# STAT 213 Transformations

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# What to Do If Conditions are Violated?

What if we have ...

- Lack of normality of residuals
- Patterns (e.g. curvature) in residuals
- Non-constant variance ("heteroskedasticity")
- Outliers: influential points, large residuals

## Transformations and Outliers

#### Data Transformations

Can (sometimes) be used to

- "Unskew" residual distribution
- "Unbend" non-linear relationships
- Stabilize (equalize) variance of residuals
- Reduce influence of outliers

#### Example: Year Length on Different Planets

Cases: Planets in our solar system Y : Length (days) of a year on each planet X : Distance (km) from the sun

Can we model Length as a function of Distance?

#### Example: Year Length on Different Planets

```
library(mosaic)
## Note: syntax to read data from a file on the web
Planets <- read.file("http://colindawson.net/data/Planets.csv")
gf_point(Year ~ Distance, data = Planets) # not linear</pre>
```



# Transforming Y

gf\_point(log10(Year) ~ Distance, data = Planets) ## overcorrected



# Transforming X

gf\_point(Year ~ log10(Distance), data = Planets) ## wrong direction



### Transforming X and Y

gf\_point(log10(Year) ~ log10(Distance), data = Planets) ## linear!



# Interpreting the Transformed Relationship

```
LogLogModel <- lm(log10(Year) ~ log10(Distance), data = Planets)
coefficients(LogLogModel)</pre>
```

(Intercept) log10(Distance) -0.001491341 1.502061101

- "For each one unit increase in  $\log_{10}(Distance)$ , the log of the Year length increases by 1.5 units"
- More understandably: "Each time distance is multiplied by  $10^1$ , year length is multiplied by  $10^{1.5}$ "
- In this case,  $\hat{\beta}_0 \approx 0$ , so

 $\widehat{\log_{10}(\text{Year})} \approx 1.5 \cdot \log_{10}(\text{Distance})$ Year  $\approx \text{Distance}^{3/2}$ 

#### Year Length and Distance

gf\_point(Year ~ I(Distance^(3/2)), data = Planets)



### Brain and Body Weight of Terrestrial Mammals

```
library(mosaic)
BrainBodyWeight <- read.file("http://colindawson.net/data/BrainBodyWeight.csv")
gf_point(BrainWeight_g ~ BodyWeight_kg, data = BrainBodyWeight) %>%
gf_smooth(method = "lm")
```



#### Brain and Body Weight of Terrestrial Mammals

brainModel <- lm(BrainWeight\_g ~ BodyWeight\_kg, data = BrainBodyWeight)
gf\_point(residuals(brainModel) ~ fitted(brainModel)) %>%
gf\_hline(yintercept = ~0)



# Brain and Body Weight of Terrestrial Mammals

gf\_qq(~residuals(brainModel)) %>%
 gf\_qqline()



### Log Brain and Log Body Weight

gf\_point(log(BrainWeight\_g) ~ log(BodyWeight\_kg), data = BrainBodyWeight) %>%
gf\_smooth(method = "lm")



# Log Brain and Log Body Weight

logBrainModel <-</pre>

lm(log(BrainWeight\_g) ~ log(BodyWeight\_kg), data = BrainBodyWeight)
## residuals by fitted

gf\_point(residuals(logBrainModel) ~ fitted(logBrainModel)) %>%

gf\_hline(yintercept = ~0)



### Log Brain and Log Body Weight

```
## QQ Plot
gf_qq(~residuals(logBrainModel)) %>%
gf_qqline()
```



### Percent Brain Weight by Body Weight

```
library(mosaic)
## Making a new variable out of old ones
BrainBodyWeight_new <- mutate(
    BrainBodyWeight,
    pctBrain = 100 * (BrainWeight_g / (BodyWeight_kg * 1000)))
gf_point(log(pctBrain) ~ log(BodyWeight_kg), data = BrainBodyWeight_new) %>%
    gf_smooth(method = "lm")
```



# Percent Brain Weight By Body Weight



# Percent Brain Weight By Body Weight



## Key Points: Transformations

- Transformations can be used to address skewed residuals, nonlinearity, nonconstant variance
- Best if the transformation is motivated by knowledge of the context
- Typically use concave transformations ( $\log$ , sqrt) with right-skewed variables
- Less common, but sometimes use convex transformations (exp, powers) with left-skewed variables
- Log turns multiplicative (proportional) change into additive change (one unit difference in log scale corresponds to a constant *ratio* in the original scale)