

A NEW TECHNIQUE FOR DEALING WITH COMPLEX STIMULI IN CONJOINT ANALYSIS

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Abstract

This paper deals with the problem of a large number of multi-attributes stimuli in Conjoint Analysis. The aim of this paper is to critically discuss some specific aspects of the bridging technique originally proposed by Bretton and Clark and to propose an innovative approach based on the same philosophy but on a different estimation method. The new technique is based on several estimation steps. It is able to make the most of the orthogonality properties related to the experimental designs. Furthermore, a validation procedure for the bridging results has been proposed. This procedure allows answering to the general question on the reliability of performing a bridging technique.

Keywords: Conjoint Analysis; Bridging technique; Multi-attribute stimuli; Multivariate Regression Model

1. INTRODUCTION

Conjoint Analysis (CA) made its first appearance in marketing research in the early '70s and its use has increased since then. CA (for a review see Green and Srinivasan, 1990) is nowadays the most applied methodology of multivariate analysis for studying and showing the consumer preferences on different products or services. Since consumers can express reliable preference judgements on products/services characterized by a lot of different and complex aspects, the construction of designs with many attributes and levels has become a necessity (Green, 1974). This involves that a large number of multi-attributes stimuli (hereafter defined "*complex stimuli*") will be submitted to consumers for the evaluation.

A survey with *complex stimuli* principally shows two different kinds of

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problems. The first problem is related to the data collection phase. A judge, probably, having to consider a lot of different and complex stimuli, will not be able to understand the real meaning of each of them. Consequently, he will have some difficulties in giving his preference. Therefore, whereas on the one hand it is possible to reduce the measurement error by including more conjoint questions in a sample survey, on the other hand the respondents could get tired and so they could no longer give reliable responses.

The second problem is directly linked to the estimation of the utility coefficients. If it is possible to consider the complexity of products by taking into account a large number of attributes and levels, the accuracy of the utility estimations can nevertheless decrease due to too few degrees of freedom

The classical solutions, proposed by the Conjoint Analysis for handling stimuli characterised by many attributes and levels, concern two main aspects: the type of experimental design to plan and the method to use for presenting the different stimuli to respondents (Pullman et al. 1999).

The selection of the design is an a-priori choice: to consider all the possible factor-level combinations (Full Factorial Designs) or only a fraction (Fractional Designs). Although a fractional design reduces the number of stimuli to submit to judges, from a statistical viewpoint it causes many difficulties in the estimation of the effects, in particular for the interaction effects. Nevertheless, from a marketing point of view, it could be not interesting to estimate all the interactions among attributes, but can be considered much more important to obtain reliable judgments on the principal effects.

As regards to the second aspect, that is the choice of the method, CA provides us with different solutions. Starting from the same number of factor-level combinations, it is possible to present all the stimuli at the same time (Full-profile methods) or by paired-comparison questions. Full-profile method has been the most popular approach to CA in the literature on the subject. But, as noted, its usefulness has been widely considered as limited to problems involving smaller number of attributes due to the respondent fatigue and inability to process a large number of attributes. Only recently some papers (Brazell and Louviere, 1998) have successfully tried to measure fatigue-effects in full-profile methods and the results are surprising: fatigue effects in full-profile may be much less important than it is widely believed. However, although the use of visual presentations can help the judges in their evaluation and the problem-size of full-profile methods may be limited, other alternative methods, that are less taxing to respondents, have been proposed.

An alternative solution to the classical CA is the use of the Adaptive Conjoint

Analysis (ACA; Johnson, 1987). The ACA consists of a computer-administered interview customized for each respondent. At each step, previous answers are used to decide which question to ask next. There are several steps. The initial steps are based on the *compositional approach*, while the successive steps are based on the *decompositional one*.

ACA is a user-friendly approach both for the analyst and the respondents (ACA 5.0, Sawtooth Software). In the ACA, respondents do not evaluate all attributes at the same time and this helps to solve the problem of “information overload” that plagues many full-profile studies. The interview can consider many attributes and levels, paying special attention to those the respondents consider more important. Questioning is done in “intelligent” way; the respondent’s utilities are continually re-estimated as the interview progresses, and each question is chosen to provide the most additional information, given what is already known about the respondent’s value. Finally, as regards to the classical CA, in ACA the number of final stimuli to submit is very limited and it is focused on stimuli considered the most important and the less important, by giving minor importance to middle stimuli. Moreover, in terms of restrictions and limitations, ACA must be computer-administered. The estimated time for a generic interview is not less than 20-25 minutes. Furthermore, ACA is a main effect model. This means that utilities for attributes are measured in an “all else equal” context, without the inclusion of attribute interactions.

On a different philosophy (Baalbaki and Malhotra, 1995), is based another method proposed as practical solution to the problem of complex stimuli: the Bridging technique (Albaum, 1989). The basic idea of this approach is to split up the planned attributes and levels in two different lists with at least two common attributes. The successive steps of the analysis are the same of those characterizing a full-profile approach, but with the realization of two different fractional factorial designs and consequently, of two different surveys on the same consumers. At the end, partial utilities and importance of the attributes will become one group of results, as if the researcher has worked with only one fractional design, with a number of attributes equal to the sum of no-common attributes plus the common attributes. This technique has been implemented in the software Bridger 1.1 (Bretton-Clark, 1988).

The aim of this paper is to critically discuss some characteristic features of the bridging technique (par. 2) and to propose an innovative approach based on the general bridging philosophy but on a peculiar estimation method. The new technique, (par. 3), here called the “GIP technique”, is based on several steps of estimation and it is able to make the most of the orthogonality properties of the

experimental designs. The proposed approach is enriched with a validation procedure (par.4) on its results; this procedure allows to answer to the general question on the reliability of performing a bridging technique. Therefore the validation procedure can be generalised for evaluating the results of a bridging technique.

2. THE BRIDGING TECHNIQUE

The Bridging philosophy (Albaum, 1989) consists in splitting several planned attributes in two or more different sets with some attributes common to all sets (“bridging-attributes”). Each set of attributes is treated like a distinct conjoint analysis. A fractional factorial design is created for each set of attributes. Respondents are asked to rate or rank two smaller sets of products rather than one large set. The utilities are calculated for each trade-off exercise independently and bridged together to create one final set of utilities. The Bridging technique is implemented in the software *Bridger 1.1* developed by Bretton and Clark (BC) in 1988. This software is jointly used with other two software proposed by the same authors, *Conjoint Designer 3.0* (1990) and *Conjoint Analyzer 3.0* (1992). The Bretton and Clark suite of programs (Carmone and Shaffler, 1995) was designed to handle most of the task in a paper-and-pencil conjoint study, for example, profile design, utility estimation, and simulations.

Conjoint Designer software provides experimental designs for the use in Conjoint Analysis studies. All generated designs continue to be only orthogonal arrays; it is not possible to estimate interactions with the class of designs. To generate a design, it is necessary to specify the type of estimation model for each factor (parth worth, linear, or quadratic), so the number of parameters to estimate can be calculated.

For initialising a Bridging procedure, two fractional experimental designs with at least one bridging-attribute are generated with *Conjoint Designer*.

Let us indicate with $\mathbf{X}_1(n_1, k_1)$, the first experimental designed matrix. This matrix has n_1 stimuli (combinations of factors and levels) as rows and k_1 columns defined by levels of the factors of the first survey. In particular, k_1 is the sum of k_1^{NB} levels of no-bridging factors and k_1^B levels of the bridging factors; $k_1 = k_1^{NB} + k_1^B$. $\mathbf{X}_2(n_2, k_2)$ is the matrix of the n_2 stimuli and k_2 ($k_2 = k_2^{NB} + k_2^B$) levels of the second survey, where $k_2^B = k_1^B$.

Successively, we collect the judgments of G judges ($g=, \dots, G$) on the n_1 stimuli in the preference matrix $\mathbf{Y}_1(n_1, G)$; the columns of this matrix are the expressed judgments. The matrix $\mathbf{Y}_2(n_2, G)$ is referred to the judgments of the same

judges on the n_2 stimuli.

The software used to enter respondent data and estimate individual utilities is the *Conjoint Analyser*. We indicate as $U_1(k_1, G)$ and $U_2(k_2, G)$ the utility matrices obtained by applying the Conjoint Analysis respectively on (Y_1, X_1) and on (Y_2, X_2) .

Furthermore, assume $U_1^{NB}(k_1^{NB}, G)$ and $U_2^{NB}(k_2^{NB}, G)$ the sub-matrices related to the estimates of the utilities only for the no-bridging factors respectively in the first and in the second survey. Therefore, $U_1^B(k_1^B, G)$ and $U_2^B(k_2^B, G)$ are the sub-matrices related to the estimates of the utilities of the bridging factors in the two cases.

The estimation method for these initial utilities is based on the Ordinary Least Squares and on the choice of the preference model (part-worth model, vector model, or the ideal-point model) for each factor used in the analysis. It is possible to statistically test the difference between an ideal point and a vector model to see which provides a better model fitting. This is, of course, done at group level, but software may be available to do this at the individual level.

As we will demonstrate in the following, the choice of the preference model is very important related to this bridging procedure.

2.1. THE ESTIMATION OF UTILITIES IN THE BRETTON CLARK'S BRIDGING PROCEDURE

It is important to underline that each consideration in this paragraph is derived and interpreted from the reading of the *Bridger 1.1* software manual and from the actual use of the Software, because it is very difficult to find papers on the estimation method proposed by Bretton and Clark.

Bridger can be divided into three basic parts. First, it looks for matching or bridging features in the two designs. Second it determines the optimal scaling factors for bridging these designs, and measures how well this scaling works. And third, it creates a new design and utility file to describe the integrated results of these operations.

In particular, in the first step Bridger verifies whether the two features were analysed using the same type of the model. If the models are not identical, the features cannot be bridged. Furthermore, if both features were analysed by the part-worth model, they would also be checked to determine whether they contain the same number of levels. Features with different number of levels cannot be used with the part-worth model, because the part-worth estimates are measured relative to the other levels of the feature.

We also observe that if the part-worth model is used and only one bridging

factor is chosen, the number of levels must be more than two. This derives from the method used for determining the "scale factor".

The "scale factor" is an important coefficient in this estimation method because it is directly linked with the basic hypothesis of the procedure. Therefore, Bridger 1.1 works considering that in the first design there are the main factors.

Therefore, the researcher must well choose the factors in the previous step of the analysis and he must decide, on the basis of a-priori knowledge, both the bridging factors and the main no-bridging factors. The hypothesis of the different role of the factors affects the whole estimation method.

Let us suppose that in X_1 there are the main factors. Bridger considers the elements of the matrix U_1^{NB} as estimates of the no-bridging utilities of the first survey. Therefore it does not modify the initial classical conjoint utilities.

Successively, *Bridger 1.1* calculates the "scale factor". This scale factor is the factor which best scales the bridging utilities of the second design, in U_2^B , for matching the corresponding utilities of the first design, in U_1^B .

In particular, the scale factor for each respondent, f_g , is derived from the following regression model:

$$\mathbf{u}_{1,g}^B = \mathbf{u}_{2,g}^B f_g + \boldsymbol{\varepsilon}_g \quad \text{with } g = 1, \dots, G \quad (1)$$

where $\mathbf{u}_{1,g}^B(k_1^B, 1)$ is the g -th column vector of U_1^B , $\mathbf{u}_{2,g}^B$ is the g -th column vector of $U_2^B(k_2^B, 1)$ and $\boldsymbol{\varepsilon}_g$ is the residual vector for g -th judge.

Because of (1), *Bridger 1.1* doesn't work if the chosen model is a part-worth model and the bridging factor is only one with two levels. Therefore, for this type of model, two factors, or one factor with at most three levels are necessary!

The procedure measures the goodness of fit of this scale factor. In particular, the scores between the corresponding bridging utilities are computed. Scores lower than twenty to thirty represent a poor fit and may be due to respondents treating the features differently in the two tasks. These respondents may be eliminated from the analysis.

The scale factor is used for weighting the no-bridging utilities for the factors of the second survey. Therefore, the matrix U_2^{NB} is re-computed by multiplying each column vector of this matrix for the scale factor f_g .

Finally, the scaling does not produce an exact match between the results.

Therefore, for obtaining an unique estimate for the utilities of the bridging attributes, the estimation method proposes an average of the obtained results. In particular, for each judge the estimates of bridging utilities are computed as:

$$\mathbf{u}_g^B = \frac{(\mathbf{u}_{1,g}^B + \mathbf{u}_{2,g}^B f_g)}{2} \quad (2)$$

2.2 CRITICAL CONSIDERATIONS

Bridging seems to be a user-friendly technique for respondents because it allows both to consider several stimuli and to submit them without respondent's fatigue. The division in two phases can represent a positive aspect, particularly when we deal with repeated surveys.

The drawbacks of this technique are in the method used for the estimation of partial utilities. This method still seems to be primitive in comparison with those methods, for example the hierarchical Bayes estimation, recently used in ACA. The hypothesis on the different importance of the two designs is justified by an a-priori knowledge of the main factors and it affects the estimates of bridging and no-bridging utilities. In particular, the scale factor is computed on the basis of this hypothesis with the aim of deriving the value that transforms the estimates of the bridging utilities, of the second survey, into the bridging utilities of the first survey. Furthermore, by using this procedure it is very difficult to reconstruct the original preferences because the first no-bridging utilities are the classical conjoint utilities, while the second ones are scaled with the "scale factor".

Finally, Bridger 1.1 has several constraints on the number of factors and levels to consider in the experimental designs.

The problem of the utility estimation of bridging-attributes has been very little discussed in the literature and it has not been definitively solved.

3. THE GIP TECHNIQUE

The *GIP* technique is based on the same philosophy of the classical *Bridging* technique, but the estimation method used is different (Ramunno, 2004). Therefore, we start with the same phases of design and survey of data, by defining the same starting matrices: $\mathbf{X}_1(n_1, k_1)$, $\mathbf{X}_2(n_2, k_2)$, $\mathbf{Y}_1(n_1, G)$ and $\mathbf{Y}_2(n_2, G)$.

Furthermore, let us indicate $\mathbf{X}_1^B(n_1, k_1^B)$ as the design sub-matrix obtained by selecting only the column vectors of the matrix $\mathbf{X}_1(n_1, k_1)$ referred to the bridging-

factors for the n_1 stimuli and $X_2^B(n_2, k_2^B)$ the design sub-matrix of the matrix $X_2(n_2, k_2)$ referred to the bridging-factors for the n_2 stimuli. Therefore $X_1^{NB}(n_1, k_1^{NB})$ and $X_2^{NB}(n_2, k_2^{NB})$ are the design sub-matrices referred to the no-bridging factors in the two survey.

The orthogonality propriety of the experimental matrix X_1 , such as for X_2 , allows us to divide this matrix into the experimental design matrices X_1^B and X_1^{NB} . Consequently it is possible to use these matrices in two separate models but obtaining the same utility estimates.

Differently from Bridging of BC, in *GIP* technique no hypothesis on the role of the factors is advanced. Furthermore, it is not required a fixed number of attributes or levels.

3.1 THE ESTIMATION OF UTILITIES IN THE GIP PROCEDURE

The *GIP* procedure starts with the estimation of bridging attribute utilities and, in particular, *GIP* aims at obtaining an unique estimation of bridging utilities by means of an unique regression model. For doing this, the procedure uses the whole possible information derivable from the preference matrices.

In fact, we define a new matrix ${}_cY(n, G)$, where the first n_1 rows are the rows of the preference matrix $Y_1(n_1, G)$ and the second n_2 rows are the rows of the matrix $Y_2(n_2, G)$, with $n = n_1 + n_2$. The G columns of this matrix are the G judges. Therefore the new matrix is obtained by the vertical concatenation of the starting two preference matrices.

In the same way, we define the new design matrix ${}_cX^B(n, k^B)$ by the vertical concatenation of the sub-matrices $X_1^B(n_1, k_1^B)$ and $X_2^B(n_2, k_2^B)$.

In the first step of the procedure, these new matrices are used for obtaining common estimates of the bridging utilities by the following multivariate multiple regression model:

$${}_cY = {}_cX^B U^B + {}_cE \quad (3)$$

where the matrix ${}_cU^B(k^B, G)$ is the matrix whose general element is the utility of each level of each bridging attribute for each respondent and ${}_cE(n, G)$ is the residual matrix.

The residual matrix ${}_cE$ of the model (3) includes all information related to the

no-bridging utilities. Therefore, we use it for computing the estimates of these utilities. In particular, exploiting again the orthogonality property, it is possible to divide \mathbf{E} into two sub-matrices $\mathbf{E}_1(n_1, G)$ and $\mathbf{E}_2(n_2, G)$ relating respectively to n_1 and n_2 stimuli. These two residual matrices can be used in two different regression models for obtaining separate utilities estimates for the no-bridging attributes.

In particular, for estimating the no-bridging utilities of the first survey the following regression model is applied:

$$\mathbf{E}_1 = \mathbf{X}_1^{NB} \mathbf{U}_1^{NB} + \mathbf{W}_1 \quad (4)$$

where $\mathbf{U}_1^{NB}(k_1^{NB}, G)$ is the matrix whose general element is the utility of each level for every single no-bridging attribute, for each respondent in the first survey and $\mathbf{W}_1(n_1, G)$ is the residual matrix.

In the same way, for the utilities of the no-bridging factors of the second survey, the regression model is:

$$\mathbf{E}_2 = \mathbf{X}_2^{NB} \mathbf{U}_2^{NB} + \mathbf{W}_2 \quad (5)$$

where $\mathbf{U}_2^{NB}(k_2^{NB}, G)$ is the matrix whose general element is the utility of each level for every single no-bridging attribute for every respondent in the second survey and $\mathbf{W}_2(n_2, G)$ is the residual matrix.

3.2 CRITICAL CONSIDERATIONS

The *GIP technique* is based on the same basic idea of Bretton Clark's Bridging technique, but it has some important differences. First of all, in GIP it is not necessary an a-priori knowledge of the main factors, moreover it is not required a fixed number of attributes or levels. Therefore, the *GIP* technique allows us to solve the problem of complex stimuli with less constraints in comparison with the other Bridging technique.

The most important contribute consists in the estimation method that takes into account the orthogonality properties making possible to reconstruct the original preferences. In particular, the orthogonality allows to separate the starting design matrices for obtaining a common estimate of the utilities of the bridging factors and allows to separate estimates of the effects of the no-bridging factors. SAS/IML routines have been developed by the authors for implementing this procedure.

However, a problem that must be considered: how reliable are the bridging

results?

For answering to this question, we introduce a validation test for evaluating the results of the *GIP* procedure. This test can be generalized to any bridging technique.

4. A VALIDATION PROCEDURE FOR THE BRIDGING RESULTS

The bridging procedures are based on two partial Conjoint experiments where some common factors lead to a global model. The bridging factors are considered relevant in the judge's assessment task and their right definition is the key for the success of the experiment. Hopefully, the presence of such important factors induces the respondent towards rational choices, so that all stimuli showing the same bridging levels could take similar scores in the two analyses.

In summary, it is assumed in the two sub-experiments that the judges give reliable responses on the bridging factors regardless on the interaction with the other non-bridging factors. We call such assumption the hypothesis of *coherent judgement*.

In many circumstances, however, it could happen that the presence of non-bridging factors highly influences the choices of the "absent-minded" respondent in one of the two sub-experiments. In this case, the estimated utility coefficients, for the bridging factors, may vary and the consequent bridging process is inadequate.

Thus, it is interesting to settle down a test procedure in order to verify the presence of incoherent judgements. Let's distinguish the two cases of metric and non-metric Conjoint models both estimated with the OLS.

4.1 THE METRIC CASE

When the overall preference is expressed by a rating on a continuous scale, the most feasible estimation procedure is based on the Ordinary Least Squares method. Conjoint Analysis can be seen both as a Multiple Linear Regression model and as an Analysis of Variance model. The classical assumptions on the distribution of the random error still hold.

In this framework, for each respondent, the hypothesis of Coherence can be tested against a significant deviation. The test statistic can be based on the difference between two estimate coefficients, for the same level of the bridging attributes, in the two different classical CA. An usual *t*-test for *independent* sample comparison can be used, because the observations (the stimuli) in the two regression models are independently evaluated, even if it is the same judge who assigns the two different sets of scores.

Actually, it is possible to test the presence of the Coherence effect by

introducing multiplicative dummy variables in the model (3) used for the estimation of the bridging factors in the *GIP* procedure.

These variables assume the value “-1” for the first set of answers and the value “+1” for the second set. Therefore, the presence of a significant difference is tested according to the usual *t*-test on the value of the dummy coefficients.

Assuming one bridging factor with k^B levels, the Conjoint Analysis model (3) becomes:

$${}_c \mathbf{y} = u_0 + u_1^B {}_c \mathbf{x}_1^B + v_1 \mathbf{d}_c \mathbf{x}_1^B + \dots + u_{k^B}^B {}_c \mathbf{x}_{k^B}^B + v_{k^B} \mathbf{d}_c \mathbf{x}_{k^B}^B + {}_c \mathbf{e} \tag{6}$$

where ${}_c \mathbf{x}_l^B$ (with $l = 1, \dots, k^B$) is the generic column vector of design matrix ${}_c \mathbf{X}^B$, \mathbf{d}_c is the dummy vector, u^B is the generic Bridging utility coefficient and v_l ($l = 1, \dots, k^B$) is the generic coefficient of the dummy variable.

The null hypothesis of Coherence on the significance of the dummy coefficients can be formulated as follows:

$$H_0 : v_l = 0; \forall l \in \{1, \dots, k^B\} \tag{7}$$

against the alternative:

$$H_1 : v_l \neq 0$$

If the null hypothesis is accepted for the whole set of levels, the judge is coherent. If the null hypothesis is rejected for at least a v_l , we have detected an incoherent judge. This judge should be eliminated from the bridging analysis. The presence of a lot of incoherent judges can suggest us the inopportunity of making the bridging procedure.

4.2 THE NON-METRIC CASE

Let’s suppose that in a bridging analysis the preferences are expressed as untied ranks. The OLS method can be still used (Saporta, 1992) at explorative aim. An empirical validation procedure of the bridging results can be performed.

Let’s consider the distribution of the part-worth estimates. This is the distribution of the means computed on the all possible subsets, of fixed dimension, drawn by blocks from the first N natural numbers. Indeed, the OLS estimate of the generic part-worth bridging coefficient, u^B , is given by:

$$u^B = \frac{1}{N} \sum_{i=1}^N x_i y_i = \frac{1}{N/L} \sum_{i=1}^{N/L} y_i \tag{8}$$

where L is the number of levels of the generic bridging factor, x_i is the coded value

$(x_i \in \{0,1\})$ of the dummy bridging factor and y_i is the generic rank $(y_i \in \{1, \dots, N\})$.

Therefore, the part-worth coefficients are averages of ranks. The distribution of the part-worth coefficients defined in (8) is the following:

$$u^B \sim N\left(\frac{N+1}{2}; \frac{1}{N} \frac{N^2-1}{12} \frac{N-(N/L)}{N-1}\right) \quad N \rightarrow \infty \quad (9)$$

In real applications, N is not so large, for example, an experimental design with seven factors at two levels and three factors at four levels needs at least $N=32$ stimuli. In the bridging technique the number of stimuli is split up in two sets. Therefore the asymptotic approximation could be doubtful. However, the distribution is approximately normal even if we have $N=8$ stimuli and $L=2$ levels (Fig. 1).

For taking a decision on the coherence of each judge we consider two bridging coefficients $-u_1^B$ and u_2^B – obtained from the analysis and we select the corresponding two cumulative frequencies, $F(u_1^B)$ and $F(u_2^B)$ on the cumulative standardized normal distribution.

Finally, we compute for each judge the squared distance

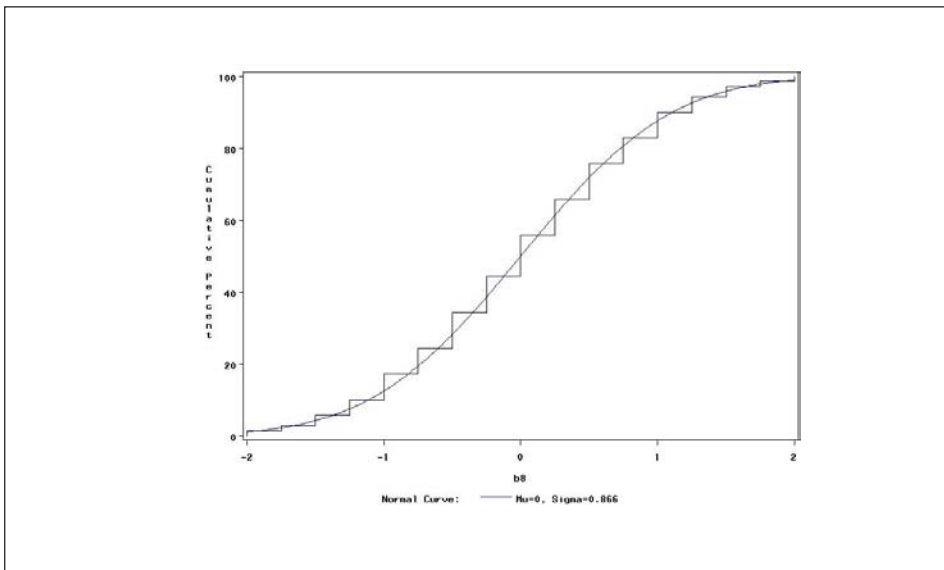


Fig.1 : Cumulative density function distribution of all samples (size 4) drawn from the set of $N = 8$ natural numbers.

$d_g^2 = \left(F(u_1^B) - F(u_2^B) \right)^2$, and if this distance is less than a given value ϵ , for the most judges, the whole process can be considered appropriate, otherwise we can detect the incoherent judges. Note that the value of ϵ can be appraised by comparing the quantiles of the exact distribution of d^2 .

CONCLUDING REMARKS

The problem of complex stimuli in Conjoint Analysis has been discussed in this paper by looking at bridging techniques. The bridging technique developed by Bretton-Clark and a new proposal (the 'GIP technique) have been described and compared. A validation procedure on the bridging results has been performed.

We have applied the GIP technique on different data sets. We have compared the GIP results with the results obtained on the same data sets with the Bridging of Bretton and Clark. The GIP performs better than the other technique because the coefficients are more similar to those obtained by applying classical conjoint analysis on the full design.

Further studies concern the extension of the bridging procedures to the case of non-metric estimation techniques (Monanova, Morals; Kruskal, 1969). Another interesting point consists in carry out the bridging procedure to surveys where it is necessary to split up the original design in more than two subsets.

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UNA NUOVA METODOLOGIA PER IL TRATTAMENTO DEGLI SCENARI COMPLESSI NELL'ANALISI CONGIUNTA

Riassunto

Questo lavoro si occupa del problema del trattamento degli stimoli complessi, (così definiti per la presenza di numerosi fattori e livelli), nell'ambito dell'Analisi delle preferenze dei consumatori. In particolare, si propone una nuova metodologia che si basa sulla filosofia del "bridging" (Albaum, 1989), cioè sull'idea di poter suddividere una indagine complessa in due sottoindagini con dei fattori in comune (fattori ponte). La metodologia nuova, denominata GIP, sviluppa un'originale tecnica di stima per passi che sfrutta l'ortogonalità dei disegni sperimentali sulla base dei quali sono state progettate le indagini. Nell'ambito del lavoro viene, inoltre, proposta una procedura per la validazione dei risultati della metodologia. Tale procedura ha il vantaggio di poter essere generalizzata e applicata a qualsiasi procedura di bridging.