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Model-Based Approach for Importance-Performance Analysis

Federica Cugnata · **Silvia Salini**

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Abstract The importance that users or customers attach to various services and products is an essential part of customer satisfaction surveys. Some proposals for linking satisfaction and importance can be found in available literature. The objective is to identify and understand the dimensions with high importance but low perceived quality. These dimensions are primary candidates for focused improvement initiatives. In this study, we propose to apply a class of statistical models, denoted as `CUB` models, generally used to estimate the *feeling* and the *uncertainty*, to measure the *importance* of items on observed overall satisfaction. A questionnaire with explicit variables of importance for each dimension is considered to compare the obtained ranks with the observed ones. Then the estimated importance and the perceived quality, both obtained with the `CUB` models, will be jointly analyzed in different datasets coming from various fields. This approach will be compared with some others reported in the literature.

Keywords `CUB` models · ordinal variables · customer satisfaction · service quality

1 Introduction

The importance that users or customers attach to various services and products is a vital part of customer satisfaction surveys, as much as the measure of the quality and the satisfaction. In some cases, the level of importance is asked explicitly in the survey questionnaire; in other cases, it is derived using statistical models. There are

F. Cugnata
Department of Economics, Management and Quantitative Methods - Università di Milano
E-mail: federica.cugnata@unimi.it

S. Salini
Department of Economics, Management and Quantitative Methods - Università di Milano
Tel.: +39-02-50321538
Fax: +39-02-50321505
E-mail: silvia.salini@unimi.it

in the literature some proposals for linking satisfaction and importance. The objective is to identify and understand the dimensions with high importance but low perceived quality or satisfaction. These dimensions are primary candidates for focused improvement initiatives. This approach is not new in the literature; the framework of importance-performance analysis (IPA) has first been presented by [20]. In the classical IPA approach explicit questions on importance are present in the questionnaire. Moreover, if the questionnaire includes a question on overall satisfaction, then it is possible to measure the impact of each dimension on overall satisfaction to determine importance. In other cases, when overall satisfaction is not asked, it is possible to obtain the latent overall satisfaction. Each time factor analysis or similar methods are used, the question of how important the various dimensions are on overall satisfaction arises.
In Section 2, some related works are presented. Section 3 is devoted to a brief presentation of `CUB` models, focusing on their use to obtain a measure of importance. Section 4 gives two different examples from diverse fields and with various data structures. The first example considers the ABC dataset.[1] The second example is the typical questionnaire filled by passengers of airline companies to evaluate a flight. The `CUB` will be compared to some of the related works. Some conclusions are drawn at the end of this paper.

2 Related Works

The just mentioned Importance-Performance Analysis ([20]) is a technique originally developed for marketing that has also seen wide application in other fields (see for example [6], [22]). For a review of IPA, see for example [8]. The IPA uses measures of importance and performance plotted in an *action grid* to identify the strengths and weaknesses of a service or company. The action grid is divided into four quadrants, usually using the mean or median of these measures as the crosshairs; see Figure 1. The four quadrants help managers and marketers focus on improving customer relationships.

If the questionnaire explicitly asks both the level of importance and the satisfaction for items, the more simple way to describe the relationship is the bivariate plot with simple descriptive indices. This descriptive approach in the context of customer satisfaction surveys is detailed [18] and called *strengths and weaknesses*. In the same book, in [15] it is discussed how standard control charts (p, c and u charts) can be used to identify significant relations. A *strength* is an area where the satisfaction is significantly high and the relative declared importance is high. A *weakness* is a problem area with significantly low satisfaction and high declared importance.

We report now some proposals in which importance is derived using more sophisticated indexes or statistical models.

[1] ABC (a fictitious but realistic company) is a typical global supplier of integrated software, hardware, and service solutions to media and telecommunications service providers, see Chapter 2 on Modern Analysis of Customer Surveys: with applications using R, Wiley, 2012 [17].

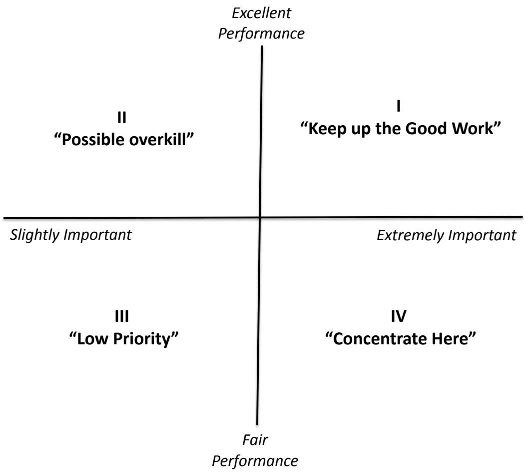

Fig. 1 Importance-performance analysis action grid

Observing that the customers' self-stated importance is not always the actual importance of a service attribute, [8] use a back-propagation neural network to derive the actual importance from overall satisfaction.

For the cases when self-stated importance is unavailable, [27] propose two different measures of importance: entropy and mutual information. Both methods are applicable to measure the spread of ordinal data by examining whether the data are spread evenly across all the categories or contained in one or a few categories. The notion is called entropy. In addition, the mutual information method can be applied to evaluate the dependence between two random variables and measures how much the entropy of one random variable is reduced by knowledge of another. Therefore, the mutual information method is an ideal measure of stochastic dependence between two random variables.

In [18], the authors present an alternative analysis called the *WOW effect*. Declared importance, as reflected by the importance rating on each item, can be compared to generated importance derived from statistical models. Each item can be represented in a bivariate plot with declared and generated importance. A *price of entry* is an item with high declared and low generated importance. Issues that statistically do not affect overall satisfaction, but are declared important by customers, are issues which must be addressed. These issues can cause dissatisfaction but do not generate significant advantage. A *key to success* is an item with high declared and high generated importance. This involves issues that statistically affect overall satisfaction and are also declared important by customers. These issues should be addressed since they are key to generating customer satisfaction. A *future opportunity* is an item with relatively low declared importance but high generated importance. These are issues that statistically affect overall satisfaction but which are not declared important by customers. Such issues are our opportunity to create a *WOW effect* by anticipating customer needs.

The above-mentioned works propose various models for the attribute importance. Other studies also focus on how to get the attribute performance, satisfaction of quality, in an alternative way to simple descriptive statistics. Most of these studies can be placed in the statistical literature for ordinal variables in the framework of evaluation of service quality.

The satisfaction for services of general interest in Europe is analyzed by [10]. They compare the nonlinear principal components analysis (NLPCA) with the Rasch Model (RM). They consider three Eurobarometer waves 2000-2002-2004, EU-15, and satisfaction for accessibility, price and quality of fixed telephone, electricity, gas and water supply services. They conduct a study that determines which items (services or aspects of a service) are more important for the consumer, as indicated by the component loadings (NLPCA), and which of these are perceived by the consumer to be of higher or lower quality, as indicated by item parameters (RM). A joint reading of the findings of RM and NLPCA is derivable from a scatter plot, where each item is represented by its component loading (horizontal axis) and item parameter (vertical axis). In particular, they identify items with low quality and high weight for which an action could be welcome, since it would lead to a substantial increase in the general level of satisfaction.

The use of multidimensional item response theory (MIRT) models is proposed by [1] to reach the same scope using a single model. In particular they interpret the parameter, known in the literature as *discriminant* in the 2 Parameters Logistic Model (2PL), as the parameter of *relevance*, and they also produce a map of the relevance and quality.

The drivers of job satisfaction, particularly the latent variable fairness of work, are analyzed by [4] and [3], using the Random Forests Tree Model. They run this algorithm, using the overall dimension as the dependent variable and the corresponding items as predictors. Moreover, they produce a map, where the horizontal axis is the *item importance* obtained with the Random Forests Tree Model, and the vertical one is the *item quality*, obtained with the Rasch Rating Scale Model.

In this paper, we propose to use a single model [23] to derive both attribute performance and attribute importance. The model, initially called `MUB` *Mixture of Uniform and (shifted) Binomial random variables* now called `CUB` for the inclusion in the mixture of *Covariates* [25], is described in detail in the following section. This model is applied because it is based on the psychological mechanism that induces a customer to choose a definite item or to manifest an expressed preference towards an object, service or brand. In the application, we will compare our approach with two approaches presented in [10] and [27].

3 Introduction to `CUB` Models

The `CUB` models are a class of statistical models introduced by Piccolo ([23]) for the specific purpose of interpreting and fitting ordinal responses. In `CUB` models, ratings are interpreted as the result of a cognitive process, where the judgement is intrinsically continuous, but is expressed in a discrete way within a prefixed scale of m categories. The rationale of this approach stems from the interpretation of the final choices of respondents as a result of two components, a personal *feeling* of the subject towards the item and some intrinsic *uncertainty* in choosing the ordinal value of the response. This is generated by several factors, intrinsically related to the choice mechanism, such as the knowledge of the problems and/or the characteristics of the objects, the personal interest, the time spent to decide, the laziness of the subject and so on. The first component is expressed by a shifted Binomial random variable. The second component is expressed by a Uniform random variable. The two components are linearly combined in a mixture distribution. Formally, the probability distribution is given by:

$$P_r(R=r) = \pi \binom{m-1}{r-1} \xi^{m-r}(1-\xi)^{r-1} + (1-\pi)\frac{1}{m}, \qquad r = 1,2,\ldots,m. \quad (1)$$

Since the distribution is well defined when parameters $\pi \in (0,1]$ and $\xi \in [0,1]$, the parametric space is the (left open) unit square:

$$\Omega(\pi,\xi) = \{(\pi,\xi) : \ 0 < \pi \leq 1, \ 0 \leq \xi \leq 1\}.$$

It is proven by [12] that such a model is identifiable for any $m > 3$.

From an interpretive point of view, $(1-\xi)$ may be understood as a measure of the *feeling* of the respondent towards the item, whereas $(1-\pi)$ reflects *uncertainty* in the final judgement. More specifically, the feeling parameter $(1-\xi)$ may be interpreted as mostly related to location measures and strongly determined by the skewness of responses: $(1-\xi)$ increases when respondents choose high ratings, and vice versa. On the other hand, the lower the weight $(1-\pi)$, the smaller the contribution of the Uniform distribution in the mixture. If $(1-\pi) \longrightarrow 1$, the respondent manifests a great propensity towards an extreme indecision in the choice. If $(1-\pi) \longrightarrow 0$, the respondent manifests a minimum propensity towards an extreme indecision, and the choice is more resolute and determined mostly by a *feeling* attitude ([14]).

In order to improve the performance of this structure, an extension of the `CUB` model with covariates has been proposed ([11]; [25]). If p and q covariates are introduced for explaining *uncertainty* and *feeling*, respectively, we will denote such a structure as a $\texttt{CUB}(p,q)$ model. The general formulation of a $\texttt{CUB}(p,q)$ model is modelled by two components:

1. A *stochastic component*:

$$Pr(R_i = r \mid \boldsymbol{y}_i; \boldsymbol{w}_i) = \pi_i \binom{m-1}{r-1} \xi_i^{m-r}(1-\xi_i)^{r-1} + (1-\pi_i)\left(\frac{1}{m}\right), \quad r = 1,2,\ldots,m;$$

for any $i = 1,2,\ldots,n$.

2. Two *systematic components*:

$$\pi_i = \frac{1}{1+e^{-\boldsymbol{y}_i\boldsymbol{\beta}}}; \qquad \xi_i = \frac{1}{1+e^{-\boldsymbol{w}_i\boldsymbol{\gamma}}}; \qquad i = 1,2,\ldots,n,$$

where $\boldsymbol{y}_i = (1, y_{i1}, y_{i2}, ..., y_{ip})'$ and $\boldsymbol{w}_i = (1, w_{j1}, w_{j2}, ..., w_{jq})'$ denote the covariates of the i-th subject, selected to explain π_i and ξ_i, respectively. $\boldsymbol{\gamma} = (\gamma_0, \gamma_1, ..., \gamma_q)'$ and $\boldsymbol{\beta} = (\beta_0, \beta_1, ..., \beta_q)'$ are parameter vectors.
For a positive increasing y_{ij}, $j = 1, 2, ..., p$ (all other things being equal), we see that the *uncertainty* $(1-\pi)$ decreases for $\beta_j > 0$, and it increases for $\beta_j < 0$; on the other hand, as w_{ik}, $k = 1, 2, ..., q$, increases, then the *feeling* $(1-\xi)$ decreases if $\gamma_k > 0$, and it increases for $\gamma_k < 0$.

This formulation is general and includes all special cases, where the dependency on covariates may be absent, restricted to one of the two parameters or related to both parameters. In order to distinguish these situations, the following acronyms are used respectively: CUB$(p,0)$, CUB$(0,q)$, CUB(p,q); the model (1) is simply denoted as CUB$(0,0)$.

The nature of the probability distribution (*Uniform and shifted Binomial*) included in the mixture and the presence of *Covariates* justify the acronym CUB.

Asymptotic statistical inference for CUB models has been developed by Piccolo ([23]); an effective EM procedure for maximum likelihood estimators has been implemented and a related software is freely available ([14]).

The CUB models show a satisfactory performance on several real datasets since they are able to model different empirical distributions. Moreover, the possibility to insert covariates into the mixture, appropriately chosen among the available variables, makes the formulation interesting for several practical applications. The CUB models have been successfully applied in several fields, ranging from sociology, evaluation research, market research and medical studies to linguistics. Some examples concern marketing ([13]; [5]), medicine ([7]), subjective perception studies ([2]; [13]) and sensometrics ([25]).

We propose to use the CUB models to measure both the *quality/performance* and the *importance/relevance* of items. The *quality/performance* value for each item is represented by the *feeling* $(1-\xi)$, obtained by estimating as many CUB(0,0) models as there are items.

In order to obtain the importance of items on observed overall satisfaction, we propose to estimate a CUB model with overall customer satisfaction as a dependent variable and items satisfaction as covariates to explain *feeling*. A similar application, even if it is not framed in the context of IPA, can be found in Iannario and Piccolo in paragraph 13.8 of [14]. We use a CUB model with q covariates to explain *feeling*, so that the *feeling* parameter is expressed as:

$$\xi_i = \frac{1}{1 + e^{-(\gamma_0 + \gamma_1 w_{1i} + \cdots + \gamma_q w_{1q})}}, \qquad i = 1, 2, \ldots, n.$$

The standardized $\gamma_1, \gamma_2, ..., \gamma_q$ coefficients reflect the importance of each item in predicting *feeling* of the overall satisfaction.

When the independent variables are highly correlated, it is not possible to determine the separate effect of any particular independent variable on the dependent variable; the assessment of importance could be difficult using a multiple model. In these cases, it is possible to fit a series of CUB(0,1) models, which include item satisfaction as covariate, to explain *feeling* of the overall satisfaction and use the standardized γ_1 coefficients for deriving reliable importance measures. The ranking of the variable importance could be also created using p-values of Wald o LR test, like in the stepwise model selection approach.

4 Applications

We now apply the proposed method to some real datasets. In the application, we use other models as a benchmark, but the intention is not to select the best model. Following the idea of information quality (*infoQ*) [16], [19], the combination and the integration of models and analysis allow the achievement of a greater number of goals and increase the knowledge.

The first example considers the previously mentioned ABC dataset. The dataset includes explicit variables of importance for each item and overall questions: *satisfaction, recommendation* and *repurchase*. Using this dataset, we verify whether the ranked order of importance, obtained by estimating a CUB model on overall satisfaction using the various dimensions as covariates, is consistent with the order of declared importance. Moreover, this dataset gives us the opportunity to do a benchmarking with other modern techniques mentioned in the related works. The second example is the typical questionnaire filled by passengers of airline companies to evaluate a flight. It contains overall variables such as *overall experience, likelihood to repurchase, likelihood to recommend* and *value of money*. Moreover, several dimensions are evaluated: *departure, booking, check-in, cabin environment, cabin crew, meal,* etc.

4.1 ABC data

The ABC dataset is the reference dataset in the Wiley book titled, *Modern Analysis of Customer Surveys: with applications using R.*[2] In order to see a complete analysis of this dataset using CUB models, see Chapter 13 of the same book. In our application, we select some dimensions only. For each variable in the ABC questionnaire, the satisfaction level (1 to 5) and the item importance level (low=1, medium=2, high=3) are present. For each dimension, overall satisfaction is asked, but not overall importance. In Figure 2, for each dimension, we compare the declared importance (D1) (described by the percentage of importance rating equal to 3 in the sub-items), with the one obtained using mutual information (MI) [27], nonlinear principal component analysis (NLPCA) [10] and CUB(0,1). We use the dimensions and not the single items because the aim in this application is to control the coherence between declared and generated importance.

The importance rankings obtained through MI and CUB are more coherent to the observed one than the ranking obtained through NLPCA. The first two consider the observed overall satisfaction; the second uses the latent dimension. This means that there is coherence between the self-declared importance and the importance deducted

[2] Download at http://eu.wiley.com/WileyCDA/WileyTitle/productCd-0470971282,descCd-DOWNLOAD.html

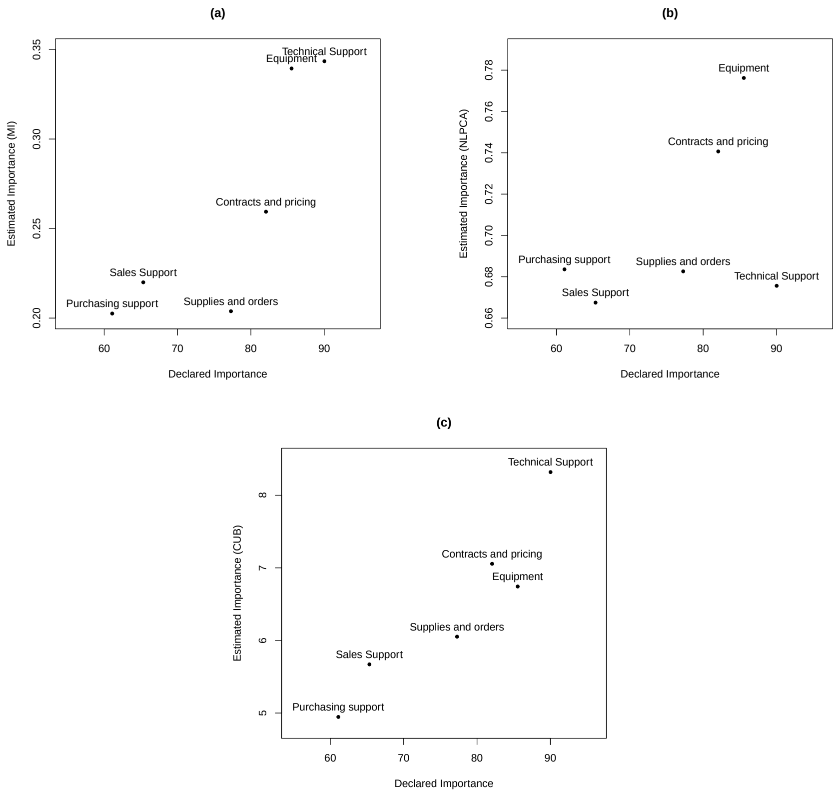

Fig. 2 (a) DI vs MI (b) DI vs NLPCA (c) DI vs CUB

from the declared overall satisfaction. However, the satisfaction (latent) obtained as a linear combination of satisfaction on the individual dimension is not the same as the declared overall satisfaction. This can be a useful information for managers. In giving an overall judgement, customers have a mental attitude that is not additive and linear.

In the following discussion, we consider also the attribute performance. It is recalled that in the CUB models, this is represented by the *feeling* parameter. Figure 3 shows the action grid in the three cases: a) IPA approach with mutual information (attribute importance) versus median (attribute performance) [27], b) NLPCA loadings (attribute importance) versus Rasch item parameters (attribute performance) [10] and c) *importance* versus *feeling* both obtained with the CUB model. As just mentioned [27], in their IPA approach, use the median to represent the attribute performance. For this reason, unlike the other two methods, the first map (a) does not discriminate the item according to the attribute performance. Anyway, for all the maps, *equipment* and *contracts and pricing* are the drivers that need immediate intervention: they are relevant in increasing both overall satisfaction and latent satisfaction, but their per-

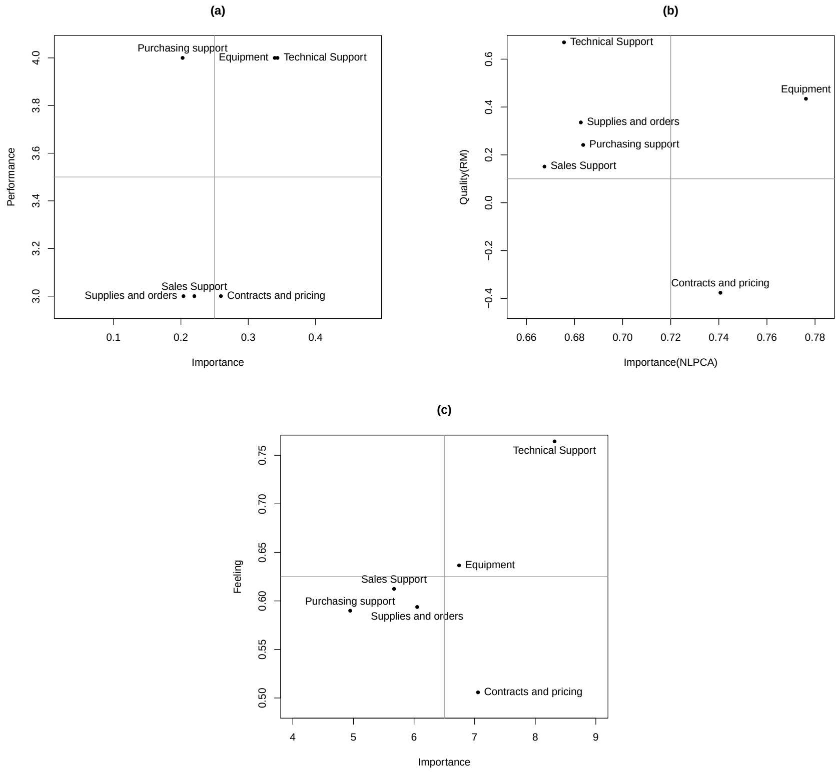

Fig. 3 (a) Median vs MI (b) NLPCA vs Rasch (c) CUB

formance/perceived quality/feeling is low. The same scatter plot as in Figure 3(b) has been proposed by [9].

4.2 Airline industry

This example considers a typical questionnaire filled by passengers of airlines companies to evaluate a flight similar to the one presented in [21]. The questionnaire contains overall variables such as *overall experience*, *likelihood to repurchase*, *likelihood to recommend* and *value for money*. Moreover, there are questions grouped by different topics: *overall booking, check-in, transfer, lounge, departure, cabin environment* and *meal*. For each topic, there is also an evaluation of overall satisfaction. The evaluation of each item is based on a seven-point scale (from 1 = extremely dissatisfied to 7 = extremely satisfied). Results refer to $n = 18619$ valid questionnaires.

In order to show the typical result of the CUB model, also considering the *uncertainty* parameter, in Figure 4 we present the results obtained by fitting CUB(0,0) models for the ten variables. We observe that passengers express judgement swith

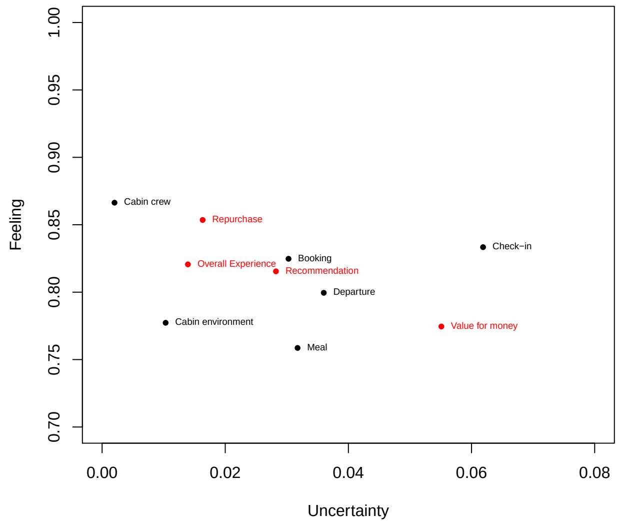

Fig. 4 CUB map: Feeling vs Uncertainty

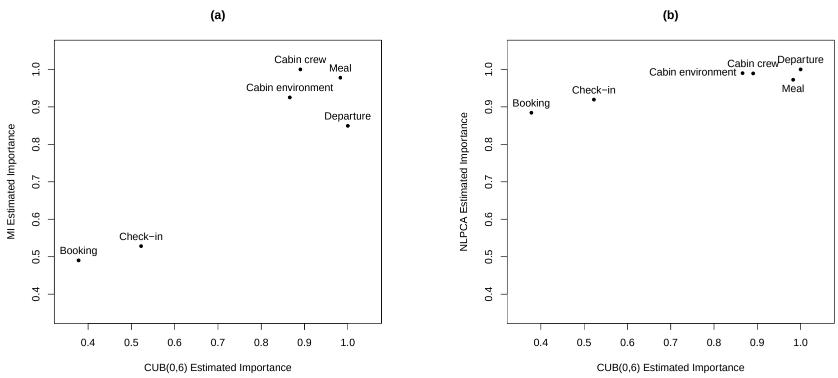

Fig. 5 (a) CUB Importance vs MI (b) CUB Importance vs NLPCA

limited uncertainty and high satisfaction. It is interesting to note that *value for money* has lower satisfaction and higher uncertainty than the other target variables.

We apply CUB(0,6), with *overall experience* as a dependent variable and the six dimensions (*booking, check-in, departure, cabin environment, meal* and *cabin crew*) as covariates for *feeling* to obtain the importance and, similar to the previous example, we compare the results with MI and NLPCA. In this case, the self-declared importance is unavailable, so we compare CUB versus MI and CUB versus NLPCA. In order to obtain a more readable figure, we normalize the importance values, dividing them by their maximum value. Figure 5 shows the results.

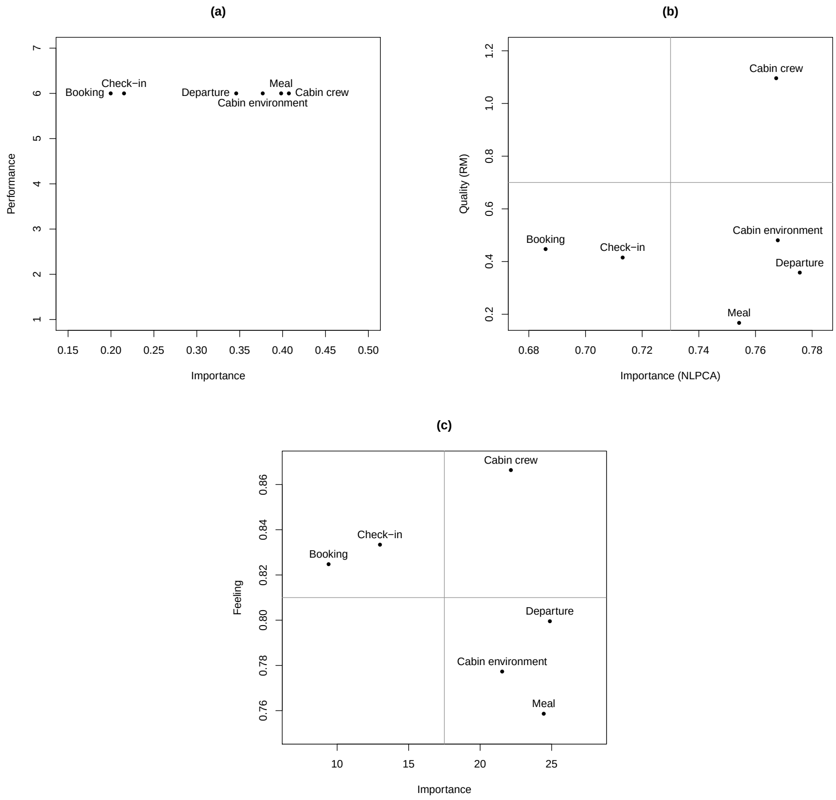

Fig. 6 (a) Median vs MI (b) NLPCA vs Rasch (c) `CUB`

The NLPCA result in this case is flatter than the other two, which instead lead to very similar results. The weights measured on latent overall satisfaction (Figure 5 b) seem very similar for all items. On the contrary, if the overall satisfaction is declared (Figure 5 a), the importance weights are more different from each other.

Figure 6, like Figure 3, is the representation of the action grid for the three approaches: a) IPA approach with mutual information (attribute importance) versus median (attribute performance) [27], b) NLPCA loadings (attribute importance) versus Rasch item parameters (attribute performance) [10] and c)*Importance* versus *feeling* both obtained with the `CUB` model.

Also in this case, the attribute performance is not clearly defined by the [27] approach: see the map in (a). Instead, on maps (b) and , *departure*, *meal* and *cabin environment* are the dimensions with highest importance but lowest perceived quality/feeling than need to be focused on immediately.

5 Summary and Future Perspectives

In conclusion, the examples presented show that the CUB model is a potentially useful tool to measure jointly the importance and the performance, when you have variables measured on an ordinal scale and an overall variable in a customer/user/patient satisfaction survey. With respect to the attribute importance, the ABC example shows that the importance derived by CUB gives the same ranking as the self-declared importance, so this is a useful method when self-declared importance is not present. The results that we have obtained are consistent with the ones produced with the mutual information approach, which use as well the observed overall satisfaction. We have also shown (see the NLPCA applications) that IPA applies also where the observed overall satisfaction is not available. Regarding the attribute performance, we can conclude than our approach is better that the simple descriptive statistics (e.g., median), and our ranking is also consistent with the one obtained with the Rasch item parameters. Future developments may proceed in different directions. The authors wish to deal with: i) comparison and integration of CUB with causal models; we could use Bayesian Networks [26] with explanatory variables to figure out what affects both satisfaction and importance; ii) the comparison and integration of CUB with other models commonly used to validate psychometric instruments; and iii) the exploration of the analytical relation between the mutual information [27] based on entropy and the CUB models that are based, through the*uncertainty* parameter, on the heterogeneity concept too.

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References

1. Andreis, F. and Ferrari, P.: Customer Satisfaction evaluation using Mulidimensional Item Response Theory models. Tech. Rep., *submitted* (2013)
2. Caliendo, G., Iannario, M.: Communicating European values in institutional discourse: a statistical model for the analysis of citizens' perception of the EU. GlottoTheory Int J Theor Linguist 2, 19-40 (2009)
3. Carpita, M. and Vezzoli M.: Combining Statistical and Algorithmic Models for Latent Variables Analysis: A Look at the Fairness of Work. Tech. Rep., *presented in IES 2011* (2011)
4. Carpita M., Zuccolotto P. : Mining the drivers of job satisfaction using algorithmic variable importance measures, *in Metodi, Modelli, e Tecnologie dell'Informazione a Supporto delle Decisioni*, Vol. I: Metodologie, eds. L. D'Ambra, P. Rostirolla, M. Squillante, Milano, FrancoAngeli, 63-70 (2007)
5. Cicia, G., Corduas, M., Del Giudice, T., Piccolo, D.: Valuing Consumer Preferences with the CUB Model: A Case Study of Fair Trade Coffee. Int. J. Food System Dynamics 1, 82-93 (2010)

6. Daniels, M.L. and Marion, J.L.: Visitor evaluations of management actions at a highly impacted Appalachian trail camping area. Environ. Manag. 38, 1006-1019 (2006)
7. D'Elia, A.: A statistical modelling approach for the analysis of TMD chronic pain data. Statistical Methods in Medical Research 17, 389-403 (2008)
8. Deng,W.-J., Chen,W.-C., Pei,W.: Back-propagation neural network based importanceperformance analysis for determining critical service attributes. Expert Syst. Appl. 34, 1115-1125 (2008)
9. Ferrari, P. and Barbiero, A.: Nonlinear Principal Component Analysis, in Modern Analysis of Customer Satisfaction Surveys, Kenett R.S. and Salini S. Editors, John Wiley and Sons, Chichester: UK (2012)
10. Ferrari, P.A. and Salini, S.: Complementary Use of Rasch Models and Nonlinear Principal Components Analysis in the Assessment of the Opinion of Europeans About Utilities. Journal of Classification, Springer Verlag, 28: 53-69 (2011)
11. Iannario, M.: A statistical approach for modelling urban audit perception surveys. Quaderni di Statistica 9, 149-172 (2007)
12. Iannario, M.: On the identifiability of a mixture model for ordinal data. Metron, LXVIII, 87-94 (2010)
13. Iannario, M., Piccolo, D.: Statistical modeling of subjective survival probabilities. Genus 66 (2), 17-42 (2010)
14. Iannario, M. and Piccolo, D.: CUB Models: Statistical Methods and Empirical Evidence, in Modern Analysis of Customer Satisfaction Surveys, Kenett R.S. and Salini S. Editors, John Wiley and Sons, Chichester: UK (2012)
15. Kenett, R.S., Deldossi, L. and Zappa, D.: The standards and control charts applied to customer surveys, in Modern Analysis of Customer Satisfaction Surveys, Kenett R.S. and Salini S. Editors, John Wiley and Sons, Chichester: UK (2012)
16. Kenett, R., Salini, S.: Modern analysis of customer satisfaction surveys: comparison of models and integrated analysis. Applied Stochastic Models in Business and Industry (2011)
17. Kenett, R.S. and Salini S.: Modern Analysis of Customer Satisfaction Surveys: with applications using R, John Wiley and Sons, Chichester: UK (2012)
18. Kenett, R.S. and Salini S.: The ABC annual customer satisfaction survey, in Modern Analysis of Customer Satisfaction Surveys, Kenett R.S. and Salini S. Editors, John Wiley and Sons, Chichester: UK (2012)
19. Kenett, R.S. and Shmueli, G.: On information quality. J. R. Statist. Soc. A, 176,4 (2013)
20. Martilla, J.A., James, J.C.: Importance-performance analysis. J. Mark. 41(1), 77-79 (1977)
21. Nicolini, G. and Salini, S.: Customer satisfaction in the airline industry: The case of British Airways. Quality and Reliability Engineering International, 22, 1-9 (2006)
22. Oh, H. : Revisiting importance-performance analysis. Tourism Manage 22:617627 (2001)
23. Piccolo, D.: On the moments of a mixture of uniform and shifted binomial random variables, Quaderni di Statistica, 5, 85-104 (2003)

24. Piccolo, D.: Observed information matrix for MUB models. Quaderni di Statistica, 8, 33-78 (2006)
25. Piccolo, D., D'Elia, A.: A new approach for modelling consumers' preferences.Food Quality and Preference 19, 247-259 (2008)
26. Salini, S. and Kenett, R.S.: Bayesian Networks of Customer Satisfaction Survey Data, Journal of Applied Statistics, Vol. 36, No. 11, pp. 1177-1189 (2009)
27. Shieh, J. I. and HungWu, H.: Applying information-based methods in importanceperformance analysis when the information of importance is unavailable. Qual Quant, 45:545557 (2011)