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Prediction of the Wine Price Purchased Using Classification Trees (Predicción del precio del vino comprado mediante árboles de clasificación)

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Resumen

En los próximos años se espera que el mercado del vino se recupere y crezca. Aunque el tamaño de este mercado es pequeño en México, se hacen esfuerzos para promoverlo en el país. El presente estudio tiene como objetivo explorar la decisión de los consumidores de pagar por un vino de precio bajo versus alto de acuerdo con los atributos del vino y las influencias externas. Un total de 290 consumidores de vino que también son conocedores de vinos, participaron en una encuesta en línea que se llevó a cabo en México. Se evaluó la relevancia que tienen once atributos sobre el precio del vino mediante la aplicación de árboles de clasificación, método que no ha sido situado previamente para explorar las decisiones de compra de vino. El resultado indica que los consumidores están más motivados por el precio que por los atributos del vino. Sin embargo, los atributos relevantes para los consumidores de vinos de bajo precio (menos de 20 USD o su equivalente en pesos mexicanos) incluyen "información de la etiqueta", "premios" y "degustación previa". Por el contrario, la decisión de compra de los consumidores de vinos caros está impulsada principalmente por el "país o región de origen" y el "reconocimiento del viñedo". Los hallazgos del estudio ofrecen sugerencias sobre los atributos del vino en los que las bodegas y los comercializadores deben centrarse para satisfacer las preferencias de los consumidores actuales en función de la sensibilidad al precio y el conocimiento del vino de los segmentos objetivo.

Palabras clave: Vino, México, Conocedores, Consumidores de vino.
Códigos JEL: C93, E37, M31

Abstract

The wine market is expected to recover and growth in the following years. Although the market size of this market is small in Mexico; efforts are being made to promote national wines. To support these actions, the current study aims to explore consumers' decision to pay for a low versus high priced wine according to wine attributes and external influences. A total of 290 wine consumers, knowledgeable about wines, participated in an online survey that took place in Mexico. The relevance that eleven attributes have on the wine price was assessed through the application of classification trees, a method that has not been previously applied to explore wine purchase decisions. The result indicate consumers are mainly driven by price than the wine attributes. However, relevant attributes for consumers of low-priced wines (less than 20 USD or its equivalent in Mexican pesos) include "label information" "awards" and "previous tasting". By contrast, purchase decision of consumers of pricey wines are mainly driven by "country or region of origin" and "vineyard recognition". The study findings offer provide suggestions on the wine attribute wineries and marketers should focus on to meet the current consumers' preferences depending on the price sensitivity and wine knowledge of target segments.

Keywords: Wine, Mexico, Wine knowledge, Wine Consumers
JEL Codes: C93, E37, M31

1. Introduction

The wine market registered a steady growth in most countries and regions before the COVID-19 pandemic. During 2019, wine consumption was 234 million Mhl[1] according to estimates of the International Organization of Wine and Vine (OIV, 2019). This represents a decrease of 3% compared to 2018 and is the lowest consumption level since 2002. Expectations indicate this decline will continue for about five years (Karlsson & Karlsson, 2021). To counteract this contraction, it is of paramount interest for the wine industry to encourage purchase by understanding what factors influence consumers wine choices and refine communication strategies highlighting the product characteristics, their external elements (e. g. country of origin), and the arousal and pleasantness of the wine consumption experience (Vigar-Ellis, Pitt, & Berthon, 2015). The outline of a marketing strategy seems to be more relevant for companies producing New-World wines (Boon & Foppiani, 2019).

Countries of the European Union (EU) contribute with about half of world's wine consumption, which has remained stable, while at the country level the USA is the biggest wine consumer worldwide. Adding other European countries such as the UK, the joint consumption of European countries and the USA accounts for 62% of the world's wine consumption. Regarding the rest of America, the largest consumer market is Argentina (9.4 Mhl) (Karlsson & Karlsson, 2021). Conversely, Mexico is a small market, however, the average wine per capita consumption doubled from 450 ml in 2012 to 960 ml in 2018. Meanwhile the domestic production of about 2.4 million boxes of wine, an amount that satisfies only 30% of the national demand (CNSPU, 2018), is almost unknown internationally. Although beer and tequila are the favorite alcoholic beverages, grape-based drinks (brandy and wine) are the third (Statista, 2022) and the wine industry has made efforts to adapt to the demand of younger generations and produce more attractive and economic packaging (Mexicanist, 2020). Additionally, the Mexican Government has defined a post-pandemic strategy to increase the sustainable production of grapes, the local wine consumption (the goal is that 50% of the national production be consumed locally) and the exportation of Mexican wines (SADER, 2021).

The large range of wine options makes difficult to identify which product attributes - brand, grape, and region of origin, among others- and external information influence the buying process and motivate consumers to buy a bottle of wine (Lockshin & Hall, 2003; Casini, Rungie, & Corsi, 2009). The marketing literature supports that the perceived value associated to a product affects consumers' behavior because individuals look to maximize the utility of their choices over other alternatives (Zeithaml, 1988). However, wine differs from other fast-moving consumer goods (FMCG) as its consumption is driven by utilitarian motives but also by hedonistic, emotional, social, and cultural ones (Charters & Pettigrew, 2008). Seemingly, only experienced wine drinkers are able to understand the interaction between certain extrinsic attributes such as region and grape variety with the wine flavor. Hence, the understanding of the wine choice process results more complex than for other FMCG and conventional consumers.

Survey data about the relative importance of wine attributes has been the usual input of models that use price as dependent variable (Arias-Bolzmann, et al., 2003). Choice-based experiments or analysis of actual purchases have used to improve the estimation of the value or utility provided by different wine attributes (Lockshin, Mueller, Louviere, Francis, & Osidacz, 2009). The recent development of analytical methods to manage ordinal/categorical variables and relax the assumptions of statistical methods (e.g. regression) provide novel options to identify which wine attributes mainly drives consumer's choices. In this work we use classification trees to link wine attributes with the range of price of the wines purchased by consumers. This analytic approach allows tracking the successive decisions consumers make based on the product attributes to finally choose a low versus high priced wine.

Traditionally, decision trees have been used for hierarchical segmentation and to classify new observations for which only the set of predictive variables is known (Román González & Lévy

[1] Million hector liter equals to 100,000,000 liters or 26,417,205.236 US liquid gallons.

Mangin, 2005). However, by analyzing the purity of final nodes, one can identify some easily understandable decision rules that state the sequence of attributes that lead to a final choice thus allowing the identification of the product characteristics and external cues that better distinguish between consumers of relatively cheap versus expensive wines. Therefore, our work contributes to the literature by exploring the attributes that influence the wine choices of a potential but relatively underdeveloped market by applying a nonconventional technique to identify the drivers of different wine-price segments.

2. Literature Review

Wine seems to be something very special for consumers to go all the difficulty to make sense of their selection. The availability of new wines from diverse parts of the world adds to the complexity of the selection of the appropriate wine for consumption. Because many wine choices are available in the market, the task of deciding which one to buy is tough (Veseth, 2013). To pick a wine, the most common strategy used by consumers is price (c.f. (Casini, Rungie, & Corsi, 200; Robertson, Ferreira, & Botha, 2018; Dodds, Monroe, & Grewal, 1991). Still, the existing literature debates constantly other wine attributes considered by consumers that could be used to outline direct marketing strategies that make consumers pay top prices for wine (Yang & Lee, 2020).

Extant research has explored the effect that wine quality attributes that can be assessed through external cues (e.g. region of origin) and intrinsic sensory attributes (e.g. taste) that require of a past consumption experience have on the wine purchase process and on wine price variability (Corduas, Cinquanta, and Ievoli, 2012; Lecocq & Visser, 2006). Because the judgment of the objective quality of wine requires of previous consumption, the management of external cues or proxies is relevant to assist consumers in the evaluation of the wine quality (Lockshin & Hall, 2003).

One of the most relevant extrinsic cues is country of origin (COO) which influences consumer's quality evaluations and willingness to pay a premium price (c.f. Wise, 2017). In the case of wine, the effect of COO changes with the marketing actions to better position brands and the improvement of the quality of wine, as it has been the case of Latin American and USA wines (Arias-Bolzmann, et al., 2003). Varietal type is another intrinsic product attribute relevant for wines of the New World (non-European origin) that refers to a wine made from a grape variety (e.g. Cabernet Sauvignon). In contrast, Old World (European) wines are predominantly identified by region. The grape varietal and more specifically the grape variety has been related to price, wines made from well-known appreciated grape varieties such as Cabernet and Pinot are generally higher priced, but rare varieties (e.g. Torrontes) would also be highly valued because of their uniqueness (Bombrub & Summer, 2003).

Regarding the region of origin, McCutcheon, Bruwer, & Li (2009) found this choice factor comprises three dimensions: region name, wine type, and grape variety. The multi-dimensional nature of the concept is supported by previous research that shows region of origin affects price depending on the grape variety. For example, (Ling & Locksmith, 2003) showed Australian regions recognized as high-quality growing regions of specific grapes are higher priced than varietal wines from less recognized production regions. The region compound attribute ranked third overall, after quality and price, but its importance depends on the consumer's profile and the type of wine preferred. Region has a larger influence on the choice behavior of females, red wine drinkers, and highly involved consumers who have participated in wine tourism.

Goodman (2013) performed a cross-country study to identify the attributes wine consumers find important/unimportant when buying wine in a retail store. The study uses the best-worst method to overcome the problems of rating attributes on an ordinal scale and ignoring the potential tradeoffs consumers make when considering several attributes. That is, consumers select products based on an acceptable combination of attributes instead of using a global ranking. Results show that across countries, tasting the wine previously, recommendations from others, grape variety, and origin of the wine (country or region) are the most critical factors. Awards, general branding, and publicity seemingly also influence wine choices while 'in store information' and 'label information' appear to be surpassed by other attributes. At the country level, wine choices in Old World wine markets, such as Italy and France, are influenced by ‘matching food’ while in New World wine markets such as China, ‘brand’ was relatively more important.

Prestige of the wine brand is a factor that provides a symbolic meaning to the brand that the consumer associate with status, uniqueness, and luxury. Consumption of a wine of a prestigious brand induces pleasure and a feeling of belonging to a privileged status. The emotional and psychological meanings of the brand along with the sensory evaluation of the wine contributes to the brand’s reliability, appealing, and trustworthiness. For example, Correia Loureiro & Pereira da Cunha (2017) show wine consumer experience and brand prestige have a positive effect on wine brand image and word of mouth through the mediation of satisfaction. They report that brand prestige had a stronger effect on satisfaction than the wine experience for visitors of the Douro region.

The opinions of wine experts act as a proxy of the intrinsic quality of wine helping consumers to be confident about their wine choices. Mueller et al. (2009) found the consensus in high quality ratings provided by experts has a stronger influence on consumers, whereas low quality ratings tend to be disregarded. Chocarro & Cortiñas (2013) performed a nested within-subject experiment considering consumers with low/high knowledge to study the effect of expert reports. The consensus on ratings (high versus low) and the low complexity of information significantly affects the overall attribute score that a consumer assigns to wines, particularly among less wine-knowledgeable consumers. Consumers with more knowledge gave lower ratings to wine than subjects with less knowledge because they judge wines by higher quality standards. Therefore, a greater marketing effort seems to be required to improve the ratings of the “wine-expert” segment as they are the most likely to be asked by recommendations from friends and family.

Wilson & Quinton (2012) claim that the increasing popularity of social media seems to lower the influence that wine experts’ ratings and awards have in growing markets such as Asia because wine involves socialization and builds communities around the sharing of the hedonistic experience. The ethnographic study performed by these authors based on the analysis of 1,500 English tweets on the wine subject suggests the emotional content of the messages can influence the recipients. Results provide evidence of community building between individuals but not between consumers and wine producers and retailers. Production regions and brands are also included in tweets providing the opportunity to spread the reputations of brands and wine tourism. In despite that consumers talk about wine in social media, this early study indicates Twitter only delivers soft value to the wine business.

3. Methodology

3.1 Sample.

A group of wine connoisseurs gathered by a specialized market research agency in Mexico composed the sample (Singh, 2007). The group was assembled from three sources. First, an open request to participate in the survey was launch on the Internet (Roos, 2002) using Facebook but no participants were recruited. Then, the administrator of Wine-Lovers Mexico, a social media group (Debreceny, Wang, & Zhou, 2019) on Facebook, was directly contacted asking to help to recruit participants for the survey generating 486 responses. Finally, the Bajalupano winemaker database was added including wine producers, distributors, sommeliers, and clients. In total, a list consisting of 506 participants was generated from which a final sample of 290 interviewees was obtained for the study, for a response rate of 57.3% after two calls. Respondents reported having from few to high wine knowledge domain: 10% declare high knowledge, 23% declare to have a good knowledge, 45% certain knowledge and 22% few knowledge. Data collection was done during the COVID-19 pandemic between September 2020 and March 2021 a time of movement restrictions in Mexico.

Regarding wine experiential knowledge or expertise, 10% rated themselves as “experts”, 23.1% stated they have “advanced expertise about wines”, the majority (45.2%) declare they have “moderate experiential knowledge” and 21.7% only “somewhat expertise”. Most of the respondents declare to buy wine mainly at retailer stores (40.7%), followed by specialized wine stores (31.7%), direct purchases at vineyards (18.3%), and finally online wine purchases (9.3%). Regarding personal characteristics, interviewees age ranges are: 23.8% are 26-35 years old, 44.1% are 36-45 years old, 21% are 46-55 years old and only 11% are aged over 55. Participants of both sexes participate in the survey, 47.2% are males and 52.8% females.

3.2. Questionnaire.

Respondents answered questions regarding their wine consumption in the last three months. A total of eleven attributes they look when purchasing a bottle of wine were included. The list of attributes is based on the revision of the literature (Casini, Rungie, & Corsi, 2009). The attributes were divided in two groups, and from each group, respondents selected the two main attributes considered when purchasing a bottle of wine. The first group includes six attributes associated to the bottle's external cues (Pentz & Forrester, 2020): grape variety, production region or country-of-origin (COO), label information, vineyard recognition, awards, and label information. The second group includes four attributes related to consumer external influences (Robertson, Ferreira, & Botha, 2018): recommendation by friend/family, advertising, influencer recommendations, and wine-brand prestige. The last attribute referred to the actual sensory evaluation of the wine by previous tasting. For classification purposes, other variables collected included the self-ratings of wine knowledge and expertise, the price range of wine purchased in the last trimester, the type of store to purchase a bottle of wine, age, sex, and place of residence.

Data Analysis. The Classification and regression tree (CART) option of the statistical software MINITAB was used to process the data. The input data set used in decision or classification trees has a predictive variable C that can take c discrete values 1, . . . , c, and a set of numeric and categorical attributes $A_1, \ldots, A_p$. The goal is to predict C given $A_1, \ldots, A_p$. In this study C takes only two values, c =1 corresponds to consumers who declared the maximum price they pay for a bottle of wine is 20 USD, and c = 2 to a price above 20 USD, while p = 1,2,…,11 identifies the different wine attributes.

Decision tree algorithms automatically split numeric attributes A_i into two ranges and split categorical attributes A_j into two subsets at each node. The goal is to maximize class prediction accuracy, that is the proportion P (C = c) at a terminal node (also called node purity) where most points belong to class c. Splitting on numeric attributes is generally based on the information gain ratio (an entropy-based measure) or the Gini index. The splitting process is recursively repeated until no improvement in prediction accuracy is achieved with a new split. The final step involves pruning nodes to reduce the tree size and to avoid model over fit. Classification trees allow the specification of misclassification costs; if the erroneous classification in one category implies higher costs than for others (e.g. fail to identify a fraudulent transaction) then one can propose to minimize the overall misclassification cost instead of the total misclassification error.

Decision tree models are mostly used to predict the result for new observations and to perform hierarchical segmentation. But decision trees can also be used to: a) select the critical variables that distinguish between categories, b) assess the relative importance of variables based on the times the variable was used to split a node and the reduction in the node impurity summed and averaged across all trees, and c) generation of a subset of decision rules (Arana, 2021). These are the main applications of interest of this work: identify the most relevant attributes that drive the selection of a high-priced wine and track which attributes successively drive the consumer's decision to purchase a low versus high priced wine.

Therefore, the output of interest is the set of rules or equivalently successive decision that go from the root to each terminal/final node which consist of a conjunction of inequalities for numeric variables ($Ai <= x$, $Ai > x$) and set limit for categorical variables ($Aj \in \{x, y, z\}$). Consider a predictive rule $\{Ai <= x\} \Rightarrow C=c$ or $\{Aj =x\} \Rightarrow C=c$. A general association rule can have multiple attributes on the consequent C, whereas in the decision tree the target attribute appears only in a terminal node (leaf) and it corresponds to one predicted value (Ordonez, 2006), say "buy a wine priced less than 20 USD."

Decision trees only find a few association rules that tend to favor a few attributes, those that initially maximize the separation of observations in the data set. It is often the case that the predictive attributes appear scattered on different branches of the tree and therefore they appear in different rules. We were interested only on rules associated to segments of a certain size, stated as at least 5% of the population, that is 15 consumers.

4. Results

All attributes that respondents may use when selecting a wine were used as predictors and "One Standard Deviation" tree, that is the smallest tree with a misclassification error within one standard error of the minimum misclassification error tree, was selected for analysis. Prior probabilities were set equal because they almost match the percentage of individuals in the low vs. high price segments (0.48, 0.52), the Gini impurity function was used to do the splitting, and the k-fold cross-validation method with the MINITAB defaults applied to estimate the misclassification error rate which would be equivalent to the misclassification cost because equal costs were assumed for both categories. The main branches of the resulting tree are shown in Figure 1.

The misclassification error rate for the training set is satisfactory (28.1%) for category 1, namely "purchase of wines priced below 20 USD" (22.9%). However, the overall error rate deteriorates considerably for the test set (42.1%) thus indicating the classification tree is highly dependent on the dataset. The complete three has 25 nodes, the other sections of the tree are shown in Figures 2a to 2c. Revising these fragments, one can notice that for the first class "purchase of wines priced at most 20 USD" the terminal nodes of highest purity tend to have low cardinality (see node 1 in Figure 1, and nodes 6 and 9 in Figure 2c).

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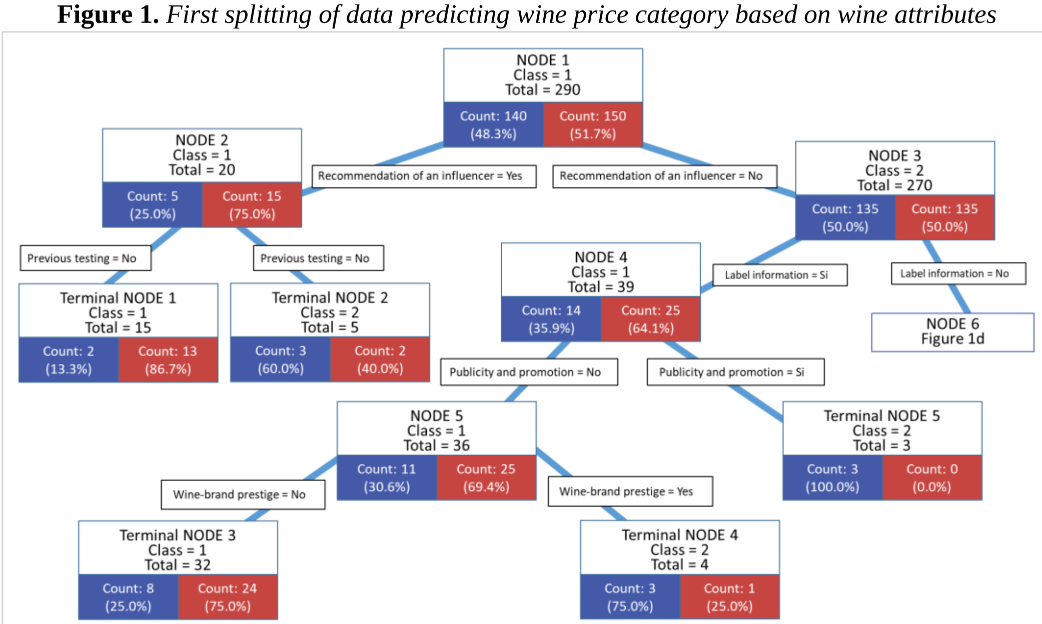
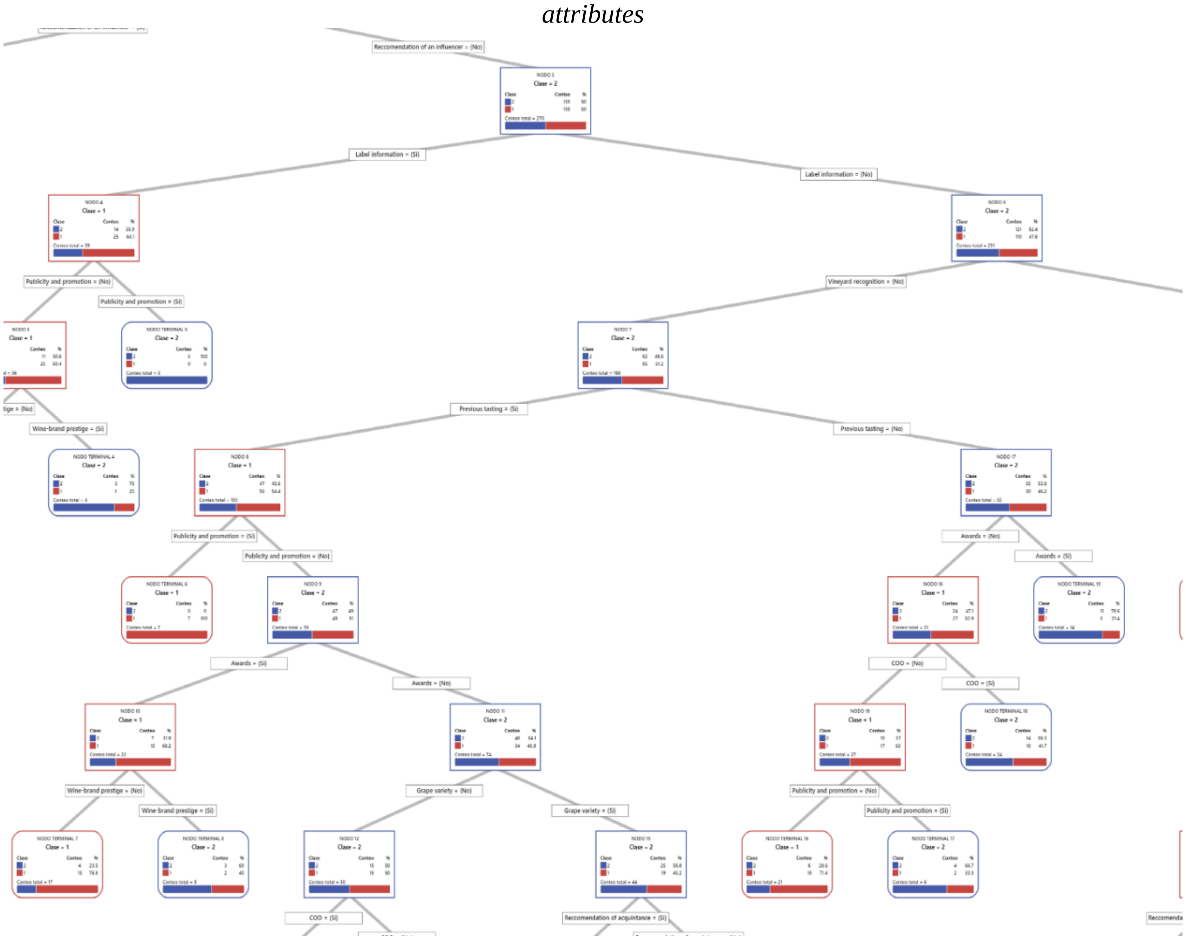
Figure 1. *First splitting of data predicting wine price category based on wine attributes*



CART reveals the successive decisions made by respondents are mainly based on non-sensory attributes. For each node, the right branch of the node is conditional on the attribute being considered when making a wine choice, and the left is conditional to the attribute being non-relevant.

For example, the diagram in Figure 1 divides respondents who are susceptible to "influencer's recommendations". Only 7% of respondents, primarily buyers of low-priced wines, are driven by influencer's opinions (terminal node 1). Another sub-segment of buyers of low-priced wines (8.3%) is influenced by the information provided in the wine's label information (terminal node 3). Finally, a third sub-segment (terminal node 7) of cheap wines but of smaller size (4.5%) are influenced by "previous wine tasting" and "awards" (see Figure 2a).

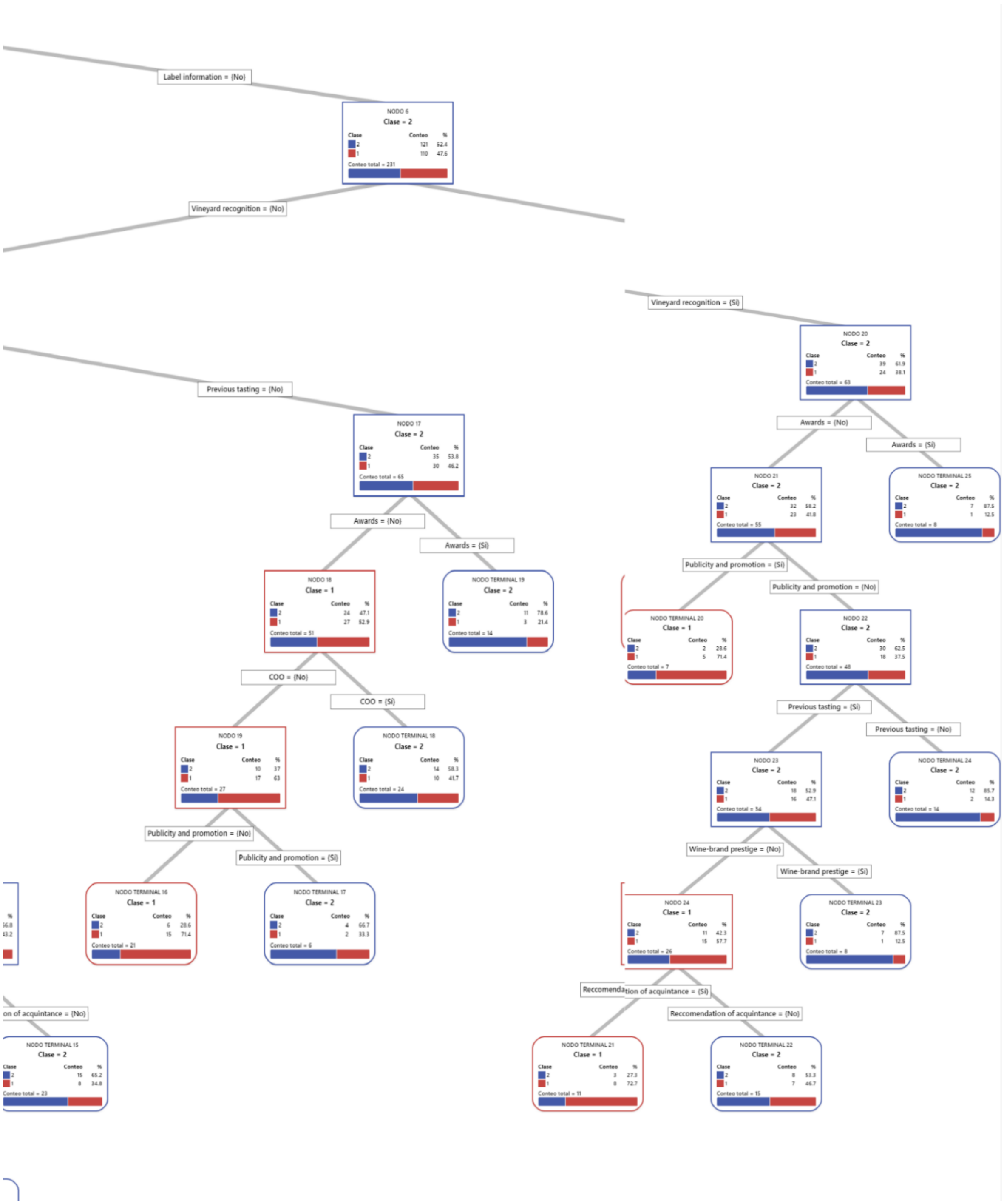
Figure 2a. *Principal right branch of the classification tree predicting wine price category based on wine attributes*



Vineyard recognition seems to be most important for the segment of buyers of high-priced wines (node 20) (see Figure 2b) and the only relevant attribute for a small subsegment (2% of participants) (see terminal node 25 in Figure 2b). Sixty-two percent of the participants who declare the vineyard recognition is relevant buy wines priced over 20 USD while only 38% of those who consider important the vineyard recognition end buying a cheap wine (odd ratio of about 5:3). Awards also seem to be a relevant attribute for a small sub-segment of buyers of costlier wines (2%). While previous tasting and wine prestige in addition to vineyard recognition predicts the higher wine price paid by 2% of participants see terminal node 23 in Figure 2b). Overall, COO is considered by several segments of wine consumers (see Figure 2b and 2c) but this unique attribute by itself does not drive the final decision of purchasing a wine in a certain range price.

CART provides a relative importance of the attributes according how frequently were they used to split nodes of high purity, the following hierarchy is uncovered: Publicity and promotion > Wine-brand prestige > Recommendation of acquaintance > Awards > Previous tasting > Recommendation of an influencer > Label information > Country of origin. Merging these results with the successive divisions in the tree, we conclude the most relevant attributes for purchasers of low-priced wines are awards, previous tasting, and recommendation of an influencer while COO and vineyard recognition are relevant to purchasers of high-priced wines.

Figure 2b. *Extreme right branch of the classification tree predicting wine price category based on wine attributes*



After revising the complete tree, no clear decision rules emerge because most of the terminal nodes include less than 5% of the participants. This finding suggests Mexican consumers are pricesensitive and directly select the wine based on price preferences more than on the wine attributes. Cox (2009) suggests that price sensitivity is more important than perceived quality among people who drink red wine weekly. Moreover, acceptable quality covers a wide range of mid-price products while the selection of pricey wines seems to depend more on enjoyment, socialization, and relaxation (Thach and Olsen, 2019).

Price categories were also predicted based on the profile of the respondents (age, gender, and wine's expertise self-assessment) and their behavior (place of purchase). From the second tree in Figure 3 we conclude that "wine experts" (terminal node 5) tend to buy more expensive wines meanwhile individuals with limited knowledge about wines (terminal node 1) are mainly low-price wine purchasers. Thus, wine expertise is the dominant characteristic as confirmed by a ji-square test ($\chi^2 = 53.687, P = 0.000$). The resulting tree has similar accuracy for the training and test set, 69.3% and 66.2% respectively. Sensitivity is 64.3% meaning a low to middle level of domain knowledge and expertise fairly predicts purchases of low-cost wine.

5. Conclusions and Implications

This research agrees with previous studies regarding the importance of wine attributes in other markets. The set of attributes considered in the wine purchasing decision-making of mostly knowledgeably Mexican wine consumers include external cues such as production region or country-of-origin (COO), label information, and vineyard recognition. While, of the second group of attributes, namely those that influence decisions, recommendation by friend/family, advertising, influencer recommendation, and wine-brand prestige were all relevant. Previous tasting was also considered in the wine choice decision process of about 5% of participants. All these attributes have been examined previously using mainly regression analysis. The importance of the wine attributes here included prevails for Mexican consumers. Wine industry professionals targeting the Mexican market might focus on the attributes here analyzed. Indeed, according to results, it can be recommending centering on price depending on the consumer's wine knowledge because consumers expressing high wine knowledge would be willing to pay higher prices than consumers with low wine knowledge.

The novelty for this researcher is the use of CART analysis. The application of this method results in a classification tree that identifies the variables that drive the decision to select a wine of a low versus high price. In our case wines prices considered a threshold of 20 USD. The prediction ability of the classification tree resulted highly dependent on the dataset. Despite the relatively high misclassification rates on the test set and the low cardinality of final pure nodes, the CART analysis provides interesting results of how different sub-segments of consumers select how much to pay for a wine. The small segment sizes and multiple variables that define a low versus high price wine segment prevent from suggesting meaningful decision rules. Further studies with larger stratified samples of consumers with different grades of wine knowledge could help to better identify key wine attributes.

This study contributes to the limited wine research literature regarding wine consumption in a wine emerging market. The findings of the study would be of help to other researchers in the field to consider classification trees as an alternative method of analysis of wine choices. On the other hand, for practitioners, this study provides an opportunity to ponder the already know variables influencing consumer wine selection according to knowledge level as well as a threshold price value. Consequently, practitioners could focus better on the segments of interest for the wine offering in the market.

Figure 2c. *Central part of the classification tree predicting wine price category based on wine attributes*

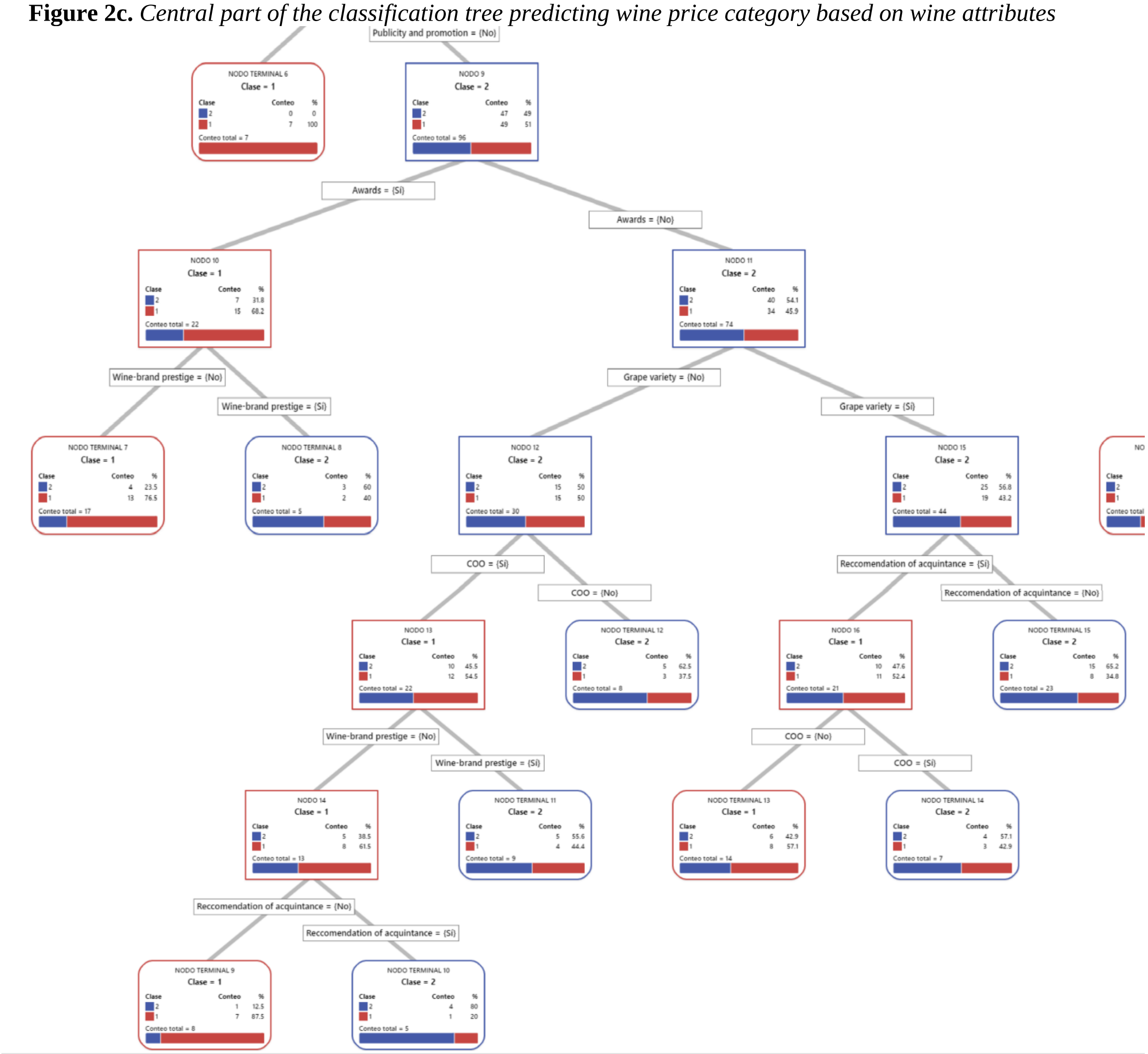
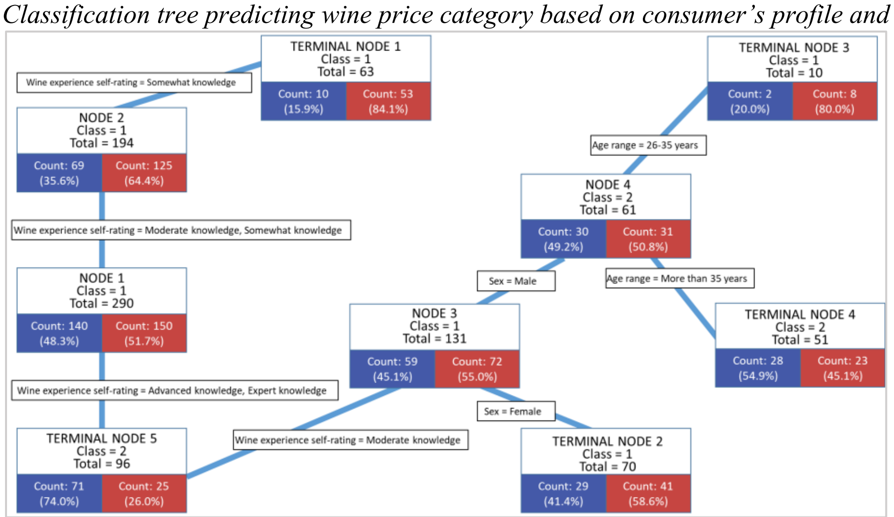


Figure 3. *Classification tree predicting wine price category based on consumer's profile and behavior.*



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