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Sensory analysis in the food industry as a tool for marketing decisions

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Abstract In the food industry, sensory analysis can be useful to direct marketing decisions concerning not only products, for example product positioning with respect to competitors, but also market segmentation, customer relationship management, advertising strategies and price policies. In this paper we show how interesting information useful for marketing management can be obtained by combining the results from CUB models and algorithmic data mining techniques (specifically, variable importance measurements from Random Forest). A case study on sensory evaluation of different varieties of Italian espresso is presented.

Keywords Sensory analysis · Ordinal data · CUB models · Italian coffee

1 Introduction

Marketing strategies traditionally involve a wide range of activities dealing with product management, price policies, distribution, advertising, customer relationships, product loyalty, and so on. However, the product remains the starting point of any marketing decision.

In general, the creation of a successful product for the market can be a difficult task, especially for a long-term perspective. In the context of food industry, sensory evaluation is one of the tools that marketing management can use in order to understand the target market, identify the most important features of a product, eliminate wasted effort during product development,

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deal with quality issues, compare their brands to others and try to ensure long shelf life. The ability to give a scientific evaluation and a quantitative measure to the appearance, aroma, flavour, and texture of a food product is critical for setting performance standards and evaluating progress.

Recently, the importance of sensory matters for the marketing management has been more and more widely recognized. For this reason, several research contributions in this sense have been proposed, by introducing the systematic use of sensory benchmarking, sensory profile evaluation, analysis of competitive advantages on sensory features (Van Trijp and Schifferstein 1995; Bogue and Ritson 2004, among others). The recognized utility of sensory analysis in marketing management is also proved by the recent proposal of extending the use of sensometrics outside the context of food products (Philippe *et al.* 2003).

Marketing decisions can take advantage of sensory evaluation made by both consumers/customers and experts: in the first case, producers directly understand the market preferences; in the second case, experts can help to orient different marketing decisions (e.g., advertising).

¿From a statistical point of view, sensory evaluation is a scientific method where experimental results are collected on a set of sampled consumers who express preferences and reactions with respect to food and drink characteristics. In fact, the expressed choice is the result of a human decision and we should assume that this process is the outcome of complex interactions conditioned by personal history, environmental variables, subjective covariates and objects' characteristics, which also interact with the modality of the survey. As a consequence, it may be relevant to study the stochastic structure of the choice process in order to adequately model the observed preferences.

Operationally, to collect sensory data, experts or untrained subjects are often asked to rate or rank different products on the basis of some sensory descriptors (items), by expressing their perceptions on hedonic response scales (usually 9-point Likert scales). In this way, affective tests transform sensory perceptions into ordinal measurements. Such scales are of qualitative nature, although it is common to use some numerical coding as the integers $\{1, 2, \ldots, m\}$, for instance. Hence, a correct statistical analysis must be related to ordinal data modelling. The current literature focuses on the models generated by distribution functions since the cumulative probabilities are able to capture the ordinal nature of rating data (McCullagh 1980; McCullagh and Nelder 1989; for a recent review, see Agresti 2010).

In this paper, following previous research in the area promoted by Piccolo (2003), we adopt a modelling strategy which assumes that the response of each consumer is the combination of a *feeling* attitude towards the product and an intrinsic *uncertainty* component surrounding the discrete choice. This class of models is called CUB and has been successfully applied in several fields (D'Elia and Piccolo 2005; Iannario 2007), and sensory analysis seems to be a favoured context for the implementation of such paradigm (Piccolo and D'Elia 2008; Piccolo and Iannario 2010; Manisera *et al.* 2012).

The main aim of this paper is to show, by means of a case study concerned with Italian *espresso* coffee, how a structured combination of statistical techniques in the mainframe of sensory analysis permits to attain results which can be exploited in different steps of the marketing strategy definition. More specifically, the body of the analysis is represented by the application of the mentioned CUB models in order to quantify the perceptions about the product. This allows the researcher to obtain sensory satisfaction indices, which can be immediately used for product development. In addition, the obtained measures can be the starting point for further quantitative analyses, according to the recorded information about the product, if available. For example, in this paper we pursue the use of the algorithmic variable importance measurement allowed by the Random Forest approach (Breiman 2001) in order to recover useful information for marketing decisions about advertising.

The paper is organised as follows: in Section 2, we discuss the fundamentals of CUB modelling approach whereas in Section 3 we describe the analysis derived by Random Forest variable importance measurement. In Section 4 we present the main results obtained from the case study. Discussion and concluding remarks follow in Sections 5 and 6, respectively.

2 CUB models

As already mentioned, the observed preferences result from the consumers' evaluation of food and drink, that is the sensory pleasantness expressed on a hedonic response scale. Perception and evaluation result from complex psychological mechanisms determined by many interacting factors of different nature (psychological, social, biological, physiological, etc.). Especially when eating and drinking behaviour is involved, the process of making human decision often occurs at a non-conscious level and sensory and marketing researches should take psychological insights into account (Köster 2003, 2009). The genesis of CUB models is perfectly in line with this approach, since feeling and uncertainty are the most prominent latent components we may combine together in order to explain the consumers' judgements (i.e., the observed discrete choices).

The *feeling* component is the degree of taste sensations (overall agreement) towards a given product and results from subjective motivations. According to the latent variable approach, it can be adequately interpreted as a continuous latent random variable, and then discretized, since the consumers' ratings assigned to an item are discrete. On the other hand, the *uncertainty* component is the indecision/fuzziness intrinsically present in any human choice and results from different facts related to the evaluation process: the limited knowledge of the topic, the nature of the chosen questionnaire and response scale, the personal interest towards the items, the ambiguity and/or vagueness of the questions, the time spent for elaborating the choice, and so on.

Such components will be explicitly considered in the CUB models by means of a mixture of two discrete random variables.

2.1 Basic issues

Given that any model contains a large amount of arbitrariness, the rationale for preferring just one of them derives from a blend of logical reasoning, empirical facts and parameter parsimony. In line with these aspects, the class of parametric models we are going to introduce aims at defining the behaviour of respondents as generated by two main latent components, according to the observed empirical evidence about rating surveys.

Specifically, *uncertainty* may be modelled with regard to the extreme choice of a person who assigns the same probability to each category, with a complete indifference. Then, for this component, we introduce the discrete Uniform random variable U defined over the support $\{1, 2, \ldots, m\}$, for a given m:

$$Pr\,(U = r) = \frac{1}{m} = U_r, \quad r = 1, 2, \ldots, m\,.$$

This random variable maximizes the entropy, among all the discrete distributions with finite support $\{1, 2, \ldots, m\}$, for a fixed m, and it is minimally informative about the choice.

Then, we model the *feeling* component by means of a shifted Binomial random variable V whose probability distribution is:

$$Pr\,(V = r \mid \xi) = \binom{m-1}{r-1} \xi^{m-r}\,(1-\xi)^{r-1} = b_r(\xi)\,, \quad r = 1, 2, \ldots, m\,.$$

The rationale for such distribution stems from heuristic and pragmatic point of views: the (shifted) Binomial distribution $b_r(\xi)$ is able to cope with different shapes of sample data and just with a single parameter. From a statistical point of view, combinatorial and pairwise arguments confirm the convenience to adopt such distribution (Iannario 2012a).

If we weight the previous components assumed for uncertainty and feeling, we introduce a (convex) ***C***ombination of a discrete ***U***niform and a shifted ***B***inomial distributions, and this justifies the CUB acronym. Then, a CUB random variable R expressing the final choice of the respondent is defined by the probability mass function:

$$Pr\,(R = r \mid \boldsymbol{\theta}) = \pi\, b_r(\xi) \;+\; (1-\pi)\, U_r\,, \qquad r = 1, 2, \ldots, m\,,$$

where $\boldsymbol{\theta} = (\pi, \xi)'$, $\pi \in (0, 1]$ and $\xi \in [0, 1]$.

The parametric space of such random variable is the (left open) unit square, $\Omega(\boldsymbol{\theta}) = \Omega(\pi, \xi) = \{(\pi, \xi) :\; 0 < \pi \leq 1;\; 0 \leq \xi \leq 1\}$. Iannario (2010) proved that CUB models are identifiable for any $m > 3$.

The class of CUB models turns out to be a very flexible parametric family since the shape of the distribution largely varies over $\Omega(\pi, \xi)$, as shown by Piccolo (2003). This allows to fit data with positive or negative skewness, any modal value on the support $\{1, 2, \ldots, m\}$ and peaked or flat distributions; in addition, these models encompass distributions with a large range of heterogeneity of responses.

Parameters are immediately related to the latent components of the responses. The *feeling parameter* (ξ) is mostly related to location measures and strongly determined by the skewness of responses: it increases when respondents prefer low ratings. Usually, high values of the responses imply high consideration towards the product. Thus, in sensory analysis, the quantity $(1-\xi)$ increases with the sensory satisfaction with the product. Instead, the *uncertainty parameter* (π) modifies the heterogeneity of the distribution and it is mostly related to the comparisons among probabilities. Then, uncertainty of the choice increases with $(1-\pi)$.

The one-to-one correspondence among a CUB random variable and the parameter vector $\boldsymbol{\theta} = (\pi, \xi)'$ suggests to represent each CUB model as a point in the unit square. This visualization is a focal point of the approach since it allows to summarize any aspect of the probability distribution and points to convenient comparisons with respect to time, space and circumstances.

Since $1-\pi$ measures the *propensity* of respondents to behave in accordance to a completely random choice, and $1-\xi$ measures the *strength of feeling* of the subjects with respect to a direct and positive evaluation of the product, hereafter we will consider the visualization of CUB model parameters over the parametric space $\Omega(\boldsymbol{\theta})$ by using the coordinates $1-\pi$ and $1-\xi$, respectively.

The expectation of R is given by: $\mathbb{E}(R) = \frac{(m+1)}{2} + \pi\,(m-1)\left(\frac{1}{2}-\xi\right)$. It confirms that the mean value moves towards the central value of the support $(m+1)/2$ depending on the sign of $(\frac{1}{2}-\xi)$. This behaviour is related to the skewness of the distribution since a CUB random variable is symmetric if and only if $\xi = 1/2$. A peculiar aspect of the expectation of R is its constancy for infinitely many values of the parameter vector $\boldsymbol{\theta} = (\pi,\, \xi)'$; as a consequence, we may obtain the same mean value for quite different rating distributions (Iannario and Piccolo 2012). In addition, the expectation does not convey all the characteristics of a complex random phenomenon since these are explained by a sequence of higher moments. The statistical consequence is that it is more convenient to assume a direct link among parameters and covariates and avoid the reference to the expected value of the response, as it will be pursued in the next subsection. Then, CUB random variables do not belong to the exponential family and there is no linear link function between expectation and parameters.

2.2 Extensions of CUB models

CUB models have been extended in several directions (Iannario and Piccolo 2011), dealing with the probability distribution of the components, the inclusion of subjects' and objects' covariates, a multilevel formulation for hierarchical data, the joint consideration of several objects/items in a multivariate context, and so on. Another generalization stems from the circumstance that respondents may sometimes prefer a quick response instead to weigh up more demanding choices. This behaviour is frequent and induces an anomalous value of the frequency of a given category, causing both biases and inefficiencies in the statistical analysis. Thus, this component should be modelled by means of CUB models with a *shelter effect* (Corduas *et al.* 2009; Iannario 2012a).

All these extensions are particularly noticeable since they allow for testing and measuring the effect of known characteristics on the responses; thus, such models are especially valuable for marketing studies (Iannario and Piccolo 2010). However, in the following, we mainly deepen the situation where subjects' characteristics (socio-demographic, economic, habits) are significantly related to the expressed feeling towards the product. If such covariates are significant, then both interpretation and fitting improve and it is possible to discriminate among subgroups of respondents.

In survey data we collect a sample $\boldsymbol{r} = (r_1, r_2, \ldots, r_n)'$ of expressed ratings, which are realizations of the random sample $(R_1, R_2, \ldots, R_n)$. Denote by $\boldsymbol{T}$ a $n \times (k+1)$ matrix of observed k covariates related to n subjects. Specifically, the row $\boldsymbol{t}_i = (t_{0i}, t_{1i}, \ldots, t_{ki})$ contains the measurements of k variables on the i-th subject, for $i = 1, 2, \ldots, n$ (the convention: $t_{0i} \equiv 1$, $\forall\, i = 1, 2, \ldots, n$ simplifies the notation). According to the significance of related tests, we extract from $\boldsymbol{T}$ the $\boldsymbol{Y}$ and $\boldsymbol{W}$ sub-matrices containing covariates useful for interpreting uncertainty and feeling, respectively.

A CUB model with p covariates to explain uncertainty and q covariates to explain feeling is specified by:

1. A *stochastic component*:

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

   for $r = 1, 2, \ldots, m$, and for any i-th subject, $i = 1, 2, \ldots, n$.
2. Two *systematic components*:

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

   where $\boldsymbol{y}_i$ and $\boldsymbol{w}_i$ are the subjects' covariates for explaining π_i e ξ_i, respectively, for $i = 1, 2, \ldots, n$.

Given these non-linear relationships, the columns of $\boldsymbol{Y}$ and $\boldsymbol{W}$ may be the same, partially coincide or completely differ. Moreover, we are not compelled to insert in the extended model only observed subjects' covariates since also scores computed by some multivariate analysis may be an important information.

In this regard, we observe that the inclusion of relevant covariates related to subgroups or clusters is able to explain some observed bimodality in current frequency distributions; thus, an improved fitting may be parsimoniously obtained without inserting further components in the basic CUB model.

2.3 Inferential issues

When sample data are available, the specification, estimation and validation of a CUB model may be consistently pursued by maximum likelihood (ML) methods which lead to efficient asymptotic properties of estimators and tests

(Iannario 2012b). Moreover, the involved mixture distribution strongly suggests the EM procedure as an effective algorithm to reach convergence almost everywhere on $\Omega(\boldsymbol{\theta})$, as shown by Everitt and Hand (1981), McLachlan and Krishnan (2008), McLachlan and Peel (2000), among others. For a general CUB model with covariates, such algorithm for ML estimation has been derived by Piccolo (2006) and extended by Iannario (2012a) to CUB models with *shelter effect*.

For the validation step, several fitting measures (specifically oriented to CUB models, as in Iannario 2009) can be considered. If sample data are summarized by the observed frequencies $(n_1, n_2, \ldots, n_m)$, we derive the *saturated* log-likelihood as $\ell_{sat} = -n\ \log(n) + \sum_{r=1}^{m} n_r\ \log(n_r)$. This quantity acts as a benchmark for comparing the effectiveness of more elaborate structures. Then, if $\ell(\hat{\boldsymbol{\theta}})$ and $\ell_0 = -n\ \log(m)$ are the log-likelihoods of the estimated CUB model and of a Uniform model, respectively, a convenient fitting measure may be introduced as:

$$\mathcal{I} = \frac{\ell(\hat{\boldsymbol{\theta}}) - \ell_0}{\ell_{sat} - \ell_0} \, .$$

A further normalized fitting measure compares observed f_r and expected $p_r(\hat{\boldsymbol{\theta}})$ relative frequencies:

$$\mathcal{F}^2 = 1 - \frac{1}{2} \sum_{r=1}^{m} \mid f_r - p_r(\hat{\boldsymbol{\theta}}) \mid ,$$

which can be interpreted as the proportion of correct predicted responses. The relation $\mathcal{F}^2 = 1 - Diss$ holds with a standard dissimilarity index $Diss$.

A program in $\boldsymbol{R}$ –where the whole inferential procedure is effectively implemented with estimation, test results, statistical indexes and graphical displays– is freely available (Iannario and Piccolo 2009).

3 Feeling measures in marketing-oriented analyses

We concentrate our discussion on the feeling component since it is the component mostly related to marketing interests. Of course, in specific studies, it may be also important to study uncertainty for assessing how much the effect of advertising campaigns modifies the resoluteness of respondents, for instance.

The strength of the feeling measured by $1 - \xi$ can be interpreted as a sensory satisfaction measure and offers some direct insights which can be interestingly exploited by marketing managers. From a statistical point of view, this numerical quantity gives the possibility to carry out several further analyses which could not be formally performed on the original ratings, due to the qualitative nature of ordinal categorical variables. In addition to the explicit formulation of CUB models with covariates (which are sensible only if the selected covariates are significant), we would analyze the sensory satisfaction measure (as expressed by $1-\xi$) by means of a regression on product characteristics, in order to identify the features or the perceptions mostly related to the customers' appreciation.

Thus, for extracting information useful for marketing from the feeling measures deriving from CUB models, we resort to the Random Forest (RF) algorithmic regression model (Breiman 2001), already applied in sensometrics for hedonic analysis (e.g., Brentari and Zuccolotto 2010, 2011). Specifically, RF approach belongs to the wider class of ensemble learning prediction methods (Friedman and Popescu 2005), which are sequences of base learners. A "base learner" is defined as a function of the predictor variables and final predictions are obtained by a linear combination of all the predictions of the base learners' sequence. Different learning ensembles can be built by defining different prediction functions as base learners. The most interesting proposals use decision trees as base learners and are then called tree-based learning ensembles. The base learners building a RF are Classification And Regression Trees (CART) proposed by Breiman *et al.* (1984), grown by the special procedure of selecting a small group of input variables to split on at random at each node. This mechanism is often applied in tandem with bagging (Breiman 1996), i.e. with a random selection of a subsample of the original training set to grow each CART. This simple and effective idea is based on a complete theoretical apparatus analytically described by Breiman (2001). The RF prediction is then computed as an average of the single CART predictions. Although RF is essentially a prediction mechanism, in this context we are not really interested to this aspect but to the extrapolation of the role played by the predictor variables in the ability of the model to explain the variability of the outcome. To this purpose, Variable Importance Measures (VIMs) are available in order to identify the most informative predictors within the predicting algorithm.

¿From a marketing perspective, we aim at identifying the product features or the consumers' perceptions mostly affecting the sensory satisfaction. So, on the one hand we could draw a grid of desirable/undesirable characteristics of a product, find out the features deserving the main part of the producer's effort, identify the attributes worthy of a specific advertising focus. On the other hand, when sensory satisfaction is found to be affected by some consumers' perceptions (such as, for example, the awareness of luxury, environmental responsiveness, brand quality, etc.), this can be profitably pursued when designing the image of the product in the consumers' thought. The two main VIMs computed along with RF are the Mean Decrease in Accuracy (MDA) and the Total Decrease in Node Impurities (TDNI). Some recent studies have shown that TDNI is affected by a bias in favour of variables with a higher number of possible cutpoints, for example numerical variables or nominal variables with a high number of categories (see, for example, Strobl *et al.* 2007). When TDNI is used, a preliminary bias-correcting procedure is thus recommended (Strobl *et al.* 2007; Sandri and Zuccolotto 2008, 2009).

4 Case study

In this Section we present the results of a case study dealing with sensory data about coffee tasting. Usually, the coffee tasting method consists of three main evaluations (sensory attributes): (i) the *visual analysis*, taking into account the colour (should not be either too light or too dark, but rather nutty-colour with dark red streaks), the texture (should be dense, with a fine texture and without any gaps), and the persistence (quite long) of the cream; (ii) the *olfactory analysis*, taking into account smell (should be pleasant and intense) and fragrances or aromas (toasted, chocolaty, floral, fruity, peanuts, spiced, etc.); (iii) the *gustatory analysis*, taking into account flavour (sweet, acidic, bitter) and aftertaste (aroma, persistence).

The data presented in this case study were collected through the 2011 edition of the survey Coffee Experience, carried out by the Centro Studi Assaggiatori (CSA, http://www.assaggiatori.com) of Brescia (Italy) along with the International Institute of Coffee Tasters (IIAC), in collaboration with the National Institute Espresso Italiano. The survey took place in occasion of the 2011 edition of Agrifood Club, the showcase of Made in Italy food excellence, held in Verona (Italy) during Vinitaly, the main Italian reference event in the wine sector. Agrifood Club is entirely dedicated to sensorial experience. In this context, Coffee Experience is probably the yearly largest coffee tasting event in the world, with strong attendance by international buyers and operators. In the 2011 edition of Coffee Experience 43 different coffee varieties were available for tasting.

Visitors were asked to formulate visual, olfactory, gustatory evaluations of the tasted coffees on a 9-point Likert scale, and to fill in a questionnaire containing personal information (gender, age, experience in tasting, attitude, habits and style of consumption, etc.). Each visitor was allowed to taste more than one coffee, of his own choice. On the whole, a total of $1,650$ visitors tasted from a minimum of 1 to a maximum of 11 coffees (more than 78% of visitors tasted exactly 5 coffee varieties, the default number of tastings per person suggested in the questionnaire). Table 1 shows some summary statistics about the $1,650$ visitors involved in the survey. As a result, in the final dataset a different number of total tastings, from a minimum of 6 to a maximum of 421, was available for each coffee variety. We decided to remove the coffee varieties evaluated by less than 60 visitors. The resulting data set turns out to be composed by 36 coffee varieties for which a total number of $7,604$ judgments on each sensory attribute are available.

4.1 Summary of CUB models approach

We fitted CUB models to each of the 36 varieties of coffees with respect to *visual*, *olfactory* and *gustatory* perceptions. The estimated models have all parameters significant and good fitting measures ($\mathcal{F}^2$ varies in [0.849, 0.973]), as shown

Table 1 Summary statistics concerning the 1,650 visitors involved in the survey: demographic information (top), coffee-drinking habits (middle), professional interest (bottom). Words in italic: names of the covariates analysed in Section 4.2.

Nationality	Italian (89.7 %), not Italian (10.3%, 36 different countries)
Gender	Male (64.5 %), Female (29.0 %), NA (6.5%)
Age	18-29 (25.6 %), 30-39 (26.8 %), 40-49 (24.1 %), $\geq$ 50 (23.5 %)
How many coffees in a day (*Frequency*)	0 (0.7 %), 1-2 (29.9 %), 3-4 (52.3 %), > 4 (16.8 %)
How many brands (*Unibrand*)	only one brand (11.9 %), many brands (88.1 %)
How much sugar (*Sweetness*)	none (33.1 %), a little (40.5 %), much (23.3 %), sugar-free artificial sweetener (1.9 %), NA (1.2 %)
Why drinking coffee	Sensory pleasure (37.2 %), Break (22.7 %), Energy (19.6 %), Other (20.4 %)
Determinants of quality	Sensory (55.4 %), Brand (23.8 %), Other (20.8 %)
Reason for interest in coffee	Like it (52.5 %), Job (45.3 %), NA (2.2 %)
Experience in tasting	No (81.9 %), Yes (15.1 %), NA (3 %)

in Figures 1-2. We notice how fitting measures for gustatory perception are associated with a lower variability.

We summarize such inferential results by plotting the estimated parameter vectors obtained for the 36 coffee varieties on the unit square (Figure 3). This kind of map describes their relative positioning with respect to the selected sensory attributes, focusing on both the level of their evaluation and the degree of uncertainty of the judgements. In this manner, the complex pattern of this experiment is simplified in a unique parametric representation which supports information about product positioning with respect to competitors and market segmentation. The rating of preferences is not constant with respect to the three evaluations and this confirms that respondents react in different ways when faced to visual, olfactory and gustatory sensations. Is seems evident that sight and smell (as related to visual and olfactory perceptions, respectively) are senses which manifest themselves with high similarity. We notice that all evaluations (except for varieties 34 and 35, located at the extreme right of the square) are expressed with a limited uncertainty, confirming that respondents are giving meditated preferences. However, the uncertainty generally

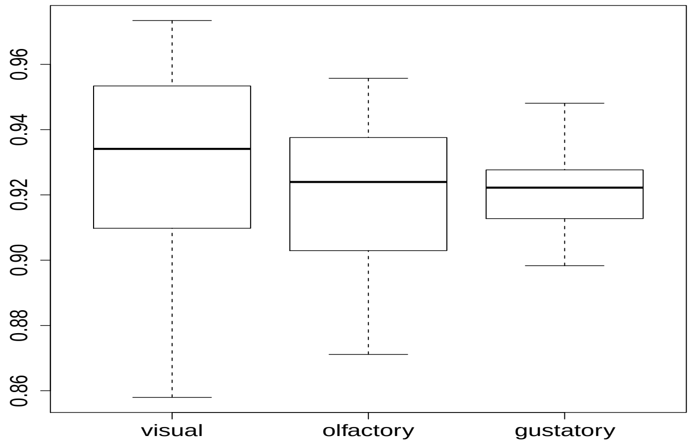

Fig. 1 Boxplots of $\mathcal{F}^2$ for the three sensory attributes.

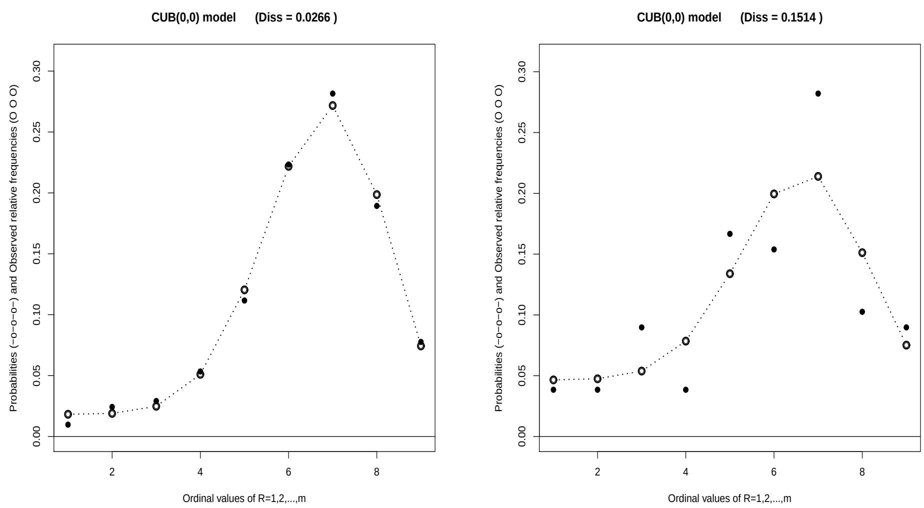

Fig. 2 Plot of estimated probabilities versus observed relative frequencies in the best (left, $\mathcal{F}^2 = 0.973$) and worst (right, $\mathcal{F}^2 = 0.849$) case, respectively.

increases when we move from visual to olfactory and, then, to gustatory perceptions. Thus, gustatory perceptions are more related to subjectivity than olfactory perceptions which, in turn, are more related to subjectivity than the visual ones. Thus, we conjecture that perceptions more heavily depend on the personal history, attitude and habits when moving from visual to gustatory feelings. These results can be useful for organizing marketing strategies for advertising, for instance.

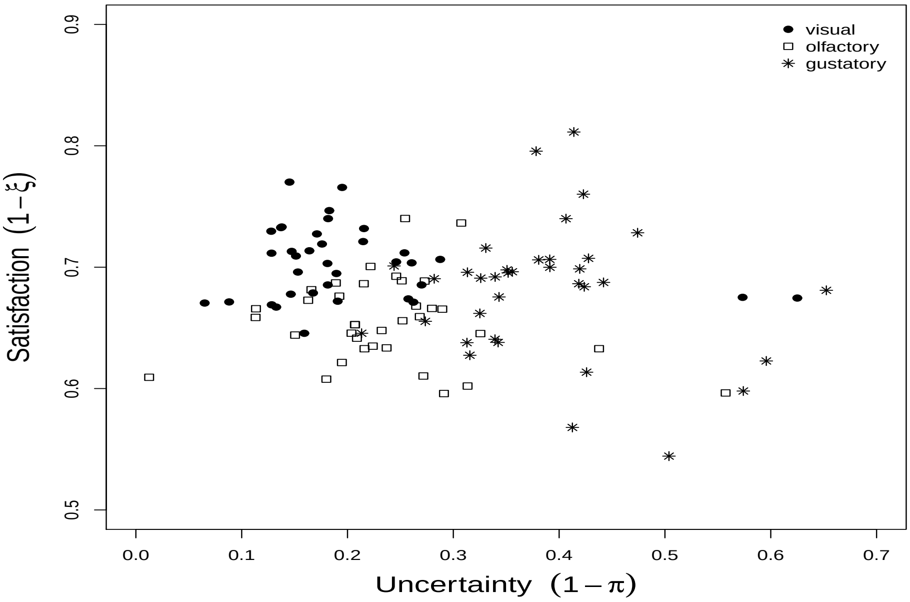

Fig. 3 CUB models visualization of visual, olfactory, gustatory perceptions of 36 coffee varieties.

In this regard, we quote that by inspecting the relationships among the judges' perceptions expressed through the visual, olfactory and gustatory ratings and the satisfaction about each coffee variety, we found that the gustatory satisfaction towards coffee is significantly dependent on both visual and olfactory ratings but olfactory is much more relevant. It is insightful to observe that the shape is regularly homogeneous for all the coffees (Manisera *et al.* 2012). This result may be usefully exploited by producers of coffees which have poor olfactory resources, since an improvement of the consumer gustatory perception towards the product seems to be highly dependent upon a positive evaluation of the coffee's smell.

4.2 Some results about CUB models with covariates

We can also check by means of CUB models which subjects' covariates may affect the respondents' satisfaction with respect to visual, olfactory and gustatory perceptions, especially with reference to the feeling component. Giving the space constraint, we limit ourselves to present the main results of our study with reference to the significant results obtained by inserting in CUB models the covariates *Age*, *Unibrand* (=if respondent usually tastes one or many brands of coffee), *Frequency* (=how many coffees on average he/she drinks per day), and *Sweetness* (=the attitude to add sugar to the coffee). Basic summary statistics of these covariates have been displayed in Table 1.

Specifically, we study the feeling as a function of a single covariate or the positioning of models in the parametric space for some selected coffees. Results shown in Figure 4 refer to the selection of coffee varieties for which the considered covariates (Age, Unibrand, Number of coffee, Sweetness) have a significant effect on the gustatory satisfaction. From a statistical point of view, significance has been verified by Wald tests on estimated parameters in the logistic link and by ascertaining a sensible improvement of the corresponding log-likelihood function.

The plots in Figure 4 are of different nature and emphasize the potential strength of the approach for inferring the significant relations among the expressed gustatory perception. In a sense, they are a sort of prototype of the kind of the interpretative results that can be achieved by using CUB models; this is possible since the probability structure we are adopting is not a mere fitting device but it is obtained as a model for the generating process that conveys the individual perception into an ordered evaluation.

In details, the top-left panel presents a direct link between satisfaction and age which is moderately increasing for three coffees and sharply decreasing for the coffee variety 22: this result surely affects the management involved with market segmentation of consumers with respect to their age and may profitably orient different advertising campaigns.

The top-right panel shows the location of some coffee varieties in the parametric space with respect to consumers which usually drink a single brand (=U) and consumers which usually change the brands (=P). For all varieties, it is evident a higher satisfaction for the former subgroups with the exception of coffee variety 12 which deserves some specific attention. Similarly, it is noticeable to observe the large difference of satisfaction registered among the two subgroups for the coffee variety 34.

The bottom-left panel shows that, for the coffee varieties 22 and 29, feeling increases with the frequency of daily consumption and also that the slope of the relationship is quite similar for both varieties.

Finally, the bottom-right panel shows how the sweetness habits of consumers is not homogeneous with respect to the coffee varieties. Indeed, we register in six cases that the satisfaction towards the product changes significantly for consumers who increase their level of Sweetness. More specifically, we register that for varieties 4, 11 and 32, the gustatory satisfaction increases with the addition of sugar, whereas the opposite holds for varieties 13, 15 and 26.

As already highlighted, from a marketing management perspective, all the described results immediately allow to understand product positioning with respect to competitors, conjecture market segmentation, manage relationships with the customers, define product development strategies.

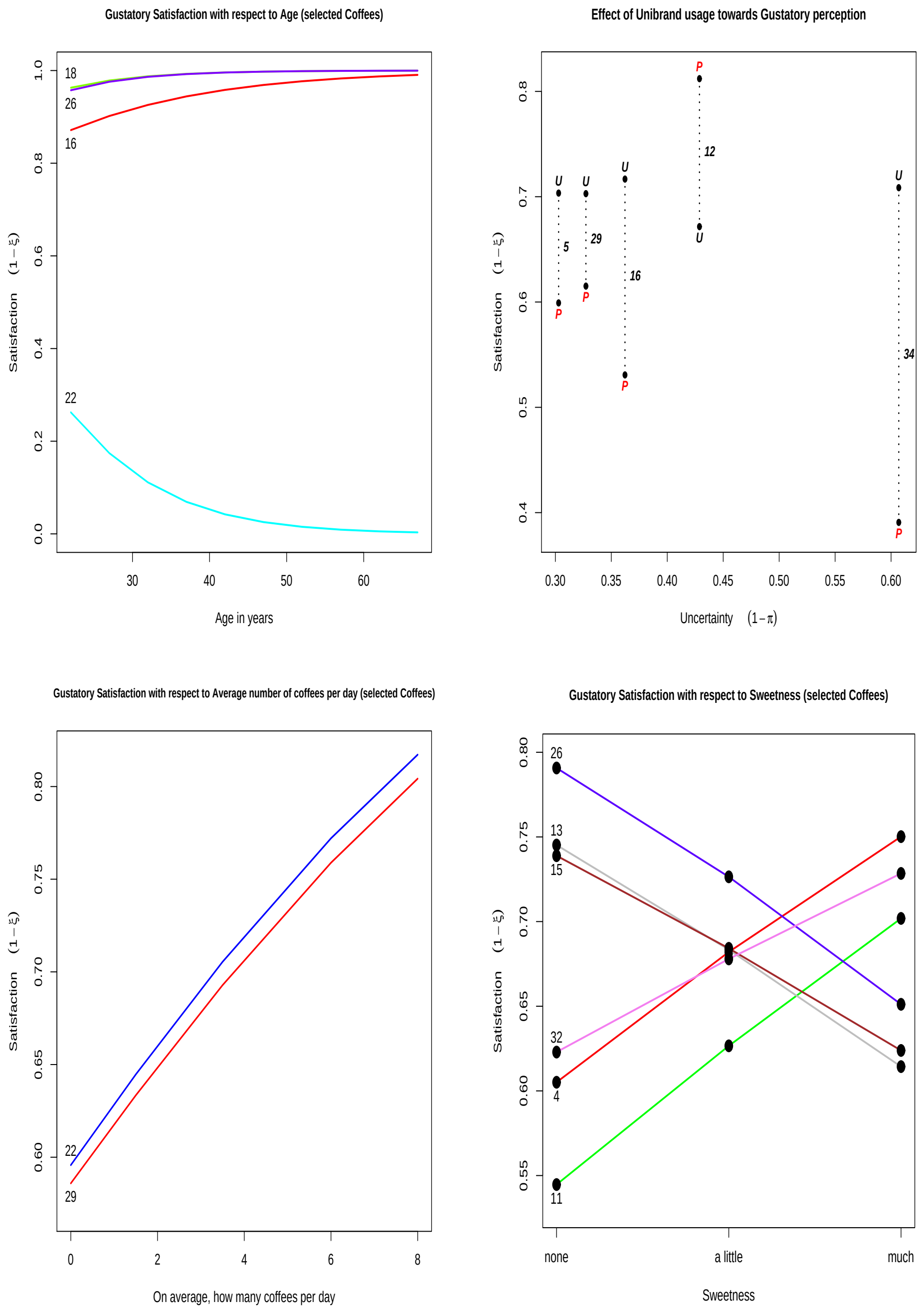

Fig. 4 Visualization of CUB models with covariates for selected coffees.

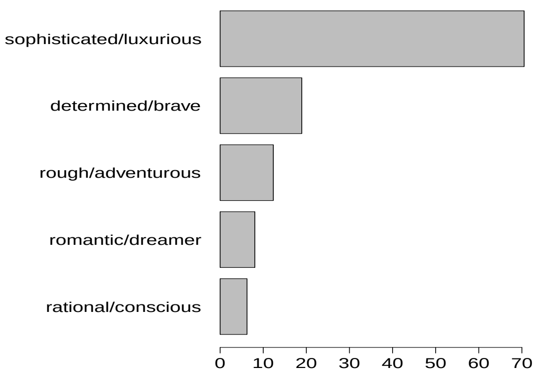

Fig. 5 Barplot of the variable importance measures from the RF algorithm.

4.3 Further results by Random Forests approach

To better investigate the satisfaction of judges and consumers towards coffees and to finally support and direct marketing decisions, we propose to combine CUB models with the RF approach, in order to extract more useful information for market analysts with algorithmic data mining techniques.

More specifically, we will show how useful information about advertising can be extracted by means of the following question posed to panellists together with the sensory evaluations: "What kind of person is suitable for drinking this coffee?" (*Kind of Person*=KP). The possible responses were "romantic/dreamer", "rational/conscious", "rough/adventurous", "determined/brave", "sophisticated/luxurious". We immediately recognize that the relationship between this opinion and the overall sensory satisfaction with the coffee gives important information about the most appropriate advertising campaigns and slogans. Since the visual, olfactory and gustatory satisfactions are highly correlated, we constructed the overall sensory satisfaction by averaging over those three components and used it as the response variable, accounting for the overall sensory satisfaction, in a RF prediction model.

For each of the 36 coffees in analysis, the frequency distribution of the categorical variable KP was computed and the relative frequency of the 5 categories were used as predictor variables. In other words, the overall sensory satisfaction of the 36 coffees is algorithmically regressed on the frequency distribution of the responses to KP for each coffee. The explained variance of the model is 28%. If used for prediction purposes, this would be considered a poor result. On the contrary, in our context, it means that almost 1/3 of the total variability of sensory satisfaction is explained by the judgements concerning the kinds of persons suitable for drinking a certain coffee. This result may be considered as a surprising evidence which can be usefully exploited in product communication.

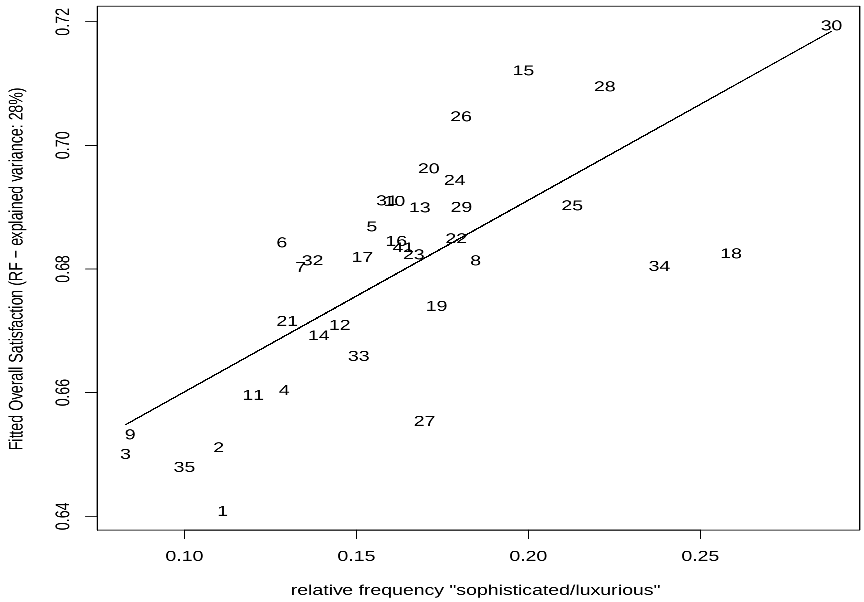

Fig. 6 Overall satisfaction estimated by RF (y-axis) versus the relative frequency of "sophisticated/luxurious" (x-axis), with regression line.

As a variable importance measure we used MDA (Mean Decrease in Accuracy) whose values, plotted in Figure 5, indicate that the most important variable in explaining the variability of the overall satisfaction is the relative frequency of "sophisticated/luxurious". This relation is direct (Figure 6), thus we could think that judges generally satisfied with a coffee tend to consider that coffee suitable for "sophisticated/luxurious" persons. If we refer to the most important brands of Italian coffee, we find that the image of a "sophisticated/luxurious" person is very rarely used in advertising where, with only few exceptions, the scene is dominated by characters recalling the domestic and every-day life as well as serenity and a sense of well-being.

CUB models and RF analysis so far proposed may be further deepened if we could insert product characteristics in the sensory analysis in order to identify, for example, which coffee varieties show a peculiar behaviour. These results are useful to better understand relationships among variety and perceptions and to direct the manufacturers' efforts to improve their competitiveness.

5 Discussion

Starting from the usefulness of sensory analysis to marketing decisions, in this paper we showed how interesting insights for marketing management can be obtained by combining advanced statistical models. In particular, we proposed to fit CUB models in order to measure the consumers' sensory satisfaction that can then be used in algorithmic data mining techniques (specifically, in RF variable importance measurement) in order to identify the drivers of sensory satisfaction. This gives different information to marketing management in order to better understand and direct decisions on product positioning, market segmentation, customer relationship management, product development strategies. The results obtained from a case study on Italian espresso coffee underline the importance of the sensory analysis, as it is also clear from the answers of the judges, and allow producers and distributors to understand the product sensory characteristics and their relationships with satisfaction and product and customers' features.

In particular, results from CUB models allow to represent in a unique representation the relative positioning of the 36 considered coffee varieties with respect to visual, olfactory and gustatory perceptions, focusing on both the level of their feeling and the degree of uncertainty of the evaluations. This map shows that respondents have evaluated the visual, olfactory and gustatory aspects of the 36 coffees with limited uncertainty. A unique ranking of the coffees consistent with all the three evaluations is not possible, since respondents assessed differently sight, smell and taste of a coffee. The uncertainty is higher for gustatory evaluations, suggesting that preferences on flavour and aftertaste are more heterogeneous since more linked with the respondents' subjective opinions. In this respect, there is more space for marketing strategies to affect consumers' choices, for example by appropriate advertising campaigns. CUB results also show that there is a significant relation between the gustatory satisfaction and the observed olfactory ratings, and this is homogeneously confirmed across the coffees. As expected, flavour sensations depend on olfactory perceptions: hence, marketing actions devoted to increase the gustatory satisfaction of a coffee should focus on improvements of the perceived smell, fragrances and aromas. Finally, CUB models with covariates indicate that the gustatory satisfaction significantly depends on the respondents' age, number of brands usually tasted, number of coffees usually drunk in a day, attitude to add sugar to the coffee. From a marketing perspective, it is interesting to note that such relationships are not homogeneous with the coffee variety. Therefore, for each coffee a different strategy should be adopted, for example by segmenting the market in order to loyalize customers or acquire new customers.

The variable importance measures drawn by the RF algorithm show that the opinion on which kind of person is suitable for drinking a certain coffee is very important in determining the overall sensory satisfaction and that respondents satisfied with a coffee tend to consider that coffee suitable for "sophisticated/luxurious" persons. This is a surprising result that should be considered in product communication to increase sales of a particular brand of coffee. Indeed, in this moment, a specific brand is advertising a commercial where a famous actor drinks expresso coffee within a context which may be precisely defined as "sophisticated/luxurious".

The approach we outlined in this paper is not merely scientific but may have several operational effects as shown by the regular joint work with the sensory experts of the Centro Studi Assaggiatori (CSA) since 2000, where advanced statistical analyses have been introduced for the marketing investigation of several products (coffee, wine, grappa, liquors, cheese, etc.) with immediate feedback on further surveys and analyses and on marketing strategies. As an instance, the Italian consumers' association "Altroconsumo" currently measures the wine quality by the ZOB index (Zironi *et al.* 2003), in order to prepare the most important wine guide in Italy. Again, Altroconsumo's wine guide is planning to conduct an in-depth analysis on the sulfur dioxide, in order to take account of the results of a statistical analysis highlighting the great impact of sulfur dioxide on the wine quality (Brentari *et al.* 2012). Thus, the results obtained by the application of our statistical methods are usually published not only on scientific journals (e.g., Brentari *et al.* 2011), but also on trade journals and presented at conferences and workshops involving experts of food and drink (Brentari and Zuccolotto 2010). More specifically, for CUB models, in addition to the standard reference for the salmon data set (Piccolo and D'Elia 2008), we register a study on the commerce of fair trade coffee (Cicia *et al.* 2010) and on wine taste (Corduas *et al.* 2012). Recently, Ministry of Agriculture in Italy promoted a project for using such models in a study on the customers' satisfaction towards extra-virgin olive oil.

A critical consideration concerns the amount of sophisticated thinking necessary for deriving the main components driving the consumers' choice. Indeed, if we move from the exploratory measures generally used in marketing researches to a more rigorous modelling approach we require more investment in careful consideration of assumptions, estimation and validation of the results. However, a statistical models offers an inferential paradigm for test, prediction and profiling customers' attitude as a noticeable by-product.

6 Concluding remarks

The proposed combined approach jointly considers product characteristics and sensory attributes with consumers' features and satisfaction. In the food and drink sector, where companies regularly dialogue with consumers through tasting and pairings, the approach we outlined may be usefully exploited by the marketing management and this is really strategic for coffee producers and distributors, given the growing worldwide interest towards the Italian espresso coffee.

In the next future, the relationship among sensory analysis and marketing decisions could be investigated by combining other statistical approaches with the CUB models, in the framework of the models and methods suitable for unobservable variables.

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References

1. Agresti A (2010) Analysis of Ordinal Categorical Data, 2^{nd} edition. Wiley, NY
2. Bogue J, Ritson C (2004) Understanding consumers perceptions of product quality for lighter dairy products through the integration of marketing and sensory information. Acta Agr Scand C-Economy 1:67-77
3. Breiman L (1996) Bagging predictors. Mach Learn 24:123-140
4. Breiman L (2001) Random Forest. Mach Learn 45:5-32
5. Breiman L, Friedman J H, Olshen R A, Stone C J (1984) Classification and Regression Trees. Chapman & Hall, NY
6. Brentari E, Carpita M, Vezzoli M (2012) CRAGGING: a novel approach for inspecting Italian wine quality. Proceedings of the 12th European Symposium on Statistical Methods for the Food Industry, Agrostat2012, Paris, pp. 343–350
7. Brentari E, Levaggi R, Zuccolotto P (2011) Pricing strategies for Italian red wine. Food Qual Prefer 22:725–732.
8. Brentari E, Zuccolotto P (2010) The implicit value of chemical and sensorial quality in the hedonic analysis of low-priced Italian red wines. Proceedings of the 11th European Symposium on Statistical Methods for the Food Industry, Agrostat2010, Benevento, Italy, pp. 269–276.
9. Brentari E, Zuccolotto P (2011) The impact of chemical and sensory characteristics on the market price of Italian red wines. Electron J Appl Stat An 4:265-276
10. Cicia G, Corduas M, Del Giudice T, Piccolo D (2010) Valuing Consumer Preferences with the CUB Model: A Case Study of Fair Trade Coffee. Int J Food System Dynamics 1:82-93
11. Corduas M, Iannario M, Piccolo D (2009) A class of statistical models for evaluating services and performances. In: M. Bini *et al.* (eds.), Statistical methods for the evaluation of educational services and quality of products, Springer, pp. 99-117
12. Corduas M, Cinquanta L, Ievoli C (2012) A statistical analysis of consumer perception of wine attributes. Quad Stat 14:77–80
13. D'Elia A, Piccolo, D (2005) A mixture model for preference data analysis. Comput Stat Data An 49:917-934
14. Everitt B S, Hand D J (1981) Finite mixture distributions. Chapman & Hall, London
15. Friedman J H, Popescu B E (2005) Predictive learning via rule ensembles. Stanford University, Department of Statistics, Technical report
16. Iannario M (2007) A statistical approach for modelling urban audit perception surveys. Quad Stat 9:149-172
17. Iannario M (2009) Fitting measures for ordinal data models. Quad Stat 11:39–72
18. Iannario M (2010) On the identifiability of a mixture model for ordinal data. Metron LXVIII:87-94
19. Iannario M (2012a) Modelling *shelter* choices in a class of mixture models for ordinal responses. Stat Method Appl 21:1-22
20. Iannario M (2012b) Preliminary estimators for a mixture model of ordinal data. Adv Data Anal Classif 6 *Forthcoming*
21. Iannario M, Piccolo D (2009) A program in `R` for CUB models inference, Version 2.0. Available at `http://www.dipstat.unina.it/CUBmodels1/`
22. Iannario M, Piccolo D (2010) A new statistical model for the analysis of Customer Satisfaction, Qual Technol Quantit Manag 7:149–168
23. Iannario M, Piccolo D (2011) CUB Models: Statistical Methods and Empirical Evidence. In: Kenett, R. S. and Salini, S. (eds.), Modern Analysis of Customer Surveys, Wiley, NY, pp. 231–254
24. Köster E P (2003) The psychology of food choice: some often encountered fallacies. Food Qua Prefer 14:359–373

25. Köster E P (2009) Diversity in the determinants of food choice: A psychological perspective. Food Qual Prefer 20:70-82
26. McCullagh P (1980) Regression models for ordinal data (with discussion). J Roy Stat Soc B 42:109–142
27. McCullagh P, Nelder J A (1989) Generalized linear models, Chapman & Hall, London
28. McLachlan G, Krishnan T (2008) The EM algorithm and extensions, Wiley, NY
29. McLachlan G, Peel G J (2000) Finite mixture models. Wiley, NY
30. Manisera M, Piccolo D, Zuccolotto P (2011) Analyzing and modelling rating data for sensory analysis in food industry, Quad Stat, forthcoming
31. Philippe F, Schacher L, Adolphe DC, Dacremont C (2003) The sensory panel applied to textile goods a new marketing tool. J Fash Mark Manag 7:235–248
32. Piccolo D (2003) On the moments of a mixture of uniform and shifted binomial random variables. Quad Stat 5:85-104
33. Piccolo D (2006) Observed information matrix for MUB models. Quad Stat 8:33-78
34. Piccolo D, D'Elia A (2008) A new approach for modelling consumers' preferences. Food Qual Prefer 19:247-259
35. Piccolo D, Iannario M (2010) A new approach for modelling consumers' preferences. Proceedings of the 11^{th} European Symposium on Statistical Methods for the Food Industry, University of Sannio, Benevento, Academy School, Afragola, pp. 139-148
36. Sandri M, Zuccolotto P (2008) A bias correction algorithm for the Gini measure of variable importance. J Comput Graph Stat 17:1–18
37. Sandri M, Zuccolotto P (2009) Analysis and correction of bias in Total Decrease in Node Impurity measures for tree-based algorithms. Stat Comput 20:393-407
38. Strobl C, Boulesteix A-L, Augustin T (2007) Unbiased split selection for classification trees based on the Gini Index. Comput Stat Data An 52:483–501
39. Van Trijp H C M, Schifferstein H N J (1995) Sensory analysis in marketing practice: comparison and integration. J Sens Stud 10:127–147
40. Zironi R, Odello L, Brentari E (2003) Un nuovo indice per misurare la qualità edonica del vino. Il Sommelier 19:15–17