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On the Similarity of Classical and Bayesian Estimates of Individual Mean Partworths

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Abstract

An exciting development in modeling has been the ability to estimate reliable individual-level parameters for choice models. Individual partworths derived from these parameters have been very useful in segmentation, identifying extreme individuals, and in creating appropriate choice simulators. In marketing, hierarchical Bayes models have taken the lead in combining information about the aggregate distribution of tastes with the individual's choices to arrive at a conditional estimate of the individual's parameters. In economics, the same behavioral model has been derived from a classical rather than a Bayesian perspective. That is, instead of Gibbs sampling, the method of maximum simulated likelihood provides estimates of both the aggregate and the individual parameters. This paper explores the similarities and differences between classical and Bayesian methods and shows that they result in virtually equivalent conditional estimates of partworths for customers. Thus, the choice between Bayesian and classical estimation becomes one of implementation convenience and philosophical orientation, rather than pragmatic usefulness.

Key words: hierarchical Bayes, maximum likelihood, choice models, mixed logit, classical statistics, Bayesian statistics

Introduction

More than any other discipline, marketing is concerned with predicting individual choice. After all, choice is what consumers do when selecting among alternatives in the marketplace. A focus on individual values provides a critical foundation for segmentation, identification of prospects and as input to market simulators (Wedel et al. 1999). However, early choice experiments had to be estimated at an aggregate level. Individual partworths were typically derived from ratings-based conjoint methods (Green and Srinivasan 1990), leveraging the greater information in the ratings of alternatives compared to a selection of one. Put differently, since choice sets provide information only about which alternative is selected, rather than the strength of preference differences within the set, choices contain less information per observation than ratings. Consequently, most choice models had achieved stability by aggregating responses across individuals.

Recently, hierarchical Bayes has provided a way to estimate remarkably stable individual models from choice alone (Allenby and Ginter 1995; Lenk, Desarbo, Green and Young 1996, Sawtooth Software 1999). Within a Bayesian framework, these models estimate the distribution of coefficients across the population and combine information with the individual's choices to derive posterior or conditional estimates of the individual's partworths. At the same time, random or mixed coefficient choice models arising from a classical framework have permitted a similar analysis by combining maximum likelihood estimates of the population distribution with individual choices (Revelt and Train, 1999). In this paper we examine the empirical differences between these classical and hierarchical Bayes estimates. Both methods share the same behavioral assumptions, but derive from quite different estimation techniques and interpretive philosophies.

It is not the intent of this paper to bridge the cultural chasm between Bayesian and classical statistians. Indeed, divisions between these frameworks have resisted twenty years of efforts to bring them together (Gelman et al. 1995). The goal of this paper is instead to show that the distinction is often irrelevant for the purposes of estimating the mean partworths of individuals. Since these individual partworths are the critical statistics needed to develop segments, identify outliers and simulate market choices, it does not matter which method is used for the majority of our practical and theoretical research.

The two procedures are related numerically.[1] When the same model is specified under the two approaches, estimates from the classical and Bayesian procedures converge asymptotically (Lindsey 1996). In small samples, the two procedures can provide numerically different results, due to the different ways of treating uncertainty in the parameters of the population distribution.[2] The relevant question is then an assessment of how different the results are in the kinds of samples used by researchers and practitioners.

We investigate this question with a sample of 361 customers, using both classical and Bayesian procedures to estimate the mean of the conditional distribution for each customer. We use a mixed or random coefficients logit specification of behavior, though other behavioral representations could be used instead. We find that the results are remarkably similar for the two approaches.

The similarity of results, asymptotically and in our typical example, means that in many contexts the differences between the two approaches arise in how the results are interpreted more than in the numerical estimates themselves. As has been found and exploited for other kinds of models, the advantages of Bayesian numerical procedures for mixed logits can be utilized while retaining a classical perspective, and classical procedures can be applied in situations where they provide numerical conveniences, without abandoning a Bayesian perspective.

In Section 1, we provide the specification of mixed logits and describe how they are conceptualized and estimated in both the classical and Bayesian perspectives. Section 2 presents our application of a mixed logit model that compares the results from the two procedures. Section 3 concludes with a discussion of the pragmatic reasons to choose one system over the other.

1. Specification of Mixed Logits

We first describe the behavioral specification, which is shared by both approaches, and then briefly describe the conceptualization and techniques of estimation, which are different for the two approaches. We assume that the partworths are normally distributed in the population. This assumption is consistent with the commercially available software for the Bayesian approach (Sawtooth Software 1999). However, it is not required for either approach, and we later discuss the use of non-normal distributions.

1.1. Behavioral Specification

Assume each customer faces a choice among J alternatives in each of T choice situations.[3] Customer n is assumed to choose the alternative in choice situation t with the highest utility. The utility of alternative i as faced by customer n in situation t is modeled as:

$$U_{nit} = \beta_n' X_{nit} + e_{nit}, \tag{1}$$

where X_{nit} is a vector of independent variables that are observed by the researcher, such as attributes of the alternative i in choice situation t. These independent variables are considered non-stochastic. By contrast, the terms β_n and e_{nit} are not observed by the researcher and are considered stochastic. The coefficient vector, β_n, is assumed to be distributed normally across the population, independent of e and X, with mean vector b and covariance matrix W. The term e_{nit} is assumed to be distributed iid extreme value. The assumption of an iid extreme value distribution for this additive error term makes the model a mixed logit instead of another type of choice model, such as random coefficient probit. In each choice situation, each customer chooses the alternative that provides the greatest utility.

1.2. Classical Estimation

The parameters b and W are considered fixed, representing the true mean and covariance of the β_n's in the population. These parameters are estimated on a sample of customers drawn from the population. The estimators, denoted $\hat{b}$ and $\hat{W}$, are stochastic due to sampling and are obtained using maximum simulated likelihood estimation. The likelihood function is $L(b, W) = \Pi_n L_n(b, W)$ where $L_n(b, W)$ is the probability of customer n's sequence of choices given b and W. Since e_{nit} is iid extreme value, this probability is an integral over β_n of a product of logits. Simulation approximates this integral, using draws of β_n from a normal distribution with mean b and covariance W. The estimator has an asymptotic distribution that is used as the approximate sampling distribution in finite samples, as given by McFadden and Train (2000). We denote this distribution as $f(\hat{b}, \hat{W})$.

For any b and W, the density of β_n conditional on customer n's sequence of choices is $G_n(\beta_n|b, W) = L_n(\beta_n)N(\beta_n|b, W)/L_n(b, W)$, where $N(\beta_n|b, W)$ is the normal population

density with mean b and covariance W, and $L_n(\beta_n)$ is the probability of the customer's sequence of choices conditional on β_n. The expectation of this density, labeled $E(\beta_n|b, W)$, is approximated through simulation, by taking draws of β_n from $N(\beta_n|b, W)$, weighting each draw by the ratio $L_n(\beta_n)/L_n(b, W)$, and averaging the results. The estimator for b and W provides the estimator $\hat{E}(\beta_n) = E(\beta_n|\hat{b}, \hat{W})$. The sampling distribution of $\hat{E}(\beta_n)$ can be approximated by taking draws of $\hat{b}$ and $\hat{W}$ from their sampling distribution $f(\hat{b}, \hat{W})$ and calculating $E(\beta_n|\hat{b}, \hat{W})$ for each draw.

$\hat{E}(\beta_n)$ can be viewed in either of two ways in classical estimation. First, $G_n(\beta_n|b, W)$ can be considered the density of β_n in the subpopulation of customers who, when facing the sequence of choice situations described by X_{nit} for all i and t, make the choices that customer n made. Then $E(\beta_n|b, W)$ is the mean β_n within this subpopulation, and $\hat{E}(\beta_n)$ is an estimator of this mean. Under this interpretation, the number of choice situations, as well as their characteristics as defined by the X_{nit}'s, are considered fixed. Second, one can consider the choice situations to be sampled from a universe of possible choice situations, such that T can rise in the same way that the number of sampled customers can rise. Under this view, $\hat{E}(\beta_n)$ is an estimator of customer n's coefficient vector, β_n. Importantly, the mean of a likelihood function that is expressed as a density is asymptotically equivalent to the maximum likelihood estimator of that likelihood function. Therefore, $\hat{E}(\beta_n)$ is asymptotically equivalent to the maximum likelihood estimator of β_n.

1.3. Bayesian Estimation

Under a Bayesian framework, b and W are considered stochastic from the researcher's perspective. The researcher has a prior distribution on b and W, denoted $p(b, W)$, and combines this prior with the likelihood function of the data to obtain a posterior distribution. The joint posterior for b, W, and β_n for all n is proportional to $\Pi_n L_n(\beta_n) N(\beta_n|b, W) p(b, W)$. Draws from this joint posterior distribution may be obtained through Gibbs sampling. That is, a sequence of conditional draws is obtained, where each parameter is drawn conditional on a draw from the other parameters. For a draw of b and W, the conditional posterior for density of β_n is $G_n(\beta_n|b, W) = L_n(\beta_n)\ N(\beta_n|b, w)/L_n(b, W)$. Note that this conditional posterior is the same as the conditional density of β_n used in the classical approach. The two approaches use the same density for β_n given values of b and W. The two approaches only differ in the values of b and W from which the density of β_n is derived.

In Gibbs sampling, draws of b are obtained from its posterior conditional on draws of W and β_n for all n. When β_n is normally distributed, as we have assumed, then the population conditional posterior for b is normal with mean equal to the average of β_n over n and covariance W/N, where N is the sample size. Drawing from this distribution is easy. Similarly, draws of W are obtained from its posterior conditional on b and β_n for all n. When β_n is normally distributed, and the prior on W is inverted Wishart, the conditional posterior for W is also inverted Wishart, which is easy to simulate (Gelman et al. 1995). The simplicity of drawing from these posteriors is one of the main computational advantages of Gibbs sampling in the Bayesian approach. In fact, the reason β_n is assumed

to be normally distributed is that, with this assumption, priors on b and W can be specified that give easy-to-draw-from posteriors.

The Gibbs sampling provides a set of draws of β_n from its posterior. The mean of these draws is denoted $\tilde{E}(\beta_n)$. It is the Bayesian analog of $\hat{E}(\beta_n)$ under the classical approach. In the next section, we calculate and compare $\tilde{E}(\beta_n)$ and $\hat{E}(\beta_n)$.

2. Application

Many states, including California, Pennsylvania, and Massachusetts, allow households to choose the company from which they buy electricity. We examine the factors that affect 361 residential customers' choice of electricity supplier, using choice-based conjoint. Surveyed customers made 12 choices each from among four suppliers that differed on the basis of five relevant attributes:

- Fixed price, in cents per kilowatt-hour (7 or 9 cents per kWh)
- Length of contract (0, 1, 2 or 3 years)
- Type of company (the local utility, a "well-known company other than the local utility", or "an unfamiliar company".)
- Time-of-use rates, with 11 cents per kWh from 8 am–8 pm and 5 cents per kWh from 8 pm–8 am
- Seasonal rates, with 10 cents per kWh in summer, 8 cents in winter, and 6 cents in spring and fall.

Details on the sample and survey are provided in Electric Power Research Institute (1998).[4]

Partworths are estimated for price, contract length, and indicator variables for whether the company was the local utility, a well-known company other than the local utility, time-of-use rates, and seasonal rates. The "unfamiliar company" is taken as the base for normalization, so that the partworths for the local utility and a well-known company are the values of these kinds of companies relative to it. Price and contract length are "linearized," in that the same partworth is applied for each one-unit increase in the variable (i.e., one-cent increase in price, or one-year increase in contract length). The prices under time-of-use and seasonal rates did not vary in the experiments; consequently, their partworths indicate the values of these rates, including the negative value of the specified prices. As stated in Section 1, we assume that all partworths are normally distributed across the population, with a full covariance matrix.

We estimate the expected partworths for each customer, conditional on that customer's observed choices. In the Bayesian procedure, this statistic is the mean of the draws of β_n for that customer. In the classical procedure, this statistic is the mean of the conditional distribution of β_n for the customer, based on the maximum likelihood estimates of the population distribution. With both procedures, the twelfth choice situation was excluded from estimation and used to test forecasts based on the expected partworths for each customer.

Table 1 displays the sample average of the expected partworths under the two procedures. Column 1 gives the average over customers of the classical estimate for each customer and column 2 gives the corresponding average of the Bayesian estimates. The two sets of estimates are quite similar. The average magnitude, or scale of the Bayesian estimates is slightly higher than that of the classical estimates. To account for the scale difference, the third column of Table 1 gives the average for the classical estimates scaled such that the average price coefficient is the same for the two procedures. With this rescaling, the two sets of averages are remarkably close.

Table 2 displays the standard deviation of the expected partworths over the sampled customers. These standard deviations are quite similar, and when the scale difference is accounted for, the two sets of standard deviations are also very close.

Table 3 arrays the correlation matrix for the vector of expected partworths under both approaches. The upper-triangular portion of the matrix gives the correlations for the

Table 1. Average of Expected Partworths

	Classical	Bayesian	Scaled Classical
Price	−1.044	−1.120	−1.120
Contract length	−0.260	−0.286	−0.279
Local utility	2.714	2.821	2.91
Well-known company	2.090	2.193	2.24
Time-of-use rates	−9.894	−10.54	−10.61
Seasonal rates	−10.11	−10.84	−10.84

Table 2. Standard Deviation of Expected Partworths

	Classical	Bayesian	Scaled Classical
Price	0.693	0.784	0.743
Contract length	0.380	0.419	0.407
Local utility	1.983	2.044	2.127
Well-known company	1.381	1.468	1.481
Time-of-use rates	6.643	7.061	7.125
Seasonal rates	6.054	6.615	6.493

Table 3. Correlation Matrix of E (b), Classical Estimates in Upper Triangle. Bayesian Estimates in Lower Triangle

	Price	Contract Length	Local Utility	Well-known Company	Time-of-use Rates	Seasonal Rates
Price	1	0.106	0.649	0.523	0.903	0.942
Contract length	0.104	1	0.335	0.245	0.083	0.036
Local utility	0.667	0.290	1	0.828	0.625	0.615
Well-known company	0.466	0.205	0.789	1	0.488	0.466
Time-of-use rates	0.898	0.116	0.651	0.433	1	0.937
Seasonal rates	0.932	0.057	0.644	0.411	0.943	1

classical estimates, and the lower-triangular portion gives the correlations for the Bayesian estimates. The corresponding upper and lower figures are quite similar. For example, the correlation between the price coefficient and the contract length coefficient is 0.106 for the classical estimates and 0.104 for the Bayesian estimates. Note that the price coefficient is very highly correlated with the time-of-use and seasonal coefficients. This correlation is expected since these variables are all price-related. Both the Bayesian and classical procedures are more prone to simulation noise when coefficients are highly correlated; stated alternatively, both methods require more draws to obtain a given level of accuracy when there is high correlation among coefficients. It is particularly noteworthy, therefore, that the two methods provide such close estimates in our study despite such high correlations.

Table 4 displays the correlation between estimates under the two methods. For example, the first row gives the correlation over the sampled customers between their expected price coefficient estimated by the Bayesian method and their expected price coefficient estimated by the classical method. The correlation is 0.975. The correlations are even higher for the other partworths. The correspondence is remarkably good, particularly given that each approach is subject to simulation noise. The two methods are giving essentially the same results, aside from the small difference in scale factors.

As stated above, the last choice experiment was retained for testing. We forecasted each customer's choice in the last choice set using the expected partworths. The results are given in Table 5. Each customer's expected partworths were used in a logit formula to calculate the probability for each alternative in the customer's last choice. The average probability for the chosen alternative over the sampled customers is practically the same for both methods: 0.6299 for the Bayesian estimates and 0.6293 for the classical estimates. Figure 1 demonstrates that the predicted probabilities of the chosen alternatives strongly correspond in their distribution of deciles across respondents. Finally, we examined the hit rates, the ability of each model to predict the alternative actually chosen out of the four alternatives. Again, the results were nearly the same: the Bayesian estimates resulted in a 71% hit rate,

Table 4. Correlation between Classical and Bayesian Estimates

Price	0.975
Contract length	0.988
Local utility	0.985
Well-known company	0.978
Time of use rates	0.981
Seasonal rates	0.979

Table 5. Prediction for Last Choice Situation

	Classical	Bayesian
Average probability of the chosen alternative	0.6293	0.6299
Number of matches out of 361	261	256

virtually identical to the 72% for the classical procedure. Importantly, the Bayesian and classical methods provide the same prediction for more than 96% of the respondents.

3. Discussion

We have applied both hierarchical Bayes and maximum likelihood estimation procedures to the same random parameter structure. Despite substantial algorithmic differences, the Bayesian and the classical estimates of the individual partworths are virtually identical. These results obtain for the estimation of a particular study involving six parameters on each of the 361 respondents who responded to 12 choices. While we believe this study sufficiently typical to enable us to project comparable results to studies with similar numbers of parameters, respondents and choices per respondent, it is appropriate to speculate which of these characteristics are likely to be most critical for convergence. In our experience, the number of respondents is less critical to this result because the aggregate distribution will stabilize fairly quickly. By contrast, the number of parameters and the number of choices per respondent will have a significant impact on the stability of the model. In the current study, having twice as many parameters as choices enabled the projection of individual parameters to be quite stable. This stability was helped by the fact that there was general agreement on the part of respondents about whether an attribute was positive or negative. That is, except for contract length, people generally agreed on the sign of the parameters. Thus, the model had less work to do in adjusting the aggregate estimates in response to individual choices. However, caution should be taken in attempting to project our results to studies in which the parameters have greater variation, or cases where there are more parameters relative to the number of choices from each respondent.

How do the two methods differ with respect to ease of use? Assuming a normal distribution of logit coefficients, both methods are fairly straightforward to implement.

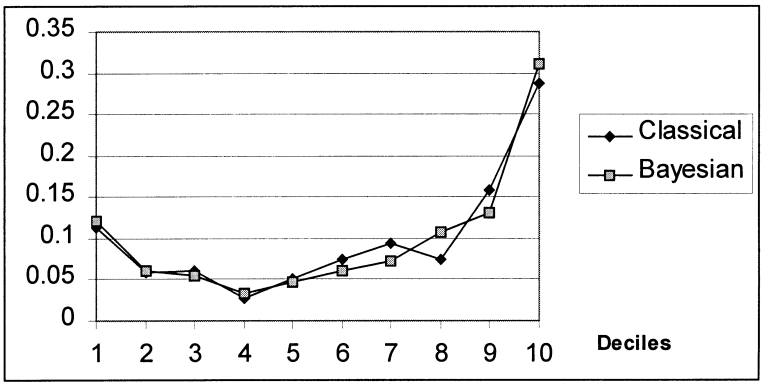

Figure 1. Predicted Probabilities of Chosen Alternatives.

With other specifications, there can be differences in the convenience attached to the computational procedures employed by each approach. The main differences that we see among them are the following.

(1) For the classic case, it can sometimes be difficult to locate the maximum of the likelihood function with some distributions and behavioral models. The likelihood function can have multiple local maxima, and assuring oneself that a local maximum is indeed the global maximum can be computationally difficult. Also, the likelihood function might not be well approximated by a quadratic. The standard numerical maximization procedures work best when the function is close to a quadratic. We have found that the maximization procedures can often fail to find an increase even though a maximum has not been located. This problem does not seem to arise with mixed logits using normal distributions for the coefficients, as we are using in the current paper. However, we have found it to arise with other distributions, particularly log-normals. (See the discussion below about non-normal distributions.) Bayesian procedures have an advantage in these circumstances because the maximum of the likelihood function does not need to be located under these procedures. Rather, draws from the posterior are taken. The average of these draws can be used as a classical estimator that is asymptotically equivalent to the maximum likelihood estimator.

(2) When the dimension of β_n is large, its covariance W has numerous elements. In classical estimation, each element of the upper diagonal of W generates a parameter that utilizes a degree of freedom. Computationally, the derivative of the likelihood function with respect to each element of W must be calculated, such that, with a full W, computation time rises with the square of the number of coefficients. To maintain a manageable number of parameters, off-diagonal elements of W are often constrained to zero under classical approaches. In contrast, the Bayesian approach can handle a full W almost as easily as a restricted W, as computation time rises much more moderately with the number of parameters.

(3) Identification is less of an issue in Bayesian, compared with classical approaches. In the classical estimation, unidentified parameters simply cannot be estimated. In the Bayesian approach, the prior can provide needed identification, or a flat prior can be specified such that unidentified parameters manifest themselves as flat areas of the posterior. Notice that the robustness of the Bayesian estimation to lack of identification can itself be problematic. Without a very large number of draws from the joint distribution of two confounded parameters, the analyst might not observe that a singularity, or near singularity exists in the model specification.

Reasons (1)–(3) provide motivation for estimation of mixed logits with Bayesian procedures even if a classical perspective is maintained. The computational disadvantage of Bayesian procedures arises from their need to draw from conditional posteriors. When the coefficients have a joint normal distribution, priors can be specified that make the conditional posteriors for b and W easy to draw from. However, changes in the distributional assumptions can be difficult to implement in the Bayesian procedures. In the classical procedure, alternative distributions can easily be specified for the coefficients. Further, some coefficients can be assumed to be fixed while others vary, and different distributions can be specified for different coefficients. For simulated maximum likelihood

the only change in the estimation procedure occurs in the line of code that specifies the draws of the coefficients. With Bayesian procedures, the situation is not as easy. For example, suppose one coefficient is assumed to be fixed while the others are jointly normal. This change cannot be implemented by simply setting the variance of the fixed coefficient to zero within the sampling algorithm for drawing the coefficients for each person. The algorithm used with mixed logits (i.e., Metropolis-Hastings) accepts new draws for some customers and rejects new draws for other customers such that the fixed coefficient would differ over customers in one iteration of draws rather than being the same for all customers. Instead, a new layer of conditioning is required in the Gibbs sampling, with draws of the fixed coefficient conditional on the mean, covariance, and values of the random coefficients. While this extra layer of conditioning is not difficult in principle, it can lead to slower convergence. Similarly, if non-normal distributions are specified for the coefficients, the conditional posteriors for the parameters of these distributions are usually less convenient. By contrast, when β_n is normally distributed, the conditional posterior of b is normal and the conditional posterior of W is inverted Wishart, under appropriate priors. With other distributions, it is not as easy to specify priors that give easy-to-draw-from conditional posteriors. Work in this area is proceeding (e.g., Boatwright, McCulloch and Rossi, 1999), but the ease of drawing from the conditional posterior remains a central concern with Bayesian methods.

Our finding of equivalence between expected partworths at the individual level does not reconcile the interpretive differences between the Bayesian and classical perspectives. Instead, our results show that the numerical procedures, independent of interpretation, converge given reasonable sample sizes. This finding suggests that each method can be applied and then interpreted from either, or both perspectives. Classicists can use the Bayesian numerical procedures and interpret the results in a classical way, and Bayesians can use the classical estimation procedures without abandoning a Bayesian perspective. In fact, the researcher can maintain both perspectives simultaneously, applying the numerical procedure that is most convenient and interpreting the results in ways that build on the conceptual insights of both traditions.

Notes

1. The relation is primarily due to the fact that the posterior distribution is proportional to the likelihood function times the prior distribution. For a flat prior (as is usually specified) or asymptotically for any prior that nowhere vanishes, the posterior distribution, which is the basis for Bayesian estimation, is therefore proportional to the likelihood function, which is used for classical estimation. Also, the mean of the posterior, taken as an estimator, is asymptotically equivalent to the maximum likelihood estimator.
2. The Bayesian approach represents the uncertainty in terms of a posterior distribution, while the classical approach represents it with the asymptotic sampling distribution of the maximum likelihood estimator.
3. T can be as low as 1. J and T can vary over customers, though we suppress the notation for this possibility.
4. We are grateful to Ahmad Farqui, of EPRI, for allowing us to use these data.

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