

Perform a Mann-Kendall Trend Test in Python

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Introduction to the Mann-Kendall Trend Test

The [Mann-Kendall Trend Test](#) is an indispensable analytical tool used extensively across disciplines such as **hydrology**, **climate science**, and **environmental monitoring**. Its fundamental purpose is to rigorously assess whether a statistically meaningful trend exists within sequential [time series data](#). Detecting changes, whether subtle shifts or pronounced increases/decreases, is critical for informed decision-making and forecasting in these sensitive fields.

This test stands out because it operates independently of standard distribution assumptions, classifying it as a **robust non-parametric test**. Unlike statistical methods that demand data conform to a normal distribution or exhibit homoscedasticity--conditions often violated by real-world environmental observations--the Mann-Kendall method remains reliable. This inherent robustness makes it the preferred choice for researchers analyzing variable, noisy, or complex temporal datasets.

This comprehensive guide details the process of applying and interpreting the Mann-Kendall test within the high-performance [Python](#) programming environment. By utilizing specialized libraries, we ensure that you can derive accurate and actionable insights from your temporal measurements, leading to trustworthy conclusions about directional change over time.

Statistical Robustness: The Non-Parametric Advantage

The power of the Mann-Kendall procedure stems from its reliance on data **ranks** rather than the actual magnitude of the observations. When analyzing a series of measurements taken over time, the test systematically compares every data point to all subsequent points. It meticulously tallies the differences: counting concordant pairs (where the subsequent value increases) and discordant pairs (where the subsequent value decreases).

This ranking methodology effectively mitigates the disproportionate influence of **outliers**, which can drastically skew the results produced by traditional parametric tests, such as linear regression. For environmental scientists dealing with highly variable inputs--like fluctuating temperature records, intermittent precipitation levels, or localized pollutant concentrations--the stability offered by this test provides a reliable metric for quantifying the direction of change. The test ultimately determines if the data exhibits a consistent monotonic trend.

The core results generated by the Mann-Kendall test include the **S statistic** and the normalized **Z statistic**. The S statistic aggregates the difference between the counts of positive and negative comparisons. A positive S value suggests an overall tendency toward an increasing trend, while a negative S value indicates a decreasing trend. The Z statistic serves to normalize S, allowing us to compare the result against the [standard normal distribution](#) to ascertain the level of [statistical significance](#).

Defining the Research Goal: Null and Alternative Hypotheses

A crucial prerequisite for conducting any statistical assessment is the precise formulation of the research hypotheses. The Mann-Kendall test is specifically engineered to evaluate the presence or absence of a **monotonic trend**--a pattern where the sequence of data is either consistently increasing or consistently decreasing over the observation period.

The formal statements guiding the statistical inquiry are defined as follows:

H0 (Null Hypothesis): There is **no monotonic trend** present in the [time series data](#). The sequence of observations is independent and randomly distributed over time.

HA (Alternative Hypothesis): A statistically significant monotonic trend **is present** in the data. This trend may be directional (either increasing or decreasing).

The ultimate decision to reject or retain the [Null Hypothesis](#) relies entirely on the calculated [p-value](#) resulting from the analysis. If the [p-value](#) falls below the predetermined significance level (known as α , typically set at 0.05 for most scientific studies), then there is sufficient statistical evidence to reject H0 and confidently conclude that a significant trend exists within the observed data series.

Python Implementation: Setup and Data Preparation

To effectively execute the Mann-Kendall Trend Test in the [Python](#) environment, we utilize specialized third-party libraries designed for environmental statistics. The most highly regarded and robust package for this specific analysis is [pymannkendall](#), which provides dedicated functions for both the Mann-Kendall test and the calculation of [Sen's slope](#).

The essential first step is the installation of this package within your development environment. This is performed via the standard Python package installer, typically executed in the terminal or command prompt as shown below:

```
pip install pymannkendall
```

Once the library is successfully installed, we must prepare our input data. The test requires a sequential array or list of observations. For demonstration purposes, we define a small sample dataset representing hypothetical measurements taken chronologically:

```
# Create sample time series dataset  
data =
```

This straightforward list structure is all that the `pymannkendall` function needs. This simplicity

allows us to transition immediately to executing the statistical test without complex data restructuring, streamlining the analytical workflow.

Executing the Test and Understanding the `pymannkendall` Output

With the data defined and the necessary library imported, we proceed to run the primary statistical function, `original_test()`. This function executes the standard Mann-Kendall calculation against our prepared dataset, generating a comprehensive statistical report:

Perform Mann-Kendall Trend Test using the imported library

```
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 resulting `Mann_Kendall_Test` object encapsulates all critical statistical metrics required for a complete trend analysis. Interpreting each element of this output is essential for accurately drawing conclusions regarding both the existence and the quantifiable magnitude of any potential trend within the data.

The output provides both qualitative assessments and quantitative measures. While the [p-value](#) is paramount for determining [statistical significance](#), other elements offer crucial context:

trend: A descriptive label indicating the test's immediate qualitative finding (e.g., 'increasing', 'decreasing', or 'no trend').

h: A Boolean flag (True or False) that summarizes the hypothesis result. **True** means H0 was rejected (significant trend found); **False** means H0 was retained (no significant trend found).

p: The calculated [p-value](#). This probability measure is the key determinant for hypothesis testing.

z: The standardized test statistic, used to calculate the [p-value](#) against the standard normal distribution.

Tau: Kendall's Tau coefficient (τ). This value ranges from -1 to +1, quantifying the strength and direction of the monotonic relationship.

slope: The [Theil-Sen estimator](#). This is a robust, non-parametric estimate of the actual rate of change (magnitude of the trend) per unit of time, providing practical context to the statistical finding.

Drawing Conclusions: Interpreting Significance and Trend

The primary focus for concluding the hypothesis test is the comparison of the calculated [p-value](#) against the predefined significance level (α). Using the conventional threshold of $\alpha = 0.05$, we analyze the result from our sample execution.

In this specific example, the resulting [p-value](#) is approximately **0.4226**. Since 0.4226 is substantially greater than the significance level of 0.05, we must consequently fail to reject the [Null Hypothesis](#) (H_0). The accompanying output variable, `h=False`, confirms this statistical finding.

Our final conclusion based on the statistical evidence is clear: there is insufficient [statistical significance](#) to assert the presence of a monotonic trend (either upward or downward) in this particular set of [time series data](#). The observed fluctuations are likely due to random variation rather than a sustained directional change.

Visual Confirmation: Plotting Data with Matplotlib

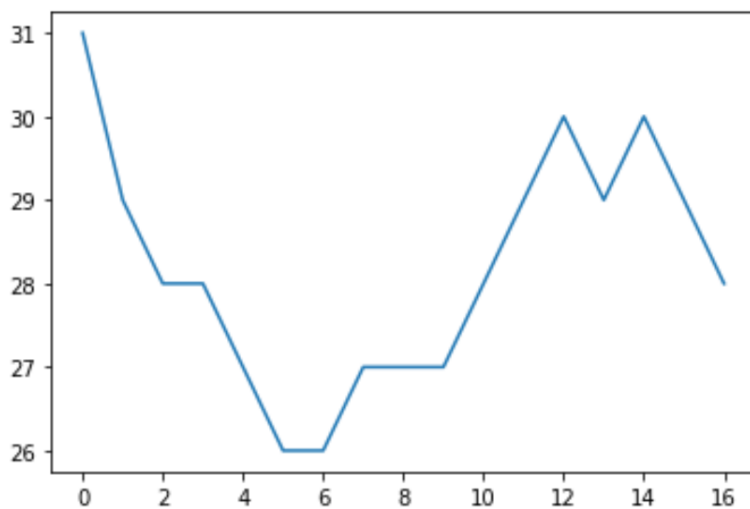
While quantitative statistical results provide definitive proof, visualizing the data offers an essential, intuitive check on the findings. It is standard best practice in data analysis to plot the [time series data](#) to visually confirm the conclusions drawn from the Mann-Kendall test. We can easily generate a clear line plot using Matplotlib, the foundational [Python](#) visualization library.

The following Python snippet imports the necessary library and generates a basic plot of our time-ordered dataset:

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

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

The resulting visual representation is displayed below:



timese

The visual pattern strongly aligns with the statistical outcome. The line plot does not display a distinct, consistent slope, confirming the statistical finding that the data lacks a sustained, statistically significant monotonic trend. The combination of rigorous statistical testing and visual confirmation provides a complete and trustworthy analysis.

Additional Resources for Advanced Analysis

To deepen your expertise in non-parametric trend analysis, particularly concerning environmental or hydrological data, we recommend consulting the authoritative documentation for the [pymannkendall](#) library. Further statistical literature on the Mann-Kendall test and the [Theil-Sen estimator](#) will provide context for advanced applications, such as handling seasonal data or assessing the magnitude of the trend.