

**On Certain Indices for Ordinal Data with Unequally  
Weighted Classes**

by

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## 1 Introduction

Various types of indices are widely used in real world applications. Some disciplines where the use of indices is widespread are index numbers (e.g., Allen (1975)), statistical quality control (e.g., Kotz and Lovelace (1998), Perakis (2002)), accounting (e.g., Wild et al. (2000)) and sample surveys (e.g., Bnerjee et al. (1999)). An interesting discussion of the historical background and the present situation on the use of statistical indicators in various fields of applications is provided by De Vries (2001).

Recently, Maravelakis et al. (2003) developed some indices, which are similar in nature with the index suggested by Perakis and Xekalaki (2002) that have applications to statistical process control. The indices introduced by Maravelakis et al. (2003) can be used to measure the degree of concentration on the “large” or “small” values of a variable in ordinal scale. In that paper, the use of these indices in sample surveys is considered, where often one is faced with questions whose answers have a somewhat natural ordering. A common example is a question whose possible answers are “Very Good”, “Good”, “Moderate”, “Bad” and “Very Bad”. To our knowledge no other authors has dealt with such indices.

Different features of such types of data can be measured through various other indices such as Cohen’s (1960) Kappa and its modifications (see e.g., Bnerjee et al. (1999) and Doner (1999)) and the measure of nominal-ordinal association proposed by Agresti (1981) and Piccarreta (2001).

In this paper, the indices suggested by Maravelakis et al. (2003) are generalised

so as to measure the observed concentration on the “small” or “large” values more objectively. Specifically, the indices proposed here, ascribe different weights to each value of the variable in question according to its rank. These indices, as those suggested by Maravelakis et al. (2003), can be used in connection with several types of ordinal data, as explained in Section 7. Nevertheless, in the sequel we focus on their use in sample surveys.

Section 2, describes the indices defined by Maravelakis et al. (2003) and gives the rationale that led to the definition of the indices proposed in this paper. In the third section, we introduce the new indices and investigate their basic properties. Section 4 is devoted to the derivation of the variances of their estimators. The construction of confidence intervals for their actual values, using three alternative bootstrap techniques, is discussed in Section 5. The performance of the three methods is tested through simulation. An illustrative example based on real data that clarifies their estimation is given in Section 6. Finally, some concluding remarks are provided in Section 7.

## **2 Motivation**

Consider a discrete valued variable that takes a finite number of values from 1 to  $k$ , or a continuous variable with values grouped in  $k$  classes. Suppose that these  $k$  values or classes have a natural ordering starting from the “best” (value 1) to the “worst” (value  $k$ ) and exhibit an inherent symmetry, i.e. the number of values characterised as “positive” coincides with that of the “negative” ones. Thus, the first  $[k/2]$  values

have a “positive” interpretation whereas the last  $[k/2]$  have a “negative” one. If the value of  $k$  is odd, the  $([k/2] + 1)$ st value does not belong to any of these two categories and in the remaining of this paper is termed “neutral”.

In this paper, we consider the case where the variable under investigation consists of the answers to a question in a study which asks a person to choose one out of  $k$  possible categories. However, the analysis can be modified readily for any other variable with the above properties.

Let  $\pi_i (p_i)$ ,  $i = 1, 2, \dots, k$  denote the true (observed) proportion of answers for each of the  $k$  categories, where  $\pi_1 (p_1)$  refers to the “best” available answer, and  $\pi_k (p_k)$  to the “worst” one. Obviously, the “neutral” answer, if such an answer exists (i.e. if  $k$  is odd), is located at the point  $[k/2] + 1$ . We should remark that among the  $k$  possible answers we include the “neutral” answer (if it exists), but we do not take into consideration answers of the type “No opinion/No answer”. If such a type of answer exists, we should recalculate the observed proportions excluding this answer and we proceed using the theory developed in the sequel.

In Maravelakis et al. (2003) three alternative indices were defined for the assessment of the degree of concentration on “positive” answers. Index  $I_1$  was defined as

$$I_1 = \frac{\sum_{i=1}^{[k/2]} \pi_i}{\pi_0},$$

where  $\pi_0 = [k/2] \cdot (1/k)$ .

Index  $I_2$ , when  $k$  is odd, is given by

$$I_2 = \frac{\sum_{i=1}^{\lfloor k/2 \rfloor} \pi_i}{\sum_{i=\lfloor k/2 \rfloor + 2}^k \pi_i},$$

whereas, when  $k$  is even, it becomes

$$I_2 = \frac{\sum_{i=1}^{\lfloor k/2 \rfloor} \pi_i}{\sum_{i=\lfloor k/2 \rfloor + 1}^k \pi_i}.$$

Finally, in situations where  $k$  is odd,  $I_3$  is defined as

$$I_3 = \frac{\sum_{i=1}^{\lfloor k/2 \rfloor + 1} \pi_i}{\sum_{i=\lfloor k/2 \rfloor + 1}^k \pi_i}.$$

The actual values of these indices can be estimated by  $\widehat{I}_1$ ,  $\widehat{I}_2$ ,  $\widehat{I}_3$ , which are defined by the above formulae by substituting  $p_i$  for  $\pi_i$ ,  $i = 1, \dots, k$ .

A drawback of these indices is that they give equal importance to all categories. This fact may cause some vagueness in the results since fixed sums of “positive” or “negative” answers lead to the same values of the indices considered, without taking into account how these sums are composed. This statement is clarified through a simple artificial example given below. Suppose that the obtained proportions of answers in two questions are as given in Table 1:

(TABLE 1)

The resulting estimates of the indices for both questions are:  $\widehat{I}_1 = 2$ ,  $\widehat{I}_2 = 16$  and  $\widehat{I}_3 = 4.75$ , even though there exist substantial differences in the proportions of the “positive” categories. Actually, in the first case the “positive” answers are mainly comprised of the answer “Good”, while in the second case of the answer “Very Good”.

Thus, one would expect larger index values for the second question since, despite the fact that the sum of the proportions of the two “positive” categories coincides with the corresponding sum of question 1, its much larger proportion in the “best” category (i.e. “Very Good”) provides evidence of a stronger tendency of the respondents to select the “positive” answers. The source of this deficiency of  $I_1$ ,  $I_2$  and  $I_3$  is related to the fact that they assign common weights (equal to unity) to all the components of the “positive” or “negative” categories and hence their values do not reflect changes in the values of each component when the sums of “positive” and “negative” answers are fixed.

### 3 The New Indices

Our purpose is to define new indices in order to overcome the problem of equal weights for all the possible answers. First, we introduce the methodology of computing the appropriate weights and afterwards we propose the new indices.

#### 3.1 The Weights

Let

$$w_j, \quad j = 1, \dots, [k/2]$$

denote the weight of the  $j$ th category of the “positive” (“negative”) answers. The value  $j = 1$  corresponds to the “best positive” and the “worst negative” answer and  $j = [k/2]$  corresponds to the “worst positive” and the “best negative” answer. An appropriate set of weights must satisfy the following conditions:

1.  $\sum_{j=1}^{\lfloor k/2 \rfloor} w_j = \lfloor k/2 \rfloor$
2. If the weight of the  $\lfloor k/2 \rfloor$  category is equal to a positive constant  $c$ , then the weight of the  $j$ th category is defined as  $(\lfloor k/2 \rfloor - j + 1)c$ . Hence, the weights for the categories 1 through  $\lfloor k/2 \rfloor$  are:  $\lfloor k/2 \rfloor c, (\lfloor k/2 \rfloor - 1)c, \dots, c$ . Obviously, these weights satisfy the property

$$w_1 - w_2 = w_2 - w_3 = \dots = w_{\lfloor k/2 \rfloor - 1} - w_{\lfloor k/2 \rfloor} = c$$

and assure that  $w_1 \geq w_2 \geq \dots \geq w_{\lfloor k/2 \rfloor}$ .

The first condition is imposed so as to assure the comparability of the values of the new indices to those of the indices proposed by Maravelakis et al. (2003). This arises from the fact that the sum of weights in both cases equals  $\lfloor k/2 \rfloor$ . The second condition ensures that the difference between the weights that correspond to any pair of equidistant categories is fixed. By this definition the weights reflect the strength of (positive or negative) views as expressed by the responses. Responses reflecting extreme situations should naturally carry more weight. The more “distant” from the “neutral” a category is, the greater its influence should be on the overall evaluation of the situation based on the totality of responses. This is indeed achieved by the suggested weights.

These conditions lead to the following system of  $\lfloor k/2 \rfloor + 1$  equations with unknowns  $w_1, w_2, \dots, w_{\lfloor k/2 \rfloor}$  and  $c$

$$\begin{matrix} \mathbf{A} & \times & \mathbf{w} & = & \mathbf{c} \\ \text{(\lfloor k/2 \rfloor + 1) \times \lfloor k/2 \rfloor} & & \text{\lfloor k/2 \rfloor \times 1} & & \text{(\lfloor k/2 \rfloor + 1) \times 1} \end{matrix}, \quad (1)$$

where

$$\mathbf{A} = \begin{bmatrix} 1 & -1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 1 & -1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 0 & 1 & -1 \\ 0 & 0 & 0 & \cdots & 0 & 0 & 1 \\ 1 & 1 & 1 & \cdots & 1 & 1 & 1 \end{bmatrix},$$

$$\mathbf{w} = \begin{bmatrix} w_1 & w_2 & \cdots & w_{[k/2]} \end{bmatrix}^\top \text{ and } \mathbf{c} = \begin{bmatrix} c & c & \cdots & c & [k/2] \end{bmatrix}^\top.$$

The system of equations in (1) has a unique solution given by

$$w_j = 2 \left( \frac{[k/2] - j + 1}{[k/2] + 1} \right), \quad j = 1, \dots, [k/2] \quad (2)$$

and

$$c = w_{[k/2]} = \frac{2}{[k/2] + 1}.$$

For example, if  $k = 7$ , the weights from the “best” or the “worst” category to the closest to the “neutral” category are  $6/4$ ,  $4/4$  and  $2/4$ , respectively. In the sequel, some generalisations of the indices  $I_1$ ,  $I_2$  and  $I_3$  are considered based on the weights defined in (2).

### 3.2 The Index $I_1^*$

Taking advantage of the weights defined in (2), the index  $I_1$  can be generalised to the form

$$I_1^* = \frac{\sum_{i=1}^{[k/2]} w_i \pi_i}{\pi_0}.$$

The values that  $I_1^*$  can take are in the interval  $[0, w_1/\pi_0]$ . The index takes a value close to 0 when only a few of the given answers belong to the  $[k/2]$  “positive” categories. On the contrary, values of  $I_1^*$  proximal to  $w_1/\pi_0$ , indicate that the respondents have a tendency to select the “positive” categories and, more specifically, the “best” of them. For example, in the case  $k = 5$ , the index  $I_1^*$  lies within the interval  $[0, 10/3]$ .

Obviously,  $I_1^*$  takes finite positive values. In addition, it is easy to compute confidence intervals for this index, not only via bootstrap, but also by using some methods for simultaneous confidence intervals for multinomial proportions (see Section 5). A drawback of this index is that it takes no account of the “negative” and “neutral” answers, thus ignoring the information provided by them.

The relationship between  $I_1^*$  and  $I_1$  is determined through the sign of the quantity  $r_1 = \sum_{i=1}^{[k/2]} \pi_i (1 - w_i)$ . Specifically, if  $r_1$  is positive (negative), then  $I_1^* < I_1$  ( $I_1^* > I_1$ ). Finally,  $I_1^* = I_1$  if  $r_1 = 0$ .

### 3.3 The Index $I_2^*$

A generalisation of the index  $I_2$  can be obtained by

$$I_2^* = \frac{\sum_{i=1}^{[k/2]} w_i \pi_i}{\sum_{i=[k/2]+2}^k w_{k-i+1} \pi_i},$$

assuming that  $k$  is odd. If  $k$  is even,  $I_2^*$  is defined as

$$I_2^* = \frac{\sum_{i=1}^{[k/2]} w_i \pi_i}{\sum_{i=[k/2]+1}^k w_{k-i+1} \pi_i}.$$

Index  $I_2^*$  takes values between 0 and infinity. When none of the respondents have chosen any of the  $[k/2]$  “positive” answers,  $I_2^*$  takes the value 0. On the other hand,

the value of the index cannot be computed (it becomes infinite) when none of the respondents has selected any of the  $[k/2]$  “negative” answers. It should be noted that, although this is an extreme case, it is a disadvantage for the index. Another drawback of  $I_2^*$  is that it excludes the “neutral” category. Furthermore, a difficulty with the use of this index is the fact that construction of confidence intervals is not possible without resorting to the method of bootstrap, since it requires knowledge of the distribution of the ratio of two weighted sums of multinomial proportions (see Section 5). However,  $I_2^*$  is more informative than  $I_1^*$  because it takes into account “negative” answers and, at the same time, its calculation is fairly easy. The mathematical formulation describing the relationship between  $I_1^*$  and  $I_2^*$  is established in the sequel.

Let  $r_2 = \left( \sum_{i=[k/2]+2}^k w_{k-i+1} \pi_i \right) / \pi_0$ . Then  $I_1^* < I_2^*$ , provided that  $r_2 < 1$ . On the other hand, in the case where  $r_2 > 1$ , it can be seen that  $I_1^* > I_2^*$ . Finally, the two indices take the same value if  $r_2 = 1$ . These relationships hold when  $k$  is odd and can be easily modified for even values of  $k$ .

### 3.4 The Index $I_3^*$

The index  $I_3^*$ , defined subsequently, can be used in situations where the total number of answers is odd. In this case, since the “neutral” category is involved in the computation, we have to assign a weight for it. In particular, the appropriate weights arise from (2) by substituting the value  $[k/2] + 1$  for  $[k/2]$ , i.e.

$$w'_j = 2 \left( \frac{[k/2] - j + 2}{[k/2] + 2} \right), \quad j = 1, \dots, [k/2] + 1.$$

Therefore, the new index is defined as

$$I_3^* = \frac{\sum_{i=1}^{\lfloor k/2 \rfloor + 1} w'_i \pi_i}{\sum_{i=\lfloor k/2 \rfloor + 1}^k w'_{k-i+1} \pi_i}.$$

Index  $I_3^*$  takes values that lie between 0 and infinity. The value 0 arises when all of the respondents have opted for a “negative” answer. On the other hand,  $I_3^*$  approaches infinity as the number of “positive” respondents increases. The fact that its value may tend to infinity is a drawback. However, it should be noted that this is not a probable scenario. Another disadvantage of  $I_3^*$  is that it is difficult to obtain confidence limits for its true value analytically. This problem can be overcome by using the bootstrap method (see Section 5). Index  $I_3^*$  surpasses a drawback of the indices  $I_1^*$  and  $I_2^*$  since it takes into account the “neutral” category.

### 3.5 Estimation

The actual values of the indices  $I_1^*$ ,  $I_2^*$ ,  $I_3^*$  can be estimated by

$$\hat{I}_1^* = \frac{\sum_{i=1}^{\lfloor k/2 \rfloor} w_i p_i}{\pi_0},$$

$$\hat{I}_2^* = \frac{\sum_{i=1}^{\lfloor k/2 \rfloor} w_i p_i}{\sum_{i=\lfloor k/2 \rfloor + 2}^k w_{k-i+1} p_i}, \text{ when } k \text{ is odd,}$$

$$\hat{I}_2^* = \frac{\sum_{i=1}^{\lfloor k/2 \rfloor} w_i p_i}{\sum_{i=\lfloor k/2 \rfloor + 1}^k w_{k-i+1} p_i}, \text{ when } k \text{ is even,}$$

and

$$\hat{I}_3^* = \frac{\sum_{i=1}^{\lfloor k/2 \rfloor + 1} w'_i p_i}{\sum_{i=\lfloor k/2 \rfloor + 1}^k w'_{k-i+1} p_i},$$

respectively. Obviously, these estimators arise by substituting  $p_i$  for  $\pi_i$ .

### 3.6 An Example

Let us now reconsider the example of Section 2 so as to clarify the estimation of the new indices and illustrate their superiority over  $I_1$ ,  $I_2$  and  $I_3$ . In the first question, the estimates of the new indices are:

$$\widehat{I}_1^* = \frac{(4/3)0.02 + (2/3)0.78}{0.4} = 1.3667,$$

$$\widehat{I}_2^* = \frac{(4/3)0.02 + (2/3)0.78}{(4/3)0.03 + (2/3)0.02} = 10.25$$

and

$$\widehat{I}_3^* = \frac{(6/4)0.02 + (4/4)0.78 + (2/4)0.15}{(6/4)0.03 + (4/4)0.02 + (2/4)0.15} = 6.3214,$$

respectively. The corresponding values for the second question are

$$\widehat{I}_1^* = \frac{(4/3)0.78 + (2/3)0.02}{0.4} = 2.6333,$$

$$\widehat{I}_2^* = \frac{(4/3)0.78 + (2/3)0.02}{(4/3)0.03 + (2/3)0.02} = 19.75,$$

$$\widehat{I}_3^* = \frac{(6/4)0.78 + (4/4)0.02 + (2/4)0.15}{(6/4)0.03 + (4/4)0.02 + (2/4)0.15} = 9.0353$$

and reflect the stronger tendency of the respondents to select the “positive” answers in the second question.

## 4 The Variances of the Estimators

In this section, the variances of the estimators of the three indices are assessed. For all the indices the method of bootstrap is implemented. Especially for  $\widehat{I}_1^*$ , a formula for finding the exact value of its variance is derived.

In the case of the index  $I_1^*$ , the parametric calculation is as follows.

Let  $\mathbf{p} = \begin{bmatrix} p_1 & p_2 & \dots & p_k \end{bmatrix}^\top$  denote the vector of observed proportions of the  $k$  answers and  $\boldsymbol{\pi} = \begin{bmatrix} \pi_1 & \pi_2 & \dots & \pi_k \end{bmatrix}^\top$  represent the corresponding true proportions. The unrestricted unbiased maximum likelihood estimator of  $\boldsymbol{\pi}$  is given by  $\mathbf{p}$  (see e.g., May and Johnson (1997)) and the covariance matrix of  $\mathbf{p}$  is

$$\boldsymbol{\Sigma} = \frac{1}{N} \begin{bmatrix} \pi_1(1 - \pi_1) & -\pi_1\pi_2 & \dots & -\pi_1\pi_k \\ -\pi_1\pi_2 & \pi_2(1 - \pi_2) & \dots & -\pi_2\pi_k \\ \vdots & \vdots & \ddots & \vdots \\ -\pi_1\pi_k & -\pi_2\pi_k & \dots & \pi_k(1 - \pi_k) \end{bmatrix},$$

where  $N$  is the number of available answers. The unrestricted maximum likelihood estimator of  $\boldsymbol{\Sigma}$  is computed by replacing  $\pi_i$  with  $p_i$  and is denoted by  $\mathbf{S}$ . Then,

$$Var(\widehat{I}_1^*) = Var\left(\frac{\mathbf{w}^\top \mathbf{p}^*}{\pi_0}\right) = \frac{1}{\pi_0^2} \mathbf{w}^\top Var(\mathbf{p}^*) \mathbf{w} = \frac{1}{\pi_0^2} \mathbf{w}^\top \boldsymbol{\Sigma}^* \mathbf{w}, \quad (3)$$

where  $\boldsymbol{\Sigma}^*$  is a partition of  $\boldsymbol{\Sigma}$  containing the first  $[k/2]$  rows and columns of  $\boldsymbol{\Sigma}$  and  $\mathbf{p}^* = \begin{bmatrix} p_1 & p_2 & \dots & p_{[k/2]} \end{bmatrix}^\top$ . For instance, when  $k = 7$ , the expression given in (3) simplifies to

$$Var(\widehat{I}_1^*) = -\frac{49}{36N} (-9\pi_1 + 9\pi_1^2 + 12\pi_1\pi_2 + 6\pi_1\pi_3 - 4\pi_2 + 4\pi_2^2 + 4\pi_3\pi_2 - \pi_3 + \pi_3^2).$$

An estimate of  $Var(\widehat{I}_1^*)$  can be obtained by replacing  $\pi_i$  ( $i = 1, \dots, k$ ) by their sample counterparts.

The derivation of exact formulae for the variance of the estimators of the indices  $I_2^*$  and  $I_3^*$  is a difficult task since these are ratios of weighted sums of multinomial

proportions. However, we may approximate the value of the variance for particular choices of  $\boldsymbol{\pi}$  and  $N$  using the method of bootstrap. (A detailed description of this method and its applications can be found in Efron and Tibshirani (1993)).

In the sequel, the method of bootstrap is implemented for the approximation of the variances of the estimators of the three new indices for various choices of  $\boldsymbol{\pi}$  and  $N$ . Specifically, assuming that we have a question with  $k$  possible answers,  $N$  observations and proportions  $\pi_1, \pi_2, \dots, \pi_k$ , we generate a large number of multinomial samples, say  $B = 1000$ , via sampling with replacement. The  $B$  samples are termed bootstrap samples. For each bootstrap sample, the value of the index  $I^*$  is calculated. The general notation  $I^*$  is used here to denote any of the three new indices. An approximation of the variance for the estimator of each index ( $S_{I^*}^2$ ) can be found through the formula

$$S_{I^*}^2 = \frac{1}{B-1} \sum_{i=1}^B \left( I_i^* - \bar{I}^* \right)^2,$$

where  $I_i^*$  is the index value assessed on the basis of the  $i$ th bootstrap sample and  $\bar{I}^*$  is the mean of the  $B$  bootstrap index values.

The obtained results, assuming  $k = 7$ , are summarized in Tables 2-5. Each of these tables corresponds to a different sample size ( $N$ ). Moreover, the proportions considered were selected to cover a wide range of cases, i.e. small, moderate or large index values.

In the case of  $I_1^*$ , the bootstrap approximations ( $A$ ) can be compared with the exact ones ( $E$ ) computed using formula (3).

(TABLE 2)

>From Tables 2-5 one may draw the following conclusions:

- As the sample size increases, the variance of all the estimators decreases
- The variance of  $\widehat{I}_1^*$  appears to be generally smaller in comparison to the variances of the estimators of the other indices
- The variance of  $\widehat{I}_1^*$  is not seriously affected by changes in the values of the proportions
- The variances of  $\widehat{I}_2^*$  and  $\widehat{I}_3^*$  increase as the degree of concentration on the “positive” answers increases
- The performance of the bootstrap method is fairly satisfactory as can be observed from the differences between the exact and the approximate (bootstrap) values of the variance of  $\widehat{I}_1^*$
- For small sample sizes, the approximations of the variances of  $\widehat{I}_2^*$  and  $\widehat{I}_3^*$  cannot be obtained in situations where the proportions of the “positive” answers are very large (see the last rows of Tables 2 and 3). This is a consequence of the fact that the values of these indices become infinite for some of the bootstrap samples.

(TABLE 3)

(TABLE 4)

(TABLE 5)

## 5 Confidence Intervals

This section is devoted to the construction of confidence intervals for the true values of the indices defined. Owing to the fact that these indices are functions of multinomial proportions, the construction of confidence intervals for them relates to the construction of simultaneous confidence limits for multinomial proportions. This is a problem dealt with by several authors (e.g. Quesenberry and Hurst (1964), Goodman (1965), Fitzpatrick and Scott (1987), Sison and Glaz (1995), Kwong (1996, 1998) and Ahmed (2000)). However, these confidence limits can be used only in the case of  $I_1^*$ . The construction of parametric confidence intervals for indices  $I_2^*$  and  $I_3^*$ , which are ratios of weighted sums of multinomial proportions, is much more complicated. For this reason, we resort to the well-known method of bootstrap for obtaining confidence intervals for them. A  $100(1 - a)\%$  confidence interval of index  $I_1^*$  is given by

$$\left( \frac{\sum_{i=1}^{\lfloor k/2 \rfloor} w_i p_L^{(i)}}{\pi_0}, \frac{\sum_{i=1}^{\lfloor k/2 \rfloor} w_i p_U^{(i)}}{\pi_0} \right), \quad (4)$$

where  $p_L^{(i)}, p_U^{(i)}$  are the lower and the upper simultaneous confidence limits for category  $i$  calculated using any of the suggested methods.

Alternatively, one may take advantage of the bootstrap method so as to assess confidence intervals for the actual values of the indices  $I_1^*, I_2^*$  and  $I_3^*$ . For simplicity, we adopt again the general notation  $I^*$  for any of these indices. For the calculation of bootstrap confidence intervals we order the  $B$  index values, obtained following the procedure described in the previous section, in a non-descending order and we denote

the  $i$ th of these values by

$$I_{(i)}^*, i = 1, \dots, B.$$

We will now describe three alternative methods that one can apply in order to create bootstrap confidence intervals. These are the standard bootstrap, the percentile bootstrap and the bias-corrected percentile bootstrap.

According to the standard bootstrap method, a  $100(1 - \alpha)\%$  confidence interval for the index  $I^*$  is given by

$$\left( \widehat{I}^* - z_{1-\alpha/2} S_{I^*}, \widehat{I}^* + z_{1-\alpha/2} S_{I^*} \right),$$

where  $z_\alpha$  denotes the  $100\alpha\%$  percentile of the standard normal distribution,  $S_{I^*}$  is the standard deviation of the  $B$  index values and  $\widehat{I}^*$  is the index value that was assessed from the initial sample.

Following the percentile bootstrap technique, a  $100(1 - \alpha)\%$  confidence interval for the index  $I^*$  is given by

$$\left( I_{(B\alpha/2)}^*, I_{(B(1-\alpha/2))}^* \right).$$

The bias-corrected percentile bootstrap method is similar to the percentile bootstrap, but involves a slight correction for the potential bias. According to this method, we firstly find the two successive values  $I_{(i)}^*$  and  $I_{(i+1)}^*$  between which the value of the index that was assessed from the initial sample ( $\widehat{I}^*$ ) lies. Then, we derive the value for which the cumulative distribution function of the standard normal distribution ( $\Phi$ ) takes the value  $i/B$ . If we denote this value by  $z_0$ , then we calculate the probabilities  $p_l$  and  $p_u$ , which are defined as  $p_l = \Phi(2z_0 + z_{\alpha/2})$  and  $p_u = \Phi(2z_0 + z_{1-\alpha/2})$ . Using

these probabilities we end up with a  $100(1 - \alpha)\%$  confidence interval of the form

$$(I_{(B \cdot p_l)}^*, I_{(B \cdot p_u)}^*).$$

The performance of the three bootstrap techniques is examined via a simulation study. The results obtained are provided in the Appendix. In this study, 10000 random samples were generated from the multinomial distribution with parameters  $N = 250$  and  $N = 500$  and various combinations of  $\pi_1, \pi_2, \dots, \pi_7$ . These combinations are the same as those considered in Section 4. The number  $k$  of the selected categories was assumed to be 7, without loss of generality.

The number of bootstrap samples generated each time is  $B = 1000$ . For any case, the observed coverage (OC) and the mean range (MR) are computed. Tables 10 and 12 refer to confidence level 0.90, whereas Tables 11 and 13 refer to confidence level 0.95. The first entry of each cell corresponds to the standard bootstrap (SB) method, the second to the percentile bootstrap (PB) and the third to the bias-corrected percentile bootstrap (BB).

On the basis of these tables one may conclude that:

- The observed coverage is not seriously affected by the sample size. Hence, one may construct confidence intervals for the true values of the indices even when the number of available observations is not very large
- The mean range of the confidence intervals produced from all the techniques reduces as the sample size increases

- For the index  $I_1^*$ , all the methods appear to attain a coverage close to the nominal. Likewise, the mean range of the confidence intervals produced from the three methods is nearly the same
- In the case of index  $I_2^*$ , despite the fact that we do not observe substantial differences in the coverage of the three methods, BB seems to provide the confidence intervals with the best coverage. The mean range of the SB confidence intervals appears to exceed the ones of the other two methods
- For index  $I_3^*$  method BB results in a coverage closer to the nominal in most of the examined cases. In addition, method SB gives the widest intervals

It should be remarked that the mean range of the confidence intervals  $I_2^*$  and  $I_3^*$  could not be computed in some cases because, for some of the generated bootstrap samples, the values of these indices become infinite.

## 6 An Illustrative Example

In the sequel, the data analysed by Jensen (1986) are used in order to illustrate the advantages of the indices  $I_1^*$ ,  $I_2^*$  and  $I_3^*$  proposed in this paper in comparison to the indices  $I_1$ ,  $I_2$  and  $I_3$  suggested by Maravelakis et al. (2003). Jensen (1986) dealt with data acquired through a questionnaire that was given between 1973 and 1976 to 60% of the students of the only Catholic high school and its two neighboring public high schools in a southeastern city of the United States. For more details on this survey, the reader is referred to Jensen (1986). The questionnaires that were given to the

students include several questions whose answers have a natural ordering. Therefore, one can take advantage of the theory developed in this paper so as to measure the observed degree of concentration on the “positive” categories in each question.

In Table 4 of Jensen (1986), the obtained results for various questions associated with students’s choices, moral evaluations and perceptions of risk are provided separately for the students of public and catholic schools. Some of these questions are:

1. *Suppose you and your friends were messing around one afternoon and they decided to steal something from a store just for kicks. Do you think it would be wrong to go along? (Public schools)*
2. *Suppose you and your friends were messing around one night and they decided to break into a place and steal some things. Would it be wrong to go along? (Catholic schools)*

In both questions the possible answers were “Definitely Yes” (DY), “Yes” (Y), “Uncertain” (U), “No” (NO), “Definitely No” (DN).

The observed proportions and the number of responses for these questions are displayed on Table 6, while in Table 7 the corresponding estimates of the values of the six indices are presented.

**(TABLE 6)**

**(TABLE 7)**

In both questions, the values of the six indices indicate a tendency of the respondents to prefer the “positive” answers. Likewise, this tendency seems to be stronger in Question 2.

Suppose now that the obtained proportions of the two questions were as shown in Table 8. Obviously, in this case the proportions of the first two categories are given in reverse order. However, as one may observe from Table 9, the indices  $I_1$ ,  $I_2$  and  $I_3$  do not reflect these changes since their values remain unchanged. On the other hand, in both cases, the values of the new indices decreased as a consequence of the fact that even though the total proportion of the “positive” answers remains constant its distribution to the two categories has changed substantially.

(TABLE 8)

(TABLE 9)

## 7 Concluding Remarks

In this paper, some new indices were introduced and their properties were studied. These indices can be considered as generalizations of the indices proposed by Maravelakis et al. (2003). Their aim is to measure the degree of concentration on the “small” or the “large” values of ordinal variables and have applications in various disciplines. The use of these indices was illustrated in connection with data obtained from sample surveys. Nevertheless, various other fields of applications where these indices may serve as a useful tool, exist. As an example, we refer to the educational

field and especially the evaluation of different groups of students in situations where their grades are in ordinal scale.

As already mentioned, indices have been used in a number of fields. A natural question in using weighted indices is how the weights are chosen. In Statistical Process Control the Exponentially Weighted Moving Average (EWMA) control chart is a statistic (index) of the current level of a process. The weights in this statistic decrease geometrically, assigning the largest weight to the most recent observation and a continuously decreasing weight from the next most recent observation to the oldest (see, e.g. Montgomery (2001)). This selection of weights stems from the fact that the newer observation gives the best outlook of the process. In the education field different weights are assigned to the factors related to the quality of education. These weights are not based on a mathematical formulation but rather on a subjective selection (see Han (1996)). In the areas of classification and clustering different indices have been proposed with various types of weighting. The criteria for selecting these weights is based on the analyst(Cox and Cox (2000)). Therefore, one may conclude that the set of weights chosen in each subject depends on the nature of the problem and even for the same problem different weights may be assigned. In the problem studied the set of weights used are based on mathematical relations with the aim to arrive at a logical selection.

Specifically, the first condition for selecting the appropriate weights in Section 3 is not a binding one because the sum of the weights could be any value. We choose the particular one for comparison purposes. On the other hand, the second condition is

crucial on the selection of the weights. In the case of a questionnaire it seems natural that the weights of symmetrical classes be equal, although there may be cases where the researcher may decide otherwise.

(TABLE 10)

(TABLE 11)

(TABLE 12)

(TABLE 13)

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**TABLE 1. An Artificial Example**

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Question	Very Good	Good	Moderate	Bad	Very Bad
1	0.02	0.78	0.15	0.02	0.03
2	0.78	0.02	0.15	0.02	0.03

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**TABLE 2. The Variances of the Estimators of the Three Indices  
for  $B = 1000$  and  $N = 50$**

							$\hat{I}_1^*$	$\hat{I}_2^*$	$\hat{I}_3^*$	
Proportions							E	A	A	A
.03	.02	.05	.45	.05	.2	.2	.0100	.0093	0.0091	0.0093
.06	.06	.08	.4	.1	.15	.15	.0195	.0187	0.0407	0.0265
.1	.1	.1	.35	.15	.10	.10	.0283	.0287	0.1707	0.0680
.15	.15	.1	.3	.1	.1	.1	.0361	.0376	0.4012	0.1484
.2	.15	.15	.2	.10	.10	.10	.0394	.0408	0.8039	0.3135
.2	.2	.2	.1	.1	.1	.1	.0370	.0378	0.7993	0.4863
.25	.25	.2	.1	.1	.05	.05	.0367	.0372	5.7835	2.1036
.25	.25	.3	.1	.05	.03	.02	.0312	.0326	-	19.148
.3	.3	.3	.05	.02	.02	.01	.0261	.0261	-	-

**TABLE 3. The Variances of the Estimators of the Three Indices  
for  $B = 1000$  and  $N = 100$**

							$\hat{I}_1^*$	$\hat{I}_2^*$	$\hat{I}_3^*$	
Proportions							E	A	A	A
.03	.02	.05	.45	.05	.2	.2	.0050	.0049	0.0045	0.0047
.06	.06	.08	.4	.1	.15	.15	.0097	.0102	0.0190	0.0127
.1	.1	.1	.35	.15	.10	.10	.0142	.0143	0.0777	0.0347
.15	.15	.1	.3	.1	.1	.1	.0181	.0181	0.1683	0.0696
.2	.15	.15	.2	.10	.10	.10	.0197	.0190	0.2182	0.1108
.2	.2	.2	.1	.1	.1	.1	.0185	.0189	0.2717	0.1789
.25	.25	.2	.1	.1	.05	.05	.0183	.0183	1.8565	0.8036
.25	.25	.3	.1	.05	.03	.02	.0156	.0160	26.303	4.9743
.3	.3	.3	.05	.02	.02	.01	.0131	.0135	-	76.386

**TABLE 4. The Variances of the Estimators of the Three Indices  
for  $B = 1000$  and  $N = 250$**

							$\hat{I}_1^*$	$\hat{I}_2^*$	$\hat{I}_3^*$	
Proportions							E	A	A	A
.03	.02	.05	.45	.05	.2	.2	.0020	.0020	0.0017	0.0018
.06	.06	.08	.4	.1	.15	.15	.0039	.0035	0.0066	0.0046
.1	.1	.1	.35	.15	.10	.10	.0057	.0055	0.0261	0.0125
.15	.15	.1	.3	.1	.1	.1	.0072	.0070	0.0578	0.0257
.2	.15	.15	.2	.10	.10	.10	.0079	.0080	0.0868	0.0452
.2	.2	.2	.1	.1	.1	.1	.0074	.0068	0.0951	0.0655
.25	.25	.2	.1	.1	.05	.05	.0073	.0072	0.6194	0.2827
.25	.25	.3	.1	.05	.03	.02	.0063	.0061	6.3119	1.5515
.3	.3	.3	.05	.02	.02	.01	.0052	.0053	79.097	16.941

**TABLE 5. The Variances of the Estimators of the Three Indices  
for  $B = 1000$  and  $N = 500$**

							$\hat{I}_1^*$	$\hat{I}_2^*$	$\hat{I}_3^*$	
Proportions							E	A	A	A
.03	.02	.05	.45	.05	.2	.2	.0010	.0010	0.0009	0.0010
.06	.06	.08	.4	.1	.15	.15	.0020	.0019	0.0036	0.0025
.1	.1	.1	.35	.15	.10	.10	.0028	.0027	0.0129	0.0062
.15	.15	.1	.3	.1	.1	.1	.0036	.0037	0.0270	0.0124
.2	.15	.15	.2	.10	.10	.10	.0039	.0039	0.0420	0.0225
.2	.2	.2	.1	.1	.1	.1	.0037	.0038	0.0504	0.0348
.25	.25	.2	.1	.1	.05	.05	.0037	.0040	0.2856	0.1391
.25	.25	.3	.1	.05	.03	.02	.0031	.0031	2.7278	0.7130
.3	.3	.3	.05	.02	.02	.01	.0026	.0026	27.230	7.1804

**TABLE 6. The Proportions and the Number of Responses  
for Questions 1 and 2 for Jensen's (1986) data**

Question	DY	Y	U	NO	DN	<i>N</i>
1	0.473	0.327	0.086	0.065	0.049	1480
2	0.623	0.243	0.052	0.030	0.052	440

**TABLE 7. Estimates of the Values of the Six Indices  
for Questions 1 and 2**

Question	$\hat{I}_1$	$\hat{I}_1^*$	$\hat{I}_2$	$\hat{I}_2^*$	$\hat{I}_3$	$\hat{I}_3^*$
1	2	2.122	7.018	7.810	4.430	5.948
2	2.165	2.482	10.561	11.112	6.851	8.981

**TABLE 8. The Proportions and the Number of Responses**

**for Questions 1\* and 2\***

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Question	DY	Y	U	NO	DN	<i>N</i>
1*	0.327	0.473	0.086	0.065	0.049	1480
2*	0.243	0.623	0.052	0.030	0.052	440

---

**TABLE 9. Estimates of the Values of the Six Indices**

**for Questions 1\* and 2\***

Question	$\widehat{I}_1$	$\widehat{I}_1^*$	$\widehat{I}_2$	$\widehat{I}_2^*$	$\widehat{I}_3$	$\widehat{I}_3^*$
1*	2	1.878	7.018	6.914	4.430	5.545
2*	2.165	1.848	10.561	8.276	6.851	7.563

**TABLE 10. The Simulation Study for  $N = 250$  and  $1 - \alpha = 0.9$** 

Proportions								$I_1^*$		$I_2^*$		$I_3^*$		
								OC	MR	OC	MR	OC	MR	
.03 .02 .05 .45 .05 .2 .2								SB	.8880	.1459	.8975	.1400	.9015	.1435
								PB	.8928	.1456	.8918	.1390	.8962	.1430
								BB	.8889	.1453	.8923	.1402	.8968	.1432
.06 .06 .08 .4 .1 .15 .15								SB	.8938	.2040	.9012	.2839	.9000	.2337
								PB	.9018	.2038	.8948	.2817	.8959	.2327
								BB	.9014	.2036	.8961	.2827	.8969	.2330
.1 .1 .1 .35 .15 .10 .10								SB	.9003	.2466	.9121	.5440	.9028	.3703
								PB	.9070	.2465	.8991	.5385	.9005	.3685
								BB	.9062	.2464	.9021	.5387	.8998	.3687
.15 .15 .1 .3 .1 .1 .1								SB	.8972	.2789	.9176	.8095	.9102	.5342
								PB	.8957	.2789	.9023	.7995	.9017	.5308
								BB	.8954	.2789	.9038	.7982	.9028	.5307
.2 .15 .15 .2 .10 .10 .10								SB	.9028	.2912	.9150	.9616	.9111	.6932
								PB	.9026	.2912	.8989	.9491	.9003	.6878
								BB	.9023	.2913	.9005	.9464	.9024	.6872
.2 .2 .2 .1 .1 .1 .1								SB	.9011	.2822	.9147	1.0674	.9111	.8789
								PB	.9076	.2822	.8980	1.0537	.8983	.8706
								BB	.9065	.2823	.9004	1.0500	.9009	.8687
.25 .25 .2 .1 .1 .05 .05								SB	.9000	.2812	.9228	2.6657	.9131	1.7879
								PB	.9005	.2812	.8927	2.6045	.8921	1.7621
								BB	.8991	.2814	.8941	2.5788	.8927	1.7529
.25 .25 .3 .1 .05 .03 .02								SB	.8977	.2592	.9399	9.0278	.9271	4.2237
								PB	.8977	.2592	.8917	8.4496	.8925	4.1226
								BB	.8969	.2594	.8943	8.2090	.8949	4.0723
.3 .3 .3 .05 .02 .02 .01								SB	.8965	.2372	.8653	-	.9385	14.703
								PB	.9028	.2372	.8784	-	.8873	13.727
								BB	.9036	.2375	.8871	-	.8916	13.275

**TABLE 11. The Simulation Study for  $N = 250$  and  $1 - \alpha = 0.95$**

Proportions								$I_1^*$		$I_2^*$		$I_3^*$		
								OC	MR	OC	MR	OC	MR	
								SB	.9386	.1739	.9387	.1668	.9463	.1710
.03	.02	.05	.45	.05	.2	.2	PB	.9431	.1732	.9432	.1621	.9445	.1706	
								BB	.9420	.1729	.9473	.1675	.9452	.1710
								SB	.9414	.2431	.9464	.3383	.9468	.2786
.06	.06	.08	.4	.1	.15	.15	PB	.9487	.2426	.9448	.3372	.9465	.2779	
								BB	.9456	.2424	.9460	.3384	.9481	.2782
								SB	.9480	.2939	.9499	.6483	.9510	.4413
.1	.1	.1	.35	.15	.10	.10	PB	.9504	.2937	.9488	.6459	.9496	.4403	
								BB	.9494	.2935	.9492	.6461	.9493	.4405
								SB	.9462	.3324	.9584	.9646	.9551	.6366
.15	.15	.1	.3	.1	.1	.1	PB	.9465	.3321	.9508	.9605	.9512	.6348	
								BB	.9471	.3320	.9504	.9590	.9517	.6346
								SB	.9504	.3470	.9560	1.1458	.9542	.8261
.2	.15	.15	.2	.10	.10	.10	PB	.9508	.3468	.9502	1.1406	.9493	.8237	
								BB	.9508	.3468	.9499	1.1376	.9495	.8227
								SB	.9482	.3363	.9559	1.2719	.9540	1.0473
.2	.2	.2	.1	.1	.1	.1	PB	.9509	.3362	.9482	1.2665	.9499	1.0438	
								BB	.9508	.3363	.9501	1.2621	.9501	1.0416
								SB	.9501	.3350	.9587	3.1764	.9549	2.1304
.25	.25	.2	.1	.1	.05	.05	PB	.9495	.3350	.9442	3.1514	.9457	2.1205	
								BB	.9478	.3352	.9447	3.1193	.9460	2.1090
								SB	.9467	.3089	.9624	10.757	.9605	5.0329
.25	.25	.3	.1	.05	.03	.02	PB	.9469	.3088	.9397	10.461	.9439	4.9899	
								BB	.9466	.3090	.9432	10.155	.9456	4.9291
								SB	.9484	.2826	.8870	-	.9636	17.519
.3	.3	.3	.05	.02	.02	.01	PB	.9530	.2825	.9333	-	.9378	17.024	
								BB	.9518	.2828	.9400	-	.9421	16.442

**TABLE 12. The Simulation Study for  $N = 500$  and  $1 - \alpha = 0.9$**

Proportions								$I_1^*$		$I_2^*$		$I_3^*$		
								OC	MR	OC	MR	OC	MR	
								SB	.8962	.1035	.8990	.0978	.8979	.1008
.03	.02	.05	.45	.05	.2	.2	PB	.8962	.1034	.8954	.0975	.8981	.1006	
								BB	.8965	.1033	.8965	.0979	.8976	.1007
								SB	.9000	.1448	.9058	.1981	.9045	.1644
.06	.06	.08	.4	.1	.15	.15	PB	.9045	.1447	.9016	.1972	.9024	.1640	
								BB	.9030	.1447	.9017	.1977	.9012	.1642
								SB	.8998	.1746	.9018	.3748	.8991	.2589
.1	.1	.1	.35	.15	.10	.10	PB	.9027	.1746	.8961	.3728	.8982	.2582	
								BB	.9030	.1746	.8975	.3730	.8993	.2584
								SB	.8999	.1974	.9062	.5555	.9021	.3728
.15	.15	.1	.3	.1	.1	.1	PB	.9029	.1973	.8983	.5522	.8995	.3716	
								BB	.9003	.1974	.8996	.5521	.8998	.3717
								SB	.9021	.2062	.9085	.6596	.9044	.4818
.2	.15	.15	.2	.10	.10	.10	PB	.9054	.2063	.9003	.6553	.8987	.4799	
								BB	.9036	.2063	.8990	.6548	.8976	.4798
								SB	.8938	.1998	.9051	.7333	.9026	.6086
.2	.2	.2	.1	.1	.1	.1	PB	.8989	.1998	.8947	.7286	.8958	.6056	
								BB	.8992	.2000	.8961	.7279	.8976	.6052
								SB	.8983	.1990	.9067	1.7864	.9012	1.2241
.25	.25	.2	.1	.1	.05	.05	PB	.9013	.1989	.8908	1.7672	.8918	1.2157	
								BB	.9011	.1991	.8917	1.7601	.8938	1.2132
								SB	.8999	.1836	.9265	5.5162	.9129	2.8152
.25	.25	.3	.1	.05	.03	.02	PB	.8988	.1836	.9002	5.3798	.8991	2.7828	
								BB	.8982	.1837	.9015	5.3161	.9003	2.7683
								SB	.9013	.1679	.9371	19.016	.9219	8.9700
.3	.3	.3	.05	.02	.02	.01	PB	.9048	.1679	.8841	17.789	.8912	8.7384	
								BB	.9025	.1681	.8895	17.267	.8947	8.6164

**TABLE 13. The Simulation Study for  $N = 500$  and  $1 - \alpha = 0.95$** 

Proportions								$I_1^*$		$I_2^*$		$I_3^*$		
								OC	MR	OC	MR	OC	MR	
								SB	.9414	.1234	.9473	.1166	.9507	.1201
.03	.02	.05	.45	.05	.2	.2	PB	.9432	.1231	.9499	.1163	.9497	.1200	
								BB	.9437	.1230	.9479	.1168	.9473	.1201
								SB	.9487	.1725	.9487	.2361	.9532	.1959
.06	.06	.08	.4	.1	.15	.15	PB	.9510	.1722	.9493	.2357	.9510	.1957	
								BB	.9513	.1722	.9505	.2361	.9510	.1958
								SB	.9484	.2081	.9486	.4466	.9494	.3085
.1	.1	.1	.35	.15	.10	.10	PB	.9502	.2079	.9485	.4457	.9482	.3081	
								BB	.9504	.2079	.9489	.4459	.9499	.3083
								SB	.9484	.2353	.9532	.6620	.9510	.4442
.15	.15	.1	.3	.1	.1	.1	PB	.9512	.2351	.9491	.6604	.9483	.4436	
								BB	.9500	.2352	.9481	.6601	.9466	.4436
								SB	.9493	.2458	.9537	.7860	.9519	.5741
.2	.15	.15	.2	.10	.10	.10	PB	.9523	.2456	.9483	.7840	.9492	.5731	
								BB	.9511	.2457	.9494	.7832	.9501	.5729
								SB	.9474	.2382	.9539	.8737	.9521	.7252
.2	.2	.2	.1	.1	.1	.1	PB	.9506	.2381	.9466	.8718	.9472	.7239	
								BB	.9483	.2382	.9456	.8707	.9463	.7236
								SB	.9458	.2371	.9545	2.1287	.9522	1.4586
.25	.25	.2	.1	.1	.05	.05	PB	.9482	.2370	.9438	2.1205	.9450	1.4547	
								BB	.9484	.2371	.9436	2.1118	.9457	1.4517
								SB	.9498	.2188	.9616	6.5728	.9548	3.3545
.25	.25	.3	.1	.05	.03	.02	PB	.9489	.2186	.9481	6.5214	.9484	3.3410	
								BB	.9486	.2188	.9489	6.4418	.9495	3.3229
								SB	.9517	.2001	.9604	22.658	.9598	10.689
.3	.3	.3	.05	.02	.02	.01	PB	.9529	.2000	.9398	22.046	.9410	10.597	
								BB	.9541	.2002	.9436	21.374	.9425	10.448