Study on Properties and Composition of Ancient Glass

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Abstract. To help archaeologists to better study the ancient glass, open the mystery of the early of the silk road, also better protect the cultural heritage at the same time, this thesis will glass types, such as grain and color and whether the relationship between the surface weathering consider as a binary classification problem, and the characteristics of three types of value through the target code into numerical characteristics, build a gradient increase tree model, to score the importance of features, it is found that type has the greatest impact on weathering, followed by ornamentation and color. For the composition reduction of weathering points, this thesis transformed the problem of weathering point reduction into a mathematical problem of adjusting the characteristic values of weathering attributes. Firstly, this thesis checked the changes of the composition, and established a prediction model for the composition reduction of the weathered sites based on the qualitative assumption that "the sum of the composition contents remains unchanged" and the characteristic equation of the weathering attributes. Finally, the reduction calculation of the weathered sites was carried out.

Keywords: Ancient glass, classification, gradient lifting tree model, reduction prediction model.

1. Introduction

While studying ancient glass, experts have discovered that it is highly susceptible to weathering due to the burial environment. In the process of weathering, the proportion of chemical composition always changes, which seriously affects the correct judgment of cultural relic experts on its category. Archeologists generally classify ancient glass into two types: high-potassium glass and lead-barium glass based on its chemical composition and other detection methods. [1] However, it is difficult to solve the problems of the relationship between the surface weathering of glass relics and the type, decoration and color of glass, the statistical rule of the weathering chemical composition content on the surface of cultural relics, and the correlation between the chemical composition of cultural relics [2]. Therefore, it is necessary for the team to use mathematical expertise to analyze and model the problem and put forward a reasonable plan to help the development of cultural relics.

2. Coding of categorical features

For category-type feature coding, the commonly used one-hot coding has the problem that it cannot be segmented on the category-type feature in the tree model, which affects the learning of decision tree [3]. Therefore, this thesis use objective coding to transform categorical features, so as to obtain a better fitting tree model. Target coding is a categorical variable coding method based not only on the feature value itself, but also on the corresponding dependent variable, so that the coded data can better contain the influence relationship between the feature and the result, considering whether weathering is a classification problem, the characteristics of glass type, ornamenting and color are replaced by the combination of the posterior probability of the dependent variable given a particular class value and the prior probability of the dependent variable on all training data.

3. Discuss the relationship between surface weathering and its glass type, ornamentation, and color

After the lifting tree is created, the importance score of each feature can be obtained through Python's Sklearn package, and the SHAP value can be calculated. The importance score provides a score indicating how useful or valuable each feature is in the building of the enhanced decision tree in the model [4]. The more critical decisions an attribute is used for in the decision tree, the higher its relative importance will be. SHAP belongs to a method of ex-post model interpretation that can increase the interpretability of the model. The core idea of SHAP is to calculate the marginal contribution of features to the model output, and then interpret the "black box model" from the global and local levels. SHAP constructs an additive explanatory model, in which all features are considered as "contributors". For each prediction sample, the model produces a predicted value, and the SHAP value is the value assigned to each feature in that sample.

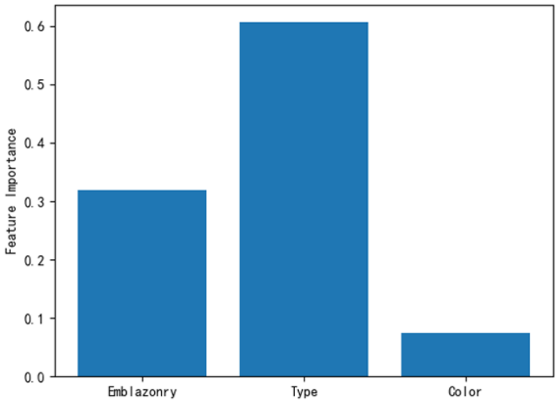

Figure 1. Feature importance score

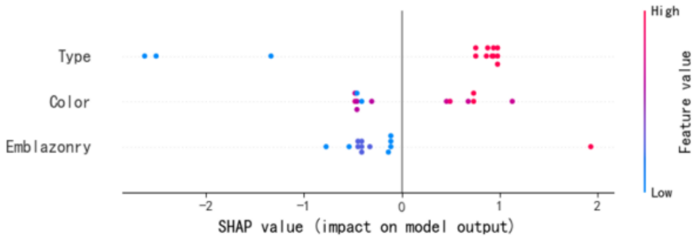

Figure 2. Feature SHAP value

It can be seen from Figure 1 that the type has the greatest impact on weathering, while in Figure 2, a point can represent a sample. The redder the color, the larger the value of the feature itself, and the bluer the color, the smaller the value of the feature itself. Based on Figures 1 and 2, it can be concluded that the type is very important to the model, and the higher the type with bonus point value, the SHAP value is greater than 0, which has a positive impact on weathering. The smaller the eigenvalue is, the SHAP is less than 0, indicating a negative effect. Horizontally, the sample distribution of type is relatively scattered, which means that the influence of this feature is greater. The ornamentation category with a low sample value has a small effect on weathering, while the ornamentation with a high sample value has a significant effect on weathering. For the color feature, the distribution of high sample value (red dots) and low sample value (blue) is more balanced than the other two features on weathering, so the influence of surface color change on weathering is relatively less significant than that of type and ornamentation, which is consistent with the conclusion obtained in Figure 1.

4. Establishment of the characteristic equation of weathering attributes

This thesis used the PCA method to find the principal components and their corresponding contribution rates, and then weighted summation of the principal components according to the contribution rates to obtain the characteristic equations that are comprehensive and contain more information about the sample state. PCA was first proposed by K.Paterson in 1901, which is a technique to reduce multiple variables into a few comprehensive indicators. From a mathematical point of view, it is to reduce the dimension of data. Statistically, variance is used to describe the degree of dispersion of data. The greater the variance, the greater the degree of dispersion of data. The characteristic equation of weathering attribute can be obtained by the weighted sum of several principal components containing more information according to the contribution rate. [5] The general steps of PCA PCA + characteristic equation establishment are as follows: This thesis calculated and processed the data in MALAB and obtained the following results: The principal components, corresponding contribution rates and overall cumulative contribution rates of the two types of glass cultural relics are shown in Table 1 and Table 2:

Table 1. High potassium glass contribution rate

	Zg1	*Zg2*	*Zg3*	*Zg4*	*Zg5*	*Mid-december, the cumulative*
High potassium glass	40.30%	18.77%	12.49%	11.65%	6.85%	90.06%

Table 2. Contribution rate of aluminum-barium glass

Zq1	*Zq2*	*Zq3*	*Zq4*	*Zq5*	*Zq6*	*Zq7*	*Zq*	*Zq_total*
Aluminum barium glass	25.54%	21.06%	11.89%	7.75%	6.48%	6.00%	5.34%	84.07%

Characteristic equation of high potassium glass weathering properties:

$$\alpha_g=0.1234X_1+0.1010X_2-0.0331X_3-0.0372X_4-0.1664X_5-0.1309X_6-0.1854X_7-0.1835X_8-0.1319X_9-0.2601X_{10}-0.1544X_{11}-0.1815X_{12}+0.049X_{13}-0.0201X_{14}$$

Characteristic equation of weathering properties of lead-barium glass:

$$\alpha_q=0.072X_1+0.0425X_2+0.1058X_3+0.0995X_4+0.1978X_5+0.1830X_6+0.0872X_7-0.1048X_8-0.0988X_9-0.0996X_{10}+0.0610X_{11}-0.0281X_{12}+0.0752X_{13}-0.0018X_{14}$$

Code the weathering type corresponding to the 67 processed samples, as shown in Table 3.

Table 3. Weathering type coding

type	unweathered	weathering
coding	0	1

The relationship between weathering type coding and weathering attribute eigenvalues of corresponding samples is shown in Figs. 3 and 4. To look at the figure 3 and figure 4 analysis, found that weathering encoding attribute values for weathering properties characteristic value has obvious segmentation, for high potassium cultural relic, the eigenvalues of the weathering samples slants big, small unweathered sample characteristic value, to lead barium relics, most small eigenvalues of weathering samples, most of the unweathered sample characteristic value is larger [6]. It is proved that it is reasonable and feasible to infer the weathering attribute by setting the critical value and comparing the characteristic value with the critical value. In order to obtain a complete judgment model for weathering attributes, appropriate critical values of weathering attributes should be selected as follows: FIG. 3 shows that, for high potassium cultural relics, the weathered and unweathered sample points are obviously on a straight line of a vertical X-axis. The midpoint of the maximum abscissa of the undifferentiated sample point set and the minimum abscissa of the differentiated sample point set is selected as the critical characteristic value of high potassium cultural relics: $L_{g,f}=(x_1+x_2)/2=(9.7+10.4)/2=10.05$.

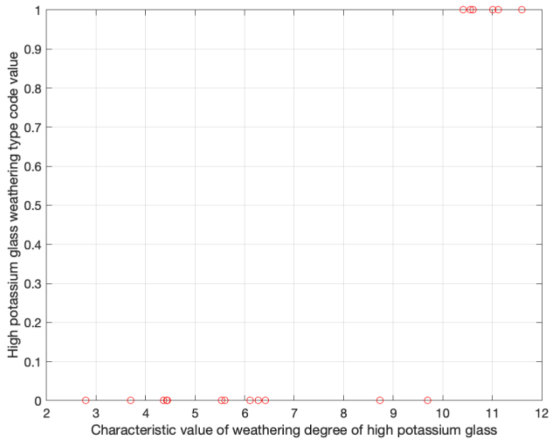

Figure 3. High potassium weathering types

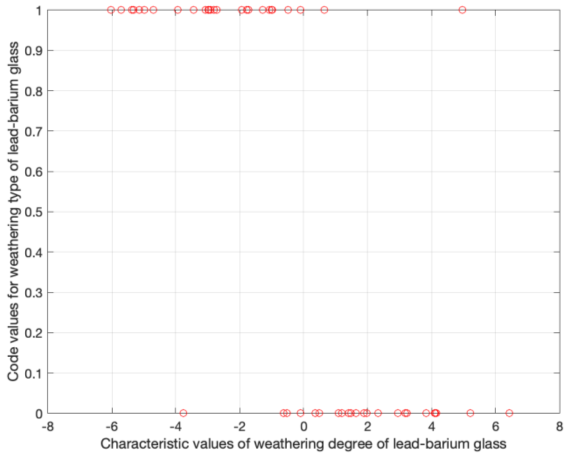

Figure 4. Lead-barium weathering type

As can be seen from Figure 4, for Pb and barium cultural relics, weathered samples and unweathered samples without barium were completely separated by a straight line perpendicular to the X-axis. In order to seek the optimal critical value, this thesis used MATALAB to select 100 candidate points within the interval [-2, 2] for calculation, and calculated that "sample points less than the critical value are weathered samples. Samples larger than the critical value are unweathered samples". It is observed that when the characteristic value of weathering degree is -0.8, the number of sample points conforming to the conjecture is the most, accounting for 89.8% of the total number of samples [7].Therefore, the critical eigenvalue of Pb and barium cultural relics is set as $L_{q,f}$=0.8.

5. Analysis of results

Table 4 shows the corresponding coefficient values of each component in the characteristic equation of weathering properties. A negative number indicates that the content of this component is negatively correlated with the corresponding type of glass relics, while a positive number indicates that the content of this component is positively correlated with the corresponding type of glass relics. In the actual production and manufacturing of glass products, the stronger the weathering resistance, the better the quality. For high-potassium glass, the smaller the characteristic value.

It means that the degree of unweathering is greater. Therefore, to improve the anti-weathering strength, negative correlation components should be increased as much as possible and related components should be reduced. However, for lead-barium glass, the opposite is true, the anti-weathering strength should be increased as much as possible and the negative correlation components should be reduced [8]. By observation of table 4, found that there are some component with the increase of them, two types of weathering strength are enhanced, they are K, Ca, Mg, Al, Fe, P, can infer that the six elements have good weathering resistance, which can be seen from the coefficient of absolute value, Mg and Al element of weathering resistance is stronger, Therefore, in the actual production of glass products, it can be considered to increase some elements to improve their weathering resistance.

Table 4. Correlation coefficient of weathering attribute characteristic equation

	SiO_2	Na_2O	K_2O	CaO	MgO	Al_2O_3	Fe_2O_3	CuO	PbO	BaO	P_2O_5	SrO	SnO_2	SO_2
High in potassium	0.1234	0.1010	0.0331	0.037	0.1664	0.1309	0.1854	0.1835	0.1319	0.2601	0.1544	0.1815	0.0490	0.0201
Lead barium	0.0720	0.0425	0.1058	0.0995	0.1978	0.1830	0.0872	0.1048	0.0988	0.0996	0.0610	0.0281	0.0752	0.0018

6. Error analysis

For high potassium cultural relics in the above mentioned, the critical eigenvalue is set as 10.05, and it is considered that the eigenvalue less than 10.05 is the unweathered point, and the eigenvalue more than 10.05 is the weathered point. The conjecture accuracy can reach 100%. For Pb and barium cultural relics, this thesis set the critical eigenvalue as -0.8, and considered the eigenvalue less than -0.8 as the weathering point, and the eigenvalue more than -0.8 as the unweathering point. The accuracy of the sample can reach 89.8%, but there are still five sample points that do not meet this conjconjism [9], among which 4 sample points are weathering points and 1 sample point is unweathering point. Combined with relevant information, this thesis analyzed that there were also unweathered areas on the surface of partially weathered cultural relics. For the unweathered cultural relics, shallow local weathering could not be excluded, which resulted in the reduction of the accuracy of the conjecture [10]. The five error sample points are shown in Table 5.

Table 5. Five error samples

Cultural relics Sampling Points	Characteristic values of weathering degree	Original weathering attribute	Modified weathering properties
02	0.0995	weathering	unweathered
11	0.4943	weathering	unweathered
24	3.7558	unweathered	weathering
48	4.9608	weathering	unweathered
49	0.6502	weathering	unweathered

7. Prediction of chemical composition content before weathering at weathering points

After correcting the above five error sample points, a total of 29 weathering monitoring points were obtained.

7.1. Establishment of prediction model

This thesis have come to in the above two types of weathering properties characteristic equation, has obtained the components with related between weathering properties and weight, so will have a process of weathering test points reduction for the unweathered monitoring can be converted into will have characteristics of weathering monitoring value reduction process for critical eigenvalue, namely by adjusting the characteristic value of the ratio between the each composition adjustment.

The pre-weathering content of a component was set as X_0, the content after weathering is X_1, that is, each major component X_1 in the process of weathering reduction to the X_0 in the process.

This thesis assume that over a long period of time, the process of weathering reduction follows the "less content, more increment; Higher content leads to fewer increments". Therefore, this thesis hypothesize that in the process of weathering reduction:

The increment ratio of each component that requires an increase in content is equal to the reciprocal of the content of each component in the current weathered state as shown below:

$$\Delta x_a : \Delta x_b : \Delta x_c = 1/x_{1a} : 1/x_{1b} : 1/x_c$$

Of the components to be reduced, the reduction ratio of each component is equal to the ratio of the content of each component in the weathering state at this time: as follows:

$$\Delta x_d : \Delta x_e : \Delta x_f = x_{1a} : x_{1e} : x_{1f}$$

The average value of each major component corresponding to each type of unweathered monitoring site was calculated as the reference value for the prediction. This thesis specified that the percentage of major components of weathering monitoring site was approximately unchanged when the difference between the percentage of major components and the reference value was less than 3%, that is, $\Delta x = 0$, and the percentage was calculated to increase or decrease when it was greater than 3%.

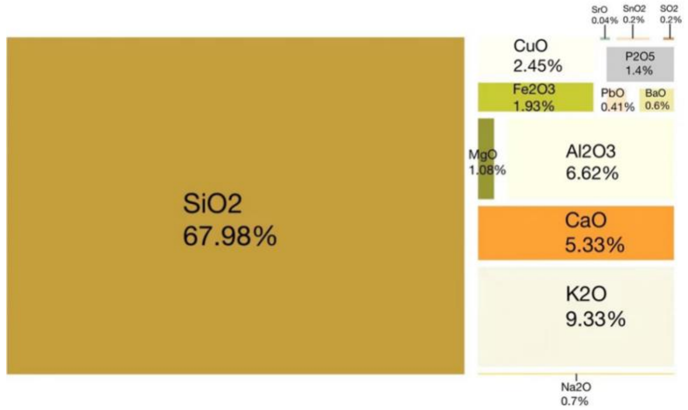

Figure 5. Reference values of the proportion of unweathered components in high-potassium cultural relics

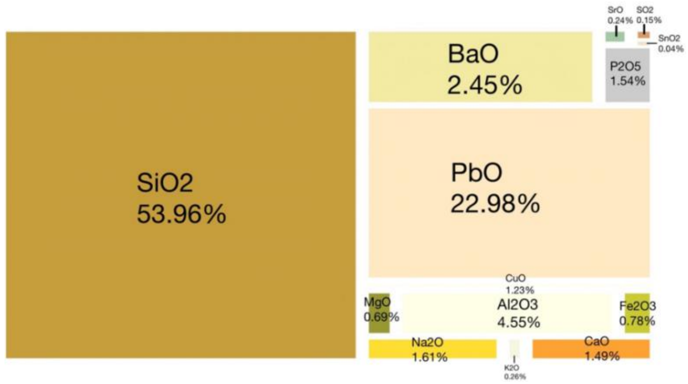

Figure 6. Reference values of unweathered components of Pb and barium cultural relics

Prerequisites:

The sum of the proportions between the components remains constant and is approximately equal to one.

In the process of reduction, the added value of the components needed to be increased is directly proportional to the content of the components in the weathering state, and the reduced value of the components needed to be reduced is directly proportional to the reciprocal of the content of the components in the weathering state.

The steps for weathering reduction are as follows:

(1) Change check: the weathering sample composition content X_1. Compared with the predicted reference value, when the difference is less than 3%, the content of this component is considered to remain unchanged in the process of weathering reduction, that is $X_0 = X_1$.

When the difference exceeds 3%, it is considered that the content of this component has undergone a non-negligible change in the process of weathering reduction, that is, $X_{in,0} = X_{in,1} + \Delta x^{*} q$, $X_{de,0} = X_{de,1} - \Delta x^{*} p$.

Δx: the sum of the increase of the component or the sum of the decrease of the component by the reduction process;

q: reduction process increases the initial component content X1 The ratio of the sum of the initial contents of all the increased components;

p: the reciprocal 1/X of the initial content of reduced components during the reduction process1 Ratio of the sum of the reciprocal of all reduced components;

(2) The change of the characteristic value of weathering attribute in the process of weathering reduction of the weathering sample is obtained, and the increase or decrease of the components checked by changes in the process of weathering reduction is judged according to the positive and negative correlation of the coefficient of the characteristic equation of weathering attribute.

(3) Set Δx as the unknown quantity, and solve the unknown quantity by using the weathering attribute characteristic equation:

$$\Delta\alpha_g=-(0.1234p_1+0.1010p_2+0.049p_3)\Delta X+(-0.0331q_1-0.0372q_2-0.1664q_3-0.1309q_4-0.1854q_5-0.1835q_6-0.1319q_7-0.2601q_8-0.1544q_9-0.1815q_{10}-0.0201q_{11})\Delta=\alpha g,0-\alpha g,1$$

$$\Delta\alpha_q=(0.072q_1+0.0425q_2+0.1058q_3+0.0995q_4+0.1978q_5+0.1830q_6+0.0872q_7+0.0610q_8+0.0752q_9)\Delta X-(-0.1048p_1-0.0988p_2-0.0996p_3-0.0281p_4-0.0018p_5)\Delta X=\alpha q,0-\alpha q,1$$

This thesis choose $\alpha_{g,0}=6(<L_{g,f})$, alpha.$_{q,0}=2(>L_{q,f})$ can be solved Δx, and further can be solved for the content of each component after weathering reduction.

7.2. Prediction calculation of weathering reduction at weathering point

The principle of analysis and calculation was programmed in MATLAB to conduct batch reduction of weathering monitoring points. The reduction results of some monitoring points are shown in Table 6 and Table 7.

Table 6. Reduced values of weathering monitoring sites of high potassium cultural relics

	SiO_2	Na_2O	K_2O	CaO	MgO	Al_2O_3	Fe_2O_3	CuO	PbO	BaO	P_2O_5	SrO	SnO_2	SO_2
07	72.69	0.00	0.00	8.06	0.00	14.92	0.17	3.24	0.00	0.00	0.61	0.00	0.00	0.00
09	70.49	0.00	6.31	6.63	0.00	14.12	0.32	1.55	0.00	0.00	0.35	0.00	0.00	0.00
10	68.47	0.00	14.34	3.27	0.00	12.63	0.26	0.84	0.00	0.00	0.00	0.00	0.00	0.00
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27	72.54	0.00	0.00	6.44	0.54	17.19	0.20	1.54	0.00	0.00	0.36	0.00	0.00	0.00

Table 7. Reduced values at monitoring sites for weathering of Pb and barium cultural relics

	SiO_2	Na_2O	K_2O	CaO	MgO	Al_2O_3	Fe_2O_3	CuO	PbO	BaO	P_2O_5	SrO	SnO_2	SO_2
08	72.69	0.00	0.00	8.06	0.00	14.92	0.17	3.24	0.00	0.00	0.61	0.00	0.00	0.00
08*	70.49	0.00	6.31	6.63	0.00	14.12	0.32	1.55	0.00	0.00	0.35	0.00	0.00	0.00
19	68.47	0.00	14.34	3.27	0.00	12.63	0.26	0.84	0.00	0.00	0.00	0.00	0.00	0.00
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41	72.54	0.00	0.00	6.44	0.54	17.19	0.20	1.54	0.00	0.00	0.36	0.00	0.00	0.00

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