

Personalized Models of Curiosity

How can one model curiosity?

- Curiosity is one's willingness to seek out novel stimuli

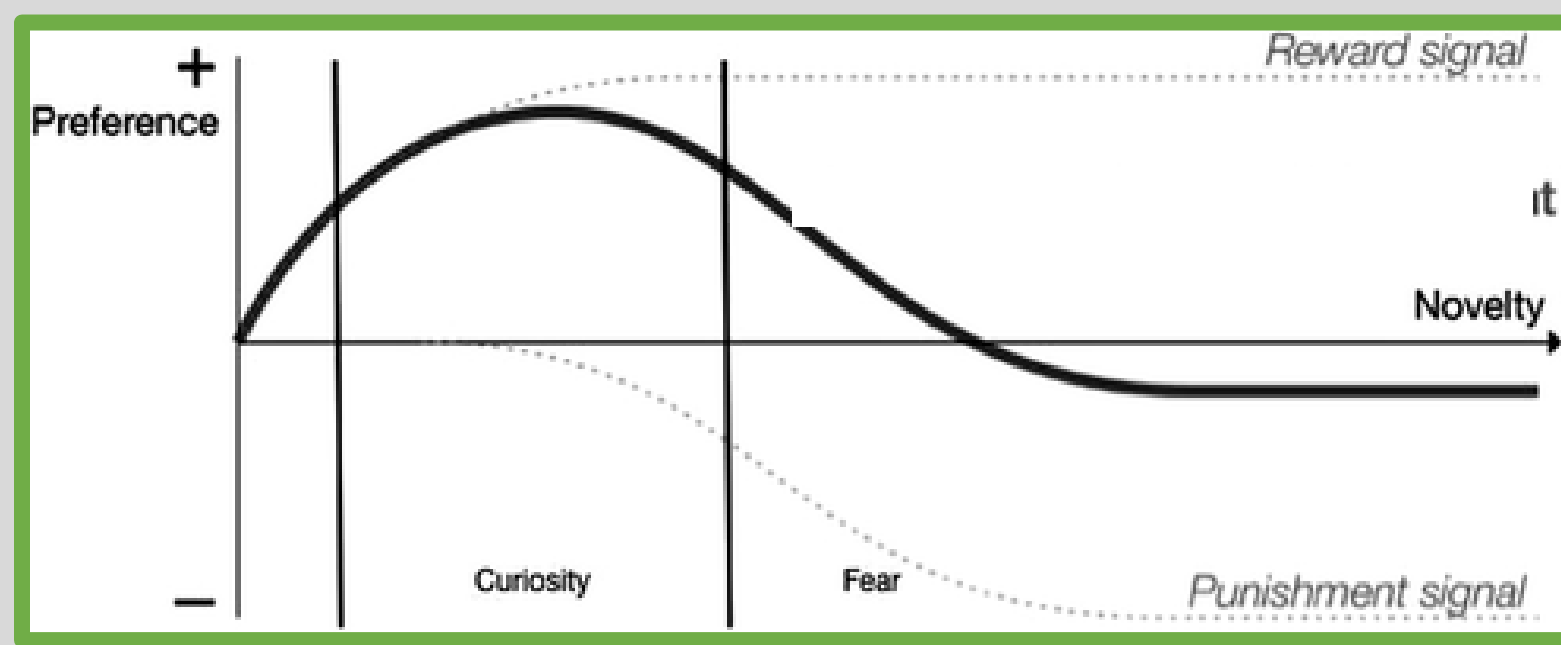


Fig 2. Wundt curve as it relates to novel stimuli

Survey

Advertised on Lab in the Wild
Collected data (61 people) on

- Demographics
 - Familiarity with foods
 - **Food Curiosity** (ex. Fig 3)
- Responses to curiosity questions were assigned quadrants

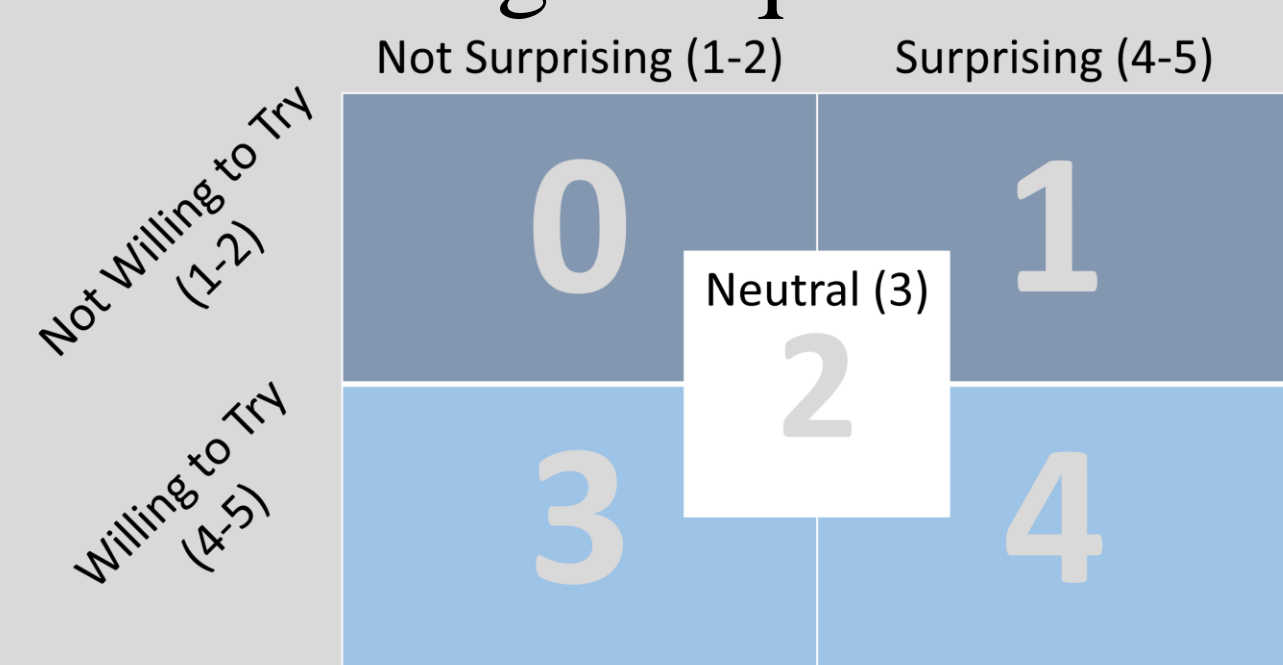


Fig 4. Encoding for curiosity quadrants using questions like in Fig 3

Food Curiosity Models

Users are represented by a 10 dimensional vector

- Values of curiosity quadrant
- K-means clustering used to derive different types of user
- People have varying levels of food curiosity
- Picky Kid – Not curious, except for sweets
Average Eater – Neutral or moderately curious
Foodie – Curious about all food

User model provides data for a personalized model of curiosity

- Highly surprising recipes will elicit a negative response to less curious people
- Food Curious survey
- Part of the Q-Chef app
 - Tool for further research

Blueberry Tofu Smoothie



Ingredients

6 ounces silken tofu
1 medium banana
2/3 cup soy milk
1 cup frozen or fresh blueberries
1 tablespoon honey
2-3 ice cubes, optional

39. * How surprising is this recipe to you?

Not very surprising 1 2 3 4 5 Very surprising

40. * How likely are you to want to try this recipe?

Not likely 1 2 3 4 5 Very likely

Fig 3. Screenshot of 10th curiosity question. Curiosity quadrant can be extracted from surprise vs willingness to try

Q-Chef Project (“Curious Sou-chef”)

- Curiosity driven approach to dietary diversity
- Elicit change and sustain it
- Surprise based recommender system
- Comprised of three elements

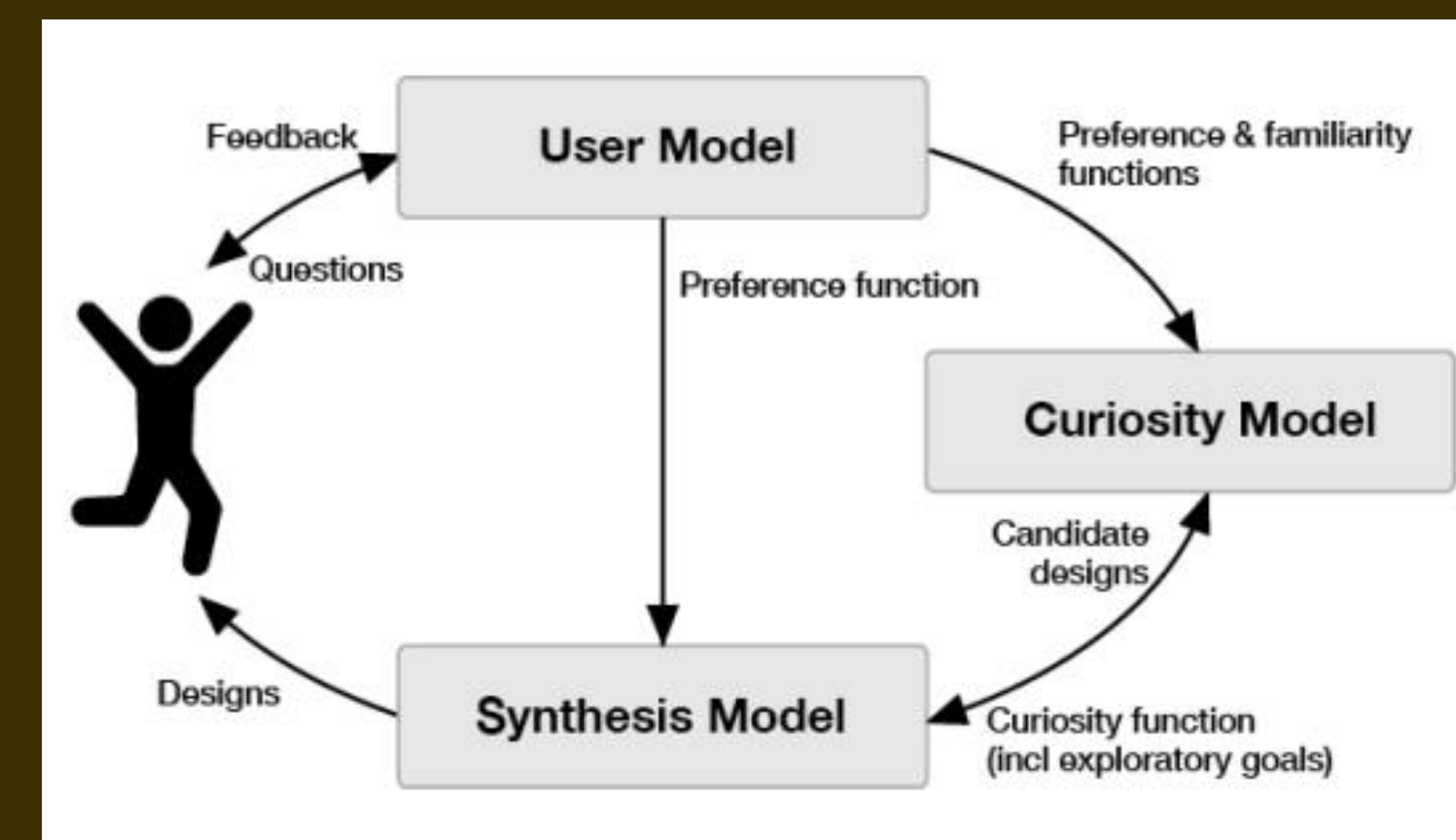


Fig 1. Model of Q-Chef's elements

Research Objectives

Cogs in the larger Q-Chef project and tools for further research to be done

- Design and develop models of personalized food curiosity using survey data
- Develop models to classify recipe data using machine learning algorithms

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Maher M.L., Grace K. (2017) Encouraging Curiosity in Case-Based Reasoning and Recommender Systems. In: Aha D., Lieber J. (eds) Case-Based Reasoning Research and Development. ICCBR 2017. Lecture Notes in Computer Science, vol 10339. Springer, Cham
Jurafsky, D., & Martin, J. H. (n.d.). Naive Bayes and Sentiment Classification. In Speech and Language Processing (3rd edn. draft). Retrieved July 21, 2017.

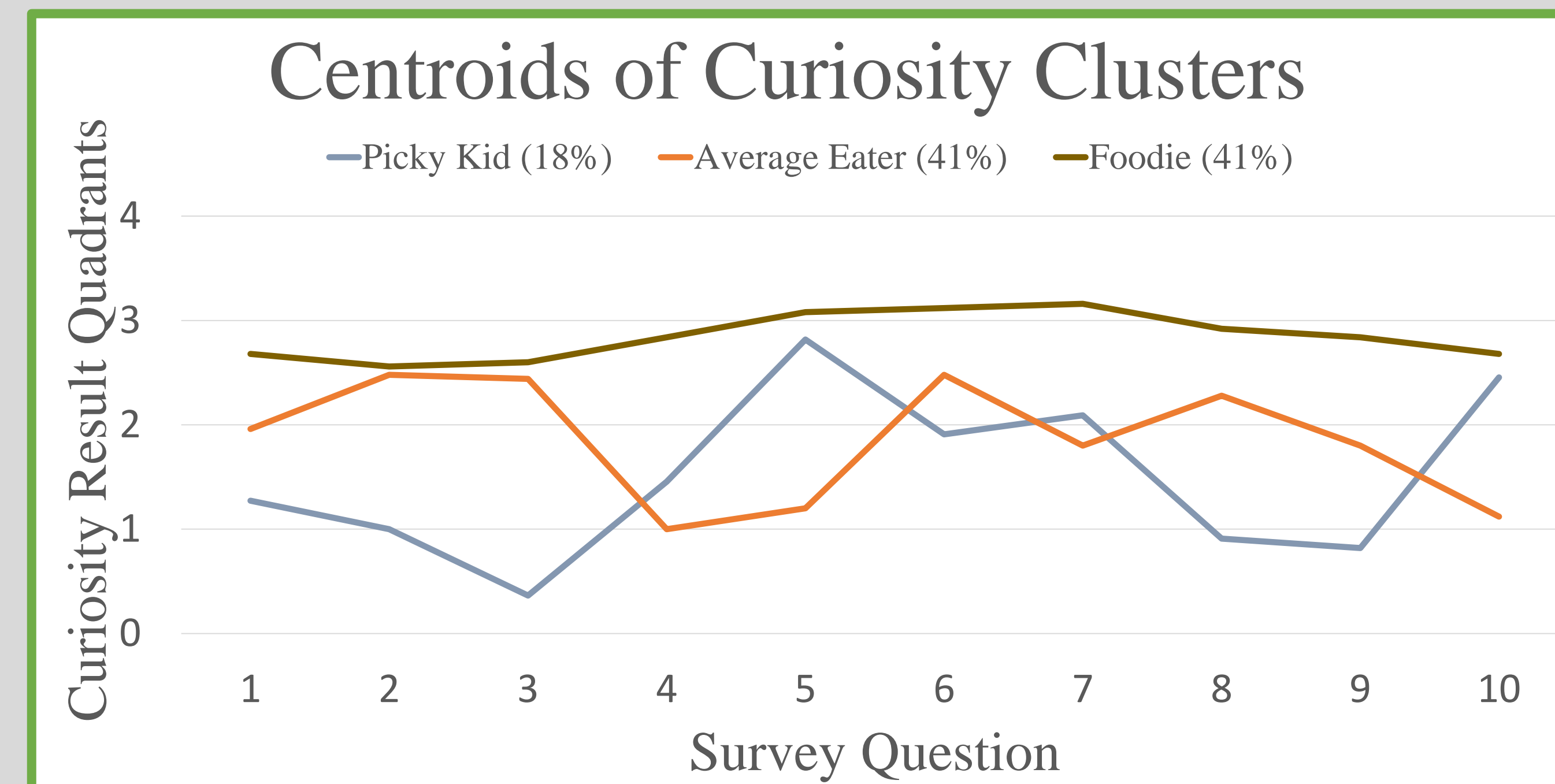


Fig 5. Centroids of each type of user. (Questions 4,5,7,10 are sweet recipes)

Classifying Recipe Data

Data was scrapped from the web

- Not consistently formatted as is
- Need to know which recipes users are familiar with
- Categories solve this with less burden users

Recipe data contains

- Title, instructions, list of categories, list of ingredients
- Categorizing by cuisine (fill gaps)
- Questions about cuisine in Food Curious survey

Category Frequencies Already Present in Recipe Data

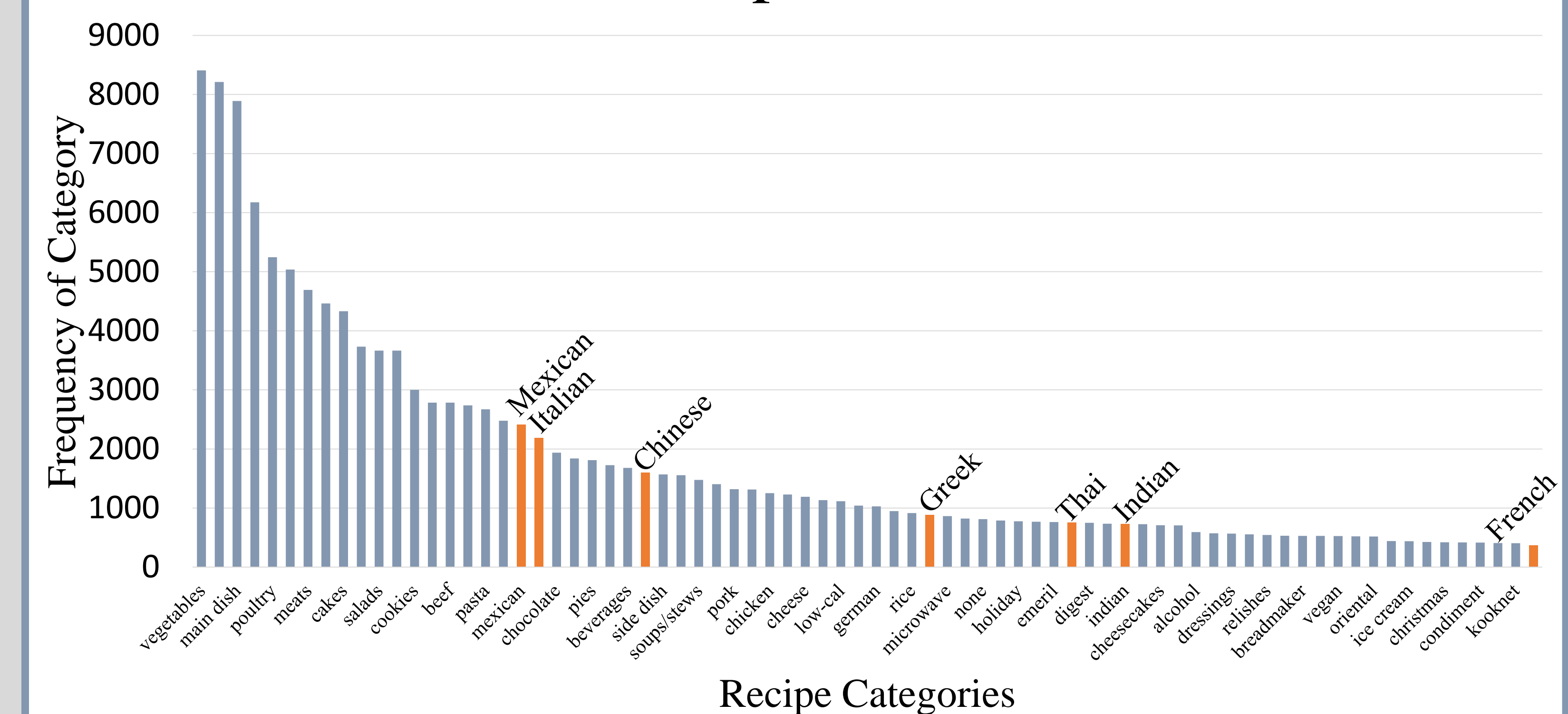


Fig 6. Distribution of categories over our data set of 86,311 recipes scrapped from the web

Machine Learning Models

Clean data of extraneous characters Naïve Bayes classification

- Only concerned with ingredients
- Pos/neg recipe for that category
- Treat recipe as a sentence containing
- Independently classified each cuisine
- Title and bare list of ingredients

Training and test data

- Independent of one another
 - Contains 50%/50% recipes are/are not of that cuisine
 - Size of 300-1000 depending on frequency of present tags (Fig 6)
- Models assign probability to words (ingredients) present
- Give likely hood of pos/neg
- Ex. Chinese model gives 56.3:1 odds to a recipe with peanut_oil

Predictive Accuracy of Cuisine Models

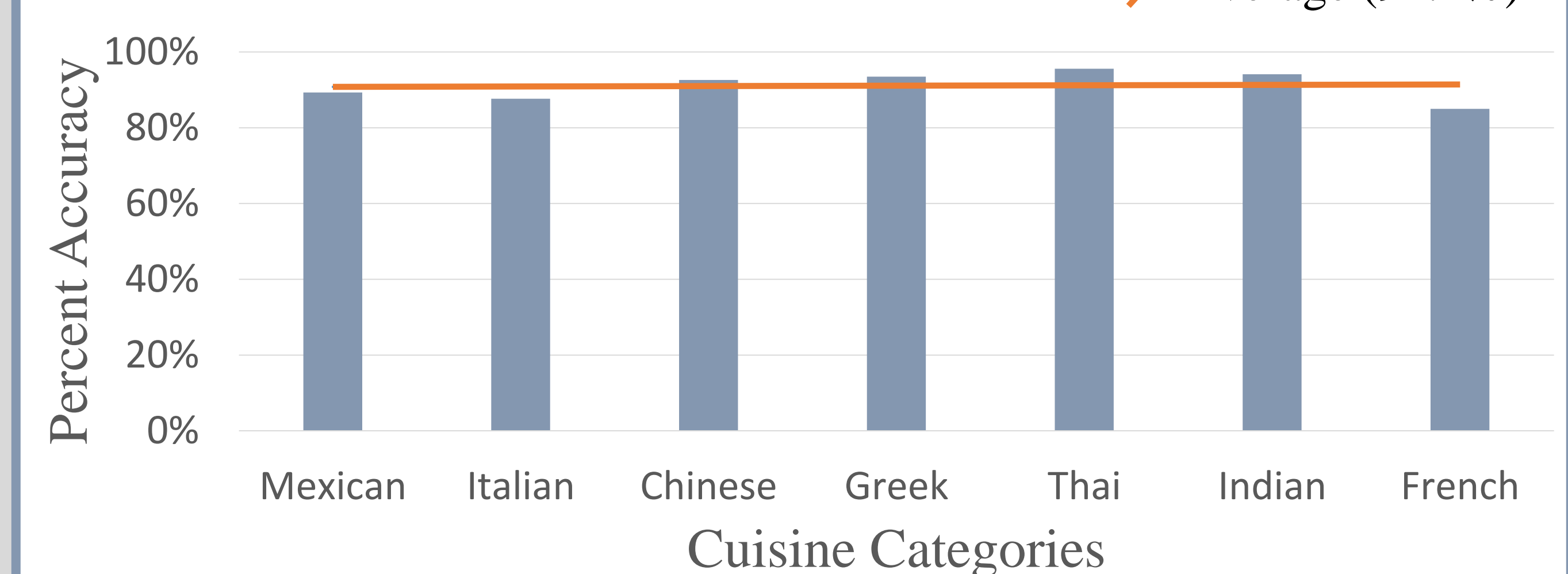


Fig 7. Percent accuracy of independent cuisine models on test data sets