**Introduction to Statistical Tests: Parametric vs. Non-Parametric**

Statistical tests are essential tools in data analysis for making inferences about a population based on sample data. Depending on the nature of your data and the assumptions it meets, you can choose between **parametric** and **non-parametric** tests.

### **🔎 What is a Parametric Test?**

A **parametric test** assumes that your data follows a specific distribution, typically a **normal distribution**. These tests rely on several assumptions, including homogeneity of variances and the continuous nature of the data. Parametric tests are generally more powerful when the assumptions are met.

**Examples of Parametric Tests:**

* ANOVA (Analysis of Variance)
* Pearson Correlation
* D'Agostino and Pearson Test (for normality)

**Pros:**

* More powerful if assumptions are met
* Provides more accurate results with normally distributed data

**Cons:**

* Requires data to meet strict assumptions (normality, homoscedasticity)
* Sensitive to outliers

### **🔎 What is a Non-Parametric Test?**

A **non-parametric test** does not assume any specific distribution for the data. These tests are more robust to violations of assumptions and are suitable for ordinal data, ranked data, or when the data does not meet the assumptions of parametric tests.

**Examples of Non-Parametric Tests:**

* Mann-Whitney U Test
* Wilcoxon Signed-Rank Test
* Kruskal-Wallis Test
* Spearman Correlation

**Pros:**

* No strict assumptions about data distribution
* Suitable for ordinal, ranked, or skewed data
* More robust to outliers

**Cons:**

* Less powerful than parametric tests when assumptions are met
* Provides less detailed information compared to parametric tests

## **Mann-Whitney U Test**

### **What it is for**

The Mann-Whitney U Test compares two independent groups to see if one group tends to have higher or lower values than the other, without assuming that the data follow a normal distribution.

### **When to use it**

* When you have **two independent samples** (e.g., Group A vs. Group B).
* When your data may **not be normally distributed**.
* Typically used for smaller sample sizes or for ordinal data.

### **Pros**

* Does **not** require normally distributed data.
* Simple to interpret: checks which group tends to have higher rankings.

### **Cons**

* Less powerful than a t-test if the data are truly normal.
* Does **not** compare means directly, it compares distributions.

### **Sample Python Code**

| import numpy as np from scipy.stats import mannwhitneyu  *# Example data for two groups* group\_A = [12, 15, 14, 10, 9, 11, 14] group\_B = [8, 7, 10, 11, 6, 9, 8]  *# Perform Mann-Whitney U test (two-sided)* u\_stat, p\_value = mannwhitneyu(group\_A, group\_B, alternative='two-sided')  print(f"U statistic: {u\_stat}") print(f"p-value: {p\_value}") |
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## **Wilcoxon Signed-Rank Test**

### **What it is for**

The Wilcoxon Signed-Rank Test compares two related (paired) samples to see if their median differences are zero. It’s the non-parametric counterpart to the paired t-test.

### **When to use it**

* When you have **paired** or **matched** data (e.g., the same group measured **before and after** an intervention).
* When your differences may **not be normally distributed**.

### **Pros**

* Does **not** assume normality of the differences.
* Great for comparing “before vs. after” scenarios.

### **Cons**

* Less powerful than the paired t-test if the data are actually normal.
* Only analyzes the signs and ranks of the differences, not the actual magnitude.

### **Sample Python Code**

| import numpy as np from scipy.stats import wilcoxon  *# Example: before & after measurements* before = [12, 13, 15, 14, 16, 20] after = [14, 14, 14, 15, 18, 22]  *# Perform Wilcoxon Signed-Rank test* w\_stat, p\_value = wilcoxon(before, after, alternative='two-sided')  print(f"Wilcoxon statistic: {w\_stat}") print(f"p-value: {p\_value}") |
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## **ANOVA (Analysis of Variance)**

### **What it is for**

ANOVA checks if there is a **difference in the mean** of a numerical variable across **three or more groups**, assuming data are roughly normal and have similar variances.

### **When to use it**

* When you have **3+ groups** (e.g., Group A, Group B, Group C).
* When data for each group are **normally distributed** and have roughly **equal variances** (check with Levene’s test or Bartlett’s test).

### **Pros**

* Lets you compare **more than two means** at the same time.
* Widely used in many fields.

### **Cons**

* If there is a significant difference, ANOVA doesn’t tell you **which** groups differ. You need a post-hoc test like Tukey’s HSD.
* Requires normality and equal variance assumptions (though fairly robust to minor violations).

### **Sample Python Code**

| import numpy as np from scipy.stats import f\_oneway  *# Example data: three groups* group\_A = [12, 14, 15, 13, 16] group\_B = [18, 17, 20, 19, 21] group\_C = [11, 10, 9, 12, 8]  *# Perform one-way ANOVA* F\_stat, p\_value = f\_oneway(group\_A, group\_B, group\_C)  print(f"F-statistic: {F\_stat}") print(f"p-value: {p\_value}") |
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## **Kruskal-Wallis Test**

### **What it is for**

Kruskal-Wallis is a non-parametric version of ANOVA. It checks if **three or more** independent groups come from the same distribution, without assuming normality.

### **When to use it**

* When you want to compare **3+ independent groups**, but data are **not normally distributed** or are **ordinal**.
* Similar to how you’d use ANOVA, but for non-normal data.

### **Pros**

* Does **not** require normality.
* Lets you handle more than two groups at once.

### **Cons**

* If significant, it doesn’t say which groups differ — you need a post-hoc test (like Dunn’s test).
* Less powerful than ANOVA when data are truly normal.

### **Sample Python Code**

| import numpy as np from scipy.stats import kruskal  *# Example data: three groups* group\_A = [12, 14, 15, 13, 16] group\_B = [18, 17, 20, 19, 21] group\_C = [11, 10, 9, 12, 8]  *# Perform Kruskal-Wallis test* H\_stat, p\_value = kruskal(group\_A, group\_B, group\_C)  print(f"H-statistic: {H\_stat}") print(f"p-value: {p\_value}") |
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## **Spearman Correlation**

### **What it is for**

Spearman Correlation measures the **monotonic relationship** between two variables. It ranks the data and calculates a correlation of those ranks. It’s a non-parametric alternative to Pearson’s correlation.

### **When to use it**

* When you want to see if as one variable increases, the other **tends** to increase (or decrease), and your data may not be linear or normally distributed.
* When you have **ordinal** data or outliers that could distort a Pearson correlation.

### **Pros**

* Does not require normality.
* Captures monotonic (not necessarily linear) relationships.

### **Cons**

* Doesn’t distinguish between different shapes of monotonic relationships (any monotonic pattern yields a positive or negative correlation).
* Less powerful than Pearson’s correlation if data are truly linear and normal.

### **Sample Python Code**

| import numpy as np from scipy.stats import spearmanr  *# Example data* x = [10, 11, 14, 15, 20, 22, 25] y = [ 3, 4, 5, 10, 12, 20, 18]  *# Compute Spearman correlation* corr, p\_value = spearmanr(x, y)  print(f"Spearman Correlation: {corr}") print(f"p-value: {p\_value}") |
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## **✅ Key Difference Between Spearman and Pearson Correlation**

| **Feature** | **Spearman Correlation** | **Pearson Correlation** |
| --- | --- | --- |
| **Measures** | **Monotonic relationship** (increases or decreases consistently) | **Linear relationship** (straight-line relationship) |
| **Data Type** | Works with **ordinal, ranked, or non-normal data** | Requires **continuous and normally distributed data** |
| **Effect of Outliers** | **Robust to outliers** | **Sensitive to outliers** |
| **Assumptions** | No strict assumptions about data distribution | Assumes **normal distribution** and **homoscedasticity** |
| **Usage** | Use when data is **not linear** or has **outliers** | Use when data has a **linear relationship** |

## **D'Agostino and Pearson Test**

### **What it is for**

The **D'Agostino and Pearson Test** checks whether a given dataset is normally distributed by combining two aspects of normality: **skewness** (asymmetry) and **kurtosis** (peakedness). It’s a more robust test for normality, especially for large datasets.

### **When to use it**

* When you need to check if your data follows a **normal distribution**.
* Particularly useful for **large sample sizes** where Shapiro-Wilk Test is not reliable.
* When you want to detect deviations from normality due to skewness or kurtosis.

### **Pros**

* Suitable for **large sample sizes**.
* Tests for both **skewness** and **kurtosis** deviations from normality.
* More robust than Shapiro-Wilk for larger datasets.

### **Cons**

* Less sensitive for small sample sizes (for small samples, Shapiro-Wilk may still be better).
* Provides a binary result (normal vs. not normal) without showing the magnitude of deviation.

### **Sample Python Code**

| import numpy as np from scipy.stats import normaltest  *# Example data* sample\_data = [12, 13, 15, 14, 16, 20, 18, 19, 17, 15, 14, 13]  *# Perform D'Agostino and Pearson Test* stat, p\_value = normaltest(sample\_data)  print(f"D'Agostino and Pearson Statistic: {stat}") print(f"p-value: {p\_value}")  *# Interpretation* if p\_value < 0.05:  print("The p-value is less than 0.05. We reject the null hypothesis. The data is not normally distributed.") else:  print("The p-value is greater than or equal to 0.05. We fail to reject the null hypothesis. The data is normally distributed.") |
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### **Interpretation**

* If **p-value < 0.05**: Reject the null hypothesis. The data **is not normally distributed**.
* If **p-value ≥ 0.05**: Fail to reject the null hypothesis. The data **is normally distributed**.

### **Summary Table (Updated with D'Agostino and Pearson Test)**

| **Test** | **Purpose** | **When to Use** | **Parametric/Non-Parametric** |
| --- | --- | --- | --- |
| Mann-Whitney U Test | Compare two independent groups | Non-normal distribution, ordinal data | Non-parametric |
| Wilcoxon Signed-Rank Test | Compare two paired groups | Before/after studies, non-normal distribution | Non-parametric |
| ANOVA | Compare means of 3+ groups | Normally distributed data, equal variances | Parametric |
| Kruskal-Wallis Test | Compare distributions of 3+ independent groups | Non-normal distribution, ordinal data | Non-parametric |
| Spearman Correlation | Measure monotonic relationship between two variables | Ordinal data, non-linear or non-normal data | Non-parametric |
| D'Agostino and Pearson Test | Test for normality | Large datasets, check for skewness and kurtosis | Parametric |