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A study on wine sensory evaluation by the statistical analysis method

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Abstract: In this paper, we construct a rating credibility model of red wine by the Analytic Hierarchy Process, achieve the classification of red grapes through the evaluation results of red wine and cluster analysis method and analyze the correlation of the physical and chemical indicators between red grapes and red wine. Thus, the paper demonstrates that aromatic substances play an important role in the quality of red wine, so we cannot evaluate the quality of wine only by the physical and chemical indicators of wine grapes and wine.

Keywords: Analytic Hierarchy Process; cluster analysis; rating credibility

Wines are made from fresh grapes. They have not only the features of inherent colors, good smell and pure flavor, but also low alcohol content and rich nutrition. They are good for our health. Today, with people's living standards and lifestyle improved, wines have become a necessity in their leisure time, so the wine business prospects are bright. Wine quality certification helps not only to protect the interests of consumers but also to improve the wine making level. Meanwhile, this certification provides decision-making information for the market positioning of wine.

Rich achievements in the study of fruit wine quality evaluation have been obtained, both in China and abroad. Cider, dandelion wine and wild kiwi fruit wine have been all reported (Peng et al. 2008; Sugintiene 2010; He & Zhang 2011); see for example Peng et al. (2008), based on the fuzzy comprehensive evaluation method and combined with chemical analysis and sensory evaluation, Peng created a new method for evaluating the cider quality. The evaluation result obtained by this method is more objective and precise than the result got by the single sensory evaluation used before. At present, we can refer to the results obtained in Chira et al. (2011), Caldas & Rebelo (2013), D'Alessankdro & Pecotich (2013), Baker & Ross (2014), Goodstein et al. (2014), and Juega et al. (2014) to evaluate wine. Besides, Cozzolino et al. (2009) found that there was an association between the near-infrared information and the sensory evaluation of wine, which could perform a sensory evaluation for different types of wine. Cortez perfectly classified different qualities of wine by the support vector machine method (Cortez et al. 2009). With the confidence interval method, Li et al. (2006) effectively reduced the differences between wine critics through reducing the variation coefficient of wine samples. Moreover, Yu et al. (2013) avoided the network instability caused by blindly introducing the data by grey correlation analysis and neural network. Liu (2012) established a new model of Hopfield neural network classifier in the wine quality evaluation. This method could achieve the classification of wine quality. Hui (2013) evaluated the correlation of the qualities between red grapes and red wine by fuzzy clustering and fuzzy comprehensive evaluation method. But she did not elucidate the specific link of the physical and chemical indicators between red grapes and red wine. It is clear that the above method can evaluate the wine quality by the physical and chemical indicators.

In this paper, we use red wine as an example. We evaluate the quality of red wine by studying its aromatic substances and the physical and chemical indicators of red grapes and red wine. Firstly, we construct

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a rating credibility model of red wine by using the Analytic Hierarchy Process. The conclusion is that the evaluation of the second set is more credible. Secondly, we construct a wine grape classification model, which regards red wine classification as the primary reference results. At the same time, combined with the cluster analysis diagram of physical and chemical indicators of red grapes, we get the classification results of red grapes. Thirdly, we build a correlation analysis model and get a quantitative relationship of the physical and chemical indicators between red grapes and red wine. Finally, using the principal component analysis, we get the result that aromatic substances play an important role in the quality of red wine. We cannot evaluate the quality of wine only by the physical and chemical indicators of wine grapes and wine. In addition, the same conclusion is also suitable for white wine. The conclusion of this paper is more intensive than the conclusion in Hui (2013) and the methods involved in this paper are widely applied in many fields (Cai & He 2006; Li & Wu 2010; Chen et al. 2014; Zhu & Xu 2014).

MATERIAL AND METHODS

Background. How to determine the wine quality? The general way is to employ a number of experienced wine critics and form a wine testing team. These people taste the wine uniformly and give scores. We can determine the quality level of wine through the scores. Questionnaire list 1 gives the results of evaluation of some wines in one year. Questionnaire list 2 and questionnaire list 3 give the composition data of wine grapes and wine in that year, respectively.

The main contents.

(i) According to questionnaire list 1, determine which set of the evaluation results is more reliable;

(ii) According to the physical and chemical indicators of wine grapes and wine quality, classify these wine grapes;

(iii) Analyze the correlation of the physical and chemical indicators between red wine grapes and red wine;

(iv) Discuss whether it is feasible to evaluate the quality of wine by the physical and chemical indicators of grapes and wine.

The data sources. As the space is limited, we give only short lists of questionnaire lists in this article. The entire contents of the questionnaire lists can be seen in Electronic Suplementary Material (ESM).

Questionnaire list 1 contains two sheets. The sheets reflect the scores of red wine samples (including 27 samples) which were given by two sets of ten wine critics from four aspects of appearance, aroma, taste and overall assessment. We use the score of red wine sample 25 given by the first set of wine critics as an example. The short list shown is Table 1.

Questionnaire list 2 lists the physical and chemical indicators of 27 kinds of red wine samples and the corresponding wine grapes. We regard this indicator content of 27 kinds of red wine as an example. The short list shown is Table 2.

Questionnaire list 3 lists the contents of 73 kinds of aroma composition in wine and the contents of 55 kinds of aroma composition in the corresponding wine grapes. We regard the contents of 73 kinds of aroma composition in wine as an example. The short list shown is Table 3.

Table 1. The score of red wine sample 25 given by the first set

Analysis	Characteristics	Score		Wine critics			
				1	2	3–9	10
		individual	sum	scores			
Appearance	clarity	5	15	4	4	…	4
	tone	10		6	8	…	6
Aroma	pure	6	30	4	4	…	4
	concentration	8		4	6	…	4
	quality	16		10	14	…	12
Taste	pure	6	44	3	5	…	4
	concentration	8		4	6	…	6
	lasting	8		4	6	…	6
	quality	22		13	16	…	13
Overall assessment			11	8	9	…	8

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Table 2. The main components of 27 kinds of red wine samples

Species number	Anthocyanins (mg L^{-1})			Tannins (mmol L^{-1})			…
Red wine	1	2	3	1	2	3	…
Wine sample 1	973.128	974.38	974.128	11.049	11.03	11.01	…
Wine sample 2	516.83	518.083	517.83	11.03	11.146	11.059	…
…	…	…	…	…	…	…	…
Wine sample 27	137.766	139.018	138.58	5.956	5.986	5.942	…

Table 3. Contents of 73 kinds of aroma composition of red wine

English name (73 kinds)	Wine sample 1	Wine sample 2	…	Wine sample 27
Acetaldehyde	1.836	1.804	…	0.829
Ethyl cetate	12.113	12.132	…	14.511
…	…	…	…	…
1,4-Benzenediol, 2,5-bis(1,1-dimethylethyl)-	1.383	1.117	…	0.841

RESULTS AND DISCUSSION

Rating credibility model for red wine

The establishment of a rating reliability model for red wine and solutions. In this section, according to the data in questionnaire list 1, we get the score, corresponding to each wine, from 10 wine critics of each set by the Analytic Hierarchy Process. And we compare the average score of each set score's coefficient of variation. At last, we get the rating credibility model of red wine. The construction course of the Analytic Hierarchy Process is as follows:

Step 1: Draw the Analytical Hierarchy Figure (see Figure 1).

Step 2: Establish the judgment matrix for each criterion. Various factors of criteria are compared with each other and we obtain judgment matrix

$$A = (a_{ij})_{10 \times 10}$$

where:

$$a_{ij} = \frac{u_i}{u_j}$$

The a_{ij} indicates the degree of importance of u_i and u_j. According to the red wine tasting score of the first group in questionnaire list 1, we get the project perfect score of each standard in criteria. That is,

$$u_1 = 5, u_2 = 10,\ u_3 = 6,\ u_4 = 8,\ u_5 = 16,\ u_6 = 6,$$
$$u_7 = 8,\ u_8 = 8,\ u_9 = 22,\ u_{10} = 11$$

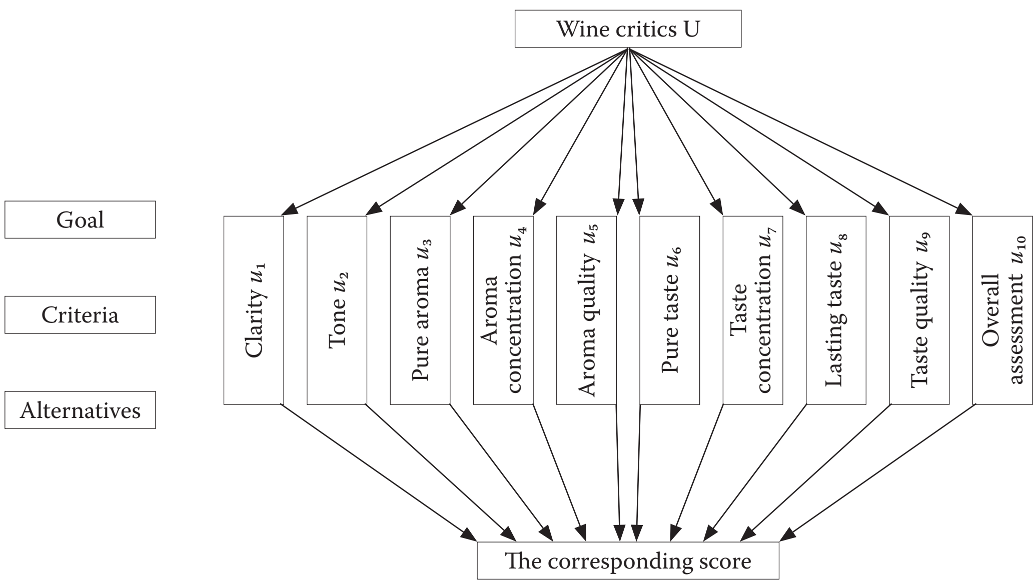

Figure 1. Analytical Hierarchy Figure

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We get judgment matrix A,

$$A=\begin{bmatrix}
1.000 & 0.500 & 0.833 & 0.625 & 0.313 & 0.833 & 0.625 & 0.625 & 0.227 & 0.455\\
2.000 & 1.000 & 1.667 & 1.250 & 0.625 & 1.667 & 1.250 & 1.250 & 0.455 & 0.909\\
1.200 & 0.600 & 1.000 & 0.750 & 0.375 & 1.000 & 0.750 & 0.750 & 0.273 & 0.545\\
1.600 & 0.800 & 1.333 & 1.000 & 0.500 & 1.333 & 1.000 & 1.000 & 0.364 & 0.727\\
3.200 & 1.600 & 2.667 & 2.000 & 1.000 & 2.667 & 2.000 & 2.000 & 0.727 & 1.455\\
1.200 & 0.600 & 1.000 & 0.750 & 0.375 & 1.000 & 0.750 & 0.750 & 0.273 & 0.545\\
1.600 & 0.800 & 1.333 & 1.000 & 0.500 & 1.333 & 1.000 & 1.000 & 0.364 & 0.727\\
1.600 & 0.800 & 1.333 & 1.000 & 0.500 & 1.333 & 1.000 & 1.000 & 0.364 & 0.727\\
4.400 & 2.200 & 3.667 & 2.750 & 1.375 & 3.667 & 2.750 & 2.750 & 1.000 & 2.000\\
2.200 & 1.100 & 1.833 & 1.375 & 0.688 & 1.833 & 1.375 & 1.375 & 0.500 & 1.000
\end{bmatrix}$$

Step 3: Weight calculation and consistency test:

(i) According to matrix $A = (a_{ij})_{10 \times 10}$, compute the weight of each indicator;

(ii) Find the largest eigenvalue denoted by λ_{max};

(iii) Find the eigenvector $W = (w_1, w_2, ..., w_n)$ corresponding to λ_{max};

(iv) Calculate the consistency index CI as follows:

$$CI = (\lambda_{max} - n)/(n - 1) \tag{1}$$

According to the consistency index, calculate the consistency ratio:

$$CR = CI / RI \tag{2}$$

Where random consistency index RI can be checked from Table 4. RI is obtained from the sample mean of CI (Xu 1998). When the consistency ratio $CR < 0.1$, we think that the judgment matrix has a satisfactory consistency.

The largest eigenvalue is calculated by using MATLAB: $\lambda_{max} = 10$. Substituting into equation (1), we have $CI = 0$. Substituting into equation (2), we have $CR = 0 < 0.1$. In summary, the judgment matrix has a satisfactory consistency. It explains the judgment of importance for each evaluation index has a higher credibility.

Step 4: Calculate the combination weight vector W as follows: establishing the weight vectors of layer 2 to layer 1:

$$w^{(2)} = (w_1^{(2)}, ..., w_{10}^{(2)})^T \tag{3}$$

and the weight vectors of each element of layer 3 to layer 2:

$$w_k^{(3)} = (w_{k1}^{(3)}, ..., w_{k10}^{(3)})^T,\ k = 1, 2, ..., 10. \tag{4}$$

Then construct matrix:

$$W^{(3)} = [w_1^{(3)}, ..., w_{10}^{(3)}]. \tag{5}$$

So the combination weight vectors of layer 3 to layer 1 are:

$$w^{(3)} = W^{(3)} \times w^{(2)} \tag{6}$$

Weight vector W is obtained as follows:

a = [0.1414 0.2828 0.1697 0.2263 0.4525 0.1697 0.2263 0.2263 0.6223 0.3111], namely the weight corresponding to 10 standards of each wine. Matrix b is formed after entering the data in questionnaire list 1 into Matlab, namely the scores, corresponding to 10 standards, of each wine. Then the score of each wine, corresponding to the 10 wine critics, is obtained by $a \times b$. The discriminate method of the rating credibility model is as follows: find standard deviation SD and mean by each row. Then the coefficient of variation CV is obtained:

$$CV = \text{SD/mean} \tag{7}$$

where:

the coefficient of variation can estimate the measure of dispersion of a set of data.

Generally speaking, the smaller the measure of dispersion of a set of data, the smaller its coefficient of variation, the more reliable is the evaluation by the group. Standard deviation SD and mean for each wine score corresponding to the 10 wine critics of the two sets are obtained by $a*b$. And substitute them into Equation 7 to get the coefficient of variation for each wine of the two sets. Then seek the mean of the coefficient of variation for each set. The results are as follows:

The mean of the coefficient of variation for the first set $CV = 0.101\,450\,098$;

The mean of the coefficient of variation for the second set $CV_2 = 0.078\,698\,31$

The coefficient of variation obtained for the two sets shows a lot of differences, so there exists a significant difference. Notice that $CV_1 > CV_2$, so the second set is more credible.

Table 4. Random consistency index (RI)

Matrix order n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

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Table 5. The evaluation of each red wine corresponding to the 10 wine critics

Sample No.	Wine critics										Mean	CV
	1	2	3	4	5	6	7	8	9	10		
1	23.7585	25.1166	29.1611	18.0168	18.7240	25.4274	24.0698	25.9365	23.7587	23.0234	23.69928	0.13173944
2	27.6904	26.5307	28.2843	25.5405	23.7586	26.3043	29.5006	25.8801	26.0214	25.0034	26.45143	0.05966639
3	29.2460	25.1730	29.1329	28.3126	22.5707	25.7671	24.5223	26.7851	26.0498	27.0397	26.45992	0.07555402
4	26.8982	27.7468	25.8802	25.8234	21.2415	26.8983	25.1161	25.8801	21.3262	25.2295	25.20403	0.08346341
5	23.2495	24.3811	28.5106	26.4457	26.6154	25.5407	24.1546	25.2578	26.0498	24.8335	25.50387	0.05563865
6	23.6458	23.9852	26.5306	21.6373	20.7889	22.6274	24.4090	23.1929	23.1365	24.4942	23.44478	0.06473353
7	24.7205	23.5328	24.9467	22.5709	16.6029	24.0980	20.2516	26.1062	25.4842	24.4378	23.27516	0.11689897
8	25.5124	24.8903	28.2279	17.6773	21.7505	23.5041	24.3248	20.9867	23.5889	21.1848	23.16472	0.11943134
9	29.4440	29.0478	29.0761	26.7568	23.9566	27.9164	29.2455	26.8983	26.2761	26.3608	27.49784	0.06100993
10	23.4191	25.9650	29.6985	21.8352	21.8919	23.0232	22.8817	24.4374	22.8817	25.6821	24.17158	0.09432540
11	22.5991	21.7506	23.3909	21.8072	17.7340	22.4294	22.2579	17.5363	22.9103	22.6275	21.50450	0.09246197
12	24.1548	24.2681	26.8416	20.7606	23.2498	25.5973	22.7971	25.5972	24.8619	25.7388	24.38672	0.06867385
13	26.5871	22.5706	22.9668	22.8817	23.9000	24.1266	23.9000	26.8982	23.7021	22.7970	24.03301	0.06031936
14	25.5124	25.5973	27.7467	22.3726	24.2680	26.8417	25.0878	28.7368	25.9931	25.7387	25.78951	0.06518965
15	21.8071	20.9021	26.0782	19.4878	21.1565	24.9751	25.0599	23.9848	23.4758	24.6640	23.15913	0.08942398
16	25.5124	23.0515	27.6619	24.1262	23.6174	24.7203	23.9003	26.3891	24.7486	25.1164	24.88441	0.05236557
17	25.6821	25.9084	26.9830	26.0498	26.3044	26.0213	26.8701	26.6154	26.5873	23.6455	26.06673	0.03463569
18	24.4942	23.5328	29.3873	20.0253	22.9669	21.8072	21.4679	26.1628	21.1566	23.5328	23.45338	0.11082863
19	25.7387	23.7589	29.7833	21.4959	22.7121	28.1993	25.8231	28.7086	26.0498	25.4558	25.77255	0.09699265
20	29.0481	26.7286	29.3025	22.7406	25.1731	30.0662	27.4640	29.4157	25.3145	25.4559	27.07092	0.08397437
21	28.7653	25.2863	26.8134	25.8234	21.8637	27.0680	22.2030	25.2012	26.1346	27.6053	25.67642	0.08141722
22	28.1430	27.5772	27.7470	21.7504	24.3529	24.6074	25.4559	25.3145	23.7303	26.3608	25.50394	0.07483834
23	27.7467	27.4074	29.1611	28.6801	23.4474	26.5021	26.8980	24.2111	29.3873	25.8515	26.92927	0.07030271
24	23.1929	23.8718	25.7105	25.9931	25.9650	23.5606	26.4742	26.6154	26.5024	24.4939	25.23798	0.04974579
25	23.6455	24.8335	30.0096	21.6656	21.3545	22.6274	23.7302	24.6919	23.1080	23.1929	23.88591	0.09650584
26	23.6455	23.2778	28.6801	22.3726	25.9931	26.2194	26.0777	27.0114	21.9485	25.9084	25.11345	0.08250910
27	25.5124	23.7305	25.7387	25.4275	24.8901	24.2677	28.9915	25.9365	25.8801	25.0598	25.54348	0.05220846
Mean	–	–	–	–	–	–	–	–	–	–	–	0.07869831

CV – coefficient of variation

The classification of wine grapes

Analysis of wine grape grading. The quality of wine grapes is not only closely connected with the quality of wine made from them, but also it is closely related to their physical and chemical indicators. If the classification of red wine is consistent with the classification results of red grapes obtained by cluster analysis, the classification of red wine is the final result of the classification of red grapes. Otherwise, the classification of red grapes should mainly be based on the classification of red wine. At the same time, we should refer to the results of red grapes obtained by cluster analysis.

The establishment of a wine classification model and solutions. The scores for each type of red wine given by the second set of 10 wine critics are obtained in previous section. The specific situation is in Table 5. On the basis of the scoring average for each type of red wine given by the 10 wine critics of Table 5, we can grade the wine. It is clear that red wine can be divided into 4 grades (see Table 6).

The establishment of a wine grape classification model and solutions. According to the physical and chemical indicators of wine grapes in questionnaire list 2, we can draw the hierarchical diagram of red grapes by SPSS

Table 6. Classification of red wine samples

Category	Premium	Great	Qualified	Bad
	Sample No.			
Red wine	3, 9, 17, 20, 23	4, 5, 14, 19, 21, 22, 24, 26, 27	1, 10, 12, 13, 16, 25	6, 7, 8, 11, 15, 18

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Table 7. Classification of red grape samples

Category	Premium	Great	Qualified	Bad
	Sample No.			
Red grape	2, 3, 9, 17, 23	4, 5, 14, 19, 20, 21, 22, 24,26, 27	1, 10, 12, 13, 16, 25	6, 7, 8, 11, 15, 18

software. The results are in Figure 2. According to the classification results of red wine and combining with the hierarchical diagram of red grapes, the red grapes can be divided into 4 grades (see Table 7).

The establishment of model which reflects the correlation of the physical and chemical indicators between red grapes and red wine and solutions

Analysis of the correlation of the physical and chemical indicators between red grapes and red wine. Using principal component analysis and correlation analysis, we get the correlation of the physical and chemical indicators between wine grapes and wine.

Simplify the physical and chemical indicators by the principal component analysis method. According to the data in questionnaire list 2, the principal component analysis is done by SPSS, and the results are as follows:

(i) For the results of red wine see Table 8 and Table 9.

(ii) The operation method of red grapes is similar to the above method in red wine.

Correlation analysis. In accordance with the principal components screened out from previous steps, we choose a physical and chemical indicator which is the most influential factor from each major component to represent other indicators at the same level and use them to participate in the correlation coefficient calculation. According to the reference (Song 2008), the correlation coefficient is defined as:

$$r = \sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}) \Big/ \sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (8)$$

Using the SPSS software, we directly calculate the correlation coefficients between 16 major indicators of red grapes and 4 major indicators of red wine. It is clear that there exists a correlation between red grape indicators and red wine indicators. The specific results are the indicators which present a positive correlation with red grapes and red wine and do not necessarily pro-

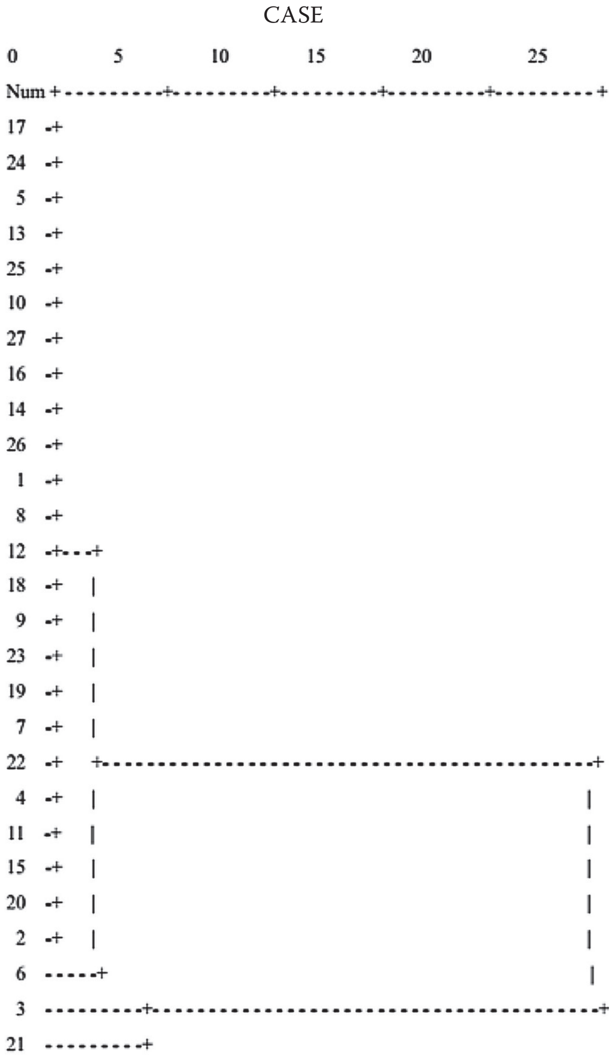

Figure 2. Hierarchical diagram of red grapes

Table 8. Component matrix of red wine

Main components	Component 1	2	3	4
X1	0.804	–0.316	0.177	0.277
X2	0.932	–0.053	–0.082	0.071
X3	0.967	–0.023	–0.075	0.055
X4	0.917	–0.030	–0.064	0.069
X5	0.501	0.725	0.183	–0.323
X6	0.584	0.633	0.102	–0.250
X7	0.088	0.657	0.294	–0.498
X8	–0.193	0.178	–0.219	0.558
X9	0.042	–0.196	0.216	–0.101
X10	0.967	0.092	–0.070	–0.008
X11	–0.815	–0.146	–0.016	–0.483
X12	–0.321	0.767	0.243	0.412
X13	–0.022	0.585	–0.749	0.037
X14	–0.131	–0.056	0.930	0.257
X15	–0.323	0.828	0.055	0.365

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Table 9. The correlation between the main components and each component of red wine

Correlation principal component	Positive correlation	Negative correlation
First	X10 (DPPH half inhibition volume) X3 (Total phenols)X2(tannins) X4 (Wine total flavonoids) X1 (Anthocyanins)	X11(Colour *L**(D65))
Second	X12 (Colour *a**(D65)) X15 (Colour C(D65))X6(Trans-piceid) X5 (Resveratrol)X7(Cis-piceid)	X9(Cis-resveratrol) X1(Anthocyanins)
Third	X14 (Colour(H(D65)X9(Cis-resveratrol) X12 (Colour(*a**(D65)))X7(Cis-piceid)	X13(Colour *b**(D65))) X8(Trans-resveratrol)
Fourth	X8 (Trans-resveratrol) X12 (Colour(*a**(D65))X15(Colour(*a**(D65)))	X7(Cis-piceid) X11(Colour *L**(D65))

X1–X10: main components ; *a**(+red;–green), *b**(+yellow;–blue), *L**(+orange;–purple)

mote each other. The indicators which present a negative correlation with red grapes and red wine do not necessarily control mutually each other. That is, the indicators which promote the growth of grapes are likely to improve the wine quality, and may reduce the wine quality. The indicators which suppress the growth of grapes are likely to improve the wine quality, and may reduce the wine quality.

The establishment of a wine comprehensive assessment model and solutions

Wine comprehensive assessment mode. In this section, we use the principal component analysis to solve the problem. The principle of the principal component analysis is as follows:

Step 1: Dimensionless processing for all index values:

$$x_{ij}^* = (x_{ij} - \bar{x}_j)/s_j \ \ (i = 1,2,\ldots, n;\ j = 1,2,\ldots, p)$$

where:

$$\bar{x}_j = \sum_{i=1}^{n}(x_{ij} - \bar{x}_j)^2 \big/ n, s_j^2 = \sum_{i=1}^{n}(x_{ij} - \bar{x}_j)^2 \big/ (n-1)$$

Step 2: Factor analysis:

(i) Find out the correlation matrix R after dimensionless processing;

(ii) According to $|\lambda I - R| = 0$, compute characteristic roots $\lambda_j\,(j = 1,\ldots, p)$;

(iii) Arrange for $\lambda_j\,(j = 1,\ldots, p) : \lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p \geq 0$

Each characteristic root corresponds to a feature vector:

$$\mu_j = (\mu_{j1},\ldots, \mu_{jp})(j = 1,\ldots, p).$$

Then we have

$$F_j = \mu_{j1}x_1^* + \mu_{j2}x_2^* + \ldots + \mu_{jp}X_p^*\ (j = 1,\ldots, p),$$

where: F_j is the j main component,

$$x_j^* = \begin{bmatrix} x_{1j}^* & x_{2j}^* & \ldots & x_{nj}^* \end{bmatrix}^T \ \ (j = 1,\ldots, p)$$

According to the contribution rate $a_j = \lambda_j / \Sigma_{j=1}^{\mathrm{P}} \lambda_j$, select the previous k principal components when the cumulative contribution rate $\Sigma\, a_j$ reaches a certain value, regard the previous k principal components as their common factors.

Step 3: All common factors expressed by these variables are linear. Construct a score function for all the factors. Seek the linear weighted values of the previous k principal components $F = \Sigma_{j=1}^{\mathrm{k}} a_j F_j$. According to the reference (Li et al. 2009), firstly, we simplify the major indicators affecting the aroma substances of red wine in questionnaire list 3 to nine key indicators such as ethyl acetate, 3-methyl-1-butanol, 2-methyl-1-propanol, ethyl lactate, ethyl caprylate, phenethyl alcohol, caprylic acid, 2-decanoic acid and diethyl succinate. Secondly, we simplify them to three indicators such as 2-methyl-1-propanol, ethyl acetate, diethyl succinate by the principal component analysis. Thirdly, we constitute a set of data with 16 sets of physical and chemical indicators (containing Z) which show a positive correlation with red grapes, 4 sets of indicators (containing X) which show a positive correlation with wine and the above 3 sets of indicators (containing V) which affect the aroma substances seriously. Then we perform the principle component analysis for the set of data. The results are in Table 10. Table 10 shows that the previous eight principal components can comprehensively reflect the major information on the quality of wine. According to the component matrix (see Table 11), we have:

(i) the first principal component has a greater positive correlation with V1, X15, X14, Z51, Z50;

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Table 10. Total variance explained of the three aspects

Component	Initial eigenvalues			Extraction sums of squared loadings		
	total	variances (%)	cumulative (%)	total	variances (%)	cumulative (%)
1	3.470	15.087	15.087	3.470	15.087	15.087
2	2.815	12.238	27.325	2.815	12.238	27.325
3	2.467	10.724	38.049	2.467	10.724	38.049
4	2.426	10.546	48.596	2.426	10.546	48.596
5	1.718	7.470	56.066	1.718	7.470	56.066
6	1.595	6.936	63.002	1.595	6.936	63.002
7	1.474	6.400	69.401	1.472	6.400	69.401
8	1.345	5.849	75.251	1.345	5.849	75.251
9	0.993	4.318	79.569	–	–	–
10	0.855	3.716	83.285	–	–	–
11	0.787	3.421	86.706	–	–	–
12	0.726	3.156	89.862	–	–	–
13	0.550	2.390	92.252	–	–	–
14	0.475	2.064	94.315	–	–	–
15	0.410	1.781	96.096	–	–	–
16	0.301	1.310	97.406	–	–	–
17	0.238	1.033	98.439	–	–	–
18	0.131	0.569	99.008	–	–	–
19	0.091	0.397	99.405	–	–	–
20	0.076	0.330	99.735	–	–	–
21	0.031	0.137	99.871	–	–	–
22	0.026	0.111	99.982	–	–	–
23	0.004	0.018	100.000	–	–	–

Table 11. Component matrix of the three aspects

Main components	Component							
	1	2	3	4	5	6	7	8
V1	0.459	0.178	0.481	0.357	0.212	0.056	–0.007	–0.359
V3	0.223	0.404	0.687	0.022	0.294	0.106	0.154	0.087
V9	–0.188	0.280	0.091	–0.012	–0.457	0.582	0.346	0.218
X3	–0.716	0.042	–0.294	0.424	0.038	–0.180	–0.147	0.032
X15	0.484	0.019	0.235	0.073	–0.041	0.301	–0.683	0.175
X14	0.520	0.612	–0.241	0.180	–0.224	–0.333	0.051	0.099
X8	0.366	–0.363	–0.330	0.180	0.251	0.367	–0.034	0.264
Z21	–0.617	0.138	–0.477	0.299	0.039	–0.297	–0.116	0.111
Z17	0.267	–0.567	0.372	0.389	–0.098	–0.191	0.068	0.083
Z57	–0.312	–0.263	0.232	–0.475	0.237	–0.113	0.502	–0.137
Z4	0.021	–0.376	0.634	0.027	–0.329	–0.287	–0.093	0.120
Z46	–0.069	–0.177	–0.023	0.532	–0.144	0.145	0.335	0.502
Z39	–0.175	0.532	0.121	0.327	0.333	0.256	–0.030	–0.334
Z36	–0.508	0.391	0.108	0.349	0.174	0.357	–0.220	0.049
Z14	–0.002	–0.488	–0.156	0.331	0.081	0.045	0.063	–0.493
Z22	–0.335	–0.430	0.341	0.346	0.244	–0.015	–0.103	0.263
Z51	0.623	–0.202	–0.391	–0.140	0.046	0.064	0.086	–0.049
Z58	–0.025	0.052	0.075	0.266	0.595	–0.088	0.449	0.191
Z44	–0.466	–0.277	0.167	–0.473	–0.070	0.365	–0.079	0.146
Z20	0.380	0.499	–0.014	0.213	–0.272	–0.138	0.298	0.184
Z50	0.560	–0.348	–0.467	0.131	0.358	0.187	0.020	0.126
Z59	0.064	0.186	0.169	–0.259	0.400	–0.479	–0.279	0.399
Z60	0.011	0.255	–0.154	–0.628	0.368	0.097	–0.003	0.224

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(ii) the second principal component has a greater positive correlation with V3, X14;
(iii) the third principal component has a greater positive correlation with V1, V3, Z4;
(iv) the fourth principal component has a greater positive correlation with V1, X3, Z17, Z46;
(v) the fifth principal component has a greater positive correlation with V1, V3, Z58, Z22;
(vi) the sixth principal component has a greater positive correlation with V9;
(vii) the seventh principal component has a greater positive correlation with V9, Z57, Z58;
(viii) the eighth principal component has a greater positive correlation with V9, X8, Z46. Obviously, aromatic substances play an important role in the quality grade of red wine. Therefore, we cannot evaluate the final quality of wine only by the indicators.

CONCLUSION

There are two highlights in this paper. Firstly, we solve successfully which group's score, given by wine critics, is more credible. The computational process is very simple. We only need some basic operations for MATLAB. Secondly, the clear specific contact for the physical and chemical indicators between wine grapes and wine is obtained by the correlation analysis model. This method makes the results more persuasive. Innovation is noted that aromatic substances play an important role in the quality of red wine. We cannot evaluate the final quality of wine only by the physical and chemical indicators of wine grapes and wine. This paper provides a new idea and reference to related research.

REFERENCES

Baker A.K., Ross C.F. (2014): Wine finish in red wine: The effect of ethanol and tannin concentration. Food Quality and Preference, 38: 65–74.

Cai Z.C., He L.M. (2006): The application of correlation analysis principle on library and information science. Modern Information, 5: 151–156. (in Chinese)

Caldas J., Rebelo J. (2013): Portuguese wine ratings: An old product a new assessment. Wine Economics and Policy, 2: 102–110.

D'Alessandro S., Pecotich A. (2013): Evaluation of wine by expert and novice consumers in the presence of variations in quality, brand and country of origin cues. Food Quality and Preference, 28: 287–303.

Cortez P., Cerdeira A., Almeida F., Matos T., Reis J. (2009): Modeling wine preferences by data mining from physicochemical properties. Decision Support Systems, 47: 547–553.

Cozzolino D., Holdstock M., Dambergs R.G., Cynkar W.U., Smith P.A. (2009): Mid infrared spectroscopy and multivariate analysis: A tool to discriminate between organic and non-organic wines grown in Australia. Food Chemistry, 116: 761–765.

Goodstein E.S., Bohlscheid J.C., Evans M., Ross C.F. (2014): Perception of flavor finish in model white wine: A time-intensity study. Food Quality and Preference, 36: 50–60.

He J., Zhang H.N. (2011): Study on optimization of fermentation conditions of wild kiwifruit wine. International Conference on Agricultural and Biosystems Engineering, Phuket, Thailand: 320–324.

Hui X.J. (2013): The classification and evaluation of wine by fuzzy mathematics. Mathematics in Practice and Theory, 43: 40–45. (in Chinese)

Chen T., Jin Y.Y., Qiu X.P., Chen X. (2014): A hybrid fuzzy evaluation method for safety assessment of food-waste feed based on entropy and the analytic hierarchy process methods. Expert Systems with Applications, 41: 7328–7337.

Chira K., Pacella N., Jourdes M., Teissedre P.L. (2011): Chemical and sensory evaluation of bordeaux wines (Cabernet-Sauvignon and Merlot) and correlation with wine age. Food Chemistry, 126: 1971–1977.

Juega M., Gonzalez-Ramos D., Bartolome B., Carrascosa A.V., Martinez-Rodriguez A.J. (2014): Chemical evaluation of white wines elaborated with a recombinant saccharomyces cerevisiae strain overproducing mannoproteins. Food Chemistry, 147: 84–91.

Li H., Liu S.D., Wang H., Zhang Y.L. (2006): Studies on the statistical analyses methods for sensory evaluation results of wine. Journal of Chinese Institute of Food Science and Technology, 6: 126–131. (in Chinese)

Li N., Wu D.D. (2010): Using text mining and sentiment analysis for online forums hotspot detection and forecast. Decision Support Systems, 48: 354–368.

Li Y., Li J.M., Jiang Z.J. (2009): Application of statistical analysis in the evaluation of grape wine quality. Liquor-Making Science and Technology, 4: 79–82. (in Chinese)

Liu Y.L. (2012): Application of new hopfield neural network classifier in the quality evaluation of grape wine.Value Engineering, 31: 181–182. (in Chinese)

Peng B.Z., Yue T.L., Yuan Y.H. (2008): A fuzzy comprehensive evaluation for selecting yeast for cider making. International Journal of Food Science and Technology, 43: 140–144.

Song T.S. (2008): Discussions on the functions of the statistics of correlation coefficient and its applications: Taking SPSS as analysis tool. Statistical Thinktank, 11: 27–31. (in Chinese)

https://doi.org/10.17221/438/2017-CJFS

Sugintiene A. (2010): Quality evaluation of dandelion wine. Annals: Food Science and Technology, 11: 16–20.

Xu S.B. (1998). Practical decision-making method – principle of analytic hierarchy process (AHP). Tianjin University Press: Tianjin: 17.

Yu H.B., Qi N., ZhaoY.J. (2013): Application of gray correlation neural network to evaluation of wine quality. Microprocessors, 34: 49–51. (in Chinese)

Zhu B., Xu Z.S. (2014): Analytic hierarchy process-hesitant group decision making. European Journal of Operational Research, 239: 794–801.

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