The importance of wine attributes for purchase decisions: A study of Italian consumers' perception

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Abstract

The importance of extrinsic and intrinsic attributes of wine for purchase decisions is the object of a lively debate. As a matter of fact, in recent decades, the shift of consumption motivations from nutritional purposes to drinking for pleasure has caused a persistent decrease in the overall demand. However, the increasing number of product varieties and brands of domestic and imported wine, as well as the increased diversity in wine styles and prices, make the identification of wine purchase drivers difficult. This article investigates the importance of product attributes for Italian consumers when choosing wine. Specifically, a class of statistical models for ordinal data, namely CUB, is taken into consideration. This type of model allows the comparison and clustering of the rating distributions that consumers express about wine features and the detection of significant similarities and differences. In addition, this technique generally helps to relate the subject’s preferences to covariates which typically summarize the socio-demographic profile, the purchase and consumption behavior.

1. Introduction

In recent decades in traditional wine producing countries, the motivations of wine consumption have been changing moving from nutritional purposes to the pleasure of drinking. Wine is consumed on special occasions and for socializing both outside and at home so that consumption behavior has turned into a more occasional drinking. The demand is consequently moving from everyday to quality products causing a persistent decrease in the volume of the overall consumption.

Understanding key drivers of wine choice and the underlying motivations is, therefore, important for wine companies in order to achieve their alignment with consumer preferences across their different market segments. But, the increasing number of product varieties and brands of domestic and imported wine, as well as the increased diversity in wine styles and prices, make the identification of purchase drivers difficult. This severely affects the producers’ ability to forecast consumer product preferences in the wine market.

Such a situation is largely due to the noticeable variability of the range of features characterizing a specific wine and the different mix and level of each attribute (Orth et al., 2007). In this regard, Lockshin and Hall (2003) reviewed over 75 articles concerning wine choice behavior. They noticed that most investigations examined consumer ratings of the following items: taste, type, alcohol content, age (of wine), color, price, brand, label/package, usability for purpose, and region of origin. In particular, price, region of origin and brand seem to be the most influential attributes which are considered in literature (see, for instance, Verdu Jover et al., 2004).

Moreover, the wine market suffers from information asymmetry: producers and purchasers have different sets of information concerning quality. The former ones pursue objective quality (related to wine production and sensory characteristics) whereas the latter usually make inferences about quality from extrinsic cues (which can be judged independently from tasting) and, only within certain limits and given the accumulated experience and involvement, from sensory evaluation at the first consumption (Lockshin and Rhodus, 1993). This makes label information, the design and other aspects of the bottle very important when choosing wine (Sáenz-Navajas et al., 2013).

Finally, lifestyle, culture and traditions influence consumption behavior across countries and, consequently, the relevance that purchasers give to the various wine characteristics (Goodman et al., 2007, 2008; Goodman, 2009).

Consumer’s perception about a product is typically studied by means of survey data: interviewees are requested to judge a list of attributes or to express their level of agreement about some statements by using a Likert type scale. They are often requested to provide information about latent factors driving their purchase behavior by answering indirect questions. The subsequent analysis of ordinal data poses, therefore, methodological problems due to the discrete nature of the random variables describing ratings.
and to the specific nature of the judgment process (Agresti, 2010; Powers and Xie, 2000; Franses and Paap, 2001; Tutz, 2012). Various approaches have originated in the literature from considering ordinal data either as generated by a latent continuous variable or as an intrinsically discrete phenomenon. Specifically, several statistical models, proposed within the Generalized Linear Models (GLM) framework, estimate cut points in order to transform the unobserved continuous latent variable into a discrete one.

The present work moves from a different stand. The importance of wine attributes for Italian consumers is investigated by means of a probability model based on a mixture distribution, known as CUB. This class of models still relies on latent variables, but the knowledge (or estimation) of cut points is not needed. For this reason, for a given ordinal data set, the CUB parametric formulation is often more parsimonious than GLM. Furthermore, CUB models allow the comparison and clustering of the rating distributions that purchasers express about various items and the detection of significant similarities and differences.

The article is organized as follows. In Section 2, we describe the main variables object of investigation and the plan of the survey. In Section 3, we briefly illustrate the statistical methodology. In particular, the CUB model is introduced and, then, a clustering technique for ordinal data based on Kullback–Liebler divergence is presented. Section 4 discusses the results and main findings. The final section contains some concluding remarks.

2. Materials and methods

2.1. The attributes affecting wine choice

Some recent contributions have examined the relevance of various wine attributes for consumer preferences with reference to the Italian market (Coppola et al., 2000; Seghieri et al., 2007; Hertzberg and Malorgio, 2008; Benfratello et al., 2009; Lai et al., 2008; Casini et al., 2009; Tempesta et al., 2010).

Wine packaging, especially the label, is crucial to selling wine since it establishes the identity of the product and gives cues to purchasers about what they should expect to find inside the bottle. For this reason, the European Union has special rules concerning labeling which specify compulsory and optional information. The regulation aims to harmonize label information among the State Members in order to help wine buyers make an informed choice while purchasing and reduce the asymmetry in the market. The sales designation of the product, the nominal volume, the actual alcoholic strength by volume, the name of the bottler or importer, the presence of specified additives are the main compulsory items which must be shown on the label. Additional information concerns traditional specific terms, the region of origin, the grape variety, the vintage year, the designation of origin. Moreover, the EU wine regulation defines two broad categories: wine with and without geographical indication (GI). The former can be further qualified with the protected designation of origin (PDO) and the protected geographical indication (PGI). These are equivalent to the Italian denomination DOC/DOCG and IGT, respectively. The latter can show, under suitable conditions, the harvest year and the grape variety on the label.

Furthermore, all the packaging cues play a relevant role for consumers’ decisions since they convey the image of wine which is strictly related to price and reputation. Charters and Pettigrew (2007) remark that medium/high involvement drinkers are more likely to perceive packaging as part of quality. This is also enforced by the motivation for consumption, the image and status that they wish to project to others. Of course, these findings depend heavily on the oenological traditions and on the culture of the country where the study is performed.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Level</th>
<th>%</th>
</tr>
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<tbody>
<tr>
<td>Age (years)</td>
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</tr>
<tr>
<td></td>
<td>25–34</td>
<td>26.2</td>
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<tr>
<td></td>
<td>35–49</td>
<td>38.2</td>
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<tr>
<td></td>
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<tr>
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<td></td>
<td>Male</td>
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<tr>
<td>Education</td>
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<td></td>
<td>Upper secondary level</td>
<td>45.8</td>
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<td></td>
<td>University level</td>
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<td>Settlement size (population)</td>
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<td>14.1</td>
</tr>
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<td></td>
<td>30,000 – 200,000</td>
<td>32.3</td>
</tr>
<tr>
<td></td>
<td>≥200,000</td>
<td>22.4</td>
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</table>

In order to investigate the key drivers of wine purchase decisions we have considered a list of extrinsic and sensory attributes (see Table 1).

2.2. The questionnaire and the sample characteristics

The study refers to a sample of 192 subjects who were interviewed during spring 2011. To increase the range of competence and the level of knowledge about wine, half of the respondents were randomly selected among visitors to Vitigno Italia and Vinitaly (2011 edition) during the general admission days. All the recruited interviewees consumed wine and, in addition, were in charge of the purchases of the product for themselves and their family.

Each interviewee was asked to rate the importance of a certain wine attribute in determining his/her purchase decision on a 7 point Likert scale (where 1 denoted “not important at all” and 7 “extremely important”).

Moreover, in order to understand the level of wine drink involvement, the respondents were asked to give a self-assessment of their expertise. As a matter of fact, the accumulated knowledge about similar products affects the way in which purchasers process information concerning quality (Beattie, 1992). Consumers, who usually inform themselves about wine characteristics, tend to utilize more information in their selection and develop an intense bond with the product (Perrotut et al., 2006; D’Hauteville and Perrotut, 2005; Lockshin et al., 2006). Finally, the socio-economic status and the purchase or consumption behavior were surveyed.

Table 2 illustrates the main variables characterizing the sample. It includes mostly men with a generally high level of education (only 10.9% have exclusively completed the compulsory education)
who prevalingly live in small or medium size towns. About 65% of the respondents are between 25 and 49 years old. Most interviewees are office workers and about 10% of them are employed in a specialized business which involves food or beverages (catering, restaurants, food shops, etc.). Moreover, in purchase situations more than half of the sample recognizes the following information sources as a trustworthy support for decision making: advice of friends, specialized books or magazines, suggestions of a restaurateur or a shopkeeper. TV programs are instead seen by most of the interviewees as unreliable sources (only 8% of the respondents rely on it) whereas internet seems to be an interesting communication medium by 26% of respondents. Finally, on average, they spend 5.1 Euros on a 750 ml bottle of wine for their daily meals.

3. A statistical model for ratings

In order to describe wine attribute ratings, we consider a statistical model based on a mixture distribution (CUB) which was introduced by Piccolo (2003) to represent ordinal data. The approach was investigated for modeling judgments or evaluations that groups of respondents express on a given item and is applicable to both ratings and rankings as discussed by D’Elia and Piccolo (2005). In this regard, numerous empirical studies proved the efficacy of CUB models in representing survey data and interesting results were achieved in various fields such as linguistics (Balirano and Corduas, 2008), medicine (D’Elia, 2008), psycho-sociology (Iannario and Piccolo, 2010), and food marketing (Piccolo and D’Elia, 2008; Ciccia et al., 2010).

CUB model originated by a simplified outline of the psychological mechanism which leads a rater to give an assessment of a certain item. In particular, the final judgment is seen as the result of two acting forces: the selectiveness/feeling, or in other words, the intimate attitude that the subject has towards the object under evaluation. The meaning of this parameter is the strength of the positive/negative feeling that the rater has towards the object under evaluation. The parameter $p$ is the weight (1

$$P(Y = y) = \pi \frac{m - 1}{y - 1} \left(1 - \pi\right)^{y-1} \pi^{m-y} + (1 - \pi) \frac{1}{m}, \quad y = 1, 2, \ldots, m$$

where $\pi \in (0,1)$, $\xi \in [0,1]$, and $m > 3$ is the number of modalities available for evaluating an item. The parameter space is given:

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

The parameter $p$ determines the role of uncertainty in the final judgment: the lower the weight $(1 - \pi)$ the smaller the contribution of the Uniform distribution in the mixture. The parameter $\xi$ characterizes the shifted Binomial distribution and $(1 - \xi)$ denotes the strength of the positive/negative feeling that the rater has towards the object under evaluation. The meaning of this parameter is, therefore, tightly connected to the specific empirical context which the CUB model is referred to. As a matter of fact, in the case study that we are investigating, $(1 - \xi)$ will represent the degree of importance that raters attach to a given item when they are meditating about wine features in order to finalize their purchase decision.

Computational issues were solved by Piccolo (2006) who provided an efficient algorithm for the maximum likelihood estimation of CUB models. Further extension and properties have been illustrated by Corduas et al. (2009), Bonnini et al. (2011), Iannario and Piccolo (2012). In particular, Iannario (2010, 2012) showed that such a model is statistically identifiable and improved its formulation to include shelter choices.

The CUB model is rather flexible since it allows for distributions with very different shapes. For a given $\pi \in (0,1]$, the peakedness increases as $\xi$ approaches the borders of the parameter space whereas the distribution is symmetric for $\xi = 0.5$, negatively skewed when $\xi < 0.5$ and positively skewed when $\xi > 0.5$. These statistical properties justify the use of the graphical representation of estimated CUB parameters within the unit square for the interpretation of the results from empirical analyses as we will see in the next section.

Our interest in this type of model is motivated by two considerations. Firstly, estimated CUB distributions can be compared and clustered (Corduas, 2011): this allows the identification of significant similarities and differences in the overall judgments expressed by raters on various attributes. Secondly, the model can account for the influence of covariates characterizing either the object of evaluation or the rater (Piccolo and D’Elia, 2008). This aspect is useful for investigating the dependence of the rating distribution from consumers’ profile. In the following we briefly illustrate these two issues.

3.1. Clustering CUB models

A strategy for comparing the estimated CUB distributions, describing the opinions of respondents about $k$ items, needs the definition of a dissimilarity measure and the selection of an appropriate clustering technique.

It is worth noticing that classical clustering is aimed at grouping subjects with respect to measurements over a set of variables. Our focus, instead, is on assimilating rating distributions which have a similar overall shape since this helps to discriminate among the preferences of consumers about a product’s features. As we will see in the following section, the interpretation of the resulting clusters is strengthened by considerations on the two unobserved components of the CUB models, the uncertainty and the feeling towards the characteristic under judgment.

In particular, the Kullback–Liebler (KL) divergence is a measure of dissimilarity between two probability distributions characterizing a random variable $Y$ under two different hypotheses (Kullback, 1957). Thus, it can be used for comparing the mixture distribution specified by various CUB models (Corduas, 2011). In addition, a result derived from Kupperman (1957) gives the asymptotic distribution of the KL divergence under suitable assumptions, and allows testing the hypothesis that two populations are described by the same probability distribution.

For this aim, consider two discrete populations each characterized by a probability distribution function having the same functional form $p(y, \theta_i)$ with unspecified vector parameters $\theta_i$, $i = 1, 2$. Also, assume that: $p(y, \theta_i) > 0$ for $y = 1, \ldots, m$.

$$H_0: \theta_1 = \theta_2$$

$$H_1: \theta_1 \neq \theta_2$$

Suppose that we have two samples of $n_1$ and $n_2$ observations randomly drawn from the specified $i$-th population, $i = 1, 2$, and we wish to decide whether they were in fact generated from the same population. In order to test the hypothesis $H_0: \theta_1 = \theta_2$, the CUB divergence statistic is defined:

$$J = \frac{n_1 n_2}{n_1 + n_2} \sum_y \frac{(p(y, \theta_1) - p(y, \theta_2)) \ln \frac{p(y, \theta_1)}{p(y, \theta_2)}}{\theta_1 - \theta_2}$$
where the vector parameters \( \theta_1 \) and \( \theta_2 \) have been replaced by the maximum likelihood estimators. Then it can be shown that under the null hypothesis \( J \) is asymptotically distributed as a \( \chi^2 \) random variable when the null hypothesis is true, being \( g \) the dimension of the vector parameter (Kullback, 1957). In the case we compare CUB distributions, the 100% critical region is simply given by \( J > \chi^2_{\alpha} \).

In conclusion, the procedure can be implemented as follows:

- The CUB model is fitted to each observed rating distribution.
- The \((k,k)\) matrix of KL divergences among fitted CUB models is evaluated.
- The above mentioned test of hypotheses is performed for each couple of CUB models at a selected significance level. The results of testing is summarized into a binary matrix where the \((i,j)\) element is 1 if the homogeneity hypothesis is not rejected and 0 otherwise.

Clusters are then identified by means of the Bond Energy Algorithm (BEA, developed by McCormick et al., 1972) which helps to rearrange rows and columns of the binary matrix into a diagonal block form (Tran-Luu and DeClaris, 1997; Corduas, 2008).

In general, this procedure operates on a \( M \times N \) matrix \( A \) of nonnegative entries and changes the arrangement of the rows and columns of \( A \) in order to maximize the expression:

\[
ME = \sum_{j=1}^{M} \sum_{k=1}^{N} a_{jk} (a_{j,k-1} + a_{j,k+1} + a_{j-1,k} + a_{j+1,k}),
\]

where the maximization is over all \( N \times M \) possible arrays that can be obtained by permuting \( A \) (with the convention that \( a_{M,k} = a_{k,0} = a_{N,N+1} = 0 \)). The idea is that large values will be drawn to other large values (and vice versa small values to other small values) so as to increase the overall sum of the products. Since the matrix of KL divergences is symmetric this algorithm can be further simplified.

Well separated unit diagonal blocks in the rearranged matrix will denote well defined clusters whereas elongated clusters will be associated to unit blocks containing very few zero values. The method is quite flexible since it does not impose any general rule for clustering detection. Moreover, it moves the clustering approach into an inferential framework since the identification of groups and isolated elements is determined according to the results of testing the homogeneity hypothesis. Finally, the proposed approach is very effective since it provides a graphical display of similar rating distributions and overcomes the common shortcomings that the use of descriptive statistical indices causes when applied to ordinal data.

3.2. The effect of respondent features

The parameters of a CUB model, that is both the subject’s feeling and uncertainty, can be related to respondent features. The general formulation introduces \( p \) covariates in order to explain the uncertainty and \( q \) covariates for modeling the feeling. Assuming that \( n \) subjects are interviewed, the model (1) is extended as follows:

\[
Pr(Y = y | X_i, w_i) = \pi_i \left( \frac{m-1}{y-1} \right)^{c_i} \left( 1 - \xi_i \right)^{y-1} + (1 - \pi_i) \left( \frac{1}{m} \right),
\]

\[
y = 1, 2, \ldots, m,
\]

with:

\[
\pi_i = \frac{1}{1 + e^{-w_i}}; \quad \xi_i = \frac{1}{1 + e^{-w_i}}; \quad i = 1, 2, \ldots, n;
\]

where \( X_i = (x_{1i}, \ldots, x_{pi}) \) and \( w_i = (w_{1i}, \ldots, w_{qi}) \) are the subject’s covariates for explaining \( \pi_i \) and \( \xi_i \), respectively.

Notice that the set of covariates affecting one parameter might (partially or fully) overlap with the set of covariates affecting the other. Moreover, differently from the GLM approach (Agresti, 2010), CUB models establish a direct connection between the probability of a specific rating and the subject’s features. As a matter of fact, in theory a given mean value can be generated by an infinite combination of parameter values since \( E(Y) = \pi (m - 1) \left( \frac{1}{m} \right) + \frac{m-1}{y-1} \xi \). For this reason, it seems more sensible to rely on a direct relationship which links the probability distribution to a set of covariates characterizing the respondents instead of working with average values. In this way, the uncertainty and the strength of the feeling, that interviewees have towards the object under judgment, can be interpreted in terms of the subject’s characteristics.

4. Models without covariates

First, we illustrate the results from fitting a CUB model to the rating distribution of each attribute. Fig. 1 displays the coefficients of the estimated CUB models in the parameter space (unit square) where, in order to facilitate the interpretation, the degree of uncertainty, \( 1 - \pi \), is shown on the horizontal axis, and the degree of importance, \( 1 - \xi \), on the vertical axis.

Consumers have a clear and precise opinion (low uncertainty) about the importance that they give to the wine complexity and taste, the aroma/bouquet, the quality–price ratio, the region of origin and the food-pairing. The estimated models of these items are located in the extreme left part of the unit square \((1 - \pi < 0.5)\). The uncertainty that is attached to the ratings of the other cues, instead, increases as far as the location of the corresponding model moves along the horizontal axis. Specifically, this factor affects the judgments about the wine producer, the elements of packaging and the presence of a certification of origin \((1 - \pi > 0.5)\).

With reference to the degree of importance of attributes for determining the purchase decision, the items appear to be well separated: the brand name and label appearance as well as the bottle shape are considered rather unimportant \((1 - \xi \) is rather small) with respect to the remaining ones whose rating distributions are dominated by medium–high scores, being \((1 - \xi) > 0.5\). As far as we move from the “producer” to the “protected geographical status” along the y-axis, each attribute receives greater consideration for purchase decision.

![Fig. 1. Estimated CUB models.](image-url)
Further insights into the problem can be gained by clustering the estimated CUB distributions. As described in Section 3.1, firstly, the homogeneity hypothesis concerning any two CUB distributions is assessed by means of the KL divergence. Secondly, the clustering algorithm is applied to the binary matrix originated from the acceptance/rejection of the homogeneity test.

The considered wine characteristics are then classified in 5 groups (Fig. 2):

- **G1** → food-pairing, aroma/bouquet, wine complexity and taste, quality/price ratio
- **G2** → grape variety, region of origin
- **G3** → producer, wine features in label information, alcoholic degree, color, drink’s pleasantness
- **G4** → bottle shape, brand name and label appearance
- **G5** → protected geographical status

The graphs capture the different emphasis that consumers put on the various items moving from the most influential attributes (G1) to the least (G4).

Specifically, the cluster G1 gathers the price and a mix of sensory features that represent the elements with which the consumers are mostly concerned. This result is in accordance with other studies which, in fact, indicate taste as one of the major perceived risks when choosing a wine, and price as one of the most recognized signal for quality when few other cues are available and when the perceived risk of making a wrong choice is high (see for instance, Mitchell and Greatorex, 1988, 1989; Speed, 1998). In this regard, in the case of Italian high quality wines, Coppola et al. (2000), Benfratello et al. (2009) investigated the relationship between prices and better quality or reputation. Corain et al. (2009) instead considered the application of nonlinear models to price decisions in the framework of rating-based product preference models, and finally, Brentari et al. (2011). Brentari and Zucolotto (2011), Lannario et al. (2012) discussed the importance of label, chemical and sensory characteristics for price formation and marketing decisions.

The cluster G2 collects the variables that design a widely accessible concept of wine reputation. The grape variety is usually related to sensory differences between wines that can be widely appreciated even if in a rough way. Similarly, the region of origin, being strictly tied to grape varieties, tends to reinforce the consumer expectations about wine quality.

Furthermore, the cluster G3 refers to aspects of packaging which are considered the least important attributes. In this regard, the brand is judged a rather unimportant cue, and this seems the effect of the large number of brands due to the remarkable fragmentation of the Italian wine industry which accounts for about 6000 firms (as estimated by Malorgio et al. (2011)). Italian purchasers, therefore, have not a clear understanding of branding in the wine market and tend to rely more on grape variety and region of origin.

Finally, the protected geographical status appears isolated with respect to all the other cues because of the great uncertainty that the raters express. This may be due to the fact that in Italy, differently from other countries, the protected status is expressed by few designations (DOC, DOCG and IGT). Although these appellatives guarantee some important production aspects, they do not provide Italian purchasers with sure signals of sensory quality. Indeed, the quality of wines can vary noticeably within those categories. This condition is typical of Italian regulation. Despite the progressive harmonization of the different wine appellations promoted by the European Union, the traditional French classification, for instance, implies a more refined scale of evaluation which may help to better discriminate wine quality.

A further aspect contributes to the increasing of consumers’ uncertainty when they have to select a wine for purchasing: the number of Italian wines which have been granted of a designation of origin is rather large (at the end of 2011, there were 330 wines labeled with the DOC designation, 73 with the DOCG and 118 with IGT).

Nevertheless, the certification is recognized by consumers as a valuable cue to wine purchasing as enhanced by the negative asymmetry of the CUB distribution. It ensures the wine regional characteristics and the continuity of local viticultural and oenological practices and, in theory, it indicates the highest quality. This is also true for the Italian market where the reduction of consumption in terms of quantity goes together with the increase in terms of value, confirming the general tendency to reallocate wine consumption in favor of high quality products (Romano, 2012; Lai et al., 2008). In 2011, DOC and DOCG wines accounted for about 37% of the total production whereas IGT wines reached 33%.

Finally, looking at the estimated CUB distributions (Fig. 2) we notice that as far as the overall believed importance of the attributes increases the uncertainty in the responses decreases. This produces a sort of ranking among the considered items which reflects the perceived risk in using a certain cue for wine selection.

**Fig. 2.** Clustered CUB models (by rows: G1, G2, G3, G4, G5).
5. Models with covariates

The consumer profile influences the expressed ratings. This effect has been investigated introducing one of the following covariates in the CUB model describing the degree of importance: the consumption occasions, the place of purchase and the self-assessed measure of competence.

Specifically, the CUB model (5) was fitted to the rating distribution of each wine attribute, having selected $p = 0$ and $q = 1$ (or 2). Moreover, the covariates are simply given by binary variables (representing a peculiar characteristic or behavior of the rater) which affect the parameter $\zeta$ (or in other words the degree of importance measured by $1 - \zeta$).

In Table 3, we anticipate the significant relationships enhanced by the estimated CUB models which will be discussed in details in the following sections.

5.1. The effect of the expertise

As mentioned above, the accumulated experience and knowledge help consumers to distinguish relevant product features. For instance, Hollebeek et al. (2007) discussed the influence of involvement on the importance that some cues, such as the region of origin, have on the purchase intention of new world wines.

In our survey, interviewees were requested to give a self-assessment of their expertise about wines over a 7 point scale (1 = not expert at all; 7 = extremely expert). The responses were then organized in a 3 level variable: low (score below 3); medium (score between 3 and 5) and high expertise (score above 5). The resulting categorization was coded by means of two binary variables:

$$w_1 = \begin{cases} 1, & \text{if the self – assessed score is less than 6;} \\ 0, & \text{otherwise;} \end{cases}$$

and

$$w_2 = \begin{cases} 1, & \text{if the self – assessed score is greater than 2;} \\ 0, & \text{otherwise.} \end{cases}$$

First, we illustrate the results obtained for the degree of importance of grape variety on consumer choices.

Table 4 summarizes the estimated CUB models (in parentheses the standard errors are given). Having considered the expertise as a covariate which influences the parameter $\zeta$ leads to a sensible improvement of the goodness of fit with respect to the model without covariate. The asymptotic likelihood ratio test: $-2(\log_l - \log_0) = 34.98$ is highly significant if compared with the 5% critical value $\chi^2 = 3.84$.

Fig. 3 clearly shows that, depending on their level of accumulated knowledge, consumers express very different ratings. Notice that despite the CUB random variable is discrete, the estimated probability distribution are represented by means of a solid line for facilitating reading. The rating distribution locates towards lower scores when the expertise is low whereas it moves gradually towards medium scores or high evaluations as far as the competence increases.

These findings are consistent with other studies in literature. Grape variety is strongly related to sensory differences among wines, thus it represents one of the most relevant cues that experienced consumers are able to recognize. As a matter of fact, these consumers usually show a closer bond with the products, look for more information about wine and tend to frequent specialized wine stores or wineries (see, for instance, Mueller and Szolnoki, 2010).

The estimated average scores vary from 4.02 (for the lower level), to 5.45 (for the middle level) and 6.08 (for the upper level). These values are very close to the observed means which are 4.00, 5.49 and 6.19, respectively.

This result highlights the possibility of improving marketing strategies in order to add strength to minor local grape cultivars which show strong links, both historical and socioeconomic, as well as ecological and biological, with local territories but whose viticultural and oenological potential is nowadays underestimated. These types of grapes may constitute one of the future opportunities for wine industries which could specifically address them to more experienced costumers. In the same line, it is worth mentioning the recent success of varietal wines that, according to new EU regulation about labeling, indicate the grape variety on their labels though they are table wines which are not entitled to any certification. This category again could more profitably benefit from specific marketing actions in order to attract more informed purchasers.

Table 3 shows the estimated model coefficients

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Item</th>
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<tbody>
<tr>
<td>Expertise level</td>
<td>Grape variety, region of origin, producer, wine complexity and taste, quality/price ratio alcholic degree, aroma/bouquet, color</td>
</tr>
<tr>
<td>Consumption frequency</td>
<td>Drink’s pleasantness</td>
</tr>
<tr>
<td>Consumption occasion</td>
<td>Color, grape variety, region of origin, geographical protected status, bottle shape, brand name and label aspect, quality/price ratio</td>
</tr>
<tr>
<td>Place of purchase</td>
<td>Aroma/bouquet, wine complexity and taste, qual/price ratio, region of origin, grape variety</td>
</tr>
</tbody>
</table>
(the standard errors are given in parenthesis), and the expected values implied by the CUB models.

The graphs of the corresponding distributions clearly depict the role of the accumulated knowledge in determining the relevance of the various cues for consumer wine choice (Fig. 4).

Finally, although they are not as informative as the whole probability distributions, the expected value of the estimated CUB distributions are displayed in Fig. 5. They increase as far as the consumers increase their expertise. The largest difference on average is obtained for the importance of wine color and the grape variety which gain more than 2 points moving from the lower to the upper group of consumers.

It is worth noticing that the rating of the importance of the remaining characteristics either do not depend on the expertise level or the dependency enhances only two levels of competence (medium–low vs. high level competence). This is the case of the importance that consumers give to the producer, the alcoholic degrees and the price/quality ratio which although positively rated are more appreciated by sophisticate consumers (see Table 6).

The level of accumulated knowledge does not lead to a marked difference between the judgments about price (see Fig. 6). Price has in fact a double role, being an indicator of quality but also a constraint which purchasers have to consider when budgeting their expenses. The differences between the two estimated rating distributions are mostly due to the considerably high probability that an expert consumer select the largest score available to measure the importance in determining his/her choice.

Amongst the features whose ratings do not depend on consumer competence about wine we find all the packaging elements, the food pairing and the drink’s pleasantness. Moreover, the same consideration applies to the certification of origin which is an objective cue and then it does not require a special knowledge to be recognized.

5.2. The effect of the consumption occasion and frequency

The situation where the consumer intends to drink wine influences his/her preferences and may modify his/her perception of a given attribute. Price importance, for instance, according to Hall and Lockshin (2000), is affected by the consumption occasions: high price corresponds to social situations when one needs to impress guests, whereas low price are more connected to personal relaxation in private. In a recent contribution, Melo et al. (2010) presented an interesting study of the dependency of wine choice from attitudes (towards the product or with reference to consumer lifestyle) as well as situational factors. Furthermore,

Table 5
CUB models (3 level of expertise: L = low, M = medium, H = high).

<table>
<thead>
<tr>
<th>Variable</th>
<th>$\pi$</th>
<th>$\gamma_0$</th>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>$\gamma_3$</th>
<th>$\gamma_4$</th>
<th>$\gamma_5$</th>
<th>$E(Y_L)$</th>
<th>$E(Y_M)$</th>
<th>$E(Y_H)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grape variety</td>
<td>0.838</td>
<td>-1.066</td>
<td>1.051</td>
<td>-1.311</td>
<td>0.496</td>
<td>0.210</td>
<td>0.085</td>
<td>4.019</td>
<td>5.459</td>
<td>6.087</td>
</tr>
<tr>
<td>(0.053)</td>
<td>(0.454)</td>
<td>(0.381)</td>
<td>(0.270)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region of origin</td>
<td>0.856</td>
<td>-1.156</td>
<td>0.729</td>
<td>-0.660</td>
<td>0.395</td>
<td>0.252</td>
<td>0.140</td>
<td>4.540</td>
<td>5.273</td>
<td>5.850</td>
</tr>
<tr>
<td>(0.054)</td>
<td>(0.401)</td>
<td>(0.292)</td>
<td>(0.293)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wine color</td>
<td>0.756</td>
<td>-0.953</td>
<td>1.253</td>
<td>-1.220</td>
<td>0.576</td>
<td>0.285</td>
<td>0.102</td>
<td>3.663</td>
<td>4.976</td>
<td>5.804</td>
</tr>
<tr>
<td>(0.072)</td>
<td>(0.688)</td>
<td>(0.645)</td>
<td>(0.270)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aroma/bouquet</td>
<td>0.956</td>
<td>-1.657</td>
<td>1.127</td>
<td>-0.826</td>
<td>0.370</td>
<td>0.205</td>
<td>0.077</td>
<td>4.743</td>
<td>5.692</td>
<td>6.425</td>
</tr>
<tr>
<td>(0.029)</td>
<td>(0.415)</td>
<td>(0.358)</td>
<td>(0.226)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wine complexity and taste</td>
<td>0.967</td>
<td>-1.447</td>
<td>0.643</td>
<td>-0.781</td>
<td>0.309</td>
<td>0.170</td>
<td>0.097</td>
<td>5.108</td>
<td>5.915</td>
<td>6.337</td>
</tr>
<tr>
<td>(0.029)</td>
<td>(0.394)</td>
<td>(0.341)</td>
<td>(0.220)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 4. Estimated CUB distribution for the degree of importance of: region of origin, wine color, bouquet, wine complexity and taste, with the 3-level expertise as a covariate (low = solid line; medium = dashed line; high = dashed line and dots).
Martínez-Carrasco et al. (2006) applied conjoint analysis in order to determine the relative importance of the designation of origin, type and price of Spanish wines considering the influence of purchase place and consumption frequency. Seghieri et al. (2007) discussed the Italian case and examined preferences, purchasing criteria and consumption behavior in order to segment the wine market.

Although in our survey the respondents were asked to select their prevalent occasion of consumption among a list of possibilities, in the modeling step we have reorganized the data by considering a simple binary covariate which labels wine consumption during daily meals against other special or formal occasions (related to business dinner, celebrations, etc.):

\[ w_i = \begin{cases} 
1, & \text{if the prevalent occasions of consumption are daily meals;} \\
0, & \text{otherwise.} 
\end{cases} \]

Such a covariate significantly affects the ratings about some attributes as illustrated in Table 7.

According to the estimated CUB models, the rating distributions in Fig. 7 show that the two groups of consumers agree on the overall judgments that they give for each item: packaging is rather unimportant for purchase decisions. However, there are significant differences in the probability of selecting certain ratings both in terms of uncertainty and selectiveness. Specifically, the everyday wine consumers give, on average, a judgment about the typical elements of packaging (bottle shape, brand name and label aspect) which is much less negative than the other group which, instead, seems more influenced by objective factors: grape variety, region of origin, protected geographical status, and wine color. As seen before, the uncertainty is larger when consumers have to rate the

Table 6

<table>
<thead>
<tr>
<th>Variable</th>
<th>( \hat{\pi} )</th>
<th>( \hat{\gamma}_0 )</th>
<th>( \hat{\gamma}_1 )</th>
<th>( \hat{\gamma}_{LM} )</th>
<th>( \hat{\gamma}_H )</th>
<th>( E(Y_{LM}) )</th>
<th>( E(Y_H) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Producer</td>
<td>0.579</td>
<td>-1.571</td>
<td>1.465</td>
<td>0.474</td>
<td>0.172</td>
<td>4.153</td>
<td>5.143</td>
</tr>
<tr>
<td>Alcoholic degrees</td>
<td>0.591</td>
<td>-1.565</td>
<td>0.900</td>
<td>0.340</td>
<td>0.173</td>
<td>4.582</td>
<td>5.048</td>
</tr>
<tr>
<td>Price/quality ratio</td>
<td>0.953</td>
<td>-2.060</td>
<td>0.633</td>
<td>0.194</td>
<td>0.113</td>
<td>5.747</td>
<td>6.286</td>
</tr>
</tbody>
</table>

Fig. 5. Expected values from CUB models (low expertise = square; medium expertise = circle; high expertise = triangle).

Fig. 6. Estimated CUB distribution for the degree of importance of: producer, alcoholic degrees, price quality ratio, with the 2-level expertise as a covariate (low-medium = solid line, high = dotted line).
packaging elements and the designation of origin. Moreover, the expected values of the estimated CUB distributions (see Table 7) differ in around half a point.

Finally, we considered consumption frequency and as before a binary variable was generated as follows:

\[ w_i = \begin{cases} 1, & \text{daily/once or more per week;} \\ 0, & \text{otherwise}. \end{cases} \]

This covariate significantly affects the importance that consumers give to the drink’s pleasantness (see Table 8). In this respect, it is worth noting that this term does not refer to the complexity or flavor of wines, but it is, instead, referred to the fact that some wines are balanced and easy to drink. The CUB model enhances that this attribute is more important for sporadic or occasional consumers. As a matter of fact, this category tends to drink wine in restaurants on special family or formal situations and thus they are more sensitive to balanced wines which are widely appreciated (Fig. 8).

5.3. The effect of the purchase place

Finally, the place where purchases are prevalently carried out is another covariate that has been considered in this study. In recent years, modern distribution has assumed a growing importance

<table>
<thead>
<tr>
<th>Variable</th>
<th>( \pi )</th>
<th>( \gamma_0 )</th>
<th>( \gamma_1 )</th>
<th>( \xi_0 )</th>
<th>( \xi_0 )</th>
<th>( E(Y_0) )</th>
<th>( E(Y_1) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grape variety</td>
<td>0.764</td>
<td>-1.160</td>
<td>-0.448</td>
<td>0.239</td>
<td>0.167</td>
<td>5.198</td>
<td>5.528</td>
</tr>
<tr>
<td>Region of origin</td>
<td>0.845</td>
<td>-0.883</td>
<td>-0.473</td>
<td>0.293</td>
<td>0.205</td>
<td>5.051</td>
<td>5.496</td>
</tr>
<tr>
<td>Protected geographical status</td>
<td>0.445</td>
<td>-1.265</td>
<td>-1.106</td>
<td>0.220</td>
<td>0.085</td>
<td>4.748</td>
<td>5.108</td>
</tr>
<tr>
<td>Bottle shape</td>
<td>0.532</td>
<td>1.395</td>
<td>1.289</td>
<td>0.801</td>
<td>0.936</td>
<td>3.038</td>
<td>2.607</td>
</tr>
<tr>
<td>Brand name and label aspect</td>
<td>0.402</td>
<td>0.736</td>
<td>1.432</td>
<td>0.676</td>
<td>0.897</td>
<td>3.575</td>
<td>3.041</td>
</tr>
<tr>
<td>Wine color</td>
<td>0.692</td>
<td>-0.681</td>
<td>-0.483</td>
<td>0.336</td>
<td>0.238</td>
<td>4.681</td>
<td>5.088</td>
</tr>
</tbody>
</table>

**Table 7**

CUB models (consumption occasion: \( D = \) daily meals, \( O = \) other occasions).

**Table 8**

CUB model for the drink’s pleasantness (consumption frequency: \( D = \) daily/once or more per week, \( O = \) once or more per month/less frequently).
among wine selling channels. The 2011 survey by Mediobanca on the first 107 wine firms, representing about 54% of the national 2010 production, enhanced that modern distribution absorbs about 46% of the production whereas the specialized shops account only for 9.2% of it and the direct sales reach about 8% (Mediobanca, 2012). In the following we will concentrate our attention on the different purchase behavior determined by the juxtaposition of anonymous distribution channels with other shopping places which require more direct consumer involvement.

The CUB model for each wine attribute was therefore estimated by introducing a binary covariate in order to select purchases done at wine shops, wine-growers cooperatives or at the producer site against those done at local food shops or supermarkets.

Table 9 shows the estimation results for those models where the presence of such a covariate resulted significant. Specifically, this concerns some cues which appear to design the essential trait of wines the grape variety, the region of origin, the wine complexity and taste.

Consumers, generally shopping at food shops or supermarkets, tend to give to those features a lower importance than that expressed by the other group of purchasers as shown by the fact that $(1 - \zeta_0) < (1 - \zeta_1)$. The estimated CUB distributions show higher probabilities that the former group select lower rates (Fig. 9). In terms of the estimated averages (Table 9), the difference between the two distributions is larger when considering the ratings of the grape variety (about 1 point). The other attributes, in fact, account for about half a point difference.

### 6. Final remarks

The Italian wine market has a rather complex structure both on the production and the demand side. The wine industry is in fact very fragmented and a large number of small firms which are strongly connected to regional and local oenological practices are present. In addition, the process which molds consumers’ preferences is evolving according to new life styles, and marketing actions of wine producers seem to have a rather limited efficacy.

The methodology illustrated in this article is useful to add further insights into the study of consumer perception of wine. In this respect, CUB models represent an effective statistical tool which helps to identify the role of two latent components: the uncertainty of respondents in rating wine attributes and the strength of attraction each attribute arouses. Besides the combined application of a clustering technique, based on KL divergence, provides an interesting approach for grouping items that are rated similarly. This allows the discrimination of cues which consumers retain important (unimportant), with a strong and definite awareness of their degree of relevance, with respect to others which again may be judged substantial (or worthless) but with a large uncertainty.

Our analysis enhanced that the former group includes consolidated elements of wine industries strategies, such as price, grape variety and region of origin, but also some fundamental expected sensory elements (aroma/bouquet, taste, complexity and food-pairing). The latter group, namely the protected geographical status, producer and label information, consists of characteristics that have to be reinforced. These features could be the object of various types of actions, for instance, in order to improve contents and target of communications concerning the product, to strengthen the level of awareness of potential purchasers, to make the quality of certified wines less variable and more adequate to an established standard.

Moreover, the analysis has shown that, in accordance with other contributions in literature, the grape variety and region of origin are relevant signals that Italian consumers can easily recognize and trust. These are more important than the producer or the wine name (which, in particular, is lowly appreciated). This casts some questions about the use of creative names which is nowadays not only addressed to more innovative wines but also to long history grapes.

The CUB model allows the estimation of the weight that uncertainty assumes in determining the probability that a consumer selects a certain rate when evaluating a given wine attribute. This weight is surely related to the system of preferences that he/she has but it may also depends on the twofold role that some wine features have. This is the case of the alcohol content whose importance attains to taste and complexity, but also to the search for conditions of lightness and pleasantness.

Other traditional signals such as the aspect of packaging (the label and bottle shape) and brand name are of little importance for Italian consumers. The probability of positive appreciation for such attributes increases in case of daily usage since everyday wine is mostly intended as a simple beverage. This consideration is further related to the known problem of brand recognition in a market where consumers are overwhelmed by too many choices and where, as mentioned before, the fragmentation of the wine

### Table 9

<table>
<thead>
<tr>
<th>Variable</th>
<th>$\hat{\alpha}$</th>
<th>$\hat{\beta}_0$</th>
<th>$\hat{\beta}_1$</th>
<th>$\hat{\beta}_2$</th>
<th>$\hat{\beta}_3$</th>
<th>$E(Y_{0s})$</th>
<th>$E(Y_{1s})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grape variety</td>
<td>0.826 (0.057)</td>
<td>-1.595 (0.129)</td>
<td>1.097 (0.204)</td>
<td>0.169 (0.378)</td>
<td>0.378 (0.564)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region of origin</td>
<td>0.830 (0.055)</td>
<td>-1.299 (0.112)</td>
<td>0.593 (0.191)</td>
<td>0.214 (0.330)</td>
<td>0.330 (0.542)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aroma/bouquet</td>
<td>0.941 (0.034)</td>
<td>-1.483 (0.096)</td>
<td>0.461 (0.181)</td>
<td>0.185 (0.265)</td>
<td>0.265 (0.577)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wine complexity and taste</td>
<td>0.958 (0.033)</td>
<td>-1.720 (0.112)</td>
<td>0.600 (0.181)</td>
<td>0.152 (0.246)</td>
<td>0.246 (0.601)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
industry complicates the branding and sales process. The label is not only used as a support to give information, but its design associate with the aspect of the bottle and seal make the product visually distinctive, standing out on the shelves, and attractive to potential purchasers. However, Italian consumers do not seem to be influenced by those elements when other information indicating objective or intrinsic features is available.

Finally, the study has shown that accumulated competence is a key variable which segments consumers and that modify the perception and the judgments concerning the various wine attributes. The results confirm that consumers having a good level of knowledge about wine tend to look for sensory quality (aroma, taste, complexity) which assume a dominant role in their purchase decisions. These are mainly based on grape variety that, even at the first purchase, can recall memory of sensory characteristics of other experienced wines which can lead them to their final wine choice.

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