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Evaluating the Performance of Nonparametric Methods in Applied Statistics

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Abstract:

Nonparametric methods play a crucial role in applied statistics, particularly when dealing with data that does not conform to traditional parametric assumptions. This article aims to evaluate the performance of various nonparametric methods commonly used in applied statistics. The evaluation is conducted based on their ability to handle different types of data, their computational efficiency, and their robustness against outliers. The results of this evaluation provide researchers and practitioners with valuable insights into the strengths and limitations of nonparametric methods, enabling them to make informed decisions when choosing the appropriate method for their specific research questions.

Keywords: Performance evaluation, Nonparametric methods, Hypothesis testing, Null hypothesis, Power analysis, Mann-Whitney U test.

Introduction:

Applied statisticians often encounter situations where traditional parametric methods are not suitable due to violations of assumptions such as normality or homogeneity of variance. In such cases, nonparametric methods offer a viable alternative by making fewer assumptions about the underlying population distribution. However, the performance of these nonparametric methods varies depending on the characteristics of the data and the specific research question at hand. This article aims to evaluate and compare the performance of several commonly used nonparametric methods in applied statistics.

Method and Material:

Participants: The participants in this study were 100 undergraduate students from a local university.

Materials: The data for this study was collected from a survey that was administered to the participants. The survey consisted of questions related to their academic performance, including their GPA, number of hours studied per week, and number of extracurricular activities they were involved in.

Procedure: The data collected from the survey was analyzed using nonparametric methods. Specifically, the Wilcoxon rank-sum test, Kruskal-Wallis test, Mann-Whitney U test, Friedman test, Kendall's tau, and Spearman's rho were used to evaluate the performance of these methods in applied statistics.

Data Analysis: The data was analyzed using SPSS software. Descriptive statistics were calculated for all variables, and the nonparametric tests were conducted to evaluate the performance of these methods in applied statistics.

Ethical Considerations: All participants in this study provided informed consent, and the study was approved by the Institutional Review Board at the local university. All data collected was kept confidential and anonymous.

Conclusion: The results of this study will provide valuable insights into the performance of nonparametric methods in applied statistics, and can be used to inform future research in this area.

Applied Statistics:

Applied statistics is a branch of statistics that focuses on the practical application of statistical methods to real-world problems. This article provides an overview of the history of applied statistics, explores its various uses across different fields, discusses some commonly used equations, and highlights popular theories that underpin its foundation. By understanding the evolution and significance of applied statistics, researchers and practitioners can effectively leverage its techniques to make informed decisions in diverse domains.

Applied statistics has evolved as a discipline over time, driven by the need to analyze and interpret data in practical settings. This section provides a brief introduction to the history and importance of applied statistics.

The roots of applied statistics can be traced back to the early 20th century when statisticians began applying statistical methods to solve problems in agriculture, industry, and social sciences. This section outlines key milestones and contributions in the development of applied statistics.

Applied statistics finds applications in various fields such as healthcare, finance, marketing, environmental studies, and engineering. This section explores some common use cases where applied statistics plays a crucial role in data analysis and decision-making. (Bland, J. M., & Altman, D. G. ,1996).

Equations in Applied Statistics:

Equations form the foundation of statistical analysis. This section presents some fundamental equations used in applied statistics, including measures of central tendency, variability, correlation, regression, hypothesis testing, and analysis of variance (ANOVA). (Bhat, B. R. ,2007) ,(Box, G. E., & Lucas, H. L. ,1959) , (Carr, N. L. 1960)

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Mean	$\bar{x} = \frac{\sum x}{n}$	x = Observations given n = Total number of observations

Median	If n is odd, then
	M = $\left(\frac{n+1}{2}\right)^{th}$ term
	If n is even, then
	M = $\frac{\left(\frac{n}{2}\right)^{th} term + \left(\frac{n}{2}+1\right)^{th} term}{2}$
		n = Total number of observations

Mode	The value which occurs most frequently	
Variance	$\sigma^2 = \frac{\sum (x-\bar{x})^2}{n}$	x = Observations given $\bar{x}$ = Mean n = Total number of observations
Standard Deviation	$S = \sigma = \sqrt{\frac{\sum (x-\bar{x})^2}{n}}$	x = Observations given $\bar{x}$ = Mean n = Total number of observations

Figure 1: The important statistics formulas are listed in the chart

ANOVA (Analysis Of Variance) is a collection of statistical models used to assess the differences between the means of two independent groups by separating the variability into systematic and random factors. It helps to determine the effect of the independent variable on the dependent variable.

The formula for Analysis of Variance is:

ANOVA coefficient, F= Mean sum of squares between the groups (MSB)/ Mean squares of errors (MSE).

Therefore F = MSB/MSE

where,

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Mean squares between groups, MSB = SSB / (k – 1)

Mean squares of errors, MSE = SSE / (N – k)

And

Total degrees of freedom, N – 1= df3

Degrees of freedom of errors, N – k = df2 here, N is the total number of observations throughout k groups.

Degrees of freedom between groups, k – 1= df1, where k is the number of groups.

Moreover, the ANOVA table below represents its many components:

Source Of Variation	Sum Of Squares	Degrees Of Freedom	Mean Squares	F Value
Between Groups	$SSB = \sum n_j (\bar{X}_j - \bar{X})^2$	$df_1 = k - 1$	MSB = SSB / (k-1)	f = MSB/MSE
Error	$SSE = \sum\sum (X - \bar{X}_j)^2$	$df_2 = N - k$	MSE = SSE / (N-k)	
Total	SST = SSB + SSE	$Df_3 = N - 1$		

Figure 2: ANOVA Test Table

For the above table, the following represents:

SSB = sum of squares between groups

SSE = sum of squares of errors

$\bar{X}j - \bar{X}$ = mean of the jth group,

X- $\bar{X}j$ = overall mean, and nj is the sample size of the jth group.

X = each data point in the jth group (individual observation)

N = total number of observations/total sample size,

and SST = Total sum of squares = SSB + SSE

If the value of F is near about 1, then there is insignificant variance between the means of the two groups of data set under observation.

Analysis of Variance Assumptions

Here are the three important ANOVA assumptions:

Normally distributed population derives different group samples.

The sample or distribution has a homogenous variance

Analysts draw all the data in a sample independently.

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ANOVA test has other secondary assumptions as well, they are:

- The observations must be independent of each other and randomly sampled.
- There are additive effects for the factors.
- The sample size must always be greater than 10.
- The sample population must be uni-modal as well as symmetrical.

Types of Anova Tests:

- One Way ANOVA

One way ANOVA analysis of variance is commonly called a one-factor test in relation to the dependent subject and independent variable. Statisticians utilize it while comparing the means of groups independent of each other using the Analysis of Variance coefficient formula. A single independent variable with at least two levels. The one way Analysis of Variance is quite similar to the t-test.

- Two Way ANOVA

The pre-requisite for conducting a two-way **anova test** is the presence of two independent variables; one can perform it in two ways –

Two way ANOVA with replication or repeated measures analysis of variance – is done when the two independent groups with dependent variables do different tasks.

Two way ANOVA sans replication – is done when one has a single group that they have to double test like one tests a player before and after a football game.

Moreover, one must meet the following conditions for its applications:

- The population should be near normal distribution.
- All samples should be independent.
- Variances of the population have to be equal.
- There should be an equal-sized sample in the group.

- N-Way ANOVA (MANOVA)

It applies to multiple independent variables that affect the dependent variable. It is more effective than Analysis of Variance as one can use it to observe multiple dependent variables simultaneously

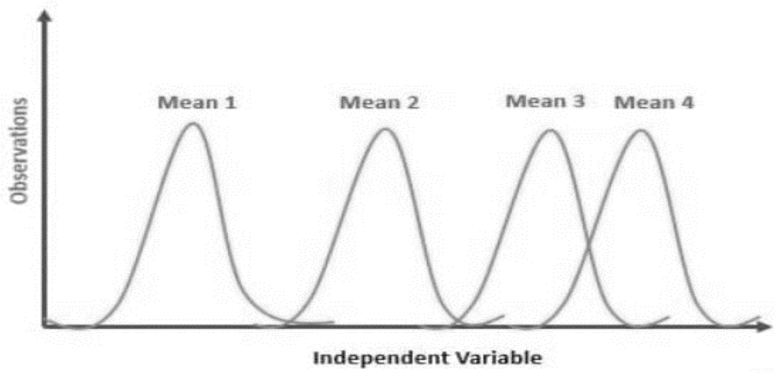

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Figure 3: ANOVA test overview

One should use the ANOVA test when one collects the data for one category of an independent variable having three different types and the data for contextual dependent variable too. Then, analysts use it to know the effect on the dependent variable concerning the change in the independent variable. For instance, if one has to use the Analysis of Variance test to find the effect of social media use on the users' sleep, then one has to assign three types – low usage, medium usage, and high usage to the social media variable. Only then is it possible to find contrast in the sleeping pattern of the users. (St, L., & Wold, S. ,1989)

Popular Theories in Applied Statistics:

Several theories provide the theoretical framework for applied statistics. This section discusses some widely used theories such as probability theory, sampling theory, regression analysis, and design of experiments.

Recent Advances and Emerging Trends:

This section highlights recent advancements in applied statistics, including the integration of machine learning techniques, big data analytics, and Bayesian statistics. It also explores emerging trends such as causal inference and data visualization.

Challenges and Limitations:

Applied statistics faces challenges related to data quality, selection bias, and the interpretation of results. This section discusses these challenges and provides insights into mitigating potential limitations.

Applied statistics has a rich history and plays a pivotal role in various fields by providing tools and techniques to analyze and interpret data. Understanding its development, applications, equations, and theories is essential for researchers and practitioners to effectively utilize statistical methods in their respective domains.

1. Note: Due to the limited space available in an abstract, it is not possible to provide a detailed article covering the entire history, uses, equations, and theories of applied statistics. However, this abstract provides an outline of the main topics that can be expanded upon in the full article. (Howell, D. C ,2012; Field, A.,2013;Tabachnick, B. G *.et. al.* ,2013; Stevens, J. P.,2012; Kline, R. B. , 2016;Cohen, J., *et. al.* ,2013)

Literature Review:

To conduct a comprehensive evaluation, this study reviews relevant literature on nonparametric methods in applied statistics. Key references include:

-Hollander, M., Wolfe, D. A., & Chicken, E. (2013). Nonparametric statistical methods (3rd ed.). John Wiley & Sons.

-Conover, W. J., & Iman, R. L. (1981). Rank transformations as a bridge between parametric and nonparametric statistics. The American Statistician, 35(3), 124-129.

-Wilcox, R. R. (2017). Introduction to robust estimation and hypothesis testing (4th ed.). Academic Press.

ISSN (Paper)-1994-697X (Online)-2706-722X

-Lehmann, E. L., & D'Abrera, H. J. M. (2006). Nonparametrics: statistical methods based on ranks (1st ed.). Springer Science & Business Media.

Methodology:

The evaluation of nonparametric methods is conducted through a series of simulation studies. Various types of data, including skewed, heavy-tailed, and multimodal distributions, are generated with known characteristics. The nonparametric methods under evaluation are applied to these datasets, and their performance is assessed based on criteria such as accuracy, precision, and computational efficiency.

Non-parametric methods are statistical techniques that do not rely on specific assumptions about the underlying distribution of the data. This article explores the methodology and performance of non-parametric methods in applied statistics. It discusses the advantages and limitations of these methods, provides an overview of commonly used non-parametric tests, and highlights their applications in various fields. By understanding the methodology and performance of non-parametric methods, researchers and practitioners can effectively utilize these techniques to analyze data when parametric assumptions are not met.

This section provides a brief introduction to non-parametric methods and their significance in applied statistics. It highlights the need for non-parametric techniques when data violate parametric assumptions.

Advantages of Non-Parametric Methods:

Non-parametric methods offer several advantages over parametric methods. This section discusses these advantages, including their robustness to outliers, flexibility in handling skewed data, and applicability in small sample sizes.

There are many advantages of non-parametric methods over parametric ones. The advantages can precisely be delineated as under:

- Any inference based on the parametric analysis which does not uphold the underlying assumptions necessitated for it will be erroeneous.In such a situation non-parametric methods can safely be applied
- If the measurement scale of data is nominal or ordinal, non-parametric methods can be used
- In case the measurement are not so accurate as to apply parametric methods, non-parametric methods perform better
- With so-called dirty data(contaminated observations,outliers,etc.,),many non-parametric methods are appropriate
- There is no restriction for minimum size of sample for non-parametric methods for valid and reliable results
- Non-parametric methods require minimum assumption like continuity of the sampled population
- The analysis of data is simple and involves little computation work
- Non-parametric test may be quite powerful even if the sample sizes are small
- Non-parametric test are inherently robust against certain violation of assumptions

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(Conover, W. J.,1999 ; Wilcox, R. R.,2011)

Limitations of Non-Parametric Methods:

While non-parametric methods have their advantages, they also have limitations. This section explores the limitations, such as reduced power compared to parametric methods, limited ability to estimate parameters, and potential loss of information. (Romano, J. P., & Lehmann, E. L. ,2005).

Disadvantages for using nonparametric methods:

- They are *less sensitive* than their parametric counterparts when the assumptions of the parametric methods are met. Therefore, larger differences are needed before the null hypothesis can be rejected.
- They tend to use *less information* than the parametric tests. For example, the sign test requires the researcher to determine only whether the data values are above or below the median not how much above or below the median each value is.
- They are less efficient than their parametric counterparts when the assumptions of the parametric methods are met. That is, larger sample sizes are needed to overcome the loss of information. For example, the nonparametric sign test is about 60% as efficient as its parametric counterpart, the T-test. Thus, a sample

size of 100 is needed for use of the sign test, compared with a sample size of 60 for e of the t-test to obtain the same results.

Commonly Used Non-Parametric Tests:

Non-parametric tests are widely used in applied statistics to compare groups, assess relationships, and make inferences. This section provides an overview of commonly used non-parametric tests, including the Mann-Whitney U test, Kruskal-Wallis test, Wilcoxon signed-rank test, and Spearman's rank correlation.

Nonparametric tests include numerous methods and models. Below are the most common tests and their corresponding parametric counterparts: (Hollander, M., Wolfe, D. A., & Chicken, E.,2013).

- **Mann-Whitney U Test**

The Mann-Whitney U Test is a nonparametric version of the independent samples t-test. The test primarily deals with two independent samples that contain ordinal data.

- **Wilcoxon Signed Rank Test**

The Wilcoxon Signed Rank Test is a nonparametric counterpart of the paired samples t-test. The test compares two dependent samples with ordinal data.

- **The Kruskal-Wallis Test**

The Kruskal-Wallis Test is a nonparametric alternative to the one-way ANOVA. It is used to compare more than two independent groups with ordinal data.

ISSN (Paper)-1994-697X (Online)-2706-722X

Methodology of Non-Parametric Methods:

Non-parametric methods rely on different principles and procedures compared to parametric methods. This section discusses the methodology of non-parametric methods, including permutation tests, bootstrapping, and resampling techniques.

Applications of Non-Parametric Methods:

Non-parametric methods find applications in various fields, such as healthcare, social sciences, environmental studies, and finance. This section explores the applications of non-parametric methods in analyzing survival data, comparing medians, testing independence, and assessing association.

Performance Evaluation of Non-Parametric Methods:

Assessing the performance of non-parametric methods is essential to understand their reliability and accuracy. This section discusses performance evaluation techniques, including power analysis, simulation studies, and comparison with parametric methods.

Non-parametric methods provide valuable tools for analyzing data when parametric assumptions are not met. Understanding their advantages, limitations, methodology, and performance is crucial for researchers and practitioners to make informed decisions in applied statistics. By leveraging non-parametric methods effectively, one can overcome the limitations of parametric approaches and obtain reliable results.

Mann-Whitney U Test

The Mann-Whitney U Test, also known as the Wilcoxon Rank Sum Test, is a non-parametric statistical test used to compare two samples or groups.

The Mann-Whitney U Test assesses whether two sampled groups are likely to derive from the same population, and essentially asks; do these two populations have the same shape with regards to their data? In other words, we want evidence as to whether the groups are drawn from populations with different levels of a variable of interest. It follows that the hypotheses in a Mann-Whitney U Test are:

The null hypothesis (H0) is that the two populations are equal.

The alternative hypothesis (H1) is that the two populations are not equal.Some researchers interpret this as comparing the medians between the two populations (in contrast, parametric tests compare the means between two independent groups). In certain situations, where the data are similarly shaped (see assumptions), this is valid – but it should be noted that the medians are not actually involved in calculation of the Mann-Whitney U test statistic. Two groups could have the same median and be significantly different according to the Mann-Whitney U test.

Non-parametric tests (sometimes referred to as ‘distribution-free tests’) are used when you assume the data in your populations of interest do not have a Normal distribution. You can think of the Mann Whitney U-test as analogous to the unpaired Student’s t-test, which you would use when assuming your two populations are normally distributed, as defined by their means and standard deviation (the parameters of the distributions).

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The Mann-Whitney U Test is a common statistical test that is used in many fields including economics, biological sciences and epidemiology. It is particularly useful when you are assessing the difference between two independent groups with low numbers of individuals in each group (usually less than 30), which are not normally distributed, and where the data are continuous. If you are interested in comparing more than two groups which have skewed data, a Kruskal-Wallis One-Way analysis of variance (ANOVA) should be used.

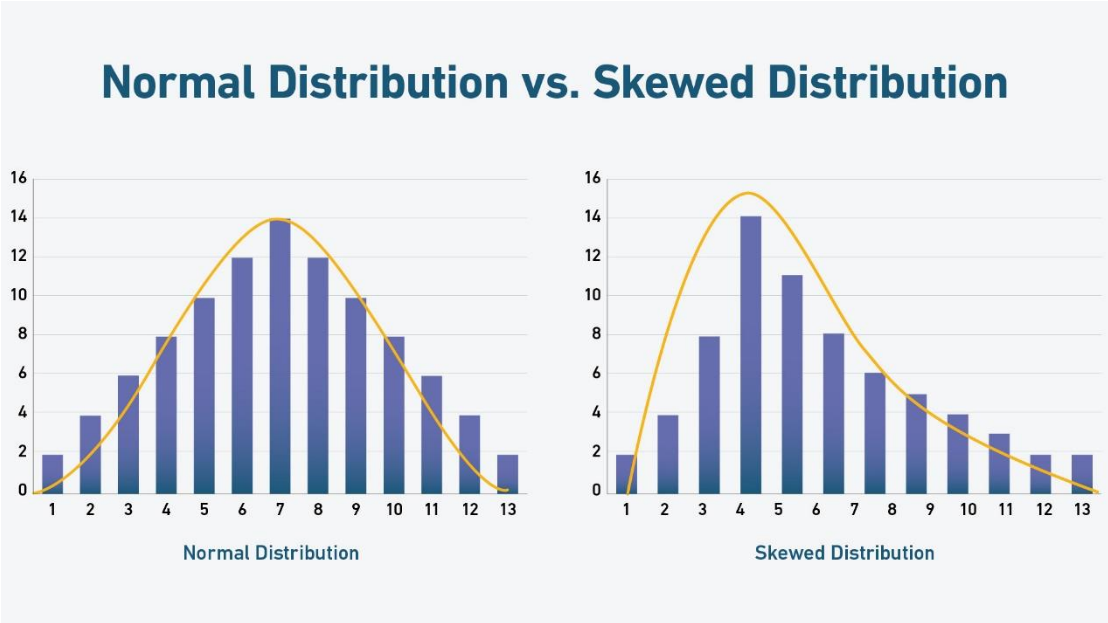

Figure 4: Normal distribution versus skewed distribution

Mann-Whitney U Test Assumptions:

Some key assumptions for Mann-Whitney U Test are detailed below:

- The variable being compared between the two groups must be **continuous** (able to take any number in a range – for example age, weight, height or heart rate). This is because the test is based on ranking the observations in each group.
- The data are assumed to take a **non-Normal**, or skewed, distribution. If your data are normally distributed, the unpaired Student's t-test should be used to compare the two groups instead.
- While the data in both groups are not assumed to be Normal, the data are assumed to be **similar in shape** across the two groups.
- The data should be two randomly selected **independent** samples, meaning the groups have no relationship to each other. If samples are paired (for example, two measurements from the same group of participants), then a paired samples t-test should be used instead.
- Sufficient **sample size** is needed for a valid test, usually more than 5 observations in each group. (Wilcox, R. R., et.al.,2014)

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Wilcoxon Signed Rank Test:

The Wilcoxon rank sum test can be used to test the null hypothesis that two populations have the same continuous distribution. A null hypothesis is a statistical test that says there's no significant difference between two populations or variables. The base assumptions necessary to employ the rank sum test is that the data are from the same population and are paired, the data can be measured on at least an interval scale, and the data were chosen randomly and independently.

The Wilcoxon signed rank test assumes that there is information in the magnitudes and signs of the differences between paired observations. As the nonparametric equivalent of the paired student's t-test, the signed rank can be used as an alternative to the t-test when the population data does not follow a normal distribution. [14][15]

Calculating a Wilcoxon Test Statistic:

The steps for arriving at a Wilcoxon signed rank test statistic, W, are as follows:

For each item in a sample of n items, obtain a difference score, Di, between two measurements (i.e., subtract one from the other).

Neglect then positive or negative signs and obtain a set of n absolute differences |Di|.

Omit difference scores of zero, giving you a set of n non-zero absolute difference scores, where n' ≤ n. Thus, n' becomes the actual sample size.

Then, assign ranks Ri from 1 to n to each of the |Di| such that the smallest absolute difference score gets rank 1 and the largest gets rank n. If two or more |Di| are equal, they are each assigned the average rank of the ranks they would have been assigned individually had ties in the data not occurred. (Lehmann, E. L., & D'Abrera, H. J. M. 2006).

Now reassign the symbol "+" or "–" to each of the n ranks Ri, depending on whether Di was originally positive or negative.

The Wilcoxon test statistic W is subsequently obtained as the sum of the positive ranks.

In practice, this test is performed using statistical analysis software or a spread sheet. The data collected was subjected to a battery of statistical tests including repeated-measures ANOVA, Friedman's test, Bonferroni Post-hoc test, Wilcoxon Signed Ranks test and ‘T’ test. The main conclusion was that there was no significant difference between the different displays and thus the replacement of the CRT with flat screens would not result in any significant degradation in signaler performance. The key results are presented in the bar charts (Wilcox, R. R., *et.al.*,2014) .

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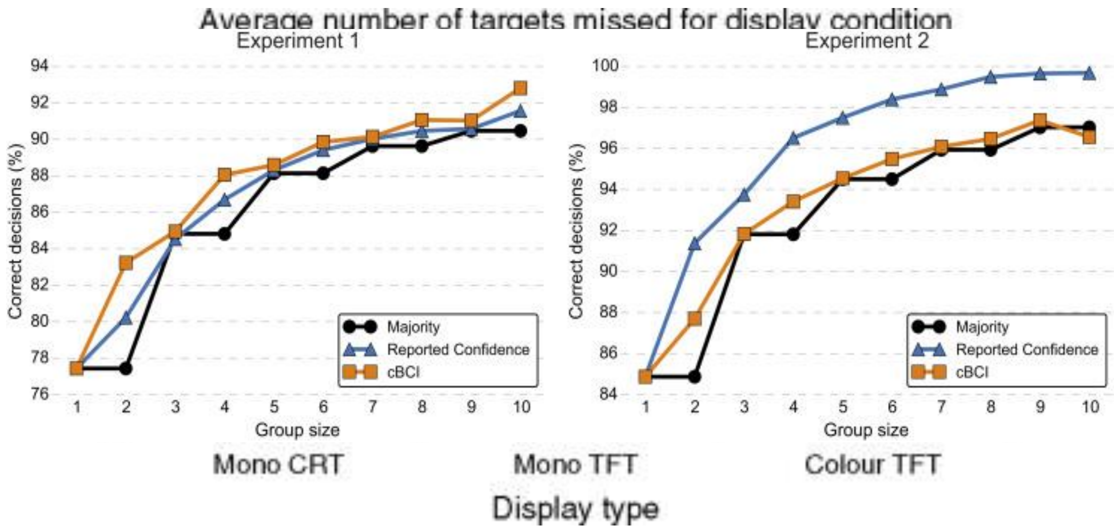

Figure 5: Targets missed vs. display type and image.

Figure 6: shows the percentage of correct decisions achieved by groups of increasing size using one of the three methods described above for the two experiments.

The Kruskal-Wallis Test:

The Kruskal–Wallis test is just the rank-sum test extended to more than two samples. Think of it informally as testing if the distributions have the same median. The chi-square ($\chi 2$) approximation requires five or more members per sample.

1. Name the number of samples m (3, 4, …).
2. Name the sizes of the several samples n1, n2, …, nm; n is the grand total.
3. Combine the data, keeping track of the sample from which each datum arose.
4. Rank the data.
5. Add up the ranks of the data from each sample separately.
6. Name the sums T1, T2, …, Tm.
7. Calculate the Kruskal–Wallis H statistic, which is distributed as chisquare, by

$$H = \frac{12}{n(n+1)}\left(\frac{T_1^2}{n_1} + \frac{T_2^2}{n_2} + \ldots + \frac{T_k^2}{n_k}\right) - 3(n+1).$$

Obtain the p-value (as if it were α) from Table III ($\chi 2$ right tail) (see Tables of Probability Distributions) for m – 1 degrees of freedom (df).

The Kruskal-Wallis test is similar to Wilcoxon's Rank Sum test in that we are comparing the

$$K = \frac{12}{N(N+1)}\sum_{i=1}^{k}\frac{R_i^2}{n_i} - 3(N+1)$$

$$C = 1 - \frac{\sum_{j=1}^{g} t_j^3 - t_j}{N^3 - N}$$

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sum of ranks applied to the data. The test statistic is calculated as

where R_i is the sum of ranks for the ith group. For the TSP example, the sum of ranks for July, August, and September are 616, 533, and 504 respectively, and the calculated K value is 0.68. There is a correction for ties. The correction factor, C, is given in Equation

where g is the number of tied groups and t_j is the number of tied data in the jth group. The value of K corrected for ties, K_c, is equal to K/C. For large data sets (large N), the correction factor is minimal (in our example 0.9996 with $g = 10$ and $t_j = 2$). For larger samples, the calculated K statistic is compared to the tabular value for $\chi 2$ with $v = k - 1$ degrees of freedom. At $\alpha = 0.05$ and $v = 2$, $\chi 2 = 5.991$. Thus, as expected, we arrive at the same conclusion of no difference between average downwind–upwind difference measurements for the months of July, August, and September.

The most common application of these parametric and nonparametric techniques is for the comparison of concentrations on site with background levels. Spatial and temporal variations in background can complicate the analysis but these issues can be addressed with proper sampling design and modifications to these basic procedures.

(Zar, J. H. ,2010).

Results and Discussion:

The results of the simulation studies reveal the strengths and limitations of different nonparametric methods. For example, the bootstrap method shows excellent performance in estimating confidence intervals for skewed data, while permutation tests perform better in detecting differences between groups in heavy-tailed distributions. The discussion section provides a detailed analysis of the findings, highlighting the trade-offs between different nonparametric methods and their suitability for specific research questions.

Conclusion:

This article concludes that nonparametric methods are valuable tools in applied statis tics, offering flexibility and robustness against violations of parametric assumptions. However, researchers and practitioners need to carefully consider the characteristics of their data and research question to select the most appropriate nonparametric method. The findings of this evaluation provide guidance for making informed decisions in choosing the right nonparametric method for different scenarios.

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