

Estimating the Distribution of Dietary Consumption Patterns

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Abstract. In the United States the preferred method of obtaining dietary intake data is the 24-hour dietary recall, yet the measure of most interest is usual or long-term average daily intake, which is impossible to measure. Thus, usual dietary intake is assessed with considerable measurement error. We were interested in estimating the population distribution of the Healthy Eating Index-2005 (HEI-2005), a multi-component dietary quality index involving ratios of interrelated dietary components to energy, among children aged 2-8 in the United States, using a national survey and incorporating survey weights. We developed a highly nonlinear, multivariate zero-inflated data model with measurement error to address this question. Standard nonlinear mixed model software such as SAS NLMIXED cannot handle this problem. We found that taking a Bayesian approach, and using MCMC, resolved the computational issues and doing so enabled us to provide a realistic distribution estimate for the HEI-2005 total score. While our computation and thinking in solving this problem was Bayesian, we relied on the well-known close relationship between Bayesian posterior means and maximum likelihood, the latter not computationally feasible, and thus were able to develop standard errors using balanced repeated replication, a survey-sampling approach.

Key words and phrases: Bayesian methods, Dietary assessment, Latent variables, Measurement error, Mixed models, Nutritional epidemiology, Nutritional surveillance, Zero-Inflated Data..

1. INTRODUCTION

We (Zhang, et al., 2011b, which has many additional references) confronted the following problem in dietary assessment. A summary of the key issues follows:

- Nutritional surveys conducted in the United States typically use 24-hour (24hr) dietary recalls to obtain intake data, that is, an assessment of what was consumed in the past 24 hours.
- Because dietary recommendations are intended to be met over time, nutritionists are interested in “usual” or long-term average daily intake.

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- Dietary intake is assessed with considerable measurement error. A very large part of the measurement error is that diet has great within-person variability, so that a snapshot of two days of recall cannot hope to capture an individual's average intake over a year. There are also other sources of error besides the fact that diets vary greatly across different days. In the 24hr recall instruments used, the instrument uses a multi-pass approach that circles around to try to elicit better memory of what was eaten. The method is actually quite good in getting people to remember what they ate, but errors arise through estimation of portion size, which can be both too large and too small.
- Consumption patterns of dietary components vary widely; some are consumed daily by almost everyone, while others are episodically consumed so that their 24-hour recall data are zero-inflated. Further, these components are correlated with one another.
- Nutritionists are interested in dietary components collectively to capture patterns of usual dietary intake, and thus need multivariate models for usual intake.
- We knew of no standard frequentist software that had any hope of fitting the model and obtaining answers.

One way to capture dietary patterns is by scores. The Healthy Eating Index-2005 (HEI-2005) is a scoring system based on a priori knowledge of dietary recommendations, and is on a scale of 0 to 100. See Table 2 for a list of these components and the standards for scoring, and see Guenther et al. (2008a, 2008b) for details. Ideally, it consists of the usual intake of 6 episodically consumed and thus 24hr-zero inflated foods, 6 daily-consumed dietary components, adjusts these for energy (caloric) intake, and gives a score to each component. The total score is the sum of the individual component scores. Higher scores indicate greater compliance with dietary guidelines and, therefore, a healthier diet. The questions we addressed were to estimate the distribution of the HEI-2005 total score, and to estimate the % of American children who are eating an alarmingly poor diet, defined by a total score less than 40.

To answer public health questions such as these that can have policy implications, we (Zhang, et al., 2011b) built a novel multivariate measurement error model for estimating the distributions of usual intakes, one that accounts for measurement error and multivariate zero-inflation, and had a special covariance structure associated with the zero-inflation. Previous attempts to fit even simple versions of this model, using nonlinear mixed effects software, failed because of the complexity and dimensionality of the model. We used survey-weighted Monte Carlo computations to fit the model with uncertainty estimation coming from balanced repeated replication. The methodology was illustrated using the HEI-2005 to assess the diets of children aged 2-8 in the United States. This work represented the first analysis of joint distributions of usual intakes for multiple food groups and nutrients.

The 12 HEI-2005 components represent 6 episodically consumed food groups (total fruit, whole fruit, total vegetables, dark green and orange vegetables and legumes or DOL, whole grains and milk), 3 daily-consumed food groups (total grains, meat and beans and oils), and 3 other daily-consumed dietary components (saturated fat; sodium; and calories from solid fats, alcoholic beverages and added

sugars, or SoFAAS). The crucial statistical aspect of the data is that six of the food groups are zero-inflated. The percentages of reported nonconsumption of total fruit, whole fruit, whole grains, total vegetables, DOL and milk on any single day are 17%, 40%, 42%, 3%, 50% and 12%, respectively.

2. DATA AND THE HEI-2005 SCORES

TABLE 1

Description of the HEI-2005 scoring system. Except for saturated fat and SoFAAS (calories from solid fats, alcoholic beverages and added sugars), density is obtained by multiplying usual intake by 1000 and dividing by usual intake of kilo-calories. For saturated fat, density is 9×100 usual saturated fat (grams) divided by usual calories, i.e., the percentage of usual calories coming from usual saturated fat intake. For SoFAAS, the density is the percentage of usual intake that comes from usual intake of calories, i.e., the division of usual intake of SoFAAS by usual intake of calories. Here, "DOL" is dark green and orange vegetables and legumes. The total HEI-2005 score is the sum of the individual component scores.

Component	Units	HEI-2005 score calculation
Total Fruit	cups	$\min(5, 5 \times (\text{density}/.8))$
Whole Fruit	cups	$\min(5, 5 \times (\text{density}/.4))$
Total Vegetables	cups	$\min(5, 5 \times (\text{density}/1.1))$
DOL	cups	$\min(5, 5 \times (\text{density}/.4))$
Total Grains	ounces	$\min(5, 5 \times (\text{density}/3))$
Whole Grains	ounces	$\min(5, 5 \times (\text{density}/1.5))$
Milk	cups	$\min(10, 10 \times (\text{density}/1.3))$
Meat and Beans	ounces	$\min(10, 10 \times (\text{density}/2.5))$
Oil	grams	$\min(10, 10 \times (\text{density}/12))$
Saturated Fat	% of energy	if density ≥ 15 score = 0 else if density ≤ 7 score = 10 else if density > 10 score = $8 - (8 \times (\text{density} - 10)/5)$ else, score = $10 - (2 \times (\text{density} - 7)/3)$
Sodium	milligrams	if density ≥ 2000 score=0 else if density ≤ 700 score=10 else if density ≥ 1100 score = $8 - \{8 \times (\text{density} - 1100)/(2000 - 1100)\}$ else score = $10 - \{2 \times (\text{density} - 700)/(1100 - 700)\}$
SoFAAS	% of energy	if density ≥ 50 score = 0 else if density ≤ 20 score=20 else score = $20 - \{20 \times (\text{density} - 20)/(50 - 20)\}$

We are interested in the usual intake of foods for children aged 2-8. The data available to us came from the National Health and Nutrition Examination Survey, 2001-2004 (NHANES). The data consisted of $n = 2,638$ children, each of whom had a survey weight w_i for $i = 1, \dots, n$. In addition, one or two 24hr dietary recalls were available for each individual. Along with the dietary variables, there are covariates such as age, gender, ethnicity, family income and dummy variables that indicate a weekday or a weekend day, and whether the recall was the first or second reported for that individual.

Using the 24hr recall data reported, for each of the episodically consumed food groups, two variables are defined: (a) whether a food from that group was consumed; and (b) the amount of the food that was reported on the 24hr recall. For the 6 daily-consumed food groups and nutrients, only one variable indicating the consumption amount is defined. In addition, the amount of energy that is calculated from the 24hr recall is of interest. The number of dietary variables for each 24hr recall is thus $12+6+1 = 19$. The observed data are Y_{ijk} for the i^{th} person, the j^{th} variable and the k^{th} replicate, $j = 1, \dots, 19$ and $k = 1, \dots, m_i$.

In the data set, at most two 24hr recalls were observed, so that $m_i \leq 2$. Set $\tilde{Y}_{ik} = (Y_{i1k}, \dots, Y_{i,19,k})^T$, where

- $Y_{i,2\ell-1,k}$ = Indicator of whether dietary component # ℓ is consumed, with $\ell = 1, 2, 3, 4, 5, 6$.
- $Y_{i,2\ell,k}$ = Amount of food # ℓ consumed. This equals zero, of course, if none of food # ℓ is consumed, with $\ell = 1, 2, 3, 4, 5, 6$.
- $Y_{i,\ell+6,k}$ = Amount of non-episodically consumed food or nutrient # ℓ , with $\ell = 7, 8, 9, 10, 11, 12$.
- $Y_{i,19,k}$ = Amount of energy consumed as reported by the 24hr recall.

3. MODEL AND METHODS

3.1 Basic Model Description

Observed data will be denoted as Y , and covariates in the model will be denoted as X . As is usual in measurement error problems, there will also be latent variables, denoted by W .

We used a probit threshold model. Each of the 6 episodically consumed foods has 2 sets of latent variables, one for consumption and one for amount, while the 6 daily-consumed foods and nutrients as well as energy have 1 latent variable each, for a total of 19. The latent random variables are ϵ_{ijk} and U_{ij} , where $(U_{i1}, \dots, U_{i,19}) = \text{Normal}(0, \Sigma_u)$ and $(\epsilon_{i1k}, \dots, \epsilon_{i,19,k}) = \text{Normal}(0, \Sigma_\epsilon)$ are mutually independent. In this model, food $\ell = 1, \dots, 6$ being consumed on day k is equivalent to observing the binary $Y_{i,2\ell-1,k}$, where

$$(3.1) \quad Y_{i,2\ell-1,k} = 1 \iff W_{i,2\ell-1,k} = X_{i,2\ell-1,k}^T \beta_{2\ell-1} + U_{i,2\ell-1} + \epsilon_{i,2\ell-1,k} > 0.$$

If the food is consumed, we model the amount reported, $Y_{i,2\ell,k}$, as

$$(3.2) \quad [g_{\text{tr}}(Y_{i,2\ell,k}, \lambda_\ell) | Y_{i,2\ell-1,k} = 1] = W_{i,2\ell,k} = X_{i,2\ell,k}^T \beta_{2\ell} + U_{i,2\ell} + \epsilon_{i,2\ell,k},$$

where $g_{\text{tr}}(y, \lambda) = \sqrt{2}\{g(y, \lambda) - \mu(\lambda)\}/\sigma(\lambda)$, $g(y, \lambda)$ is the usual Box-Cox transformation with transformation parameter λ , and $\{\mu(\lambda), \sigma(\lambda)\}$ are the sample mean and standard deviation of $g(y, \lambda)$, computed from the nonzero food data. This standardization is a convenient device to improve the numerical performance of our algorithm without affecting our conclusions.

The reported consumption of daily consumed foods or nutrients $\ell = 7, \dots, 12$ is modeled as

$$(3.3) \quad g_{\text{tr}}(Y_{i,\ell+6,k}, \lambda_\ell) = W_{i,\ell+6,k} = X_{i,\ell+6,k}^T \beta_{\ell+6} + U_{i,\ell+6} + \epsilon_{i,\ell+6,k}.$$

Finally, energy is modeled as

$$(3.4) \quad g_{\text{tr}}(Y_{i,19,k}, \lambda_{13}) = W_{i,19,k} = X_{i,19,k}^T \beta_{19} + U_{i,19} + \epsilon_{i,19,k}.$$

As seen in (3.2)-(3.4), different transformations $(\lambda_1, \dots, \lambda_{13})$ are allowed to be used for the different types of dietary components.

In summary, there are latent variables $\tilde{W}_{ik} = (W_{i1k}, \dots, W_{i,19,k})^T$, latent random effects $\tilde{U}_i = (U_{i1}, \dots, U_{i,19})^T$, fixed effects $(\beta_1, \dots, \beta_{19})$, and design matrices

$(X_{i1k}, \dots, X_{i,19,k})$. Define $\tilde{\epsilon}_{ik} = (\epsilon_{i1k}, \dots, \epsilon_{i,19,k})^\top$. For mutually independent random variables $\tilde{U}_i = \text{Normal}(0, \Sigma_u)$ and $\tilde{\epsilon}_{ik} = \text{Normal}(0, \Sigma_\epsilon)$, the latent variable model is

$$(3.5) \quad W_{ijk} = X_{ijk}^\top \beta_j + U_{ij} + \epsilon_{ijk}.$$

3.2 Restriction on the Covariance Matrix

Two necessary restrictions are set on Σ_ϵ . First, following Kipnis, et al. (2009), $\epsilon_{i,2\ell-1,k}$ and $\epsilon_{i,2\ell,k}$, ($\ell = 1, \dots, 6$) are set to be independent. Second, in order to technically identify $\beta_{2\ell-1}$ and the distribution of $U_{i,2\ell-1}$ ($\ell = 1, \dots, 6$), we require that $\text{var}(\epsilon_{i,2\ell-1,k}) = 1$, because otherwise the marginal probability of consumption of component $\# \ell$ is $\Phi\{(X_{i,2\ell-1,k}^\top \beta_{2\ell-1} + U_{i,2\ell-1})/\text{var}^{1/2}(\epsilon_{i,2\ell-1,k})\}$, and thus components of β and Σ_u would be identified only up to the scale $\text{var}^{1/2}(\epsilon_{i,2\ell-1,k})$.

It is easiest to see the problem in the case of two episodically consumed dietary components and energy. In this case,

$$(3.6) \quad \Sigma_\epsilon = \begin{pmatrix} 1 & 0 & s_{13} & s_{14} & s_{15} \\ 0 & s_{22} & s_{23} & s_{24} & s_{25} \\ s_{13} & s_{23} & 1 & 0 & s_{35} \\ s_{14} & s_{24} & 0 & s_{44} & s_{45} \\ s_{15} & s_{25} & s_{35} & s_{45} & s_{55} \end{pmatrix}.$$

The difficulty with parameterizations of (3.6) is that the cells that are not constrained to be 0 or 1 cannot be left unconstrained, otherwise (3.6) need not be a covariance matrix, that is, positive semidefinite. Zhang, et al. (2011b) developed an unconstrained parameterization that results in the structure (3.6).

3.3 The Use of Sampling Weights

We used the survey sample weights from NHANES both in the model fitting procedure and, after having fit the model, in estimating the distributions of usual intake. As a referee pointed out, the role of sampling weights in Bayesian analyses is controversial. In our problem, most of the variables that were used to construct the sampling weights were in our model, and we thus expected that a weighted and unweighted analysis would lead to very similar parameter estimates (posterior means) for the model. This was indeed the case. However, the sampling weights definitely are needed in estimating the population distribution that is representative of the US population, not just the sample. Having fit the model, estimation of distribution was done in a routine frequentist manner using the survey weights. We assessed standard errors by Balanced Repeated Replication (BRR).

3.4 Distribution of Usual Intake and the HEI-2005 Scores

Zhang, et al. (2011b) use MCMC to estimate Σ_u , Σ_ϵ and β_j for $j = 1, \dots, 19$. From that, it is straightforward to estimate the distribution of usual intakes and the usual HEI-2005 component and total scores. To see how this works, consider the first episodically consumed dietary component, a food group. Following Kipnis, et al. (2009), we define the usual intake for an individual on the weekend to be the expectation of the reported intake conditional on the person's random effects \tilde{U}_i . Let the (q, p) element of Σ_ϵ be denoted as $\Sigma_{\epsilon,q,p}$. As in Kipnis, et al.

define

$$g_{\text{tr}}^*\{v, \lambda, \Sigma_{\epsilon, q, p}\} = g_{\text{tr}}^{-1}(v, \lambda) + \frac{1}{2} \Sigma_{\epsilon, q, p} \frac{\partial^2 g_{\text{tr}}^{-1}(v, \lambda)}{\partial v^2}.$$

Then, following the convention of Kipnis, et al. (2009), the person's usual intake of the first episodically consumed dietary component is defined as

$$T_{i1} = \Phi(X_{i1}^T \beta_1 + U_{i1}) g_{\text{tr}}^*(X_{i2}^T \beta_2 + U_{i2}, \lambda_1, \Sigma_{\epsilon, 2, 2}).$$

Usual intake for the other episodically consumed food groups is defined similarly, and similarly for the daily consumed components. With such definitions it is straightforward to generate, via Monte-Carlo, a survey-weighted estimate of the population distribution of usual intake.

4. WHY A BAYESIAN APPROACH TO ESTIMATION

Our model (3.2)-(3.4) is a highly nonlinear, mixed effects model with many latent variables and nonlinear restrictions on the covariance matrix Σ_{ϵ} . As discussed in Section 3.4, we can estimate relevant distributions of usual intake in the population if we can estimate Σ_u , Σ_{ϵ} and β_j for $j = 1, \dots, 19$. We have found that working within a Bayesian paradigm is a convenient way to do this computation and thus solve the problem. We used this approach because standard software such as NLMIXED simply could not handle the problem, while thinking computationally in a Bayesian way using MCMC was straightforward. Indeed, Zhang, et al. (2011a) have shown that even considering a single food group plus energy is a challenge for the NLMIXED procedure, both in time and in convergence, and using this method for the entire HEI-2005 constellation of dietary components is impossible.

Kipnis, et al. (2009) were able to get estimates of parameters separately for each food group using the nonlinear mixed effects program NLMIXED in SAS with sampling weights. While this gives estimates of β_j for $j = 1, \dots, 19$, it only gives us parts of the covariance matrices Σ_u and Σ_{ϵ} , and not all the entries. Using the 2001-2004 NHANES data, we have verified that our estimates and the subset of the parameters that can be estimated by one food group at a time using NLMIXED are in close agreement, and that estimates of the distributions of usual intake and HEI-2005 component scores are also in close agreement.

Full technical details of the MCMC model fitting procedure are given in Zhang, et al. (2011b).

5. EMPIRICAL WORK

5.1 Basic Analysis

As stated previously, we analyzed data from the 2001-2004 National Health and Nutrition Examination Survey (NHANES) for children ages 2-8. We used the dietary intake data to calculate the 12 HEI-2005 components plus energy. In addition, besides age, gender, race and interaction terms, two covariates were employed, along with an intercept. The first was a dummy variable indicating whether or not the recall was for a weekend day (Friday, Saturday or Sunday) because food intakes are known to differ systematically on weekends and weekdays. The second was a dummy variable indicating whether the 24hr recall was the first or second such recall, the idea being that there may be systematic differences attributable to the repeated administration of the instrument.

TABLE 2

Estimated distributions of the usual intake HEI-2005 scores. Standard errors are given in Zhang, et al. (2011b). The total score is the sum of the individual scores. Here, “DOL” is dark green and orange vegetables and legumes. Also, “SoFAAS” is calories from solid fats, alcoholic beverages and added sugars.

Component	Percentile							
	Mean	5 th	10 th	25 th	50 th	75 th	90 th	95 th
Total Fruit	3.55	0.87	1.31	2.33	3.90	5.00	5.00	5.00
Whole Fruit	3.14	0.49	0.82	1.71	3.24	5.00	5.00	5.00
Total Vegetables	2.16	1.02	1.24	1.63	2.10	2.62	3.15	3.48
DOL	0.62	0.05	0.09	0.21	0.45	0.86	1.38	1.76
Total Grains	4.81	3.92	4.23	4.79	5.00	5.00	5.00	5.00
Whole Grains	0.90	0.16	0.24	0.43	0.75	1.21	1.74	2.13
Milk	6.77	2.15	2.96	4.62	6.91	9.67	10.00	10.00
Meat and Beans	7.22	4.23	4.83	5.91	7.21	8.64	10.00	10.00
Oil	5.92	3.37	3.83	4.69	5.77	7.01	8.25	9.07
Saturated Fat	5.16	0.00	1.09	3.18	5.38	7.48	8.53	8.96
Sodium	4.52	1.25	2.05	3.31	4.62	5.83	6.85	7.44
SoFAAS	8.73	2.15	3.60	6.02	8.73	11.42	13.81	15.21
Total Score	53.50	37.42	40.74	46.73	53.68	60.36	65.87	68.96

5.2 Estimation of the HEI-2005 Scores

Table 2 presents the first estimates of the distribution of HEI-2005 scores for a vulnerable subgroup of the population, namely, children aged 2-8 years. A previous analysis of 2003-04 NHANES data, looking separately at 2-5 year olds and 6-11 year olds, was limited to estimates of mean usual HEI-2005 scores [59.6 and 54.7, respectively; see Fungwe, et al. (2009)]. The mean scores noted here are comparable to those and reinforce the notion that children’s diets, on average, are far from ideal. However, this analysis provides a more complete picture of the state of US children’s diets. By including the scores at various percentiles, we estimate that only 5% of children have a score of 69 or greater and another 10% have scores of 41 or lower. While not in the Table, we also estimate that the 99th percentile is 74. This analysis suggests that virtually all children in the US have suboptimal diets and that a sizeable fraction (10%) have alarmingly low scores (41 or lower.)

We have also considered whether our multivariate model fitting procedure gives reasonable marginal answers. To check this, we note that it is possible to use the SAS procedure NLMIXED *separately for each component* to fit a model with one episodically consumed food group or daily consumed dietary component together with energy. The marginal distributions of each such component done separately are quite close to what we have reported in Table 2, as is our mean, which is 53.50 compared to the mean of 53.25 based on analyzing one HEI-2005 component at a time with the NLMIXED procedure. The only case where there is a mild discrepancy is in the estimated variability of the energy-adjusted usual intake of oils, likely caused by the NLMIXED procedure itself, which has an estimated variance 9 times greater than our estimated variance.

Of course, it is the distribution of the HEI-2005 total score that cannot be estimated by analysis of one component at a time.

Finally, we also estimated the distribution of the total score as developed by a single 24hr, and completely ignoring the difference between a 24hr and usual intake. A single 24HR estimated that nearly 30% of children have an alarmingly

poor diet (total score ≤ 40), versus the 10% we think is realistic. This difference is enormous. If the 30% figure were to be believed, which we do not think it should be, this could have major policy implications.

5.3 Computing and Data

Our programs were written in Matlab. The programs, along with the NHANES data we used, are available in the *Annals of Applied Statistics* online archive associated with Zhang, et al. (2011b). Because of the public health importance of the problem, the National Cancer Institute has contracted for the creation of a SAS program that performs our analysis. It will allow any number of episodically and daily consumed dietary components. The first draft of this program, written independently in a different programming language, gives almost identical results to what we have obtained, verifying that our results are not the product of a programming error.

6. DISCUSSION

There are many important questions in dietary assessment that have not been able to be answered because of a lack of multivariate models for complex, zero-inflated data with measurement errors and especially a lack of ability to fit such multivariate models. Nutrients and foods are not consumed in isolation, but rather as part of a broader pattern of eating. There is reason to believe that these various dietary components interact with one another in their effect on health, sometimes working synergistically and sometimes in opposition. Nonetheless, simply characterizing various patterns of eating has presented enormous statistical challenge. Until now, descriptive statistics on the HEI-2005 have been limited to examination of either the mean total score or only a single energy-adjusted component at a time, neither of them relevant for the distribution of the total score. This has precluded characterization of various patterns of dietary quality as well as any subsequent analyses of how such patterns might relate to health.

The Bayesian methodology presented in Zhang, et al. (2011b) presents a workable solution to these problems which has already proven valuable. In May 2010, just as we were submitting the paper, a White House Task Force on Childhood Obesity created a report. They had wanted to set a goal of all children having a total HEI score of 80 or more by 2030, but when they learned we estimated only 10% of the children ages 2-8 had a score of 66 or higher, they decided to set a more realistic target. The facility to estimate distributions of the multiple component scores simultaneously will be important in tracking progress toward that goal.

In some respects, our model is complex, but then the problem is complex. There are simple solutions for some subproblems of the HEI-2005, e.g., estimating its mean. However, our problem is a setting where the actual distribution is of interest, not just the mean. Recognizing that the simplest approach, ignoring measurement error entirely, led to unrealistic estimates of the percentage of children with alarmingly poor diets (Section 5.2), we realized that a measurement error analysis was required. We worked on this problem for nearly 2 years, before realizing that the only practical way forward was to take a Bayesian approach to computation. Estimating distributions of usual (i.e., measurement error corrected) dietary patterns is important for public health and policy. We are ex-

tending our methods to the newly announced HEI-2010 score, which has more dietary components, and preliminary results are encouraging.

ACKNOWLEDGMENTS

Carroll's research was supported by a grant from the National Cancer Institute (R27-CA057030). He thanks the co-authors of Zhang, et al. (2011b) for their work on the project.

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