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Interval Type-2 Fuzzy Application for Diet Journaling

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ABSTRACT

In this article, an improved system is constructed using interval type-2 fuzzy sets (IT2FS) and a fuzzy logic controller (FLC) with non-singleton inputs. The primary purpose is to better model nutritional input uncertainty which is propagated through the Type-2 FLC. To this end, methods are proposed to (1) model nutrient uncertainty in food items, (2) extend the nutritional information of a food item using an IT2FS representation for each nutrient incorporating the uncertainty in the extension process, (3) accumulate uncertainties for IT2FS inputs using fuzzy arithmetic, and (4) build IT2FS antecedents for FLC rules based on dietary reference intakes (DRIs). These methods are then used to implement a web application for diet journaling that includes a client-side Type-2 non-singleton Interval Type-2 FLC. The produced application is then compared with the previous work and shown to be more suitable. This is the first known work on diet journaling that attempts to model uncertainty for all anticipated measurement error.

KEYWORDS

Diet Journaling, Food Recommendation, Fuzzy Arithmetic, Fuzzy Diet, Fuzzy Nutrition, Type-2 Non-Singleton Interval Type-2 Fuzzy System

INTRODUCTION

Consider how the aspects of food are fuzzy. Each food contains a multitude of nutrients. Many of these have been measured, but there is a great deal of variance depending on a number of factors.

Additionally, the amount of a nutrient a person should consume is not some discrete value, but mimics a dose-response curve as shown in figure 1. Insufficient Vitamin C would result in scurvy. Too much Vitamin C is toxic, but there is no crisp value immediately below which one would be healthy and above which one would be unhealthy or vice versa. The degradation of health is in direct response to the degree of intake.

There is also individual vagueness such as how well each nutrient is absorbed, and sources of uncertainty in how much food an individual consumes.

The idea that nutrition should be approached in terms of continuous logic, rather than discrete, was first noted in (Uthus & Wirsam, 1996). The authors of this work found this compelling, and in their previous work (Krbez & Shaout, 2013), the literature was explored for uses of fuzzy logic in

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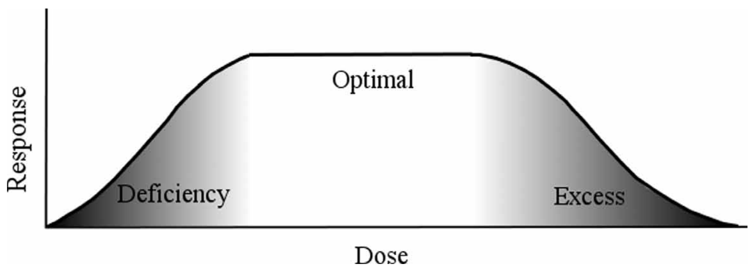
Figure 1. The dose-response curve for essential elements



nutrition oriented systems and deployed an FLC to inform the user of nutrients to seek out or avoid based on a dose-response. This proof of concept showed the benefit of fuzzy logic in nutrition logging.

In this work, the authors take several approaches towards furthering the use of fuzzy logic in nutrition logging systems:

- Review past work in fuzzy nutrition systems;
- Explore features used in popular nutrition logging systems;
- Identify uncertainties that haven't been modeled in past works;
- Discuss how non-singleton interval type-2 fuzzy logic may be more useful for nutrition than the type-1 fuzzy used in the previous work's prototype (Krbez & Shaout, 2013);
- Implement a web application based on the most useful concepts above.

The article is organized as follows: In the next section, background information is covered. Past work on combining fuzzy logic and nutrition is reviewed. The features of non-fuzzy diet journaling software are enumerated and evaluated. An overview of Type-1 and Type-2 fuzzy logic controllers is given, including the strength of Type-2 over Type-1 in its representation of uncertainty. The differences between singleton and non-singleton inputs are evaluated. Fuzzy arithmetic is explained, especially with regard to piecewise linear fuzzy sets, which can be used to model uncertainty when accumulating input data. Modeling nutrient value uncertainty as fuzzy geometries is discussed, followed by an overview of uncertainty for nutrition labels and a standard reference database, culminating in a methodology of combining these data to extend a model of nutritional uncertainty with an IT2FS. Dietary reference intakes are explained and used to produce antecedents for an IT2FS.

In the system requirements/design section, a philosophy of uncertainty is given, and the topics covered in the background section are combined to describe a coherent diet journaling system that models all the previously described nutritional uncertainty in its calculations.

Then, in the system architecture section, the component architecture is described, including class diagrams for each managed component. The user interface for the developed system is described in the user interface section. Following that is a section comparing the system in this work and the previous work (Krbez & Shaout, 2013). Finally, the last section makes conclusions based on the results of the implemented system.

BACKGROUND

Combining Fuzzy Diet and Nutrition

The previous work (Krbez & Shaout, 2013) explored the literature for works that used fuzzy logic on diet or nutrition information. The authors identified, explained and discussed the applications of eleven such works, shown in Table 1. The most versatile notion of the dose response curve as a basis

Table 1. Consolidated past work on "Fuzzy Diet" from (Krbez & Shaout, 2013)

	Technique	Inputs	Output
(Lee, et al., 2011)	Multi-tier T2FO	Diet goal User profile	Meal plan
(Wang, et al., 2010)		Diet log Expert data	Healthiness level
(Wang, Lee, Hsieh, Hsu, & Chang, 2009)		Diet log Expert data User profile	Healthiness level
(Wang, et al., 2010)		Macronutrients of consumed foods	Healthiness level
(Lee, et al., 2011)	Genetic Algorithm + Fuzzy/FML	Macronutrients of consumed foods	Healthiness level
(Ko & Li, 2007)	HCA + Ontology Naming Tree	Food Database Expert Ranking of nutrients	Ontology Naming tree
(Li, Ko, & Tung, 2007)		Food Database User weight Food preferences	Food Substitutions
(Sandham, Hamilton, Japp, & Patterson, 1998)	Neural network	Blood glucose level (BGL) Diet, Exercise & Insulin (DEI), and health issues	Optimum DEI regime for best BGL control
(Buisson & Garel, 2003)	Fuzzy Interval	Food item nutrients & expert-described fuzziness. User profile (age, height, weight, physical activity, and health issues)	Suggestions for slight changes to diet
(Li, et al., 2010)	FIS	Frying Time and Temperature	Food Density
(Uthus & Wirsam, 1996)	Fuzzy Sets	Nutrients consumed	Foods to consume

for fuzzy reasoning was highlighted and ultimately used to adapt a pre-existing nutrition logging system to use a Fuzzy Logic Controller (FLC).

Using the same method as (Krbez & Shaout, 2013), one can find additional applications in the years since the review, shown in Table 2.

In (Asghari, Ejtahed, Sarsharzadeh, Nazeri, & Mirmiran, 2013), a Type-1 fuzzy system is used to inform the user in whether the number of servings consumed for each of six food groups are classified as fuzzy values of normal, attention, or danger. The system in (Wang, et al., 2016) implements a very similar system to (Lee, Wang, & Hagras, A Type-2 Fuzzy Ontology and Its Application to Personal Diabetic-Diet Recommendation, 2010), (Lee, Wang, Hsu, & Hagras, 2009), (Wang, Lee, Hsieh, Hsu, & Chang, 2009), and (Wang, et al., 2010). A creative use of fuzzy systems may be found in (Chavan, Sambare, & Joshi, 2016), where a specific cultural evaluation of food is modeled in a fuzzy system. In (Namdari, et al., 2014) one sees how fuzzy regression can be used to find significant correlations, in this case child appetite levels as they relate to employment status of the mother. (Safitri & Abadi, 2015) aims to help consumers buy more nutritious noodles, and similarly (Nakandala & Lau, 2013) aims to help shoppers get as much nutrient density as they can afford by evaluating foods with a fuzzy expert system, scoring each food on whether or not to purchase. It is found in (Sivamani, Kim, Shin, Park, & Cho, 2016) that fuzzy inference can help plan more cost-effective livestock diets, tailored to the attributes of each individual cow.

Table 2. Consolidated past work on "Fuzzy Diet" subsequent to (Krbez & Shaout, 2013)

	Technique	Inputs	Output
(Asghari, Ejtahed, Sarsharzadeh, Nazeri, & Mirmiran, 2013)	"Fuzzy Pattern"	Number foods consumed per food group	Food group level classifications
(Wang, et al., 2016)	Multi-tier T2FO	Expert Data User Profile Macronutrients Food Groups	Healthiness level
(Chavan, Sambare, & Joshi, 2016)	T2FO	User data Season	Foods to consume
(Namdari, et al., 2014)	Fuzzy logistic regression	Serum folate	Improved appetite
(Safitri & Abadi, 2015)	Fuzzy Sets	Noodle macronutrients and price	Noodles with best overall nutrition for price
(Nakandala & Lau, 2013)	T1 fuzzy expert system	Healthiness level (derived from macronutrients and sodium)	Purchase decision as percentage
(Sivamani, Kim, Shin, Park, & Cho, 2016)	FIS	Individual livestock weight, age, pregnancy status, healthiness level	Food plan

Importance and Originality of This Work

If even precise measurement-based nutrition labels can be wrong by up to 20% and user measurements can be wrong by orders of magnitude more, then isn't it true that crisp models fall significantly short of representing reality?

It has become a trend in cross-functional studies, to identify problems that are unserved by a known solution. The authors do not believe that fuzzy is leveraged as well as it could be for modeling quantitative data in nutrition logging. In none of the previous work is uncertainty defined on all quantitative measurements used in the system. More often than not, the concepts are fuzzified but the measurements are simply translated to fuzzy words with linguistic uncertainty but without measurement uncertainty. It is the opinion of the authors that the imprecise nature of diet logging is a good fit with the model of a certainty which Interval Type-2 fuzzy systems provide. The lack of ubiquity of fuzzy systems for empirical data in diet logging software is unfortunate, and the goal of this work is to increase visibility to potential solutions that fuzzy systems can bring to diet modeling.

The authors also wish to demonstrate that a full application can be developed that embraces nutrient uncertainty in a way the other applications do not, that it is viable to model a significant feature vector of interval type 2 fuzzy models on a typical web browser using JavaScript, serving as a proof of concept. The system can also make uncertainty visible to the user, so that sophisticated users can decrease uncertainty and drive a more precise solution, if desired.

Uncertainty adds a layer of complexity to any application. It can make it more difficult to implement and therefore many developers have ignored the uncertainties problem in diet applications. Clearly most diet applications are crisp, as are all popular applications. The authors attempt to show here that the problem is not complicated when using a fuzzy system as an aide. As usual a fuzzy logic controller can be used to simplify otherwise complicated models of uncertainty, thus demonstrating that uncertainty can be easily embraced and modeled rather than ignored.

Diet Journaling Features

Currently there are hundreds of diet journaling applications available, but none take advantage of Fuzzy Logic. A web search of *diet journal app* and *diet diary app* revealed several popular diet journaling applications. The 13 most popular are: *Calorific, CRON-O-Meter, FatSecret, Lose It!, My Food Diary, MyFitnessPal, MyNetDiary Calorie Counter, MyPlate by Livestrong, Nutrition Menu, Shroomies Nutrition Menu, SparkPeople Diet & Food Tracker, The Eatery,* and *Weight Watchers Mobile*. For this work, these applications where reviewed for the features that are directly related to diet logging, which are displayed in Table 3.

What follows is a brief explanation of each feature, how pervasive the feature is, and its applicability to the system to be built. Calorie tracking is perhaps the most basic feature available. However, there are two applications (*Calorific* and *The Eatery*) that don't track calories, but instead a size category (large, medium small), and a user-voted start tracking system, respectively. These deviations appear to be for the benefit of the user, who seeks more qualitative information unconventional among diet journaling systems, as it seems the usual purpose of a diet journal is to gather quantitative information that would otherwise be neglected by the user. It is a given that Calories are a precise quantitative measurement and so calorie tracking will be incorporated into the system.

The *Basic Nutrition Facts* feature involves tracking the nutrients that are required to be reported on nutrition labels per FDA standards, whereas *Additional Micronutrients* involves tracking voluntarily reported nutrients. There is widespread but not universal support for tracking these nutrients. This system will be heavily quantitative to leverage the advantages of fuzzy logic, and so all available nutrient data will be tracked.

Sharing and *Social Networking* features are common in diet journaling software. Although one explanation of this is the popularity of social networks, it has been shown that successful dieters benefit from the use of social support (Wing & Jeffery, 1999), and so sharing what one eats is an effective feature. Unfortunately, a new (and therefore unpopular) application is unlikely to immediately benefit from this feature, and so it will not be included in the system's first iteration.

Many applications allow users to enter a custom food from a nutrition label for example. Some systems allow users to build recipes from the foods in the database. Nutrition label entry will be included in this application. The system will be designed to handle entered recipes, and future releases will aim to include the user interface to do so.

Charting is a common feature and has a variety of forms. For example, calories may be charted against a goal. Certain nutrients may be selected by the user to be tracked. The system being designed

Table 3. Features of popular diet journaling applications

Feature	Number of Apps With Feature
Calorie Tracking	11
Basic Nutrition Facts	8
Sharing/Social Networking	7
Additional Micronutrients	5
Custom Food Entry	4
Recipe Entry	4
Charting	4
Food Score	2
Food Recommendation	2
Weight Prediction	2

will present graphs that show the internal workings of the fuzzy system, and also give the user an understanding of which nutrients (s)he should eat more or avoid.

Two of the diet journals reviewed included a *Food Score*, which is essentially a compression of all aspects of a food into a number that symbolizes how good or bad the food is on what tries to be an objective scale. It seems that such independent reduction of the value of a food neglects the importance of context. For instance, grape juice is healthy due to the presence of resveratrol (Jang, et al., 1997), but unhealthy due to its high sugar content (Rozenberga, Howellb, & Aviram, 2006). A system that recommends food in context of other foods eaten may suggest grape juice to a user who has not consumed much sugar for the day, or not recommend it if the user has consumed an overabundance of sugar. To present a more extreme example to drive home this point, one may infer from established data that fried chicken is unhealthy. However, when the user has no other food source available, it hardly seems reasonable to imply that starvation is a better alternative. Therefore, food scores are not included in the system, and it will instead use dietary context to judge the fitness of a food.

Food recommendation is included in some applications, mainly in the form of diet plans or recommended recipes. This form of content would need to be contributed by users or paid experts, resources unavailable to this system. However, it is possible to derive a fitness value for each food based on other nutrients consumed in a specified day, and relay the foods with best fitness to the user. This is extremely compatible with fuzzy logic, and so the system will implement this strategy.

Weight prediction based on the current day's nutrients consumed is an uncommon but useful feature. This is somewhat out of scope for nutrient tracking and so the system will forego this enhancement in its first iteration.

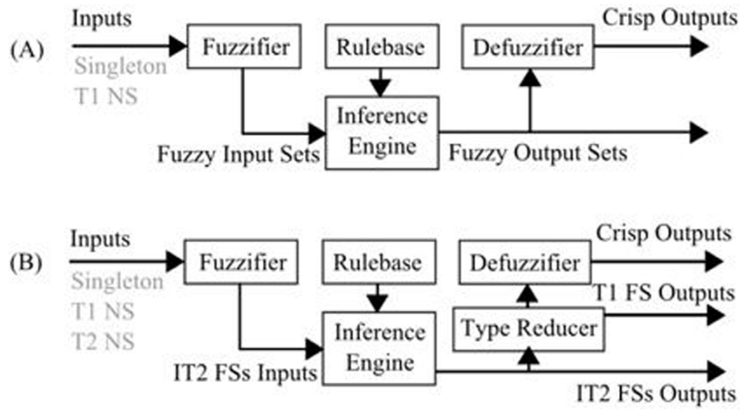
Type-2 Fuzzy Logic Controller

Fuzzy Logic extends classical set theory to include the concept of partial membership (Zadeh, Fuzzy Sets, 1965), which entails degradations in membership normalized on the interval [0, 1]. One criticism of these "Type-1" fuzzy systems is that they do not incorporate uncertainty, as the name "fuzzy" implies. Type-2 fuzzy logic adds an additional degree of freedom to traditional type-1 fuzzy systems, embedding another membership function to denote the uncertainty in the degree of membership (Zadeh, The Concept of a Linguistic Variable and Its Application to Approximate Reasoning, 1975). Although general Type-2 fuzzy systems are very complex, interval Type-2 fuzzy systems reduce the embedded membership function to crisp values 0 or 1 that are convex over a vertical slice, resulting in a footprint of uncertainty (FOU) that can be described by two type-1 fuzzy sets: the upper (UMF) and lower (LMF) membership functions (Mendel, Type-2 Fuzzy Sets and Systems: An Overview, 2007). Such interval type-2 fuzzy systems allow type-1 fuzzy mathematics to be used, which results in reduced computational complexity and increased availability to users that may not have time to learn the advanced math necessary to deploy general type-2 fuzzy systems (Mendel, John, & Liu, 2006; Li, 2017; Li & Wan, 2017; Yu, Li, Qiu, & Zheng, 2018). In this work, Interval Type-2 Fuzzy Systems are considered to the exclusion of general Type-2 Fuzzy Systems.

Type-2 fuzzy logic may be used to implement a Fuzzy Logic Controller (FLC). An FLC is a specific design pattern for how fuzzy logic may be usefully implemented in software. The components of an FLC and flow of information are represented in figure 2 for both type-1 and type-2 systems, showing similarities and differences between these systems. What follows is a brief explanation of the processes within each component of an FLC.

In an FLC, the fuzzifier takes raw inputs from the system and outputs their corresponding fuzzy values to the inference engine. The inference engine translates input fuzzy sets into output fuzzy sets using the rule-base. Each rule is interpreted as a fuzzy implication, and is composed of antecedent and consequent logic. A t-norm operation of fuzzy inputs and fuzzy antecedents are performed, which produces a firing level. This firing level is then applied to the consequent, and usually the t-conorm is used to combine the consequents of multiple rules on an output domain (though alternatively there are other methods including combination at the defuzzification step (Wu & Mendel, 2014).

Figure 2. Graphical representation of (A) a Type-1 FLC and a (B) Type-2 FLC



The output of the inference step is still a fuzzy set that may or may not need to be turned into a crisp number, depending on the application. In a Type-1 fuzzy system, the inference output is a T1FS that may be defuzzified immediately, but in a Type-2 fuzzy system an additional type reduction step is necessary to reduce the IT2FS to a T1FS before defuzzification is possible. This usually involves a center-of-sets (COS) computation. If a crisp output is not the best fit for the application, a T1FS or IT2FS may be output by the FLC, bypassing type-reduction or fuzzification.

The difference between T1FS and IT2FS stems from the uncertainty produced by the FOU. That is, the area between UMF and the LMF, which can be both considered embedded T1FSs (an embedded T1FS is any T1FS that is bounded by the FOU). A Type-1 fuzzy system may be thought of as a Type-2 system where the FOU disappears (Mendel, Type-2 Fuzzy Sets: Some Questions and Answers, 2003), meaning the LMF and the UMF are equivalent. Considering this, it is not surprising that most of the same math that is used for type-1 Fuzzy Systems can be applied to the UMF and LMF, making type-2 fuzzy systems more accessible (Mendel, Type-2 Fuzzy Sets and Systems: An Overview, 2007). Type-2 systems have been found to be superior to Type-1 systems, especially in uncertain conditions (Hagras & Wagner, 2012; Deng-Feng Li, 2016), and also notably in fuzzy diet applications (Lee, Wang, & Hagras, A Type-2 Fuzzy Ontology and Its Application to Personal Diabetic-Diet Recommendation, 2010), (Lee, Wang, Hsu, & Hagras, 2009). It has been suggested that the extra degree of freedom added to the type-2 system is the cause for increased precision, but it turns out that type-2 systems perform better because the Type-2 FLC propagates uncertainty through the different FLC stages (Cara, Rojas, Pomares, Wagner, & Hagras, 2011).

Singleton vs. Non-Singleton Inputs

The inputs to the fuzzifier may either be singleton, or non-singleton (NS). An FLC with a singleton input essentially has a crisp input to the fuzzifier. A non-singleton FLC has inputs that are modeled as fuzzy numbers and can be used to represent noisy inputs or noisy training data (Mendel, Uncertain Rule-Based Fuzzy Logic Systems: Introduction and New Directions, 2001). The NS inputs used in a system may be T1FSs or T2FSs, resulting in a Type-1 non-singleton Type-2 Fuzzy System, or a Type-2 non-singleton Type-2 Fuzzy System, respectively.

A fuzzifier that accepts a singleton input merely outputs the single fuzzy value corresponding to the crisp number on the interval [0, 1], whereas NS outputs a fuzzy set. The real difference between singleton and NS FLCs disappears after the firing interval computation of the FLC, specifically at the t-norm operation on the fuzzified inputs and each rule's antecedent (Mendel, Uncertain Rule-Based Fuzzy Logic Systems: Introduction and New Directions, 2001).

Fuzzy Arithmetic

Fuzzy Numbers

According to (Hanss, 2005), a fuzzy set is considered a fuzzy number if all of the following are true:

1. The fuzzy set is normal, i.e. max (μx) = 1
2. The fuzzy set is convex, i.e. no "valleys" exist in the graph, only peaks
3. There is only one segment where μx = 1(i.e. the core)
4. The membership function is continuous, at least piecewise continuous

Because of this definition, a fuzzy number may be split into an L-R representation, such that the curves to the left and right of the core are evaluated separately allowing fuzzy arithmetic operations on any fuzzy number (Hanss, 2005) .There are discrete and continuous applications, but one drawback of using fully continuous numbers in fuzzy arithmetic is that there are an infinite number of input values that lead to the output value, making the involved computations impractical. For practical purposes, continuous numbers may be discretized such that they are represented as discrete fuzzy sets, permitting application of the extension principle without problems (Hanss, 2005).

Fuzzy Geometry

There are two types of fuzzy numbers commonly used to describe a normal distribution. The most natural form is a Gaussian, and then the most basic discretized form of the Gaussian is a triangular function. The triangular fuzzy number is the most frequently used due to the simplicity of its linear-typed membership function (Hanss, 2005; Li, & Liu, 2015). There are some drawbacks to using the triangular membership function (Olunloyo, Ajofoyinbo & Ibidapo-Obe, 2011), but as previously mentioned, fuzzy arithmetic on a continuous Gaussian number is troublesome. For practical purposes, this work explores the concept of fuzzy addition only on piecewise linear fuzzy sets discretized at their vertices.

Fuzzy Arithmetic

Using fuzzy numbers that are piecewise linear allows for a simplified depiction of fuzzy arithmetic because when evaluating the x at each μx, simple linear interpolation may be used to get the corresponding values for both fuzzy numbers being added, and this may be depicted easily. The use of fuzzy arithmetic on the L-R representation is shown in figure 3.

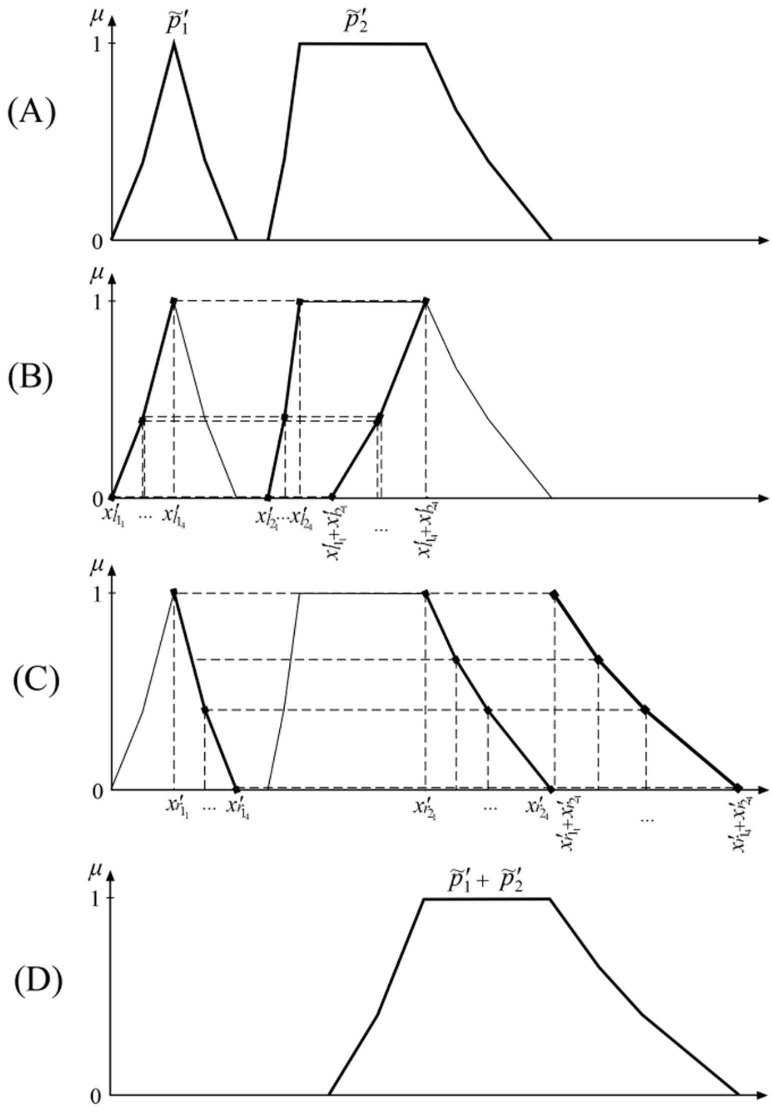
An algorithm to perform such addition is as follows.

For left and right curves:

1. Set $h = \dfrac{hgt\left(p1\right) + \mathrm{hgt}\left(p2\right)}{2}$ where p_1 and p_2 are the input fuzzy sets.
2. Normalize fuzzy sets p_1 and p_2
3. For each $y_{1=}\mu x_1$ in fuzzy set p_1, find corresponding x_2 by linear interpolation
4. For each $y_2 = \mu x_2$ in fuzzy set p_2, find corresponding x_1 by linear interpolation
5. For each for each y in $Y_1 \cup Y_2$, add x_1+x_2 for the resulting x value for $y = \mu x$
6. Scale the height of the resulting fuzzy set p by the value h calculated in step 1.

Note that steps 1, 2 & 6 are added so that this same method may be used on the LMF of a piecewise linear IT2FS. Of course, the algorithm still works an already-normalized fuzzy set as normalizing already-normalized set results in the same set. An abbreviated depiction of this IT2FS fuzzy arithmetic is shown in figure 4. Note that with regard to fuzzy arithmetic this work is only concerned with fuzzy

Figure 3. Discrete L-R fuzzy arithmetic on piecewise linear fuzzy set. Both fuzzy sets to multiply are in (A). (B) and (C) show left and right arithmetic, respectively. (D) shows resulting fuzzy set.



addition of two sets and fuzzy multiplication by a scalar. Fuzzy scalar multiplication is comparatively simple: multiply each x value in the set by the scalar value (Hanss, 2005).

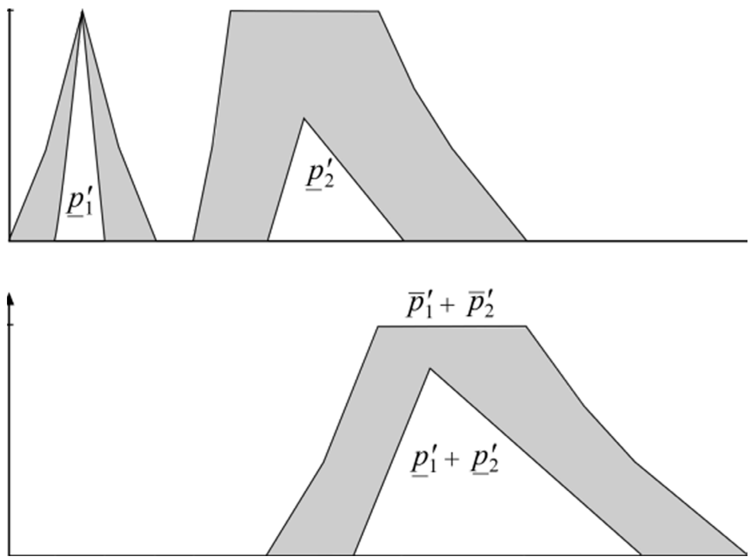
Nutrient Uncertainty

The following subsections discuss how to express nutrient uncertainty as a type-2 fuzzy set.

Fuzzy Geometries

Nutrient values for a food may be specified on a nutrition label or in a nutrition database. These values indicate the most likely amount of each nutrient in each corresponding food. There is no guarantee

Figure 4. Two IT2FSs (A) may be added, resulting in another IT2FS (B)



that a food has exactly the specified amount of each nutrient, but the possibility is greatest at the values specified, and surrounding values have less possibility, proportional to their distance from the specified value. This can be represented by either a Gaussian function or a triangular approximation (Hanss, 2005) as covered in F.2).

When two foods are indiscernible to the user, the nutrient values for each food can be expanded based on the two values rather than the one. For simplification, one can say that these two possibilities are equal, and that any possibilities in between are as well, but that the possibility of values outside the range between the minimum and maximum values of the indiscernible (related) foods taper off as they get further away from the endpoints of that interval. This is best represented by a trapezoidal membership function where the vertices are represented by the two values. This is similar to the methodology proposed in (Liu & Mendel, July 2007).

FDA Regulated Nutrition Labels

Within the Code of Federal Regulations (CFR) Title 21, established by the Food and Drug Administration (FDA) of the United States, there are requirements for proper nutrition labeling. Sections 3 through 5 define classifications of nutrients for the purposes of compliance. As described in table 4, the FDA is concerned with food labelers listing values either greater than 80% of the actual measured value, or less than 120%, with leeway in either direction depending on whether the nutrient is generally recognized as healthy or unhealthy.

It is difficult to find any motivation for a manufacturer to underreport healthy nutrients, or to over report unhealthy nutrients. It is also reasonable to accept that this tolerance exists for practical reasons, such as measurement error and variations in production. It follows that the consumer can reasonably expect any nutrient value reported on the package to be within 80% and 120% of the actual value, with the most likely value being that which is reported on the label. Therefore, the values of each nutrient on the label may be modeled by a triangular fuzzy number, depicted in Figure 5.

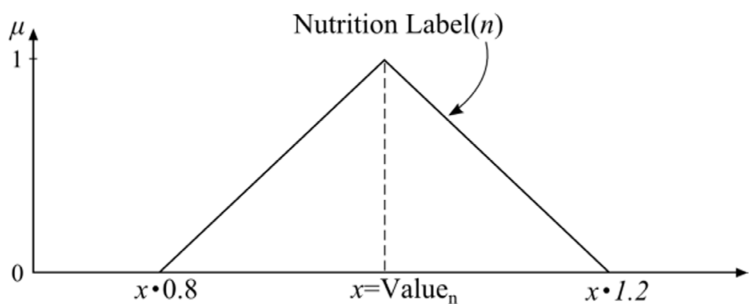
USDA Standard Reference

The United States Department of Agriculture (USDA) publishes a Standard Reference (SR) database that lists nutrient values for many food items within its *NUT_DATA* table. For each food, this table

Table 4. FDA Nutrient Content Claims Requirements from CFR Title 21, Sec. 101.9 Nutrition labeling of food

Nutrient Class	Nutrient	Requirement
(4)(i) Class I vitamin/mineral (Added nutrients)	protein	listed > actual
	dietary fiber	
	potassium	
(4)(ii) Class II vitamin/mineral (indigenous nutrients)	protein	listed*0.8 > actual
	total carbohydrate	
	dietary fiber	
	other carbohydrate	
	polyunsaturated fat	
	monounsaturated fat	
	potassium	
(5)	calories	listed*1.2 < actual
	sugars	
	total fat	
	saturated fat	
	trans fat	
	cholesterol	
	sodium	

Figure 5. Modeled input T1FS for nutrient on nutrition label



contains a *Nutr_Val* field with the expected nutrient value, and also *Min* and *Max* fields with the minimum and maximum measured values of all samples. One may assume that the measurement methods used on a per-nutrient basis share the same worst case spread (*Max-Min*) as a percentage of *Nutr_Val*. Therefore, the *NUT_DATA* table was parsed for the least *Min* and greatest *Max* of each nutrient as a percentage of *Nutr_Val*. The results of this are presented in Table 5.

It is reasonable to expect that for each Nutr_Val in the database, the value falls within the interval:

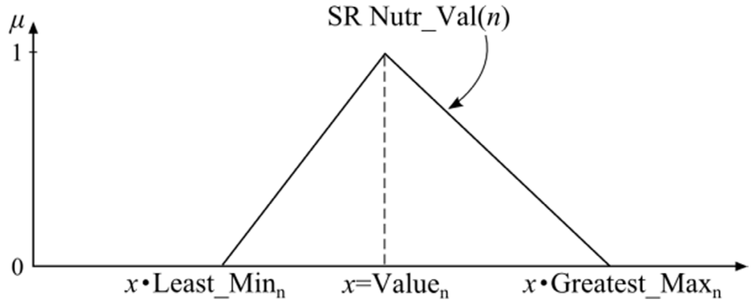
[Least_Min*Nutr_Val,Greatest_Max*Nutr_Val]

It is also reasonable to expect the most likely value is Nutr_Val, for any food in this database. Therefore, the values of each nutrient in the database may be modeled by a triangular fuzzy number, depicted in Figure 6.

Table 5. USDA SR26 least min and greatest max per nutrient as a percentage of Nutr_Val

Nutrient	Least_Min	Greatest_Max
Carbohydrate, by difference	0.938205944	1.073728845
Protein	0.919513924	1.084121136
Cholesterol	0.904933273	1.102526616
Sugars, total	0.886150564	1.113564064
Total lipid (fat)	0.891817989	1.118781305
Phosphorus, P	0.889998036	1.122213019
Magnesium, Mg	0.887143348	1.127758819
Fatty acids, total saturated	0.866234655	1.131085858
Pantothenic acid	0.872751864	1.139196086
Sodium, Na	0.861814303	1.156677837
Potassium, K	0.853425689	1.160017639
Choline, total	0.875760834	1.179256114
Fiber, total dietary	0.843745819	1.18264214
Zinc, Zn	0.833568117	1.193067939
Vitamin B-12	0.824238758	1.20441218
Folic acid	0.818239292	1.212422949
22:5 n-3 (DPA)	0.833272925	1.215023559
Vitamin B-6	0.821718444	1.22056162
20:5 n-3 (EPA)	0.842839657	1.228298654
Calcium, Ca	0.803237364	1.234177906
Iron, Fe	0.796388479	1.244031011
Manganese, Mn	0.815061968	1.246147275
Vitamin E (alpha-tocopherol)	0.772186263	1.264067967
Folate, total	0.75007934	1.273087909
Fatty acids, total monounsaturated	0.766452633	1.287788512
Fatty acids, total polyunsaturated	0.590864386	1.290168652
22:6 n-3 (DHA)	0.657708674	1.325335516
Selenium, Se	0.666093263	1.337499643
Copper, Cu	0.745789597	1.342992835
Vitamin A, IU	0.73072747	1.39421256
Vitamin C, total ascorbic acid	0.647802614	1.474363832
Fatty acids, total trans	0.421863926	1.52037562
Vitamin D	0.568404184	1.60652834
Vitamin K (phylloquinone)	0.682088861	1.660590867
Fluoride, F	0.475891674	1.852294753

Figure 6. Modeled input T1FS for nutrient in USDA SR record



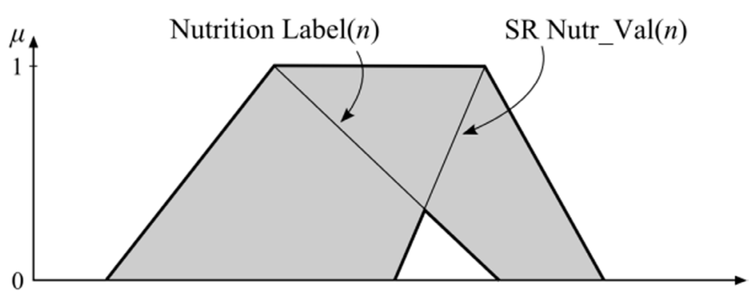
The intervals in the USDA SR are usually slightly smaller than those of nutrition labels. There are 16 nutrients for which min/max values are unavailable in the USDA SR, and for these values the more conservative multipliers of 0.8 and 1.2 may be used for the spread.

Missing Nutrient Data

The nutrients listed on food labels are often very incomplete. For unhealthy nutrients, failure to list usually means that the nutrient is not present. For other nutrients, lack of listing simply means the manufacturer is not interested in the extra cost of determining the nutrient values, or it may indicate a fear of regulatory action if the listed values are not accurate. For the USDA SR database, all values for which there is data are listed, providing a higher fidelity nutrient reference for foods that are in the database. However, there are fewer foods in the SR database than foods with nutrition labels, and often times a generic food in the SR coincides with a food that has a nutrition label. In this last case, the choice between nutrition label and SR can be viewed as the problem of accuracy vs. precision; the nutrition label is more accurate to the specific food and the SR has higher precision for each nutrient. It can also be viewed as a multiple expert opinions problem; or one can consider the nutrition label as the imprecise expert opinion of the manufacturer based on its knowledge of the food's synthesis, and the SR record as the expert opinion of the government (based on a systematic review of the scientific literature) of the precise nutritional value of all foods of that type. Feilong et al. (Liu & Mendel, 2007) have provided a method for combining expert opinions by treating each opinion as an embedded T1FS within an IT2FS. Figure 7 shows how this method can be used to combine nutritional data for a food item that is in the SR and has a nutrition label when the T1FSs of the two values overlap.

However, it isn't clear what to do when the values do not overlap. The algorithm described in (Liu & Mendel, 2007) treats non-overlapping T1FSs as outliers and removes them until only sets that

Figure 7. Application of the fuzzy union proposed in (Liu & Mendel, July 2007), when nutrition label and SR values for a nutrient are interpreted as expert opinions



overlap remain, but this isn't possible when there are only two T1FSs. Therefore, the following two intuitive methodologies are proposed. Method 1 follows intuitively from the meaning of the FOU, and assumes that numbers at the center of a set constructed for this specific purpose are at least 10% more likely than those at the extremities. It therefore defines the left and right ends of the trapezoid as 0 for the LMF, and the center between these points as 0.1, as shown in Figure 8.

Method 2 is an extrapolation of the LMF construction in (Liu & Mendel, July 2007). When the T1FSs overlap the LMF is based on the intersection of their legs, intuitively when the T1FSs are disjoint, the LMF might be based on the triangle formed by the mirror image of their legs over a vertical line at $\mu_x=0$. This idea is depicted in Figure 9, but turns out to be troublesome, as when the T1FSs move further apart the LMF height grows to 1, and then proceeds to cover an ever-increasing interval with a missing FOU. For this reason, we consider method 1 to be the more appropriate model and consequently, a more practical IT2FS.

Food Quantity Uncertainty

When a user enters a food quantity into a diet database, there is a certain level of uncertainty associated with it. To deal with this problem, the Type-2 Fuzzy Ontologies (T2FOs) in (Lee, Wang, & Hagras, 2010) (Lee, Wang, Hsu & Hagras, 2009) (Wang, Lee, Hsieh, Hsu & Chang, 2009), and (Wang et al., 2010) have a certain level of uncertainty based on the measurement the user enters (bowl, glass, plate, etc.) However, none of the popular diet logging systems (listed in Table 2) appear to tackle this problem.

We approach this problem by allowing the user to enter a percentage uncertainty, and then transforming T1FSs described in Figures 5 and 6 into an IT2FSs by expanding the FOU to be proportionate to the uncertainty entered by the user, as represented in Figure 10.

For the case of related nutrients, similarly expand the FOU outward as depicted in Figure 11.

Figure 8. Method 1 of LMF deduction for union of non-overlapping T1FSs

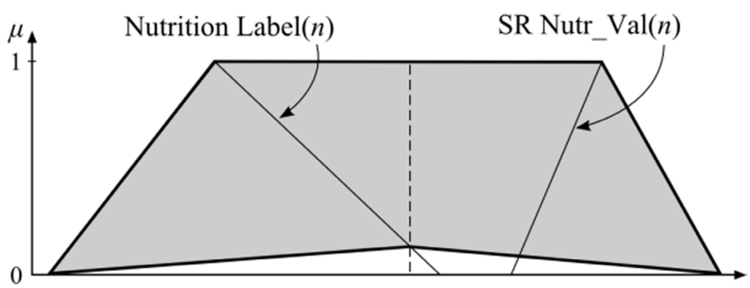


Figure 9. Method 2 of LMF deduction for union of non-overlapping T1FSs

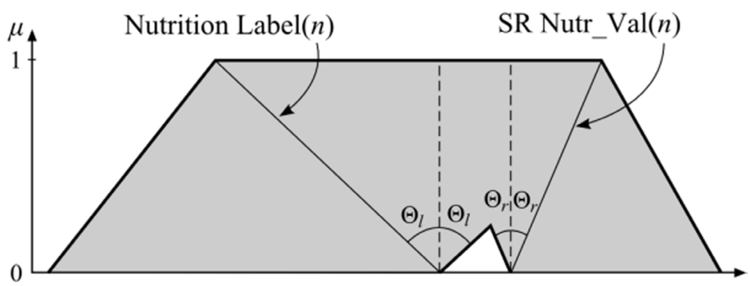


Figure 10. Expanding the FOU for user-entered uncertainty

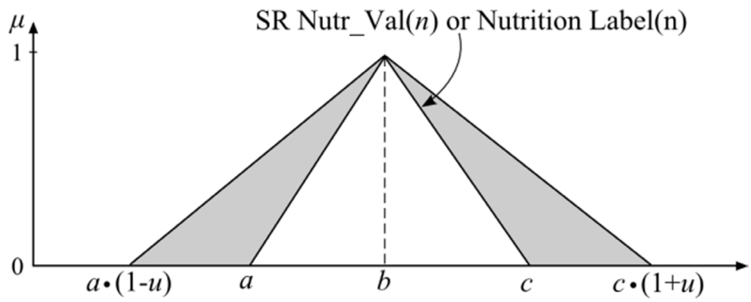
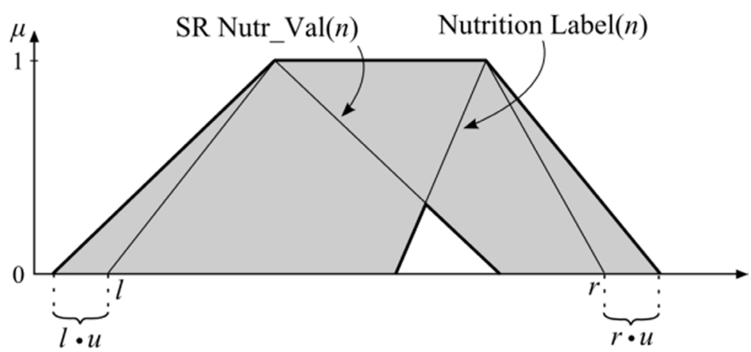


Figure 11. Expanding uncertainty for an IT2FS union of T1FSs



Dietary Reference Intakes

Dietary Reference Intake (DRI) tables are published by the USDA, and are available in reports that include age and gender tables (Dietary Reference Intakes, 2017). The dietary reference intakes describe various limits. The World Health Organization (WHO) and Center for Disease Control (CDC) also publish dietary recommendations. The table of DRIs was transcribed into a data object from these sources and has the following definitions, denoted in Table 6.

These parameters are not all present for all nutrients. Some nutrients are not considered harmful and so do not have an UL. RDA/AI values are supplanted by AMDR MIN/MAX values for macronutrients. From the above data, for each user 5 classes of fuzzy membership functions can be

Table 6. Dietary reference intake interpreted values

Variable	Definition
rda_ai	Recommended Daily Allowance (RDA) - sufficient to meet the needs of nearly all individuals (Dietary Reference Intakes, 2017), or Adequate Intake (AI) - calculated if insufficient evidence to support an RDA (Dietary Reference Intakes, 2017)
amdr_min	The minimum recommended proportion of a macronutrient from total calories
amdr_max	The maximum recommended proportion of a macronutrient from total calories.
ul	The upper limit of an indigenous nutrient.
ul_pharm	The upper limit of an added nutrient, or supplement.

constructed for the fuzzy words: Inadequate, Adequate, and Excessive, depending on the existence of each of these parameters given the user's gender and age. The fuzzy words are shown in Figure 12.

Due to the linear piecewise continuous nature of this fuzzy system, fuzzy trapezoids approximate the dose-response curve. Each of the three fuzzy words has innate fuzzy boundaries that overlap. Upper membership functions overlap completely. Lower membership functions meet at a midpoint between the boundaries. This is inspired by the robot tracking implementation in (Linda & Manic, 2011), as consumption of a single nutrient is analogous to steering. Note that the FOU decreases as the boundaries recede, showing increased certainty towards the less-encroached middle of each fuzzy set.

Excessive is slightly different from the other two fuzzy words. At the UL, the high end is to be entirely certain that the limit is reached, but the lowest uncertainty is itself uncertain. One can know that as the value increases beyond the UL, the certainty that intake is excessive increases. Therefore, leave the LMF at 0.5 for the UL and set $\mu_x = 1$ to 50*UL, a value that will not be reached in the overwhelming majority of cases, somewhat approximating a logarithmic function. This can be seen in Figure 13.

Unfortunately, unlike the robot tracking problem in (Linda & Manic, 2011), nutrient intake usually doesn't have immediate observable results, so tuning the system must be performed using data from the literature and some intuition.

SYSTEM REQUIREMENTS/DESIGN

Uncertainty Strategies

Two strategies are available for unknowns in the accommodation of uncertainty into the design of the system:

1. Assume everything is as uncertain as possible;
2. Only use uncertainty where there is evidence of uncertainty.

If full uncertainty were assumed in every case, it would result in an impractically useless system. If all uncertainty and partial membership were removed, a crisp system would result. Here it's possible to take the middle ground and assume all the information to judge uncertainty is available. An example of this strategy is that when there is just one related item to a food that is logged, and the value is undefined for the nutrient in that food but not the related food, one can use that item's IT2FS representation just as for the original food. Another example is that when there is a missing nutrient for a food, one can skip that nutrient in the fuzzy arithmetic, as though the food had none of it.

Definitions

An object that represents a certain food, say a banana or an orange, is defined as a *FoodItem*. Each FoodItem has values for 50 nutrients, a "nutrient vector", which will be abbreviated henceforth as *nutrivector*. Additionally, each food may be related to another food in the nutrition database, or be unrelated, per sections II.H and II.I. For this work, these are called *related FoodItems* and *unrelated FoodItems*, respectively.

Fuzzy Nutrivector Calculation

When a FoodItem is logged as eaten in the diet journal, a quantity of the food and an uncertainty value regarding the quantity are logged. A T1FS is generated in accordance with the methodology in section II.H using the value for each nutrient in the nutrivector and entered uncertainty for the Food Log (Figures 5 and 6) to model nutrient measurement uncertainty. The user may relate two or more FoodItems as indiscernible, and in this case the fuzzy union methodologies in Figures 7 and 8 are used. This model the increased vagueness introduced by the user's food identification. It also helps

Figure 12. MFs definitions vary depending on nutrient parameters

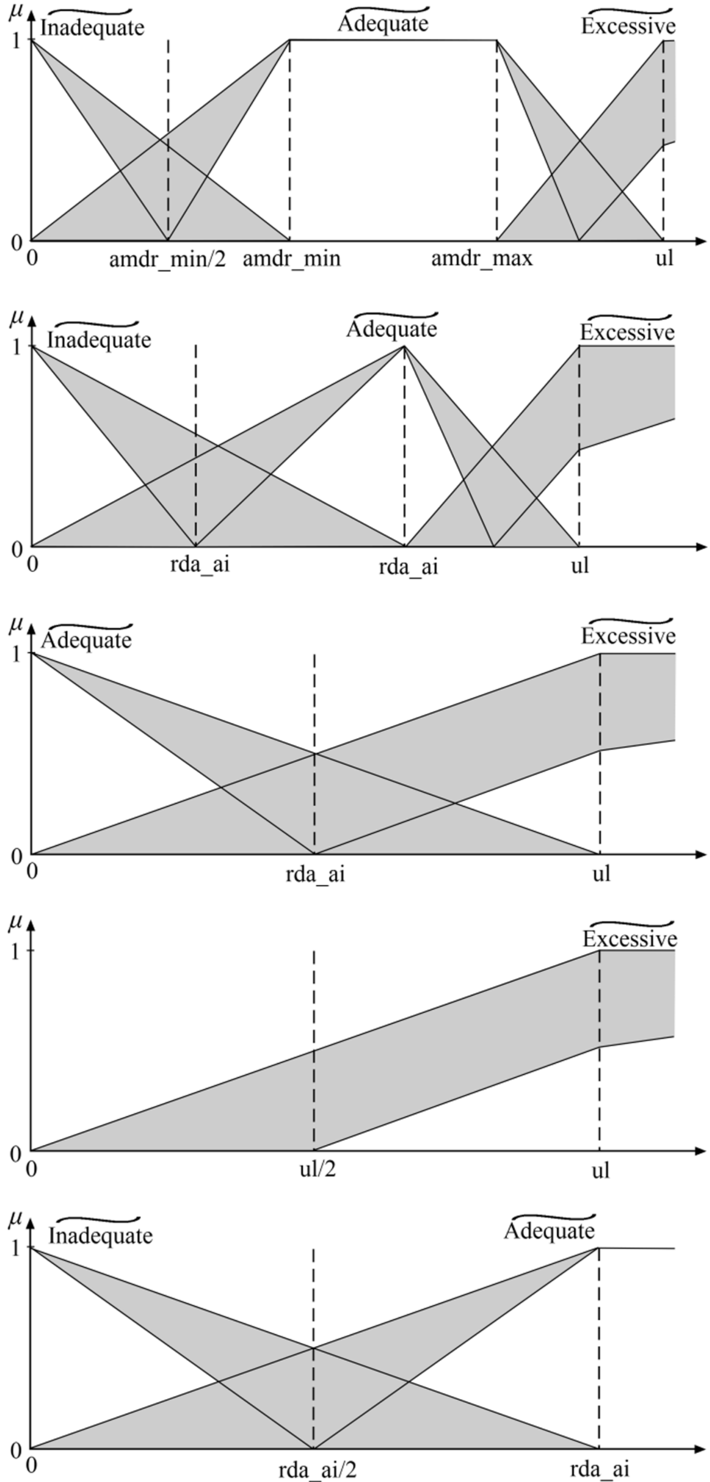
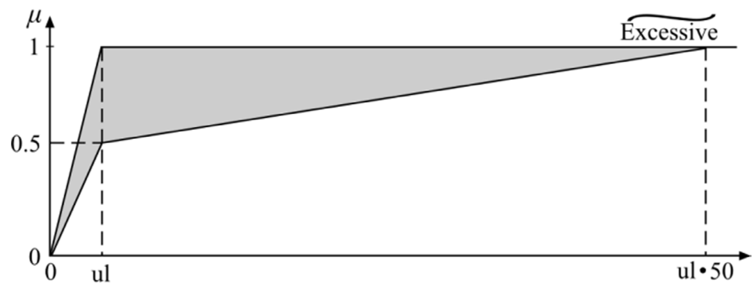


Figure 13. Logarithmic approximation for "Excessive" LMF



to fill in information that may be missing from one of the nutrivectors, but present in the other. This increases precision without sacrificing uncertainty. At this point, unrelated FoodItems have equal UMFs and LMFs, and related FoodItems have a UMF and LMF built from the t-conorm and t-norm of related foods, respectively. The user-entered uncertainty is added to each nutrient resulting in nutrient IT2Fs resembling Figures 10 and 11 for unrelated and related FoodItems, respectively. Then, the scalar quantity entered by the user is multiplied by each nutrient's IT2FS. When taken together, all the IT2FSs for a FoodItem make up a FoodItem's Fuzzy Nutrivector (FNV). These FNVs may be added together, resulting in an aggregate known as a Total Fuzzy Nutrivector (TFNV) The most common TFNV is the Day's Fuzzy Nutrivector (DFNV).

There are some exceptional side effects of using the lower and upper bounds provided by the FDA nutrition label guidelines. One is that zero cannot be scaled by a multiplier, so the representation of zero becomes problematic. Another is the concept of undefined. There are a number of conditions that allow a nutrient not to be present on a label, only one being its lack of presence in the food. A solution for these problems as follows: When a food label has zero of a particular nutrient, the nutrient value will be represented as an IT2FS with UMF and LMF as fuzzy triangles:

UMF: $\mu_x(\text{-nutr}_{min}) = 0$
$\mu_x(0) = 1$
$\mu_x(\text{nutr}_{min}) = 0$
LMF: $\mu_x(\text{-nutr}_{min}*1.2) = 0$
$\mu_x(0) = 1$
$\mu_x(\text{nutr}_{min}*1.2) = 0$

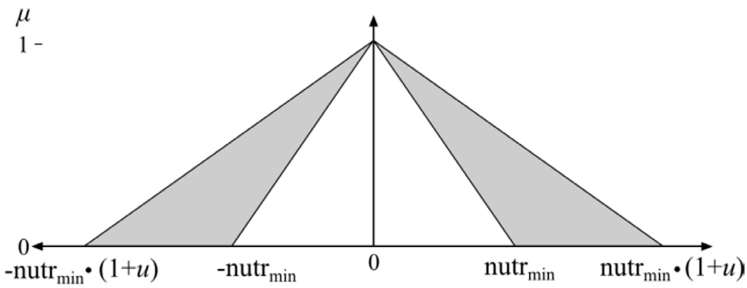
where nutr_{min} is the minimum nonzero measured amount of the nutrient reported per 100g of any food in the USDA SR (*Min* column of table *NUT_DATA*), or 0.001 for any nutrient not defined in the USDA SR (0.001 is the minimum of the minimum of all minimum measured values for nutrients that are defined in the SR, and so using strategy 2 from section A, assuming the least uncertainty in the absence of evidence for uncertainty). The negative nutr_{min} value is necessary to show the fuzzy number is about zero, and does not contain the set of negative numbers. This case is depicted in Figure 14.

When a Food label has an undefined amount of a particular nutrient, the value will be ignored at each fuzzy calculation. For instance, when adding the values for Vitamin A from food items *a* and *b* (VitA_a and VitA_b):

$$\text{VitA}_a + \text{VitA}_b = \text{VitA}_a$$

where:

Figure 14. Fuzzy zero value of any nutrient



VitA_b = unknown and $\mathrm{VitA}_a \neq$ unknown
$\mathrm{VitA}_a + \mathrm{VitA}_b$ = unknown

where:

VitA_a=unknown and VitA_b=unknown

As mentioned, the strategy to fill in the unknowns is the fuzzy union methodology introduced in section II.H.

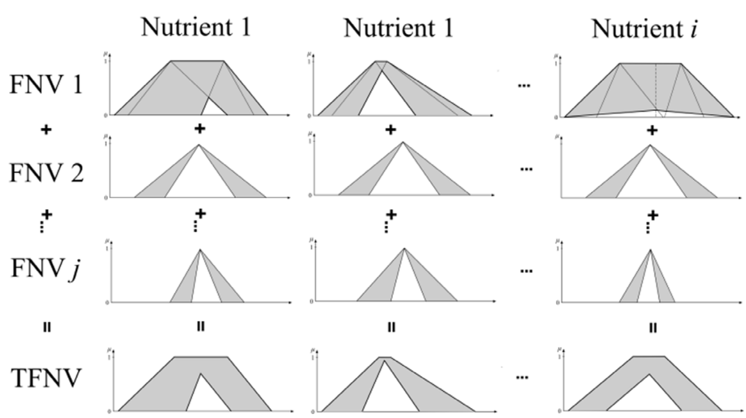
To compute a TFNV, all of the FNVs are added up on each nutrient axis using fuzzy arithmetic on piecewise linear IT2FSs, as detailed in section II.F (Figure 4). The full FNV arithmetic is depicted in Figure 15.

This results in a TFNV which is a sum of all the nutrients and all known uncertainty, aggregating the uncertainty of the individual logged FoodItems. In this way, the DFNV (the TFNV for a day time period), models the nutrient consumption uncertainty for the day, and can be used as the input vector into a Type-2 fuzzy FLC.

Fuzzy Rules

The fuzzy rules are similar to those developed in the previous work (Krbez & Shaout, 2013), the main differences being that the fuzzy controller is implemented in client-side JavaScript, the inputs are Interval Type-2 non-singleton instead of singleton, and the antecedents are now IT2FSs. These antecedents are described in figures 12 & 13 in section II.J.

Figure 15. Fuzzy arithmetic used to create a Total Fuzzy Nutrivector



Fuzzy Inference

A disjunction is performed on each DFNV with the three antecedent type-2 fuzzy memberships, as depicted in Figure 16.

The firing intervals for each are interpreted as the likelihood that each nutrient needs to be sought, and are placed into a search vector that is used for user feedback and food suggestions.

User Feedback

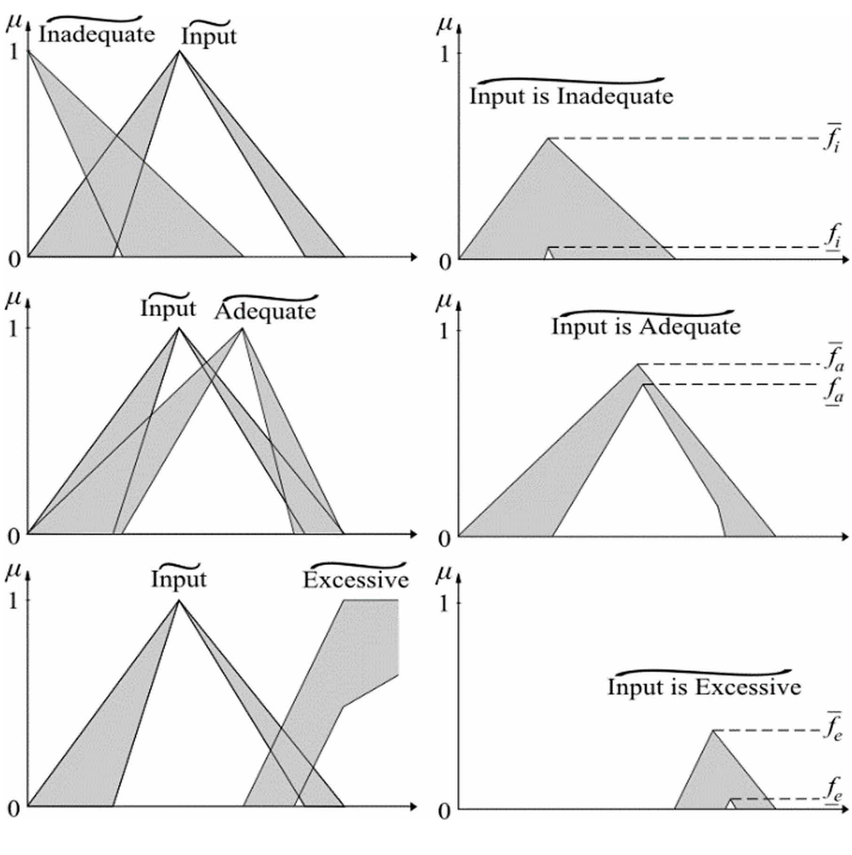
Like in the previous work (Krbez & Shaout, 2013), the most important, most actionable user feedback is suggested foods, but in this a differing method is used to generate suggestions. The user's food log is queried over a specified time period (e.g. a week) for the foods consumed and the quantities consumed. Each of these food logs is added to the DFNV to create a hypothetical DFNV that is evaluated for fitness by the FLC. The food that increases the nutrivector fitness the most is the first suggestion. This stands in contrast to the previous work (Krbez & Shaout, 2013), where a search algorithm is used to search on crisp values of set 100g food values in a normalized database.

SYSTEM ARCHITECTURE

Component Architecture

The system is composed of a client-side JavaScript program, a Python server-side program, and a Postgres database accessed through an object relational model (ORM) known as SQLAlchemy

Figure 16. Calculating firing values based on input and antecedent IT2FSs



(SqlAlchemy, 2017). The Server-side program gathers nutrient data and log information from the database and transmits it to the client-side program via an Asynchronous JavaScript and XML (AJAX) style JSON interface over HTTP. The client-side program implements the fuzzy controller and user interface. The user interface and AJAX transactions are enriched through use of the Dojo Toolkit, which is an open-source module JavaScript library (Dojo Toolkit, 2017). Figure 17 shows the component architecture of the system.

Client-Side Class Architecture (JavaScript)

The client-side JavaScript architecture is formed using Asynchronous Modular Definition (AMD), a method of loading JavaScript objects that adds modular capabilities to JavaScript (Asynchronous Module Declarations, 2017).

The basic architecture of the Client-side application is the Dispatcher design pattern, depicted in Figure 18.

The remainder of the class architecture is shown in Figure 19.

Server-Side Class Architecture

The server-side class diagram is shown in Figure 20. The food_item and food_collection classes gather, consolidate, and scale relevant FoodItem data from the Postgres database using SQLAlchemy. There are various ways the data must be altered and grouped depending on the command from main, which is initiated by the client.

USER INTERFACE

For brevity, only the most pertinent portions of the user interface are explained here.

In order to model diet log measurement uncertainty, when a user enters an item they are asked to select the uncertainty with regards to the food item and quantity.

When the user selects “Show Fuzzy Values” from a food, it shows the type-2 FNV for that food, based on the food and on related foods, as shown in Figure 21.

Figure 17. System component architecture

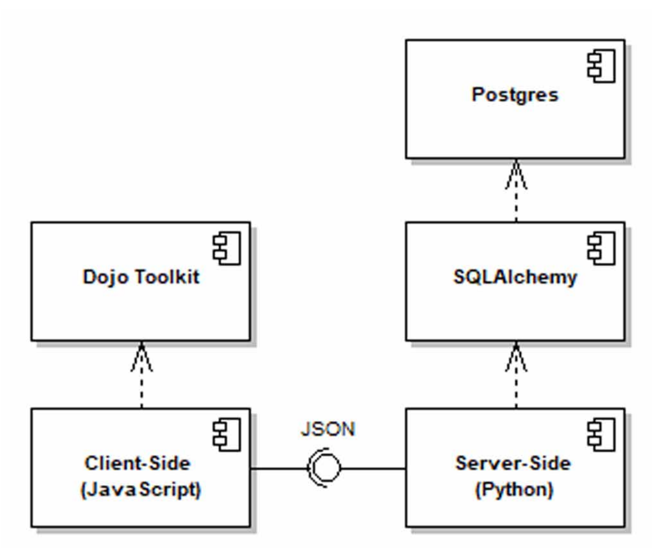
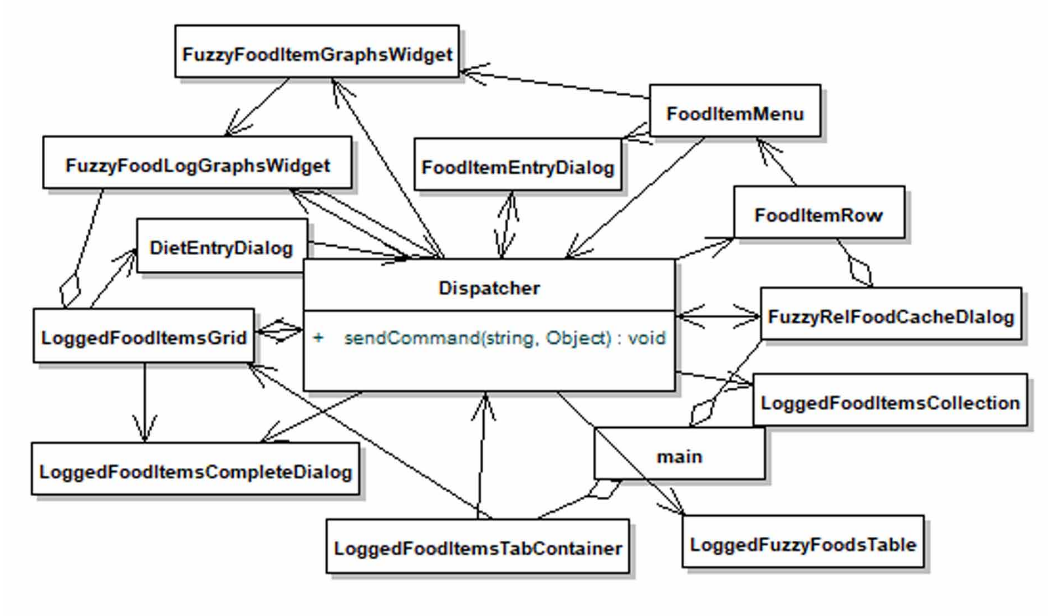


Figure 18. Classes that call and/or are called by the dispatcher



After the user enters foods into the daily log, construction of a DFNV is possible. Selection of a Fuzzy Graph icon above each day's Fuzzy Food Log Grid shows a Fuzzy Log Graphs window with an Arithmetic tab at leftmost. This tab contains a visual representation of the calculation of the DFNV along the nutrient axis. It shows how much each food contributes to the nutrient, the total IT2FS for that nutrient as the result of type-2 fuzzy arithmetic, and then a preview of the fuzzy inference by means of the fuzzy antecedent math against the modeled input value. This is performed for each of the relevant DRI fuzzy words. Figure 22 displays part of an example window.

The next tab is a totals tab that uses the totals from the previous tab, only this is along every one of the nutrients. It also contains the t-norm of the input IT2FS for each nutrient against 1-3 of the fuzzy antecedents. An excerpt is presented for the math of all nutrients in an example day in Figure 23.

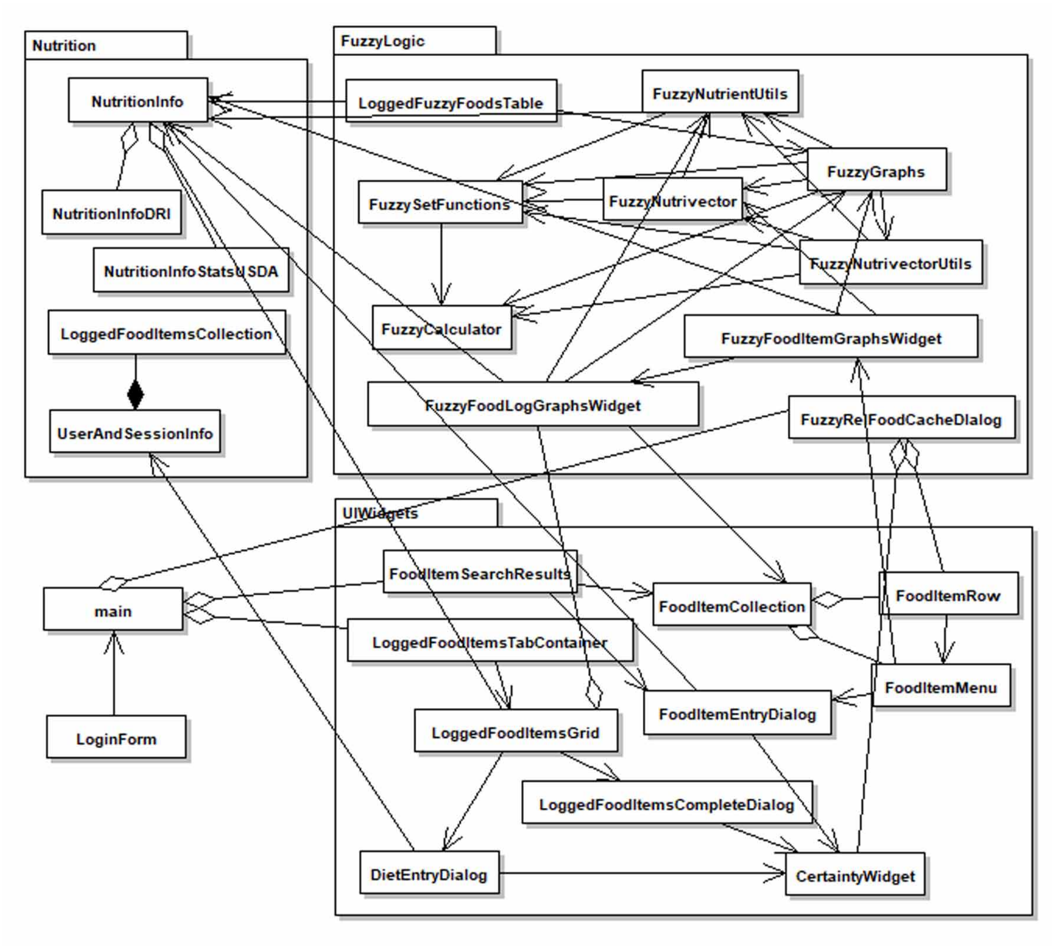
The max of the LMF and UMF are used to compose the type-2 firing interval. The consequents are eating more and avoid, which are shown in the *Conclusions* tab.

The *Suggestions 1.0* tab shows the results of an ORM-adapted instance of the previous work's (Krbez & Shaout, 2013) algorithm using the average firing level as an input. For each nutrient in the *eat more* consequent, a search is performed that minimizes all nutrients in the *avoid* consequent. An example of the results is shown in Figure 24.

The Calculations 2.0 tab contains the list of all foods logged in the previous 7 days, along with their fitness when added to the current DFNV to produce a hypothetical TFNV. The average firing value of both the *eat more* and *avoid* consequents is listed. Any foods that have an unacceptable addition of avoid nutrients, that is a delta over threshold, resulting in >=0.5 average firing value, are listed as unacceptable, whereas other nutrients allow some acceptable further encroachment into the avoid membership for the sake of reducing the *eat more* value.

The Suggestions 2.0 tab shows the results of this work's FoodItem suggestion algorithm. This is shown in Figure 25. These are the suggested foods. The user may select any of the FoodItems in the list and log it as eaten.

Figure 19. Full class architecture with the exception of the dispatcher



RESULTS: PREVIOUS VS. CURRENT WORK

Qualitative Analysis

The previous work introduced a singleton Type-1 fuzzy system that suggested foods based on seeking and avoidance of certain nutrients from fuzzy implications. It iteratively showed one food per nutrient being sought, taking into account all the nutrients being avoided. The fuzzy system was implemented as a python "plug-in" for an existing PHP system with a monolithic architecture that would initiate page reloads for every server transaction.

The current work introduces a full strategy for modeling the uncertainty that comes from user inputs and nutrient measurement error of FoodItems in the database, and a Type-2 Non-Singleton Type 2 Fuzzy System that suggests foods based on the fitness of a "hypothetical TFNV" vs. the "current DFNV". This allows assessment of more than one sought nutrient at a time while also avoiding excessive nutrients, so only one food need be suggested at a time, rather than one for each nutrient. Furthermore, it allows the creation of relationships between FoodItems which in turn allows missing data to be established as a fuzzy number that also models the uncertainty involved in the relationship process. This work's system uses AJAX communications that do not require page reloads

Figure 20. Full class architecture of the server-side application

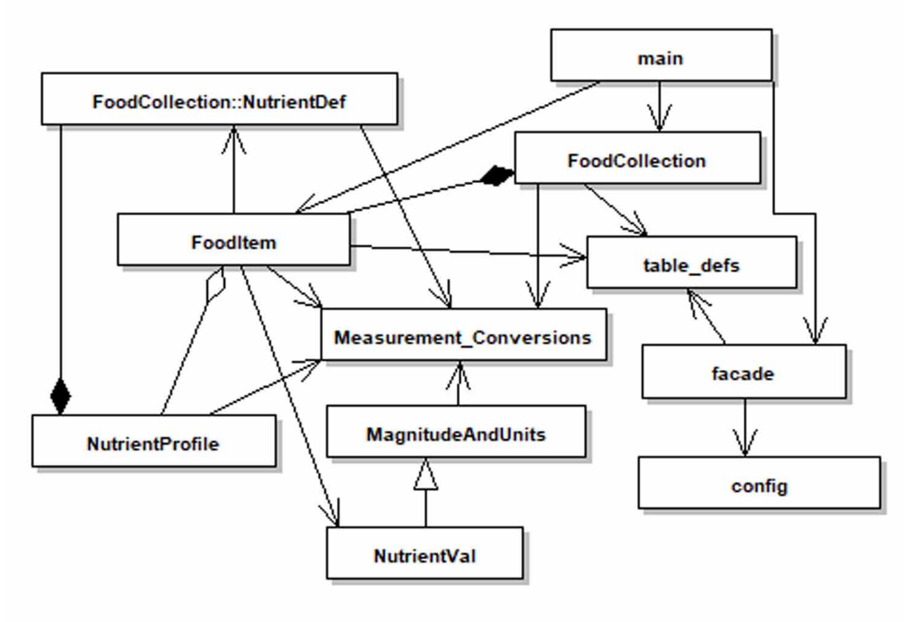


Figure 21. Partial nutrivector vs. fuzzy DRI T2FSs

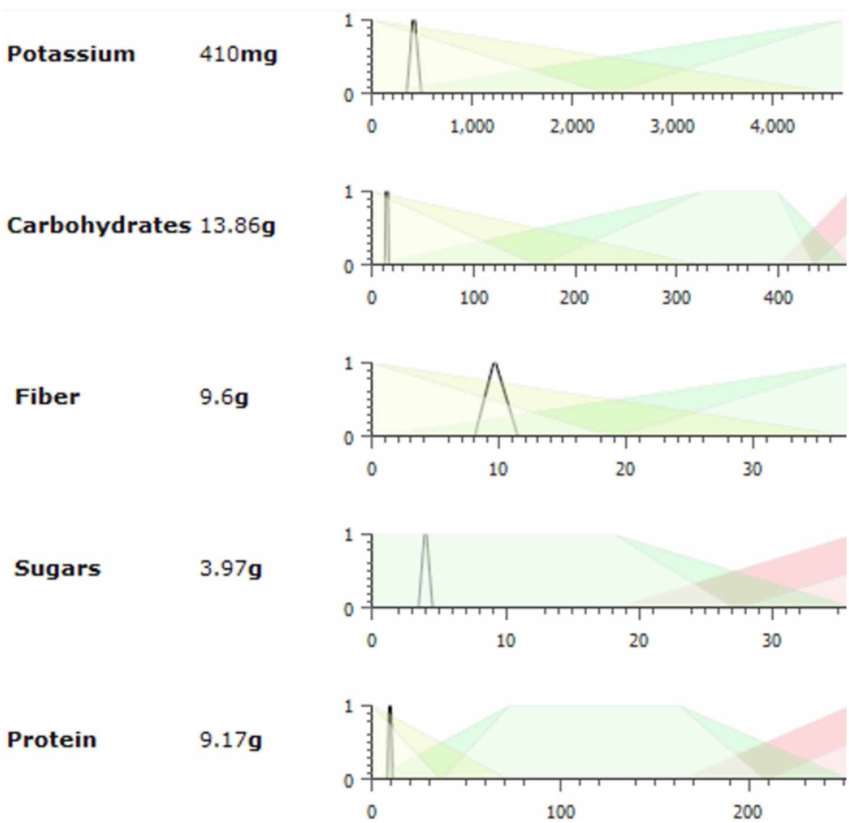
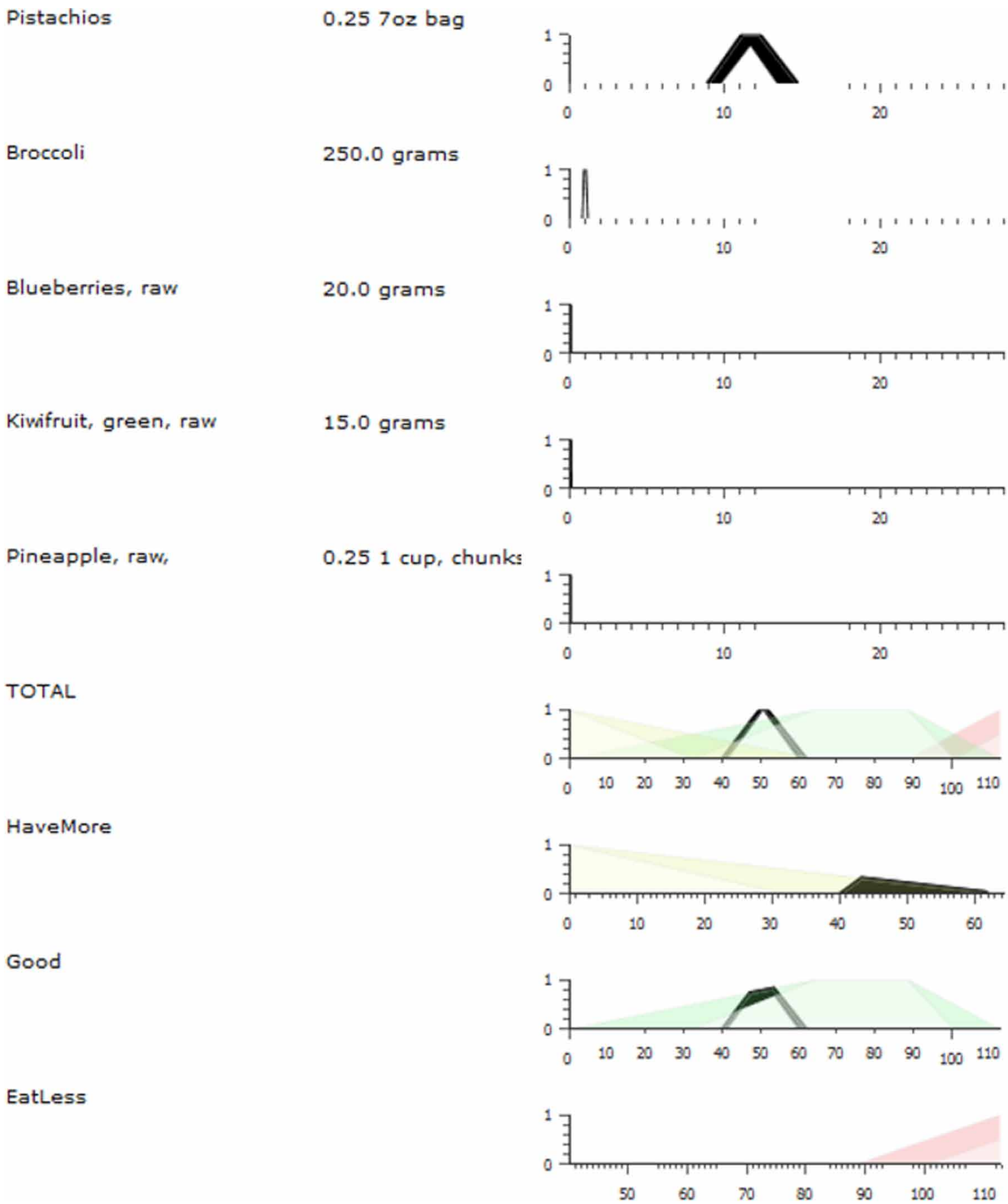


Figure 22. Display fuzzy arithmetic



to communicate with the server, unlike the previous work. The current work also expands the number of nutrients evaluated, and models user uncertainty.

The only identical traits between the two systems are: (1) The UMFs of the DRI (Antecedent) fuzzy sets are the same in the current work as the Type-1 DRI (Antecedent) fuzzy sets in the previous work, and (2) The server-side algorithm is included in the current work for comparison purposes (“Suggestions 1.0” vs. “Suggestions 2.0”)

Figure 23. Display fuzzy antecedent math

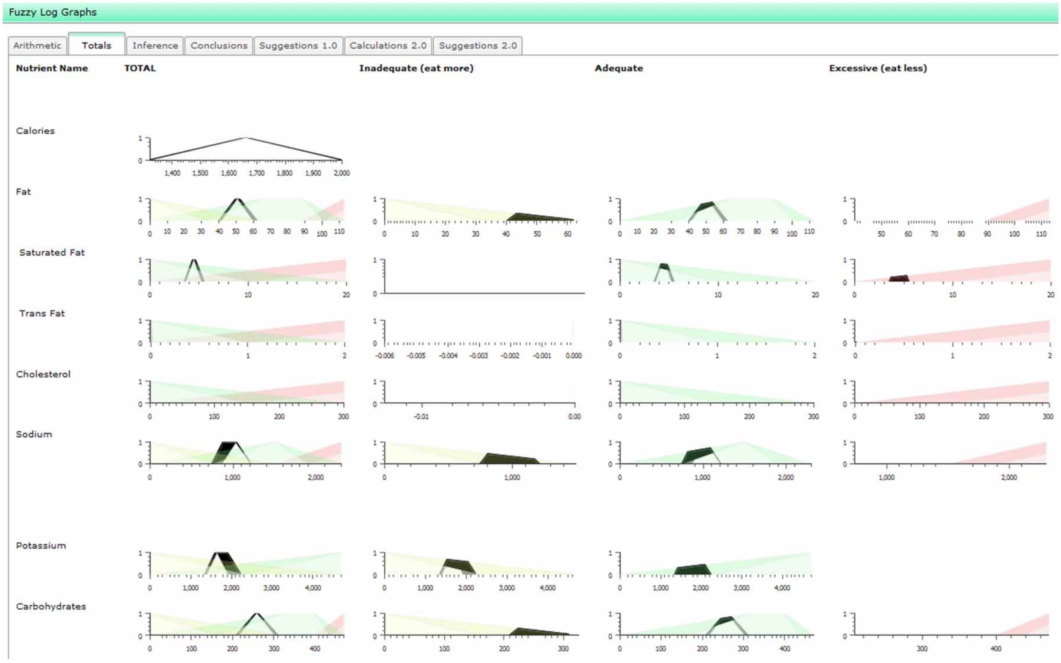
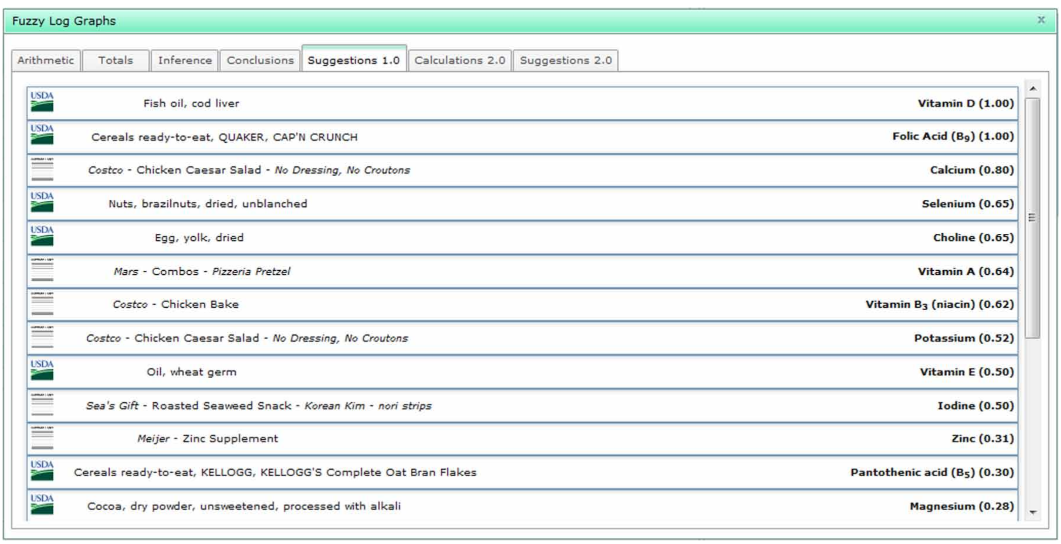


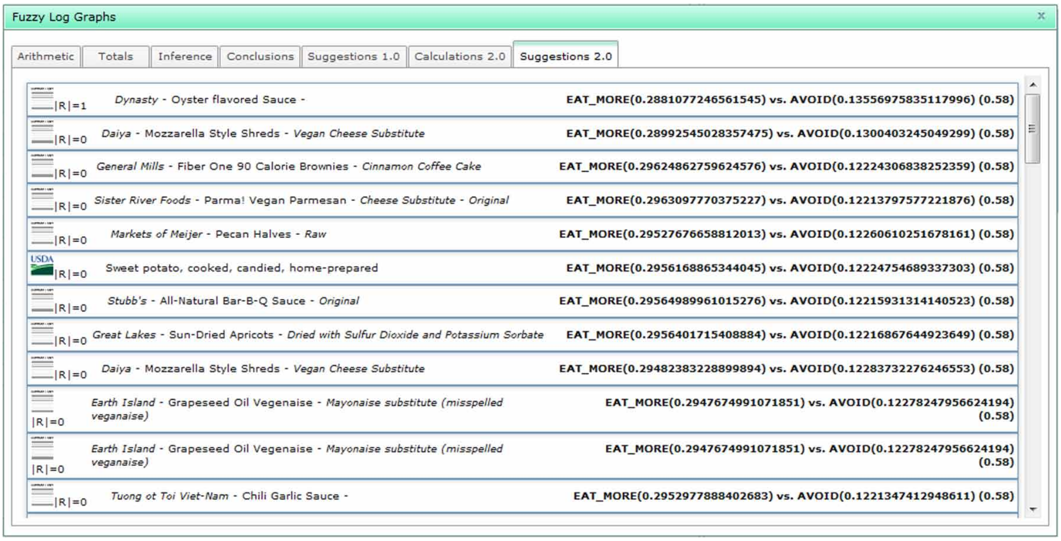
Figure 24. Display fooditem suggestions 1.0



Quantitative Analysis

It is clear that more precision and uncertainty are modeled in the current work than the previous work, resulting in a more comprehensive system. However, it is difficult to determine the accuracy of the improved system without performing analysis on a population sample from the FoodItems, and comparing the actual measured nutrient values to the system's determination. This process would

Figure 25. Display FoodItem suggestions 2.0



be cost prohibitive. It is possible, however, to isolate the differences in the two systems and identify trends in how the same data is evaluated due to these differences. What follows is a comparison of (1) the singleton type-1 and NS type-2 FLCs for the same inputs (2) the Suggestion Algorithm for the same inputs, and (3) a closer look at nutrient bias in each suggestion algorithm.

FLC Comparison

Firstly, isolating the singleton Type-1 and NS Type-2 aspects of the two systems, and gathering average firing values for each day in a year of data, it can be seen in table 7 that the type-1 system has significantly lower firing values for both the "eat more" and "avoid" classifications. This could be explained in that the singleton fuzzy number has less overlap between the two opposing antecedents than the non-singleton fuzzy set. If this were the case, one would expect that the type-1 firing values are consistently smaller than their type-2 counterparts.

For some insight into this, it makes sense to look into the distribution of firing values, which is the number of times each firing value was seen in the year of analyzed data. In Figure 26 are the distribution of nutrient-level firing values between 0.01 and 0.99, inclusive.

From the distribution, it is clear that the firing values for the type-1 system are consistently smaller. One can see in the graph there is a bias towards 0.5 for the min firing value, which comes from the method used to approximate a logarithmic increase in the "avoid" classification (Figure 13 in section II.J). This can be confirmed by looking at the distribution of nutrient-level firing values for only the "eat more" classification, shown in Figure 27, and confirming that there is no longer a spike around the 0.5 value.

Table 7. Algorithm fitness comparison to previous work

	S Type-1	NS Type-2
Avg. "Eat More" firing value	0.26830841	0.334895307
Avg. "avoid" firing value	0.054573195	0.172149867

Figure 26. Nutrient-level firing values, Type-1 vs. Type-2

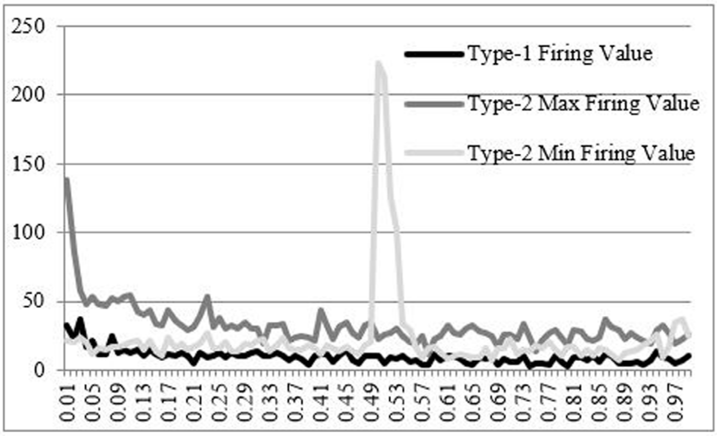
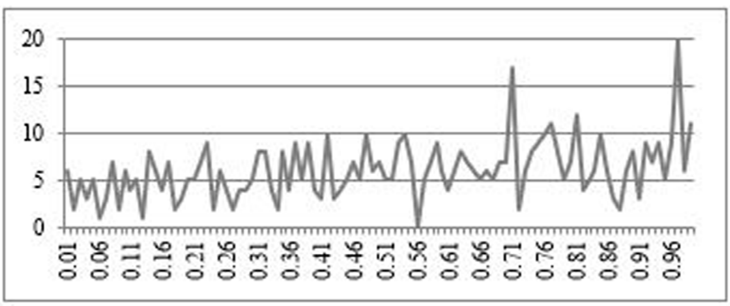


Figure 27. Nutrient-level minimum firing values for Type-1 "eat more"



In Table 8 are the nutrient-level firing values for 0 and 1 (separate from the graph because their magnitude causes the intermediate values to be difficult to discern).

It is clear from these data that the distribution of resulting values is more even in the NS Type-2 system than it is in the singleton Type-1 system, which in part explains the significantly lower firing values in the interval between 0.1 and 0.99 in the type-1 system.

Suggestion Algorithm Comparison

To compare the relative fitness of the top suggested foods of the previous work and current work on a quantitative scale. In this way, it can be determined whether the previous or current algorithm provides a more effective solution. To determine this, the same fitness calculation is

Table 8. Nutrient-Level Firing Values of 0 and 1, Type-1 vs. Type-2

	# Type-1 Firing Value	# Type-2 Firing Intervals/Value		
		Max	Min	Average
0	16966	11309	16468	11127
1	1917	3700	765	764

used as was provided earlier. Fitness is evaluated both with and without the added data of the new system. The suggested foods are added to each populated DFNV over 165 days of actual food log data collected by the user to create a TFNV that is evaluated for fitness. Both suggestion algorithms are performed on each day's data. The results are shown in Table 9, and Boxplots of these results are shown in Figure 28.

These results show algorithm 2.0 is better at avoiding nutrients, keeping "Avoid" low, whereas algorithm 1.0 is better at improving/lowering the "Eat more" score. The use or lack of use of additional nutrient data closes the "Eat More" gap between the two algorithms, making algorithm 2.0 more sufficient when both fitness perspectives are taken into account.

Suggestion Algorithm Nutrient-Level Bias

Of great interest is whether nutrient-level values are changing significantly when selecting a suggested food? That is, if a suggested food were consumed, what is the difference in the "eat more" or "avoid" firing levels on the TFNV? Because the Suggestion 1.0 algorithm from the previous work would target a particular nutrient, and had access to a greater database, one would expect greater difference in values, and quite likely some bias when compared to the Suggestions 2.0 algorithm, which takes a complete look at all nutrients when making its suggestions. This can be seen when comparing nutrient firing levels for the "eat more" and "avoid" antecedents for the Suggestions 1.0 and 2.0 algorithms. These can be seen in Figures 29 and 30, where Suggestions 1.0 and 2.0 are denoted S1 and S2, respectively.

From these graphs it is clear that the change in nutrient desirability or undesirability in the Suggestions 1.0 algorithm is greater than that in the Suggestions 2.0 algorithm for nearly every nutrient. One also sees there appear to be biases towards Vitamin E, Vitamin K, and Fat. Notably, foods with saturated fat were suggested and ranked highly by algorithm 1.0. The foods that contribute these higher saturated fat values contain other nutrients that were being sought.

The fact that algorithm 1.0 took a broader look at nutrient fitness rather than seeking one nutrient a time appears to have given it an advantage over algorithm 2.0.

CONCLUSION AND FUTURE WORK

This work implemented a fuzzy system involving IT2FSs to improve precision, providing more complete data and modeling an appropriate level of uncertainty. It is clear based on the results of this work that fuzzy sets work very well with nutrition data, and that type-2 system is better suited to judge nutrient intake than the type-1 system. Unfortunately, it remains to be seen whether users desire this level of completeness or precision in their diet logging.

What was created in this work is a food logging application and framework that may be deployed to users in order to answer many questions about effective food logging. The system may be built upon with more comprehensive fuzzy data or expanded with fuzzy Ontologies

Table 9. Algorithm fitness comparison to previous work

Algorithm	With Relationships		Without Relationships	
	Eat More	Avoid	Eat More	Avoid
1.0	0.306810468	0.190417377	0.341930662	0.175972078
2.0	0.320792204	0.172723585	0.350609332	0.157142161

Figure 28. Algorithm 1.0 vs. Algorithm 2.0 Results

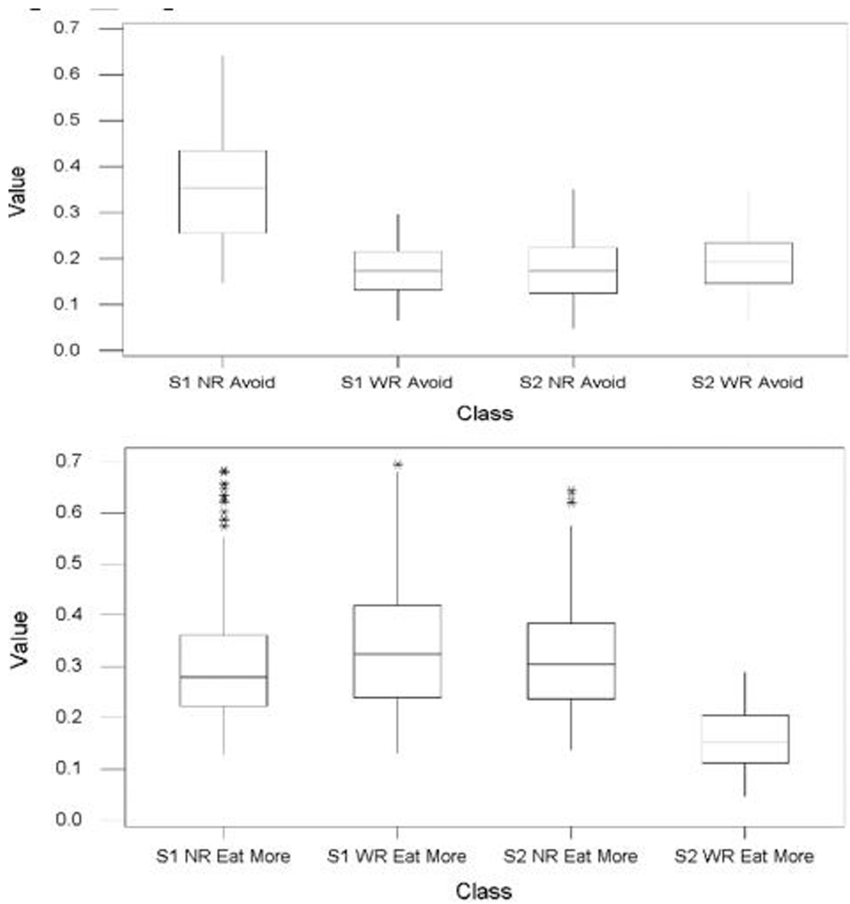


Figure 29. Nutrient-level difference in "eat more" after following suggestions

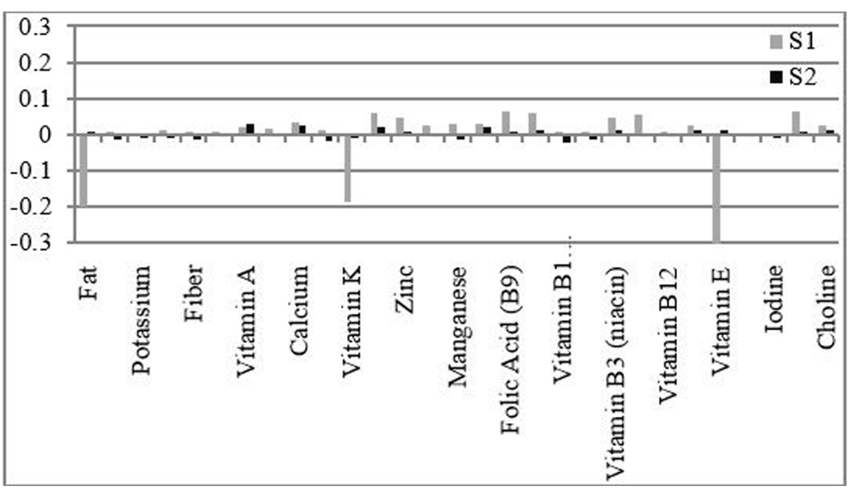
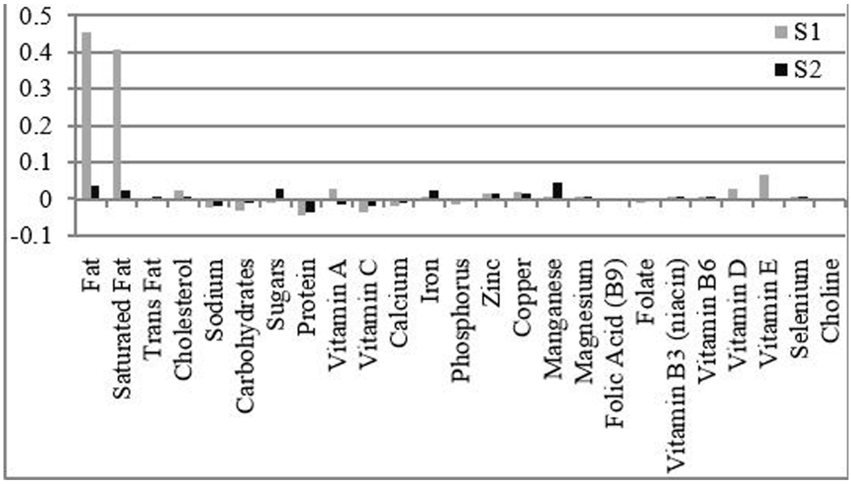


Figure 30. Nutrient-level difference in “avoid” after following suggestions



to represent FoodItem constituents such as phytonutrients not represented in the USDA SR or Nutrition Labels (e.g. Lutein, Flavenoids, etc.), or to represent studies that present the positive or negative aspects of a particular food class and use inductive logic to present the user with consequences of a particular entry.

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