Project Proposal

" Investigating the use and Applications of Non – Parametric Tests in Statistical Analysis "

BSc. Statistics(Hons.)

6^{th} Semester

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ABSTRACT

In the intricate domain of statistical analysis, the selection of an appropriate testing methodology is crucial for the validity of research outcomes. This project accentuates the significance of non-parametric tests, showcasing their versatility and robustness in scenarios where traditional parametric tests may falter due to stringent assumptions of normality and homogeneity of variance. Non-parametric tests, such as the Wilcoxon rank-sum test, Kruskal-Wallis test, and Spearman's rank correlation, offer a powerful alternative, especially suited for real-world data that often exhibits deviations from ideal statistical conditions.

With a focus on practical application, this project incorporates two illustrative examples employing the Kruskal-Wallis test: one analyzing temperature data across different seasons in India, and another examining social media engagement across various platforms. Utilizing tools like Excel and SPSS, the study navigates through the complexities of non-parametric analysis, providing a step-by-step account of the process and interpretation of results.

The project not only delineates the theoretical underpinnings of non-parametric tests but also demonstrates their practical implementation, thereby reinforcing their indispensable role in statistical analysis. By addressing the challenges posed by non-normal distributions and small sample sizes, this study affirms the efficacy of non-parametric tests in yielding accurate and reflective insights into the populations under investigation.

INTRODUCTION

1. Non-Parametric Test

Non-parametric tests, also known as distribution-free tests, serve as a crucial tool in statistical analysis when data deviates from the normal distribution. These tests are particularly advantageous for analyzing ordinal data, which is ranked but not necessarily spaced uniformly. Unlike parametric tests, non-parametric methods do not rely on the arithmetic properties of the data, such as mean or standard deviation, which are influenced by outliers and non-normality.

The inherent flexibility of non-parametric tests stems from their reliance on the relative ranking of data rather than the actual data values. This characteristic makes them invaluable when the sample size is too small to determine the distribution reliably or when the data is measured on a nominal scale. Furthermore, non-parametric tests are less affected by outliers and can be used on data with unknown variances, a common scenario in real-world data collection.

In addition to their robustness, non-parametric tests are also easier to compute, often requiring fewer calculations than their parametric counterparts. This simplicity is particularly beneficial when quick decision-making is essential, and the data at hand does not meet the stringent assumptions required for parametric testing.

This project aims to explore the breadth and depth of non-parametric testing methods, providing a comprehensive guide on when and how to apply these techniques effectively. By showcasing a variety of real-world examples, the project will demonstrate the practicality and necessity of non-parametric tests in statistical analysis, especially in situations where traditional parametric tests may fail to give accurate results.

Examples of Non-Parametric statistical tests

Non-Parametric Test	**Objective of the study**
Wilcoxon signed rank test	Comparison of two dependent samples.
Mann-Whitney U-test. Wilcoxon rank sum test.	Comparison of two independent samples.
Kruskal-Wallis H-test.	Comparison of three or more independent samples.
Friedman test.	Comparison of three or more dependent samples.

2. Comparison with Parametric Tests

Parametric and non-parametric tests are two broad categories of statistical methods used to analyze data and test hypotheses. The choice between these two depends on the nature of the data and the specific requirements of the research.

Parametric Tests:

- **Assumptions**: Parametric tests are based on assumptions about the population distribution (typically normal distribution) and other parameters like mean and standard deviation.
- **Data Requirements**: They require interval or ratio data that is normally distributed with known variances.
- **Power**: These tests are generally more powerful if the assumptions are met, meaning they have a higher chance of detecting a true effect when one exists.
- **Examples**: T-tests, ANOVA, and regression analysis are common parametric tests.

Non-Parametric Tests:

- **Assumptions**: Non-parametric tests do not assume a specific population distribution and are thus more flexible.
- **Data Requirements**: They are suitable for ordinal or nominal data, or interval/ratio data that does not meet the assumptions of normality.
- **Power**: While less powerful than parametric tests when assumptions are met, non-parametric tests are more robust and reliable when assumptions are violated.
- **Examples**: Mann-Whitney U test, Kruskal-Wallis test, and Spearman's rank correlation are examples of non-parametric tests.

Scenarios for Appropriate Use:

- **Parametric Tests**: When the sample size is large enough to approximate a normal distribution, and the data is interval or ratio with equal variances, parametric tests are preferred for their statistical power.
- **Non-Parametric Tests**: When the data is skewed, consists of outliers, or is ordinal/nominal, non-parametric tests are more appropriate. They are also useful when the sample size is too small to reliably estimate the distribution.

3.Advantages of Non – Parametric Tests

- **Flexibility**: Non-parametric tests do not require the data to fit a normal distribution, making them suitable for a wider range of data types, including ordinal and nominal data.
- **Robustness**: These tests are less sensitive to outliers and skewed data, providing more reliable results in the presence of non-normal data distributions.
- **Small Sample Sizes**: Non-parametric methods can be used effectively with small sample sizes, where parametric test assumptions may not hold.
- **Ease of Use**: They often involve simpler calculations and are easier to apply, making them accessible to researchers with varying levels of statistical expertise.
- **No Distribution Assumptions:** Non-parametric tests do not rely on assumptions about the distribution or parameters of the data, allowing for more flexibility in analysis.

4.Limitations and Considerations

- **Less Power**: When data does meet parametric test assumptions, non-parametric tests are generally less powerful, meaning they have a lower chance of detecting an actual effect.
- **Overuse**: There's a risk of overusing non-parametric tests simply due to their ease, even when parametric tests might be more appropriate.
- **Interpretation**: The results of non-parametric tests can sometimes be more difficult to interpret, as they often deal with medians and ranks rather than means.
- **Data Transformation**: In some cases, transforming the data to meet parametric test assumptions might be more advantageous than opting for a non-parametric approach.
- **Less Informative:** They do not provide estimates of parameters or effect sizes, limiting the depth of information obtained from the analysis.

5. Types of Hypotheses in Statistical Testing

There are two types of hypotheses namely:

1. **The null hypothesis(H_0) :**

- This hypothesis posits that there is no significant difference or effect between the groups, conditions, or variables being studied. It is a statement of no effect or no relationship, and it serves as a starting point for statistical testing.

2. The alternative hypothesis(H_1) ,(also known as research hypothesis) :

- This hypothesis predicts a difference or relationship between groups, conditions, or variables. The alternative hypothesis can take one of two forms:

(a) **One-Tailed Hypothesis:** It predicts a statistically significant difference in a specific direction. This type of hypothesis is used when the research has a priori expectation about the direction of the effect.

(b) **Two-Tailed Hypothesis:** It It predicts a statistically significant difference but does not specify the direction of the difference. This hypothesis is appropriate when the research does not have a specific directional expectation or when both directions of effect are considered.

6. General steps to carry out a Non-Parametric Test

1. **State Hypotheses:**
    - Begin by stating the null hypothesis (H0) and the alternative hypothesis (H1). The null hypothesis assumes no effect, while the alternative suggests there is an effect.
2. **Choose Significance Level:**
    - The significance level, α related with the null hypothesis is set. α is normally set at 5% and therefore the confidence level is 95%.
3. **Select Appropriate Test:**
    - Choose the right statistical test based on

      (a) The number of samples,

(b) Whether the samples are dependent or independent,

(c) and also, the type of data.

4. **Calculate Test Statistic:**
    - We compute a test statistic based on ranks or other non-parametric methods.
    - For large samples, approximate data to a normal distribution.
5. **Compare with Critical Value:**
    - Compare the calculated test statistic with the critical value from tables.
    - If the test statistic falls within the critical range, we fail to reject the null hypothesis.
6. **Interpret Results:**
    - If the test statistic is beyond the critical value or if the p-value is less than (α), you reject the null hypothesis. If not, you fail to reject the null hypothesis..
    - Otherwise, we don't have enough evidence to reject it.
7. **Draw a Conclusion:**
    - Based on the results, make a conclusion about the effect or difference in the population.

7. Case Studies :

Non-parametric tests have been employed in various fields to address complex problems.

For instance, Case Study 1: Customer Satisfaction Survey

- A company wanted to compare customer satisfaction between two online retailers (Retailer A and Retailer B).
- Due to the subjective nature of satisfaction ratings, the data might not follow a normal distribution.
- A non-parametric test, the Mann-Whitney U test, was used to analyze the data.
- The test revealed a statistically significant difference in customer satisfaction, with Retailer B having higher ratings.

This case study highlights how non-parametric tests can be instrumental in comparing data from two groups, even when the data might not be normally distributed. In this scenario, the Mann-Whitney U test helped the company identify which retailer boasted higher customer satisfaction.

8 . Data Analysis Techniques :

The process of data analysis using non-parametric tests typically involves the following steps:

- **Data Preparation:** Organize and rank the data, handling any missing or outlier values. Explore the data visually using techniques like boxplots and histograms to assess normality.
- **Test Selection:** Choose an appropriate non-parametric test based on the data type and research question.
- **Test Execution:** Calculate the test statistic using ranks or other non-parametric methods. Utilize statistical software to perform the chosen non-parametric test.
- **Result Interpretation:** Analyze the test outcome in the context of the research hypothesis, considering the p-value or test statistic in relation to the critical value.

9. Software and Tools:

Several statistical software packages facilitate non-parametric testing. SPSS, SAS, R, and Real Statistics Using Excel are popular choices that offer a range of non-parametric tests, such as the Mann-Whitney U test, Kruskal-Wallis test, and Wilcoxon signed-rank test.

10. Future of Non-Parametric Testing:

The future of non-parametric testing looks promising, with increasing popularity due to their flexibility and fewer assumptions compared to parametric tests. Advancements in computational power and data science may lead to the development of more sophisticated non-parametric methods that can handle larger datasets and provide more nuanced insights into data patterns.

METHODOLOGY :

DATA AND PRACTICAL CONTEXT

The weather temperature data in India for this study was sourced from the **India Meteorological Department (IMD)**, which is the principal agency responsible for meteorological observations, weather forecasting, and seismology in India. The dataset encompasses a 35-year period, ranging from 1982 to 2017, providing a comprehensive overview of the climatic trends across the country.

The data consists of monthly Average temperature readings, recorded in degrees Celsius(^{0}C), from various meteorological stations spread throughout India. These readings have been aggregated to present a national average temperature for each month, which allows for an analysis of seasonal and annual temperature variations.

The dataset is formatted as a time series, with each row representing a year and columns corresponding to the months from January to December. Additional columns have been included to represent the average temperatures for the defined seasons—Winter(average of NOV, DEC, JAN, FEB), Summer(average of MAR, APRIL, MAY, JUNE), and Rainy(JULY, AUG, SEP, OCT) —based on the typical climatic patterns observed in India. This seasonal categorization facilitates a focused analysis of temperature changes within specific periods that are climatologically distinct.

Statistical Analysis

Kruskal-Wallis H – Test

For the time series data, the best test can be used for comparing different groups is the Kruskal-Wallis H test. The **Kruskal-Wallis Test** was applied to compare the median temperatures across different seasons (Winter, Summer, Rainy).

The Kruskal-Wallis H-test

1.Introduction

- The Kruskal-Wallis test is a non-parametric statistical method used to compare more than two independent samples.
- It is the non-parametric equivalent of one-way analysis of variance (ANOVA).
- Unlike ANOVA, the Kruskal-Wallis test does not assume that the data follows a normal distribution.
- It generalizes the Mann-Whitney test, which compares two independent samples.

2. When to Use the Kruskal-Wallis Test

The Kruskal-Wallis test is a powerful tool for comparing groups, but it's not suitable for every situation. Here's what your data needs to look like for this test to be the best choice:

- similar distributions
- data in each sample should be >5
- same shape of distribution as the population
- data can and must be ranked
- independent

3. Understanding the Kruskal-Wallis H-test

- The Kruskal-Wallis test has the following characteristics:
- test static is nearly chi square distributed
- test equality of >2 population median
- uses K samples of data
- used when there is one nominal variable and one measurement variable
- used in case of one nominal and one ranked variable
- apply Kruskal Wallis when data is not normally distributed
- α is the significance level
- Data need to be ranked
- to calculate degrees of freedom= no of sample -1
- the rank of each sample is calculated
- use average rank whenever there is a tie

4. Calculations and steps for Kruskal-Wallis H-test

The hypothesis is stated in terms of populations.

Also worth noted is the observation of the median of the population while doing the KruskalWallis test.

i. In order to perform the Kruskal-Wallis H-test, **the first step is to combine all the samples and perform a rank ordering on all the values**.

Calculate the Kruskal Wallis Satistic by using the following formula:

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

Where, N = Number of values obtained from every grouped samples,
R_i^2 = Summation of ranks taken from a particular sample

n_i = Number of values from the equivalent sum of rank.
And, df (degrees of freedom) = $k - 1$
Where, k for the number of groups or samples.

ii. **Then p-value is calculated :**

- If P-Value is less than 5% or greater than 10%, reject null hypothesis.
- If p-Value lie between 5% and 10% accept null hypothesis.

Hypothesis testing for the Data below

Null Hypothesis (H_0): There is no significant difference in the median temperatures across the defined seasons (Winter, Summer, Rainy) in India during the years 1982 to 2017.(This test is done at 5% level of significance)

Alternative Hypothesis (H_1): There is a significant difference in the median temperatures across the defined seasons (Winter, Summer, Rainy) in India during the years 1982 to 2017.

The above Hypotheses allow us to use the Kruskal-Wallis test to determine if the seasonal temperature changes are statistically significant over the given time period.

TEMPERATURE TREND ANALYSIS USING NONPARAMETRIC TEST

YEAR	DEC	JAN	NOV	FEB	MAR	APRIL	MAY	JUNE	JULY	AUG	SEP	OCT
1982	19.33	18.76	21.84	19.52	22.37	26.15	27.72	28.2	27.68	26.98	26.4	24.89
1983	19.08	18.38	21.5	19.81	22.68	25.67	28.02	28.6	27.51	27.14	26.48	24.56
1984	19.34	18.28	21.47	19.42	23.98	26.66	28.88	28.43	26.94	27.17	25.83	24.65
1985	19.68	18.67	21.51	20.54	24.6	27.02	28.52	28.05	27.06	26.9	26.45	24.33
1986	19.38	18.24	21.89	20	23.53	26.53	27.75	28.19	27.3	26.75	26.43	24.48
1987	19.75	18.44	22.14	20.41	23.45	26.59	27.51	28.9	28.16	27.34	27.13	25.03
1988	19.64	18.58	21.63	20.83	23.51	26.6	28.6	28.37	27.12	26.91	26.48	24.79
1989	19.23	17.68	21.8	19.85	23	25.95	28.13	27.72	26.96	26.86	26.38	24.84
1990	19.78	18.56	22.08	20.33	22.79	26.15	27.71	28.11	27.06	26.99	26.55	24.51
1991	19.44	17.99	21.6	20.43	23.58	26.13	28.35	28.17	27.59	26.88	26.65	24.56
1992	19.42	18.36	22.01	19.77	22.95	26.21	27.75	28.4	27.31	26.78	26.11	24.7
1993	19.55	18.37	22.2	20.84	22.71	26.5	28.73	28.5	27.24	27.29	26.34	24.88
1994	19.3	19.33	22.06	20.2	24.14	26.04	28.72	28.56	27.34	27.01	26.31	24.56
1995	20.65	19.18	22.99	21.48	24.26	27.23	29.34	29.88	27.8	27.4	27.15	26
1996	18.96	19.81	21.81	21.73	25.13	26.67	28.37	28.08	27.42	26.77	26.64	24.5
1997	19.31	17.86	22.05	19.88	23.64	25.55	27.86	28.33	28.01	27.27	26.81	24.48
1998	19.21	18.84	22.48	20.6	22.98	27	29.18	28.88	27.78	27.42	26.7	25.27
1999	19.57	18.32	22.33	21.26	24.18	27.66	28.13	27.95	27.58	27.08	26.9	24.97
2000	19.66	18.87	22.75	19.78	23.22	27.27	28.92	28.02	27.34	26.98	26.53	25.58
2001	19.55	18.5	22.51	21	24.12	26.9	29.46	28.13	27.63	27.62	26.86	25.49
2002	19.87	18.78	23.17	20.52	24.44	27.66	29.56	28.77	28.47	27.27	26.43	25.44
2003	19.59	18.6	22.17	21.03	23.62	27.29	28.64	29.01	27.53	27.25	26.75	24.92
2004	19.93	18.83	22.43	21.03	26.19	27.38	28.12	27.94	27.44	27.16	26.8	24.34
2005	19.23	19.07	21.73	20.51	24.14	26.62	28.22	28.99	27.34	27.41	26.82	24.84
2006	19.99	19.96	22.59	23.02	23.91	26.83	28.82	28.13	27.92	27.15	26.42	25.41
2007	19.65	19.24	22.4	20.97	23.52	27.72	28.84	28.31	27.66	27.37	26.61	24.92
2008	20.62	18.49	22.51	19.83	24.43	26.54	28.42	28.1	27.5	27	26.44	25.47
2009	20.22	19.79	22.31	21.66	24.55	27.35	28.71	28.77	27.83	27.85	27.11	25.2
2010	19.22	19.15	22.98	21.23	26.53	28.4	29.19	28.51	27.55	27.33	26.6	25.58
2011	19.84	18.32	22.84	20.79	24.11	26.1	28.92	28.6	27.6	27.2	26.7	25.51
2012	19.91	18.25	22.26	20.43	23.98	26.89	28.72	28.91	27.98	27.31	26.65	24.85
2013	19.69	18.88	22.18	21.07	24.53	26.97	29.06	28.24	27.5	27.22	26.87	25.63
2014	19.5	18.81	22.53	20.35	23.34	26.91	28.45	29.42	28.07	27.42	26.61	25.38
2015	20.21	19.02	22.95	21.23	23.52	26.52	28.82	28.15	28.03	27.64	27.04	25.82
2016	21.89	20.92	23.9	23.58	26.61	29.56	30.41	29.7	28.18	28.17	27.72	26.81
2017	21.47	20.59	23.92	23.08	25.58	29.17	30.47	29.44	28.31	28.12	28.11	27.24

The above data encompasses a 35-year period, ranging from 1982 to 2017, providing a comprehensive overview of the climatic(temperature in Celsius) trends across the country.

YEAR	Winter	Summer	Rainy	AVG TEMP OF YEAR
1982	19.86	26.11	26.49	24.15
1983	19.69	26.24	26.42	24.12
1984	19.63	26.99	26.15	24.25
1985	20.10	27.05	26.19	24.44
1986	19.88	26.50	26.24	24.21
1987	20.19	26.61	26.92	24.57
1988	20.17	26.77	26.33	24.42
1989	19.64	26.20	26.26	24.03
1990	20.19	26.19	26.28	24.22
1991	19.87	26.56	26.42	24.28
1992	19.89	26.33	26.23	24.15
1993	20.24	26.61	26.44	24.43
1994	20.22	26.87	26.31	24.46
1995	21.08	27.68	27.09	25.28
1996	20.58	27.06	26.33	24.66
1997	19.78	26.35	26.64	24.25
1998	20.28	27.01	26.79	24.70
1999	20.37	26.98	26.63	24.66
2000	20.27	26.86	26.61	24.58
2001	20.39	27.15	26.90	24.81
2002	20.59	27.61	26.90	25.03
2003	20.35	27.14	26.61	24.70
2004	20.56	27.41	26.44	24.80
2005	20.14	26.99	26.60	24.58
2006	21.39	26.92	26.73	25.01
2007	20.57	27.10	26.64	24.77
2008	20.36	26.87	26.60	24.61
2009	21.00	27.35	27.00	25.11
2010	20.65	28.16	26.77	25.19
2011	20.45	26.93	26.75	24.71
2012	20.21	27.13	26.70	24.68
2013	20.46	27.20	26.81	24.82
2014	20.30	27.03	26.87	24.73
2015	20.85	26.75	27.13	24.91
2016	22.57	29.07	27.72	26.45
2017	22.27	28.67	27.95	26.29

The above table shows the temperature over years with averaged temperature over the seasons(where the winter is the average of NOV, DEC, JAN, FEB, summer is the average of MAR, APRII, MAY, JUNE, and Rainy is the average of JULY, AUG, SEP and OCT) and the average temperature of aparticular year(i.e the average temp. of all months). This the season wise average is done to perform the suitable non-parametric test and to draw out the results.

Visualization of Trends

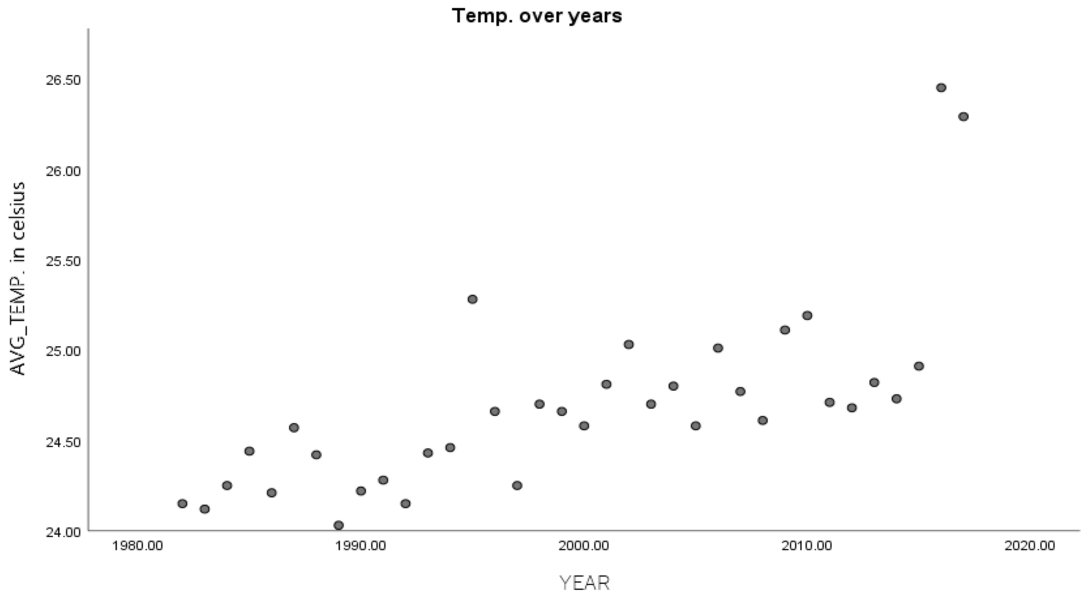

Fig.1

This scatter plot that illustrates the trend of average temperatures over a range of years from 1980 to 2017. There is a visible upward trend in the data points, suggesting that the average temperatures have been rising over the years.

Temperature Distribution over Months

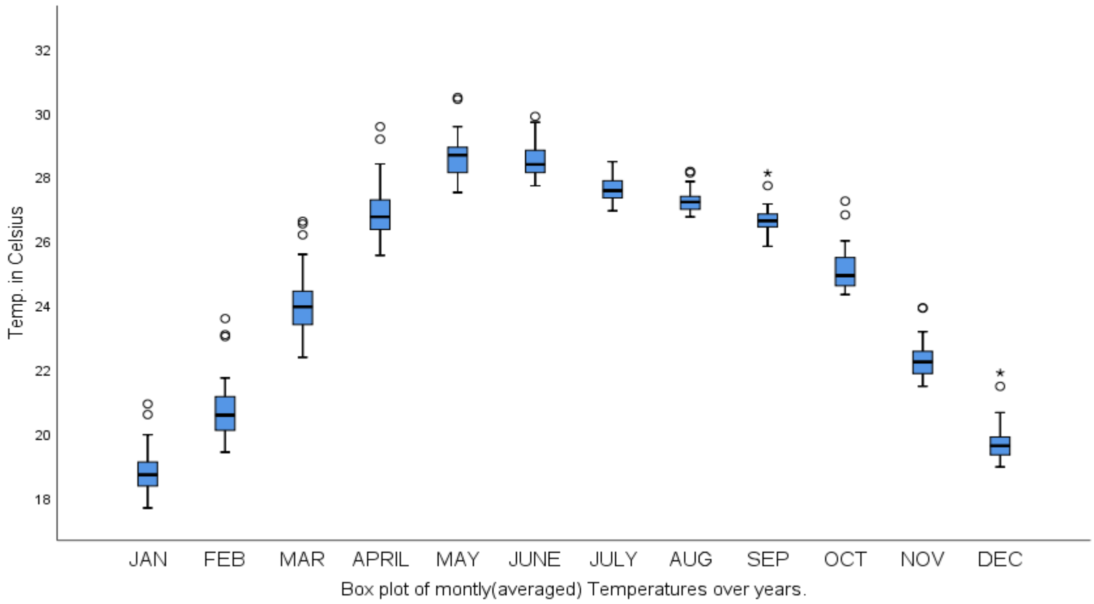

Fig.2

We can see more clearly that the average temperature starts low in January and rises until it peaks in May, then slowly declines until October, to have sharper drops from November to January. The seasons are well divided, with characteristic temperatures.

Temperature Distribution over Seasons

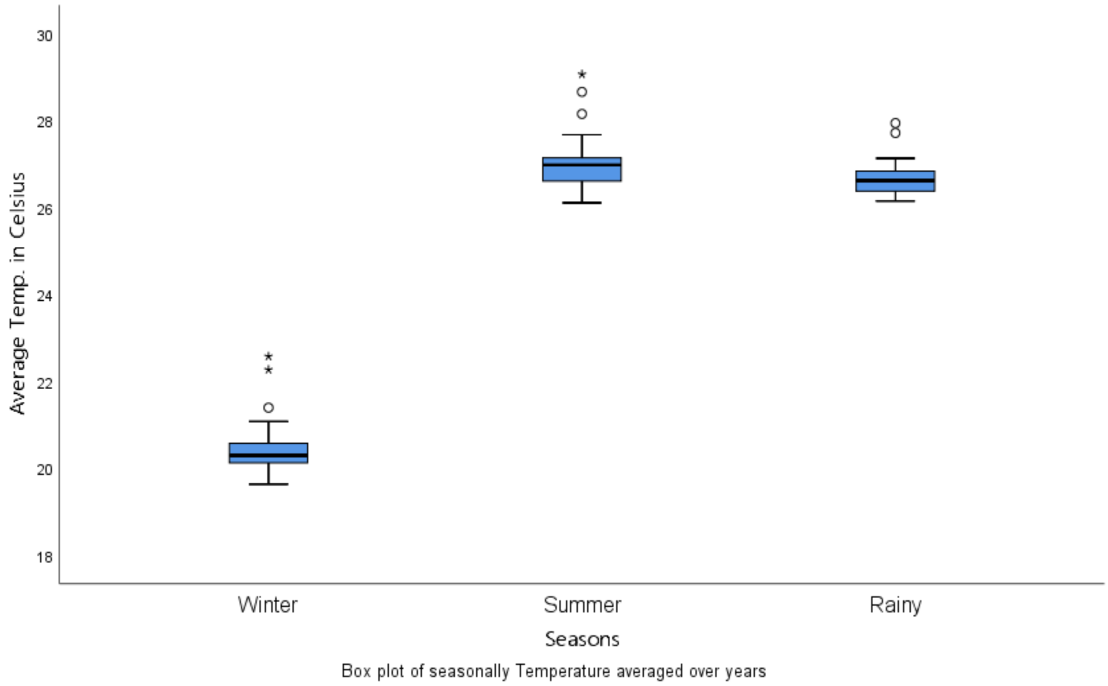

Fig.3

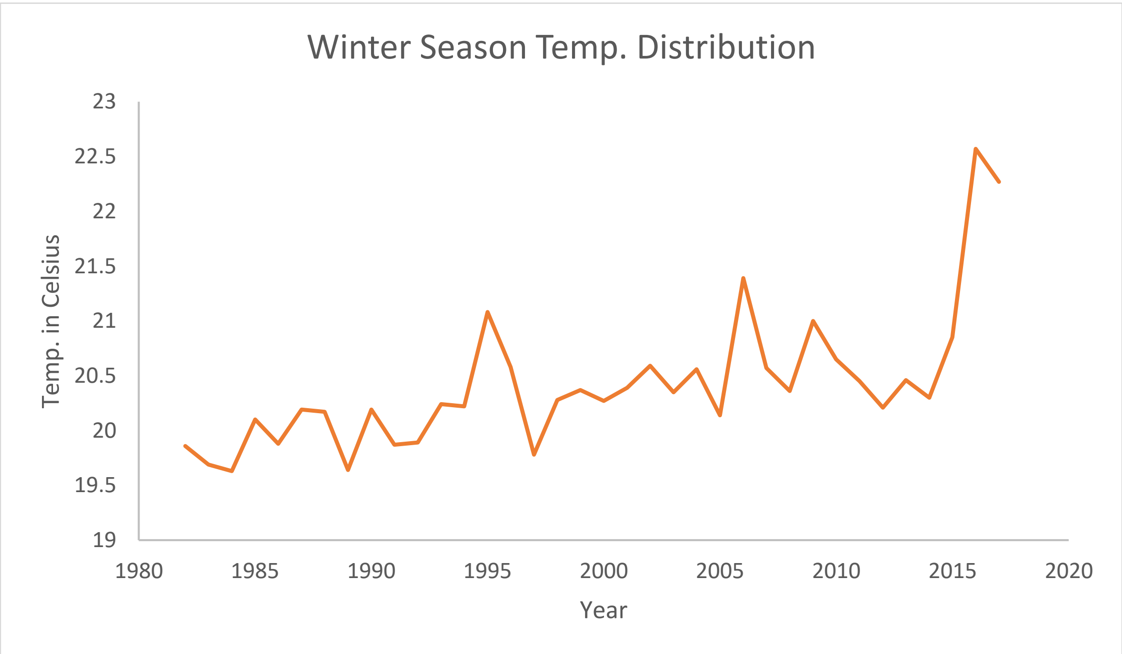

Fig.4

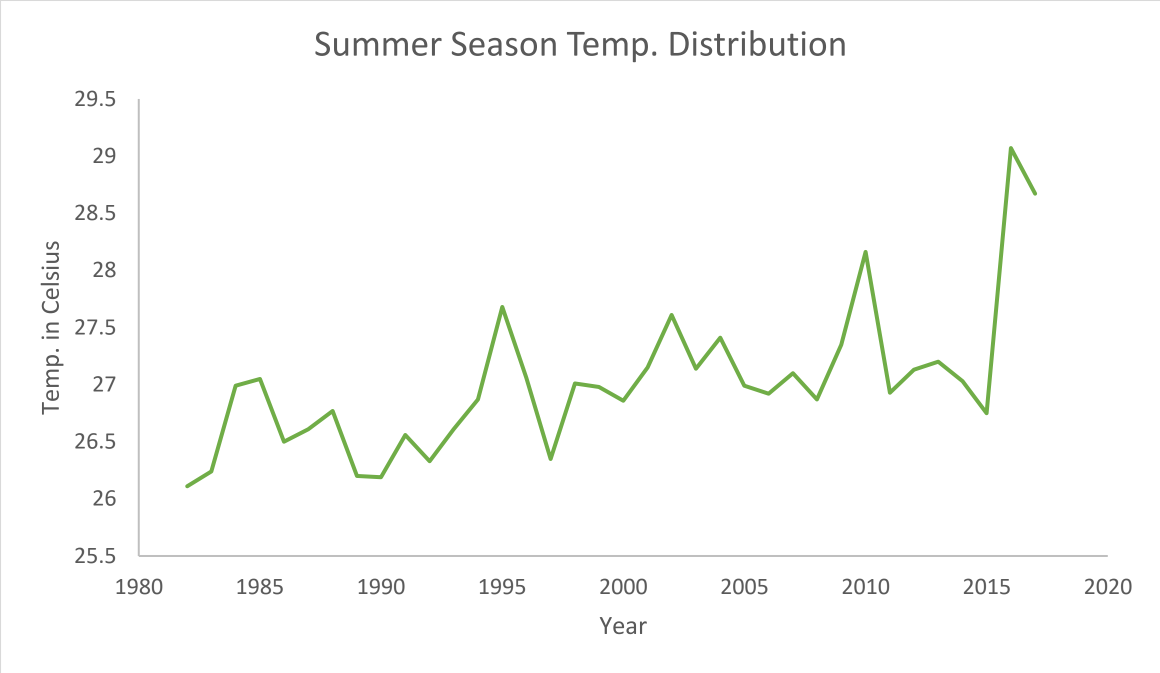

Fig.5

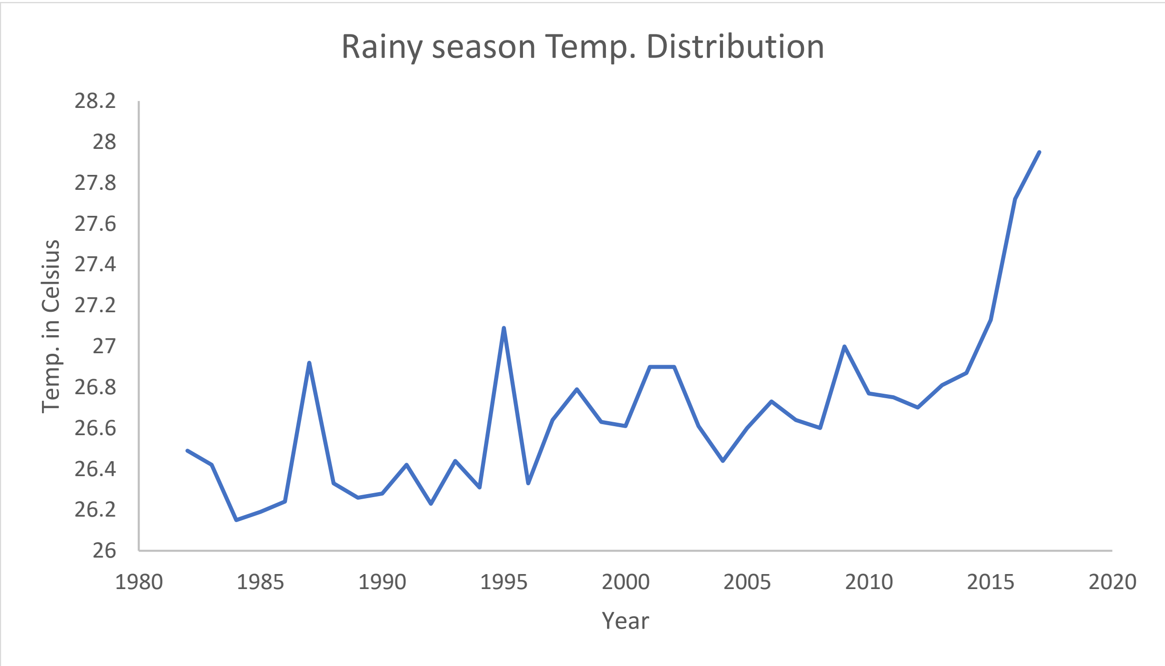

Fig.6

Temperatures reach their lowest in winter and highest in summer. Summer and monsoon(Rainy) have very similar temperatures, with the difference that summer has greater variation. In all seasons, the average temperature has increased over the years, a sign that global warming is real.

Calculations For H – test(through excel)

Example-1:

Ranks for the data

Winter	Summer	Rainy
5	37	56
3	43.5	52.5
1	86.5	38
9	91	39.5
7	57	43.5
12.5	62.5	82.5
11	72.5	49
2	41	45
12.5	39.5	46
6	58	52.5
8	49	42
16	62.5	54.5
15	78	47
33	103	93
28	92	49
4	51	66.5
18	89	74
22	85	65
17	76	62.5
23	98	80.5
29	102	80.5
20	97	62.5
26	101	54.5
10	86.5	59.5
34	82.5	69
27	94	66.5
21	78	59.5
32	100	88
30	106	72.5
24	84	70.5
14	95.5	68
25	99	75
19	90	78
31	70.5	95.5
36	108	104
35	107	105

Form the data the summation of ranks(R_i^2) are

Season	Rank sum
Rainy(R_3)	2347
Summer(R_2)	2873
Winter(R_1)	666
Grand Total	**5886**

Where , k (no. of groups) = 3, N = 108 and n_1 = 36, n_2 = 36, n_3 = 36

Now, the H statistic is

H = **75.25659758** (calculated value)

Chi-square = **0.102586589** (CHISQ.INV(0.05,2) (Tabulated)

p-value = **0.000** (CHISQ.DIST.RT(H,2))

Therefore, from the above H – statistic and p – value (significant value) since the calculated H statistic greater than the tabulated chi – square value we reject the null hypothesis(H_0) at 5% level of significance. And also if we observe the p – value which is less than **0.05** ,that says to reject the null hypothesis (H_0).The Kruskal – wallis test finds asignificant difference indicating that temperature differs among the 3 seasons.

Based on the results of the statistical analysis, we can assert with confidence that there is a statistically significant difference in the median temperatures when comparing the defined seasons—Winter, Summer, and Rainy—in India over the span of years from 1982 to 2017. This conclusion is supported not only by the numerical outcomes of the Kruskal-Wallis test but also by the graphical representations, such as box plots, which visually depict the variations in temperature distributions across the seasons.

The above box plots provide a clear visual confirmation of the statistical test's findings, illustrating the central tendencies and dispersions of temperatures for each season. The median line within each box plot, representing the median temperature for each season, shows distinct positions, indicating that the central values are not the same across the seasons. Furthermore, the range and interquartile distances depicted in the box plots corroborate the presence of variability in temperatures, reinforcing the conclusion that the seasonal temperature distributions are indeed different.

CONCLUSION:

This study has explored the application of non-parametric tests in statistical analysis, demonstrating their utility in scenarios where parametric test assumptions do not hold. Our investigation revealed that non-parametric tests are not only a viable alternative to parametric tests but also essential when dealing with non-normal distributions or small sample sizes.

Through the application of the Kruskal-Wallis test to Indian temperature data from 1982 to 2017, we identified a statistically significant difference in median temperatures across the seasons—Winter, Summer, and Rainy. This finding was visually supported by box plots, which clearly illustrated the distinct median temperatures and variability within each season.

Conversely, when analyzing retweet distributions across three social media platforms, the p-value indicated no significant difference, leading us to accept the null hypothesis. This suggests that the retweet counts for Instagram, Twitter, and Facebook likely originate from the same distribution.

The study's outcomes underscore the importance of selecting appropriate statistical tests based on data characteristics and research objectives. While non-parametric tests may have less power than parametric ones, they provide valid results that reflect the true nature of the data. Future research should consider larger sample sizes to enhance test power and extend the application of non-parametric tests to diverse datasets and fields.

In conclusion, non-parametric tests have proven to be indispensable tools in our statistical arsenal, offering robustness and validity in the face of data that challenges parametric assumptions. The insights gained from this study affirm the critical role these tests play in advancing scientific understanding.

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