

How to Easily Transform Data in Excel: Log, Square Root, and Cube Root Transformations

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Introduction: Addressing Assumptions in Data Analysis

In the realm of quantitative research and data science, performing rigorous statistical tests is often necessary to draw meaningful conclusions about a population based on sample data. Crucially, many parametric tests--such as ANOVA or t-tests--are predicated on the assumption that the underlying datasets are normally distributed. This fundamental assumption ensures that the calculations for test statistics and subsequent p-value determinations are accurate and reliable. However, real-world data frequently defies this ideal distribution, often exhibiting severe skewness, high kurtosis, or heterogeneity of variance.

When the assumption of normality is significantly violated, the results derived from these powerful statistical methods may become invalid or misleading. For instance, violating normality can lead to an inflated Type I error rate (falsely rejecting a true null hypothesis) or decreased statistical power (failing to detect a real effect). Therefore, addressing non-normality is a critical step in the data preparation phase of any analysis.

One of the most effective and widely utilized solutions for mitigating non-normality is data transformation. Transformation involves applying a mathematical function to every value in the dataset, effectively changing the shape of the data distribution to bring it closer to a Gaussian (normal) form. While transformation does not guarantee perfect normality, it often significantly improves the distributional characteristics, thereby validating the use of parametric statistical procedures. Below, we explore three common transformations--Log, Square Root, and Cube Root--and demonstrate their implementation within the powerful spreadsheet environment of Microsoft Excel.

Overview of Common Data Transformations

Choosing the correct transformation depends heavily on the initial distribution of the data, particularly the degree and direction of its skewness. If the data is strongly right-skewed (meaning the tail extends to the higher positive values), power transformations are typically employed to compress the larger values relative to the smaller ones. These transformations belong to a family known as the Box-Cox transformations, though we focus here on three specific, commonly applied variations that are easily executed in Excel.

The three transformations serve as progressively less severe adjustments to the data distribution. The variable y represents the original data value:

Log Transformation: Transform the values from y to $\log(y)$. This is often the most powerful transformation for reducing severe right-skewness and stabilizing variance, especially when the data span several orders of magnitude. It is typically applied using the natural logarithm (base e) or the base-10 logarithm, as demonstrated in Excel.

Square Root Transformation: Transform the values from y to \sqrt{y} . This is a less drastic measure than the log transformation. It is particularly useful when dealing with count data (e.g., frequencies) or data where variance is proportional to the mean.

Cube Root Transformation: Transform the values from y to $y^{1/3}$. The cube root represents a relatively mild correction. A significant advantage of the cube root transformation over the log and square root methods is its ability to handle zero and negative values, which is essential if your dataset includes these figures.

By applying these mathematical functions, we aim to redistribute the values such that the transformed dataset more closely adheres to the bell-shaped curve that defines a normally distributed variable. This process is essential for ensuring the validity of subsequent statistical modeling.

Implementing Log Transformation in Excel

The Log Transformation is frequently the first choice when encountering highly positive-skewed data. In Excel, the most common functions for this purpose are `LOG()` (which allows you to specify the base) or `LOG10()`. The latter, which computes the base-10 logarithm, is often preferred for interpretation due to its intuitive scale.

To apply a log transformation to a dataset housed in a column in Excel, you use the `=LOG10()` function, referencing the cell containing the original data value. For instance, if your data starts in cell A2, you would enter `=LOG10(A2)` into the corresponding cell in the new column (e.g., B2) and drag the formula down. This action systematically calculates the logarithm of every data point. The resulting dataset, now consisting of transformed values, is then analyzed to assess its distributional improvements.

The following visual example illustrates the application of the log transformation. Observe how the formula is applied to the raw data column, generating the new, transformed values.

| | A | B | C | D | E | F | G | H |
|----|---|-------------|------------------|------------|---|---|---|---|
| 1 | | Data | Log(Data) | | | | | |
| 2 | | 1 | 0 | =LOG10(B2) | | | | |
| 3 | | 1 | 0 | | | | | |
| 4 | | 1 | 0 | | | | | |
| 5 | | 2 | 0.30103 | | | | | |
| 6 | | 2 | 0.30103 | | | | | |
| 7 | | 2 | 0.30103 | | | | | |
| 8 | | 2 | 0.30103 | | | | | |
| 9 | | 2 | 0.30103 | | | | | |
| 10 | | 2 | 0.30103 | | | | | |
| 11 | | 2 | 0.30103 | | | | | |
| 12 | | 3 | 0.477121 | | | | | |
| 13 | | 3 | 0.477121 | | | | | |
| 14 | | 6 | 0.778151 | | | | | |
| 15 | | 7 | 0.845098 | | | | | |
| 16 | | 8 | 0.90309 | | | | | |
| 17 | | | | | | | | |
| 18 | | | | | | | | |
| 19 | | | | | | | | |
| 20 | | | | | | | | |
| 21 | | | | | | | | |
| 22 | | | | | | | | |
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| 25 | | | | | | | | |

The Jarque-Bera Test: A Criterion for Normality

After applying a data transformation, it is imperative to verify its effectiveness. Simply inspecting a histogram can be misleading; therefore, we rely on formal goodness-of-fit tests, such as the Jarque-Bera test, to statistically confirm if the data has achieved sufficient normality. This test evaluates how closely the data's skewness and kurtosis match those of a perfect normal distribution (where skewness is 0 and kurtosis is 3, or excess kurtosis is 0).

The test statistic for the Jarque-Bera (JB) test is mathematically defined as follows:

\$\$

$$JB = \left(\frac{n}{6}\right) \times \left(S^2 + \frac{C^2}{4}\right)$$

\$\$

where the variables are defined as:

n: The number of observations in the sample.

S: The sample skewness coefficient, measuring the asymmetry of the distribution.

C: The sample excess kurtosis, measuring the "tailedness" of the distribution compared to the

normal distribution.

Under the null hypothesis of perfect normality, the JB statistic asymptotically follows a Chi-squared distribution with 2 degrees of freedom ($JB \sim \chi^2(2)$). The null hypothesis (H_0) states that the data is normally distributed. We aim to retain this null hypothesis for the transformed data. If the resulting p-value corresponding to the test statistic is less than a chosen significance level (e.g., $\alpha = 0.05$), we must reject the null hypothesis, concluding that the data is still non-normal. Conversely, a large p-value (greater than 0.05) indicates that we cannot reject the null hypothesis, suggesting that the data is statistically consistent with a normal distribution.

The image below illustrates the results of applying the Jarque-Bera test to both the raw data and the log-transformed data.

| | A | B | C | D | E | F | G | H |
|----|---------------------|-------------|------------------|----------------------------|---|---|---|---|
| 1 | | Data | Log(Data) | | | | | |
| 2 | | 1 | 0 | | | | | |
| 3 | | 1 | 0 | | | | | |
| 4 | | 1 | 0 | | | | | |
| 5 | | 2 | 0.30103 | | | | | |
| 6 | | 2 | 0.30103 | | | | | |
| 7 | | 2 | 0.30103 | | | | | |
| 8 | | 2 | 0.30103 | | | | | |
| 9 | | 2 | 0.30103 | | | | | |
| 10 | | 2 | 0.30103 | | | | | |
| 11 | | 2 | 0.30103 | | | | | |
| 12 | | 3 | 0.477121 | | | | | |
| 13 | | 3 | 0.477121 | | | | | |
| 14 | | 6 | 0.778151 | | | | | |
| 15 | | 7 | 0.845098 | | | | | |
| 16 | | 8 | 0.90309 | | | | | |
| 17 | | | | Formulas used | | | | |
| 18 | n | 15 | 15 | =COUNT(C2:C16) | | | | |
| 19 | Skewness | 1.499564 | 0.58723 | =SKEW(C2:C16) | | | | |
| 20 | Kurtosis | 1.072465 | -0.23689 | =KURT(C2:C16) | | | | |
| 21 | JB Statistic | 6.340593 | 0.89717 | =(C18/6)*(C19^2+(C20^2)/4) | | | | |
| 22 | p-value | 0.041991 | 0.638531 | =CHISQ.DIST.RT(C21, 2) | | | | |
| 23 | | | | | | | | |
| 24 | | | | | | | | |
| 25 | | | | | | | | |
| 26 | | | | | | | | |
| 27 | | | | | | | | |
| 28 | | | | | | | | |

Upon examining the results, notice the significant difference in the p-values. The raw data yields a p-value that is less than 0.05, leading us to reject the hypothesis of normality. However, the p-

value for the log-transformed dataset is considerably higher (and greater than 0.05). This outcome allows us to retain the null hypothesis, confidently concluding that the log transformation successfully produced a dataset that is statistically normally distributed, thereby validating its readiness for subsequent parametric statistical tests.

Applying the Square Root Transformation in Excel

When data shows moderate positive skewness, or when the data consists of counts (e.g., biological measurements or frequencies), the square root transformation often provides an adequate correction without the extreme compression caused by the log transformation. It is a preferred method when the variance tends to increase linearly with the mean, as it helps stabilize the variance alongside improving normality.

To perform this operation in Excel, the dedicated **=SQRT()** function is used. Similar to the log transformation, you would enter the formula `=SQRT(A2)` in the first cell of the transformation column and fill the formula down. This yields \sqrt{y} for every observation y . It is important to remember that, like the log transformation, the square root method is only applicable to non-negative data ($y \geq 0$).

Once the transformation is complete, the resulting data is again subjected to the Jarque-Bera test to ensure the transformation was successful. In many cases, the square root transformation provides a sufficient shift toward normality.

The following screenshot demonstrates the application of the square root transformation in Excel, alongside the corresponding normality test results:

| | A | B | C | D | E | F | G | H |
|----|---------------------|-------------|-------------------|----------------------------|---|---|---|---|
| 1 | | Data | Sqrt(Data) | | | | | |
| 2 | | 1 | 1 | =SQRT(B2) | | | | |
| 3 | | 1 | 1 | | | | | |
| 4 | | 1 | 1 | | | | | |
| 5 | | 2 | 1.414214 | | | | | |
| 6 | | 2 | 1.414214 | | | | | |
| 7 | | 2 | 1.414214 | | | | | |
| 8 | | 2 | 1.414214 | | | | | |
| 9 | | 2 | 1.414214 | | | | | |
| 10 | | 2 | 1.414214 | | | | | |
| 11 | | 2 | 1.414214 | | | | | |
| 12 | | 3 | 1.732051 | | | | | |
| 13 | | 3 | 1.732051 | | | | | |
| 14 | | 6 | 2.44949 | | | | | |
| 15 | | 7 | 2.645751 | | | | | |
| 16 | | 8 | 2.828427 | | | | | |
| 17 | | | | Formulas used | | | | |
| 18 | n | 15 | 15 | =COUNT(C2:C16) | | | | |
| 19 | Skewness | 1.499564 | 1.133197 | =SKEW(C2:C16) | | | | |
| 20 | Kurtosis | 1.072465 | 0.347779 | =KURT(C2:C16) | | | | |
| 21 | JB Statistic | 6.340593 | 3.285935 | =(C18/6)*(C19^2+(C20^2)/4) | | | | |
| 22 | p-value | 0.041991 | 0.193405 | =CHISQ.DIST.RT(C21, 2) | | | | |
| 23 | | | | | | | | |
| 24 | | | | | | | | |
| 25 | | | | | | | | |
| 26 | | | | | | | | |

In this example, the p-value derived from the Jarque-Bera test for the transformed data is clearly not less than the critical threshold of 0.05. This confirms that the square root transformation was effective in producing a dataset that does not significantly deviate from a normal distribution.

Executing the Cube Root Transformation in Excel

The cube root transformation, or the power of $1/3$, is the least severe of the three power transformations discussed here. It applies an even gentler compression to the larger values compared to the square root or logarithm. Its mathematical simplicity and unique robustness make it highly valuable in specific analytical scenarios.

A crucial advantage of the cube root transformation ($y^{1/3}$) over both log and square root methods is its ability to handle datasets that contain zero or negative values. Since the cube root of a negative number is defined (e.g., $\sqrt[3]{-8} = -2$), this transformation maintains the relative ordering and scale of negative data points while still working to normalize the distribution shape.

This makes it a highly flexible tool for general data transformation when the data domain is unrestricted.

To apply the cube root transformation in Excel, you utilize the exponentiation operator: **=DATA^(1/3)**. For example, if the raw data is in cell A2, the formula would be `=A2^(1/3)`. This instructs Excel to raise the value in A2 to the power of one-third.

The results below show the successful implementation of the cube root transformation and the associated normality test:

| | A | B | C | D | E | F | G | H |
|----|---------------------|-------------|-------------------|----------------------------|---|---|---|---|
| 1 | | Data | Data^(1/3) | | | | | |
| 2 | | 1 | 1 | | | | | |
| 3 | | 1 | 1 | | | | | |
| 4 | | 1 | 1 | | | | | |
| 5 | | 2 | 1.259921 | | | | | |
| 6 | | 2 | 1.259921 | | | | | |
| 7 | | 2 | 1.259921 | | | | | |
| 8 | | 2 | 1.259921 | | | | | |
| 9 | | 2 | 1.259921 | | | | | |
| 10 | | 2 | 1.259921 | | | | | |
| 11 | | 2 | 1.259921 | | | | | |
| 12 | | 3 | 1.44225 | | | | | |
| 13 | | 3 | 1.44225 | | | | | |
| 14 | | 6 | 1.817121 | | | | | |
| 15 | | 7 | 1.912931 | | | | | |
| 16 | | 8 | 2 | | | | | |
| 17 | | | | Formulas used | | | | |
| 18 | n | 15 | 15 | =COUNT(C2:C16) | | | | |
| 19 | Skewness | 1.499564 | 0.971302 | =SKEW(C2:C16) | | | | |
| 20 | Kurtosis | 1.072465 | 0.12497 | =KURT(C2:C16) | | | | |
| 21 | JB Statistic | 6.340593 | 2.368332 | =(C18/6)*(C19^2+(C20^2)/4) | | | | |
| 22 | p-value | 0.041991 | 0.306001 | =CHISQ.DIST.RT(C21, 2) | | | | |
| 23 | | | | | | | | |
| 24 | | | | | | | | |
| 25 | | | | | | | | |
| 26 | | | | | | | | |

As evidenced by the large p-value in the Jarque-Bera test statistic, the cube root transformation also proved effective in this instance. The p-value is well above the 0.05 threshold, indicating that we accept the null hypothesis of normality. This demonstrates that all three primary methods--Log, Square Root, and Cube Root--can be viable solutions for addressing non-normality in data.

Conclusion: Comparing Transformation Effectiveness

We have successfully demonstrated how three standard data transformation methods can be easily applied in Excel using built-in functions or simple arithmetic operations. Crucially, all three transformations effectively mitigated the initial severe non-normality of the raw data, allowing us to proceed with parametric statistical tests. This highlights the importance of incorporating transformation techniques into the data preparation pipeline whenever the assumptions of normality or homoscedasticity are challenged.

When multiple transformations prove successful (i.e., all yield a non-significant Jarque-Bera test result), the analyst must decide which transformed dataset is the "best" representation for modeling. Generally, the optimal transformation is the one that results in the highest p-value in the normality test. A larger p-value suggests that the data is most statistically consistent with a normal distribution, meaning it has achieved the closest possible match to zero skewness and ideal kurtosis.

In our comparative analysis, the log transformation yielded the largest p-value, suggesting it made the data the "most" normally distributed among the three applied methods. While all methods were technically successful, this ranking provides a quantitative basis for selecting the superior transformation for downstream analytical tasks. Choosing the most effective transformation is key to maximizing the power and validity of any subsequent statistical inferences derived from the data.