

Descriptive Statistics

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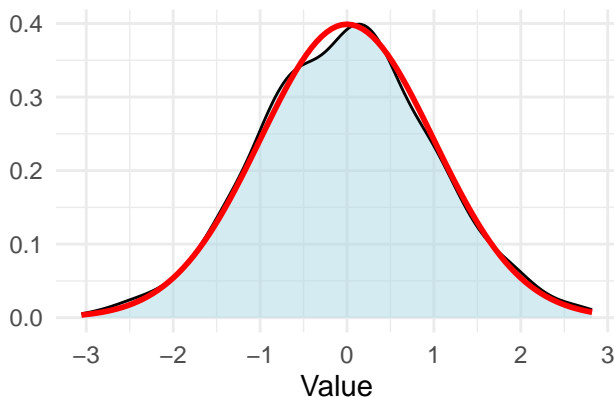


Why describe data?

- 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.

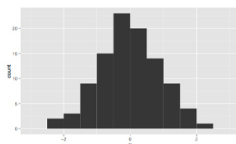
Data description and visualization

- 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.

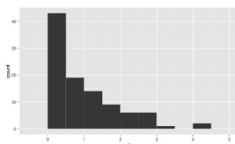


Histogram basic

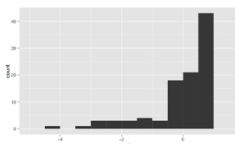
- Continuous data are most commonly visualized using Histograms.
- Histograms display the distribution of data by grouping values into intervals or bins, allowing for an understanding of the frequency and spread of the data.



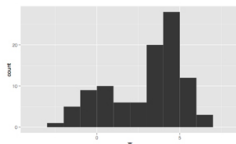
Symmetric, unimodal



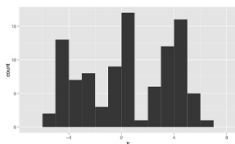
Skewed right



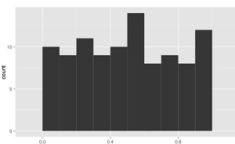
Skewed left



Bimodal



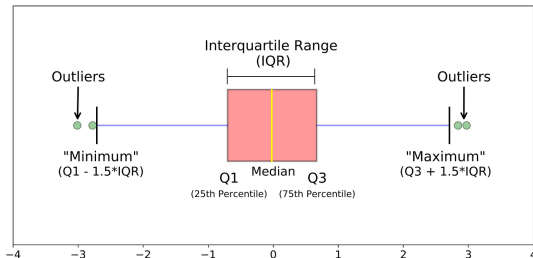
Multimodal



Symmetric

Box and Whisker Basics

- Box plots are used to visualize the distribution of continuous data, showing the **median**, **interquartile range (IQR)**, and **potential outliers**.
- The **box** represents the middle 50% of the data (from the first quartile $Q1$ to the third quartile $Q3$).
- The **line inside the box** shows the median (50th percentile).
- **Whiskers** extend from the box to the smallest and largest values within 1.5 times the IQR from $Q1$ and $Q3$.
- **Data points outside the whiskers** are considered potential outliers.



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** $\left(\frac{\sum x}{n}\right)$:

- ▶ 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

- $\left(\bar{X} = \frac{\sum X}{n}\right)$
 - ▶ where X represents individual data points and n is the number of observations.
- 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

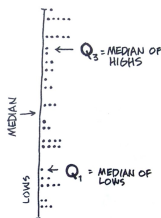
- Percentiles are used to define the percent of cases equal to and below a certain point on a distribution.
 - ▶ The median **is the 50th percentile**, meaning *half of all observations fall at or below this value*.
- But lots of other percentiles are also important.

A little about Percentiles

- Quartiles (i.e., divide data into four equal parts: 25%, 50%, 75%) are a common percentile used to represent the value below which.
 - 25% (Q1 or first quartile)
 - 75% (Q3 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

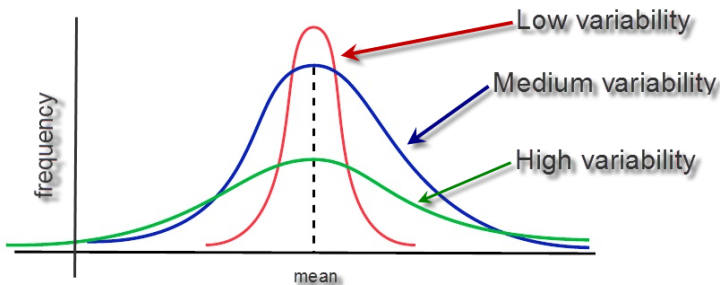
- Use the **Mode** when the data are categorical:
 - ▶ **Mode**: is the value that occurs most frequently in your data.
 - ▶ This is because having the same value occur for measurements with many significant digits is highly unlikely.
- Use the **Median** when you have extreme scores:
 - ▶ **Median**: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



Metrics to Describe data distribution.

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 - ▶ **Variability (standard deviation, variance, quantiles)**
 - ▶ Skew
 - ▶ Kurtosis (Peakedness)

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:

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

- s : The **sample standard deviation**, which measures the spread or variability of the data points around the sample mean \bar{x} .
- n : The **sample size**, or the number of observations in the dataset.
- x_i : Each individual data point in the sample.
- \bar{x} : The **sample mean**, or the average of the sample data.

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:

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

- **Variance is always larger than the Standard Deviation (SD)** because variance is the square of SD. For example, if the SD is 3, the variance will be $3^2 = 9$.

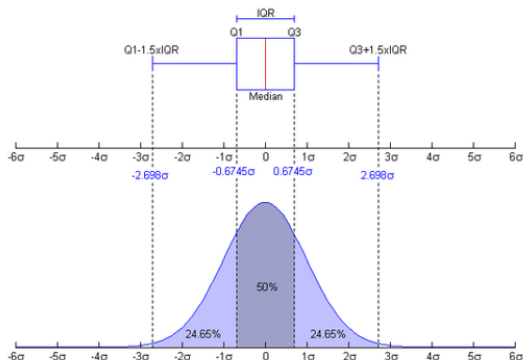
Variability: Range

- **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

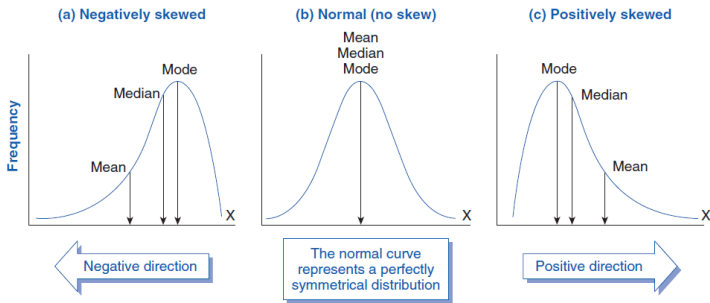
- Use the **Standard deviation (SD)** in most cases.
 - ▶ SD quantifies how far, on average, each observation is from the mean.
 - ▶ The larger the SD, the more highly variable your data.
- Use **range (R)** when describing predictive models.
 - ▶ R is simply the maximum minus the minimum value in your 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.

- 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)

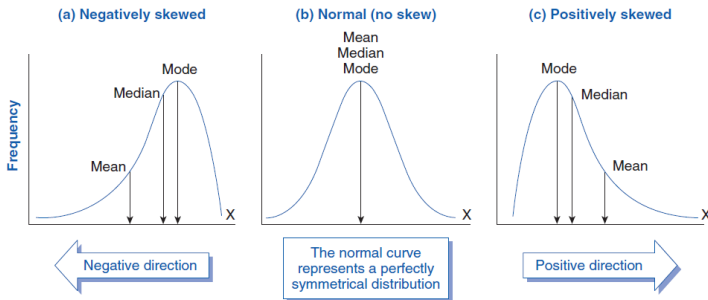
Skewness

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



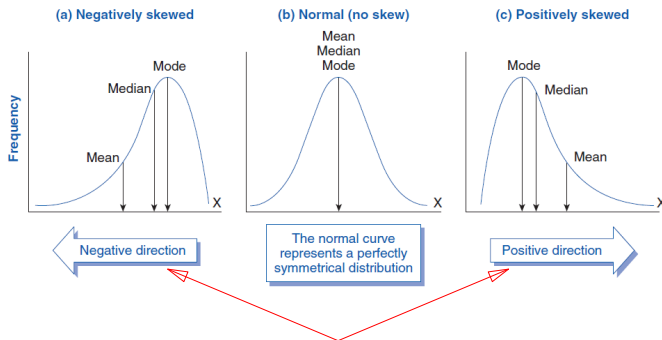
Skewness

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



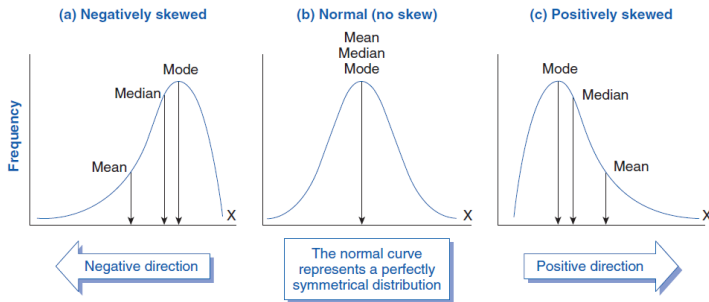
Skewness

- 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
- Zero = Normal distribution

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

- where:
 - ▶ \bar{x} is the **sample mean**, representing the average of all data points.
 - ▶ **Median** is the middle value in a dataset when sorted in ascending or descending order.
 - ▶ **SD** (Standard Deviation) measures the spread of the data points around the mean.

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

$$ses = \sqrt{\frac{6}{n}}$$

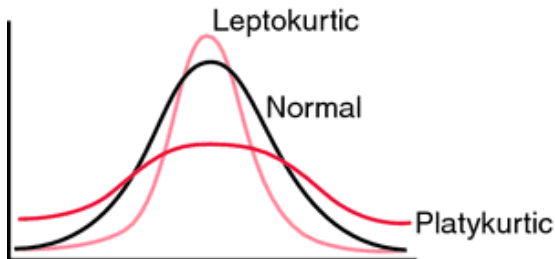
$$\text{Skewness} = \frac{3(\bar{x} - \text{Median})}{SD}$$

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.

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

- where:
 - ▶ x_i represents each individual data point.
 - ▶ \bar{x} is the **sample mean**, the average of all data points.
 - ▶ **SD** (Standard Deviation) is the measure of how spread out the data points are from the mean.
 - ▶ n is the number of data points in the sample.
 - ▶ The subtraction of 3 is to adjust for the kurtosis of a normal distribution, which has a kurtosis of 3.

Kurtosis: Significant?

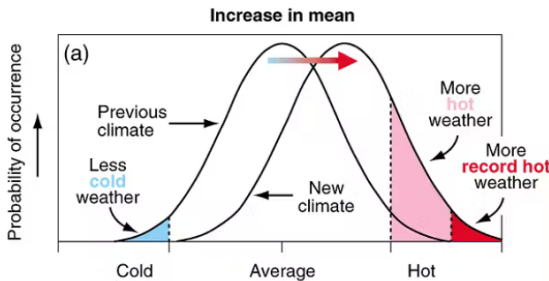
- To determine if this deviation from zero in the kurtosis statistic is likely a significant departure from normality, compare it to the **standard error of kurtosis (sek)**.
- If the kurtosis you have calculated is more than **twice the sek**, you likely have **non normal data** and should consider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

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

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

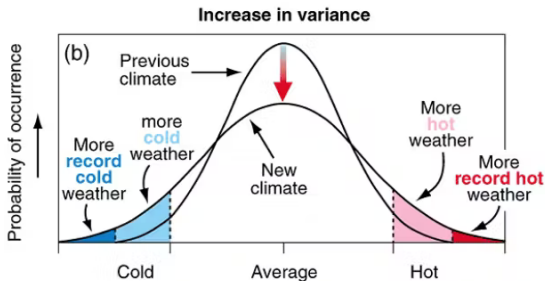
Some Visual Examples

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



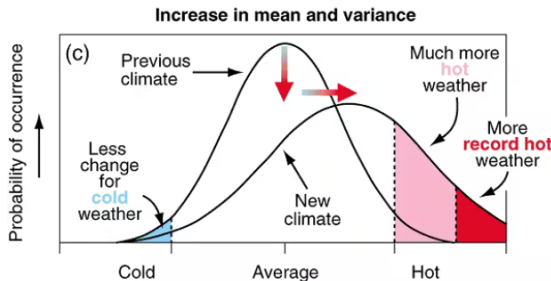
Some Visual Examples

- 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.

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

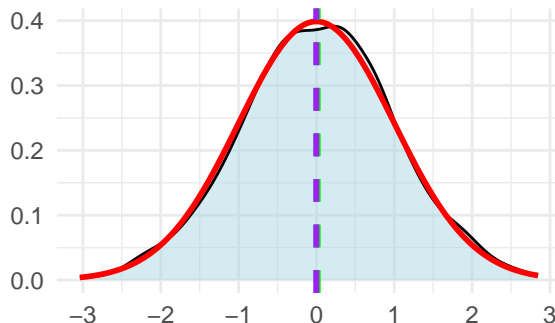
This means that \bar{X}_n (the average of your sample) will approximately follow a normal distribution with a mean of μ and a standard deviation of $\frac{\sigma}{\sqrt{n}}$, especially if your sample size n is large.

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.
 - ▶ **IQR:** $Q_3 - Q_1$
 - ▶ **Lower Threshold:** $Q_1 - (1.5 * IQR)$
 - ▶ **Upper Threshold:** $Q_3 + (1.5 * IQR)$
- 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**

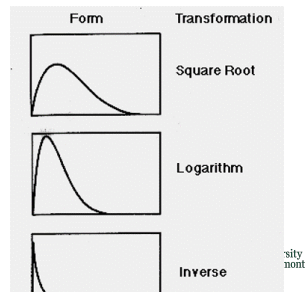
Working with non-normal Data.

- 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:
 - ★ for moderate skew.
 - ▶ log:
 - ★ for positively skewed data.
 - ▶ Inverse:
 - ★ for severe skew.
 - ▶ 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**.