

Descriptive Statistics

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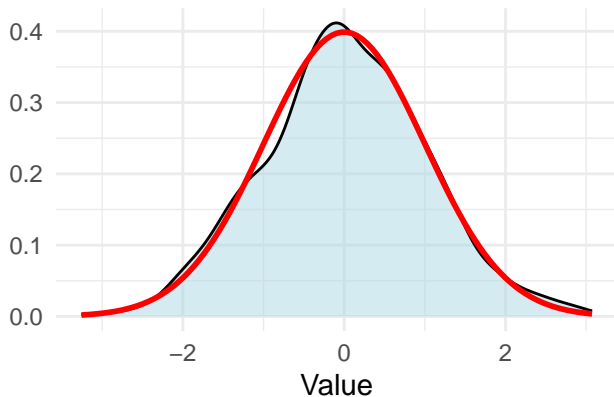


Why describe data?

- Determine if our sample reflects the population of interest.
- Identify outliers.
- Obtain metrics necessary for inferential tests.
- Understand the distribution of our data values (i.e., test for normality).
- Identify the type of statistical test to run.

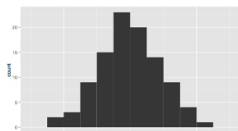
Data description and visualization

- We can examine our data and run statistical tests to see if the distribution approximates a normal curve.
- Typically, we start by visualizing our data.

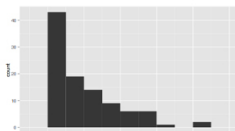


Histogram basic

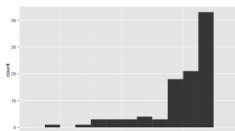
- Continuous data are most commonly visualized using Histograms.



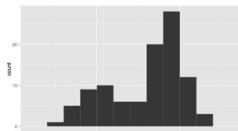
Symmetric, unimodal



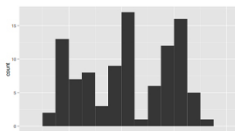
Skewed right



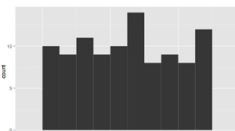
Skewed left



Bimodal

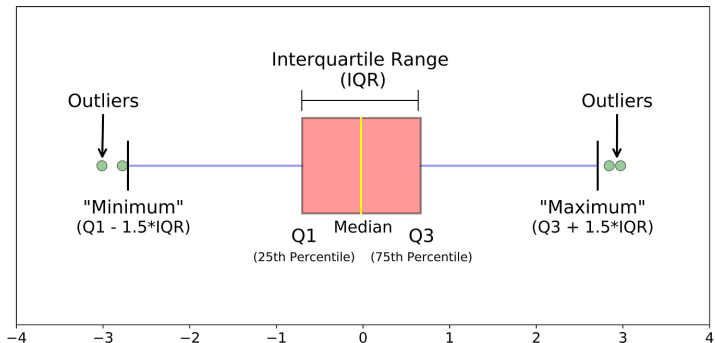


Multimodal



Symmetric

Box and Whisker Basics



Metrics to Describe data distribution.

- Data and their associated distributions can be described in four primary way:
 - ▶ Central Tendency (mean, median, mode)
 - ▶ Variability (standard deviation, variance, quantiles)
 - ▶ Skew
 - ▶ Kurtosis (Peakedness)

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Central tendency

- Mean (Sum of scores/ N)
 - ▶ Most often used measure of central tendency.
 - ▶ Works well with normal and relatively normal curves.
- Median (50th Percentile)
 - ▶ No formula. Rank order observations then find the middle.
 - ▶ The second most used measure of central tendency.
 - ▶ Works best with highly skewed populations.
- Mode (Most Frequent Score)
 - ▶ Least used measure of central tendency.
 - ▶ Works best for highly irregular and multimodal distributions.

Central tendency: Mean

- Sample mean is the measure of central tendency that best represents the population mean.
- Mean is **very** sensitive to extreme scores that can “skew” or distort findings.

Central tendency: Median

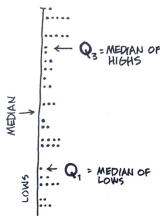
- Percentiles are used to define the percent of cases equal to and below a certain point on a distribution.
 - ▶ The median **is the 50th percentile** half of all observations fall at or below this value.
- But lots of other percentiles are also important.

A little about Percentiles

- Quartiles are a common percentile used to represent the value below which.
 - ▶ 25% (Q_1 or first quartile)
 - ▶ 75% (Q_3 or third quartile)

HERE'S THE RECIPE:

- 1)** PUT THE DATA IN NUMERICAL ORDER.
- 2)** DIVIDE THE DATA INTO TWO EQUAL HIGH AND LOW GROUPS AT THE MEDIAN. (IF THE MEDIAN IS A DATA POINT, INCLUDE IT IN BOTH THE HIGH AND LOW GROUPS.)
- 3)** FIND THE MEDIAN OF THE LOW GROUP. THIS IS CALLED THE FIRST QUARTILE, OR Q_1 .
- 4)** THE MEDIAN OF THE HIGH GROUP IS THE THIRD QUARTILE, OR Q_3 .



When to use What

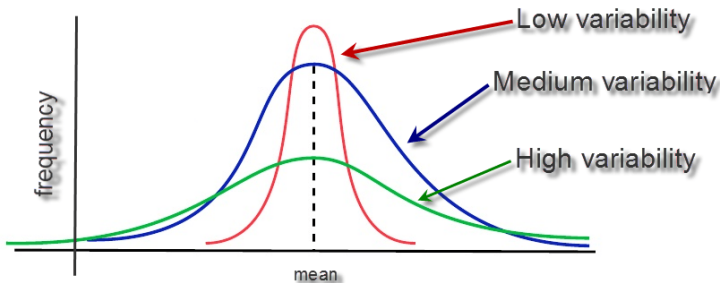
- Use the **Mode** when the data are categorical:
 - ▶ **Mode**: is the value that occurs most frequently in your data.
 - ▶ This is because having the same value occur for measurements with many significant digits is highly unlikely.
- Use the **Median** when you have extreme scores:
 - ▶ **Median**: is simply the value that falls in the middle of all your data.
- Use the **Mean** the rest of the time.



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Variability



Variability: Standard Deviation

- Standard Deviation measures how spread out the numbers in a dataset are around the mean.
- The sample standard deviation s is calculated as:

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

Variability

- **Variance** measures the average of the squared differences from the mean, indicating how spread out the data points are.
- The variance σ^2 is calculated as:

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

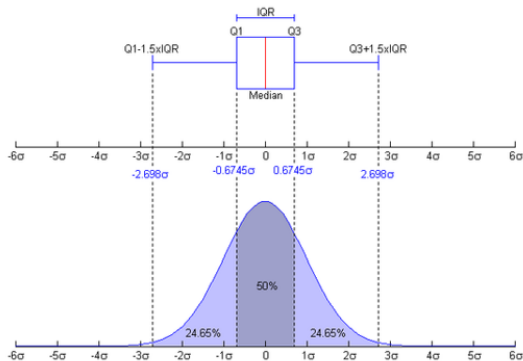
Variability: Range

- **Range** is the difference between the largest and smallest values in a dataset, providing a measure of the spread or dispersion of the data.
- The range is calculated as:

$$\text{Range} = \max(x) - \min(x)$$

Percentiles are useful for spread too

- You can use percentiles to get a feel for how spread out the data is and where most of your observations are contained:
 - ▶ Inter-quartile range (IQR) = $Q3 - Q1$



Identifying outliers

- An outlier is an observation that lies outside the overall pattern of a distribution (Moore and McCabe 1999).
- Usually, the presence of an outlier indicates some sort of problem. (e.g. an error in measurement or sample selection).
- But they may also be an indicator of novel data or identification of unique and exciting observations.

Identifying outliers

- The first and third quantiles (Q1 and Q3) are often calculated to identify outliers.
- One method for systematically identifying outliers uses:
 - ▶ $Q1 - (1.5 * \text{the inter-quartile range})$
 - ▶ $Q3 + (1.5 * \text{the inter-quartile range})$
- Others identify outliers as any values below the 0.5th or above the 99.5th percentile.

When to use What

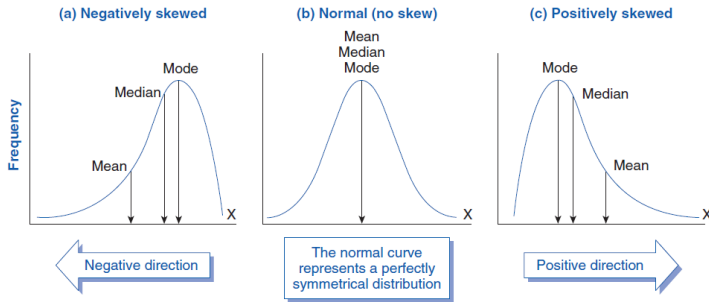
- Use the **Standard deviation (SD)** in most cases.
 - ▶ SD quantifies how far, on average, each observation is from the mean.
 - ▶ The larger the SD, the more highly variable your data.
- Use **range (R)** when describing predictive models.
 - ▶ R is simply the maximum minus the minimum value in your data set
 - ▶ R is important when modeling or making predictions, since your algorithms are valid only over the range of values used to calibrate your predictive model
- Use the **IQR** to identify and test potential outliers in your data.

Metrics to Describe data distribution.

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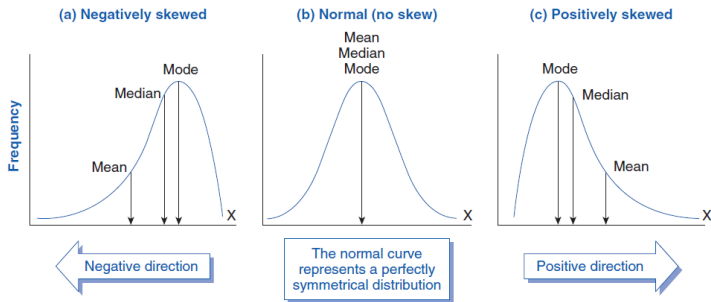
Skewness

- Skewness: This metric quantifies how balanced (symmetrical) your distribution curve is.



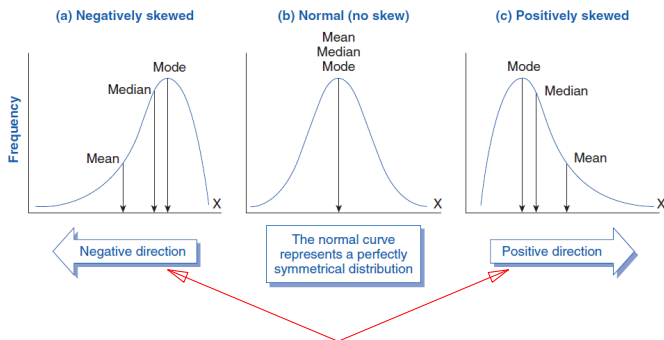
Skewness

- A normal distribution will have its mean and median values located somewhere near the center of its range.



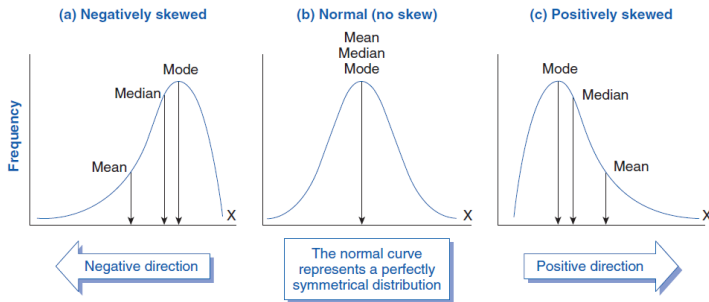
Skewness

- Skew of this peak away from center is common when extreme values pull the median away from the mean.



Skewness

- **Positive Skew:** the “slide” takes you in a positive direction.
 - ▶ The mean is bigger than the median (which is why the slide is being pulled to higher values).
- **Negative Skew:** the “slide” takes you in a negative direction.
 - ▶ The mean is smaller than the median (which is why the slide is being pulled to lower values).



Calculating Skew

- Negative value = Negative Skew.
- Positive value = Positive Skew
- Positive value = Normal distribution

$$\text{Skewness} = \frac{3(\bar{x} - \text{Median})}{\text{SD}}$$

Skewness: Significant?

- To determine if this deviation from zero in the skew statistic is likely a significant departure from normality, compare it to the **standard error of skew (ses)**.
- If the skew you have calculated is more than **2 times the ses**, then you likely have significant skew, which means you have **non normal data** and should consider a nonparametric test for your statistical analyses

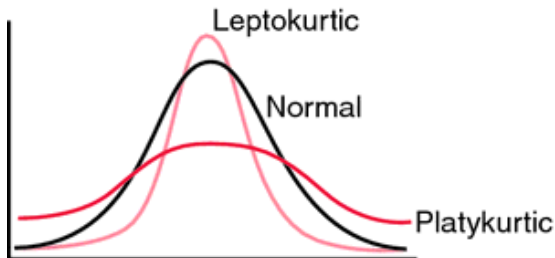
$$\text{ses} = \sqrt{\frac{6}{n}} \qquad \text{Skewness} = \frac{3(\bar{x} - \text{Median})}{\text{SD}}$$

Metrics to Describe data distribution.

- Data and their associated distributions can be described in four primary way:
 - ▶ Central Tendency (mean, median, mode)
 - ▶ Variability (standard deviation, variance, quantiles)
 - ▶ Skew
 - ▶ **Kurtosis (Peakedness)**

Kurtosis

- **Kurtosis** is simply a measure of how pointy or flat the peak of your distribution curve is.
- Any deviation from a bell shape, with the peak either too flat (platykurtic) or too peaked (leptokurtic), suggests that your data are not normally distributed.



Kurtosis

- Positive values = Leptokurtic.
- Zero = Mesokurtic = normal (bell-shaped).
- Negative values = Platykurtic.

$$\text{Kurtosis} = \frac{\sum \left(\left(\frac{x_i - \bar{x}}{SD} \right)^4 - 3 \right)}{n}$$

Kurtosis: Significant?

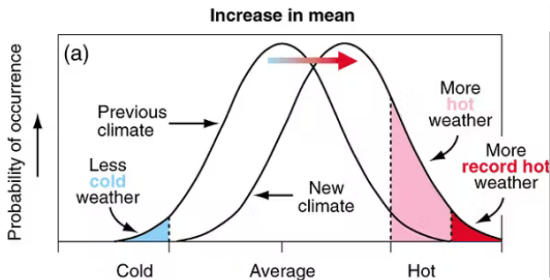
- To determine if this deviation from zero in the kurtosis statistic is likely a significant departure from normality, compare it to the **standard error of kurtosis (sek)**.
- If the kurtosis you have calculated is more than **twice the sek**, you likely have **non normal data** and should consider a nonparametric test for your statistical analyses.

$$sek = \sqrt{\frac{24}{n}}$$

$$\text{Kurtosis} = \frac{\sum \left(\frac{x_i - \bar{x}}{SD} \right)^4 - 3}{n}$$

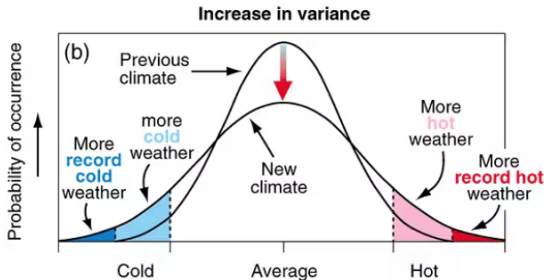
Some Visual Examples

- How can climate change?
- Change in **central tendency**.



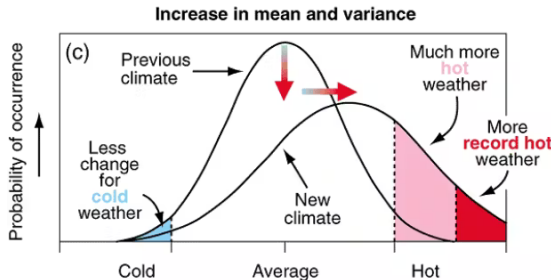
Some Visual Examples

- How can climate change?
- Change in **spread and shape**.



Some Visual Examples

- How can climate change?
- Change in **both**.



Data Distributions

Data Distributions

- There are various types of data distributions, each with its own unique properties and implications.
- In nature, most data are normally distributed.
- The central limit theorem (CLT) states that the distribution of sample means approximates a normal distribution as the sample size gets larger, regardless of the population's distribution.

$$\bar{X}_n \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

- \bar{X}_n : The sample mean of size n .
- $N(\mu, \frac{\sigma^2}{n})$: The normal distribution with mean μ (the population mean) and variance $\frac{\sigma^2}{n}$, where σ^2 is the population variance and n is the sample size.

Why do we care if our data is normal?

- The math “under the hood” of many analyses **expects that data is normally distributed** - if it isn't, you'll still get an answer, but it won't actually be saying what you think it is saying.

Why do we care about **skew** and **kurtosis**?

- Because many statistical analyses assume a normal distribution of the data, testing for normality must always be a precursor to any analysis.
- Normally Distributed Data is:
 - ▶ Unimodal (one mode)
 - ▶ Symmetrical (no SKEW)
 - ▶ Bell Shaped (no KURTOSIS)
 - ▶ Mean, Mode and Median are all centered
 - ▶ Asymptotic (tails never reach 0)

Why do we care about **skew** and **kurtosis**?

- We can examine all of these different descriptors individually, but the easiest and most complete way to test for normality is to test the **goodness of fit** for a normal distribution.

```
# Generate random data from a normal distribution
```

```
set.seed(123)
```

```
data <- rnorm(100, mean = 0, sd = 1)
```

```
# Shapiro-Wilk normality test
```

```
shapiro.test(data)
```

```
##
```

```
## Shapiro-Wilk normality test
```

```
##
```

```
## data: data
```

```
## W = 0.99388, p-value = 0.9349
```


What to do about non-normal data?

- Once you discover that your data is non-normal you have several options:
 - ▶ Analyze and potentially remove outliers
 - ▶ Transform the data mathematically
 - ▶ Conduct non-parametric analyses

Outliers?

- How to find outliers:
 - ▶ Outlier box plots (visual) use the $IQR * 1.5$ threshold.
 - ▶ percentiles (often < 2.5 th or above 97.5th percentile).
- These can help identify potential outliers but **do not justify their removal**.
- Sometimes outliers are **real, correct (although extreme) observations** that we are truly interested in.
- We can only remove outliers if we know the data is **incorrect**

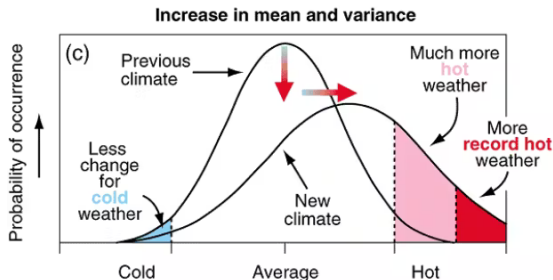
Working with non-normal Data.

- Transformations:

- ▶ To transform your data, apply a mathematical function to each observation, then use these numbers in your statistical test.
- ▶ There are an infinite number of transformations you could use, but it is better to use one common to our field.

Working with non-normal Data.

- Non-normal data happens. Especially with counts, percents, rare events.
- Common transformations in our field:
 - ▶ square-root
 - ▶ log
 - ▶ Inverse
 - ▶ Rank



Square root Transformation

- **Square-root transformation:** This consists of taking the square root of each observation.
- In R use: **sqrt(X)**

```
data <- c(1, 4, 9, 16, 25, 36, 49, 64, 81, 100)
# Apply square-root transformation
sqrt_data <- sqrt(data)
# Goodness of fit test
shapiro.test(sqrt_data)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  sqrt_data
## W = 0.97016, p-value = 0.8924
```

Square root Transformation

- If you apply a square root to a continuous variable that contains values negative values, decimals and values above 1, you are treating some numbers differently than others..
 - ▶ So a constant must be added to move the minimum value of the distribution to 1.

Log Transformation

- Many variables in biology have log-normal distributions.
- In R use: **log(X)**

```
# Sample data (e.g., positive values)  
data <- c(1, 10, 100, 1000, 10000, 100000)  
# Apply log transformation (log base 10)  
log_data <- log10(data)  
# Goodness of fit test  
shapiro.test(log_data)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: log_data  
## W = 0.98189, p-value = 0.9606
```

Log Transformation

- The logarithm of any negative number is undefined and log functions treat decimals differently than numbers >1 .
 - ▶ SO a constant must be added to move the minimum value of the distribution to 1.

Inverse transformation

- **Inverse transformation:** This consists of taking the inverse (X^{-1}) of a number.
- In R use: $1/X$ or $(X)^{-1}$

```
# Sample data (e.g., positive values)  
data <- c(1, 2, 4, 8, 16, 32, 64)  
# Apply inverse transformation (reciprocal)  
inverse_data <- 1 / data
```

- Tends to make big numbers small and small numbers big a constant must be added to move the minimum value of the distribution to 1

Reflecting Transformations

- Each of these transformations can be adjusted for negative skew by taking the reflection
- To reflect a value, multiply data by -1 , and then add a constant to bring the minimum value back above 1.0
- For example:
 - ▶ Square root \sqrt{X} becomes
 - ★ $\sqrt{[(X*-1)+c]}$
 - ▶ Log $\ln(X)$ becomes $-\ln([X*-1] + c)$

Rank Transform

Transformation Rules to Live By

- Transformations work by altering the relative distances between data points.
- If done correctly, all data points remain in the same relative order as prior to transformation.
- However, this might be undesirable if the original variables were meant to be substantively interpretable.
- Therefore. . .

Transformation Rules to Live By

- Don't mess with your data unless you have to.
- Are there true outliers? Remove and retest.
- If you have to mess with it, make sure you know what you are doing. Try different transformations to see which is best.
- Include these details in your methods.
- Back transform to original units for reports of central tendency and variability.
- Sometimes transformations don't work, don't panic, you will just get to run **nonparametric tests**.