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*RESEARCH ARTICLE*

# THE COMPARISON OF HYPOTHESIS TESTS DETERMINING NORMALITY AND SIMILARITY OF SAMPLES

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## ABSTRACT

*A number of hypothesis tests are used to obtain information about the characteristics of one or more populations. While parametric tests are based on the assumption of normal distribution, non-parametric tests are performed with highly ordered series from the original series. The main purpose of this study is to check whether two independent samples taken from two different populations of normally distributed samples fit the normal distribution with Kolmogorov-Smirnov and Shapiro-Wilk tests. And to determine the similarities of Kolmogorov-Smirnov and Sign test to samples with normal distribution by Wilcoxon test and those with non-normal distribution. As a result, it is aimed to compare the strength and effectiveness of the applied tests. We used the MATLAB function in our work which is considered to be useful for researchers.*

**Keywords:** *Parametric Tests, Non-parametric Tests, Kolmogorov-Smirnov, Shapiro-Wilk, Wilcoxon, Sign Tests.*

## ÖZ

*Bir ya da daha fazla yığının karakteristikleri hakkında bilgi edinmek için bir takım hipotez testleri kullanılır. Parametrik testler normal dağılım varsayımı üzerine kurulu iken, parametrik olmayan testler orijinal serilerden ziyade yüksek dereceli serilerle gerçekleştirilir. Bu çalışmanın temel amacı normal dağılımlı iki yığından alınan iki bağımsız örneğin Kolmogorov Smirnov ve Shapiro Wilk testleriyle normal dağılıma uyup uymadığının kontrol edilmesidir. Test sonucunda normal dağılıma uygun olan örneklerin Wilcoxon testi ile normal dağılıma uymayan örneklerin ise Kolmogorov Smirnov ve İşaret testi ile benzerliklerinin belirlenmesi sağlanır. Sonuç olarak uygulanan testlerin güç ve etkinliğinin karşılaştırılması hedeflenmiştir. Araştırmacılar için yararlı olduğu düşünülen çalışmamızda MATLAB fonksiyonunu kullandık.*


**Anahtar Kelimeler:** *Parametrik Olmayan Testler, Parametrik Testler, Kolmogorov-Smirnov, Shapiro-Wilk, Wilcoxon, İşaret Testi.*

## 1. INTRODUCTION

Hypothesis tests are tests that investigate whether the difference between a sample and the mean of the population in which the sample is drawn is significant. If we are interested in the difference between the averages of the two populations; we can see if the difference is correct by testing hypotheses on the difference between the averages of the samples taken from them [1].

Before performing statistical analysis, it should be checked whether the data are categorical or continuous. While non-parametric statistics are used in categorical data (sex, color, marital status), parametric statistics are used in continuous data.

Many of the traditional tests are based on the assumptions of descriptive statistical classes in the examples, also called parameters. These tests are also called parametric tests [2]. It is known that the results obtained when the parametric tests are based on the assumption of normal distribution and on abnormal distributions are not reliable [3]. If the sample size is large, deviation in the normal distribution may not significantly affect the reliability of the parametric tests (Central Limit Theorem). Non-parametric tests are done with highly ordered series from the original series. For this reason they are not affected by excessive values.

One of the assumptions of parametric tests is that the distributions of the populations in which the samples are selected are normal. When parametric tests are used, it must be ensured that this assumption about the distributions of the population is satisfied. For this reason, a number of tests are carried out for the suitability of normal distribution of selected samples. The purpose of these tests is to decide whether the sample data conforms to the predicted distribution. Goodness of fit tests can also be called for these types of tests [5].

The purpose of this study is to determine normality and similarity of the samples. Kolmogorov-Smirnov and Shapiro-Wilk tests will be used to determine normality. In the second part of our study, we will try to determine similarities of the groups of samples drawn from the populations. If both samples are normal, Wilcoxon test will be applied to parametric tests. If normal distribution is not appropriate for any of the sample groups, Kolmogorov-Smirnov and sign test will be applied for non-parametric tests. Tests related to position can also be called for these tests [5]. All tests will be carried out on different sized specimens randomly generated and taken from populations meeting normal dispersion.

## 2. GOODNESS OF FIT TESTS

Goodness of fit tests are used to determine whether the distribution of observational values in the samples conforms to a particular theoretical or experimental population distribution. The researcher who tests the goodness of fit wants to prove that he does not come normally. On the other hand, in the majority of other statistical tests it is hoped that the investigator rejects the null hypothesis, that is to say that one or more of the samples does not come from a particular kit or the same kit. It should also be noted that, if the null hypothesis is rejected, the alternative hypothesis for the goodness of fit does not predict a more suitable distribution for data [6]. Two normality tests used in the study are described in detail below.

**2.1. Shapiro-Wilk Test**

One of the tests that can be used for normality is the Shapiro-Wilk test. Generally, less than 50 observations do not yield correct results for the values [7]. Hypotheses for this test;

$H_0$: *F(x)* is a normal distribution function whose mean and variance are unknown.

$H_1$: *F(x)* isn't a normal distribution function whose mean and variance are unknown.

Let *n* be a random sample of size $X_1, X_2, X_3 ..... X_n$. For this random sample, the sequential statistics are $X_{(1)}, X_{(2)}, X_{(3)} ..... X_{(n)}$. The sum of the squares of the differences between the measured values and the arithmetic mean is denoted by *D*.

$$D = \sum_{i=1}^{n} (X_i - \overline{X})^2 \tag{2.1}$$

If the data is converted to frequency distribution;

$$D = \sum (X_i - \overline{X})^2 f_j \quad , \quad \overline{X} = \frac{\sum X_j f_j}{n} \tag{2.2}$$

formulas are used.

The $a_1, a_2, a_3 ..... a_k$ constants are found in the $a_1$ coefficient table for the Shapiro-Wilk test with $k = n / 2$ and the Shapiro-Wilk statistic indicated by *W* is defined as follows;

$$W = \frac{1}{D} \left[ \sum_{i=1}^{k} ai(X_{(n-i+1)} - X_{(i)}) \right]^2 \tag{2.3}$$

In the Shapiro-Wilk test for normality, the value calculated for the W stat is determined by the value of $P(W < W_h)$. If $P(W < W_h) < \alpha$, the $H_0$ hypothesis is rejected.

### 2.2. Kolmogorov-Smirnov Test

Kolmogorov-Smirnov is a compliance test that can be applied to continuous therapy. In a group, the Kolmogorov-Smirnov goodness-of-fit test is used to determine how well a random sample of a given distribution (flat, normal, or poisson) Using the test, it can be determined whether a series is normally distributed [3].

The distributions suggested in the Kolmogorov-Smirnov test hypothesis are made by comparison of the sample cumulative distribution function. A cumulative distribution function is defined by the following equation.

$$F(x) = P(x \leq k) \tag{2.4}$$

The solved values of this function provide the following relation for the cumulative binomial and poisson distributions.

$$P(x \leq k) = \sum_{i=1}^{k} P(x) \tag{2.5}$$

When a random sample of n volume with a cumulative distribution function unknown is selected, this data consists of independent observation results such as $x_1, x_2, x_3 ..... x_n$. $F_0(x)$ is the cumulative distribution function of the distribution given in the hypothesis, whereas the null hypothesis and the opposite hypothesis are as follows.

$H_0: F(x) = F_0(x)$, for all x values

$H_1: F(x) \neq F_0(x)$, for at least one x value

The observed cumulative distribution function $S(x)$ is the ratio of the number of sample units with values equal to or less than x to the sample volume of the number. So;

$$S(x) = \frac{\text{The number of sample units with values less than or equal to } x}{n} \tag{2.6}$$

The D statistic value is the largest vertical length between $F_0(x)$ and $S(x)$. $S(x)$ is discrete when $F_0(x)$ is continuous. For this reason, for a selected sample, there are two different results for $|S(x)- F_0 (x)|$ at the two ends of any range that *X* does not value. Because of this feature, the value of the Kolmogorov-Smirnov statistic is calculated by the following formula when $F_0 (x)$ is continuous and *S(x)* is intermittent;

$$D = TheBiggest \{\square|S(xi) - F0\,(xi)|\,, |S(xi-1) - F0\,(xi)|\ \} \tag{2.7}$$

The value calculated by this method is called the corrected value of the D statistic. If Kolmogorov-Smirnov statistic is discrete at $F_0 (x)$ then *D* calculated by;

$$D = TheBiggest\ |S(xi) - \mathbf{F0}\ (xi)| \tag{2.8}$$

## 3. SIMILARITY TESTS FOR TWO SAMPLE GROUPS

Even if one of the two independent samples does not come from the normal distribution and if the small volume samples are used, the use of the parametric tests is not correct. And also even if one of the samples does not come from a normal distribution and the sample volumes are not large enough, non-parametric tests should be preferred instead of parametric tests. In this section, the Wilcoxon for the equality hypothesis of the positional parameters of the population positions of two dependent samples and the Kolmogorov-Smirnov test for the equality hypothesis of the position parameters of the heights of the two independent samples of the mark test are introduced.

### 3.1. Wilcoxon Signed-Rank Test

When testing hypotheses in two sample problems, the Wilcoxon rank-sum test is often used to test the position parameter, and this test has been discussed by many authors over the years [14]. A nonparametric test used to determine whether two interdependent samples taken from the population show the same distribution.

$H_0$: Equal test results. The sum of positive and negative differences between test results is equal to each other.

$H_1$: Peer trial results are not equal to each other. The sum of negative differences is too small or too large compared to the sum of positive differences.

Differences between peer trial results are determined algebraically. We then take the absolute values of these differences and rank them either from the smallest to the largest or from the largest to the smallest, always taking note of the ranks of the absolute values with positive differences and those with negative differences [15]. The probability and importance of observing the $T$ statistic is determined. The probability of observing $T$ is determined in two ways, depending on the number of units [9].

i. If the unit number is $6 \leq n \leq 25$, the Wilcoxon $T$ criterion table is used. The significance of $T$ is determined by considering these $T_\alpha$ critical values.

ii. If n>25, the probability of observing $T$ and the significance of $T$ are determined by taking advantage of the assumption that $T$ statistic shows normal distribution with $\mu T$ and $\sigma^2 T$ parameters.

$$\mu T = \frac{n(n+1)}{4} \quad ; \qquad \sigma T = \sqrt{\frac{n(n+1)(2n+1)}{24}} \quad ; \qquad Z = \frac{T - \mu T}{\sigma T} \tag{3.1}$$

As a result, the test statistic is calculated by the following formula.

$$Z = \frac{T - \frac{n(n+1)}{4}}{\sqrt{\frac{n(n+1)(2n+1)}{24}}} \tag{3.2}$$

**3.2. Sign Test**

The sign test is used to test whether the distribution of sample values is random. By using the median values in the application of the test, the sample values are divided into large and small according to the media. The sign test is designed to test the hypothesis about the central location of the population distribution [4].

For two dependent samples, the sign test requires defining a new variable from the *X* and *Y* variables. As $D_i = X_i - Y_i$ ; $i = 1, 2, 3, \ldots\ldots, n$ we define this new variant as *D*;

$$\delta i = \begin{cases} 1, & Di > 0 \\ 0, & Di < 0 \end{cases} \quad \text{to be} \quad k = \sum_{i=1}^{n} \delta i \qquad (3.3)$$

is formulated.

While the null hypothesis is correct, this statistic has binomial distribution. In other words;

$$f(k) = \binom{n}{k}\left(\frac{1}{2}\right)^{k}\left(\frac{1}{2}\right)^{n-k} = \binom{n}{k}\left(\frac{1}{2}\right)^{n} \; ; k = 0, 1, 2, 3, \ldots, n \qquad (3.4)$$

The hypothesis of absence in the sign test for two dependent samples;

$H_0$: $D_i$ The median of the population of differences is zero is expressed. The decision rule for the different cases of the $H_1$ hypothesis with the value calculated for the *K* statistic being $k_h$ can be expressed as follows.

| $H_1$ | Decision Rule | |
|---|---|---|
| $D_i$ the median of differences population is less than zero | $k_h \leq k_\alpha$ | $H_0$ is rejected. |
| $D_i$ the median of differences population is greater than zero | $k_h \geq k'_\alpha$ | $H_0$ is rejected. |
| $D_i$ the median of differences population different from zero | $k_h \leq k_{\alpha/2}$ or $k_h \geq k'_{\alpha/2}$ | $H_0$ is rejected. |

$k_\alpha$ , $k'_\alpha$ , $k_{\alpha/2}$ ve $k'_{\alpha/2}$ are critical values. It is found as follows;

$$P(k_h \leq k_\alpha) = \alpha \qquad P(k_h \geq k'_\alpha) = \alpha$$
$$P(k_h \leq k_{\alpha/2}) = \alpha/2 \qquad P(k_h \geq k'_{\alpha/2}) = \alpha/2$$

**3.3. Kolmogorov-Smirnov Test**

Two independent samples of volume n1 and n2 are represented by $X_1$, $X_2$, $X_3$..... $X_{n1}$ and $Y_1$, $Y_2$, $Y_3$..... $Y_{n2}$ . To determine if two samples come from the same stack;

$F_1(x)$ : Unknown distribution function of the population on which the first sample arrives

$F_2(x)$ : Unknown distribution function of the population on which the second sample arrives

$H_0$: $F_1(x) = F_2(x)$, for all $x$ values

$H_1$: $F_1(x) \neq F_2(x)$, below are the definitions for obtaining the Kolmogorov-Smirnov test statistic for at least one x value;

$S_1(x)$ : The observed distribution function for the first group of sample

$S_2(x)$ : The observed distribution function for the first group of sample

$$S1(x) = \frac{\text{In the first example, the number of sample units with values less than or equal to } x}{n1} \tag{3.5}$$

$$S2(x) = \frac{\text{In the second example, the number of sample units with values less than or equal to } x}{n2} \tag{3.6}$$

For the two-sided test, the test statistic is defined as follows;

$$D = TheBiggest\ |S1(x) - S2(x)| \tag{3.7}$$

If the null hypothesis is true (if two samples are selected from similar populations) $S_1(x)$ and $S_2(x)$ show a close approximation for all observation values. If the value of the $D$ statistic is zero or as small as possible this will support the null hypothesis.

## 4. NORMALITY TESTS

In the first part of our studies, randomly produced different size populations are used. We will determine by Kolmogorov-Smirnov and Shapiro-Wilk tests whether the two groups of different sizes samples taken from the normal distribution populations. Matlab's Statistical Tools are used for these tests.

"*X = mvnrnd(meanX, varX, N)*" matlab function is used for randomly generated populations. In this function, we need to specify the average, variance and the size of the populations. Two different groups of samples are randomly selected with the Matlab function *"randperm (N)"* from the different sized populations with the selected normal distribution.

"*[hypResult, pValue, testStats, approxCritVal] = kstest(X_normed)*" matlab function is the Kolmogorov-Smirnov test that tests for normal dispersion. Since the Matlab statistical tool that performs the Shapiro Wilks test is paid, this function is used as open source code via internet.

### 4.1. First Computation Results

The following graphs can be used to examine the information of two randomly generated samples with average of *(μX)* 90, variance of ($\sigma^2$X) 30 and the size of 10000 randomly selected population of 1000 samples.

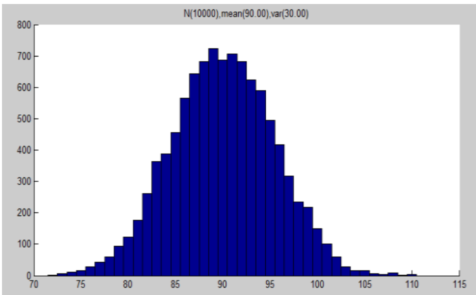


**Figure 1.** Randomly generated population

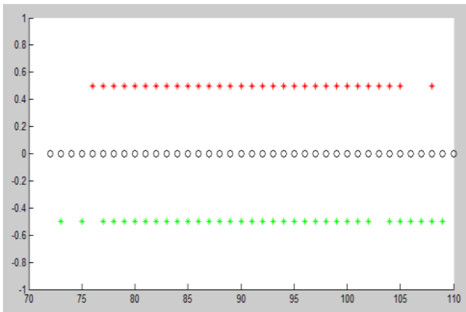

**Figure 2.** Two samples

Figure 1 shows the graph of the population, characteristics given above and Figure 2 shows the first group of samples randomly drawn from population in red plus sign (upper side) and the second group of samples in green plus sign (bottom side).

The test statistic values are 0.05019 and 0.046384 when tested with Kolmogorov-Smirnov where two groups of samples have normal distribution. If the same test is performed with Shapiro-Wilk, the test statistic values are found to be 0.005677 and 0.0008442, which is also normal distribution.

### 4.2. Second Computation Results

The following graphs can be used to examine the information of two randomly generated samples with average of (μX) 90, variance of ($\sigma^2$X) 30 and the size of 1000 randomly selected population of 500 samples.

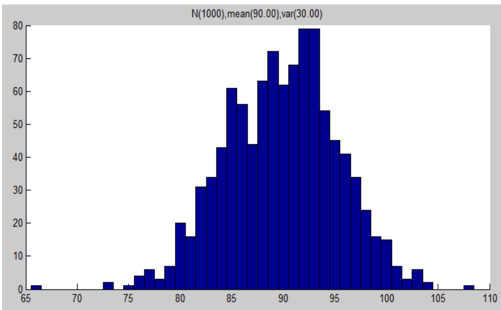


**Figure 3.** Randomly generated population

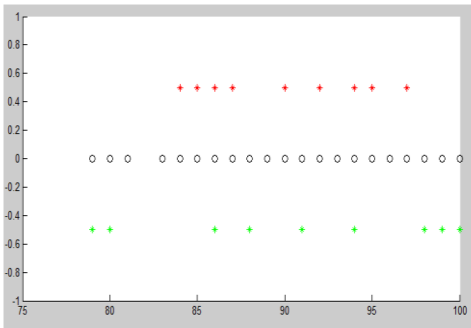

**Figure 4.** Two groups of samples

Figure 3 shows the graph of the population, characteristics given above and Figure 4 shows the first group of samples randomly drawn from population in red plus sign (upper side) and the second group of samples in green plus sign (bottom side).

The test statistic values are 0.066488 and 0.052887 when tested with Kolmogorov-Smirnov where two groups of samples have not normal distribution. If the same test is performed with Shapiro-Wilk, the test statistic values are found to be 0.00034782 and 0.03019 which is normal distribution.

## 5. SIMILARITY TESTS OF SAMPLE GROUPS

As a result of the tests performed in the fourth chapter, the similarity of Wilcoxon test for the groups with normal distribution also Kolmogorov-Smirnov and Mark test for the groups without normal distribution were investigated. The following Matlab Functions have been used to identify the similarities of sample groups;

Wilcoxon test *[wilc.p,wilc.h]= ranksum(A,B),*
Sign test *[signTest.p, signTest.h, signTest.stats] = signtest(A,B)*
Kolmogorov-Smirnov *[kolmog2.h, kolmog2.p, kolmog2.t] = kstest2(A,B)*

The tests were carried out on sample groups of 5, 15, 25, 100 and 1000 observations from 100, 1000 and 10000 data sets. The largest and smallest observation values are limited to 30 variances. The test result is shown below. Accordingly, the following table shows the size of the population used in the tests, the size of the sample taken from the population, the limits of the observation values, whether the groups are similar to normal distribution, and whether they are similar or not according to whether they are normal or not.

Let's explain the line of table that population size is 100 and sample size is 25. The observations of sample change from 69 to 109 because of the variance. It was observed that 25 observations in both groups had non-uniform distribution which tested by Kolmogorov-Smirnov. The similarity of the 9% with the Wilcoxon test was found to be similar to the groups twice. It is found similar 2 times by the test of Kolmogorov-Smirnov and their positions in the row (rng 8996, rng 2760) were found. It was also observed that 91% of the samples were similar to the Signal test and their location (rng 4208) was determined.

If we were to examine for a different value, let's expose the line with a table size of 10000 and a sample size of 1000. Because the variance is 30, sample observations range from 65 to 115. With the Kolmogorov-Smirnov test, 8% of group A and 12% of group B were observed to have unusual distribution for 1000 observations in both groups, whereas the normal distribution of the whole was observed by Shapiro-Wilks test. The similarity of the 97% portion with the Wilcoxon test was tested and found to be similar to the groups 3 times and found in their positions (rng 9616, rng 7808 and rng 8371).

**Table 1.** List of A and B group observation values in normal distribution and unavailability of both groups

| Population Size | Sample Size | Min. Observation | Max. Observation | Kolmogorov-Smirnov Test | | | | Shapiro-Wilks Test | | | | Wilcoxon Test | | Kolmogorov-Sim. | | Sign Test | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Non-Normal Dist. | | Normal Distribution | | Non-Normal Dist. | | Normal Distribution | | Non Similar Samples | Similar Samples | Non Similar Samples | Similar Samples | Non Similar Samples | Similar Samples |
| | | | | Group A | Group B | Group A | Group B | Group A | Group B | Group A | Group B | | | | | | |
| 100 | 5 | 67 | 111 | 100 | 100 | 0 | 0 | 93 | 93 | 7 | 7 | 0 | 0 | 96 | 4 | 100 | 0 |
| 100 | 15 | 70 | 114 | 100 | 100 | 0 | 0 | 93 | 93 | 7 | 7 | 0 | 0 | 100 | 0 | 97 | 3 |
| 100 | 25 | 69 | 109 | 100 | 100 | 0 | 0 | 91 | 91 | 9 | 9 | 2 | 0 | 98 | 2 | 99 | 1 |
| 100 | 100 | 69 | 109 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 100 | 1000 | 69 | 109 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1000 | 5 | 64 | 114 | 100 | 100 | 0 | 0 | 96 | 96 | 4 | 4 | 0 | 0 | 94 | 6 | 100 | 0 |
| 1000 | 15 | 66 | 113 | 100 | 100 | 0 | 0 | 94 | 94 | 6 | 6 | 0 | 0 | 99 | 1 | 98 | 2 |
| 1000 | 25 | 66 | 116 | 100 | 100 | 0 | 0 | 98 | 98 | 2 | 2 | 0 | 0 | 98 | 2 | 99 | 1 |
| 1000 | 100 | 66 | 114 | 99 | 100 | 1 | 0 | 93 | 93 | 7 | 7 | 0 | 0 | 98 | 2 | 95 | 5 |
| 1000 | 1000 | 66 | 114 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10000 | 5 | 63 | 116 | 100 | 100 | 0 | 0 | 93 | 93 | 7 | 7 | 2 | 0 | 93 | 7 | 100 | 0 |
| 10000 | 15 | 64 | 117 | 100 | 100 | 0 | 0 | 91 | 91 | 9 | 9 | 0 | 0 | 97 | 3 | 99 | 1 |
| 10000 | 25 | 64 | 117 | 100 | 100 | 0 | 0 | 95 | 95 | 5 | 5 | 0 | 0 | 97 | 3 | 99 | 1 |
| 10000 | 100 | 65 | 116 | 100 | 100 | 0 | 0 | 91 | 91 | 9 | 9 | 1 | 0 | 98 | 2 | 97 | 3 |
| 10000 | 1000 | 65 | 115 | 8 | 12 | 92 | 88 | 0 | 0 | 100 | 100 | 97 | 3 | 0 | 0 | 0 | 0 |

| Parametric/Non-Paramateric Test and Size of Population | Sample Size | Where in Sample | Avarage | Variance |
|---|---|---|---|---|
| Non-parametric Klmogorov2 Test succeded for N(100) | n_a(5) | rng(9532) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(100) | n_a(5) | rng(1728) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(100) | n_a(5) | rng(1834) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(100) | n_a(5) | rng(6093) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(100) | n_a(15) | rng(202) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(100) | n_a(15) | rng(6626) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(100) | n_a(15) | rng(1908) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(100) | n_a(25) | rng(4208) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(100) | n_a(25) | rng(8996) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(100) | n_a(25) | rng(2760) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(1000) | n_a(5) | rng(9786) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(1000) | n_a(5) | rng(6151) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(1000) | n_a(5) | rng(4923) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(1000) | n_a(5) | rng(7690) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(1000) | n_a(5) | rng(4093) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(1000) | n_a(5) | rng(9562) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(1000) | n_a(15) | rng(4525) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(1000) | n_a(15) | rng(1287) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(1000) | n_a(15) | rng(9046) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(1000) | n_a(25) | rng(1297) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(1000) | n_a(25) | rng(588) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(1000) | n_a(25) | rng(1811) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(1000) | n_a(100) | rng(3629) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(1000) | n_a(100) | rng(3629) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(1000) | n_a(100) | rng(193) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(1000) | n_a(100) | rng(2429) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(1000) | n_a(100) | rng(2743) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(1000) | n_a(100) | rng(4841) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(1000) | n_a(100) | rng(3453) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(5) | rng(423) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(5) | rng(6955) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(5) | rng(3868) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(5) | rng(4541) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(5) | rng(3514) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(5) | rng(2656) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(5) | rng(3168) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(15) | rng(7372) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(15) | rng(7793) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(10000) | n_a(15) | rng(7793) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(15) | rng(6597) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(25) | rng(6963) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(25) | rng(5011) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(10000) | n_a(25) | rng(8410) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(25) | rng(8420) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(100) | rng(3197) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(10000) | n_a(100) | rng(3197) | meanX(90) | varX(30) |
| Non-parametric Klmogorov2 Test succeded for N(10000) | n_a(100) | rng(8896) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(10000) | n_a(100) | rng(3817) | meanX(90) | varX(30) |
| Non-parametric Sign Test succeded for N(10000) | n_a(100) | rng(2408) | meanX(90) | varX(30) |
| Parametric Wilcoxon Test succeded for N(10000) | n_a(1000) | rng(9616) | meanX(90) | varX(30) |
| Parametric Wilcoxon Test succeded for N(10000) | n_a(1000) | rng(7808) | meanX(90) | varX(30) |
| Parametric Wilcoxon Test succeded for N(10000) | n_a(1000) | rng(8371) | meanX(90) | varX(30) |

## 6. CONCLUSION

In general, the Shapiro-Wilk test is more robust than the Kolmogorov-Smirnov test for all distributions and sample sizes among the two tests considered for normality tests. However it can be said that the Shapiro-Wilk test is better than the Kolmogorov-Smirnov test for small sample size.

While parametric statistical techniques are commonly used with ratio data, nonparametric statistical techniques use nominal and rank order data [11]. That is, nonparametric tests are the ones that have the power of the sequence numbers as well as naturally analyze the interspersed data. That is, the researcher can say that only one of them has more or less features than the other, how much or less he can not say.

**Table 2.** Use of statistical methods according to years

| Statistical Methods | 1978–1979 | 1989 | 2004-2005 |
|---|---|---|---|
| t-tests (one-sample, two-sample, and matched-pair) | 44% | 39% | 26% |
| Non-parametric tests (Wilcoxon-Mann-Whitney, sign, and Wilcoxon signed rank sum) | 11% | 21% | 27% |

And also, it was also observed in the study that the normal distribution within random samples taken from a suitable population of normal distributions is difficult to find a suitable sample.

Errors in reaching conclusions or decisions lead to adverse effects on the reliability, validity and validity of the results. Failure to use these statistical tests, failures to comply with multiple comparisons, failure to identify and explain the statistical test used, and failure to estimate sample size [11].

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