

# What's the difference between interquartile range and standard deviation?

Authored by  
**stats writer**

December 6, 2025

## RECOMMENDED CITATION

stats writer (2025). *What's the difference between interquartile range and standard deviation?*. PSYCHOLOGICAL SCALES. Retrieved from <https://scales.arabpsychology.com/?p=106542>

## Understanding Measures of Variability

In the field of statistics, understanding the characteristics of a dataset requires more than just knowing its center. While measures like the mean, median, and mode describe the central tendency, it is equally critical to quantify the spread or dispersion of the data points. This concept of variability helps researchers and analysts determine how representative the central value is and how spread out the individual observations are. Two of the most commonly employed metrics for measuring this spread are the **interquartile range (IQR)** and the **standard deviation**. Although both serve the general purpose of quantifying dispersion, they approach the task through fundamentally different mathematical philosophies, making them suitable for distinct types of data distributions and analytical goals. Recognizing these differences is essential for accurate data interpretation and robust decision-making across scientific, financial, and sociological disciplines.

The choice between using the interquartile range or the standard deviation often hinges on the shape of the data's distribution, particularly its symmetry and the presence of extreme values. A metric is often preferred based on whether the data is normally distributed or heavily skewed. For instance, the standard deviation is intrinsically linked to the mean, making it most effective when the distribution is relatively symmetric and follows a normal curve, where the mean is a good representation of the center. Conversely, the interquartile range is based on positional statistics (quartiles) and is much more robust against distortions caused by non-symmetric distributions or significant outliers. This inherent difference in calculation methodology dictates when and why one measure of variability should be prioritized over the other in professional statistical analysis.

This comprehensive guide will meticulously detail the definition, calculation, and interpretation of both the interquartile range and the standard deviation. We will explore their underlying mathematical principles, demonstrate their application using a shared dataset, and critically examine the key operational differences--specifically, how each metric handles the influence of atypical data points or **outliers**. By the end of this discussion, you will possess the clarity needed to confidently select the appropriate measure of dispersion for any given dataset, ensuring the integrity and accuracy of your statistical findings.

### Defining the Interquartile Range (IQR)

The **interquartile range** (IQR) is a non-parametric measure of statistical dispersion that describes the range of the middle portion of a data set. Unlike the total range (maximum value minus minimum value), the IQR focuses specifically on the central 50% of the observations. This measurement method is based on partitioning the ordered dataset into four equal sections, known as quartiles. These quartiles divide the data points such that 25% of the data falls below the first quartile (Q1), 50% falls below the second quartile (Q2, which is the median), and 75% falls below the third quartile (Q3).

The IQR is fundamentally defined as the difference between the third quartile (Q3, the 75th percentile) and the first quartile (Q1, the 25th percentile). Mathematically, this relationship is expressed simply as  **$IQR = Q3 - Q1$** . Because the IQR only relies on these two specific positional values, it inherently ignores the extreme observations at both the lower and upper tails of the distribution. This attribute gives the IQR its characteristic strength: it is highly resistant to the influence of extreme values or skewed distributions. If a dataset contains severe outliers, the IQR remains stable, offering a reliable estimate of the typical spread of the bulk of the data, which is a significant advantage over metrics that incorporate every single observation.

The IQR is most frequently employed in exploratory data analysis and is a key component in constructing a **boxplot** (or box-and-whisker plot), a graphical representation designed to display the five-number summary (minimum, Q1, median, Q3, maximum). Furthermore, the IQR plays a vital role in formal outlier detection. Using the "1.5 \* IQR rule," data points falling more than 1.5 times the IQR below Q1 or above Q3 are generally flagged as potential outliers. This systematic method of identifying unusual observations is central to data cleaning and validating assumptions prior to deeper statistical modeling.

## Calculating and Interpreting the IQR

To calculate the interquartile range, the dataset must first be sorted in ascending order. The next step involves locating the median (Q2), which splits the data into two halves. Q1 is then the median of the lower half of the data, and Q3 is the median of the upper half. Consider the following example dataset used in the original analysis:

**Dataset:** 1, 4, 8, 11, 13, 17, 19, 19, 20, 23, 24, 24, 25, 28, 29, 31, 32

This dataset contains 17 observations ( $n=17$ ). The process of calculating the quartiles involves specific procedures for handling both odd and even sample sizes. For this particular dataset, the calculation yields the following key quartile values:

**Q1 (First Quartile):** 12

**Q3 (Third Quartile):** 26.5

Applying the IQR formula, we find:  **$IQR = Q3 - Q1 = 26.5 - 12 = 14.5$** . This resulting value of 14.5 is the measure of spread for the central 50% of the data. Interpretation of the IQR is straightforward: it tells us the width of the interval containing the middle half of the scores. A larger IQR suggests greater variability in the core data, while a smaller IQR indicates that the central data points are tightly clustered around the median. This measure is highly descriptive and intuitive, especially when analyzing skewed distributions where the distance from the median is more informative than the distance from the mean.

To illustrate the robustness of the IQR, we can re-examine the calculation when an extreme value is introduced. If we append a massive **outlier** to the dataset, 378, the structure of the central 50% remains largely unchanged. The new Q1 and Q3 positions are minimally affected because they are based on count rather than value magnitude, resulting in a new IQR of 15.0. This negligible change demonstrates its key advantage: the IQR provides a stable assessment of typical variability, making it the preferred measure of dispersion when the underlying distribution is non-normal, heavily skewed, or contaminated by measurement errors or genuine anomalies.

## Defining the Standard Deviation

The **standard deviation** (SD) is perhaps the most ubiquitous and mathematically sophisticated measure of dispersion in descriptive statistics. Unlike the IQR, which uses only two data points (Q1 and Q3), the standard deviation incorporates every single value in the dataset into its calculation. It is defined as a measure of the typical distance or deviation of individual data points from the dataset's **mean**. A low standard deviation indicates that the data points tend to be very close to the mean, meaning the data is highly clustered. Conversely, a high standard deviation indicates that the data points are spread out over a wider range of values, suggesting greater overall variability.

The standard deviation is fundamentally rooted in the concept of variance, which is the average of the squared differences from the mean. The standard deviation itself is simply the square root of the variance. This squaring operation serves a critical mathematical function: it eliminates the negative signs that result when calculating the differences between values below the mean and the mean itself, ensuring that all deviations contribute positively to the measure of spread. More importantly, the act of squaring disproportionately emphasizes larger deviations, meaning that data points far away from the mean contribute significantly more to the final standard deviation value than those close to the mean. This mathematical sensitivity is both the strength and the weakness of the standard deviation.

The formula for calculating the sample standard deviation ( $s$ ) is given as:

$$s = \sqrt{\frac{\sum(x_i - \bar{x})^2}{(n-1)}}$$

Where:  $x_i$  represents each individual value,  $\bar{x}$  represents the sample **mean**, and  $n$  represents the sample size. The use of  $(n-1)$  instead of  $n$  in the denominator is known as **Bessel's correction** and is applied when calculating the sample standard deviation to ensure it is an unbiased estimator of the population standard deviation. Because the standard deviation uses the mean in its calculation and employs all data points, it is categorized as a parametric statistic, ideally suited for data that is approximately normally distributed.

## Calculating and Interpreting the Standard Deviation

Calculating the standard deviation is a multi-step process that demands attention to detail. Using our previous example dataset, we first determine the mean, then calculate the difference between each data point and the mean, square those differences, sum the squared differences (resulting in the Sum of Squares), calculate the variance, and finally, take the square root to obtain the standard deviation.

**Dataset:** 1, 4, 8, 11, 13, 17, 19, 19, 20, 23, 24, 24, 25, 28, 29, 31, 32

For this specific dataset, the calculated sample mean is approximately 19.88. Following the multi-step formula (which is typically handled by statistical software or calculators), the sample standard deviation is found to be **9.25**. This value of 9.25 indicates the typical spread of data points around the mean. In normally distributed data, the standard deviation has a powerful interpretive property: approximately 68% of the data falls within one standard deviation of the mean, and about 95% falls within two standard deviations. This property forms the basis for numerous inferential statistical techniques, including confidence intervals and hypothesis testing.

However, the extreme sensitivity of the standard deviation becomes dramatically apparent when the dataset is contaminated by an **outlier**. Let us re-examine the dataset including the extreme value 378:

**Dataset with Outlier:** 1, 4, 8, 11, 13, 17, 19, 19, 20, 23, 24, 24, 25, 28, 29, 31, 32, **378**

The inclusion of 378 not only shifts the **mean** significantly but also drastically inflates the variance due to the squaring of the large deviation  $(378 - \text{new mean})^2$ . While the standard deviation for the original dataset was 9.25, the addition of the outlier causes it to surge to **85.02**. This massive increase highlights that the standard deviation is a comprehensive, but fragile, measure of spread: it reflects the magnitude of every observation, including anomalies, providing a complete picture of variability but sacrificing robustness.

## Key Similarities and Fundamental Differences

Despite their distinct mathematical underpinnings, the interquartile range and the **standard deviation** share the fundamental goal of measuring the dispersion of values within a dataset. Both metrics quantify variability--how spread out the observations are--and are used to complement measures of central tendency. A general rule of thumb is that if the IQR is small, the standard deviation will also likely be small, assuming no extreme outliers are present, because both indicate tight clustering of data points.

The most profound difference lies in their sensitivity to extreme values. The IQR is categorized as

a **resistant** measure because it is based on positional data--the 25th and 75th percentiles. The calculation effectively ignores the 25% of data at the lower tail and the 25% of data at the upper tail, making it entirely unaffected by any value changes outside of the Q1 and Q3 boundaries. This resilience makes the IQR the ideal measure of spread for data distributions that are highly skewed, contain numerous potential errors, or have confirmed **outliers**.

Conversely, the standard deviation is highly **sensitive** to extreme values. As demonstrated, the standard deviation incorporates every observation, and the crucial step of squaring the deviations ensures that large distances from the **mean** are heavily weighted. When an outlier is present, the standard deviation provides a measure of spread that encompasses the entire range of variability, but this comprehensive nature means it is easily inflated and may no longer accurately represent the variability of the typical data points. Furthermore, the standard deviation is always paired with the mean, while the IQR is paired with the median (Q2), reflecting their suitability for symmetric versus skewed data, respectively.

Finally, another significant difference is the ease of mathematical manipulation and use in inferential statistics. The standard deviation, derived from the mathematically elegant concept of variance, is a crucial parameter in advanced statistical models, including regression analysis, ANOVA, and all forms of parametric testing. It is mathematically traceable and linked to the properties of the normal distribution. The IQR, while useful for descriptive purposes and non-parametric statistics, does not possess the same analytical utility or mathematical tractability for complex modeling as the **standard deviation**.

## Practical Guide: Choosing the Right Metric

Selecting between the interquartile range and the standard deviation depends entirely on the context of the analysis, the nature of the data distribution, and the intended purpose of the summary statistic. A good statistician understands that no single measure is inherently superior; rather, the most appropriate choice is the one that best communicates the underlying phenomenon without distortion.

### When to use the Interquartile Range (IQR):

The IQR is the preferred measure of variability when the assumptions required for parametric statistics are violated, specifically when the data is known to contain anomalies or is distributed non-symmetrically. If your dataset is heavily skewed (e.g., income data, reaction times, survival data) or if you are deliberately using the median as your measure of central tendency, the IQR provides the most stable and representative measure of spread. It accurately characterizes the clustering of the central data points without being misleadingly stretched by a few extreme values. This robustness is paramount in fields like finance or quality control, where extreme fluctuations or errors can significantly distort results if the standard deviation were used.

## When to use the Standard Deviation:

The **standard deviation** should be used when the dataset approximates a normal distribution, or at least is reasonably symmetric, and when the **mean** is chosen as the measure of central tendency. Since the standard deviation uses all observations, it provides a comprehensive view of the total variation present. Furthermore, if the goal of the analysis is to perform inferential statistical tests, such as comparing means between different groups or building predictive models, the standard deviation is mandatory, as these methods rely on the mathematical properties derived from variance. If outliers are present but are deemed genuine and relevant to the study (e.g., recording high-risk events), the standard deviation provides a true measure of the total variation, reflecting the full impact of those extreme values.

## Summary of Key Comparisons

The fundamental distinction between the interquartile range and the standard deviation rests on how they handle every data point. The IQR discards the tails to find a resistant measure of central spread, while the standard deviation incorporates the squared distance of every point to the mean, providing a sensitive measure of total variance. This difference dictates their applicability, transitioning from descriptive analysis where robustness is key, to inferential modeling where mathematical tractability is essential.

To finalize the comparison, observe the contrasting impact of an extreme **outlier** in our example:

### Original Dataset Spread:

**Interquartile Range:** 14.5

**Standard Deviation:** 9.25

### Dataset with Outlier (378) Spread:

**Interquartile Range:** 15.0 (Minimal change)

**Standard Deviation:** 85.02 (Massive inflation)

This stark numerical contrast underscores the importance of choosing the correct measure of dispersion. If your objective is to understand the typical variation experienced by the majority of your observations, especially when contamination is possible, the **IQR** is the superior descriptive statistic. However, if the variability caused by extreme events is a critical component of the phenomenon being studied, or if advanced parametric testing is required, the **standard deviation** is indispensable. Mastery of these two metrics allows for a nuanced and accurate characterization of any statistical population.