

How to Perform a Mann-Kendall Trend Test in Python

Authored by
stats writer

December 12, 2025

RECOMMENDED CITATION

stats writer (2025). *How to Perform a Mann-Kendall Trend Test in Python*.

PSYCHOLOGICAL SCALES. Retrieved from <https://scales.arabpsychology.com/?p=107237>

The Mann-Kendall Trend Test is a powerful, non-parametric statistical test specifically designed to assess whether a given dataset exhibits a statistically significant monotonic trend over time. This method is exceptionally popular in fields such as hydrology, environmental science, and climatology, where researchers often analyze long-term measurements of natural phenomena. Unlike parametric tests, the Mann-Kendall test makes no assumptions about the underlying distribution of the data, making it robust against outliers and non-normal distributions.

To successfully execute this analysis in Python, we typically utilize specialized libraries. Although the original concept can be derived from packages like SciPy, dedicated packages such as `pymannkendall` offer simplified, pre-packaged functionality. The core principle involves analyzing the sequential order of the data points. If the data shows a consistent upward or downward movement (a trend), the test quantifies this relationship using the Kendall Tau correlation coefficient. If this coefficient is significantly different from zero, we have evidence to reject the null hypothesis of 'no trend,' suggesting a genuine change is occurring in the time series.

A **Mann-Kendall Trend Test** is fundamentally used to determine the existence and nature of a trend within time series data. Because it is a non-parametric test, it stands out for its flexibility, as it does not rely on the restrictive assumption that the data must follow a standard probability distribution, such as the normal distribution. This characteristic is particularly valuable when analyzing real-world environmental data, which often fails to meet strict normality assumptions.

The evaluation process of the test is centered around comparing the relative magnitudes of the observed data values. Specifically, it assesses whether subsequent data values tend to be consistently larger or smaller than preceding values. This rigorous approach allows researchers to confidently state whether observed changes are merely random fluctuations or if they represent a true underlying shift over the monitoring period.

The hypotheses for the test are formally stated to provide a clear framework for statistical decision-making:

H₀ (null hypothesis): There is no trend present in the time series data. The data points are considered independent and randomly ordered.

H_A (alternative hypothesis): A statistically significant trend is present in the data. This trend can be either positive (increasing values over time) or negative (decreasing values over time).

The ultimate conclusion of the Mann-Kendall test hinges on the calculated p-value. If this p-value is observed to be lower than a predetermined significance level (often denoted as α , with common choices being 0.10, 0.05, or 0.01), then we possess sufficient statistical evidence to reject the null hypothesis. Rejecting H₀ implies that the observed trend is statistically significant and unlikely to have occurred by random chance.

This detailed guide focuses on leveraging the strengths of the [Python](#) ecosystem to efficiently calculate and interpret the results of the Mann-Kendall Trend Test.

Understanding the Mann-Kendall Trend Test

The Mann-Kendall test is widely favored due to its resilience to data distribution anomalies and its ability to handle missing values, a common issue in environmental monitoring. It operates by comparing all possible pairs of data points (x_i and x_j , where $i < j$) in the time series. For each pair, it determines the sign of the difference ($x_j - x_i$). If the difference is positive, it contributes +1 to the score (S). If negative, it contributes -1. If the difference is zero (tied values), it contributes 0.

The overall test statistic, S, is the sum of these comparisons. A large positive S indicates a strong increasing trend, while a large negative S suggests a strong decreasing trend. If S is close to zero, it means the upward trends and downward trends roughly cancel each other out, suggesting no monotonic change over the observation period.

Furthermore, the test calculates the variance of S, which is necessary to compute the standardized test statistic (Z). This Z statistic is then used to find the corresponding p-value. The strength and direction of the monotonic relationship are also summarized by the Kendall Tau correlation coefficient (τ), which ranges from -1 (perfect negative correlation) to +1 (perfect positive correlation).

Setting Up the Python Environment: Required Libraries

To execute the Mann-Kendall test efficiently within the Python environment, we rely on external libraries. While the core mathematical components can be found in standard scientific libraries like NumPy and SciPy, the dedicated `pymannkendall` package provides a highly optimized and user-friendly wrapper specifically tailored for this test, offering immediate, comprehensive results.

The first prerequisite is ensuring this necessary package is installed in your development environment. This installation is straightforward and uses the standard Python package installer, `pip`. Open your terminal or command prompt and execute the following command:

```
pip install pymannkendall
```

Once the installation is complete, the functionality of `pymannkendall` is readily available for importation and use in any Python script or Jupyter notebook session. It is always good practice to ensure your environment is updated to prevent any dependency conflicts before proceeding with statistical analysis.

Implementing the Mann-Kendall Test in Python (Example)

We will now proceed with a practical example, applying the Mann-Kendall Trend Test to a synthetic set of time series data. This dataset could represent any sequence of measurements taken over time, such as daily average temperatures, monthly pollutant levels, or annual stream flow volumes. The data array is a simple sequence of numerical observations.

After successfully importing the library, we define our dataset. The dataset used here contains 17 data points: . We then call the `original_test` function provided by the `pymannkendall` module, passing the data as the sole argument.

The following code block demonstrates the setup and execution, resulting in a structured output object containing all the critical statistics calculated by the test:

```
# Define the time series dataset for analysis
```

```
data =
```

```
# Perform the Mann-Kendall Trend Test
```

```
import pymannkendall as mk
```

```
mk.original_test(data)
```

```
Mann_Kendall_Test(trend='no trend', h=False, p=0.422586268671707,
```

```
z=0.80194241623, Tau=0.147058823529, s=20.0,
```

```
var_s=561.33333333, slope=0.0384615384615, intercept=27.692307692)
```

The output object, labeled `Mann_Kendall_Test`, encapsulates several key statistical measures. Understanding each component is essential for drawing accurate conclusions about the dataset's underlying trend. We will now dissect these results in detail to demonstrate how the statistical findings relate back to our original hypotheses.

Detailed Interpretation of the Test Output Parameters

The result object returned by `pymannkendall` provides a wealth of information, moving beyond a simple pass/fail indication to offer context regarding the strength and calculation methodology. Here is a comprehensive breakdown of the output fields:

trend: This is a categorical summary of the test's conclusion. Possible states include `increasing` (positive significant trend), `decreasing` (negative significant trend), or `no trend` (insufficient evidence to reject H0).

h: This is a boolean indicator (True/False) reflecting the statistical decision. `True` signifies that a

trend is present (H0 is rejected), while `False` indicates that no trend is statistically confirmed (H0 is accepted).

p: The p-value of the test. This value is critical for hypothesis testing; if $p < \alpha$ (the chosen significance level, e.g., 0.05), the result is deemed significant.

z: The normalized test statistic. This value measures the distance between the calculated S score and its expected value (zero under H0) in terms of standard deviations. A high absolute Z value typically leads to a low p-value.

Tau: The Kendall Tau correlation coefficient (τ). This measures the strength and direction of the monotonic relationship, ranging from -1 to 1.

s: Mann-Kendall's Score. This is the raw count of concordant and discordant pairs, as described in the methodology section.

var_s: The Variance of S. This value is calculated taking into account potential ties in the data and is used in the calculation of the Z statistic.

slope: The Theil-Sen estimator, or the median slope. This non-parametric measure provides a robust estimate of the true slope (rate of change) in the data, offering a quantitative estimate of the trend magnitude.

intercept: The intercept of the Kendall-Theil Robust Line. This is the point where the estimated trend line crosses the y-axis (the starting value of the trend).

The most pivotal value for making a statistical decision is the **p-value**, as it directly informs us whether the observed trend is statistically robust or merely a product of randomness. If the p-value is small, it suggests the data aligns poorly with the null hypothesis.

Analyzing the Statistical Outcome

In our specific example, the resulting p-value is **0.4226**. To interpret this, we must compare it against a standard significance level, typically $\alpha = 0.05$. Since 0.4226 is substantially greater than 0.05, we cannot reject the null hypothesis (H0).

The conclusion is that there is insufficient evidence to claim a statistically significant monotonic trend in the provided time series data at the 5% level of significance. This finding is further corroborated by the `trend` output, which states 'no trend,' and the boolean `h` value, which is `False`.

Although the Kendall Tau correlation coefficient (τ) is positive (0.147), indicating a slight positive relationship, this correlation is not strong enough, nor is the sample size sufficient, to cross the threshold of statistical significance defined by the chosen alpha level. The magnitude of the change, as measured by the Theil-Sen estimator (slope = 0.038), confirms this minimal rate of change over time.

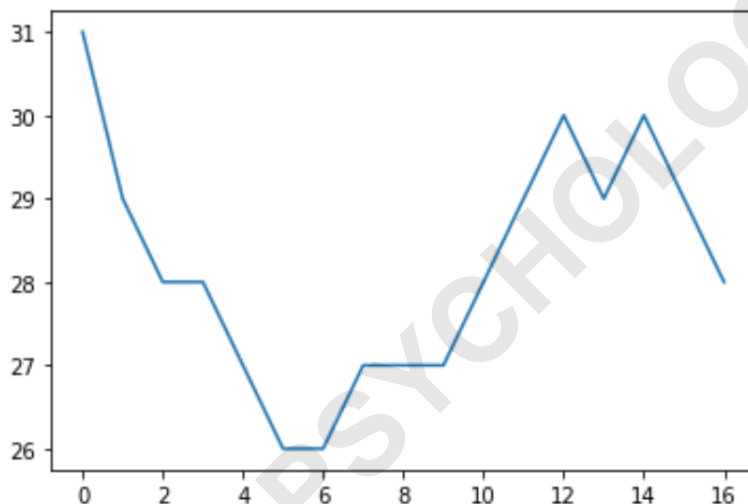
Visualizing Time Series Data with Matplotlib

Statistical tests provide concrete numerical evidence, but visualization is crucial for confirming and communicating the results effectively. A simple line plot of the time series data can offer intuitive support for the Mann-Kendall conclusion. We will use the powerful [Matplotlib](#) library, a cornerstone of data visualization in [Python](#), to generate this plot.

By plotting the data points sequentially, we can visually inspect whether the data exhibits a clear, directional movement or if the fluctuations appear random and centered around a constant mean.

```
import matplotlib.pyplot as plt
```

```
plt.plot(data)
```



timese

Observing the generated line plot, it is evident that the data exhibits considerable variability without a sustained, consistent direction. The values oscillate, starting slightly high, dropping in the middle, and slightly recovering towards the end. This visual evidence of oscillation and randomness strongly supports the formal statistical conclusion derived from the Mann-Kendall test: there is no clear monotonic trend in the data.

Conclusion: Robustness and Applications

The Mann-Kendall Trend Test, implemented efficiently through Python's `pymannkendall` package, provides a robust and non-parametric method for identifying underlying changes in time series data. Its ability to operate without assumptions of normality makes it an invaluable tool for analyzing environmental and geophysical datasets where distributions are often complex or unknown.

While our example concluded that 'no trend' exists, the methodology remains identical for datasets that exhibit significant positive or negative trends. The combination of the calculated p-value, the Theil-Sen estimator, and visual confirmation ensures that any conclusion drawn about the presence or absence of a trend is statistically sound and practically justifiable.

For researchers working with seasonal data (e.g., monthly temperature averages), it is important to note that variations of this test, such as the Seasonal Mann-Kendall Test, exist to account for inherent seasonality that might otherwise mask or falsely inflate a long-term trend. The fundamental principles, however, remain centered on comparing pair ranks to assess directional change over time.

Further Considerations for Advanced Trend Analysis

When applying the Mann-Kendall test in real-world scenarios, it is necessary to consider the impact of serial correlation (autocorrelation) in the time series. Positive serial correlation tends to inflate the variance calculation, potentially leading to an overly optimistic rejection of the null hypothesis (i.e., finding a trend where none truly exists).

For data exhibiting strong autocorrelation, modifications to the standard Mann-Kendall test, such as the Modified Mann-Kendall test (e.g., using methods proposed by Hamed and Rao or Yue and Wang), should be employed. These modifications adjust the variance of the S statistic to account for the dependencies between consecutive data points, preserving the integrity of the statistical inference. Always verify the assumptions of the specific test variant being used to ensure the validity of your conclusions regarding long-term environmental or economic shifts.