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GETTING THE 'CORRECT' ANSWER FROM SURVEY RESPONSES: A SIMPLE APPLICATION OF THE EM ALGORITHM

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The final draft of this article is appended.

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Summary

This note addresses a problem that can arise in surveys, in which some respondents misinterpret the rating method and so assign high ratings when they intended to assign low ratings, and vice versa. We present a method that allows these misinterpretations to be corrected with high probability, and more meaningful conclusions drawn. The method is illustrated with data from a community value survey.

Keywords: Community Value Survey, Missing data, EM algorithm, regression mixture.

1. Introduction

In many sample surveys, responses are commonly recorded as ratings on, say, a 10-point scale with 1 corresponding to Poor, and 10 to Excellent. For some questions, the sense of the scale may be reversed, and a high score may correspond to an undesirable outcome. Switching the sense of scales may be very natural in the context of the question, but can often lead to confusion on the part of the respondents, who unwittingly report a score the reverse of that intended by the framers of the survey. If this is sufficiently common, the analysis of the survey is obviously compromised.

In this note, we describe a survey where this problem was particularly intractable, and propose a generally applicable method for adjusting the data to obtain more sensible

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results. Since our application is to a community value survey, we first provide some background on this type of study.

1.1 Community Value Surveys

A *Community Value Survey* (Fisher, Cribb and Peacock 2008) is a structured approach to surveying community attitudes towards a specific issue, in which the community's overall perception of the *Value* of the work done by a research agency is elaborated in terms of a *Community Value Tree* of *Drivers* and their *Attributes*. The method is an analogue of a Customer Value survey, a well-established methodology for managing customer value (Kordupleski and Simpson 2002), and has proved useful in practice, for reasons analogous to those discussed by Kordupleski and Simpson, namely:

- the approach provides a means of connecting customer results to business results;
- the data are actionable;
- it is possible to check that no important driver of Customer Value has been omitted; and
- the data provide a means of generating customer focus throughout the enterprise.

The Community Value case study reported by Fisher *et al.* (2008) related to the use of genetically modified viruses to manage a population of pest mice in order to avoid the devastating economic and social consequences of a mouse plague. More recently, a weekly national Community Awareness Survey has been conducted in Australia to monitor the community's attitudes towards so-called 'invasive animals' and how they might be managed. (The term 'invasive animal' is not restricted to exotic species, but includes such things as rabbits, Indian Mynah birds, seagulls, European carp, kangaroos, *etc.* that are living where they are not wanted.)

The starting point for any Value survey, in this context, a Community Value survey, is to define a concept for the *Value* that the research agency provides to the Community. In

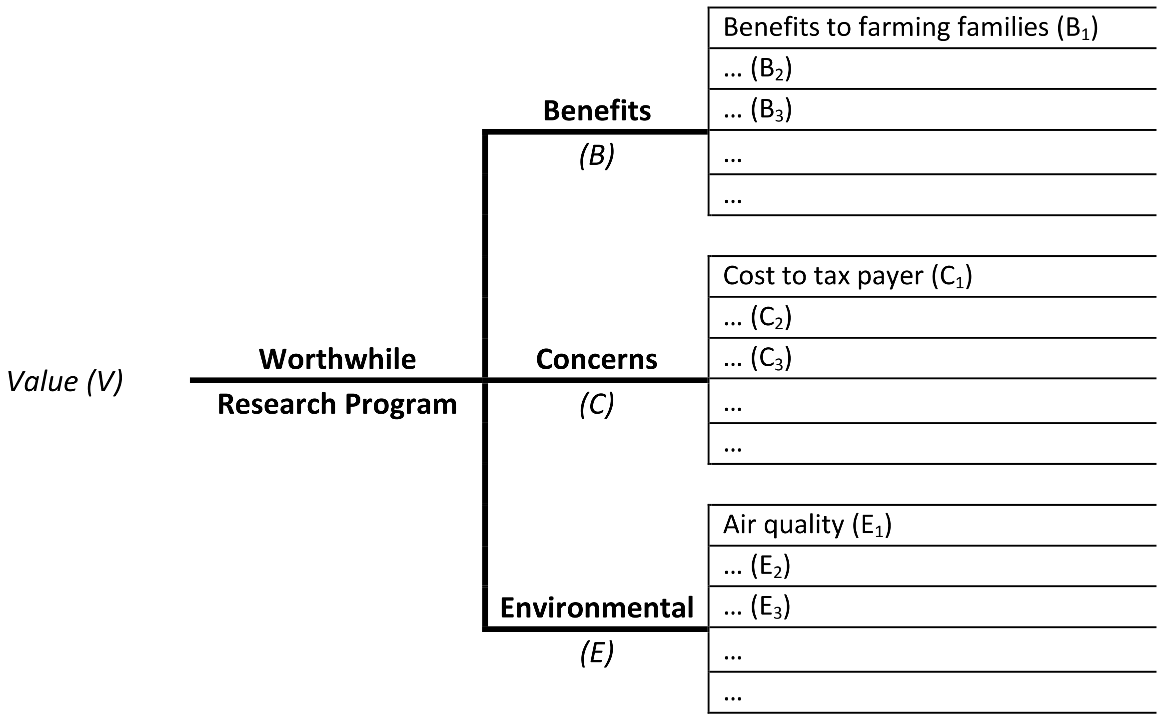

Figure 1: *Typical structure of a Community Value Tree. The concept of Value is captured by Worthwhile Research Program. The communitys overall perception of Value is modelled in terms of the perceived Benefits of the research, the perceived Concerns about the research, and perceptions about investing in research into environmental problems. In turn, each of these is modeled in terms of attributes derived from market research. (The parenthetical letters are variable names.)*

the case study, *Value* is interpreted as "Worthwhile Research Program". The Community Value Tree that formed the basis of the survey had the structure shown in Figure 1.

The community's overall perception of Value is modelled in terms of respondents' perceptions about

- Benefits of the research;
- Concerns about the research; and
- Investment of funding in Environmental Research.

In turn, each of these is further modelled as a function of attributes derived from focus groups of experts and of community representatives.

By analogy with the Customer Value approach, requests to the survey respondent take the following form:

> *On a scale of 1 to 10, where 1 = Poor and 10 = Excellent, please rate the Agency's program on the following potential Benefits associated with its work:*
>
> Benefits to farming families
>
> Attribute 2
>
> Attribute 3
>
> ...
>
> *Overall, please rate the Agency's program on the Benefits of the research.*

There are also similar set of questions relating to Concerns about the research, and another set probing the respondent's attitude as to which environmental issues require research. The final question asks respondents to rate the overall value of the program:

> *Overall, then, please rate the agency on carrying out a worthwhile research program.*

Thus, each respondent produces a tree-structured set of ratings. The resulting sample of tree-structured responses can be analyzed using hierarchical regression modelling to yield fitted models of the form:

$$V = \alpha_0 + \alpha_1 B + \alpha_2 C + \alpha_3 E + e,$$

$$B = \beta_0 + \beta_1 B_1 + \beta_2 B_2 \cdots + \beta_r B_r + e,$$

$$C = \gamma_0 + \gamma_1 C_1 + \gamma_2 C_2 + \cdots + \gamma_s C_s + e,$$

$$E = \delta_0 + \delta_1 E_1 + \delta_2 E_2 + \cdots + \delta_t E_t + e.$$

Here, we have denoted the overall scores for Value, Benefits, Concerns and Investment in Environmental Research by V, B, C and E respectively. The subsidiary drivers of

Benefits are denoted by $B_1, \ldots, B_r$, with a similar notation for Concerns and Investment in Environmental Research. See Fisher, Lee & Sparks (2005) for a discussion of the statistical modelling and analysis issues and related references.

One advantage of this sort of structured survey is that it is possible to assess, at each level of model-fitting, whether all the most important explanatory variables have been included (using the adequacy of fit of each model). Improvement priorities can then be assigned based on those attributes that are rated relatively low and that have a relatively large regression coefficient. Kordupleski and Simpson (2002) provide a detailed explanation.

1.2 Interpretation errors in the survey

All of this appears straightforward. However, an awkward problem occurs in relation to the choice of rating scale for *Concerns*. Two opposing approaches are:

(a) On a scale of 1 to 10, where 1 = Unconcerned and 10 = Very Concerned, please rate the Agency's program on the following attributes:

Cost to taxpayer

Attribute 2

Attribute 3

...

or

(b) On a scale of 1 to 10, where 1 = Very Concerned and 10 = Unconcerned, please rate the Agency's program on the following attributes:

Cost to taxpayer

Attribute 2

Attribute 3

...

Approach (a) has the advantage that increasing *Concerns* are associated with increasing ratings, which appears to be a more natural association than the reverse, based on responses in a number of surveys. On the other hand, this rating approach is the opposite of that used for *Benefits*, and so can lead to confusion. Approach (b) is in sympathy with the rating approach to *Benefits*, but is counterintuitive for some people.

In fact, despite extensive experimentation with wording using both approaches over a number of weeks of the Community Awareness Survey, and with other guidance provided in an attempt to reinforce the correct interpretation of the rating, it has proved impossible to avoid confusing some 10–20 percent of respondents. In essence, when rating Concerns, some people continue to provide a rating of $11 - C$ instead of C. This is clearly the case, because people are invited to provide reasons for assigning the summary ratings on *Value*, *Benefits* and *Concerns*, and in numerous cases the reasons are not consistent with the ratings they have assigned. For example, a rating of 10, under interpretation (a) supposedly associated with a high level of concern about the use of pest control using genetically modified viruses, might be accompanied by a comment along the lines "*I don't care how you get rid of carp from the river, even if you have to nuke them. Just get rid of them*". Since not all respondents provide reasons, there is no way to make the corrections by this means. For some unknown reason (which might be as simple as failure to read the request carefully, in their haste to complete the survey), it appears that some people lose track of whether high ratings correspond to high or to low levels of concern.

However, there is a way of fitting the models in spite of these errors, by resorting to the EM algorithm.

2. Extracting the 'right' estimates from the wrong data

There are two cases to be distinguished:

(i) Modelling *Concerns* C as a function of $C_1, \ldots, C_s$,

(ii) Modelling *Value* V as a function of B, C and E.

Case (i) does not present a problem, provided that it is reasonable to assume C has been rated in the same way as $C_1, \ldots, C_s$ (*i.e.* all correctly or all incorrectly). Study of scatterplots of C versus each individual C_i supports this assumption.

Case (ii) however, is different. B and V have been scored in a particular way (*1 = Poor* and *10 = Excellent*), whereas we are unsure about C. However, the problem can be handled by fitting a mixture of two regression models. Such mixtures of regression models have been employed in different contexts by several authors; for example Desarbo et al. (2001) in marketing research, Kaplan (2005) in behavioral analysis, van Horn et al. (2009) in developmental psychology and Gaffney et al. (2007) in climate research. The fitting of these models is described in McLachlan and Peel (2000).

In our context, we imagine that respondents fall into two groups: those who correctly interpret the Concerns question according to the instructions, and those who don't. In the survey, respondents were instructed to use interpretation (b) above, so that higher scores should be associated with less concern, and the regression coefficient for *Concern* should be positive. Responses from the first group are modelled by the equation

$$V = \alpha_0 + \alpha_1 B + \alpha_2 C + \alpha_3 E + e$$

while responses from the second follow

$$V = \alpha_0 + \alpha_1 B + \alpha_2 (11 - C) + \alpha_3 E + e.$$

Denote the proportion in the first group by p. Then, assuming the regression errors are normally distributed with zero mean and standard deviation σ, a randomly chosen response has density

$$\frac{p}{\sigma}\phi_1(V) + \frac{1-p}{\sigma}\phi_2(V)$$

where ϕ is the standard normal density,

$$\phi_1(V) = \phi\left(\frac{V - \alpha_0 - \alpha_1 B - \alpha_2 C - \alpha_3 E}{\sigma}\right)$$

and

$$\phi_2(V) = \phi\left(\frac{V - \alpha_0 - \alpha_1 B - \alpha_2 (11 - C) - \alpha_3 E}{\sigma}\right).$$

2.1 Model fitting

Fitting the model requires maximizing the log-likelihood corresponding to this density; this is done using the EM algorithm (Dempster, Laird and Rubin 1979). There is some specialized software available to do this, for example the R package FlexMix (Leisch, 2004). However, the EM algorithm in this case is equivalent to a series of repeated weighted linear regression fits, so can easily be performed using standard software.

To do this, we introduce group labels z_{ij}, where $z_{ij} = 1$ if the jth respondent is in group i, else 0. Since the z's are unobservable, we regard them as missing data. If we did know their values, the log-likelihood of the complete data $(V_j, B_j, C_j, E_j, z_{1j}, z_{2j}), j = 1, \ldots, n$ would be

$$\sum_{j=1}^{n} z_{1j} \log p + \sum_{j=1}^{n} z_{2j} \log(1-p) - \frac{n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum_{j=1}^{n} z_{1j}(V_j - \alpha_0 - \alpha_1 B_j - \alpha_2 C_j - \alpha_3 E_j)^2 - \frac{1}{2\sigma^2} \sum_{j=1}^{n} z_{2j}(V_j - \alpha_0 - \alpha_1 B_j - \alpha_2(11 - C_j) - \alpha_3 E_j)^2. \quad (1)$$

The expected value of the complete data log-likelihood, conditional on the observed data, is obtained by replacing z_{1j} and z_{2j} by their conditional expectations,

$$\tau_{1j} = \frac{p\phi_1(V_j)}{p\phi_1(V_j) + (1-p)\phi_2(V_j)},$$

and $\tau_{2j} = 1 - \tau_{1j}$. These parameters are the posterior probabilities of correctly interpreting (respectively misinterpreting) the survey instructions for Concerns, and may be used to correct the responses.

The EM algorithm consists of a series of iterations, where at each iteration we evaluate this expected conditional log likelihood using the current values of the parameters (the E-step) and then maximize the result with respect to the parameters (the M step). In this case, the maximum value of p occurs when $p = \sum_j \tau_{1j}/n$. The maximising value of the regression coefficients are obtained by fitting a regression to $2n$ data points with responses $V_1, \ldots, V_n, V_1, \ldots, V_n$, weights $\tau_{11}, \ldots \tau_{1n}, \tau_{21}, \ldots \tau_{2n}$ and covariates $B_1, \ldots, B_n, B_1, \ldots, B_n$; $C_1, \ldots, C_n, 11-C_1, \ldots, 11-C_n$; $E_1, \ldots, E_n, E_1, \ldots, E_n$. Finally, the value of σ is updated using $\sigma^2 = RSS/n$ where RSS is the (weighted) residual sum of squares from the regression. Note that this is not the estimate of σ that will be be returned by the regression program.

These maximizing values then become the input parameters for the next iteration. Thus the mixture log-likelihood is maximized by repeatedly applying the E and M steps, starting with a set of initial values for p, σ and the α's.

A potential difficulty is that different starting values may lead to different local maxima of the mixture log-likelihood. In particular, it is clear that the log-likelihood (1) remains unchanged if we make the transformations $p \to (1-p)$, $\alpha_0 \to (\alpha_0 + 11\alpha_2)$ and $\alpha_2 \to -\alpha_2$. Thus, the likelihood has two equal global maxima. By convention, we will take the maximum to be the one where the coefficient α_2 is positive. If we start the EM iterations with a starting value for which α_2 is positive, our experience has shown that the iterations converge to this solution.

2.2 Standard errors

Using the results of Louis (1982), we can calculate the observed information matrix $I^{(inc)}$ for the incomplete data as

$$\begin{aligned} I^{(inc)} &= E[I^{(c)}|Observed\ data] - \sum_{j=1}^{n} E[S_j^{(c)} {S_j^{(c)}}^T|Observed\ data] \\ &\quad + \sum_{j=1}^{n} E[S_j^{(c)}|Observed\ data] E[S_j^{(c)}|Observed\ data]^T \qquad (2) \end{aligned}$$

where $I^{(c)}$ is the complete data observed information matrix, and $S_j^{(c)}$ is the complete data score for the jth respondent. Explicit forms for these, and a simple computational formula for $I^{(inc)}$ are given in the Appendix. The standard errors can then be obtained in the usual way by inverting $I^{(inc)}$.

3. An example

In the Community Awareness Survey mentioned in the Introduction, part of the survey is structured as a Community Value Survey. Figure 2 shows a graph of jittered values of the pairs (*Value*, *Concerns)* for the most recently acquired data, comprising responses from 1129 respondents, together with a lowess fit, which indicates the basic problem with the responses (the corresponding graphs of Value against the other two Drivers do not manifest this effect).

If we fit an ordinary linear regression to the data, with Value as response, we obtain the following results:

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.62456    0.19948  13.157  < 2e-16 ***
B             0.42977    0.01835  23.418  < 2e-16 ***
C            -0.06952    0.01573  -4.418 1.09e-05 ***
E             0.28234    0.01952  14.463  < 2e-16 ***

Residual standard error: 1.174 on 1125 degrees of freedom
Multiple R-squared: 0.482,      Adjusted R-squared: 0.4807
F-statistic:   349 on 3 and 1125 DF,  p-value: < 2.2e-16
```

The R^2 of 0.482, together with the very small (negative!) coefficient for C, suggest that a non-trivial number of respondents were confused. We assume that, had no confusion existed, the regression coefficient of C would be positive. Starting the EM algorithm with values (0,0,1,0) for the $\alpha's$, yields the estimates

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.15246    0.21187   5.440 5.34e-08 ***
B            0.40964    0.01826  22.429  < 2e-16 ***
C            0.23352    0.02546   9.174  < 2e-16 ***
E            0.25775    0.01937  13.308  < 2e-16 ***
```

and an estimated value of p of 0.315 with a standard error of 0.014. This indicates that some confusion does indeed reign, with over 30% of the respondents appearing to have misinterpreted the rating scale. Note that the standard errors above have been calculated by inverting the information matrix for the incomplete data as described in Section 2.2.

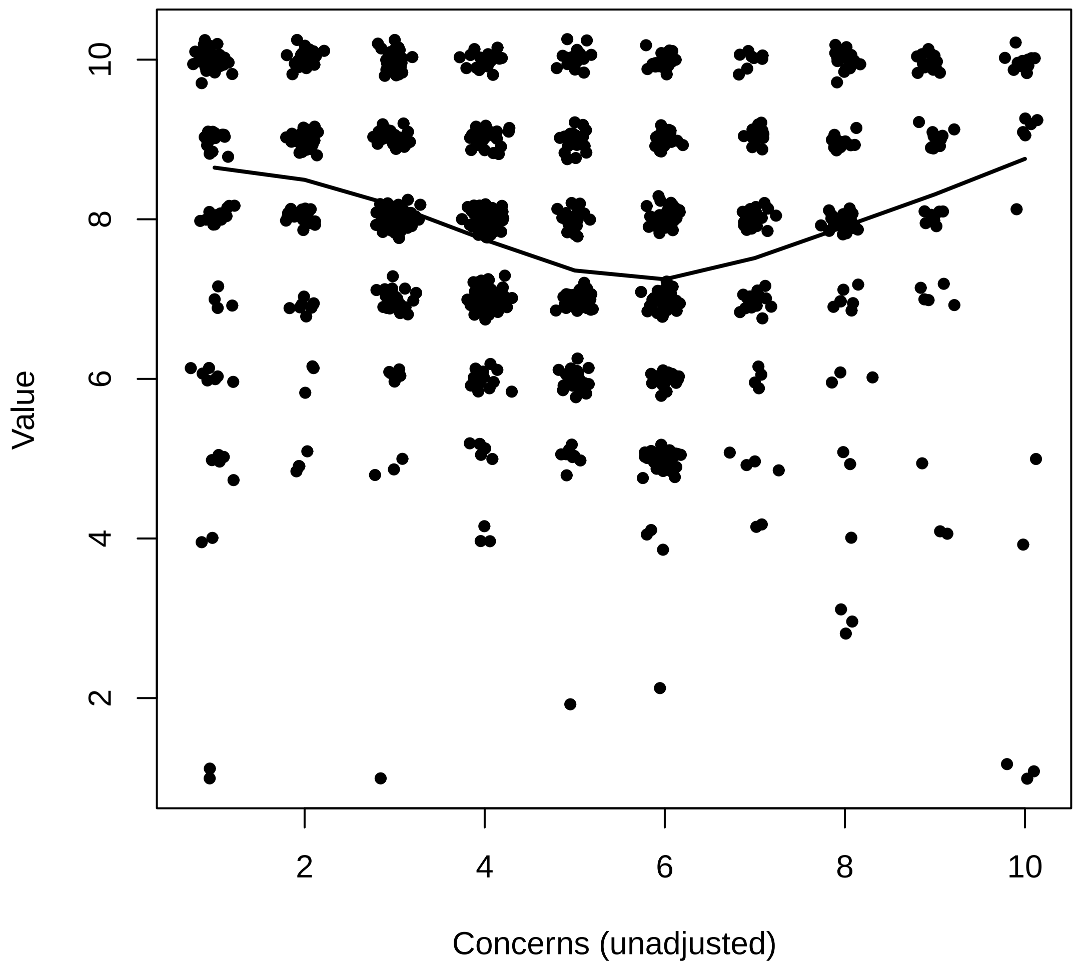

Figure 2: Plot of *Value* against *Concerns* for a sample of 1129 responses from a Community Value Survey. The responses have been jittered to avoid the overplotting of the discrete-valued responses and so provide a sense of the density of the points, and a lowess fit has been superimposed. The effect of misinterpretation of the rating system is evident, with both low and high ratings of Concerns associated with high ratings for Value (which makes no sense).

We also identified the "confused" respondents as those for whom $\tau_{1j} < \tau_{2j}$, *i.e.* the respondents having a greater probability of confusion. We then "corrected" their ratings for C to conform with the correct interpretation by changing them from C to $11 - C$, and ran an ordinary regression on the corrected data. The results were

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.15246    0.17867    6.45 1.66e-10 ***
B            0.40964    0.01667   24.58  < 2e-16 ***
C            0.23352    0.01450   16.11  < 2e-16 ***
E            0.25775    0.01773   14.54  < 2e-16 ***

Residual standard error: 1.068 on 1125 degrees of freedom
Multiple R-squared: 0.5718,     Adjusted R-squared: 0.5707
F-statistic: 500.8 on 3 and 1125 DF,  p-value: < 2.2e-16
```

with an R^2 of 0.5718, representing a considerable improvement over the fit of the uncorrected regression. Note in particular that the coefficient of the *Concerns* variable C now has the correct sign. Of necessity, the regression coefficients from the "corrected data" regression agree exactly with those from the EM solution, although the standard errors are no longer correct, being those calculated by the usual linear regression formula. Figure 3 shows a plot of jittered pairs (*Value,* adjusted *Concerns*), by way of comparison with Figure 2. There is now a much more plausible relationship between Value and the corrected Concerns.

4. Conclusions

Attitudinal surveys provide an ongoing challenge, in terms of using simple, unambiguous language to ensure that respondents interpret the survey questions correctly and apply the rating system appropriately. Community Value surveys provide one example where it proves very difficult to ensure that some respondents do not unintentionally apply the reverse ratings for some sets of questions. We have shown how regression mixture models can be applied in such tree-structured surveys to correct data in surveys where there is confusion over the rating scales employed. We have presented a rather simple

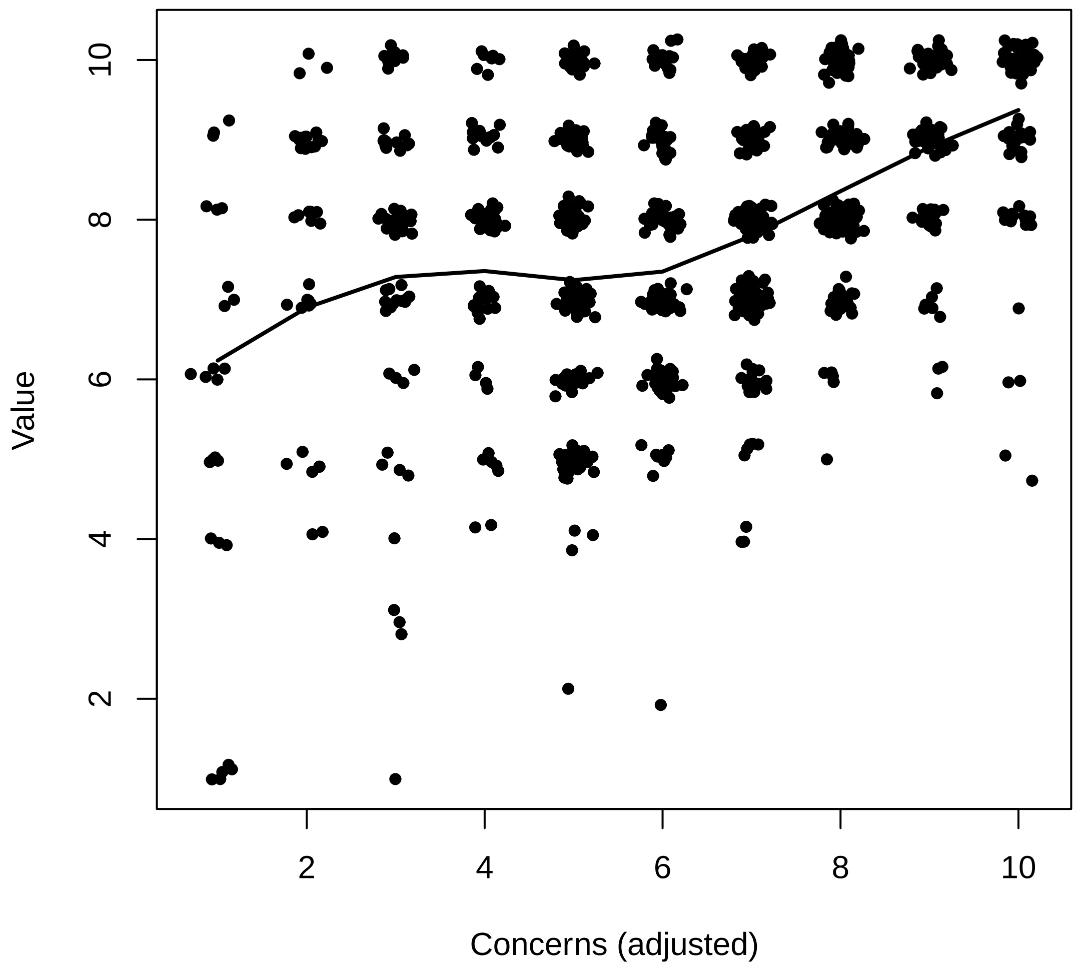

Figure 3: Plot of *Value* against adjusted *Concerns*, suggesting a more plausible linear relationship between the variates than in Figure 2.

example where the confusion over the rating scale was confined to a single variable, and have demonstrated the effectiveness of the EM algorithm in alleviating this problem in post-survey analysis. However, the same technique could be applied if the confusion applied to other variables in the regression. Exactly the same technique will work; we simply need to apply the transformation $C \to 11 - C$ to each affected covariate in the regression and proceed as before. For example, if we had an unambiguous covariate X, and two further covariates C_1 and C_2 subject to misinterpretation, we could consider a mixture of four models:

$$\begin{aligned}
V &= \alpha_0 + \alpha_1 X + \alpha_{21} C_1 + \alpha_{22} C_2 + e, \\
V &= \alpha_0 + \alpha_1 X + \alpha_{21} (11 - C_1) + \alpha_{22} C_2 + e, \\
V &= \alpha_0 + \alpha_1 X + \alpha_{21} C_1 + \alpha_{22} (11 - C_2) + e, \\
V &= \alpha_0 + \alpha_1 X + \alpha_{21} (11 - C_1) + \alpha_{22} (11 - C_2) + e.
\end{aligned}$$

If it is reasonable to assume that respondents confused about one of C_1, C_2 will be confused about both, only the first and last of these four models need be considered. Modification of the EM algorithm to cover the case of four models is straightforward.

Even more simply, the same technique could be applied to correct single variables in surveys, where the scale (say a 10 point scale) is sufficiently fine to assume the responses are effectively normally distributed. This involves consideration of the normal mixture

$$pN(\mu, \sigma^2) + (1 - p)N(11 - \mu, \sigma^2).$$

Appendices

Appendix 1: Derivation of the standard errors

The complete data observed information is of the form

$$I^{(c)} = \begin{pmatrix} I^{(c)}_{\alpha\alpha} & 0 & 0 \\ 0 & I^{(c)}_{\sigma\sigma} & 0 \\ 0 & 0 & I^{(c)}_{pp} \end{pmatrix}$$

where

$$\begin{aligned} I^{(c)}_{\alpha\alpha} &= \frac{1}{\hat\sigma^2}\sum_i\sum_j z_{ij}x_{ij}x_{ij}^T \\ I^{(c)}_{\sigma\sigma} &= \frac{2}{\hat\sigma^2} \\ I^{(c)}_{pp} &= \sum_j \frac{z_{1j}}{\hat p^2} + \sum_j \frac{z_{2j}}{(1-\hat p)^2}. \end{aligned}$$

The complete data scores are

$$S^{(c)}_j = \begin{pmatrix} \frac{1}{\hat\sigma^2}\sum_i z_{ij}r_{ij}x_{ij} \\ \frac{1}{\hat\sigma^3}\sum_i z_{ij}r^2_{ij} \\ \frac{z_{1j}-\hat p}{\hat p(1-\hat p)} \end{pmatrix},$$

where we have written $x_{1j}^T = (1, B_j, C_j, E_j)$, $x_{2j}^T = (1, B_j, 11 - C_j, E_j)$ and $r_{ij} = y_j - x_{ij}^T\alpha$. After some algebra, we can write the incomplete observed information (2) as

$$\left(\begin{array}{c|c} X^T(W - D_0 - D^TD)X & X^T(C_1 - C_2)r \\ \hline r^T(C_1 - C_2)X & \sum \tau_{1j}\tau_{2j}/\hat p^2(1-\hat p)^2 \end{array}\right) \tag{3}$$

where

$$X = \begin{pmatrix} X_1 \\ \hline X_2 \end{pmatrix},$$

X_i has jth row $(x_{ij}, r_{ij}/\sigma)$, $r = (r_{11}, \ldots, r_{1n}, r_{21}, \ldots, r_{2n})/\hat{\sigma}$ and

$$\begin{aligned} W &= \mathrm{diag}\{\hat{\sigma}^2 \hat{\tau}_{ij}\}, \\ D_0 &= \mathrm{diag}\{r_{ij}^2 \hat{\tau}_{ij}\}, \\ D &= (\mathrm{diag}\{r_{1j}\hat{\tau}_{1j})|\mathrm{diag}\{r_{2j}\hat{\tau}_{2j}\}), \\ C_1 &= \mathrm{diag}\{\hat{\tau}_{1j}/p, -\hat{\tau}_{2j}/(1-p)\}, \\ C_2 &= \mathrm{diag}\{(\hat{\tau}_{1j} - \hat{p})\hat{\tau}_{1j}, (\hat{\tau}_{1j} - \hat{p})\hat{\tau}_{2j}\}/\hat{p}(1-\hat{p}). \end{aligned}$$

Appendix 2: Different ways of attempting to avoid ambiguity in the wording of survey statements

In the section of the survey relating to Concerns, various wordings of the request were tested, to see if misinterpretation of the scoring system could be eliminated. This provided not to be possible. The following attempts were made:

1. *First attempt:* Please rate following possible Concerns using the scale of 1 to 10, where 1 = Unconcerned and 10 = Very concerned etc.

2. *Second attempt:* Earlier in the survey, you rated a number of different approaches to managing pest animals. The results of carrying out research into some of these approaches may provide some people with cause for concern.

   Some of the most important Concerns that have been identified by the community are listed below. Please rate these using the scale of 1 to 10, where 1 = Unconcerned and 10 = Very Concerned. In other words, the greater your concern with a particular item, the higher the rating you should assign to the item.

3. *Third attempt:* Earlier in the survey, you rated a number of different approaches to managing pest animals. The results of carrying out research into some of these approaches may provide some people with cause for concern. Some of the most important Concerns that have been identified by the community are listed below.

Please rate these using the scale of 1 to 10, where 1 = Unconcerned and 10 = Very Concerned.

In other words, the greater your concern with a particular item, the higher the rating you should assign to the item.

To check that this has been explained clearly, lets look at a couple of extreme cases. Using the scale of 1 to 10, where 1 = Unconcerned and 10 = Very Concerned, please rate the following:

	1	2	3	4	5	6	7	8	9	10	DK
Use of nuclear weapons	O	O	O	O	O	O	O	O	O	O	O
Capture and release in a safe and secure environment	O	O	O	O	O	O	O	O	O	O	O

Did you rate the first one a very high score? We hope so! This outcome of the research program would be a matter of high concern for most people. And did you rate the second one a very low score? Again, we hope so, as this is about the most humane way possible for handling pests, even if it may not be feasible. Please bear these examples in mind when you complete your answers on the next page. The greater your concern, the higher the rating.

4. *Final wording adopted:* (with intention to use EM-based correction) Using the scale of 1 to 10, where 1 = Unconcerned and 10 = Very Concerned, please rate the following Concerns about possible outcomes of the IA-CRC's research into managing Invasive Animals.

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