An investigation of the significance of the association of each attribute of ancient glass products based on cardinal distribution

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Abstract. The Silk Road was a key channel for trade and cultural exchange between China and the West in ancient times, and one of the gems of the early exchange was glass products. The composition and properties of glass from the East and the West often differ greatly because of the different production processes, but the problem of glass identification has been an ancient challenge. For the analysis of the composition and origin of ancient glass products, this paper is a mathematical approach to model design, avoiding the duplication of labor into this area. This paper uses chi-square test and correspondence analysis to first determine which factors are significantly correlated with glass products, and then further determine the correlation with the factors. The use of box-line plots allows for a very visual analysis of the statistical patterns of the presence or absence of chemical composition content on the surface of artifact samples. For predicting the chemical composition content before weathering, the approximate chemical composition content was first estimated based on the average rate of change of each chemical composition before and after weathering, and then a multiple linear regression model was used to correct for the chemical composition content. It was finally concluded that the weathering of glass surface was significantly correlated with glass type, and high potassium glass was not easily differentiated, while lead-barium glass was easily weathered; the silica content changed most significantly before and after weathering of high potassium glass, with an average change rate of 25.98%, and the silica and lead oxide content changed most significantly before and after weathering of lead-barium glass, with average change rates of 29.75% and 23.77%, respectively.

Keywords: Chi-square test, multiple regression analysis, feature engineering, Spearman correlation test.

1. Introduction

The Silk Road has a long history and is a beautiful treasure left to the world by our country, which greatly promoted the cultural exchanges between China and the West in ancient times [1]. And one of the most reflective of the cultural differences, the best-selling Silk Road glass products. After the introduction of glass into China, it quickly gained localized technical support in our country, and with the origin of the differentiation of different processes, has a very high artistic value [2]. The chemical composition of glass made by different processes often differs, and glass is highly susceptible to weathering in easy burial environments, which in turn can cause changes in its internal components, making the identification of glass objects a popular research problem in archaeology [3].

Based on chemical, mathematical, and information science methods, this paper theoretically explores a model of this problem, explores the correlation between the degree of weathering, appearance, and glass, and on the basis of this initial investigation, further quantitative analysis and class subdivision of glass components, and provides an intuitive classification standard for newly excavated unclassified glass objects, and continues to explore the differences in the relationship between the chemical components of different classes of glass on the basis of this problem, providing a new direction for archaeological research on the process speculation of glass.

2. Model Assumptions and Notation

2.1. Assumptions[4]

Assume that the type of weathering has no effect on the results of artifact identification

Assume that the content of all undetected components is 0

Assume that different parts of the artifacts are made with the same type of glass

Assume that there is no error in the classification of artifacts in all valid data

It is assumed that the weathering process is not subject to much environmental pollution and does not cause the production of new chemical components.

2.2. Notations

Important notations used in this paper are listed in Table 1.

Table 1. Notations

Symbols	Description
R^2	Goodness of fit
MAPE	Absolute percentage error
MSE	Mean square error
K	Percentage of corresponding elements in oxide species
M(R)	Molar mass of a substance
W	Percentage of corresponding oxides in the glass component
S_i	The average distance between the point inside the class and the center of mass of the class
M_{ij}	Distance between two class centers
R_{ij}	Similarity index

3. Model construction and solving

3.1. Analysis of the relationship between surface weathering and its glass type, decoration and color

The frequency of each subcategory with and without weathering was counted separately for type, decoration, color, and subcategory, and its chi-square distribution, P value, was calculated. The results are shown in Table 2.

Table 2. Results of cardinality test [5] analysis

Category	Name	Surface weathering condition		Frequency	X^2	P
		No weathering	weathering			
Glass Type	Lead Barium	12	28	40	6.880	0.009***
	High potassium	12	6	18		
Decoration	A	11	11	22	4.957	0.084*
	B	0	6	6		
	C	13	17	30		
Color	/	4	0	4	9.432	0.307
	Light green	1	2	3		
	Light Blue	12	8	20		
	dark green	4	3	7		
	Dark Blue	0	2	2		
	Violet	2	2	4		
	Green	0	1	1		
	Blue-Green	9	6	15		
	Black	2	0	2		

Note: ***, **, * represent 1%, 5%, 10% significance levels, respectively.

With a P-value less than 0.05, the possibility of occurrence of coincidence is less than 5%, the original hypothesis can be rejected, and the difference between the two groups is significant, to determine whether it presents significance.

For the case of surface differentiation, the significance P-value is 0.009 < 0.05, which presents significance at the level and rejects the original hypothesis, so for surface weathering and glass type data there is a significant difference.

For surface weathering, the significance P-value is 0.084 > 0.05, which does not present significance at the level and accepts the original hypothesis, therefore there is no significant difference for the surface weathering and ornamentation data.

For surface weathering, the significance P-value is 0.307 > 0.05, which does not present significance at the level, and the original hypothesis is accepted, therefore there is no significant difference for surface weathering and color data.

It can be concluded that surface weathering only shows a significant correlation with glass type, in order to further investigate the positive and negative correlation between glass type and weathering or not, the results of the correspondence analysis are shown in Fig. 1:

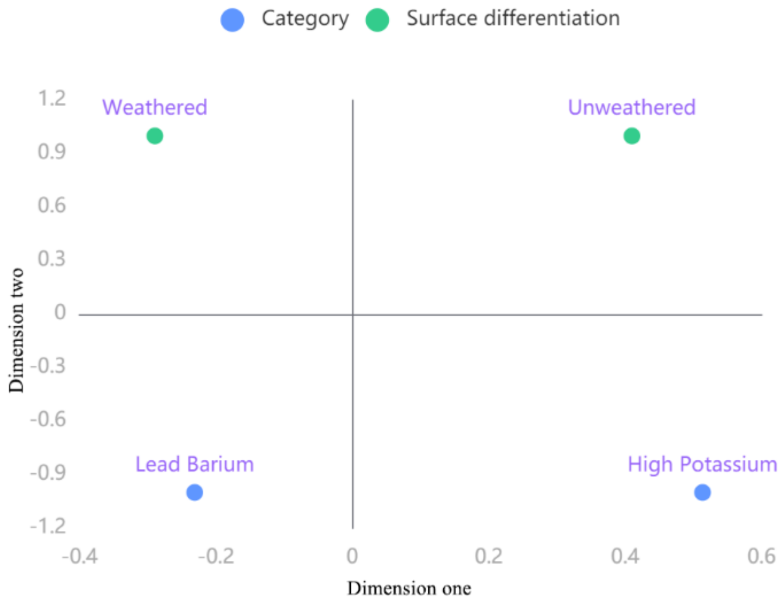

Figure 1. Correspondence Analysis

From Fig. 1, it can be seen that the points of lead-barium type and surface weathering are closer on the coordinate axis and in the same plane (left half-plane), which means that the lead-barium type of glass is more prone to weathering, and the points of high potassium type and surface non-weathering are closer and in the same plane (right half-plane), which means that the high potassium type of glass is not prone to weathering.

3.2. Statistical law of the content of chemical components with and without weathering

In order to more visually analyze the statistical patterns of chemical content with and without weathering on the surface of the artifact samples, box line plots [6] were used to display the percentage of chemical content of four types: unweathered high potassium glass, weathered high potassium glass, unweathered lead-barium glass, and weathered lead-barium glassp. As shown in Fig. 2.

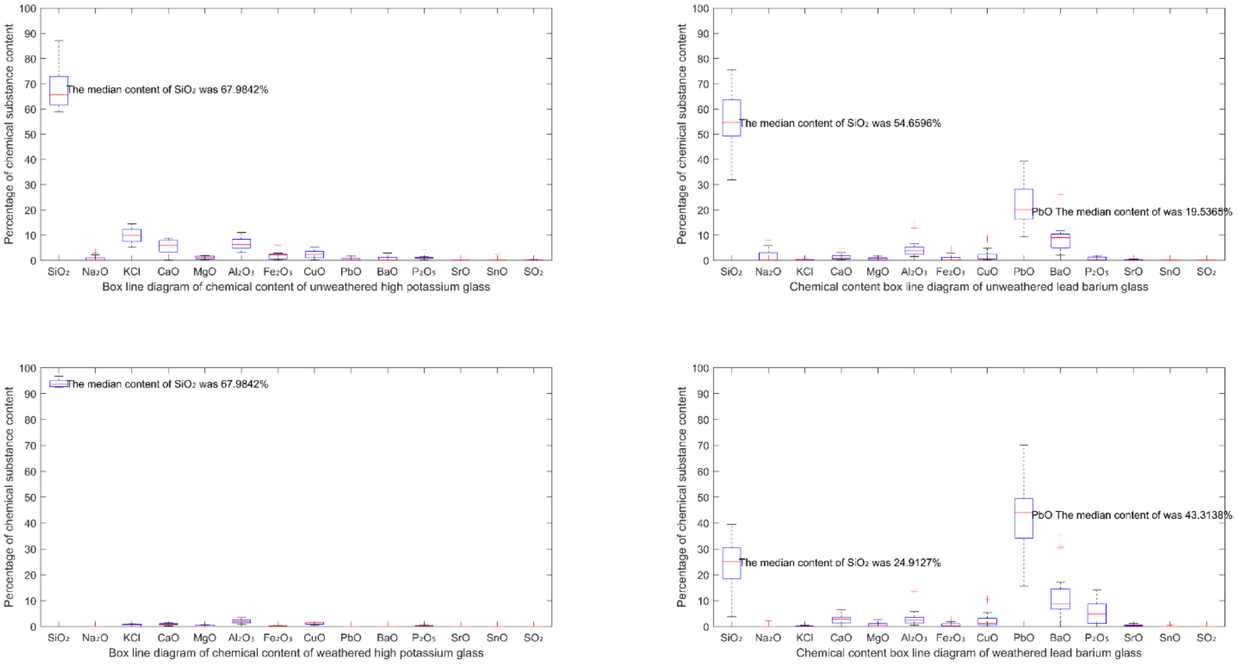

Figure 2. Box line diagram

As can be seen from Fig. 2, for the high potassium glass, the content of silica significantly increased after weathering, with an average increase of 25.98% up, the shorter the corresponding box line graph, which indicates that the silica content after weathering accounts for a smaller variance.

For lead-barium glass, there is a significant decrease in the content of silica and a significant increase in the content of lead oxide after weathering, with an average decrease and increase of 29.75% and 23.77%, respectively.

In order to better demonstrate the changes in other trace chemicals, the contents of silica and lead dioxide are not shown in Fig. 3.

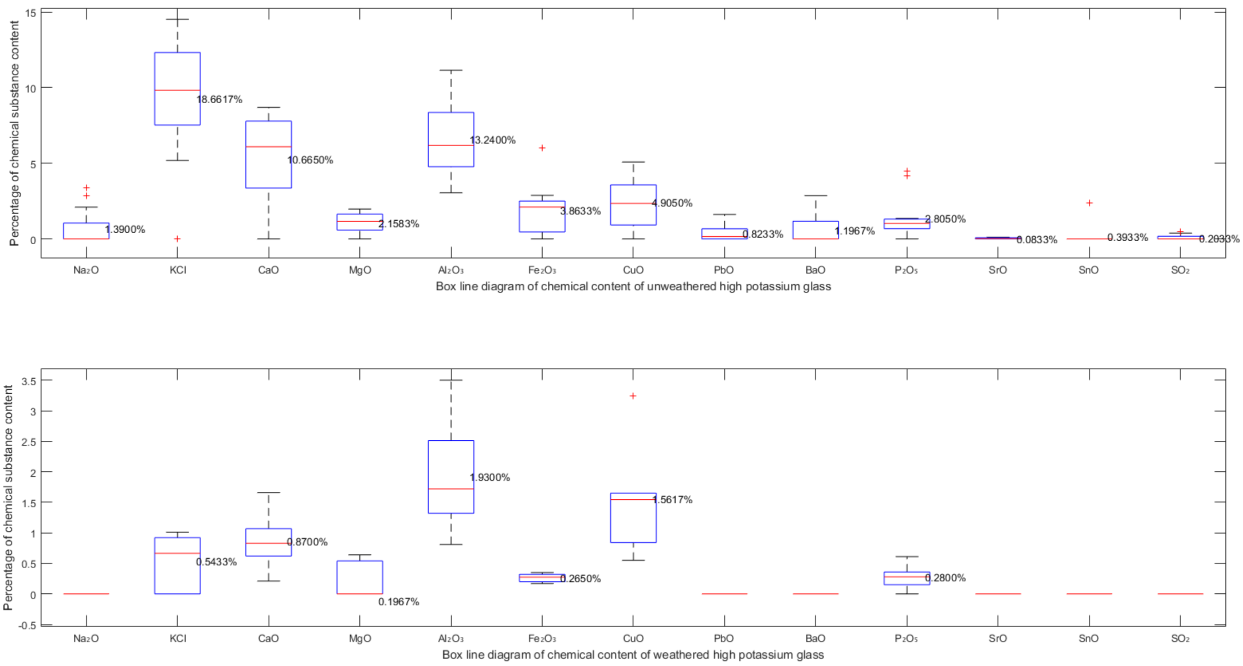

Figure 3. Box line diagram

As can be seen from Fig. 4, the chemical contents of calcium oxide, magnesium oxide, copper oxide, barium oxide, phosphorus pentoxide, strontium oxide, potassium oxide, aluminum oxide, iron oxide, and sodium oxide, tin oxide, and sulfur oxide are all weathered and do not exist after weathering.

The weathering of glass products in real life is mainly dominated by Na, S, and Zn elemental ions [7], and the above statistical results show that only silica is not easily weathered in high potassium glass, and all other chemical components are weathered, resulting in a significant increase in silica content. While in lead-barium glass silica is easily differentiated and lead oxide is not weathered.

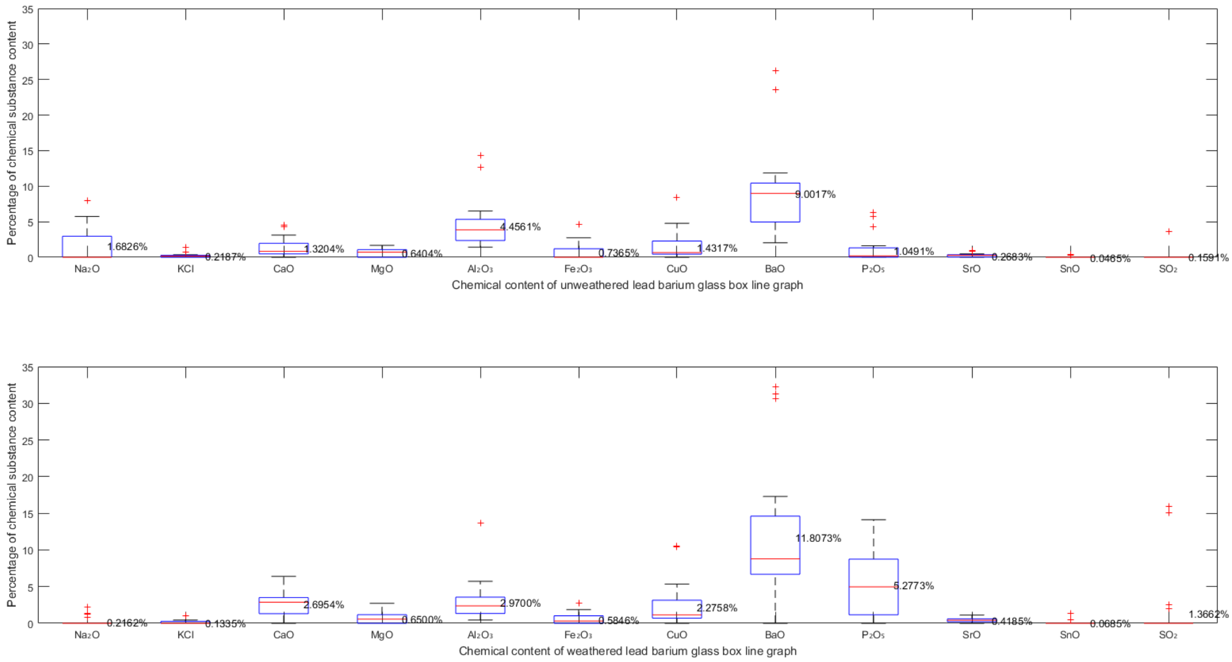

Figure 4. Box line diagram

3.3. Predicting the chemical composition content of weathered material before weathering

(1) Modeling

Based on the chi-square distribution, it was concluded that glass type showed significant correlation with surface weathering, so it can be assumed that the before and after weathering of high potassium glass and lead-barium glass are very different. The data were classified according to glass type to establish a set of multiple linear regression equations for high potassium glass and lead-barium glass, respectively.

The multiple linear regression equations were established with silica content as the dependent variable and 13 other chemical components as the independent variables, respectively; and then the multiple linear regression equations were established with the content of nitrogen oxide as the dependent variable and 13 other chemical components as the independent variables; .... with sulfur dioxide content as the dependent variable and the content of other 13 chemical components as independent variables to establish a multiple linear regression equation.

The model of multiple linear regression analysis was:

$$\begin{cases} y = \beta_0 + \beta_1 x_1 + \beta_2 x_1 + \cdots \beta_m x_m + \varepsilon \\ \varepsilon \sim N(0, \sigma^2), \end{cases} i = 1,2,\cdots,n \tag{1}$$

Assuming that, there is a linear relationship between the dependent variable and the respective variable, then the linear overall regression model between them can be expressed as

$$\begin{cases} y_1 = \beta_0 + \beta_1 x_1 + \beta_2 x_{12} + \cdots \beta_3 x_{13} + \beta_4 x_{14} + \beta_5 x_{15} + \varepsilon_1 \\ \vdots \\ y_{14} = \beta_0 + \beta_1 x_1 + \beta_2 x_{12} + \cdots \beta_3 x_{13} + \beta_4 x_{14} + \beta_5 x_{15} + \varepsilon_{14} \end{cases} \tag{2}$$

In summary, 14 multiple linear regression equations corresponding to the chemical composition of high potassium glass and 14 multiple linear regression equations corresponding to the chemical composition of lead-barium glass were obtained.

(2) Solving of the model

The flow chart of the predicted chemical substance content solution is shown in Fig. 5.

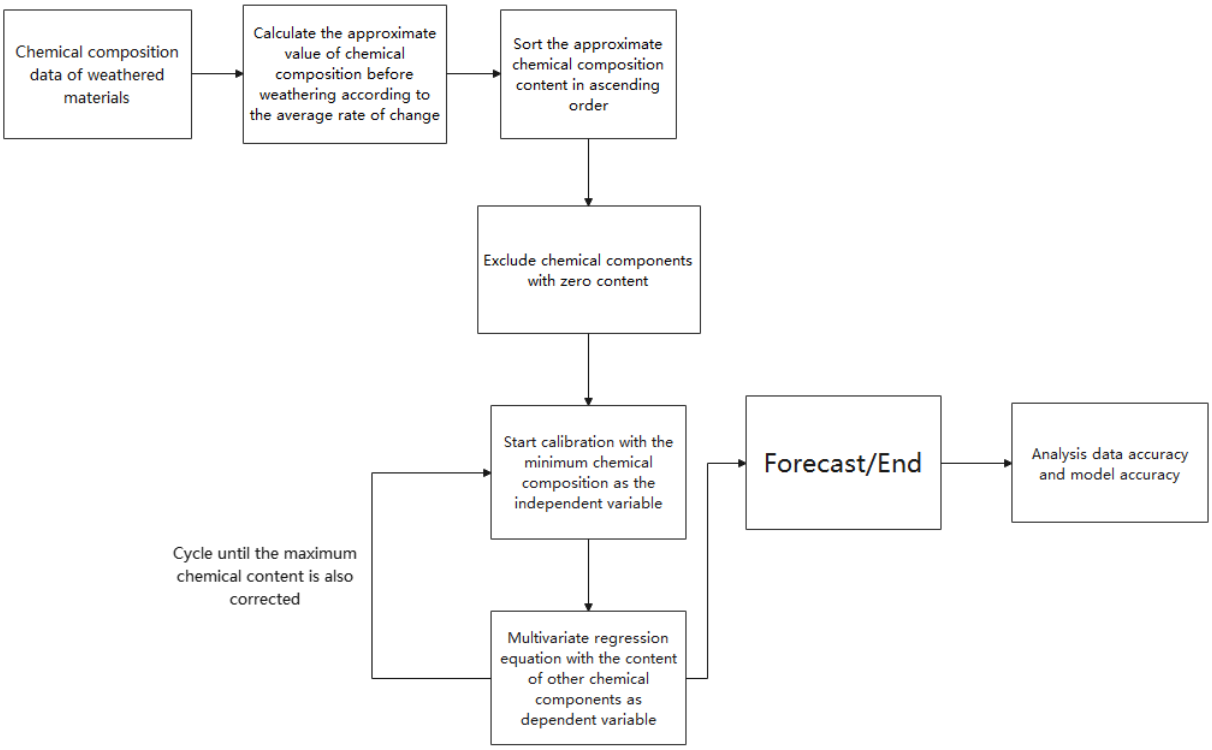

Figure 5. Flow chart for solving for predicted chemical content

3.4. Model testing

(1) Description of the formula

For the goodness of fit, three indicators are chosen as criteria for judging the goodness of fit in this paper, which are MSE (mean square error), MAPE (percentage absolute error), and R^2 (goodness of fit), and their formulas are [8].

$$MSE = \frac{1}{n}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 \tag{3}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{4}$$

$$R^2 = 1 - \frac{\sum(Y_{actual} - Y_{predict})^2}{\sum(Y_{actual} - Y_{mean})^2} \tag{5}$$

MSE takes the average of the squared interpolated values of the actual and predicted values to measure the fit of the data. The lower the MSE, the higher the accuracy of the fit of the data and the more stable the fit as a whole. And MAPE is by taking the percentage share of the absolute error against the value itself, it can visually measure exactly how much deviation occurred, and can illustrate the absolute fitting effect in the overall statistical situation without considering individual cases. And R^2 is the most commonly used parameter to test the fit effect, which can most directly indicate whether the fit is valid or not.

Through the analysis of the above parameters, it was found that, except for the large deviations in the MAPE of individual values (which can be considered as poor correlation), the regression has a relatively good effect overall, and therefore, it can be considered valid within a certain confidence level, and the conclusions based on this model departure are of practical significance.

The goodness-of-fit R^2 for all 14 chemical components of high potassium glass is close to 1, indicating a good fit, and the p-value test is greater than 0.05 for only the chemical component of tin oxide, which rejects the original hypothesis and does not hold significantly, due to the small value of tin oxide and the fact that only one sample of high potassium glass contains tin oxide, and the error variance of this chemical component equation is small. Lead barium glass has three chemical components corresponding to the multiple regression equation does not significantly hold, but because the average value of these three chemical components is less than 0.5%, the composition of the predicted overall chemical composition is very small interference, within the error range, so do not carry out the rejection of the chemical components corresponding to the multiple linear regression equation.

(3) Error analysis

The entire sample of heritage sampling points into the set of regression equations, the predicted value of the multiple regression equation for each chemical substance, and heritage sampling points for comparison with the true value, the calculation of MSE, MPSE.

According to the analysis of the MSE and MPSE values, it is concluded that the error of the multiple regression equation set corresponding to the 14 chemical substances of high potassium glass is very small, only 0.0310, and the maximum percentage error is only 2.7%, and the average is only 0.8022%. Therefore, the predicted values of high potassium glass before and after differentiation are more accurate. The set of multiple regression equations corresponding to the 14 chemical substances of lead-barium glass had larger errors, all of which were 1.3869, and the percentage errors were all 5.3533% errors, which were within the acceptable range. Therefore, the prediction results of high potassium glass were more accurate than those of lead-barium glass.

3.5. The degree of correlation between the two types of glass

Based on spss software to test the normality [9, 10] of each chemical composition, taking lead barium glass as an example, we got Table 3.

Table 3. Normality test

Variable name	Sample size	Median	Average value	Standard deviation	S-W test
Silicon dioxide(SiO2)	49	35.78	38.876	18.646	0.102
Sodium oxide(Na2O)	49	0	0.904	1.813	0.000***
Copper oxide(CuO)	49	0.79	1.88	2.47	0.000***
Lead oxide(PbO)	49	31.9	33.349	14.947	0.116
Phosphorus pentoxide(P2O5)	49	1.41	3.293	3.909	0.000***
Sulfur dioxide(SO2)	49	0	0.8	3.139	0.000***
Calcium oxide(CaO)	49	1.48	2.05	1.635	0.003***
Potassium oxide(K2O)	49	0	0.173	0.276	0.000***
Iron oxide(Fe2O3)	49	0.23	0.656	0.948	0.000***
Aluminum oxide(Al2O3)	49	3.06	3.668	3.009	0.000***
Strontium oxide(SrO)	49	0.31	0.348	0.264	0.008***
Tin oxide(SnO2)	49	0	0.058	0.213	0.000***
Magnesium oxide(MgO)	49	0.61	0.646	0.63	0.000***
Barium oxide(BaO)	49	8.94	10.49	8.331	0.000***
According to the above table it is concluded that only silica and lead oxide P-values greater than 0.05 reject the original hypothesis and are normally distributed, so the Spearman model is used to specifically explore the sample data that do not obey the normal distribution. The correlation between the components of high potassium glass and lead-barium glass was investigated based on the distribution of spss software, and the correlation design was obtained as shown in Table 4 and 5 below					

Table 4. Correlation between the components

Color scale diagram of chemical composition correlation of high potassium glass														
Correlation	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
SiO_2	1.000	-0.475	-0.781	-0.752	-0.546	-0.831	-0.783	-0.430	-0.443	-0.346	-0.530	-0.524	0.070	-0.284
Na_2O	-0.475	1.000	0.606	0.640	-0.223	0.313	0.218	-0.113	0.266	-0.236	-0.221	-0.110	-0.108	-0.198
K_2O	-0.781	0.606	1.000	0.690	0.256	0.506	0.457	0.179	0.241	-0.010	0.156	0.404	0.070	0.307
CaO	-0.752	0.640	0.690	1.000	0.087	0.521	0.537	0.344	0.256	-0.073	0.023	-0.052	-0.374	0.389
MgO	-0.546	-0.223	0.256	0.087	1.000	0.735	0.569	0.204	0.295	0.521	0.643	0.666	0.214	0.429
Al_2O_3	-0.831	0.313	0.506	0.521	0.735	1.000	0.748	0.246	0.602	0.473	0.518	0.511	-0.164	0.246
Fe_2O_3	-0.783	0.218	0.457	0.537	0.569	0.748	1.000	0.643	0.323	0.539	0.517	0.409	-0.374	0.313
CuO	-0.430	-0.113	0.179	0.344	0.204	0.246	0.643	1.000	0.047	0.483	0.466	0.141	-0.398	0.354
PbO	-0.443	0.266	0.241	0.256	0.295	0.602	0.323	0.047	1.000	0.682	0.121	0.368	-0.186	-0.341
BaO	-0.346	-0.236	-0.010	-0.073	0.521	0.473	0.539	0.483	0.682	1.000	0.471	0.565	-0.128	-0.236
P_2O_5	-0.530	-0.221	0.156	0.023	0.643	0.518	0.517	0.466	0.121	0.471	1.000	0.500	0.304	0.246
SrO	-0.524	-0.110	0.404	-0.052	0.666	0.511	0.409	0.141	0.368	0.565	0.500	1.000	0.306	-0.023
SnO_2	0.070	-0.108	0.070	-0.374	0.214	-0.164	-0.374	-0.398	-0.186	-0.128	0.304	0.306	1.000	-0.108
SO_2	-0.284	-0.198	0.307	0.389	0.429	0.246	0.313	0.354	-0.341	-0.236	0.246	-0.023	-0.108	1.000

Table 5. Correlation between the components

Color scale diagram of chemical composition correlation of lead barium glass														
Correlation	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
SiO_2	1.000	0.405	0.308	-0.490	0.123	0.425	0.044	-0.447	-0.757	-0.280	-0.538	-0.552	0.098	-0.313
Na_2O	0.405	1	0.067	-0.367	0.023	0.145	-0.204	-0.102	-0.357	0.087	-0.57	-0.149	-0.093	-0.209
K_2O	0.308	0.067	1	-0.035	0.362	0.512	0.149	-0.198	-0.336	-0.001	-0.14	-0.167	0.14	-0.022
CaO	-0.490	-0.367	-0.035	1.000	0.325	0.123	0.411	-0.037	0.351	-0.157	0.502	0.308	0.284	0.078
MgO	0.123	0.023	0.362	0.325	1	0.674	0.258	-0.266	-0.076	-0.435	0.153	0.074	0.259	-0.368
Al_2O_3	0.425	0.145	0.512	0.123	0.674	1.000	0.387	-0.325	-0.389	-0.369	-0.019	-0.197	0.333	-0.385
Fe_2O_3	0.044	-0.204	0.149	0.411	0.258	0.387	1.000	-0.390	0.081	-0.443	0.225	-0.116	0.363	-0.337
CuO	-0.447	-0.102	-0.198	-0.037	-0.266	-0.325	-0.390	1.000	0.094	0.495	0.221	0.182	-0.356	0.449
PbO	-0.757	-0.357	-0.336	0.351	-0.076	-0.389	0.081	0.094	1	-0.1	0.361	0.362	-0.092	-0.108
BaO	-0.28	0.087	-0.001	-0.157	-0.435	-0.369	-0.443	0.495	-0.1	1	-0.169	0.182	-0.02	0.467
P_2O_5	-0.538	-0.570	-0.140	0.502	0.153	-0.019	0.225	0.221	0.361	-0.169	1.000	0.255	-0.033	0.200
SrO	-0.552	-0.149	-0.167	0.308	0.074	-0.197	-0.116	0.182	0.362	0.182	0.255	1	0.014	0.227
SnO_2	0.098	-0.093	0.14	0.284	0.259	0.333	0.363	-0.356	-0.092	-0.02	-0.033	0.014	1	-0.113
SO_2	-0.313	-0.209	-0.022	0.078	-0.368	-0.385	-0.337	0.449	-0.108	0.467	0.200	0.227	-0.113	1.000

According to the Spearman color scale diagram, it can be observed that the color scale diagram of high potassium glass has more gray grids and is darker than that of lead-barium glass, which indicates that the correlation between the chemical components of high potassium glass as a whole is higher than that of lead-barium glass, and the correlation between the chemical components of lead-barium glass is more independent than that of high potassium glass.

(2) Correlation degree analysis

Based on the solved multiple linear regression equations for each chemical composition, the absolute value of the coefficients of the independent variables was used as an index to judge the correlation degree, and the color scale of the correlation degree was drawn, as shown in Table 6 and 7 below

Table 6. Related degree color scale chart

Color scale diagram of chemical composition correlation of high potassium glass														
Correlation	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
SiO_2	1	-0.98581	-1.11007	-0.95398	-2.66569	-0.9767	-1.2706	-1.23667	-0.52812	-0.71414	-0.57823	13.14902	-1.42798	-0.63842
Na_2O	-0.37492	1	-0.33542	-0.39184	-0.69995	-0.25548	-0.36918	-0.25004	0.180837	-1.00595	-0.49004	-0.99869	-0.61312	-4.12679
K_2O	-0.8384	-0.66611	1	-0.71309	-2.57552	-0.81498	-1.19982	-1.11089	-0.61255	-0.32295	-0.34158	16.09978	-0.99486	1.171353
CaO	-0.80355	-0.86783	-0.79527	1	-1.89577	-0.71639	-0.66424	-0.91188	-0.29908	-0.80049	-0.88551	3.664142	-1.28556	-1.68583
MgO	-0.2015	-0.13912	-0.25777	-0.17013	1	-0.13497	-0.27847	-0.31663	-0.27409	0.113083	-0.10833	5.170404	-0.03841	1.350824
Al_2O_3	-0.76358	-0.52517	-0.8436	-0.66492	-1.3959	1	-1.11464	-0.98568	-0.21206	-0.56775	-0.06106	10.19568	-1.55975	-0.78171
Fe_2O_3	-0.52326	-0.39976	-0.65422	-0.32476	-1.51714	-0.58716	1	-0.70372	-0.35714	-0.17601	0.093034	12.27021	-0.71405	0.771726
CuO	-0.64044	-0.34048	-0.76172	-0.56065	-2.16924	-0.65294	-0.88494	1	-0.66085	0.140091	-0.1856	11.72149	-0.75235	2.363325
PbO	-0.1959	0.176371	-0.30083	-0.1317	-1.34496	-0.10061	-0.32168	-0.47334	1	0.81062	-0.07842	7.250179	0.170418	3.525098
BaO	-0.15394	-0.57016	-0.09217	-0.20486	0.322478	-0.15654	-0.09213	0.058312	0.471082	1	-0.28782	-2.63906	-0.55535	-4.12359
P_2O_5	-0.29387	-0.65485	-0.22986	-0.5343	-0.72834	-0.0397	0.114815	-0.18215	-0.10744	-0.67861	1	-2.30658	-0.29448	-2.61342
SrO	0.015982	-0.00319	0.025909	0.005287	0.083135	0.015851	0.036214	0.02751	0.023757	-0.01488	-0.00552	1	0.002853	-0.19069
SnO_2	-0.32493	-0.36683	-0.29972	-0.34728	-0.11564	-0.45397	-0.39453	-0.33057	0.104541	-0.58621	-0.13184	0.534163	1	-2.292
SO_2	-0.00597	-0.10147	0.014503	-0.01872	0.167109	-0.00935	0.017524	0.042675	0.088869	-0.17889	-0.04809	-1.46711	-0.09419	1

Table 7. Related degree color scale chart

Color scale diagram of chemical composition correlation of lead barium glass														
Correlation	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
SiO_2	1	-1.15233	-0.39974	-1.30603	-1.02564	-0.92492	-0.90362	-0.27044	-1.01696	-1.33937	-1.33353	1.993334	0.764868	-0.34272
Na_2O	-0.39569	1	-0.4497	-0.55296	-0.12759	-0.38577	-0.59103	-0.14295	-0.42651	-0.53511	-0.60214	1.310267	-0.20596	-0.16227
K_2O	-0.00665	-0.02178	1	-0.0262	0.14673	0.02074	0.05851	-0.01467	-0.00302	0.002091	-0.02447	-0.14733	-0.06334	0.006087
CaO	-0.26986	-0.33273	-0.32546	1	0.259713	-0.17787	0.078478	-0.00279	-0.23989	-0.36368	-0.29882	-0.10327	0.708814	0.001675
MgO	-0.0519	-0.0188	0.446422	0.063608	1	-0.03156	-0.08758	-0.03116	-0.06413	-0.08972	-0.03299	0.606657	0.203687	-0.05274
Al_2O_3	-0.51978	-0.63135	0.700736	-0.48378	-0.35047	1	-0.66328	-0.14438	-0.58991	-0.76343	-0.69448	1.889191	2.590253	-0.20243
Fe_2O_3	-0.13216	-0.25174	0.514492	0.055551	-0.25311	-0.17262	1	-0.08647	-0.15855	-0.19384	-0.16957	0.558621	0.414866	-0.10364
CuO	-0.15284	-0.23527	-0.4984	-0.00764	-0.34797	-0.14519	-0.3341	1	-0.18432	0.056837	-0.11953	1.447268	-1.45932	-0.39932
PbO	-0.9417	-1.15017	-0.16791	-1.07506	-1.17342	-0.97201	-1.00378	-0.30202	1	-1.27637	-1.24603	2.781546	0.83274	-0.36961
BaO	-0.65433	-0.76132	0.061427	-0.85988	-0.86616	-0.66366	-0.64745	0.049134	-0.67339	1	-0.89207	1.478901	1.175969	-0.08219
P_2O_5	-0.60489	-0.79541	-0.66728	-0.656	-0.29573	-0.56054	-0.52588	-0.09594	-0.61037	-0.82828	1	1.394058	-0.05225	-0.14785
SrO	0.023719	0.045404	-0.1054	-0.00595	0.142644	0.04	0.045447	0.030473	0.035743	0.036021	0.03657	1	0.00402	0.028206
SnO_2	0.006693	-0.00525	-0.03332	0.030018	0.03522	0.040332	0.024821	-0.0226	0.007869	0.021063	-0.00101	0.002957	1	-0.00884
SO_2	-0.33815	-0.46626	0.361083	0.007998	-1.02823	-0.35541	-0.69918	-0.69718	-0.39383	-0.16599	-0.32161	2.338867	-0.99683	1

According to the color scale diagram of the correlation degree, it can be observed that strontium oxide has the strongest correlation degree with other chemical components among the two types of glasses, and strontium oxide is more closely correlated with each chemical component in high potassium glass, while strontium oxide is only less correlated with potassium oxide, calcium oxide and tin oxide in lead-barium glass, and more correlated with other chemical components. The chemical components with the highest degree of correlation are strontium oxide, sulfur dioxide and magnesium oxide, and the chemical components with the lowest degree of correlation are tin oxide, barium oxide and aluminum oxide; the chemical components with the highest degree of correlation are strontium oxide, barium oxide and lead oxide, and the chemical components with the lowest degree of correlation are copper oxide, calcium oxide and potassium oxide. The chemical components with the lowest correlation are copper oxide, calcium oxide and potassium oxide.

4. Conclusion

In this paper, the correlations of the existing excavated glass artifacts are analyzed in terms of superficial attributes, such as glass type, decoration type, color, and weathering, etc. Because the correlations are classified rather than quantitative, the cardinality distribution is used to explore the significance of the correlations.

In this paper, the correlations of the components of high potassium glass and lead-barium glass were investigated one by one and the differences between them were compared, considering that if the main class-subclass classification method was used, the number of each sample set would be relatively small, which would lead to distortion of the analysis results, therefore, only the broad class classification method was considered.

Finally, a gray correlation was considered, but the results obtained were not good. The problem was solved by combining the Spearman correlation model on top of the model.

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