Four general ways to address violations:

- **Ignore**
  - Sometimes you can use a method even if assumptions are violated
  - Thank the Central Limit Theorem for robustness
    - *means of large samples are normally distributed*
    - **tests that are based on** comparing sample **means** will be robust when they have sufficient sample size
    - **this doesn't help with F-test etc.**
  - Especially true if sample sizes are large ($n_i >> 50$) and violations are not extreme
    - **sample size must increase to accommodate how extreme violations are between groups**
      - especially if two samples both differ in opposite directions
  - Even with CLT we can't always ignore:
    - **outliers**
    - **frequency distribution between groups is very different**

Four general ways to address violations:

- Ignore
  - sometimes you can use a method even if assumptions are violated
  - especially true if sample sizes are large an violations are not extreme
- Transform
  - attempt to force normality and other assumptions onto data
  - We will investigate various tools
    - Usually boils down to: ***take the log of the data***
    - *Changes each measurement in the same way (1 to 1 correspondence) so that you can* ***transform back to get original data without ambiguity***
      - **monotonic relationship with original values**
      - remember to transform back the upper and lower limits for a Confidence Interval
  - work that does not always pay off but you at least maintain power of the test that you are using (since nonparameteric tests usually reduce power)

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- Use Non-parametric method
    - classes of methods that do not require assumption of normality
    - not cost free! Often lose power etc

Power = 1-P[FTR Ho|Ho is incorrect] = P[reject|Ho is incorrect]

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- Use Non-parameter method
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- **Computationally Intensive Methods**
  - Simulation
  - Bootstrap
  - randomization/permutation test

Data Transformation:

- a data transformation changes each data point by some simple mathematical formula
  - Used to improve fit of the normal distribution to the data to make standard deviation more similar between groups
  - 1 to 1 correspondence between transformed data and original scale
    - requires the same transformation be applied to each individual
    - Monotonic relationship with original values
    - e.g. larger values stay larger

Data Transformation:

- you can try out different transformations until you find one that makes he data fit assumptions

- you cannot keep trying until you manage to get a P-value < 0.05

Remember: Repeated testing leads to inflated Type I error

Just a reminder of an earlier question:

Two independent studies are performed to test the same null hypothesis.

What is the probability that one or both of the studies obtains a significant result and rejects the null hypothesis ***even if the null hypothesis is true***? Assume that in each study there is a 0.05 probability of rejecting the null hypothesis.

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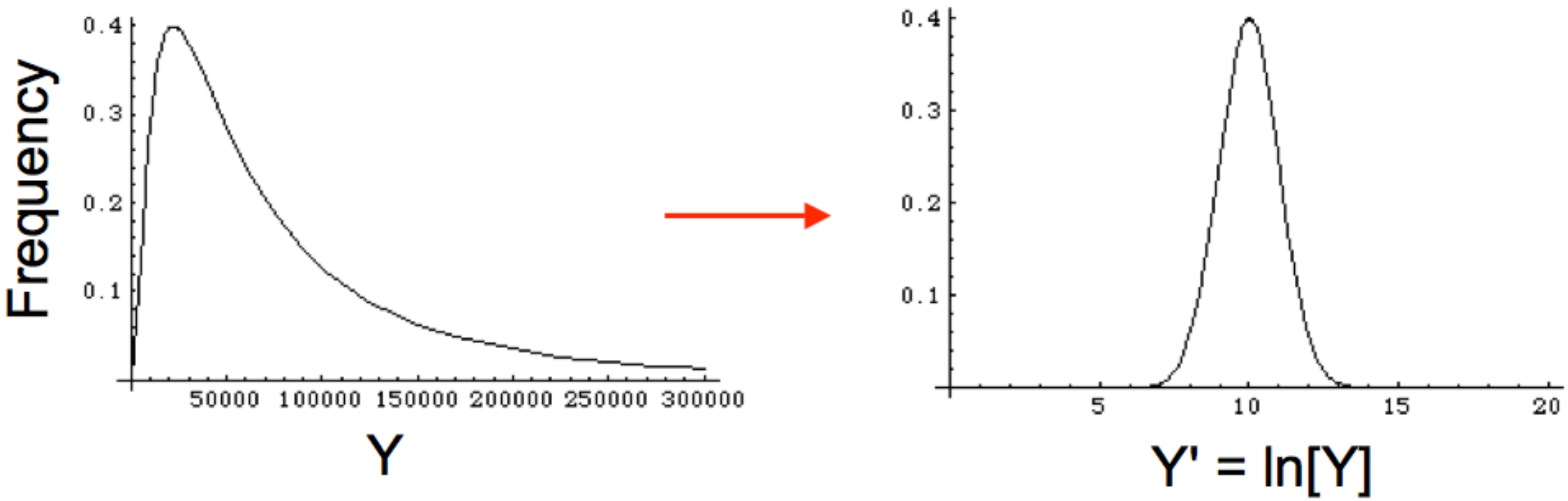
a. **0.10**
b. **0.075**
c. **0.05**
d. **0.0975**

Log Transformation

$$Y' = \ln[Y]$$



Log Transformation

$$Y' = \ln[Y]$$

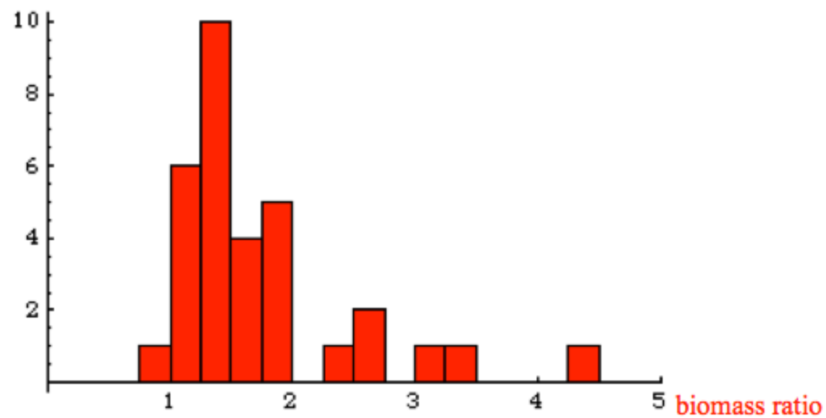
- most common
- It is most helpful when:
  - data spans several orders of magnitude
  - variables are > 0 (Ln(0) is undefined)
  - the variable is likely to be the result of the multiplication of several factors
    - log(ab) = log(a)+log(b)
  - the frequency distribution of the data is skewed to the right
  - the variance seems to increase as the mean gets larger (in comparison across groups)

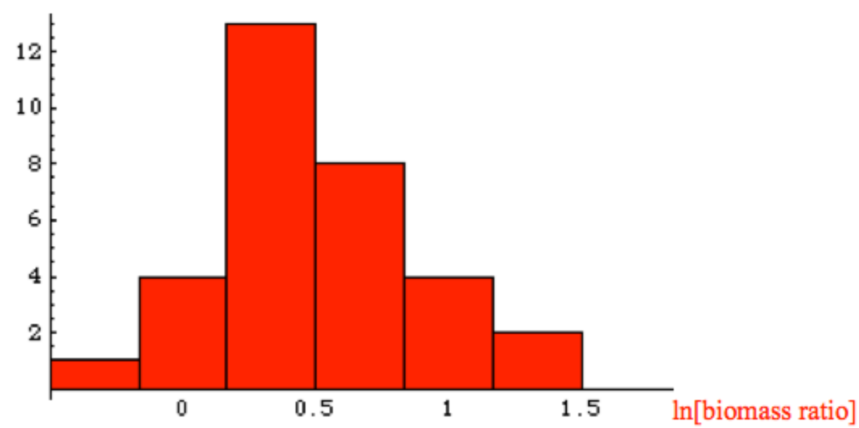
Log Transformation

$$Y' = \ln[Y]$$

Right skewed

Biomass ratio	ln[Biomass Ratio]
1.34	0.30
1.96	0.67
2.49	0.91
1.27	0.24
1.19	0.18
1.15	0.14
1.29	0.26

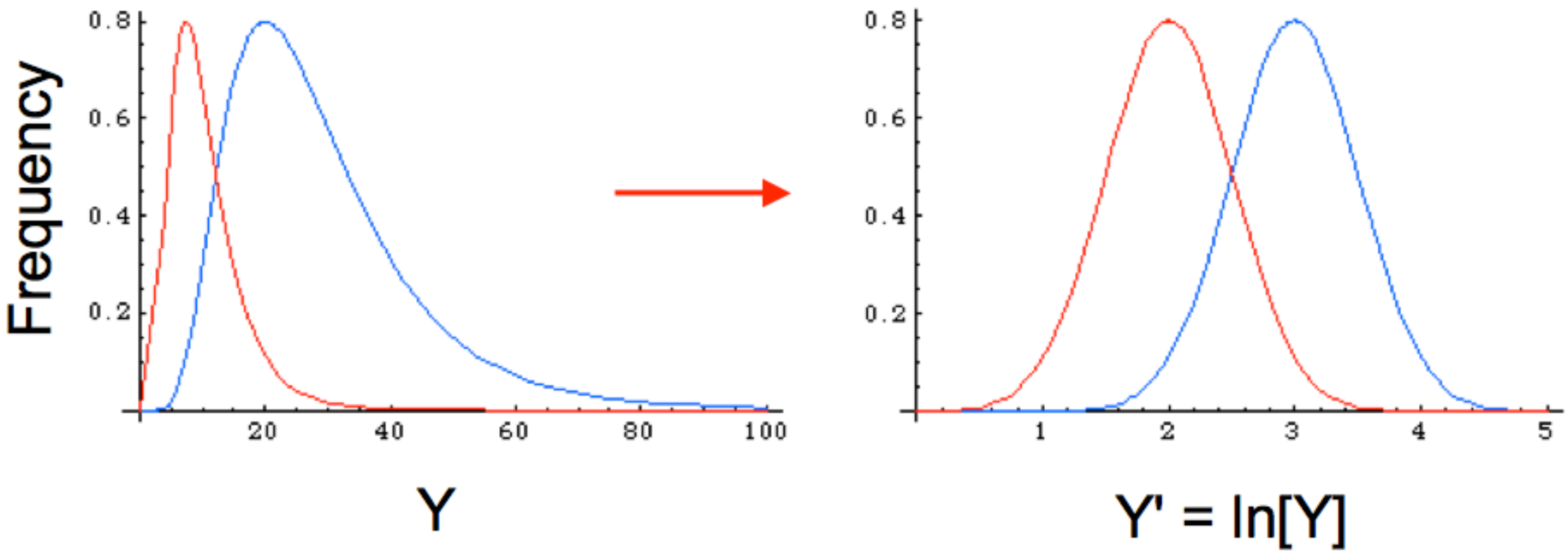




Log Transformation

$$Y' = \ln[Y]$$

Variance increases



Log Transformation

$$Y' = \ln[Y]$$

Use the same transformation on your hypothesis tests as you do on your data

H_0: The mean biomass ratio is unaffected by reserve protection(μ=1)

H_A: The mean biomass ratio is affected by reserve protection ($\mu \neq 1$)

H_0: The mean biomass ratio is unaffected by reserve protection(μ' =0)

H_A: The mean biomass ratio is affected by reserve protection ($\mu' \neq 0$)

Log Transformation

Y' = ln[Y]

Example: Confidence Interval with log-transformed data

Data:	5	12	1024	12398
Log Data:	1.61	2.48	6.93	9.43

$$\bar{Y}' = 5.11$$

$$s_{\ln[Y]} = 3.70$$

$$\bar{Y}' \pm t_{0.05(2),3} \frac{s_{\ln[Y]}}{\sqrt{n}} = 5.11 \pm 3.18 \frac{3.70}{\sqrt{4}} = 5.11 \pm 5.88$$

$$-0.773 < \mu_{\ln[Y]} < 10.99$$

$$e^{-0.773} < e^{\mu_{\ln[Y]}} < e^{10.99}$$

$$0.46 < \mu < 59278$$

Which one of these transformation helps to equalize standard deviations between groups when the group with the higher mean also has the higher standard deviation.

A- Arcsine transformation

B- Log transformation

C- Square root transformation

D- A and C

E- All the choices above

Other Common transformations:

Arcsine	• Exclusively on proportion data since they don't have equal standard deviations	$p' = \arcsin[\sqrt{p}]$
Square-root	• data counts	$Y' = \sqrt{Y + 1/2}$
Square	•Frequency dist^{n} skewed left	$Y' = Y^2$
Antilog	•Data skewed right	$Y' = e^Y$
Reciprocal	• When square transformation doesn't work	$Y' = 1/Y$