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Cochran's Q test for analyzing categorical data under uncertainty

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Abstract

Motivation: The Cochran test, also known as Cochran's Q test, is a statistical procedure used to assess the consistency of proportions across multiple groups in a dichotomous dataset

Description: This paper introduces a modified version of Cochran's Q test using neutrosophic statistics to handle uncertainty in practical situations. The neutrosophic Cochran's Q test determines whether the proportions of a specific outcome are consistent across different groups, considering both determinate and indeterminate parts.

Results: An application of the proposed test is presented using production data to assess the capabilities of machines during different days of the week. The comparative study demonstrates the advantages of the proposed test over the classical Cochran's Q test, providing insights into the degree of indeterminacy and enhancing decision-making in uncertain scenarios.

Conclusion: This study introduces a modified version of the Cochran test, utilizing neutrosophic statistics to address uncertainty in practical scenarios. The neutrosophic Cochran's Q test effectively assesses the consistency of outcome proportions across various groups, accounting for both determinate and indeterminate factors. The application of this novel approach to machine capabilities assessment, based on production data collected over different days of the week, unveils its superiority over the traditional Cochran's Q test. This superiority is reflected in the insights it offers into the degree of indeterminacy, thereby enhancing decision-making in contexts marked by uncertainty. The simulation study further underscores the critical role of indeterminacy in affecting test statistics and decision outcomes, highlighting the significance of the proposed method in capturing real-world complexities. In essence, the neutrosophic Cochran's Q test presents a refined and pragmatic tool for addressing the uncertainties inherent in diverse datasets, rendering it invaluable in practical decision-making scenarios.

Keywords: Uncertainty quantification, Categorical data analysis, Statistical inference, Neutrosophic logic, Hypothesis testing

Introduction

The Cochran test, also referred to as Cochran's Q test, is a statistical procedure used to evaluate the consistency of proportions across multiple groups in a dichotomous (binary) dataset. It is commonly applied to analyze categorical data arranged in an $n \times K$

contingency table, where n represents the number of observations and K represents the number of groups being compared. The purpose of the Cochran test is to determine whether the proportions of a specific outcome (e.g., success or failure) are consistent across the different groups. The null hypothesis assumes equal proportions across all groups, while the alternative hypothesis suggests that at least one group differs in its proportion. Performing the Cochran test helps determine if there are any significant differences in proportions across categories, making it a useful tool in various fields, such as medicine, social sciences, and market research, where researchers often examine categorical data to identify patterns or associations. A novel sample size formula is introduced for Cochran's test that incorporates additional information on stratum-specific success rates by [1]. Kulinskaya and Dollinger [2] addressed the limitations of using the chi-square distribution for Cochran's Q statistic in testing homogeneity in meta-analysis when the effects of the studies are logarithms of odds ratios. Okeh et al. [3] proposed a novel statistical method for analyzing sample data characterized by dichotomous responses, where only two mutually exclusive values are considered. Stephen and SAZ [4] explored the practical application of Cochran's Q test and pairwise McNemar test in analyzing the proportions of responses obtained from Multiple Responses Analysis (MRA). Van Aert et al. [5] Reported confidence intervals along with point estimates of between-study variance aid the interpretation of meta-analytic results. Two recommended methods, Q-profile and generalized Q-statistic, utilize the Q-statistic to create these confidence intervals. More applications of Cochran's Q statistic can be seen in [3, 6].

Neutrosophic statistics is a specialized field that combines the principles of neutrosophic logic and statistical analysis, see [7]. Neutrosophic logic deals with the concept of indeterminacy and uncertainty, introducing a third truth value called "indeterminate" in addition to true and false. Neutrosophic statistics aims to provide a framework for analyzing data that contains imprecise, vague, or uncertain information. In traditional statistics, assumptions of precise and definite values are made, which may not always reflect the reality of complex or ambiguous situations. Neutrosophic statistics, on the other hand, acknowledges and embraces the presence of indeterminacy, allowing for a more comprehensive analysis of uncertain data. The principles of neutrosophic statistics enable researchers and analysts to handle incomplete or vague information and incorporate it into their statistical models. This approach can be particularly valuable in fields where uncertainty plays a significant role, such as decision-making processes, risk assessment, and fuzzy systems. By integrating neutrosophic logic into statistical analysis, neutrosophic statistics offers a powerful tool for addressing uncertainties and dealing with imperfect or incomplete data. It provides a means to represent and reason with ambiguous information, ultimately leading to more robust and nuanced statistical conclusions. According to a study conducted by Smarandache [8], it was demonstrated that neutrosophic statistics exhibit higher efficiency compared to both interval statistics and classical statistics. More information on neutrosophic statistics and various algorithms can be seen in [9–14].

Neutrosophic statistical tests are a specialized class of statistical methods that integrate neutrosophic logic into the analysis of data. Neutrosophic logic introduces the concept of indeterminacy, allowing for a more comprehensive treatment of uncertainty and ambiguity. Neutrosophic statistical tests provide a framework to handle situations where data or parameters are imprecise, vague, or uncertain. Unlike traditional statistical methods that assume precise values, neutrosophic statistical tests acknowledge and accommodate the inherent uncertainty in data analysis. By incorporating neutrosophic set theory and neutrosophic probability, these tests enable decision-making and inference in the presence of incomplete or uncertain information. The application of neutrosophic statistical tests spans various fields, including medicine, economics, and decision sciences, where dealing with imprecise or incomplete data is common. By considering the indeterminacy and ambiguity inherent in real-world data, neutrosophic statistical tests provide a valuable approach to modeling and analyzing complex and uncertain situations. Neutrosophic statistical tests contribute to the advancement of statistical methodology by offering a means to handle uncertainty beyond classical statistical approaches. They provide a robust and flexible framework for making informed decisions in scenarios where traditional methods may fall short. With their ability to handle imprecise and vague information, neutrosophic statistical tests offer a promising avenue for addressing the challenges posed by uncertainty in statistical analysis.

In their study, AlAita and Aslam [15] introduced an analysis of variance test specifically designed for neutrosophic data. Similarly, Polymenis [16] proposed a t-test tailored for the autoregressive process. Aslam [17], on the other hand, presented the F-test specifically for counts data in the presence of indeterminacy. For further information on this type of test, comprehensive details can be found in the work of [18–22].

Although the existing Cochran's Q test is a widely used statistical procedure for analyzing the consistency of proportions across multiple groups in a dichotomous dataset, it assumes that the data is recorded without any uncertainty. However, in practical situations involving complexity, it is often not feasible to have precise data. For this paper, the main contribution is to introduce a modified version of Cochran's Q test that can handle uncertainty in practical situations and provide a more comprehensive analysis of uncertain data. The proposed research introduces a modified version of Cochran's Q test using neutrosophic statistics to handle uncertainty in practical situations. Neutrosophic statistics is a specialized field that combines neutrosophic logic and statistical analysis, allowing for the analysis of data that contains imprecise, vague, or uncertain information. The novelty lies in integrating neutrosophic logic into the analysis of categorical data, providing a framework to handle incomplete or vague information and incorporating it into statistical models. This approach offers a more robust and nuanced analysis of uncertain data compared to traditional statistical methods. The comparative study highlights the benefits of considering indeterminacy in decision-making and provides insights into the degree of uncertainty in uncertain scenarios. Additionally, a simulation study examines the effect of the degree of indeterminacy on the test statistic and its impact on decision outcomes, contributing to a better understanding of the proposed test's performance. The contribution of this research is twofold. First, it proposes a modified version of Cochran's Q test using neutrosophic statistics, which allows for the analysis of categorical data under uncertainty. This modified test considers both determinate and indeterminate parts, providing a more comprehensive assessment of the consistency of proportions across different groups. Second, it demonstrates the advantages of the proposed test over the classical Cochran's Q test through an application using production data. The constraints of the proposed test encompass its applicability solely in scenarios where data uncertainty is present. Moreover, decision-makers must exercise caution concerning the extent of uncertainty, as it can potentially result in erroneous decisions (Table 1).

Methods

Adhering to the methodology outlined by Kanji [23], the operational procedure of the existing Cochran's Q test can be summarized as follows: begin by arranging an $n \times k$ table, where k represents treatments applied to n elements. Calculate the row totals R_i $(i = 1, 2, \ldots n)$ and column totals $C_i\left(j = 1, 2, \ldots k\right)$. The test statistic Q is then computed using the formula $Q = \frac{K(k-1)\sum_j \left(C_j - \overline{C}\right)^2}{KS - \sum_i R_i^2}$, where $S = \sum_i R_i = \sum_i C_i$ and $\overline{C} = \frac{\sum_j C_j}{K}$. It's important to note that this test statistic follows a chi-square distribution with $(k-1)$ degrees of freedom. Rejecting the null hypothesis becomes appropriate if the calculated Q value exceeds the critical tabulated value. The conventional Cochran's Q test assumes that the data is recorded without any uncertainty. However, in practical situations involving complexity, it is often not feasible to have precise data. As a result, the standard Cochran's Q test may not be applicable for decision making. Within this section, we are about to present an enhanced iteration of Cochran's Q test, incorporating the principles of neutrosophic statistics. This refined Cochran's Q test, within the realm of neutrosophic statistics, holds the capacity to incorporate the degree of uncertainty inherent in the available data. Notably, the adapted Cochran's Q test within the framework of neutrosophic statistics will revert to the conventional Cochran's Q test within the scope of classical statistics when no degree of ambiguity is evident in the dataset. This adapted Cochran's Q test, grounded in neutrosophic statistics, can be effectively employed to assess the null hypothesis under conditions of uncertainty. Suppose that we have $n \times k$ table, suppose that $R_{iN}(i = 1, 2, 3, \ldots, n)$ denotes the row totals and $C_{iN}\left(j = 1, 2, 3, \ldots, K\right)$ denotes the column totals, suppose that C_{IK} be the total of uncertain items. The $n \times k$ table under neutrosophic statistics is designed as.

where $S_N = \sum_i R_{iN} = \sum_i C_{iN}$

The test statistic for neutrosophic Cochran's Q test is defined by

$$Q_N = Q_L + Q_U I_N; I_N \epsilon [I_L, I_U] \tag{1}$$

By following [23], the neutrosophic Cochran's Q test can be written as

Table 1 The $n \times k$ table under neutrosophic statistics

	Treatment 1	Treatment 2	…	Treatment k	Indeterminacy	Total
Block 1	X_{11}	X_{12}	…	X_{1k}	I_{11}	R_{1N}
Block 2	X_{21}	X_{22}	…	X_{2k}	I_{21}	R_{2N}
Block 3	X_{31}	X_{32}	…	X_{3k}	I_{31}	R_{3N}
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
Block n	X_{n1}	X_{21}	…	X_{nk}	I_{n1}	R_{nN}
Total	C_{1N}	C_{2N}	…	C_{kN}	C_{IK}	S_N

$$Q_N = \frac{K(k-1)\sum_j \left(C_{jL} - \overline{C}_L\right)^2}{KS - \sum_i R_{iL}^2} \pm \frac{K(k-1)\sum_j \left(C_{jU} - \overline{C}_U\right)^2}{KS - \sum_i R_{iU}^2} I_N; I_N \epsilon [I_L, I_U] \quad (2)$$

Note here that $Q_L = \frac{K(k-1)\sum_j (C_{jL} - \overline{C}_L)^2}{KS - \sum_i R_{iL}^2}$ present the test statistic under classical statistics and $\frac{K(k-1)\sum_j (C_{jU} - \overline{C}_U)^2}{KS - \sum_i R_{iU}^2} I_N$ present the indeterminate part and $I_N \epsilon [I_L, I_U]$ is the measure of indeterminacy. Not that the neutrosophic Cochran's Q test reduces to $Q_L = \frac{K(k-1)\sum_j (C_{jL} - \overline{C}_L)^2}{KS - \sum_i R_{iL}^2}$ when I_L=0. Note that neutrosophic Cochran's Q test follows the chi-square distribution with $(K-1)$ degree of freedom and $\overline{C}_N = \frac{\sum_j C_{jN}}{K}$.

The proposed neutrosophic Cochran's Q test will be used to test the null hypothesis $H_0 : K$ samples belonging to one dichotomous distribution vs. the alternative hypothesis $H_1 : K$ samples do not belong to one dichotomous distribution. The calculated value of Q_N will be compared with the tabulated value. The null hypothesis will be rejected if the calculated value of Q_N is larger than the tabulated value at the specified level of significance α.

To conduct the proposed Cochran test, follow these steps:

Step 1: set up the contingency table: create a $n \times K$ table that displays the counts of the outcome of interest for each group. The *ijth* entry in $n \times K$ table will be 0 if misclassified, the *ijth* entry in $n \times K$ table will be 1 if classified correctly, otherwise *ijth* entry in $n \times K$ table will be added for uncertain case.

Step 2: calculate the marginal totals: compute the row R_{iN}, column totals C_{iN} and total of C_{IK} for each group.

Step 3: compute the following neutrosophic Cochran statistic $Q_N \epsilon [Q_L, Q_U]$

$$Q_N = \frac{K(k-1)\sum_j \left(C_{jL} - \overline{C}_L\right)^2}{KS - \sum_i R_{iL}^2} \pm \frac{K(k-1)\sum_j \left(C_{jU} - \overline{C}_U\right)^2}{KS - \sum_i R_{iU}^2} I_N; I_N \epsilon [I_L, I_U]$$

Step 4: determine the critical value: the critical value required for the Cochran test depends on the chosen significance level (α) and the degrees of freedom. The degrees of freedom (df) is equal to $(K-1)$.

Step 5: compare the neutrosophic Cochran statistic $Q_N \epsilon [Q_L, Q_U]$ to the critical value: if the Cochran statistic is larger than the critical value, the null hypothesis is rejected; other the null hypothesis is not rejected.

Application

The application of the proposed Cochran's Q test will be given with the aid of the data obtained from the production process. In the industry, the product is manufactured under some set standard. The item manufactured according to a given set of standards is declared as a "good product" and the item not manufactured according to the given set of standards is declared as a "bad item", otherwise the item will be declared an "indeterminate/uncertain". We consider the product manufactured by 10 mechanizes on the first three days of the week. For the implementation of the proposed Cochran's Q, the good product is represented by 1, the bad product is represented by 0, and otherwise, it will be added to uncertain/indeterminate items. The

Table 2 The production data

Machines	Monday	Tuesday	Wednesday	Number of uncertain items	Total
1	1	1	1	0	[3, 0]
2	1	–	1	1	[1, 2]
3	1	–	1	1	[1, 2]
4	0	–	1	1	[1]
5	–	–	1	2	[1, 2]
6	–	1	–	2	[1, 2]
7	0	1	–	1	[1]
8	1	–	0	1	[1]
9	–	0	1	1	[1]
10	–	1	–	2	[1, 2]
Total	[4]	[4]	[6]	[12]	[26, 26]

Note that 1 presents good, 0 presents bad,—shows uncertainty in labeling

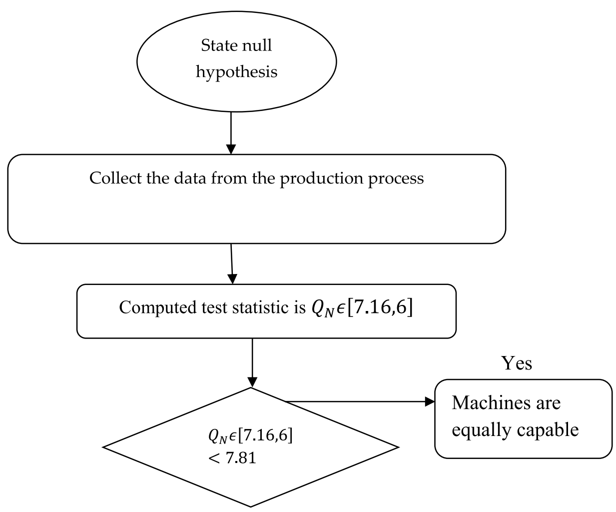

Fig. 1 The procedure of the proposed Cochran's Q test for production data

layout of the proposed Cochran's Q test is shown in Table 2. The row totals R_{iN} and column totals are also shown in Table 2. Here K=4 and $S = [26, 26]$. The neutrosophic Cochran's Q test for the data is given as $Q_N = 7.16 - 6I_N; I_N \epsilon [0, 0.1933]$. The tabulated value when $\alpha = 0.05$ is 7.81. The proposed test for the data is given as.

Step 1:H_0: the machines are equally capable during the first three days of the week vs. H_1: the machines are not equally capable during the first three days of the week.

Step 2: COMPUTED value of the neutrosophic Cochran statistic is $Q_N \epsilon [7.16, 6]$

Step 3: the critical value required for the Cochran test is 7.81.

Step 5: as $Q_N \epsilon [7.16, 6]$ is less than the critical value of 7.81, the null hypothesis is not rejected.

Based on the analysis, it is concluded that the machines are equally capable during the first three days of the week. The operational procedure of the proposed test for the production data is explained with the help of Fig. 1.

Comparative study

As previously mentioned, the proposed Cochran's Q test is an extension of the classical Cochran's Q test, specifically designed for neutrosophic statistics. When there is no uncertainty present in the data, the proposed test reduces to the classical version. In the previous section, using the given data, the calculated neutrosophic form of the test statistic was determined to be $Q_N = 7.16 - 6I_N; I_N \epsilon [0, 0.1933]$, where $I_N \epsilon [0, 0.1933]$. It is important to note that the value 7.16 represents the test statistic under classical statistics, while the term $6I_N$ denotes the indeterminate part with a degree of uncertainty of 0.1933. This analysis emphasizes that in an uncertain environment, decision-making should not solely rely on the determinate value of 7.16. Instead, decision-makers need to be aware that the value of the test statistic can range from 7.16 to 6, depending on the degree of uncertainty, which in this case is 0.1933. Therefore, when employing the proposed Cochran's Q test, decision-makers should consider both the determinate value and the degree of uncertainty associated with it. Furthermore, it is worth noting that the existing Cochran's Q test mentioned in [23] provides a decision on whether to reject or not reject the null hypothesis. In contrast, the proposed test offers additional information regarding the degree of indeterminacy when implementing Cochran's Q test. Taking all these factors into account, the analysis leads to the conclusion that the proposed Cochran's Q test is more suitable for application under uncertainty compared to the traditional Cochran's Q test. By incorporating the concept of neutrosophic statistics and providing insights into the degree of indeterminacy, the proposed test offers decision-makers a more comprehensive framework for making informed judgments in uncertain scenarios.

Simulation study

Now, let us delve into the impact of the degree of indeterminacy on the test statistic. In this simulation study, we assume the neutrosophic form of the test statistic as $Q_N = Q_L - Q_U I_N$, where $I_N \epsilon [I_L, I_U]$, and Q_L is equal to Q_U. For the sake of illustration, let's take Q_L to be 7.16, which results in $Q_N = 7.16 - 7.16I_N$, with $I_N \epsilon [0, I_U]$. To investigate the effect of the degree of indeterminacy, we examine the values of the test statistic $Q_N \epsilon [Q_L, Q_U]$ for various degrees of impression, as presented in Table 2. Assuming α to be 0.05 and the tabulated value to be 7.81, we also provide the decisions regarding the null hypothesis at different values of $I_N \epsilon [I_L, I_U]$ in the same table. Analyzing the results in Table 2, we observe that there is a decreasing trend in the range of $Q_N \epsilon [Q_L, Q_U]$ as the degree of uncertainty increases. For instance, when $I_U = 0.01$, the resulting test statistic value is $Q_N \epsilon [7.16, 7.0884]$, whereas for $I_U = 0.90$, the resulting test statistic value is $Q_N \epsilon [7.16, 0.716]$. This analysis highlights that the measure of uncertainty significantly affects the range of the test statistic, $Q_N \epsilon [Q_L, Q_U]$. Although the decision regarding the null hypothesis remains "Do not reject H_0" in both cases, it is important to note that the decrease in the range of $Q_N \epsilon [Q_L, Q_U]$ increases the error rate and, consequently, reduces

Table 3 The effect of I_N on $Q_N\epsilon[Q_L, Q_U]$

$I_N\epsilon[I_L, I_U]$	$Q_N\epsilon[Q_L, Q_U]$	Decision on H_0
$I_N\epsilon[0, 0.01]$	[7.16, 7.0884]	Do not reject H_0
$I_N\epsilon[0, 0.05]$	[7.16, 6.802]	Do not reject H_0
$I_N\epsilon[0, 0.10]$	[7.16, 6.444]	Do not reject H_0
$I_N\epsilon[0, 0.15]$	[7.16, 6.086]	Do not reject H_0
$I_N\epsilon[0, 0.20]$	[7.16, 5.728]	Do not reject H_0
$I_N\epsilon[0, 0.25]$	[7.16, 5.37]	Do not reject H_0
$I_N\epsilon[0, 0.30]$	[7.16, 5.012]	Do not reject H_0
$I_N\epsilon[0, 0.35]$	[7.16, 4.654]	Do not reject H_0
$I_N\epsilon[0, 0.40]$	[7.16, 4.296]	Do not reject H_0
$I_N\epsilon[0, 0.45]$	[7.16, 3.938]	Do not reject H_0
$I_N\epsilon[0, 0.50]$	[7.16, 3.58]	Do not reject H_0
$I_N\epsilon[0, 0.60]$	[7.16, 2.864]	Do not reject H_0
$I_N\epsilon[0, 0.70]$	[7.16, 2.148]	Do not reject H_0
$I_N\epsilon[0, 0.80]$	[7.16, 1.432]	Do not reject H_0
$I_N\epsilon[0, 0.90]$	[7.16, 0.716]	Do not reject H_0

the power of the test. This reduction in power can lead to incorrect decision-making. Hence, based on this simulation study, it becomes evident that the degree of uncertainty not only impacts the values of the test statistic, $Q_N\epsilon[Q_L, Q_U]$, but also diminishes the test's power, thereby potentially leading to erroneous conclusions (Table 3).

Concluding remarks

In conclusion, the proposed neutrosophic Cochran's Q test provides a modified version of the conventional Cochran's Q test that can be used to test the null hypothesis under uncertain conditions. By incorporating the concept of neutrosophic statistics, this test allows for decision-making when data is recorded with uncertainty. A comparative study was conducted to highlight the advantages of the proposed test over the classical Cochran's Q test. The proposed test, which incorporates the degree of indeterminacy, offers decision-makers a more comprehensive framework for making informed judgments in uncertain scenarios. It provides additional insights into the range of the test statistic and the degree of uncertainty associated with it, allowing for a more nuanced analysis. A simulation study was also performed to investigate the impact of the degree of indeterminacy on the test statistic. The results showed that as the degree of uncertainty increased, the range of the test statistic decreased. This reduction in the range of the test statistic decreased the test's power and increased the error rate, emphasizing the importance of considering the degree of uncertainty in decision-making. In summary, the proposed neutrosophic Cochran's Q test offers a valuable approach for testing the null hypothesis in situations involving uncertainty. By incorporating the concept of neutrosophic statistics and providing insights into the degree of indeterminacy, this test provides decision-makers with a more comprehensive understanding of the data and facilitates informed judgments in uncertain environments. The proposed test has some limitations in that the outcomes are sensitive to the degree of indeterminacy and might lead to different decisions regarding the null hypothesis. The applicability of the proposed test is limited to situations where the data contains imprecise, fuzzy, or interval observations. Various statistical properties of the proposed test can be studied as future research.

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