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A Review Article about

Spearman rank correlation Test

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Spearman Rank Correlation Coefficient Test

Abstract:

In 1942, Wolfowitz used the phrase "non-parametric" for the first time. In statistics, "non-parametric" it doesn't quite mean that you have no knowledge of the population. It usually indicates that you are aware that population data is not normally distributed. The assumptions behind parametric statistics relate to the distribution of the population from which the sample is drawn. Since nonparametric statistics do not depend on assumptions, that is, data can be collected from a sample that does not follow a specific distribution. So sometimes we call them distribution-free tests. throughout this review we will look at "Spearman Rank Correlation Coefficient Test" in non-parametric. A statistical test called the Spearman's Rank Correlation Coefficient looks at the degree, if any, of correlation between two data sets. While a scatter plot of the two data sets might suggest whether or not there is a correlation between them, Spearman's Rank provides a numerical number indicating the strength of the connection—or, conversely, the strength of the non-correlation. For researchers who are not quite sure in their mathematical abilities, it is a rather simple analysis. The researcher needs paired sets of data that are connected in some way (like the location where the data were gathered in the field) in order to use Spearman's Rank. To ensure a highly significant result, the researcher should have at least ten pairs of data to work with for the analysis. If this number is lower, the result is more likely to be the product of chance than true correlation. Computationally Spearman's correlation coefficient is simply Pearson's correlation coefficient applied to the ranks of the observations. The coefficient's value can range from -1 (perfectly negative correlation) to +1 (perfectly positive correlation), or 0 (complete independence between rankings). It offers a test of a monotonic trend in the original data because it measures the linearity of the ranked observations. It should be noted, however, that a non-monotonic trend, such as one in which Y first rises with X but subsequently falls at higher values, cannot be detected using this method. For this reason, relationships should always be plotted before the coefficient is determined.

Keywords: Non parametric, Spearman rank Correlation, Correlation Coefficient.

1. Introduction:

A nonparametric indicator of the direction and strength of a relationship between two variables measured on at least an ordinal scale is the Spearman rank-order correlation coefficient, or simply Spearman's correlation. The symbol r_s, or the Greek letter ρ, pronounced rho, is used to represent it.

When data in the form of rank orders are available, the Spearman rank correlation coefficient can be used to measure the relationship between two variables. It was intended to employ the Pearson correlation coefficient in conjunction with variables that had a normal distribution. In actual application, however, it is applied to many kinds of data sometimes in an erroneous way. With nonnormally distributed data, it could be preferable to apply a modification proposed in 1904 by eminent British psychometrician Spearman rather than the Pearson correlation coefficient. Spearman proposed a ranking system for both the values of X and Y. The calculation for the sample Pearson correlation coefficient then uses these rankings in place of the real values of Y and X. The sample Spearman rank correlation coefficient, or rs, is the outcome of this computation. The Spearman rank correlation coefficient may be used to ordinal data as well as nonnormal continuous data. Ties—where two or more subjects have precisely the same value for a variable—are likely to happen while rating the data. When two observations are tied, they are assigned the same average rank. For instance, the ranks involved are 3, 4, and 5 if three observations of X are tied for the third-smallest value. All three of the observations would be awarded a rating of 4, which is the average of these three rankings. When the Pearson method is used with the rankings, the frequency of ties has no effect on the Spearman correlation coefficient computation.

The typical process for figuring out if two variables are connected in a population involves using a sample to calculate a correlation statistic (p). The result is compared to a theoretical likelihood of an extreme result that originates from a theoretical distribution of possible possibilities. This theoretical distribution may be created by taking an endless number of samples of a certain size from a reference population that has a particular population value. There is no relationship between the two variables in the reference population that is often used to evaluate a correlation statistic. As stated otherwise, the process investigates the particular null hypothesis H_0: p = 0, which holds that there is no population association between the two variables and that the observed correlation statistic's value varies from zero solely by coincidence. The null hypothesis cannot be disproved, and no relationship is accepted if the likelihood of the observed result is greater than a predefined proportion.

1. 1. Computing the Coefficient

The formula for Spearman's rank coefficient is:

$$\rho = 1 - \frac{6\Sigma\, \mathrm{d}_i^2}{n(n^2-1)}$$

ρ = Spearman's rank correlation coefficient

di = Difference between the two ranks of each observation

n = Number of observations

1.2 Tied Ranks

If two or more data points have the same value, then they are said to be "tied," and each of their ranks may be equal to the mean of the ranks of the positions they occupy in the ordered data set. For example, In the data set 70, 74, 74, 78, and 79 kg, data 2 and 3 are tied; the mean of 2 and 3 is 2.5, so the ranks of the five data are 1, 2.5, 2.5, 4, and 5. In the data set 1.6, 1.7, 1.9, 1.9, and 1.9m, data 3, 4, and 5 are tied. The mean of 3, 4, and 5 is 4, so the ranks of the five data points are 1, 2, 4, 4, and 5.

1.3. Testing Hypotheses

The Spearman rank correlation coefficient (ρ_s), commonly known as "Spearman's rho," is an estimate of r_s, which is computed from a sample of data. ρ_s is the value that would be produced from the whole population of data from which that sample originated. In rank correlation analysis, it is typical to want to test the two-tailed hypotheses H_0: $\rho_s = 0$ vs. H_a: $\rho_s \neq 0$ (see Hypothesis Testing) in order to test the null hypothesis that there is no correlation in the population between the paired ranks. There are several tables with r_s's critical values; if r_s is higher than the applicable critical value, H_0 is rejected.

1.4. The Fisher Transformation

The Spearman correlation coefficient may be transformed using the Fisher z transformation if n is at least somewhat large.

$$z = 0.5 \ln \frac{1 + r_s}{1 - r_s}$$

2. Review:

In 2014 (Philip M. Sedgwick) published an article about Spearman's rank correlation coefficient .Researchers looked at the relationship between Australia's suicide rate and antidepressant prescription practices. Between 1991 and 2000, a retrospective investigation of national databases was conducted. Participants have to be at least 15 years old. The rates of antidepressant prescription and suicide by gender and age categories (15–24, 25–34, 35–44, 45–54, 55–64, 65–74, 75–84, and ≥85 years) were documented. The variations in suicide rates between 1986 and 1990 and 1996 and 2000 were calculated. The drug's estimated average daily dosage when taken by adults for its primary indication served as the basis for the defined daily dose. The shift in the prescription of antidepressants between 1991 and 2000 was deduced. The researchers found that between 1986 and 1990 and 1996 to 2000, there was an increase in suicide rates among younger men and women and a drop in suicide rates among older men and women. Prescription rates of antidepressants rose for both men and women in all age categories between 1991 and 2000. The relationship between shifts in suicide rates and antidepressant prescriptions was assessed using Spearman's rank correlation coefficient. There was a negative association for both men and women, with the age groups seeing the biggest decreases in suicide rates also showing the highest increases in antidepressant prescriptions. In women (r_s=−0.74; P=0.04), the correlation was significant; in males (r_s=−0.62; P=0.10), it was not. (Philip M. Sedgwick, 2014).

In 2015 (Ilaria L. Amerisea & Agostino Tarsitano) published an article about Correction methods for ties in rank correlations, The way ties are handled in rank correlation is obviously problematic and crucial as the method used may significantly affect the sign and size of the coefficients. Numerous research' empirical and theoretical conclusions demonstrate that when two or more scores are identical in one or both of the variables, the significance levels and the power of the independence tests based on rank correlations are altered. Since ties cause the absolute value of rank correlations to increase, it is preferable to fix r_h using a correction factor. This challenge may sometimes be lessened by computing or documenting the scores to extra significant numbers. Any practical technique of breaking ties may be used when the spread ($r_h^+ - r_h^-$) is near to zero, and the resulting alteration to the tests is not worth the bother. If the difference between the extremes is determined to be sufficiently great but not excessively so, a more advanced method is required. (Ilaria L. Amerisea & Agostino Tarsitano, 2015).

In 2016 (Joost C. F. de Winter, Samuel D. Gosling, Jeff Potter) published an article about Comparing the Pearson and Spearman Correlation Coefficients Across Distributions and Sample Sizes. In psychological research, the Spearman rank correlation coefficient (r_s) and the Pearson product-moment correlation coefficient (r_p) are often used. Three criteria are used to compare r_p with rs: robustness to an outlier, bias with regard to the population value, and variability. We demonstrate that, for normally distributed variables, r_p and rs have comparable expected values, but rs is more variable, particularly when the correlation is strong, using simulations from low (N ~ 5) to large (N ~ 1,000) sample sizes. Nevertheless, r_p is more variable than r_s when the variables have a large kurtosis. They then carried out a sample investigation using two Likert-type survey datasets, one with light-tailed distributions and the other with heavy-tailed distributions, as well as a psychometric dataset with symmetrically distributed data with light tails. In the psychometric dataset, r_p was less variable than r_s, which was in line with the models. r_s was less variable than r_p in survey datasets, especially those including heavy-tailed variables, and it often matched the population Pearson correlation coefficient (Rp) more closely than r_p did. Selecting r_s over r_p may minimize variability in terms of standard deviations by around 20%, according to simulations and sample studies. In contrast, the r_s and r_p standard deviations are reduced by 41% when the sample size is increased by a factor of 2. (Joost C. F. de Winter, Samuel D. Gosling, Jeff Potter, 2016).

In 2016 (Wen-Yao Zhang, Zong-Wen Wei, Bing-Hong Wang, Xiao-Pu Han) published an article about Measuring mixing patterns in complex networks by Spearman rank correlation coefficient, rather of using the Pearson coefficient to quantify the mixing patterns in complex networks, they use the Spearman rank correlation coefficient. their studies indicate that the Pearson coefficient and the Spearman coefficient result for networks of moderate size are quite similar. It is evident that the Pearson coefficient fails to show mixing patterns as network size increases, soon converges to zero. The size-independent nature of the Spearman coefficient allows it to function well in this situation anyway. Furthermore, they disclose a universal property of complex networks: the linear connection between the normalized rankings of stubs and links is suited by a linear function with a correlation coefficient equal to the Spearman coefficient. This linear connection based on the Spearman coefficient motivates us to develop a straightforward technique that enables the direct creation of networks with a specified Spearman coefficient. they demonstrate that the final network closely resembles the one achieved via the laborious process of rewiring connections. Their exponential model is really the bare minimum. In order to get better findings in future investigations, certain additional models, such the Gaussian function, might be investigated. They would then be able to comprehend the behaviors and architecture of their real-world networks better. (Wen-Yao Zhang, Zong-Wen Wei, Bing-Hong Wang, Xiao-Pu Han, 2016).

In 2017 (Oscar L. Olvera Astivia, and Bruno D. Zumbo) published an article about the population models and simulation methods of the Spearman rank correlation. This work was primarily focused on two objectives: one was to educate the technique of Monte Carlo simulations in the behavioral sciences more generally, and the other was to particularly address the simulation studies of the Spearman rank correlation coefficient. In order to help psychologists and educational researchers with a qualitative bent become familiar with some of the formalism regarding the rank correlation and how this formalism helps guide the design and implementation of simulation studies, the theoretical derivations and simulation study results presented here were intended to achieve both goals. The population model for Spearman's rho underscores the concept that this kind of correlation estimates a parameter whose characteristics may or may not coincide with those of the Pearson product-moment correlation coefficient (Borkowf, 2002). Despite this, there are instances in the literature where the Pearson and Spearman correlations are interpreted as if they consistently pertain to the same population parameter. To the best of the authors' knowledge, this paper is one of the rare ones in the quantitative behavioral sciences literature where the data-generation mechanism and the theoretical model underlying the Spearman rank correlation match. Additionally, the results of the simulation study vary depending on the simulation design employed. (Oscar L. Olvera Astivia and Bruno D. Zumbo, 2017).

In 2018 (ToruKitagawa, MartinNybom, and JanStuhler) published a paper about Measurement Error and Rank Correlations. In order to account for mistakes in variable biases in the estimate of rank correlation coefficients (Spearman's and Kendall's), this study describes and suggests a technique. Firstly, we study the adequate circumstances that cause the sample rank correlations to be biased toward zero due to measurement errors. Next, we provide a workable nonparametric bias-corrected estimator that utilizes the small error variance approximation approach. We evaluate its effectiveness in both empirical and simulated applications, estimating intergenerational rank correlations in income using extensive Swedish data. In modestly large samples (n = 1,000), the technique already lowers the mean squared error by 50–85 percent, demonstrating its effectiveness in both scenarios. (ToruKitagawa, MartinNybom, and JanStuhler, 2018).

In 2018 (Qi Liu, Chun Li, Valentine Wanga and Bryan E. Shepherd) published an article about Covariate-Adjusted Spearman's Rank Correlation with Probability-Scale Residuals. Spearman's rank correlation should be modified for variables, yet current methods have drawbacks. For instance, the conditional Spearman's correlation specified using copulas cannot be readily applied to discrete variables, and the generally defined partial Spearman's correlation lacks a logical population parameter. Using concordance–discordance probabilities, we establish population parameters for both partial and conditional Spearman's correlation. The definitions apply to any orderable random variable and are generic expansions of Spearman's rank correlation in the presence of covariates. We demonstrate that probability-scale residuals (PSRs) provide a clean expression for them. (Qi Liu, Chun Li, Valentine Wanga and Bryan E. Shepherd, 2018).

In 2021 (Svetlana K. Eden, Chun Li, Bryan E. Shepherd) published an article about Nonparametric estimation of Spearman's rank correlation with bivariate survival data. Two nonparametric techniques for measuring correlation with bivariate right-censored data have been put forward by us. Within a limited area, Spearman's correlation is calculated using one estimator, $\hat{}\rho S|\Omega R$. By computing Spearman's correlation for an estimable bivariate distribution, the alternative estimator, $\hat{}\rho H\ S$, is comparable to allocating the highest rank values to data that has been censored outside of the estimable zone. For the total Spearman's correlation, $\hat{}\rho H\ S$ is consistent with unbounded censoring. Since most events occur in the confined zone under generalized type I censoring, $\hat{}\rho H\ S$ may be thought of as an approximation of the total Spearman's correlation. Our techniques offer potential benefits over parametric and semiparametric approaches since they do not presuppose either joint parametric distributions or marginal distributions. The primary reasons for our estimators' limitations are related to the difficulties in nonparametrically estimating the bivariate survival surface. (Svetlana K. Eden, Chun Li, Bryan E. Shepherd, 2021).

In 2022 (Essam F. El-Hashash and Raga Hassan Ali Shiekh) published an article about the correlation coefficient is one of the most widely used statistical metrics in all domains and areas of science, particularly statistics. Based on data on quantitative characteristics of cotton, this research compared the performances of the Pearson (), Spearman's Rank (), and Kendall's Tau () correlation coefficients under three sample sizes. The study's descriptive statistics demonstrated the existence of genetic diversity for the properties of cotton under investigation. Under the three sample sizes, the amount, direction, and significance of the correlation determined by varied sometimes from the other approaches; the converse was true for and. Under N = 30 observations and under N = 20 observations showed the greatest number of positive correlations among the qualities under study. Since they had the lowest RMSE values, the correlation approaches that were investigated in terms of their performance were found to be excellent estimators of correlation: t and appea. The N = 10 and N = 20 as well as the N = 30 groups had the greatest RMSE values. In this investigation, where the PCA1 was substantially positively connected with the three techniques examined for N = 10 observations as well as with and for N = 20 observations, the PCA findings may be relevant and helpful. (Essam F. El-Hashash and Raga Hassan Ali Shiekh, 2022).

In 2023 (Mahmoud Eltehiwy, Abu Bakr Abdul-Motaal) published an article about A new Method for Computing and Testing The significance of the Spearman Rank Correlation. The Spearman correlation coefficient is employed as a test statistic, and the differences between ranks are utilized to calculate and assess the significance of the Spearman rank correlation coefficient. An effective rank correlation formula similar to the one previously developed by Spearman has been presented in this work. Unlike Spearman's formula, which is based on the difference between the rankings, this formula is based on a novel statistic that relies on the total of the ranks. Real data was used to create and test the formula. Therefore, the outcome indicates that the formula yields the same result as Spearman's formula if there are no connections in the data. The formula is easy to use and does not compute with a negative sign. By using the precise distribution of the Spearman rank correlation coefficient, they determine the precise distribution of the new test statistic and elucidate the link between it and the correlation coefficient. In the event that there are no ties, this formula should be used. They created a different method for calculating and evaluating the rank correlation coefficient's significance. For this reason, they used the sums of rankings rather than the differences between ranks, and a novel test statistic is presented. They demonstrated how RS and the new test statistic relate to one another. Using the precise distribution of r_s, they created the exact distribution of the new test statistic. The findings of the Spearman correlation coefficient test statistic and the new test statistic, which is used to evaluate the significance of the rank correlation coefficient, are identical. (Mahmoud Eltehiwy, Abu Bakr Abdul-Motaal, 2023).

3. Discussion and Comparison

Instead of using the Pearson coefficient to quantify the mixing patterns in complex networks, they use the Spearman rank correlation coefficient. Their studies indicate that the Pearson coefficient and the Spearman coefficient results for networks of moderate size are quite similar. It is evident that the Pearson coefficient fails to show mixing patterns as network size increases and soon converges to zero. The size-independent nature of the Spearman coefficient allows it to function well in this situation anyway. In psychological research, the Spearman rank correlation coefficient (r_s) and the Pearson product-moment correlation coefficient (r_p) are often used. Three criteria are used to compare r_p with rs: robustness to an outlier, bias with regard to the population value, and variability. We demonstrate that, for normally distributed variables, r_p and r_s have comparable expected values, but r_s is more variable, particularly when the correlation is strong, using simulations from low (N ~ 5) to large (N ~ 1,000) sample sizes. Nevertheless, r_p is more variable than r_s when the variables have a large kurtosis. They then carried out a sample investigation using two Likert-type survey datasets, one with light-tailed distributions and the other with heavy-tailed distributions, as well as a psychometric dataset with symmetrically distributed data with light tails. In the psychometric dataset, r_p was less variable than r_s, which was in line with the models. r_s was less variable than r_p in survey datasets, especially those including heavy-tailed variables, and it often matched the population Pearson correlation coefficient (Rp) more closely than r_p did. Selecting r_s over r_p may minimize variability in terms of standard deviations by around 20%, according to simulations and sample studies. In contrast, the r_s and r_p standard deviations are reduced by 41% when the sample size is increased by a factor of. The Spearman correlation coefficient is employed as a test statistic, and the differences between ranks are utilized to calculate and assess the significance of the Spearman rank correlation coefficient. An effective rank correlation formula similar to the one previously developed by Spearman has been presented in this work. Unlike Spearman's formula, which is based on the difference between the rankings, this formula is based on a novel statistic that relies on the total of the ranks. Real data was used to create and test the formula. Therefore, the outcome indicates that the formula yields the same result as Spearman's formula if there are no connections in the data. The formula is easy to use and does not compute with a negative sign. By using the precise distribution of the Spearman rank correlation coefficient, they determine the precise distribution of the new test statistic and elucidate the link between it and the correlation coefficient. In the event that there are no ties, this formula should be used. They created a different method for calculating and evaluating the rank correlation coefficient's significance. For this reason, they used the sums of rankings rather than the differences between ranks, and a novel test statistic is presented. They demonstrated how RS and the new test statistic relate to one another. Using the precise distribution of r_s, they created the exact distribution of the new test statistic. The findings of the Spearman correlation coefficient test statistic and the new test statistic, which is used to evaluate the significance of the rank correlation coefficient, are identical.

4. Conclusion

In summary, this thorough examination highlights the critical function of the Spearman rank correlation coefficient across a wide range of scientific fields. The research shows that the Spearman coefficient provides a size-independent solution and, in contrast to the Pearson coefficient, retains its efficacy in capturing mixing patterns as the sample size grows. In psychological research, the robustness of r_s is shown by comparing the Spearman (r_s) and Pearson (r_p) coefficients. This is especially true in situations where there are significant correlations or heavy-tailed distributions. Furthermore, by creating a new rank correlation formula and test statistic that coincide with the Spearman correlation coefficient, correlation studies become more effective and applicable. Notwithstanding, the research recognizes constraints associated with nonparametric estimation difficulties, namely in the estimation of bivariate survival surfaces. The practical difficulties in managing ties in rank correlation are discussed, with a focus on the significance of suitable correction factors. In addition to offering strategies based on spread size, the research sheds light on breaking ties and strengthens rank correlation studies. Additionally, the work presents a nonparametric bias-corrected estimator for rank correlation coefficients and illustrates how it may be used to reduce mean squared error in simulated and empirical situations. Lastly, the study's practical applicability is shown by the correlation analysis used to examine Australia's suicide rate and antidepressant prescribing procedures. The link between antidepressant prescriptions and suicide rates is negatively correlated, especially in certain age groups. This highlights the usefulness of correlation analysis in explaining intricate social phenomena. To sum up, this study succeeds in accomplishing its two goals of furthering methodological issues and offering helpful advice on correlation analysis. The Spearman rank correlation coefficient is highlighted in this study, and the improvements and uses that are suggested make it an invaluable tool for scientists and researchers in a variety of fields.

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