and Foody* were used to describe the abstract clusters. Each cluster has unique attributes that led us to pick those labels. The foody can be assumed to be more curious about food as they are willing to try most foods, even if it is surprising. Most interestingly is the differences between the picky kid and average eater. The picky kid is less curious about all foods besides sugary recipes when compared to the average eater (note questions 4, 5, 7, and 10, are for sugary recipes).

2. *Use machine learning to uniformly clean and tag recipe data.*

Currently, we've scrapped 86,311 recipes from the web. Recipes contain a title, instructions, a list of categories, and a list of ingredients, but categories and ingredients are not consistently formatted. The ingredient lists were first cleaned to only contain strings of alphabetic characters of length 3 or greater. Each recipe is treated as a sentence containing the recipe's title and ingredients.

Using a classification algorithm, recipes can be classified as positive or negative (similar to sentament analysis) for the following categories: Mexican, Italian, Chinese, Greek, Thai, Indian, and French [7]. This analysis was done with the Naïve Bayes and Max Entropy classification algorithms to identify various tags from the Food Curious survey. Surprisingly, Naïve Bayes outperformed the Max Entropy discriminative algorithm; this begins to raise questions on the connectivity of features in recipes, because Naïve Bayes treats features as independent of one another.

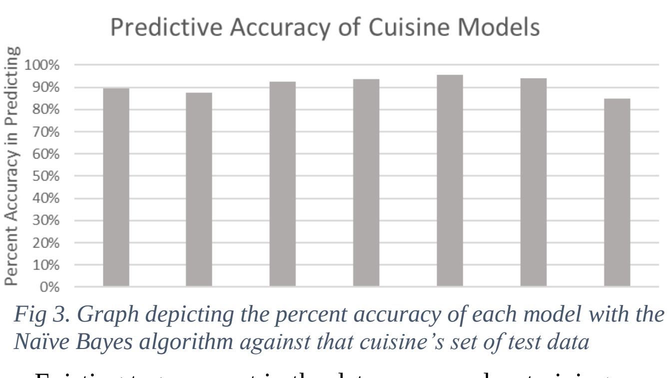

Fig 3. Graph depicting the percent accuracy of each model with the Naïve Bayes algorithm against that cuisine's set of test data

Existing tags present in the data were used as training for the classification models and different data was used to verify accuracy of each algorithm; training and test data ranged from 300-1000 recipes in size with half being positive for that cuisine. The average accuracy of all 7 models was 91 percent (see Fig 3).

3 Future Developments

The next step in development for the topics covered in this paper come in the form of solidifying our personalized model of surprise. The popular community research site Lab in the Wild is advertising our survey. As we collect more data through them we can begin to create more types of users. Additionally, these user models will incorporate data from other parts of the survey.

More work needs to be done with categorizing recipes as well. We will explore classifying recipes with other tags present in the data, besides cuisines. Additionally, these category models need to be run on the rest of our data to add categories for recipes that are missing tags.

4 Acknowledgements

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5 References

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