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ANALYSIS OF THE RELATIONSHIP BETWEEN TRAITS THAT ARE MEASURED ON A NOMINAL SCALE

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Abstract. The article reviews an important section of economics - correlation analysis: the terminology is given, the properties of the nominal measurement scale are considered, methods of revealing and evaluating the degree of correlation between phenomena - correlation coefficients are given. On the basis of the collected information, a study of the consistency of S.G. Svetunkov's new correlation coefficient for nominal data has been made. Calculation of the coefficient values on various data allowed us to conclude about its consistency.

Keywords: correlation analysis, nominal scale, correlation coefficient, contingency table, Yule's coefficient of association, Yule's association coefficient, Pearson correlation coefficient

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АНАЛИЗ ВЗАИМОСВЯЗИ МЕЖДУ ПРИЗНАКАМИ, ИЗМЕРЯЕМЫМИ ПО НОМИНАЛЬНОЙ ШКАЛЕ

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Аннотация. В статье рассмотрен важный раздел экономической науки - корреляционный анализ: дана терминология, рассмотрены свойства номинальной шкалы измерения, приведены методы выявления и оценки степени корреляции между явлениями - коэффициенты корреляции. На основе собранной информации выполнено исследование состоятельности нового коэффициента корреляции С.Г. Светункова для номинальных данных. Расчет значений коэффициента на различных данных позволил сделать вывод о его согласованности.

Ключевые слова: бизнес-модель, бизнес-концепция, компонентный подход, потребительская ценность, бизнес-архитектура, операционная модель, модель дохода

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Introduction

The study of dependencies and relationships between processes and phenomena plays a crucial role in economics. It gives an insight into the deep interrelationship of relationships and the cause-and-effect relationship between phenomena. The possibility to quantitatively and qualitatively measure the depth of cause-and-effect relationships and to identify their mutual influence on each other plays a great role. This will provide a more accurate understanding of the phenomena under study and interrelations and the choice of the right options for management decisions.

To identify the types, forms, influences and their strength, correlation analysis is actively used. Correlation analysis helps to investigate related factors, allows you to adjust economic processes, which leads to the desired result (Svetunkov, Chanysheva, 2022).

This article discusses the basic provisions of correlation analysis: terminology, nominal measurement scale and its properties, various correlation coefficients are given, the applicability of the new correlation coefficient is examined using examples, the conclusion about the consistency of the proposed coefficient is made.

Materials and Methods

Nominal measurement scale

A measurement scale is a homomorphic image of the measured object (Baker et al. 1966). Any measurement scale is defined by four characteristics:

– description,
– order,
– distance,
– starting point.

The simplest scale is the nominal scale. This scale has only the characteristic of description - a set of items is given, of which one item should be specified, and not as a result of comparison, but as a result of identification. The mathematical actions in this scale: equality and inequality (Li R., 2022). The numbers on this scale cannot be compared to each other. In the nominal scale, they work not with the numbers (data) themselves, but with the number of observations of these data, which is expressed in the metric scale, but in it you can perform any action. In this case, most often we speak not about data, but about attributes, because it's this property that is recorded during the observation of objects.

An important way to analyze information quantitatively is to establish the relationship between a series of properties using contingency tables. Which uses the information about the number of observed features (Narkevich, 2022). These quantitative values allow us to assess the possibility of the existence of a relationship between the two observed features, using a conjugacy table:

Table 1. Contingency table

Value	x_0	x_1	Result
y_0	a	b	a + b
y_1	c	d	c + d
Result	a + c	b + d	N = a + b + c + d

If the table contains probabilistic values, then they can be processed using statistical methods. If the table contains probabilistic values, then they can be processed using statistical methods.

Correlation Analysis

Correlation analysis is a statistical method for studying the relationship between two or more random variables. Correlation analysis is a very popular method of analytical statistics. According to A.M. Grzhibovsky (Billard et al., 2003), in Russian scientific publications, correlation analysis is in second place among the methods used in scientific articles, after Student's criterion. Correlation or correlation dependence is a kind of dependence of two or more random variables. The essence of correlation analysis is to find the relationship between these variables. Paired correlation studies the relationship between two random variables, multiple correlation studies the relationship between a large number of random variables. (Correlation and regression analysis)

The peculiarity of the analysis is that the presence of a relationship is characterized by how pronounced it is. The main task of correlation analysis is to identify and assess the relationship between random variables.

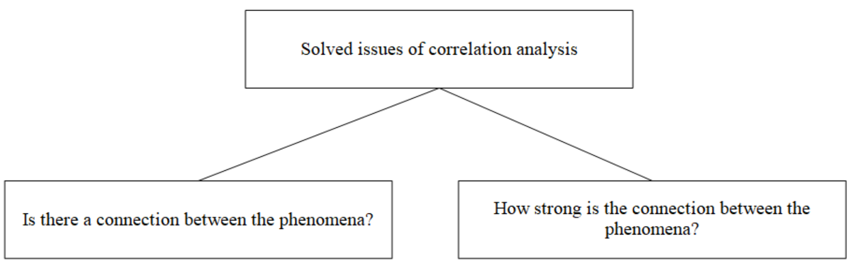

Fig. 1. The essence of correlation analysis

Despite the apparent simplicity of correlation analysis, there are a number of points worth paying attention to:

First, it is necessary to fulfill the condition of having a sufficient number of observations to study. In practice, it is believed that the number of observations should be at least 5-6 times greater than the number of factors (also there is a recommendation to use a proportion of not less than 10 times greater than the number of factors). Secondly, the initial set of values should be qualitatively homogeneous (Bonett, 2007).

Types of correlation coefficients

An indicator that reflects the closeness of two correlated quantities is a certain criterion, called the correlation coefficient. The correlation coefficient can take values from -1 to +1. The closer in modulo its value is to unity, the stronger is the connection between the values. A value of zero or close to it indicates a lack of connection. The presence of correlation may indicate that one of the highlighted phenomena is the cause of the other, or these phenomena are the consequences of common causes. The generally accepted gradation of the strength of the connection is represented by the Chertok scale.

Table 2. Scale of Chertok

№	Correlation coefficient	Characteristics of the strength of the connection
1	$\lvert r_8 \rvert < 0,1$	Practically no connection
2	$0,1 < \lvert r_8 \rvert < 0,3$	Weak connection
3	$0,3 < \lvert r_8 \rvert < 0,5$	Moderate correlation
4	$0,5 < \lvert r_8 \rvert < 0,7$	Medium strong correlation
5	$0,7 < \lvert r_8 \rvert < 0,9$	Strong link
6	$0,9 < \lvert r_8 \rvert < 1$	Very strong link

The correlation relationship cannot be absolutely complete and accurate. Detection of correlation doesn't give us grounds to assert a causal relationship of phenomena, but gives us the right to judge about a certain relationship between the factors. The main disadvantage of the methodology is the complexity of interpretation and the search for causal relationships and their interpretation (Yadov, 1998).

The choice of correlation coefficient depends on several factors:

1. The type of scale of the variable.
2. If both variables are quantitative, then the choice of coefficient is explained by the form of distribution and other characteristics.

Yule's coefficient of association

The easiest to use when examining the correlation of data measured on a nominal scale is Yule's coefficient of association. It, taking into account the introduced notations, has the form:

$$Q = \frac{ad - bc}{ad + bc} \tag{1}$$

A modification of this coefficient is the Yule's colligation coefficient:

$$Q = \frac{\sqrt{ad} - \sqrt{bc}}{\sqrt{ad} + \sqrt{bc}} \tag{2}$$

These coefficients vary from -1 to +1. The closer the coefficient is to unity in modulo, the stronger the connection between the measured attributes. If it has a negative value, then this indicates that an increase in the values of one attribute leads to a decrease in the values of another attribute (Eliseeva et. al., 2002.). The disadvantage of Yule's coefficient of association is that it's still not a very precise assessment of the relationship between the factors, since if, for example, at least one cell of the contingency table will be zero, the Yule's coefficient of association will be equal to one, but it does not indicate an unambiguous correlation between the factors. The Pearson correlation coefficient is free from this disadvantage (Shulenin, 2020).

Pearson correlation coefficient

Pearson correlation coefficient is the most popular correlation coefficient among others in scientific publications, although it has significant limitations.

$$\chi = \frac{ad - bc}{\sqrt{(a+c)(b+d)(a+b)(c+d)}} \tag{3}$$

The disadvantage of using the Pearson correlation coefficient is its strong sensitivity to outliers. In the presence of a single outlier in the sample, the value of the Pearson correlation coefficient can significantly decrease (Bolshakova, 2021). The Pearson correlation coefficient is always smaller than the Yule's coefficient. Usually, a relationship is said to be confirmed if Yule's coefficient modulo is greater than 0.5 and Pearson's contingency coefficient modulo is greater than 0.3 (Chen, 2019).

Often researchers encounter a situation where completely unrelated factors have a high value of the pairwise correlation coefficient. This phenomenon is called "false correlation". The term was suggested by K. Pearson himself, who justified the formula for the paired correlation coefficient. To demonstrate this phenomenon K. Pearson showed that if two factors x_{1i} and x_{2i} independent of each other have a common denominator x_{3i}, then between series $\left\{\frac{x_{1i}}{x_{3i}}\right\}$ and $\left\{\frac{x_{2i}}{x_{3i}}\right\}$ the pair correlation coefficient will be calculated, far from zero, and testifying to the presence of a linear relationship between factors (Ivanovna, 2021).

In some cases, these coefficients fail the task of correlation analysis. S.G. Svetunkov gives examples when the coefficients (1) – (3) incorrectly reveal the correlation between the features. This proves the relevance of the task of finding new approaches and methods for identifying and evaluating the degree of correlation between nominal data. He proposed a new coefficient, the essence of which is as follows (Mogilko, 2022).

Considering the contingency table graphically in three-dimensional space. Its axes are the signs x and y, and the number of observed occurrences of each sign n. Four points in the three-dimensional space are projected onto each of the planes that make up the space. The planes of interest are $n0y$ and $n0x$. On which the angles of the lines ac, bd, ab, and cd are calculated (Knight et.al., 2001). If at least one of the features doesn't react to changes of the conjugate feature, and remains constant, then a straight line passing through the projections of such points will be characterized by the fact that the tangent of such an angle will be equal to zero (no correlation). Taking into account this fact and the generally accepted representation, correlation coefficients varying from -1 to +1, S.G. Svetunkov proposed the following coefficient: (Dmitriev, 2018):

$$S_{gs} = \left(\frac{a-c}{|a-c|}\cdot\frac{b-d}{|b-d|}\cdot\frac{a-b}{|a-b|}\cdot\frac{c-d}{|c-d|}\right)\sqrt[4]{(a-c)\cdot(b-d)\cdot(a-b)\cdot(c-d)} \tag{4}$$

The author of the coefficient performed preliminary research. A comparative analysis of such a coefficient study on two examples is presented in Table 3.

Table 3. Comparative analysis of correlation coefficient calculations

Name of the coefficient	The value of the coefficient in the absence of correlation	The value of the coefficient in the presence of correlation
Yule's coefficient of association	-0,905	0
Yule's colligation coefficient	-0,635	0
Pearson correlation coefficient	-0,510	0
Coefficient S_{gs}	0	0,369

It follows from the examples that the new coefficient shows the presence of connection where there is one, and signals the absence of connection where there is none.

Interpret the strength of the relationship depending on the S_{gs} coefficient values as follows:

$|S_{gs}| \leq 0,199$ – the absence of relationship between the considered features;

$0,199 \leq |S_{gs}| \leq 0,414$ – weak correlation relationship;

$0,414 \leq |S_{gs}| \leq 0,668$ – medium level correlation;

$0,668 \leq |S_{gs}|$ – strong correlation.

Results and Discussion

Comparative analysis of the calculation of correlation coefficients

Since the coefficient has been recently introduced into the scientific circulation, it is necessary to investigate the possibility of its practical use. Our study will compare the calculated values of Yule, Pearson and Svetunkov coefficients (1) - (4) on real examples of phenomena with actually established relationship, as well as on phenomena, the relationship between which is only assumed (Yadov, 2007).

Consider *Example 1* (table 4). In the contingency table we enter data on the frequency of recommendations of strength exercises in the specialized literature and on Web sites.

Table 4. Contingency table

Significance of signs	x_0 – recommended	x_1 – not recommended	Result
y_0 – book	52	9	61
y_1 – web-site	32	7	39
Result	84	16	100

Both the first and second conjugate signs y_0 and y_1 react to the transition from feature x_0 to feature x_1. The table shows that regardless of the source of information about the strength exercise, this source is more likely to recommend it than not. Substituting the values from Table 4 into formulas (1) – (4) to calculate the correlation coefficients, we estimate their consistency (Svetunkov, 2020).

Table 5. Comparative analysis of the calculation of correlation coefficients

Name of the coefficient	The value of the coefficient according to Table 4
Yule's coefficient of association	0,116564
Yule's colligation coefficient	0,058481
Pearson correlation coefficient	0,042503
Coefficient S_{gs}	0,27693

In this example, we see that the coefficient S_gs=0,27693 shows a weak direct correlation relationship (0,199 <=|S_gs |<0,414), while all other studied coefficients do not reveal any correlation.

Example 2. Consider the data for the first attempt of the test as a function of students' attendance at lecture classes that we have collected. The data to calculate correlation coefficients for the two features – attendance of lectures and passing the test are presented in the contingency table (Ye, Zhang, 2021).

Table 6. Contingency table

Significance of signs	<<Eqn037.eps>> – passed the test the first time	<<Eqn038.eps>> – failed the test on the first time	Result
<<Eqn039.eps>> – student attended lectures	34	3	37
<<Eqn040.eps>> – student didn’t attend lectures	5	26	31
Result	39	29	68

When examining Table (6), it becomes almost obvious that attending lectures has a positive effect on passing the test at the first attempt. By substituting the values from Table 4 into formulas to calculate correlation coefficients, we will evaluate their consistency (Yadov, 2013).

Table 7. Comparative analysis of the calculation of correlation coefficients

Name of the coefficient	The value of the coefficient according to Table 6
Yule's coefficient of association	0,96663
Yule's colligation coefficient	0,769500
Pearson correlation coefficient	0,762969
Coefficient S_{gs}	0,75500

In Example 2, each of the coefficients under consideration is far from zero and, to some extent, close to one, which confirms the strong correlation between the traits, which we observed from the data in the contingency table. At the same time, the coefficient S_gs shows a minimum value. But since according to S.G. Svetunkov's scale at 0.668 <=|S_gs | a strong correlation relationship is diagnosed, it should be noted that in this case it is above the limit, indicating a strong correlation. Consequently, only two coefficients are in the situation of a strong.

Example 3. Let's test whether a student's affiliation with a particular department affects a positive outcome of the test. After surveying 359 students in the Sociology and Psychology departments, we will record the data on the contingency table.

Table 8. Contingency table

Value	x_0 – psychologists	x_1 – sociologists	Result
y_0 – pass	45	54	99
y_1 – fail	171	79	250
Result	216	133	359

Table 8 shows that on the transition from the feature x_0 to the feature x_1 the first conjugate feature y_0 reacts by a slight increase in the number of observations, and the second conjugate feature y_1, on the contrary, reacts by a significant decrease in the number of observations. All three coefficients (1)-(3) react equally badly to this relationship between the signs, they are far from the maximum value equal to one and show an inverse relationship between the signs.

Table 9. Comparative analysis of the calculation of correlation coefficients

Name of the coefficient	The value of the coefficient according to Table 8
Yule's coefficient of association	-0,39497
Yule's colligation coefficient	-0,205853
Pearson correlation coefficient	-0,185447
Coefficient S_{gs}	-0,248386

The S_{gs} coefficient, as well as coefficients (1) – (3) show a weak correlation relationship between the signs. Consequently, the new method of identifying and assessing the degree of correlation between nominal data is viability.

Conclusion

In this article we have considered the main provisions of correlation analysis: terminology, nominal measurement scale and its properties, described the types of correlation coefficients - methods for identifying and evaluating the degree of correlation between signs. Based on the information collected, we considered the applicability of the new correlation coefficient by S.G. Svetunkov for nominal data. Calculation of the coefficient values on various data examples allowed us to make a conclusion about its validity.

According to the results of the study it can be stated that:

Competent correlation analysis should rely on different correlation coefficients, which have their own specifics and many conditions of application. The ability to correctly interpret the indicators of the coefficients, the difference between them will allow a deeper understanding of the dependence and the relationship in a given sample.

Interpretation of the results obtained is not simply to mention in the text of the article the obtained correlation coefficient, it is necessary to draw a conclusion and justification of the results obtained.

Making research on concrete examples, we made consideration of a new coefficient, which behaves very differently on different data. In some examples (1 and 3) we observe its superiority (the most accurate measures of the strength of the relationship) over the other coefficients under consideration (Yule, Pearson). In some cases, it diagnoses the same strength of correlation as the other coefficients. This shows that the Sgs coefficient can be recommended for detecting correlation between nominal data presented in conjugation tables with two nominal numbers of each trait.

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