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Predicting Nominal Variable Relationships with Multiple Response

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ABSTRACT

For forecasting purposes, it is useful to predict the most likely response of an individual to a nominally-scaled variable using the response to a predictor variable which is also nominally scaled. Traditional statistical approaches are not suitable when respondents provide multiple responses. For practical applications it is desirable to provide a simple measure of prediction that is easy to calculate and understand. Two situations are described where predictions of multiple response are implemented and two indices of predictive association are developed for the situations. These indices provide predictive explanations where none were possible using traditional methods of predictive association. The need to complement these indices with conditional probabilities and log-linear models is suggested. The evaluation and implications of these indices are discussed.

KEY WORDS Multiple response; multiple index of predictive association

INTRODUCTION

There are a number of reasons why managers and researchers would be interested in predicting the nominal responses of a variable using another nominal variable. For example, demographic and other classifying variables are widely used in creating and targeting market segments (cf. Crawford, 1994). In many cases it is possible to use a classifying variable to predict if a consumer is more (or less) likely to be a current or future user of a product. Further, in the manufacturing of products, it is possible to decide the likelihood of a buyer being interested in a second attribute given that the buyer desires the first attribute. For instance, automobile manufacturers might find that those who wish to purchase cars with anti-lock brakes also prefer passenger-side airbags. Another example may involve allocation of resources within a firm; this may be accomplished by deciding on market-share changes from the previous year. Firms might find that it is most optimal in terms of profitability to allocate increased promotional resources for the next year to those product lines that gained share this year and allocate reduced resources to those that had declining market share. Numerous other applications exist where it is necessary to predict the values of a nominal variable using the levels of another nominal variable; these three examples are meant to show the multi-faceted applicability of such prediction in practical settings.

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Analysis and interpretation of multiple response data based on nominal variables are commonly encountered challenges in both experimental and survey-based research. For instance, respondents may provide multiple responses when asked the following question:

Which of the following makes of cars have adequate quality for your needs?

(a) Domestic (b) Japanese (c) European or other

Some respondents might check only one response. However, others may check two of the makes (for example, Domestic and Japanese), and others may check all three.

The Goodman and Kruskal (1954) Index of Predictive Association was the traditional approach to measuring the predictive power of one nominal variable in classifying the category of another nominal variable. Their Index of Predictive Association is based on the improvement over a null model in the correct prediction of one nominal variable using a predictor nominal variable. According to their null model, the most frequent category, measured over all respondents, is the predicted category for all respondents. The index has been widely used and can be found today in numerous research and methodology books (cf. Reynolds, 1983). However, it is impossible to use this traditional index of predictive association when multiple responses are present in the data. The traditional methods of analysing association between nominal variables, such as the repeated measures ANOVA or MANOVA (Keppel, 1982) or the contingency coefficient (Leimann, 1985), cannot be modified to handle multiple responses. The use of repeated measures ANOVA or MANOVA requires variables to be continuous and normally distributed (Keppel, 1982). The contingency coefficient equation does not have a provision to include more than one response. Calculating the traditional index of predictive association for one response option at a time and averaging across all response options provides misleading results because it does not take into account the joint occurrence of two or more responses.

The current methods that are used to analyse multiple response data are limited and do not provide an index that indicates the magnitude of the relationships between such variables. Survey researchers typically report the total number of responses in each category with the sum of all responses exceeding 100%. Most commonly available statistical packages are, at best, able to tabulate and cross-tabulate multiple response data without providing an estimate of predictive association (e.g. SAS, 1990; SPSS-X, 1988). Researchers in the areas of binary multidimensional scaling (DeSarbo and Hoffman, 1987) and correspondence analysis (Hoffman and Franke, 1986) have used multiple response data to plot data points—commonly respondents and brands—in a multidimensional joint space. These methods are based on using data of the type 'pick any /n' or 'pick k/n' (Levine, 1979). The terms for the data imply the choice of an unspecified number of alternatives out of n alternatives or k out of n alternatives, respectively. However, it should be pointed out that these methods do not provide a measure of the predictive association between two such variables.

PURPOSE OF RESEARCH

The aim of this study is to present a method to evaluate the predictive association between nominal variables that contain multiple responses. The specific research objectives for this paper are as follows:

(1) Derive two versions of the Index of Predictive Association between two nominal-scale, multiple-response variables, henceforth referred to as the Multiple Index of Predictive Association.
(2) Illustrate its application in several situations.

APPLICATIONS THAT ENCOUNTER MULTIPLE RESPONSE PREDICTIONS

In this paper we discuss two situations which lead to multiple responses and present two proposed indices, Lambda-L and Lambda-M, that provide a quantitative index of predictive relationships.

(1) At Least One Measure, Lambda-L

Consider a situation in which a researcher wishes to use one variable to predict at least one of many choices or options of a consumer. As an example, consider the design and introduction of new products (Crawford, 1994). If the manufacturer of a new frozen dessert product wants to test three different versions with the intention of introducing only one of them, it would be useful to relate the brand preferred to the psychographic or demographic characteristics of respondents. By knowing the consumer profile (e.g. income) of the group that finds the product most appealing, the manufacturer can decide on the segment to appeal to and select the media with similar income profiles. Since the manufacturer intends to introduce only one of the products, it is sufficient to know how many respondents prefer a particular product irrespective of the other products that the respondents prefer. An average measure of prediction based on predicting all the categories would not be meaningful here. Hence, a new measure of association is needed that can predict at least one of the responses to the dependent variable.

The At Least One measure, called Lambda-L, is developed to provide a measure of how well the demographic variable influences the product choice. According to this measure, a respondent is said to be correctly classified if it is possible to predict at least one of the responses of the dependent variable provided by the respondent, using the information in an independent variable. If a respondent provides two responses to a question, he or she is said to be classified correctly if either of the responses is correctly predicted.

(2) At Most Measure, Lambda-M

Many new products fail in the marketplace, in the sense that their actual market shares are much less than was forecasted (Crawford, 1994). In the new-product introduction decision discussed earlier, some manufacturers may wish to be conservative in their forecasting of new product success. As such, a manufacturer may decide to count only those respondents who specify that they will buy only the firm's product. This approach is based on the premise that the respondents who rated both the firm's brand and competitive brands as their multiple choices might end up buying the other brands listed in their multiple response. Thus, respondents who provide multiple responses are considered to be classified as predicted incorrectly under this framework. The corresponding statistic is Lambda-M.

As the two conditions discussed in this section are commonly encountered in many studies, Lambda-L and Lambda-M will be developed and illustrated in the remainder of this study.

MULTIPLE INDEX OF PREDICTIVE ASSOCIATION IN THREE SITUATIONS

We shall look at three situations, with the following combinations of conditions: (1) the dependent variable has multiple response and the independent variable has a single response, (2) the dependent variable has multiple response, as does the independent variable, and (3) the dependent variable has single response and the independent variable has multiple response. For each of these conditions, separate indices are defined based on predicting (a) at least one of the responses (Lambda-L) and (b) all responses (Lambda-M).

To illustrate the two indices of predictive association, 400 undergraduate students at a large university were surveyed. The questionnaire consisted of eight questions, some of which had potential multiple-response categories. All questions were related to automobiles or to the demographic characteristics of the respondent and are presented next in the context of the three situations. The purpose of conducting the survey was to illustrate the two indices. Therefore, the sole criterion for selecting illustrative questions was that some were single response (e.g. sex of respondent) and others had the potential for multiple response.

Situation 1

The simplest application of Multiple Index of Predictive Association involves using one independent variable without multiple responses to predict a dependent variable that has multiple responses. The two questions were

(1) Are you (a) Male (b) Female
(2) Which of the following makes of cars have adequate quality for your needs?
    (a) Domestic (b) Japanese (c) European or other

For calculating the At Least One measure, Lambda-L, the total sample was made up of 400 respondents, of whom 216 are male and 184 are female. (For convenience, the expression 'European or other' is shortened to 'European' henceforth in the text and tables.) For the 216 male respondents, the analysis provided the following breakdown: (a) only Domestic = 37, (b) only Japanese = 19, (c) only European = 30, (d) Domestic and Japanese = 22, (e) Domestic and European = 18, (f) Japanese and European = 21, and (g) Domestic, Japanese and European = 69. For the 184 female respondents, the responses break down as follows: (a) only Domestic = 15, (b) only Japanese = 43, (c) only European = 21, (d) Domestic and Japanese = 25, (e) Domestic and European = 14, (f) Japanese and European = 29, and (g) Domestic, Japanese, and European = 37.

The number of respondents in each cell of Table I(a) is obtained by adding all the multiple responses. For instance, for the 'adequate quality' question, 19 males responded 'only Japanese', 22 responded 'both Domestic and Japanese', 21 responded 'both Japanese and European', and 69 responded 'all three'—yielding a total of 131 males for whom at least one of the preferred makes of cars is Japanese. Similar allocations are provided for the other cells.

The column sums provide a basis for deciding the most likely category of make of car under the situation of having no knowledge about the sex of the individual. The best estimate for the

Table I. Cross-tabulation of sex of respondents versus their perception of the cars' quality

Sex of respondent	Perceived quality			Total
	Domestic	Japanese	European	
(a) Calculating Lambda-L				
Male	146	131	138	216
Female	91	134	101	184
Total	237	265	239	400
(b) Calculating Lambda-M				
Male	37	19	30	216
Female	15	43	21	184
Total	52	62	51	400

Note:
Dependent variable has multiple response and independent variable has single response.

randomly chosen respondent is the Japanese category by which a researcher would correctly predict 265 of the individuals. If sex of the individual was known, more of the respondents could be correctly classified. A randomly chosen male respondent could be classified as perceiving Domestic makes to have adequate quality, and the researcher would be able to classify 146 of the male respondents correctly. Similarly, a randomly chosen female respondent would be assumed to perceive adequate quality in Japanese cars, and 134 females would be correctly classified on this basis. Thus, knowing the sex of the individual, a total of 280 (=146 + 134) respondents are correctly classified versus only 265 without the use of the independent variable. The Lambda measure is based on the improvement in prediction from the inclusion of the independent variable:

$$\text{Lambda} = (KI - NI)/(N - NI) \tag{1}$$

where:

KI = number correctly classified after knowing the level of the independent variable
NI = number correctly classified with no information on the independent variable
N = total sample

This is a general formula and holds true for Lambda-L and Lambda-M. Equation (1) can be rewritten as follows:

$$\text{Lambda} = \frac{[\text{Sum of (MR)}] - \text{MCS}}{N - \text{MCS}} \tag{2}$$

where:

Sum of (MR) = sum over all rows of the maximum cell value in each row
MCS = maximum value of any column sum
N = total sample size

Using the data from Table I(a) which pertains to the At Least One measure, Lambda-L, this formula yields the following:

$$\text{Lambda-L} = \frac{280 - 265}{400 - 265} = 0.111$$

This formula is similar to the traditional index of predictive association in that the basic principle in both formulas is the *correct classification of a sample of respondents*. The number 0.111 provides a measure of the predictive power of sex of respondent in predicting perceived quality. The index varies in the range of 0–1. Note that the number of responses in each cell in the first row is greater than the row total (which equals the 216 male respondents). Although multiple responses are allocated to more than one cell in a row, double-counting is avoided in the actual estimation of the index because, by definition, only the cell with the largest frequency in each row yields the correct prediction. Thus, Lambda-L provides a measure of the prediction of values for a multiple response dependent variable, using a nominal scaled independent variable.[1] The implications of Lambda-L are discussed in a later section.

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1 It is possible to calculate an approximate χ^2 statistic that we will term Pseudo χ^2. However, this statistic should be treated with caution and used only as an approximation. Some of the responses, i.e. the multiple responses, are not independent of each other. In Table I(a), under the null hypothesis of no association, the expected value of the Male/Domestic cell is 128. This number is calculated in a manner similar to that in the single-response contingency table, i.e. (marginal row sum × marginal column sum)/total size of sample, which equals (237 × 216)/400. After calculating all the expected cell values, the Pseudo χ^2 statistic was calculated using the traditional approach to contingency tables. The calculated Pseudo χ^2 (2 d.f.) equals 9.06, which indicates a statistically significant relationship ($p < 0.05$).

Lambda-M is defined in a framework where a respondent is said to be correctly classified only if all his or her responses can be correctly predicted (Table I(b)). Without prior information about the sex of the respondent, the best estimate for the randomly chosen respondent's perception of quality is Japanese (62 respondents preferred only Japanese). With prior information, 37 males are classified as preferring Domestic and 43 females as preferring Japanese. The number of correct predictions is increased from 62 to 80 (=37 + 43). Although the allocation of respondents to cells is different from Table I(a), equation (2) can again be used to calculate Lambda-M:

$$\text{Lambda-M} = \frac{80 - 62}{400 - 62} = 0.053$$

The two measures, Lambda-L and Lambda-M, yield estimates that were consistent with their definitions. Lambda-M, being a conservative measure, has a smaller magnitude than Lambda-L, which is a liberal measure of predictive association. The magnitude of Lambda-L suggests a relatively stronger predictive power of the independent variable. This conclusion is a consequence of the way Lambda-L is defined: the dependent variable is said to be correctly predicted if even one of the response categories can be correctly predicted. The implication and usefulness of the measures relating to this situation as well as the next two situations are discussed in the Discussion and Conclusions section.

Situation 2

The indices, Lambda-L and Lambda-M, are also applicable where both the dependent and independent variables have multiple responses. The cross-tabulation needs to be structured a little differently from that of the first application wherein only the dependent variable had multiple responses. The question used as the independent variable is as follows:

(3) Which of the following makes of cars have adequate quality for your needs?
(a) Domestic (b) Japanese (c) European

The variable that is being predicted is as follows:

(4) If you asked your parents' opinion, what make of car would they recommend you buy?
(a) Domestic (b) Japanese (c) European

The tabulated data for calculating Lambda-L are presented in Table II(a). A total of 52 respondents felt that only Domestic cars had adequate quality for their needs. Of these 52 respondents, 38 were classified in the first cell as they felt that their parents would recommend Domestic cars alone or in combination with non-domestic cars. When these 38 respondents were asked what cars their parents would recommend, 34 said 'only Domestic', one said 'both Domestic and Japanese', and three said 'all three'. With no prior information, a randomly selected respondent's parents' recommendation will be for the purchase of a Domestic car, as the column sum is the highest for this category. Hence, 217 of the respondents are correctly classified under this rule. With the information of the respondents' perception of a car's quality, 261 of the respondents are correctly classified (based on adding the maximum cell in each row):

$$\text{Lambda-L} = \frac{261 - 217}{400 - 217} = 0.240$$

The data used for calculating Lambda-M are presented in Table II(b). The independent variable has the potential for multiple responses. A separate row is defined for each response category.

Table II. Cross-tabulation of cars' quality versus recommendation of car to purchase

	Recommend purchase			
Perceived quality	Domestic	Japanese	European	Total
(a) Lambda-L				
Domestic	38	12	9	52
Japanese	18	38	8	62
European	20	16	25	51
Domestic/Japanese	33	23	9	47
Domestic/European	18	8	12	32
Japanese/European	14	33	17	50
All	76	54	31	106
Total	217	184	111	400
(b) Lambda-M				
Domestic	34	8	6	52
Japanese	17	36	7	62
European	14	10	20	51
Domestic/Japanese	17	7	6	47
Domestic/European	12	7	7	32
Japanese/European	8	21	8	50
All	43	21	7	106
Total	145	110	61	400

Note:
Both variables have multiple responses.

Without considering the independent variable, 145 of the respondents are correctly classified. With the inclusion of the independent variable, 183 respondents are classified correctly.

$$\text{Lambda-M} = \frac{183 - 145}{400 - 145} = 0.149$$

Situation 3

In the third type of analytical situation, the independent variable has multiple responses (as in question (2) on perception of cars' quality) and the dependent variable has single response (as

Table III. Cross-tabulation of perceived quality and sex of respondent

	Sex of respondent		
	Male	Female	Total
Perceived quality			
Domestic	37	15	52
Japanese	19	43	62
European	30	21	51
Domestic/Japanese	22	25	47
Domestic/European	18	14	32
Japanese/European	21	29	50
All	69	37	106
Total	216	184	400

Note:
Independent variable has multiple response and dependent variable has single response.

in question (1) on respondents' sex). Interestingly, in this situation (Table III), Lambda-L and Lambda-M are equal, because the dependent variable does not have multiple responses. Consequently, the sum of column cells and row cells are equal to the marginal number of respondents in each of the row and column categories, respectively. In each case, without the independent variable, 216 of the respondents are correctly classified. With the inclusion of the independent variable information, 251 are correctly classified:

$$\text{Lambda-L} = \text{Lambda-M} = \frac{251 - 216}{400 - 216} = 0.190$$

ADDITIONAL AND ALTERNATIVE MEASURES

Conditional probabilities

The indices developed so far can be complemented with additional measures and statistics to provide greater insights to the analyst. The conditional probabilities of cells across rows provide the likelihood of each dependent variable level being observed for each level of independent variable. For instance, in Table I(a), the probability of a male (i.e. conditional on being male) perceiving Domestic, Japanese, and European cars to have adequate quality are 0.68, 0.61, and 0.64, respectively. These probabilities are calculated by dividing the cells frequencies by row totals. Similarly a female respondent has the conditional probabilities of 0.49, 0.73, and 0.55 of viewing US, Japanese, and European cars, respectively, as having adequate quality. These conditional probabilities are in the framework of predicting at least one of many choices of the consumer. The conditional probabilities of prediction under the 'at most measure' framework can be obtained by dividing the cells in Table I(b) by the row totals. Overall, the multiple index of predictive association provides an estimate of the increase in the total number of observations being correctly classified knowing *all* levels of the independent variable, while the conditional probabilities provide estimates, separately, for *each* level of the dependent variable based on *each* level of the independent variables.

Log-linear models

The contingency tables obtained with multiple response data can be analysed using the log-linear model approach. Log-linear models provide estimates of the probability that a randomly chosen observation will fall into cells defined by levels of the nominal variables. In addition, the effect of each independent variable and combinations of two or more independent variables can be determined. To provide a comparison with the index of predictive association, the log-linear model analysis was performed on the data used for Tables I and III. The multiple-response question on the perceived quality being adequate was split into three yes/no variables. The first variable was coded 0–1 corresponding to whether a domestic car had adequate quality or not. Similarly, the second and third variables were coded 0–1 based on whether Japanese and European cars had adequate quality, respectively. (Unlike the traditional dummy variable approach where the number of dummy variables equals one less than the number of levels of a multichotomous variable, with multiple-response data it is necessary to define three dummy variables for three levels as the coding of two of the dummy variables does not automatically define the response for the third dummy variable.) The fourth variable was the male/female dummy variable. The transformation resulted in a $2 \times 2 \times 2 \times 2$ design.

The results of the log-linear analysis are presented in Table IV. First, the main effects model with no interactions was nan and the chi-squared values associated with each variable was

Table IV. Maximum likelihood estimates of log-linear model analyses of data

(a) Main effects only

Effect	Parameter	Estimate	Standard error	Chi-square	Significance prob.
Male/Female	1	−0.0802	0.0502	2.55	0.1100
Domestic	2	−0.0905	0.0518	3.04	0.0810
Japanese	3	−0.2226	0.0540	16.99	0.0000
European	4	−0.0997	0.0520	3.68	0.0549

Model Likelihood Ratio chi square with 9 d.f. = 61.05 ($p<0.0001$)

(b) Main effects and three two-way interactions

Effect	Parameter	Estimate	Standard error	Chi-square	Significance prob.
Male/Female (MF)	1	−0.0602	0.0578	1.08	0.2976
Domestic	2	−0.0837	0.0527	2.52	0.1126
Japanese	3	−0.2333	0.0554	17.73	0.0000
European	4	−0.0964	0.0523	3.40	0.0651
MF* Domestic	5	0.1885	0.0527	12.78	0.0004
MF* Japanese	6	−0.0969	0.0554	3.06	0.0804
MF* European	7	0.1025	0.0523	3.85	0.0499

Model Likelihood Ratio chi square with 6 d.f. = 39.19 ($p<0.0001$)

Note:
Two cells had zero observations—the Male and neither Domestic, Japanese, or European cell and the Female and neither Domestic, Japanese, or European cell.

obtained (Table IV(a)). Next, the log-linear model was run with main effects and three two-way interactions—the male/female dummy variable crossed separately with the three car sources. Significance of the three interaction terms, taken together, would indicate that there was a relationship between the original variables of interest—the male/female variable and the perceived quality of Domestic, Japanese, and European cars. The chi-squared statistic was used to test the relationship. The maximum likelihood chi-squared statistic reported in standard log-linear software provides a measure of the variance remaining in the data after the model parameters are estimated. If all possible interactions including higher-order interactions are introduced into the model, leading to a fully saturated model, the remaining variance is fully explained by the model. Thus, the difference in the chi-squared statistic in the two models as reported in Table IV reflects the effect of the three two-way interactions. The chi-squared value of 21.86 (=61.05 − 39.19) with 3 degrees of freedom is significant ($p<01$). Further, as a rough indicator of the strength of this relationship, the proportional reduction in the overall chi-squared statistic for the model by adding the three interaction terms equals 21.86/61.05 = 0.36.

The net conclusion one can draw from comparing the log-linear model and the multiple index of predictive association to analyse multiple-response data is that neither approach is clearly superior—their suitability depends on the specific application. The index provides an indication of the net gain in correct classification of observations based on knowing the levels of the independent variable. It is an aggregate measure and provides the total gain in the number correctly classified. It is possible that some observations that were correctly classified prior to using the information on the independent variable are subsequently misclassified using the levels of the independent variable. A non-zero multiple index of predictive association merely implies that the number of such misclassifications are less than the number of the previously misclassified observations that get correctly classified following the use of the independent variable. In contrast, the use of log-linear models does not provide such diagnostics from the data, rather, indicating the effect of independent variable influence on the cell counts (or cell probabilities). In addition, the index comes in two versions, Lambda-L and Lambda-M. The two versions for the two situations are not a part of the general log-linear model.

Finally, log-linear models are more complex in their formulation and their results are not as easy to interpret, particularly in regard to the number of observations correctly classified. Needless to say, log-linear models offer several advantages in those situations which require overall statistical significance, significance of individual parameters, the overall significance of the relationship, and distributional properties of estimates. If these properties are of interest, then the analyst must give log-linear models a strong consideration. If estimating the predictive properties in terms of the net gain in the correct classification are of interest then the multiple index of predictive association must be used. Nothing precludes the use of both techniques, particularly where there is a need for extensive and broad evaluation of multiple response data.

DISCUSSION AND CONCLUSIONS

This paper has presented and illustrated two Indices of Predictive Association for analysing multiple-response data. Both the prediction of at least one of the multiple response categories, Lambda-L, and the prediction of all multiple response categories, Lambda-M, were discussed. The three combinations of responses were single-response independent variable with a multiple-response dependent variable; a multiple-response independent variable with a multiple-response dependent variable; or a multiple response independent variable with a single-response dependent variable. The calculations of Lambda-L and Lambda-M have been demonstrated for each of these three situations.

As a first step, the magnitudes of Lambda-L and Lambda-M, in each of the three combinations of variables, measure the ability of one nominal variable to predict the value of another nominal variable. Further, they measure the net gain in the number of respondents classified correctly by taking into account the values of the independent variable divided by the number of respondents misclassified when the independent variable values are unknown. A positive value for the indices indicates that the net gain in correct classification is positive, although those classified correctly prior to the use of the independent variable could be misclassified as a result of of knowing the values of the predictor variable. Consequently, if Lambda-L equals 0.3, it implies that there is a 30% net gain in correct classification by the use of the predictor variable. Correct classification for Lambda-L is based on predicting at least one of the multiple responses correctly. Similarly, a value of 0.3 for Lambda-M refers to a 30% gain in correct classification—with the term 'correctly classified' referring to At Most rules of correct classification.

The magnitude of Lambda-L and Lambda-M may be viewed in the context of effect sizes observed in consumer research and marketing studies. Peterson *et al.*, (1985) observed that the average effect size or omega-squared in such studies was 0.1, suggesting a norm of a medium effect size when an equivalent magnitude is encountered in a study. In contrast, researchers in the area of experimental designs (Cohen, 1988) classify 0.3 as a low effect size when comparing population differences. The benchmark for Lambda-L and Lambda-M is developed taking into consideration these two figures. Lambda-L and Lambda-M are bounded by the range

0–1, unlike differences between population means, which can exceed one. In contrast, the omega-squared measure is, in some sense, a square of the effect size and is excepted to be typically lower than Lambda-L or Lambda-M. Using these two benchmarks, the following guideline for judging the magnitude of Lambda-L and Lambda-M is posited: an effect size of 0.1 is small, 0.3 is medium and 0.5 is large. Using these guidelines many of the effect sizes encountered in this study are small with a few approaching the level of medium effect size.

The two indices provide a range of the predictive association between variables. It is useful to complement these measures with other statistics depending on the needs of the forecaster. For instance, the probability-based index developed by Umesh *et al.* (1992) serves as a useful complement. The indices are concise in that they provide a numerical parameter that summarizes the prediction. However, the indices being numbers oriented, a more complete picture of the data might be needed in some situations. Providing conditional probabilities in the cells, cell counts or using log-linear model analysis might help increase the understanding of the nature of the predictive relationships in the data.

This study has shown that it is possible to quantify the predictions with one nominal variable of another nominal variable when one or both have multiple responses. The indices developed here should be applied in a variety of forecasting applications before they are widely accepted in the field. However, these two indices provide a first step towards understanding the degree of forecasting capability of multiple-response variables.

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