A Statistical Method for Component Analysis and Identification of Differentiated Glass Products

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Abstract. As the most widely used product in human daily life, glass was used as important material evidence for trade in ancient times. With the continuous development of my country's archaeological undertakings, the analysis and identification of the components of ancient glass products have become a research topic of practical significance. In order to predict the chemical composition content before weathering, we first analyze the relationship between surface weathering and the three variables of glass type, texture, and color from two aspects: correlation and difference. According to the discrete distribution state after quantification of qualitative data does not meet the normal distribution, Spearman correlation analysis and chi-square test model are used to draw the conclusion: relatively speaking, the degree of correlation between glass surface weathering and glass type is relatively high; glass type is closely related to the other three There are significant differences among the variables, decoration, and color. From the analysis of the influence of chemical composition, combined with relevant chemical data and verification, we can draw the following conclusions. In a certain range, the increase of CaO content is beneficial to increase the stability of the glass. From the point of view of numerical fitting solutions, we consider that the ridge regression model prediction model has higher sensitivity than other models such as Lasso regression due to the large difference in component values. Therefore, in this paper, we use the ridge regression model to fit the functional relationship between weathering and different categories of attributes and then use the prediction model obtained by ridge regression to solve the content before weathering.

Keywords: Correlation Analysis, Difference Analysis, Ridge Regression.

1. Introduction

The early glass was often made into bead-shaped ornaments in West Asia and Egypt and introduced to my country. Ancient glass in my country absorbed its technology and made it locally. Therefore, it is similar to foreign glass products in appearance, but the chemical composition is different. The main raw material for making glass is quartz sand, whose main chemical composition is silica (SiO2). Depending on the flux added in the production process, glass can be divided into two types: high potassium and lead and barium. High-potassium glass is fired from substances with high potassium content such as plant ash as a flux, while lead-barium glass is made of lead ore as a flux in the firing process, and its lead oxide (PbO), barium oxide (BaO)) content is higher. Glass cultural relics are highly susceptible to weathering by the burial environment. During the weathering process, a large number of internal elements and environmental elements are exchanged, resulting in changes in their composition ratios and different surface colors, thus affecting the correct judgment of their categories.

Therefore, it is an important task to analyze the statistical law of surface chemical composition content of cultural relics with different weathering types and to predict the chemical composition content of glass cultural relics before weathering using weathering point detection data.

In order to obtain the relationship between surface weathering and the three variables of glass type, texture and color, correlation analysis can be used to make an intuitive judgment. Among them, the correlation coefficient is an important indicator to measure the correlation between two variables. Common methods for solving correlation coefficients are the Pearson method and the Spearman method. In this paper, the qualitative glass data is considered to be discrete distribution, therefore, this paper uses the Spearman correlation coefficient solution method and the chi-square test to solve the problem. we make a bold assumption that CaO content has a certain influence on glass weathering after consulting a large number of relevant data and drawing a scatter plot A simple verification was carried out, considering the influence of glass color, decoration, type, and differentiation on the content of chemical components, and after quantifying the classification data, Lasso regression and ridge regression were used for regression analysis because there were many missing values in some data during the regression process. Considering the defects of Lasso regression, ridge regression was used to obtain the linear relationship between each component and each variable. According to the known linear relationship, the content of each chemical component in the weathered glass before unweathering can be predicted. Since the component data of the glass data has many values, the accuracy of the regression fit is not high. Therefore, it is necessary to collect a large amount of data to perform the regression again.

Machine learning models such as neural networks with nonlinear methods are not suitable for small sample datasets, because insufficient modeling sample size causes the model to fall into overfitting to small samples and underfitting to the overall task, lacking generalization ability [1] and are prone to extremely low model accuracy. As for linear models, although the regularization method of weight delay is applied to linear models such as Ridge regression and Lasso regression to reduce the overfitting of the model, we still need to carefully consider the choice of L1 and L2 regularization. L1 regularization Items are not always better than L2. For datasets such as this subject with small precision, low span, high sensitivity, and no negative values, L2 is more suitable.

2. Assumption

To facilitate problem modeling and solution, we make the following common assumptions:

1. Assuming that the samples selected from the attached dataset are extensive and typical, the sample data after excluding outliers is in line with reality.

2. It is assumed that the components contained in the sample are representative and cover all the main components of the sample.

3. It is assumed that for the weathering situation, there are significant boundaries between parts of the sample with different degrees of weathering.

3. Problem formulation and algorithm design

In this section, we model the problems and propose corresponding algorithms to solve them.

We first analyze the relationship between glass surface weathering and its type, texture, and color [2].

3.1. Spearman correlation analysis (spearman)

The Spearman correlation coefficient is a nonparametric measure of the dependence between two variables, and it ranges from -1 to +1, with 0 implying no correlation between the two parameters [3]. If there are no repeated values in the data, and the two variables are completely monotonically correlated, the Spearman correlation coefficient is +1 or -1. Let X and Y be the data of two groups of variables. When X increases, Y tends to increase, and Spearman's correlation coefficient is +1 or -1. The Pearman correlation coefficient is positive, while the Spearman correlation coefficient is negative as X increases and Y tends to decrease.

Spearman (rank) correlation coefficient can be obtained as follow:

$$. \qquad r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n\left(n^2 - 1\right)} \tag{1}$$

Among them, d_i is the level difference between X_i and Y_i (level, is the location of this number after sorting the column of data it is in from small to large).

3.2. Chi-square test

The Chi-square test is a method of hypothesis testing. It belongs to the category of non-parametric testing. It is mainly used to analyze the relationship between categorical data and categorical data. The fundamental idea is to compare the degree of agreement between the theoretical frequency and the actual frequency. The goodness of fit problem.

The calculation method of the chi-square test:

$$\chi^2 = \sum \frac{\left(\mathrm{f}_o - \mathrm{f}_e\right)^2}{\mathrm{f}_e} \tag{2}$$

Where o represents observation, which is the observed frequency; e represents expectation, which is the expected frequency. The numerator represents the deviation of the actual value from the expected value, while the denominator is the normalization process. Therefore, the smaller the value of the chi-square, the closer the observed value is to the expected value (theoretical value), and the more consistent the chi-square distribution between the two variables [4]. The premise of the chi-square distribution is that the variables are independent of each other, so the smaller the chi-square value, the more independent the two variables are.

3.3. Ridge regression model

Ridge regression is a biased estimation regression method for small sample data to deal with multicollinearity of independent variables (generally VIF value is greater than 10). Ridge regression improves the normal equation system by introducing a positive number, providing a biased estimation method to eliminate the effect of collinearity. When K=0, it is the least square estimation. Since the ridge regression is a biased estimation, the value of K should be as small as possible. Ridge regression abandons the unbiased estimation of the ordinary least squares method and loses some information, so the R^2 of the ridge regression equation is usually slightly lower than that of the ordinary least squares regression, but the estimated partial regression coefficients are often closer to the real situation, so the stability and reliability of the model are improved, and it has a good effect on the repair and fitting of ill-conditioned data.

Different from the L1 regularization term of the Lasso regression method, Ridge adds the L2 regularization term to prevent overfitting. The L2 regular term can ensure that the value of the ridge regression coefficient is within a limited range, and play the role of shrinking the range. At the same time, the shrinking force can be balanced by λ to optimize the final fitting effect of the regression function.

The L2 regular term is expressed as follows:

$$\frac{1}{\mathrm{m}} \frac{\lambda}{2} \sum_{\mathrm{t}} \sum_{\mathrm{k}} \sum_{\mathrm{j}} \mathrm{W}_{\mathrm{kj}}^{|\mathrm{t}|2} \tag{3}$$

The objective function of ridge regression is as follows:

$$\begin{cases} \hat{\beta}^{\mathrm{ridge}} = \arg\min \left\{ \sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{y_i} - \beta_0 - \sum_{\mathrm{j}=1}^{\mathrm{p}} \mathrm{x_{ij}} \beta_{\mathrm{j}})^2 \right\} \\ \sum_{\mathrm{j}=1}^{\mathrm{p}} \beta_{\mathrm{j}}^2 \leq \mathrm{t} \end{cases} \tag{4}$$

Exposing the objective function to geometry yields the following 3D image as shown in Figure 1, where the cylinder represents the formula as follows:

$$\hat{\beta}^{\text{ridge}} = \arg\min\left\{\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2\right\} \tag{5}$$

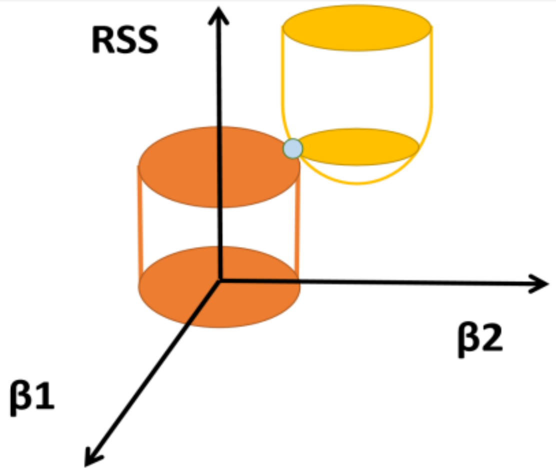


Figure 1. 3D map of the objective function of ridge regression.

The blue intersections shown in Figure 1 represent the optimal ridge regression coefficient values. Although Lasso regression is better than ridge regression in variable selection, when the span of eigenvalue dimensions is large, ridge regression has a stronger ability to retain decimals of eigenvalues. For the problem of the large difference of effective values between variables, the test fitting accuracy of the ridge regression model is higher, which is more in line with the actual situation."

4. Result

In this section, we show the results of solving the problem.

We used the dataset provided by the 2022 Higher Education Club Cup National Undergraduate Mathematical Contest in Modeling. Among them, Attachment Form 1 gives the classification information of these cultural relics, and Attachment Form 2 gives the proportion of the corresponding main components (blank spaces indicate that the components were not detected). The cumulative sum of the proportions of each component should be 100%. Due to the detection methods and other reasons, the cumulative sum of the proportions of the components may not be 100%. We consider the cumulative sum of the proportions of components between 85% and 105% as valid. According to the data in Form 2, it is found that when the sampling points of cultural relics are 15 and 17, the cumulative sum of the proportions of the components is 79.47% and 71.89% respectively, and the rest of the data meet the definition of valid data. Integrate data from Forms 1 and 2 for subsequent joint analysis.

4.1. Correlation and difference analysis between variables

4.1.1. Correlation analysis

We grouped the four variables of surface differentiation, glass type, glass texture and glass color into pairs, and used Spearman's rank correlation coefficient formula to obtain the correlation coefficient table.

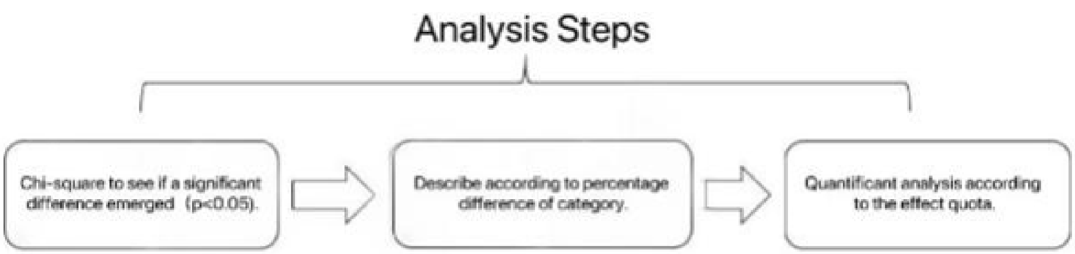


Figure 2. Spearman correlation analysis flow chart.

Use SPSS software to get the correlation coefficient table of four variables X: {surface weathering, decoration, type, color}:

Table 1. Spearman correlation coefficient table.

	Surface weathering	Ornamentation	Type	**Color**
Surface weathering	1.000(0.000***)	0.128(0.358)	0.316(0.020**)	-0.112(0.421)
Ornamentation	0.128(0.358)	1.000(0.000***)	0.370(0.006***)	0.481(0.000***)
Type	0.316(0.020**)	0.370(0.006***)	1.000(0.000***)	0.541(0.000***)
Color	-0.112(0.421)	0.481(0.000***)	0.541(0.000***)	1.000(0.000***)

Note: ***, **, *each represent 1%, 5%, 10% significance level.

We mainly consider that the surface weathering is affected by the other three factors. It can be seen from the table that the correlation between glass surface weathering and type is high. In order to more intuitively see the magnitude of the correlation between the four variables, a heat map of the correlation coefficient is made and shown in Figure 3.

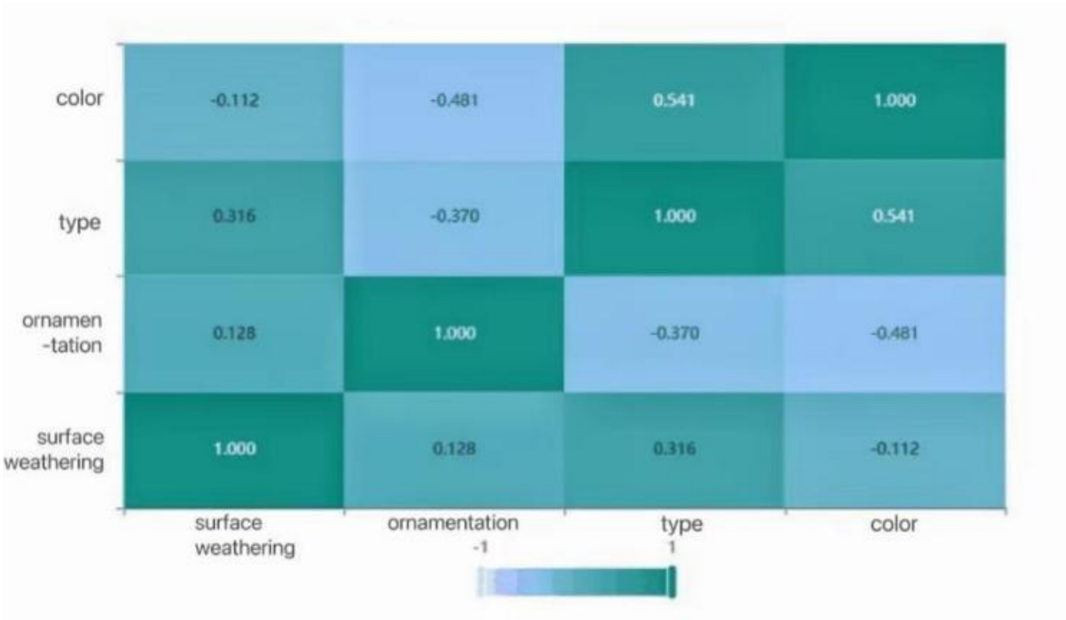


Figure 3. Spearman correlation coefficient heat map.

It can be seen from Figure 3 that the correlation coefficient of glass surface weathering and glass type 0.316 is greater than the correlation coefficient between surface weathering and the other two variables (texture 0.128, color -0.112), that is, the correlation between glass surface weathering and glass type is higher, and the correlation coefficient between surface weathering and glass type is higher. The other two variables are less correlated.

4.1.2. Difference analysis

Since the data are categorical, we use a nonparametric hypothesis test - chi-square test to observe the difference between glass surface weathering and glass type, texture and color

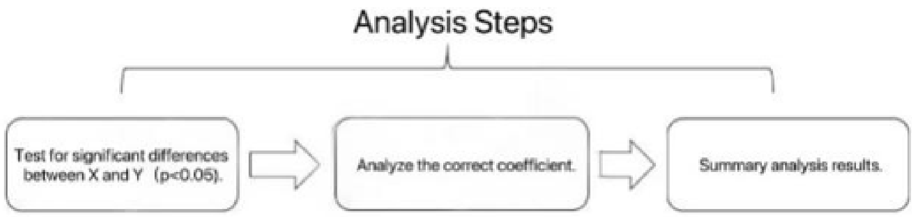


Figure 4. Chi-square test analysis flow chart.

The chi-square test was performed using SPSS, and the results were obtained:

Table 2. Type, decoration, color and surface differentiation chi-square test analysis results table.

Title	Class	Type		Total	X^2	CorrectingX^2	P
		High-potassium	Lead-barium				
Ornamentation	C	6	22	28	13.886	13.886	0.001***
	A	6	14	20			
	B	6	0	6			
Total		18	36	54			
Color	Aquamarine	12	3	15	22.693	22.693	0.002***
	Light blue	4	16	20			
	Purple	0	4	4			
	Dark green	1	6	7			
	Dark blue	1	1	2			
	Light green	0	3	3			
	Black	0	2	2			
	Green	0	1	1			
Total		18	36	54			
Surfacing weathering	Non-wearthering	12	12	24	5.400	4.134	0.020**
	Weathering	6	24	30			
Total		18	36	54			
Note: ***, **, *each represent 1%, 5%, 10% significance level.							

The results of the chi-square test analysis in Table 2 show that:

(a) Based on type and decoration, the significant P value is 0.001***, which is significant at the level, rejecting the null hypothesis, so there is a significant difference for type and decoration data.

(b) Based on type and color, a significant P value of 0.002*** is significant at the level, rejecting the null hypothesis, so there is a significant difference for type and color data.

(c) Based on type and surface weathering, a significant P value of 0.020** is significant at the level, rejecting the null hypothesis, so there is a significant difference for type and surface weathering data.

Therefore, there are significant differences between the type and the other three variables (see Appendix 1 for the cross-heat map). Next, we analyze the differences between the texture and surface weathering and color, and get the chi-square test result table:

Table 3. Pattern-color-surface weathering chi-square test analysis results.

Tittle	Class	Ornamentation			total	X^2	Correcting X^2	P
		C	A	B				
Color	Aquamarine	3	6	6	15	38.109	38.109	0.001***
	Light blue	10	10	0	20			
	Purple	4	0	0	4			
	Dark green	7	0	0	7			
	Dark blue	0	2	0	2			
	Light green	3	0	0	3			
	Black	0	2	0	2			
	Green	1	0	0	1			
Total		28	20	6	54			
Surfacing weathering	Non-wearthering	13	11	0	24	5.747	5.747	0.056*
	Weathering	15	9	6	30			
Total		28	20	6	54			
Note: ***, **, *each represent 1%, 5%, 10% significance level.								

The results of the chi-square test analysis in Table 3 show that:

(a) Based on the texture and color, the significance P value is 0.001***, which is significant at the level, rejecting the null hypothesis, so there is a significant difference between the texture and color data.

(b) Based on texture and surface weathering, the significant P value is 0.056*, which is not significant at the level, accepting the null hypothesis, so there is no significant difference between texture and surface weathering data.

In order to see the difference between decoration and color more intuitively, we make a chi-square cross heat map as shown in Figure 5.

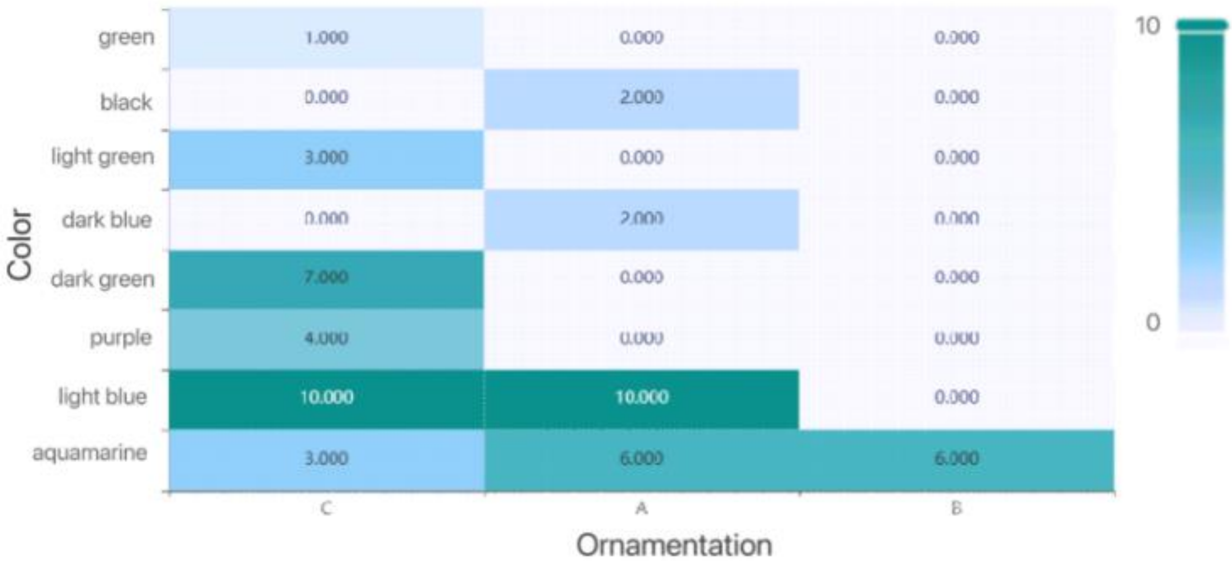


Figure 5. Ornament-color heat map.

Finally, by studying the difference between glass color and glass surface weathering, we made the chi-square test results shown in Table 4.

Table 4. Color-surface weathering chi-square test analysis result table.

Tittle	Class	Color								Total	X^2	Correcting X^2	P
		Aquamarine	Light blue	Purple	Dark green	Dark blue	Light green	green	black				
Surfacing weathering	Non-weathering	6	8	2	3	2	2	1	0	24	6.287	6.287	0.507
	Weathering	9	12	2	4	0	1	0	2	30			
Total		15	20	4	7	2	3	1	2	54			
Note: ***, **, *each represent 1%, 5%, 10% significance level													

The results of the chi-square test analysis in Table 4 show that: Based on the color and surface weathering, the significant P value is 0.507, which is not significant at the level, and the null hypothesis is accepted, so there is no significant difference between the color and surface weathering data. We draw the following conclusions: For the correlation between glass surface weathering and its type, texture and color, the correlation between glass surface weathering and type is high, and the correlation with the other two variables is low; for the correlation between the four variables In terms of differences, there are significant differences between type and the other three variables, and there are also significant differences between glass decoration and color.

Relevant research shows that the more metal oxides in the ingredients of glass production, the larger the sodium ion enrichment area, the more non-bridging cations, the greater the possibility of

Xicheng "Si-O-Na" type structure, and the possibility of mildew. The greater the sex. Therefore, under normal circumstances, various colored glasses such as brown, green, and sapphire are more prone to mold than ordinary flat glass [5].

It can be seen that the appearance changes such as glass color and decoration may be closely related to the chemical composition changes during the glass weathering process. In order to explore the factors associated with glass weathering in more depth, we begin by examining the linear relationship between glass composition and whether the glass is weathered, appearance, and type.

4.2. Statistical rule of chemical composition content

Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads.

In order to more comprehensively count the chemical composition content, we will analyze the relationship between the chemical composition content in the glass and the presence or absence of weathering, glass color, decoration and type.

Minerals and rocks undergo mechanical disintegration and rupture in situ under the influence of changes in surface atmospheric temperature and freezing and thawing of water bodies. Physical weathering only disintegrates the rock without changing its chemical composition. Common physical weathering methods include temperature difference weathering, ice splitting weathering (freeze-thaw weathering), salt crystallization and deliquescence, and spallation. Among them, the deliquescence and oxidation of salt crystals are closely related to chemical elements.

The deliquescence effect of salt crystallization is that in arid and semi-arid climate regions, the evaporation is large, and the salt-containing solution in the rock crack is easy to be saturated and crystallized, the volume increases during crystallization, and pressure is also applied to the two walls. The crystallized salts deliquescence into a solution, which further penetrates into the rock and breaks the rock. Oxidation refers to the process in which rock minerals are freed by the atmosphere and dissolved and oxidized in water to form high-value compounds [6].

According to a large number of relevant literatures on the weathering of silicate glass [7], we believe that the content of CaO has a certain influence on the weathering of glass [8]; for weathering, we can refer to logistic regression, set the unweathered as 1, and the weathered as 1 0, then add the CaO content, and make a scatter plot for simple subjective judgment:

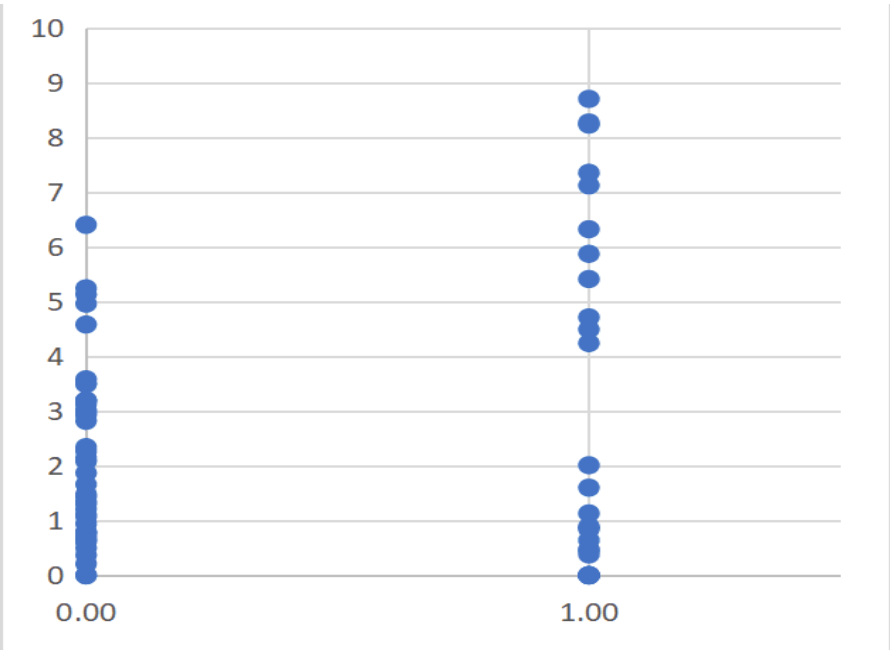


Figure 6. Scatter plot of CaO content.

It can be easily seen from the scatter diagram 10 that the CaO content of the weathered glass is mainly concentrated in the low-value area, while the calcium oxide content of the unweathered glass is mainly concentrated in the high-value area, so it can be easily observed that the increase of the CaO content is beneficial to the increase of the glass Stability and protection from weathering.

Therefore, we mainly study the relationship between the content of oxides and salt crystals in glass cultural relics and the degree of weathering, so as to select the main components that have the greatest impact on glass weathering.

4.3. Using Regression to Predict the Chemical Composition Content of Weathered Glass Before Weathering

To predict the chemical composition content before weathering based on the weathering point detection data, a quantitative description can be used by regression analysis, and 13 variables are determined according to Forms 1 and 2:

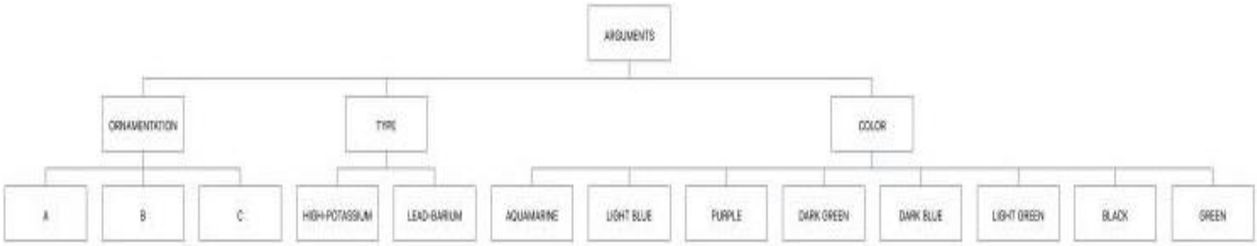


Figure 7. Classification diagram of independent variables.

We screened out the unweathered cultural relic detection point data and processed the data according to the 0-1 rule. If the data exists, it is 1, and if it does not exist, it is 0. Take the first seven cultural relics samples as an example, from top to bottom, they are 01, 03 part 1, 03 part 2, 04, 05, 06 part 1, 06 part 2.

Table 5. Variable quantification value table.

orn_A	orn_B	orn_C	type_hp	type_lb	color_lg	color_lb	color_dg	color_db	color_p	color_g	color_a	color_b	non_wea	wea
0	0	1	0	1	0	0	0	0	0	0	1	0	1	0
1	0	0	1	0	0	1	0	0	0	0	0	0	0	1
1	0	0	0	1	0	0	0	0	0	0	1	0	1	0
1	0	0	0	1	0	0	0	0	0	0	1	0	1	0
1	0	0	0	1	0	0	0	0	0	0	1	0	1	0
1	0	0	0	1	0	0	0	0	0	0	1	0	1	0
1	0	0	0	1	0	0	0	0	0	0	1	0	1	0

The regression fitting methods include Lasso regression and ridge regression. We first use Lasso regression to fit, and get the abnormal situation of Na2O regression as shown in Figure 7, where the blue is the true value, and the green is the predicted value [9].

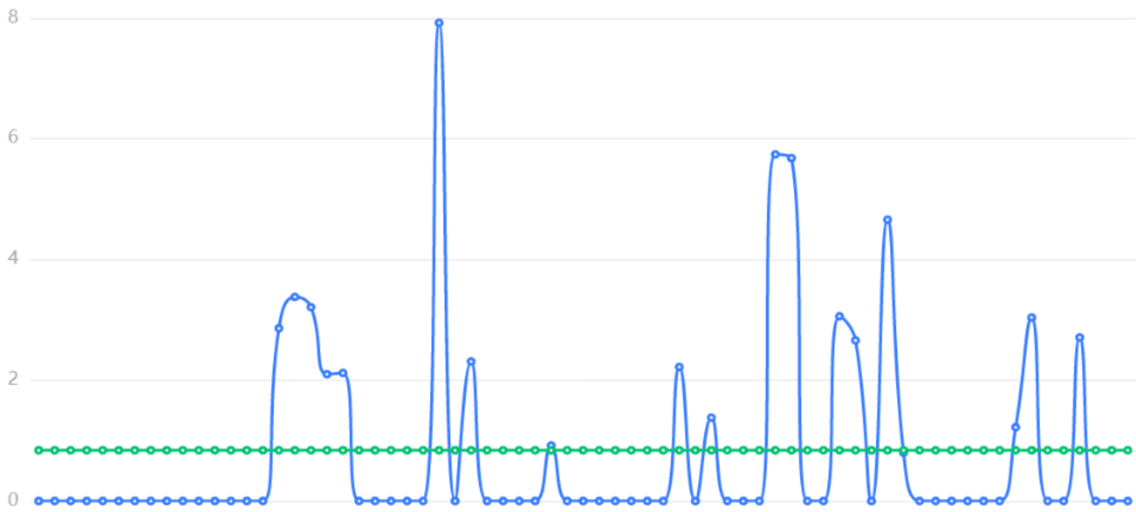


Figure 8. Lasso regression true value and predicted value fitting results.

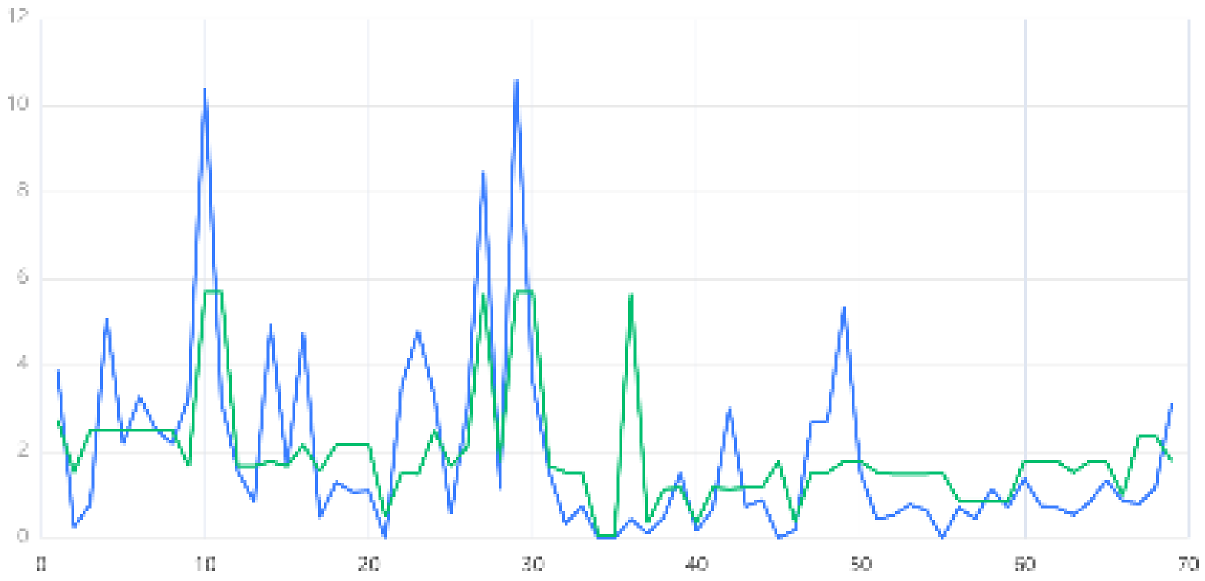
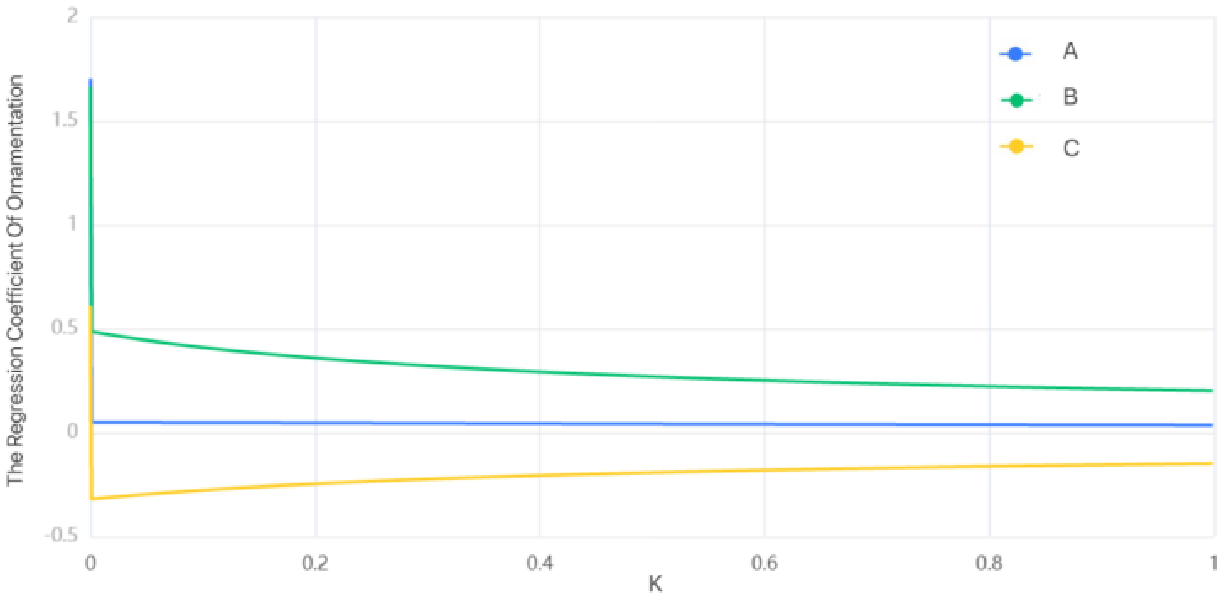


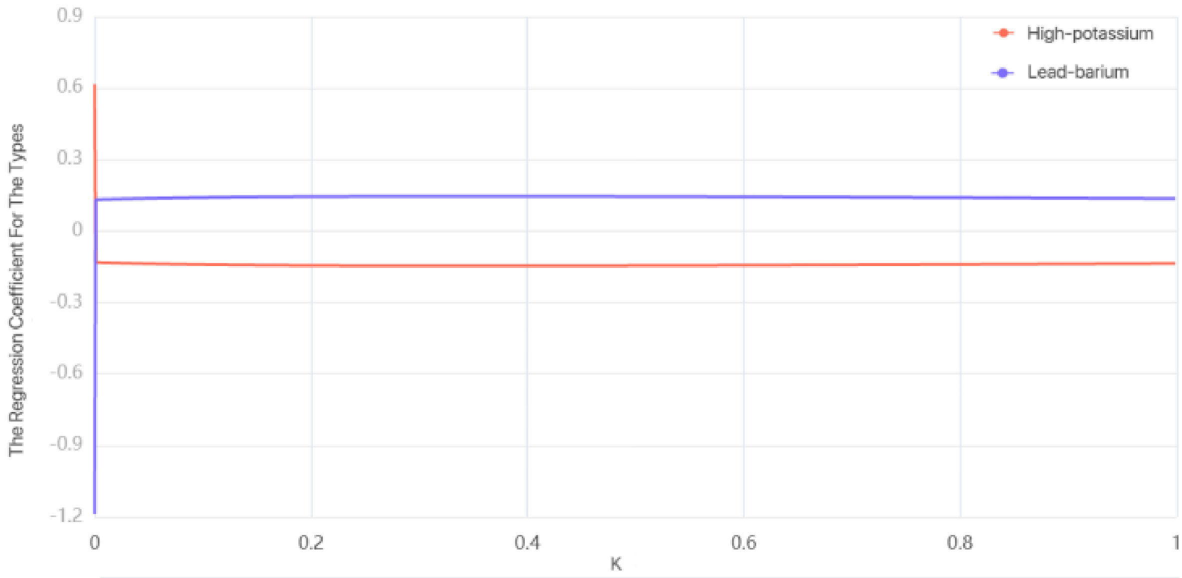
Figure 9. Ridge regression true value and predicted value fitting results

However, Lasso regression seeks an approximate solution. You can use Lasso regression to filter out several related variables, and then perform normal multiple regression. Ridge regression finds an exact solution [10].

The predicted value of Na2O content in Fig. 8 becomes a straight line and is constant. We believe that this situation may be related to the large number of missing values of Na2O content. In order to avoid this situation, we use ridge regression to fit, which will have a better degree of fit, as shown in Figure 9. Ridge regression was used to obtain the qualitative relationship between the content of each component and the independent variables glass texture, type and color. Taking SiO2 as an example, we first visualized the situation when the standardized coefficients of the independent variables of the model tend to be stable as shown in Figure 10.



(a)



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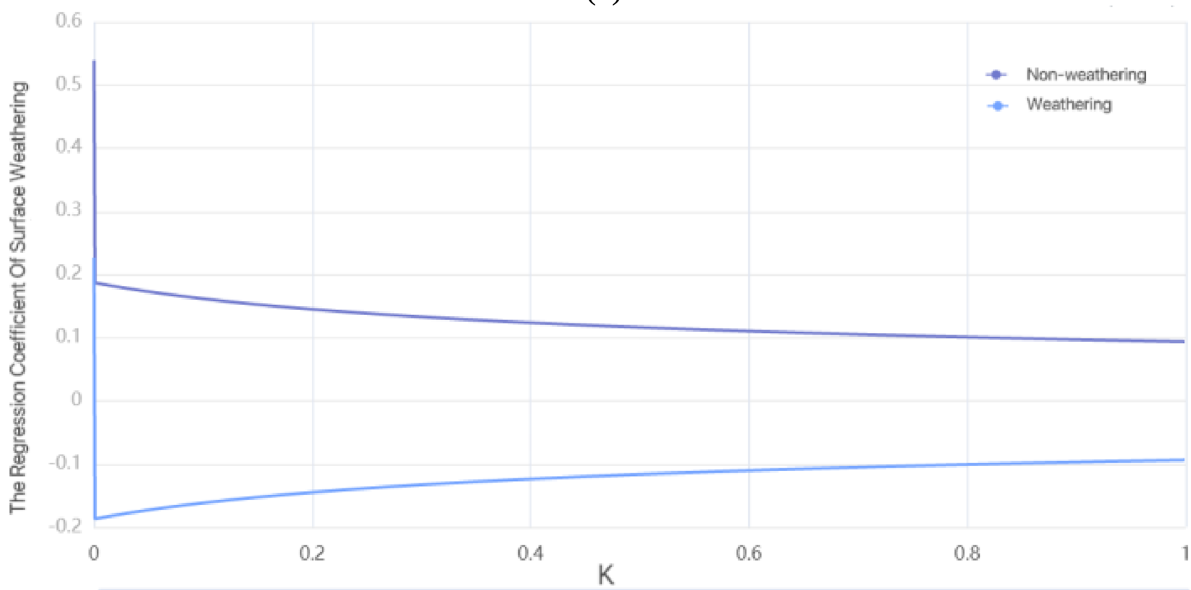
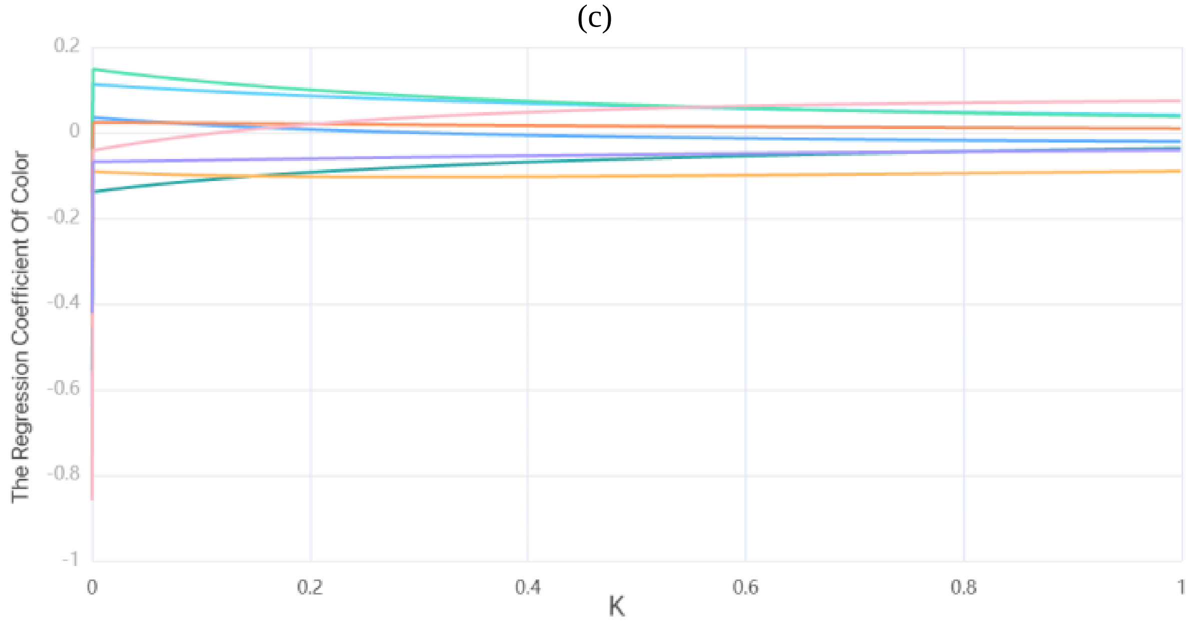


(c)



(d)

Figure 10. Ridge trace diagram of SiO2 regression coefficient.

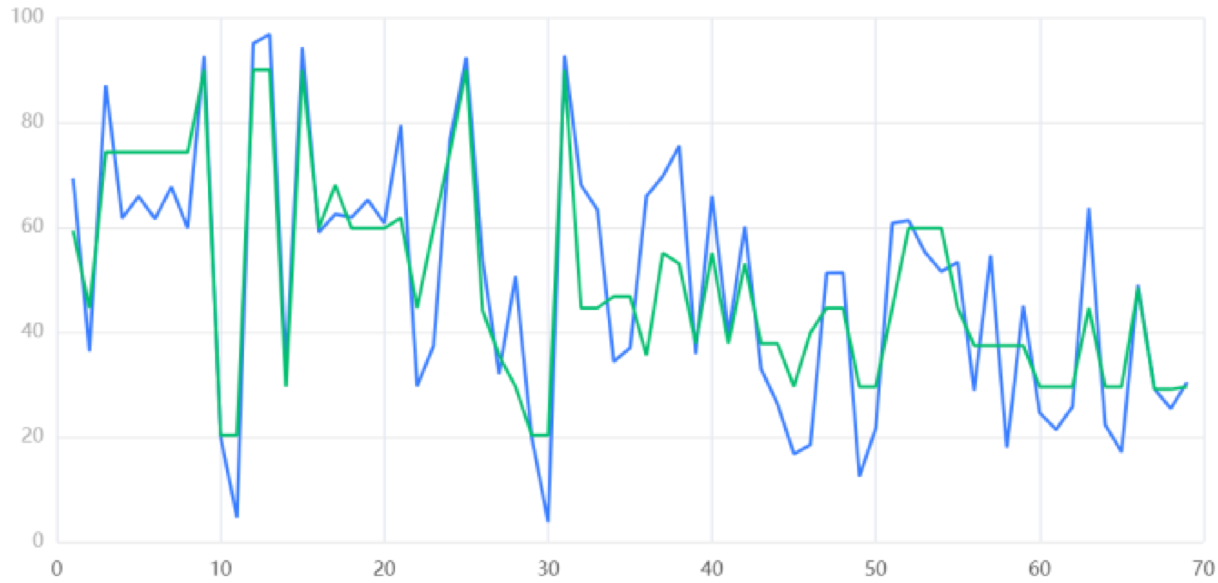


Figure 11. Visualization of the gap between the actual value and the predicted value of SiO2

We get the regression function between SiO2 and the respective variables

y=27.054+1.926*X2(pattern_A)+40.805*X2(pattern_B)+(-15.677)*X2(pattern_C)+6.598*X2(type_lead barium)+20.456*X2(type_ High potassium)+16.807*X2(color_light green)+5.352*X2(color_light blue)+15.346*X2(color_dark green)+(-12.637)*X2(color_dark blue)+(-4.097) *X2(color_purple)+8.352*X2(color_green)+1.279*X2(color_blue-green)+(-3.348)*X2(color_black)

Then, the weathered cultural relic detection points are screened out, and the prediction calculation is carried out according to the obtained regression equation to obtain the content of various components of the detection point before weathering. , 03 part 1, 03 part 2, 04, 05, 06 part 1, 06 part 2.

Table 6. Contents of the components of the weathered cultural relics before they are not weathered.

Si02	Na20	K20	Ca0	Mg0	A1203	Fe203	Cu0	Pb0	Ba0	P205	Sr0	Sn02	S02
69. 33	0	9. 99	6. 32	0. 87	3. 93	1. 74	3. 87	0	0	1. 17	0	0	0. 39
36. 28	0	1. 05	2. 34	1. 18	5. 73	1. 86	0. 26	47. 43	0	3. 57	0. 19	0	0
87. 05	0	5. 19	2. 01	0	4. 06	0	0. 78	0. 25	0	0. 66	0	0	0
61. 71	0	12. 37	5. 87	1. 11	5. 5	2. 16	5. 09	1. 41	2. 86	0. 7	0. 1	0	0
65. 88	0	9. 67	7. 12	1. 56	6. 44	2. 06	2. 18	0	0	0. 79	0	0	0. 36
61. 58	0	10. 95	7. 35	1. 77	7. 5	2. 62	3. 27	0	0	0. 94	0. 06	0	0. 47
67. 65	0	7. 37	0	1. 98	11. 15	2. 39	2. 51	0. 2	1. 38	4. 18	0. 11	0	0

4.4. Regression model test

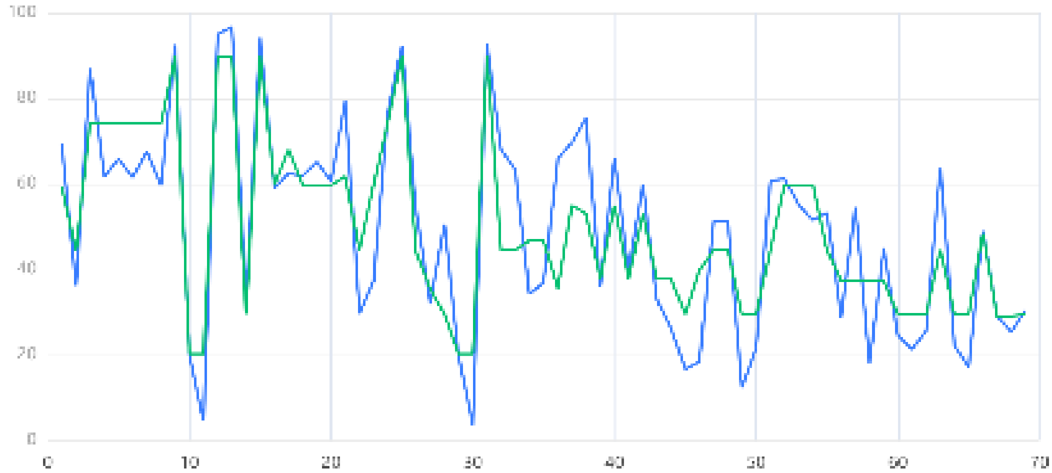
We use the goodness of fit to test the degree of fit of the regression function. The average prediction effect of components with more valid data is about 0.8, as shown in Table 7.

Table 7. R-squared size of each component regression function.

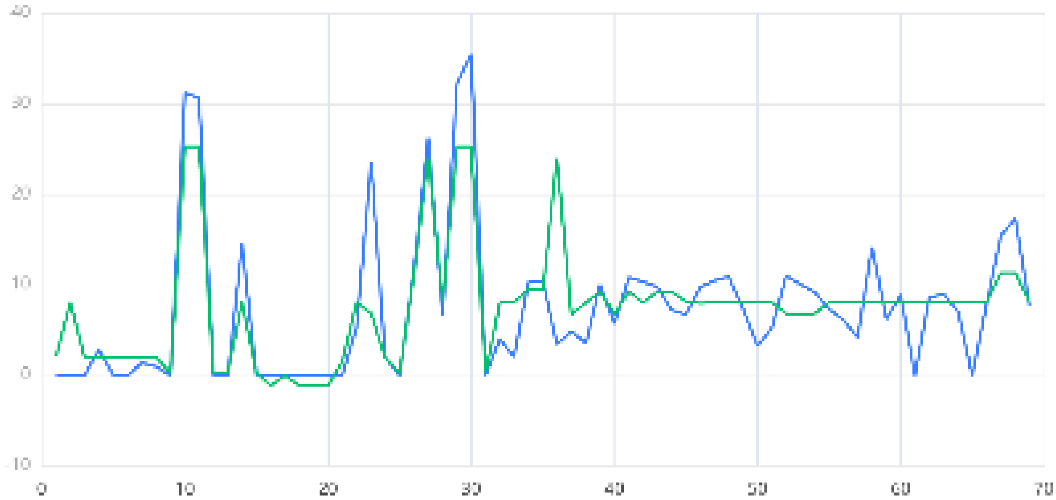
Composition	Sqrt(R)	Composition	Sqrt(R)
Potassium oxide	0.814	Lead oxide	0.771
Silica	0.761	Barium oxide	0.689
Tin oxide	0.478	Aluminium oxide	0.45
Copper oxide	0.432	Strontium oxide	0.425
Sulphur dioxide	0.41	Phosphorus pentoxide	0.358
Magnesium oxide	0.351	Calcium oxide	0.291
Iron oxide	0.273	Sodium oxide	0.216

By making a visual image between the actual value and the predicted value of each component regression function, the effect of fitting can be seen more intuitively, in which the blue line is the actual value, and the green line is the predicted value. It can be seen from the image combined with the R-square value that the blue and green lines generally have a high degree of coincidence, and the overall good fitting effect is shown in Figure 12.

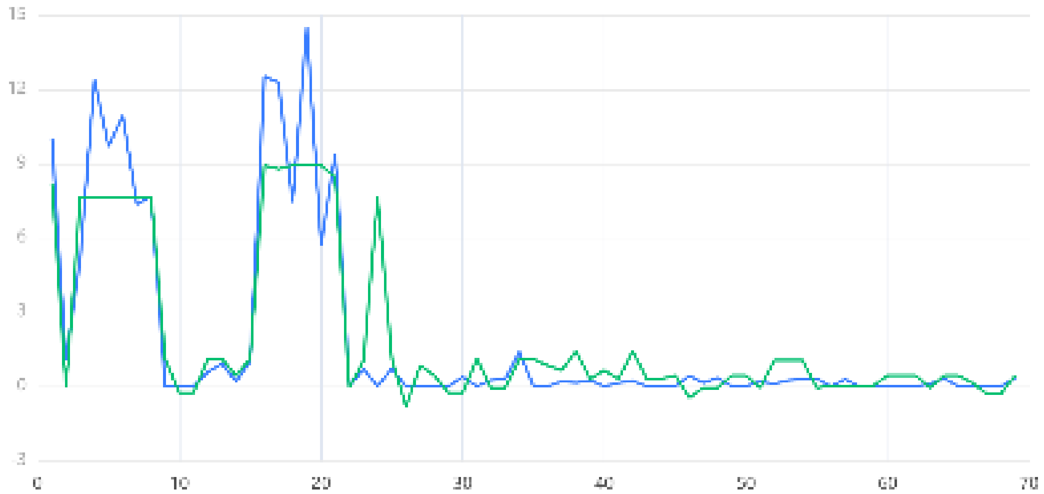
From Figure 12, we can draw the conclusion that Potassium oxide, Lead oxide, Silica and Barium oxide in cultural relics can be basically and accurately predicted from the four qualitative variables of weathering on the surface of cultural relics, texture type, color and glass type. content of ingredients.



(a) Potassium oxide



(b) Lead oxide



(c) Silicon dioxide

Figure 12. The overall good fitting effect.

5. Conclusion

This paper considers how to combine the type of glass to analyze the statistical law of weathering chemical composition content on the surface of cultural relic samples, and predict the chemical composition content before weathering according to the weathering point detection data. We designed a unified and versatile model, and used the ridge regression model to fit the functional relationship between weathering and different types of attributes, and then used the prediction model obtained by the ridge regression to solve the pre-weathering content. The experimental results show that the relationship equations between the content of some chemical components and variables such as weathering and color obtained by our regression have a high degree of fit and can be directly applied in archaeology.

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