Linear models

Modeling. . . linearly!

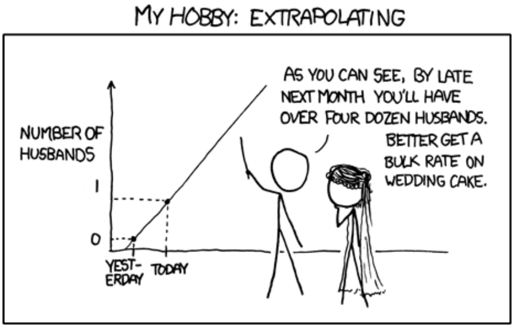
Samuel Robinson, Ph.D.

Sep. 22, 2023

Part 1: How do they work?

Outline

- What are linear models? How do I fit them?



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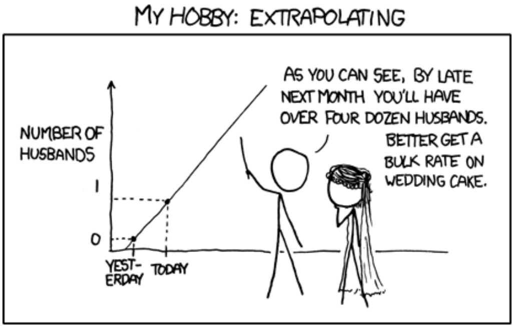

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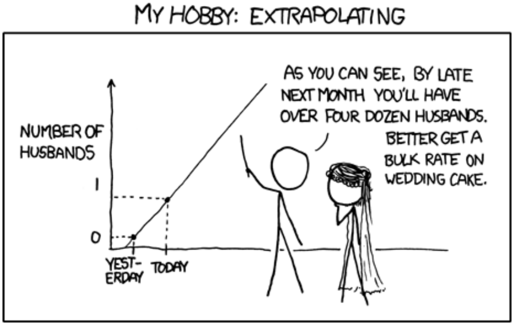
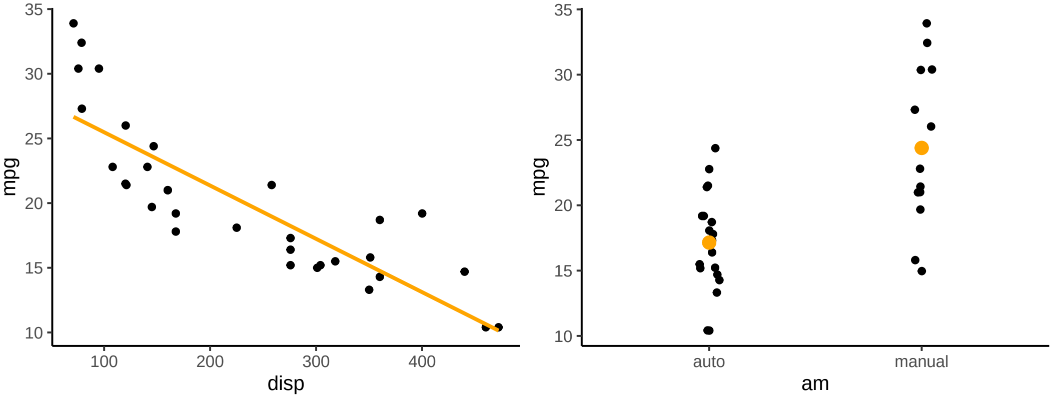
- What are linear models? How do I fit them?
- Making sure the model is working properly
- Plotting and interpreting model results



Motivation

- *I measured 2 things and I want to know if they're related to each other*
- *I have groups of data, and I want to know whether the means are different*



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I use a set of terminology that I find very helpful, from Berliner (1996). I'll be using it here, as well as for describing more complex models.

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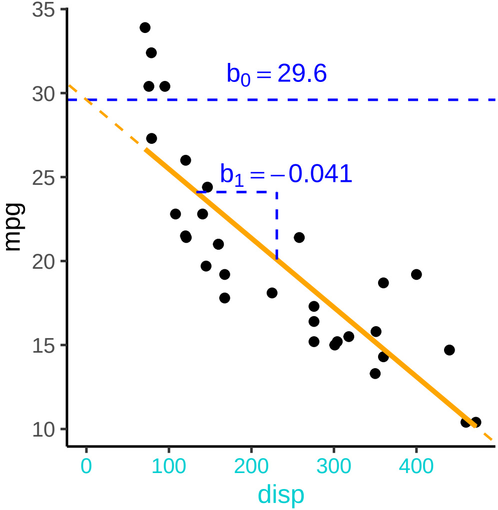
This may look terrifying, but let's use a simple example:

Example



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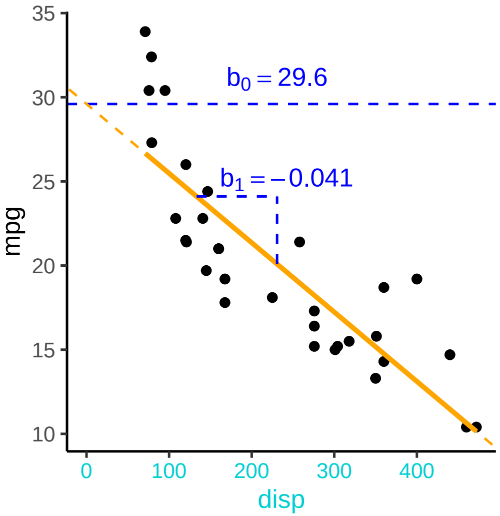

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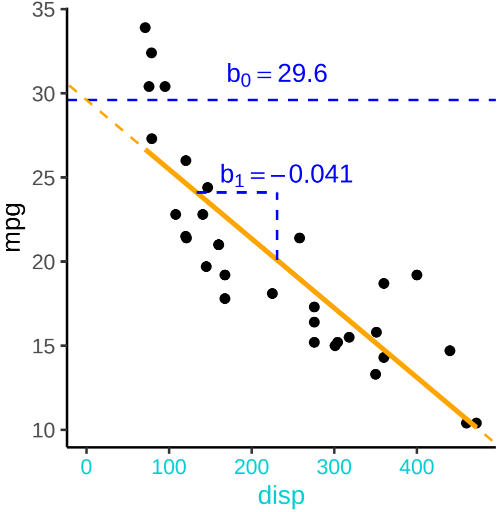

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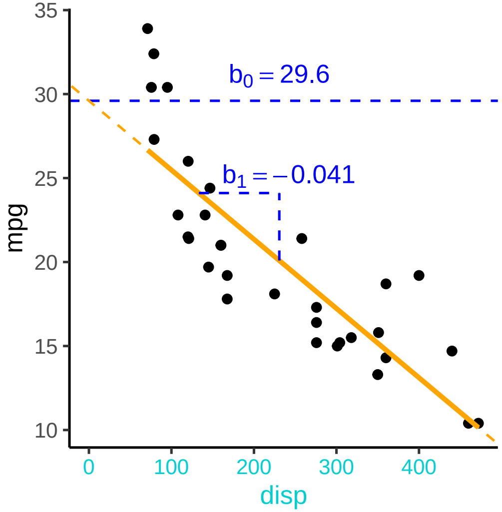

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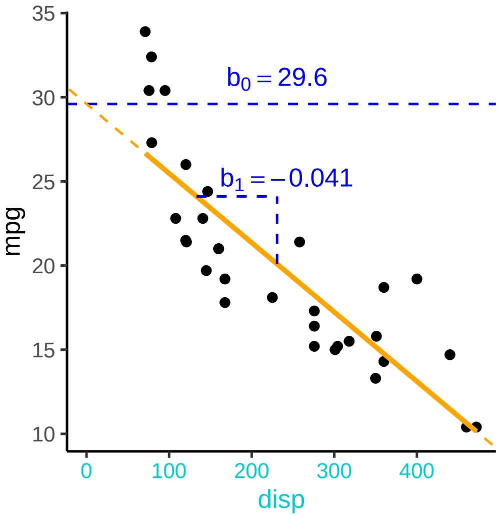

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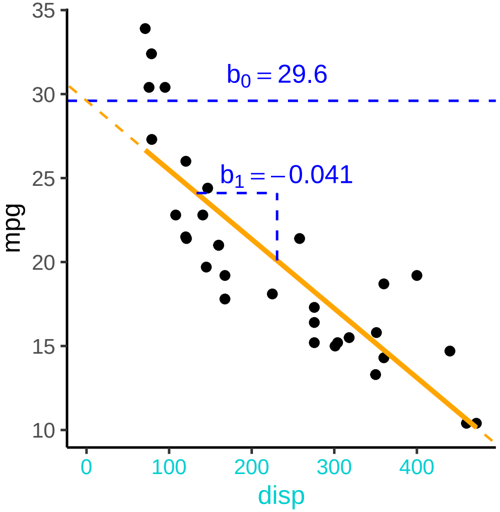

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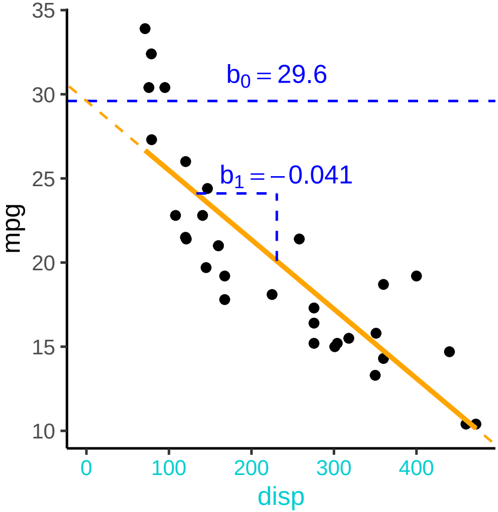

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- σ isn't displayed on the figure. Where is it?

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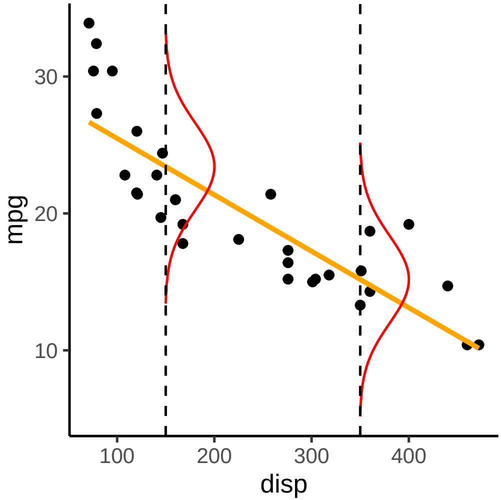

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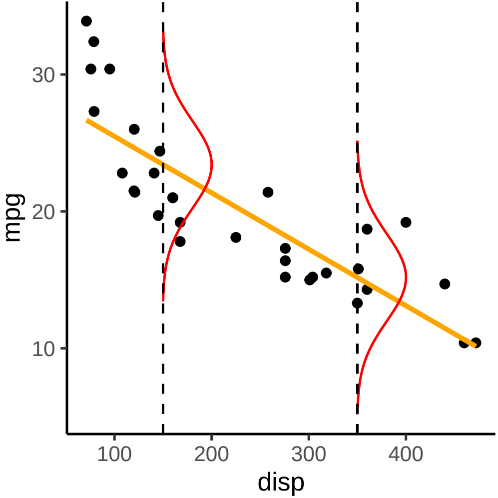

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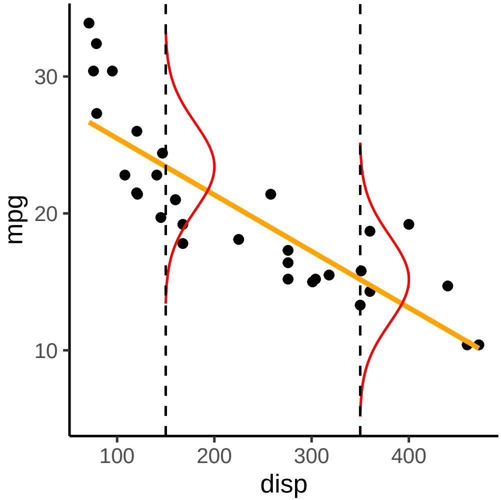

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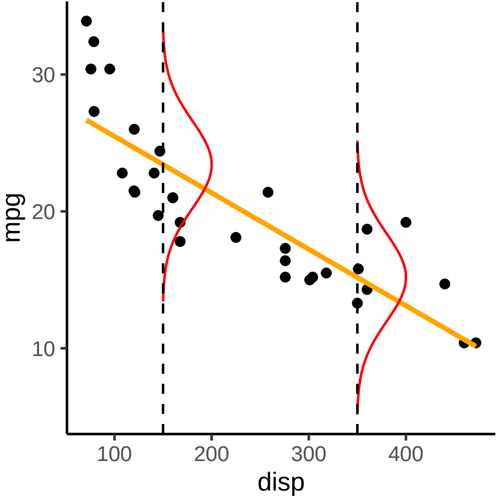

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- If you took a vertical slice at each part of the x-axis, the distribution would be *Normal*

How do I get R to fit this model?

`lm` is one of the main functions used for linear modeling:

```r
#Formula= y ~ x, data = Name of the dataframe containing mpg & disp
mod1 <- lm(mpg ~ disp, data = mtcars); summary(mod1)
```

```
##
## Call:
## lm(formula = mpg ~ disp, data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.8922 -2.2022 -0.9631  1.6272  7.2305
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 29.599855   1.229720  24.070  < 2e-16 ***
## disp        -0.041215   0.004712  -8.747 9.38e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.251 on 30 degrees of freedom
## Multiple R-squared:  0.7183, Adjusted R-squared:  0.709
## F-statistic: 76.51 on 1 and 30 DF,  p-value: 9.38e-10
```

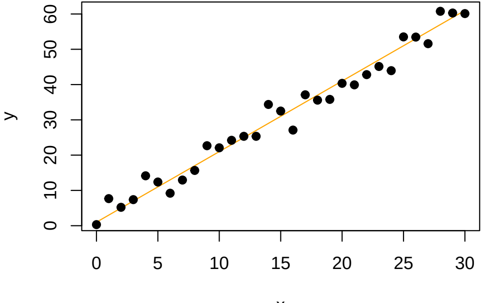
For a detailed breakdown of `lm`'s output, click here

Simulate data

Now that we know how linear models work, we can simulate our own data:

```r
#Parameters:

b0 <- 1 #Intercept
b1 <- 2 #Slope
sigma <- 3 #SD

#Make up some data:

x <- 0:30 #Predictor values

#Predicted y values
pred_y <- b0 + b1*x

#Add "noise" around pred_y
actual_y <- rnorm(n = length(pred_y),
                  mean = pred_y,
                  sd= sigma)
```

```r
#Plot the data we just made
plot(x,pred_y,col='orange',pch=19,type='l',
     ylab='y')
points(x,actual_y,col='black',pch=19)
```



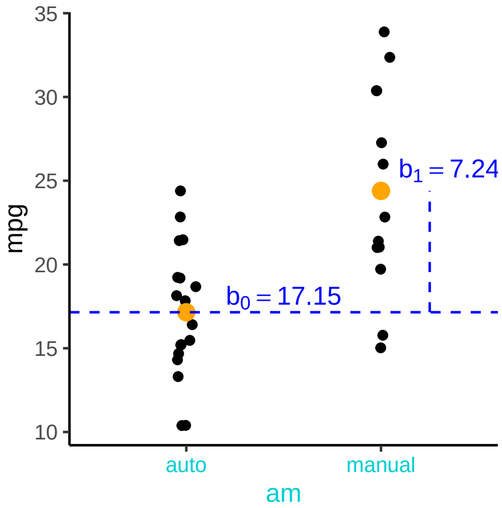
Fit a model from simulated data

How does R do at finding the coefficients? Remember: $b_0 = 1, b_1 = 2, \sigma = 3$

```r
fakeDat <- data.frame(x = x, y = actual_y, pred = pred_y) #Simulated data in a dataframe
mod1sim <- lm(y ~ x, data = fakeDat); summary(mod1sim) #Fit model
```

```
##
## Call:
## lm(formula = y ~ x, data = fakeDat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.7568 -1.7623 -0.2176  1.9419  5.3572
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.02974    1.00445   2.021   0.0526 .
## x            1.92670    0.05751  33.499   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.864 on 29 degrees of freedom
## Multiple R-squared:  0.9748, Adjusted R-squared:  0.9739
## F-statistic:  1122 on 1 and 29 DF,  p-value: < 2.2e-16
```

What about categorical data?



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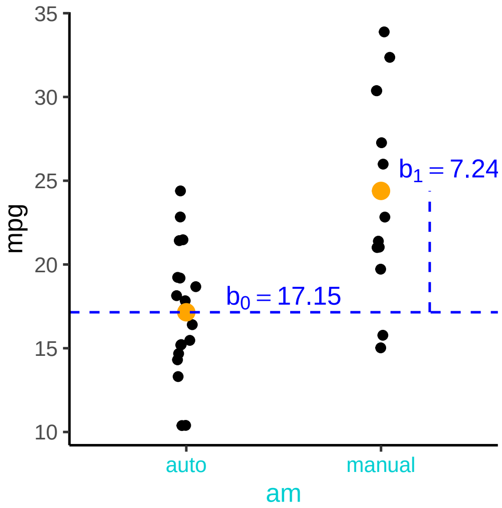

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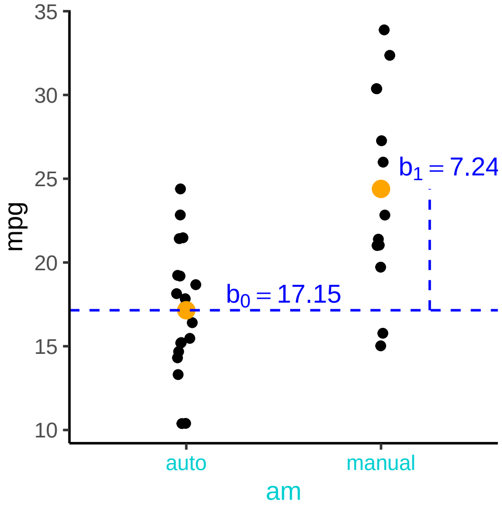

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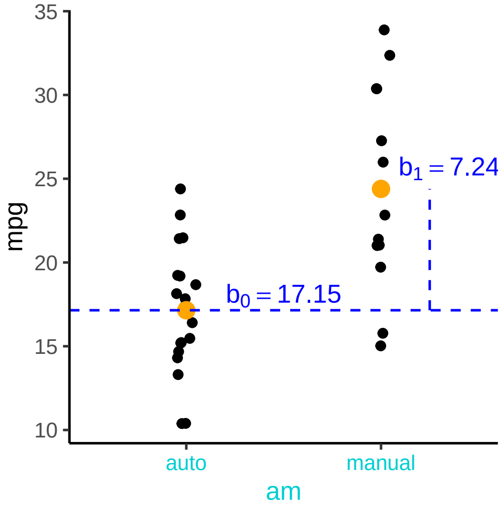

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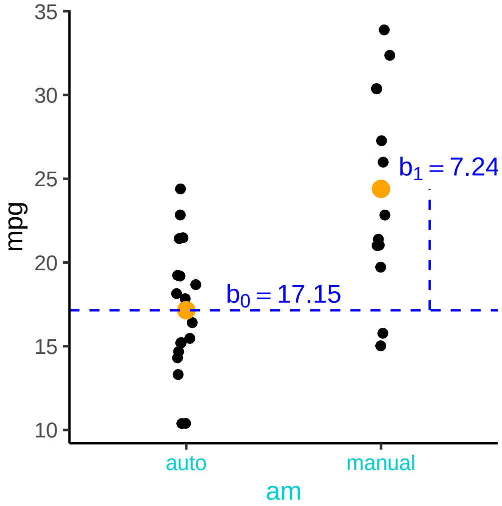

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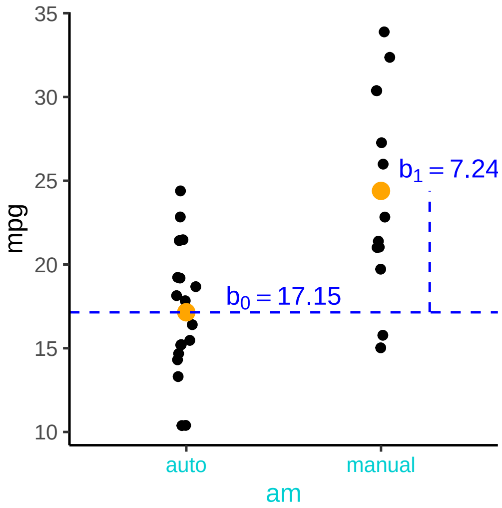

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- Where is σ?

How do I get R to fit this model?

Syntax is exactly the same for this model

```
#Formula structure: y ~ x
mod2 <- lm(mpg ~ am, #mpg depends on am
           data = mtcars) #Name of the dataframe containing mpg & am
summary(mod2)
```

```
##
## Call:
## lm(formula = mpg ~ am, data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.3923 -3.0923 -0.2974  3.2439  9.5077
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   17.147      1.125  15.247 1.13e-15 ***
## am             7.245      1.764   4.106 0.000285 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.902 on 30 degrees of freedom
## Multiple R-squared:  0.3598, Adjusted R-squared:  0.3385
## F-statistic: 16.86 on 1 and 30 DF,  p-value: 0.000285
```

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  - Useful command: `rnorm` (generate normally-distributed data)
    - e.g. `rnorm(n=100,mean=0,sd=1)`
- Use `lm` to fit a model to the data you just simulated

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  - Useful command: `rep` (replicate)
    - e.g. `rep(x=c(0,1),each=10)`
  - Useful command: `rnorm` (generate normally-distributed data)
    - e.g. `rnorm(n=100,mean=0,sd=1)`
- Use `lm` to fit a model to the data you just simulated
  - How does R do at guessing your coefficients?

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All of these can be changed, as we'll see during the following weeks!

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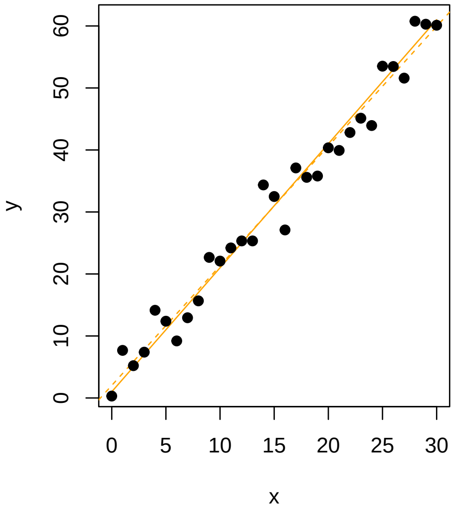
$$\hat{y} = b_0 + b_1 x$$

$$y \sim Normal(\hat{y}, \sigma)$$

$b_0 = 1, b_1 = 2, \sigma = 3$: "True" values

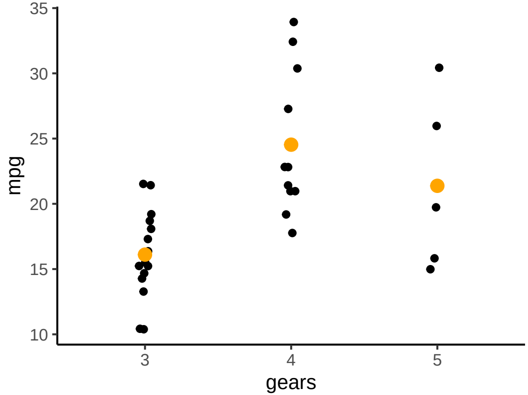
$\hat{b_0} = 2.0, \hat{b_1} = 1.9, \hat{\sigma} = 2.9$: Estimated values

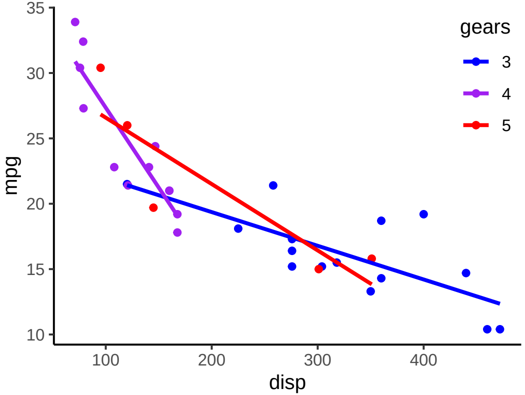


Part 2: More bells and whistles

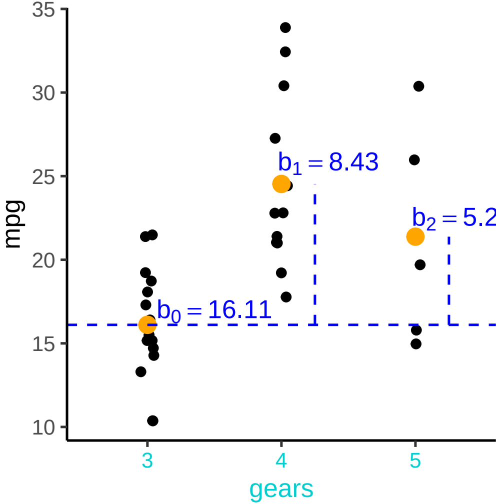
Motivation

- *I have 2+ groups of data, and I want to know whether the means are different*
- *I have 2+ groups of bivariate data, and I want to know whether the relationships differ between groups*





Categorical data, 3 categories



The more factor levels, the more coefficients:

$$\hat{mpg} = b_0 + b_1 gears_4 + b_2 gears_5$$
$$mpg \sim Normal(\hat{mpg}, \sigma)$$

- *mpg* is the thing you're interested in predicting

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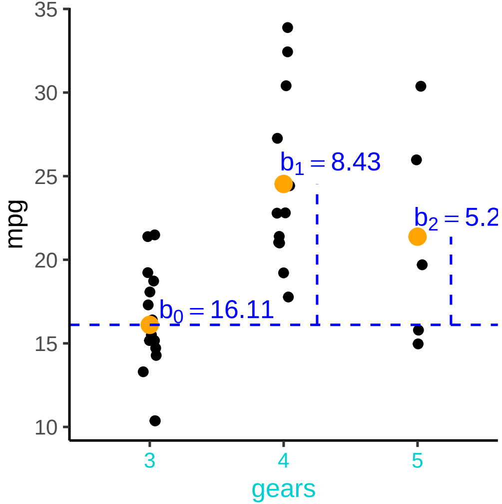

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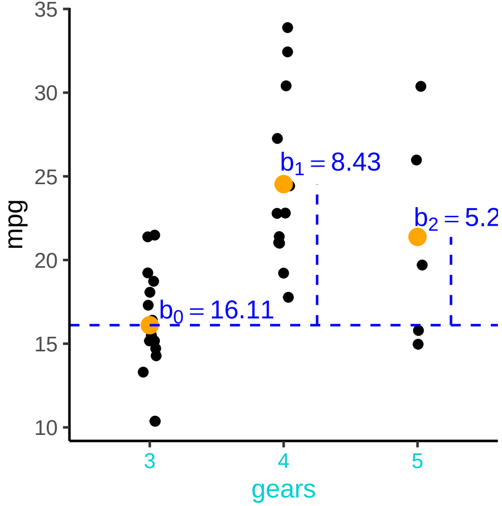

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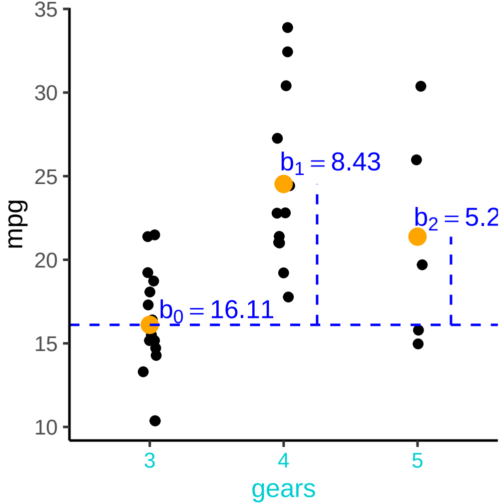

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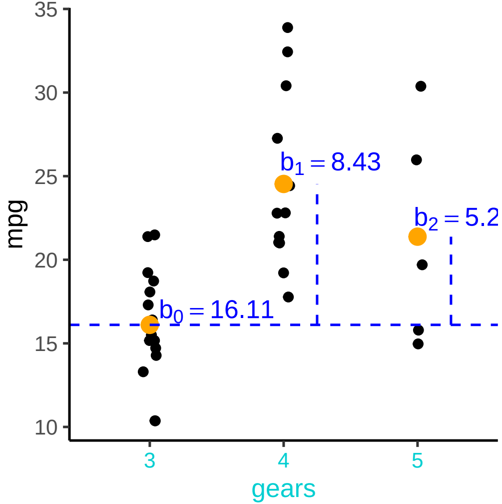

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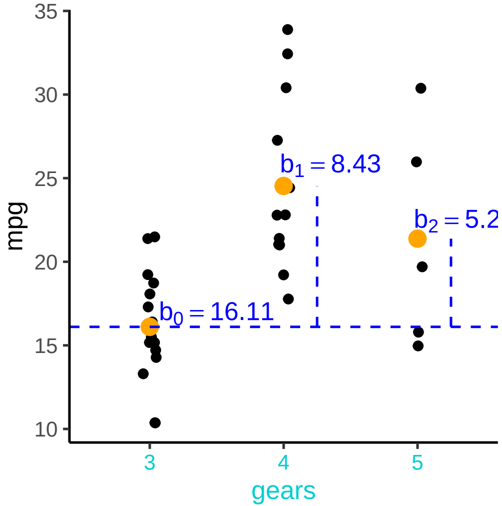

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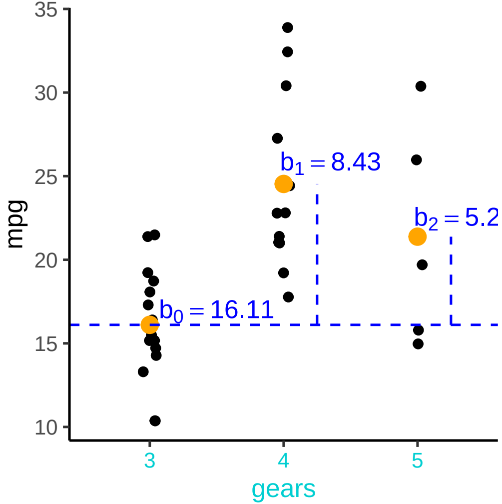

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  - set of 0s and 1s
  - $gears_4$ = "is this data point from a 4-gear car?"
- b_0 = *intercept* (first level of `gear` factor)
- $[b_1, b_2]$ = are *coefficients* for *gears*

How do I get R to fit this model?

```r
#Formula structure: y ~ x
mod1 <- lm(mpg ~ factor(gear), #mpg depends on gears
           data = mtcars) #Name of the dataframe containing mpg & gears
summary(mod1)
```

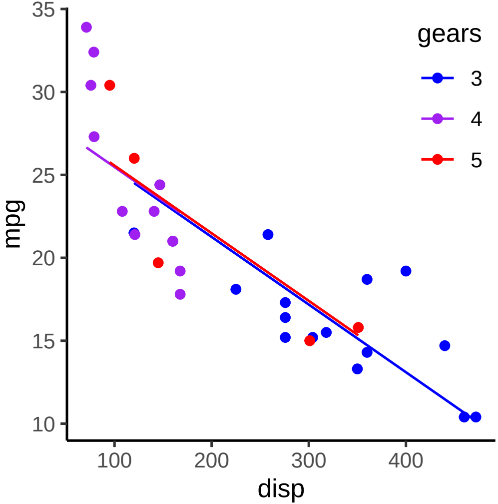
```
##
## Call:
## lm(formula = mpg ~ factor(gear), data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.7333 -3.2333 -0.9067  2.8483  9.3667
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)     16.107      1.216  13.250 7.87e-14 ***
## factor(gear)4    8.427      1.823   4.621 7.26e-05 ***
## factor(gear)5    5.273      2.431   2.169   0.0384 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.708 on 29 degrees of freedom
## Multiple R-squared:  0.4292, Adjusted R-squared:  0.3898
## F-statistic:  10.9 on 2 and 29 DF,  p-value: 0.0002948
```

Dummy variables

```r
mod1Matrix <- model.matrix(mod1) #Get model matrix (columns used to predict mpg)
head(mod1Matrix,20) #Show first 20 rows of model matrix
```

```
##                     (Intercept) factor(gear)4 factor(gear)5
## Mazda RX4                     1             1             0
## Mazda RX4 Wag                 1             1             0
## Datsun 710                    1             1             0
## Hornet 4 Drive                1             0             0
## Hornet Sportabout             1             0             0
## Valiant                       1             0             0
## Duster 360                    1             0             0
## Merc 240D                     1             1             0
## Merc 230                      1             1             0
## Merc 280                      1             1             0
## Merc 280C                     1             1             0
## Merc 450SE                    1             0             0
## Merc 450SL                    1             0             0
## Merc 450SLC                   1             0             0
## Cadillac Fleetwood            1             0             0
## Lincoln Continental           1             0             0
## Chrysler Imperial             1             0             0
## Fiat 128                      1             1             0
## Honda Civic                   1             1             0
## Toyota Corolla                1             1             0
```

What if 2 things are *both* important?



$$\hat{mpg} = b_0 + b_1 disp + b_2 gears_4 + b_3 gears_5$$

$$mpg \sim Normal(\hat{mpg}, \sigma)$$

- Suppose that both *disp* and *gears* are important for predicting *mpg*?

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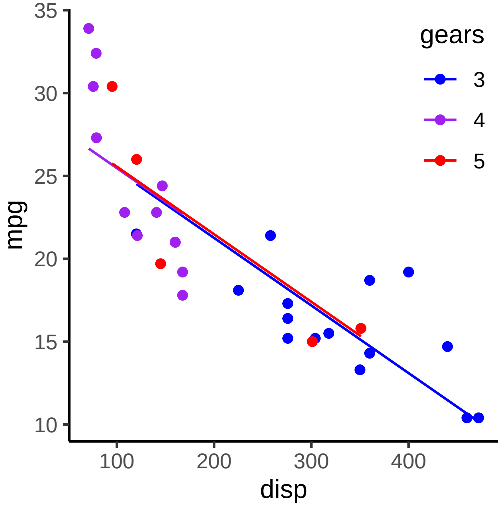

$$\hat{mpg} = b_0 + b_1 disp$$
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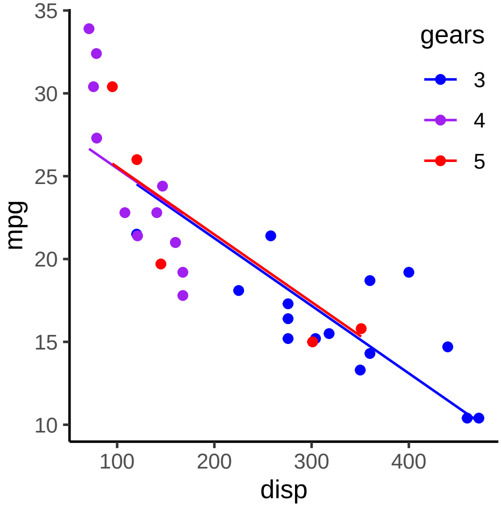

$$\begin{aligned}\hat{mpg} &= b_0 + b_1 disp \\ &\quad + b_2 gears_4 + b_3 gears_5 \\ mpg &\sim Normal(\hat{mpg}, \sigma)\end{aligned}$$

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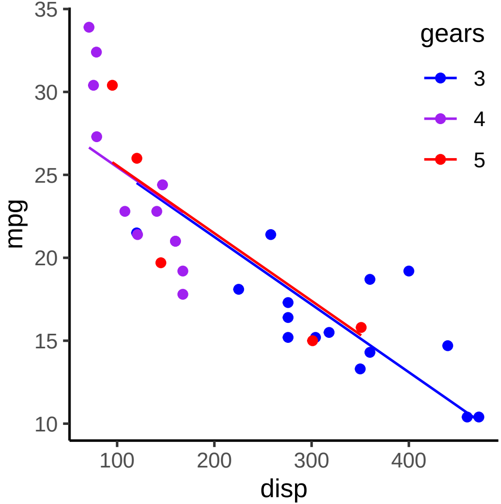

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- Suppose that both *disp* and *gears* are important for predicting *mpg*?
- This is very similar to the last example, except that now we've added *disp*
- *gears* now changes the intercepts, while *disp* changes the overall slope
- Now that both variables are included, does it look like *gear* is very important?

How do I get R to fit this model?

```r
#mpg depends on disp and gears
mod2 <- lm(mpg ~ disp+factor(gear), data = mtcars)
summary(mod2)
```

```
##
## Call:
## lm(formula = mpg ~ disp + factor(gear), data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.9155 -2.1892 -0.9054  1.5790  7.2498
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   29.411183   2.627966  11.192 7.58e-12 ***
## disp          -0.040774   0.007601  -5.364 1.03e-05 ***
## factor(gear)4  0.138017   2.021332   0.068    0.946
## factor(gear)5  0.224712   1.976090   0.114    0.910
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.365 on 28 degrees of freedom
## Multiple R-squared:  0.7185, Adjusted R-squared:  0.6883
## F-statistic: 23.82 on 3 and 28 DF,  p-value: 7.31e-08
```

Dummy variables

```
mod2Matrix <- model.matrix(mod2) #Get model matrix (columns used to predict mpg)
head(mod2Matrix,20) #Show first 20 rows of model matrix
```

```
##                     (Intercept)  disp factor(gear)4 factor(gear)5
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- `lm` model input:

```
model1 <- lm(y ~ x1 + x2 + ..., data = myDataFrame)

summary(model1)
```

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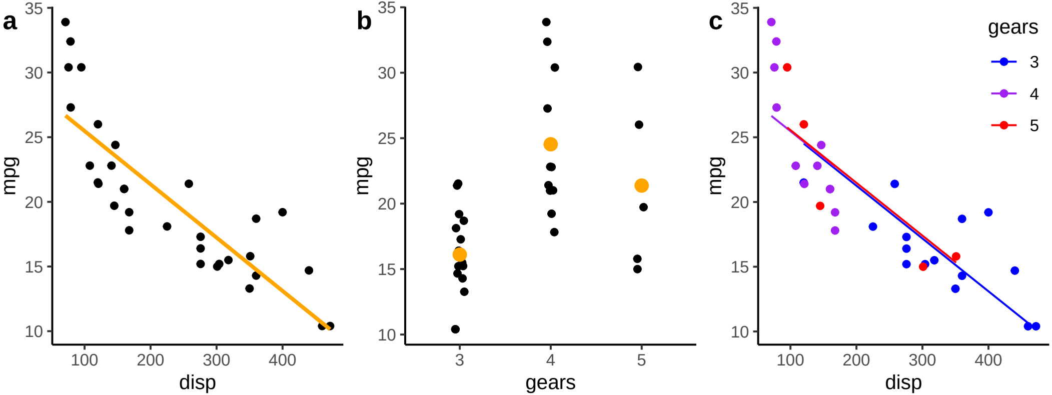

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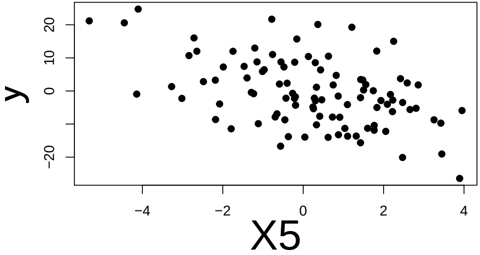
Incorrect example, using raw data:

```
#Fit model with 5 variables (all important)
simMod <- lm(y~X1+X2+X3+X4+X5,data=pred)
#Plot x5 and y
plot(y~X5,data=pred,pch=19,cex.lab=3)
```



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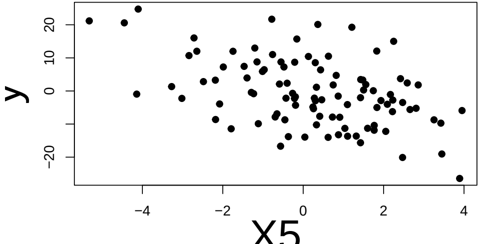
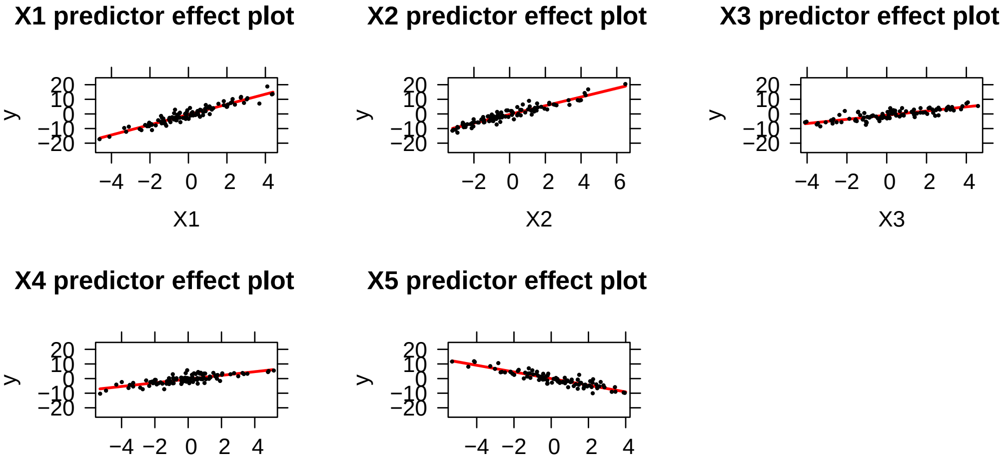


The effect of *X5* is actually **very** strong ($p < 0.0001$), but it doesn't look like it from this plot!

Partial effects plots - using *effects*

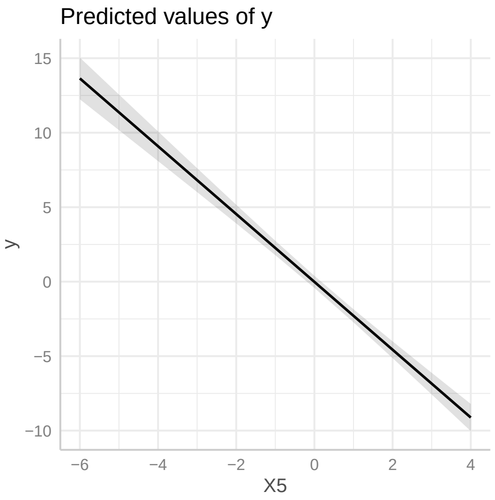
```
library(effects) #Load effects package
simModEff <- predictorEffects(simMod,partial.residuals=TRUE) #Calculate partial effects
#Plot partial effects
plot(simModEff,lines=list(col='red'), partial.residuals=list(pch=19,col='black',cex=0.25))
```



Partial effects plots - using *ggeffects*

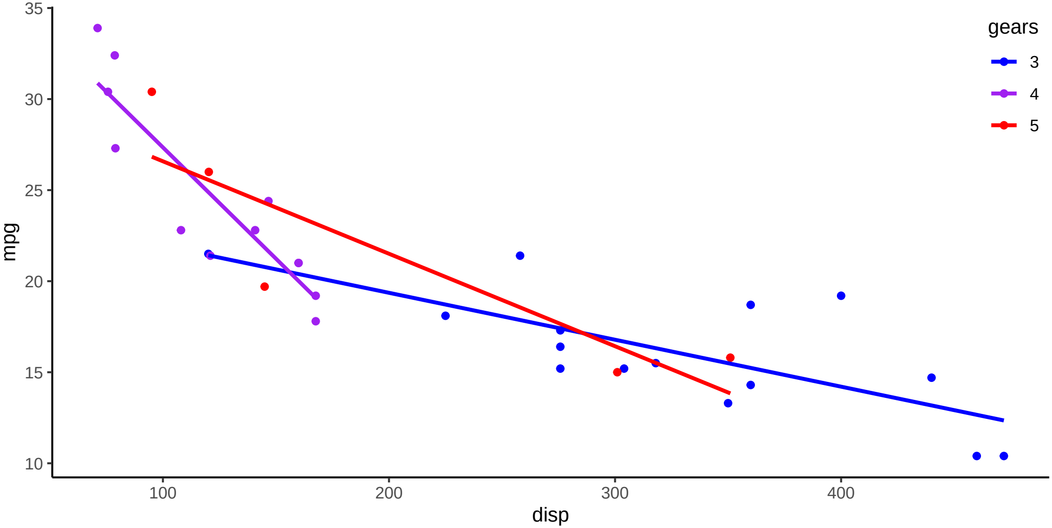
```r
#Load ggeffects package
library(ggeffects)

#Calculate partial effects for X5
simModEff2 <- ggeffect(simMod,terms=c('X5'))

#Plot the effect of X5
plot(simModEff2)
```

- You can also turn `ggeffect` objects into a dataframe and make your own custom plots



Interactions

What if the slopes *and* intercepts differ between groups?



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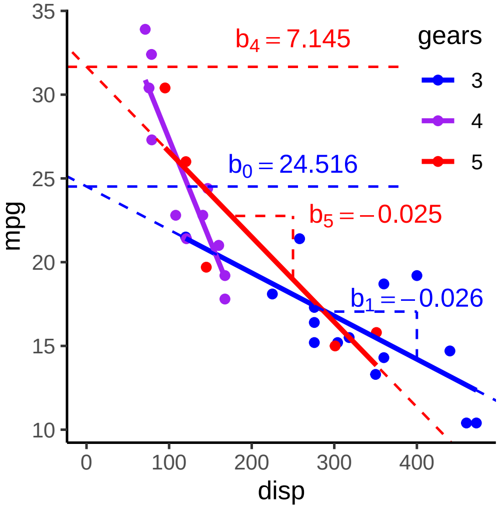
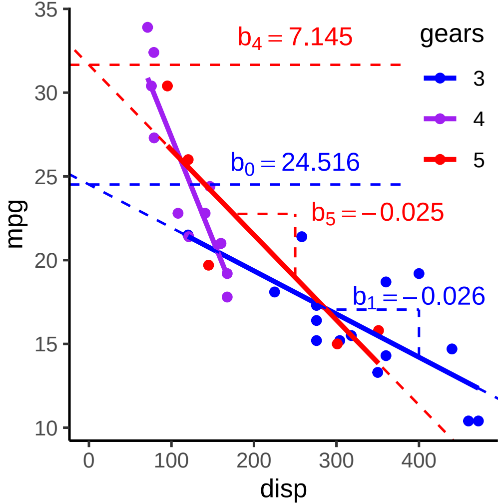


$$
\begin{aligned}
\hat{mpg} &= b_0 + b_1 disp \\
&\quad + b_2 gears_4 + b_3 gears_5 \\
&\quad + b_4 (disp \times gears_4) \\
&\quad + b_5 (disp \times gears_5) \\
mpg &\sim Normal(\hat{mpg}, \sigma)
\end{aligned}
$$

- Interactions occur when predictors are *multiplied*

Interactions



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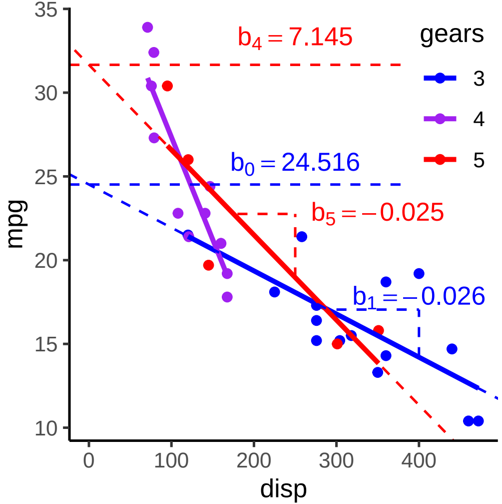

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- Interactions occur when predictors are *multiplied*
- In this case, *disp* is multiplied by $gears_4$ and $gears_5$
- *gears* now changes the intercept and the slope of the relationship between *mpg* and *disp*

How do I get R to fit this model?

```r
#mpg depends on disp interacted (*) with gears
mod2 <- lm(mpg ~ disp*factor(gear), data = mtcars)
summary(mod2)
```

```
##
## Call:
## lm(formula = mpg ~ disp * factor(gear), data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5986 -1.5990 -0.0143  1.6329  4.9926
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        24.515566   2.462431   9.956 2.32e-10 ***
## disp               -0.025770   0.007265  -3.547 0.001505 **
## factor(gear)4      15.051963   3.558043   4.230 0.000256 ***
## factor(gear)5       7.145380   3.535913   2.021 0.053711 .
## disp:factor(gear)4 -0.096442   0.021261  -4.536 0.000114 ***
## disp:factor(gear)5 -0.025005   0.013320  -1.877 0.071742 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.579 on 26 degrees of freedom
## Multiple R-squared:  0.8465, Adjusted R-squared:  0.817
## F-statistic: 28.67 on 5 and 26 DF,  p-value: 8.452e-10
```

Beware of fitting too many interactions, or else the *Bilbo effect* occurs!

Dummy variables

```
mod2Matrix <- model.matrix(mod2) #Get model matrix (columns used to predict mpg)
colnames(mod2Matrix) <- gsub('(factor\\(|\\))','',colnames(mod2Matrix)) #Shrink column headers
head(mod2Matrix,20) #Show first 20 rows of model matrix
```

Third challenge

- Make some plots of your model results using `ggeffects`

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  - `lm (y ~ X1 * X2 * X3)`: Full model (everything interacts)
  - `lm (y ~ X1 + X2 + X3 + X2:X3)`: interaction only between `X2` and `X3`

Part 3: Models behaving badly

Motivation

Are my model results reliable?

- Residual checks

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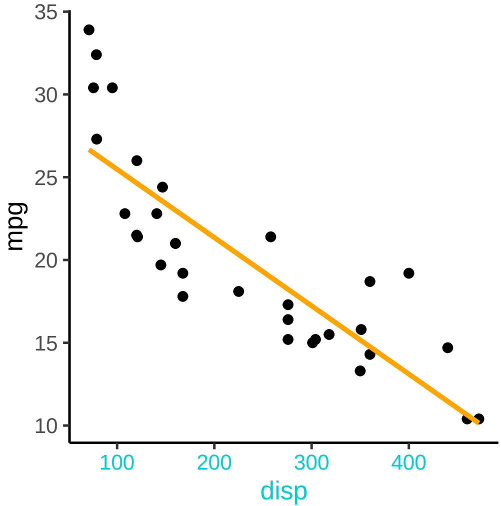
- Collinearity

Motivation

Are my model results reliable?

- Residual checks
- Transformations
- Collinearity
- How much stuff should I put into my model?

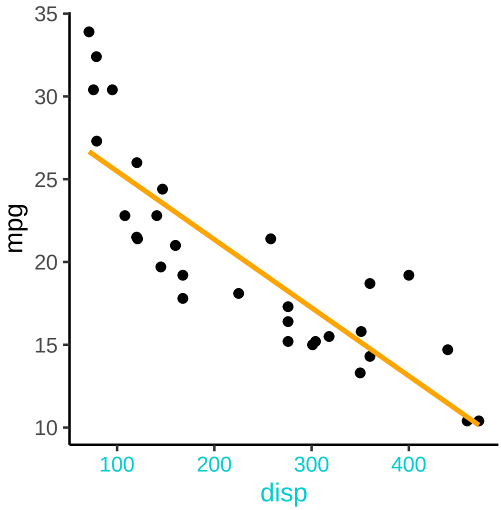
Assumptions of linear regression



$$\hat{mpg} = b_0 + b_1 \, disp$$
$$mpg \sim Normal(\hat{mpg}, \sigma)$$

There are 3 main assumptions to this model:

Assumptions of linear regression



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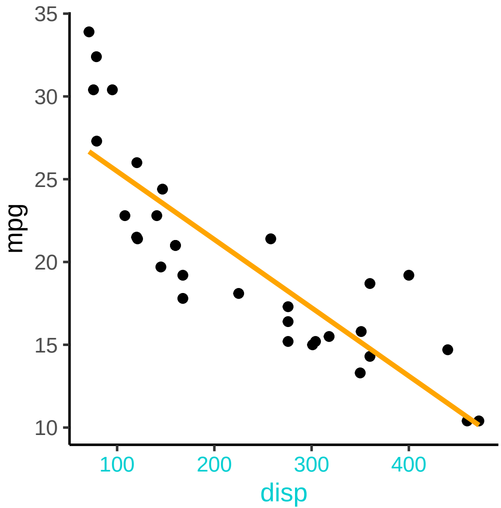

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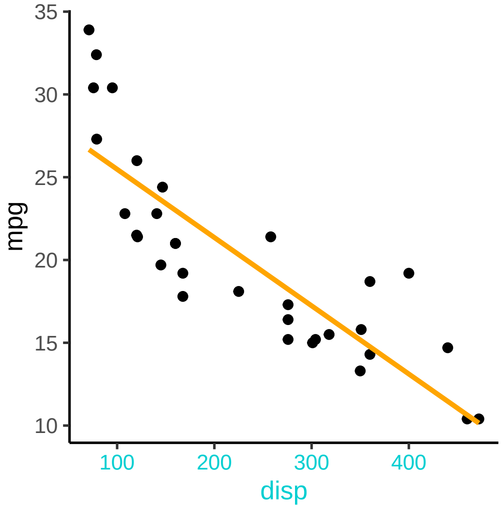

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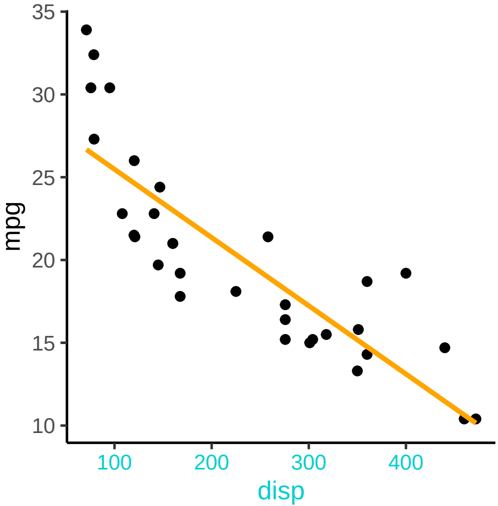

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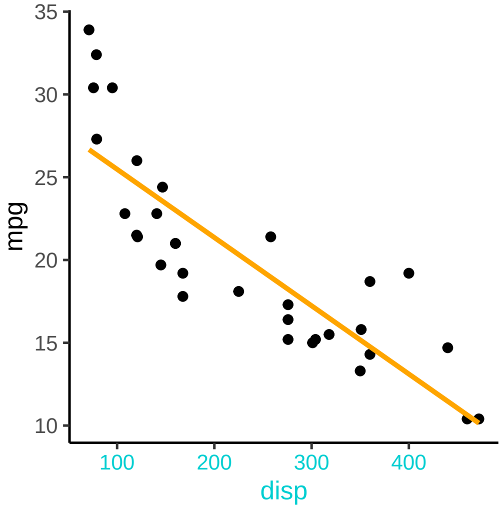

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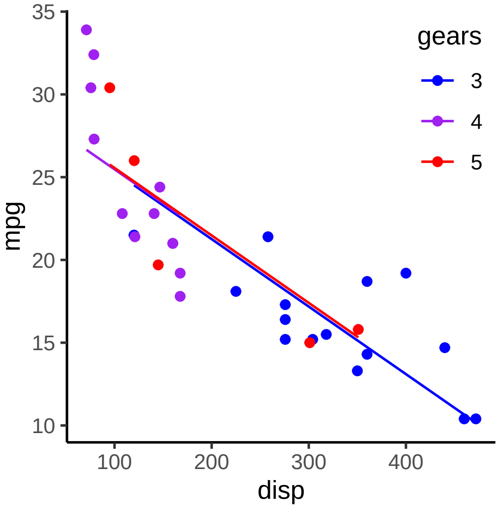
3. σ is the **same everywhere**

This is pretty easy to see if you only have 1 variable, but. . .

What if I have many variables?



- Difficult to see if the assumptions are met

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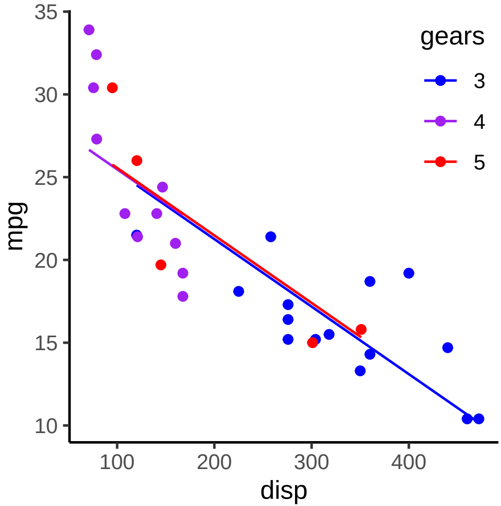
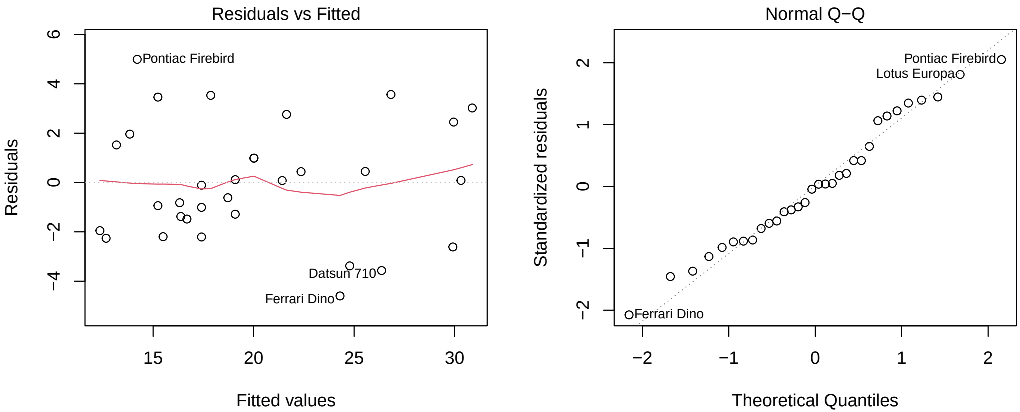


- Difficult to see if the assumptions are met
- In general, we use **residual plots** or **simulation** to assess whether model assumptions are met

Solution: residual checks

Some common ways of checking the assumptions: **residual plots**



- Points in Plot 1 should show *no pattern* (shotgun blast)

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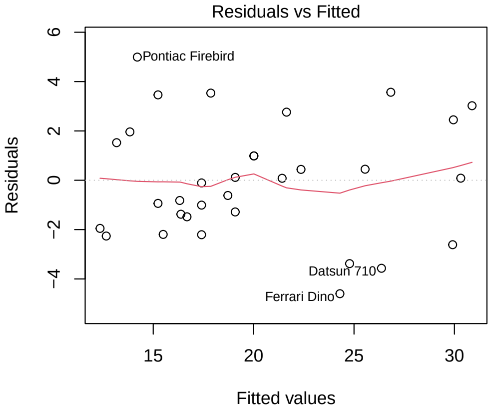
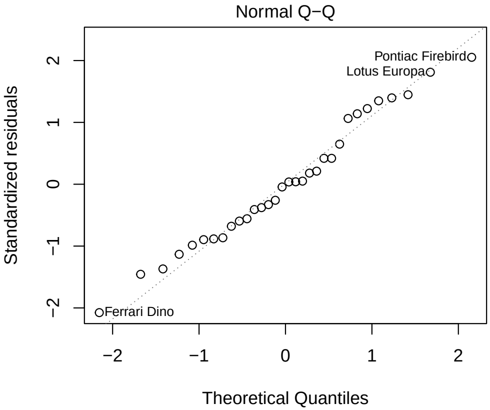
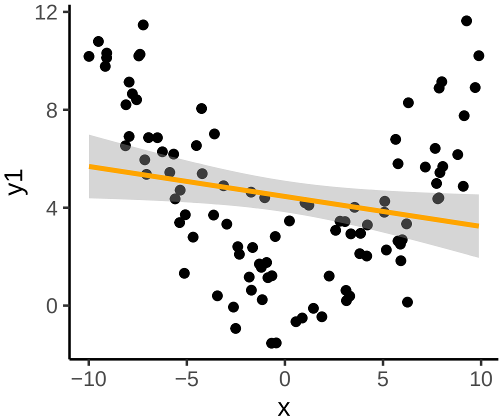
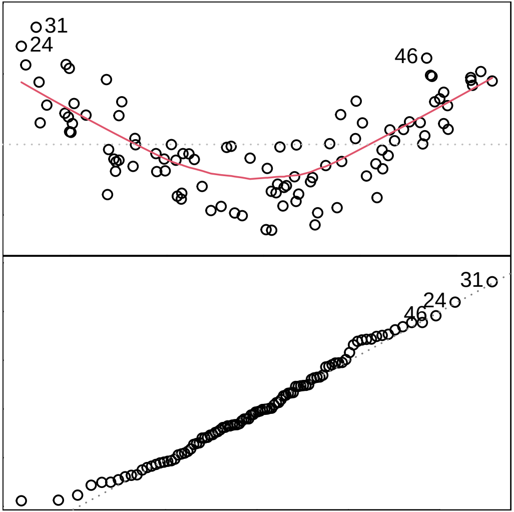




- Points in Plot 1 should show *no pattern* (shotgun blast)
- Points in Plot 2 should be *roughly* on top of the 1:1 line

Problem 1: Non-linear relationship

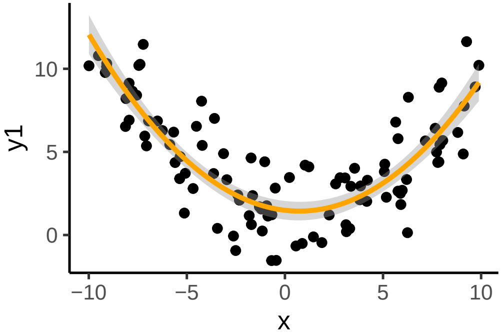




Model: `lm(y1~x,data=d1)`

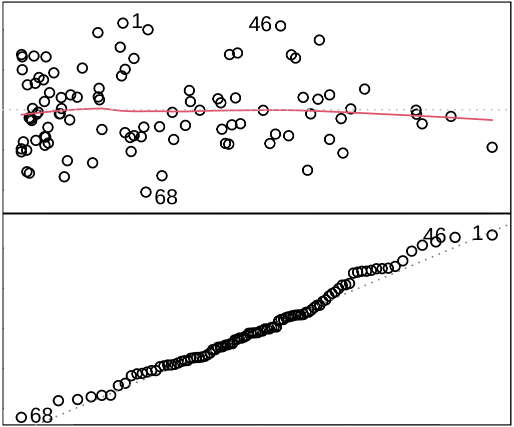
- $y1$ clearly follows a U-shaped relationship, not a linear one

Solution: transform predictors



Model: `lm(y1~poly(x,2),data=d1)`

- *log* and *square-root* transformations are common



- Warning: Polynomials can do weird things; consider whether this is biologically reasonable!

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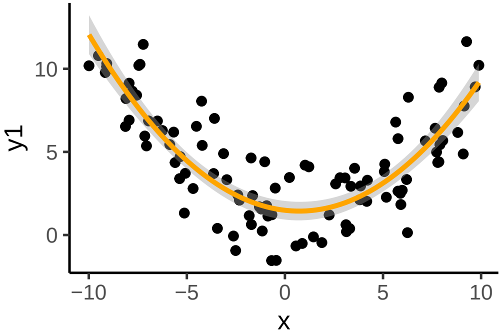
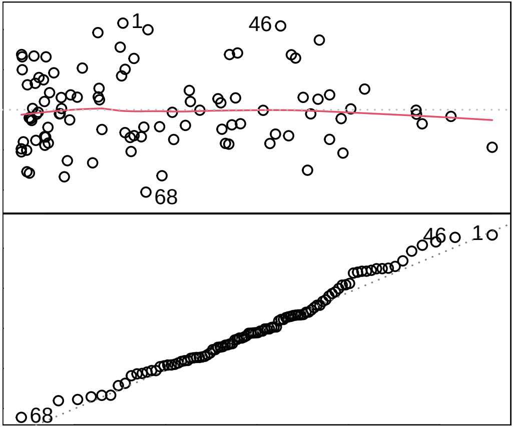


Model: `lm(y1~poly(x,2),data=d1)`

- *log* and *square-root* transformations are common
- Can also use *additive* (wiggly) models



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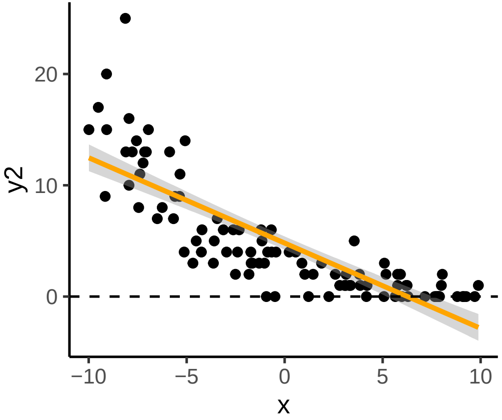
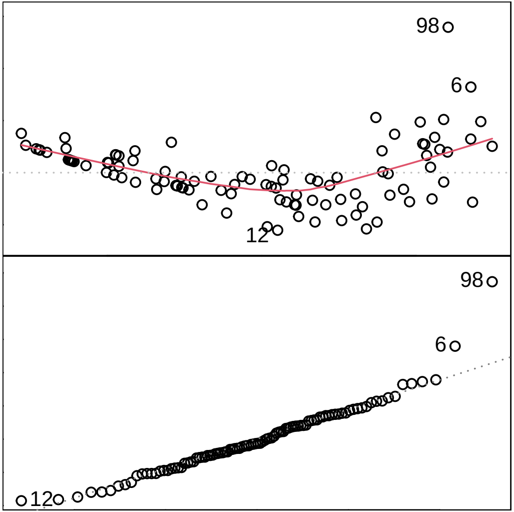
Problem 2a: Non-normal response

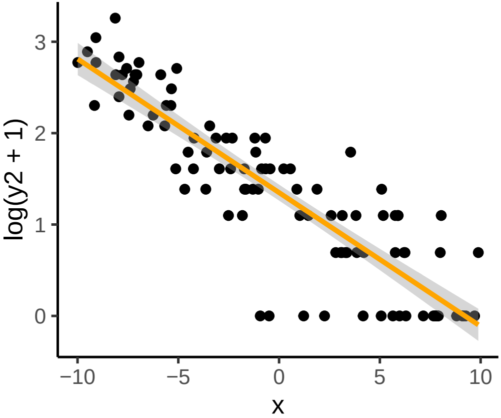


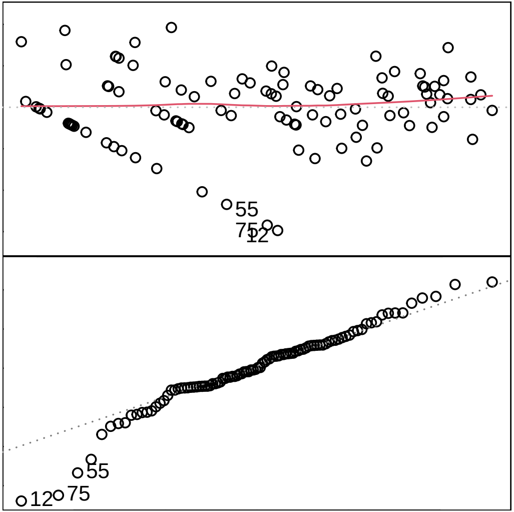


Model: `lm(y2~x,data=d1)`

- $y2$ is count data (integers ≥ 0). *Very* common in ecological data.

Solution: transform data to meet assumptions

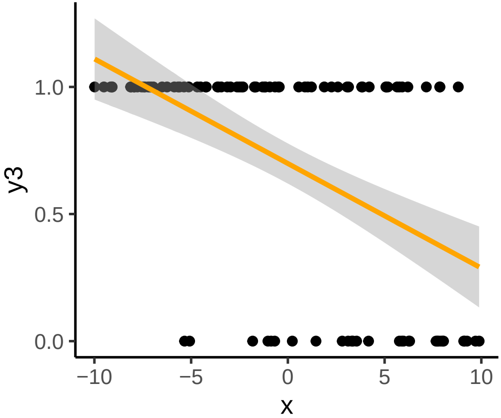


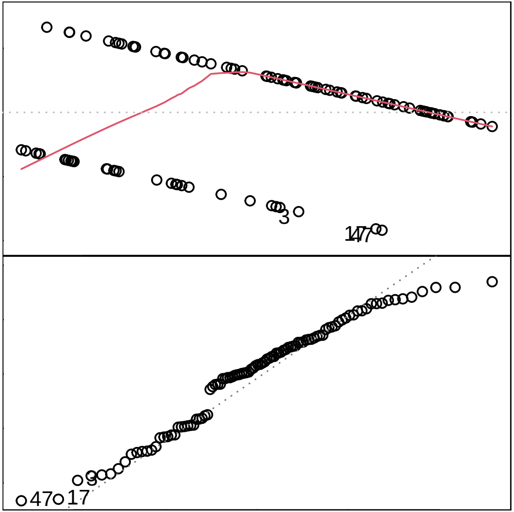


Model: `lm(log(y2+1)~x,data=d1)`

- Square-root transformations are also common

Problem 2b: Non-normal response

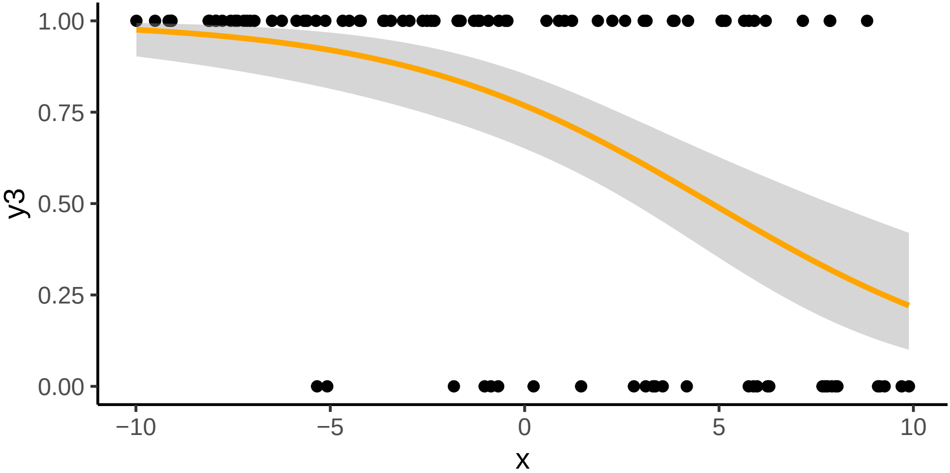




Model: `lm(y3~x,data=d1)`

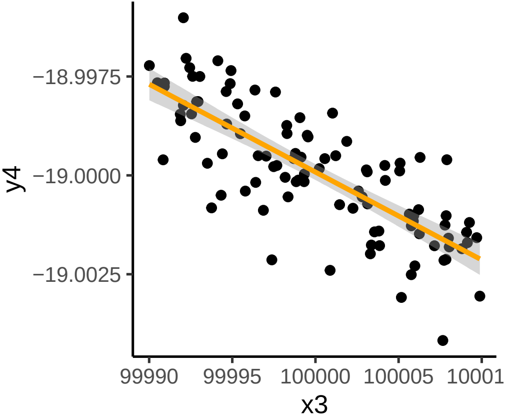
- $y3$ is binomial data (success/failure). *Very* common in ecological data.

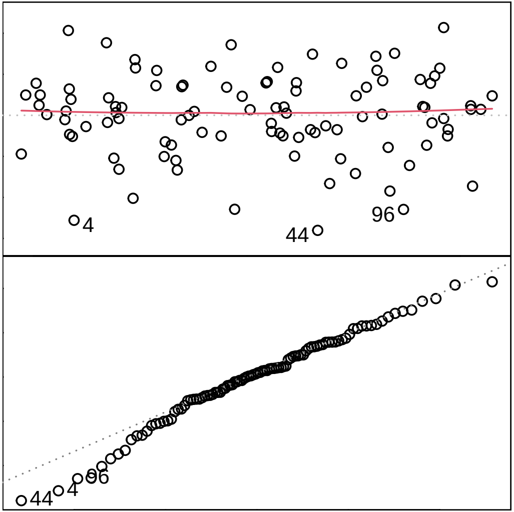
Solution: use a Generalized Linear Model (GLM)



- This is a topic for another lecture. Hold tight!

Problem: variables are on different scales





Model: `lm(y4~x3,data=d1)`

- $y4$ is tiny, while $x3$ is huge

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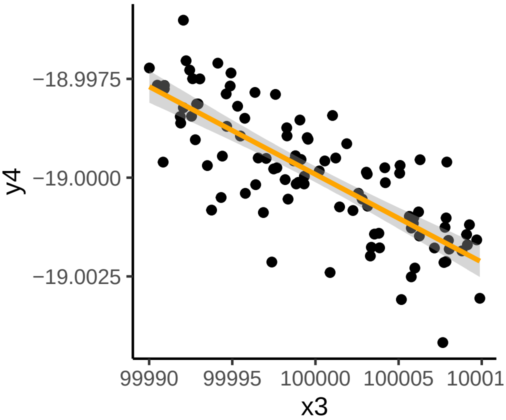
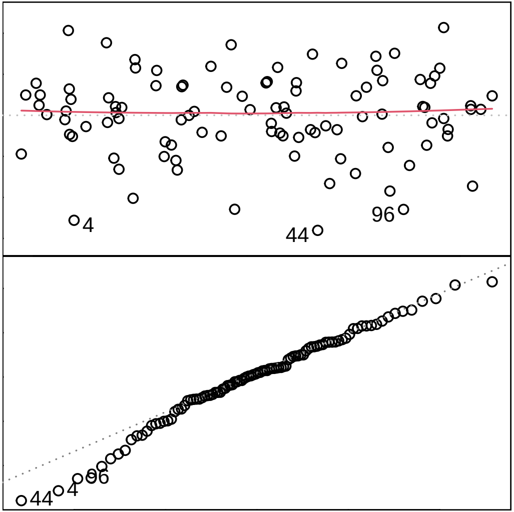
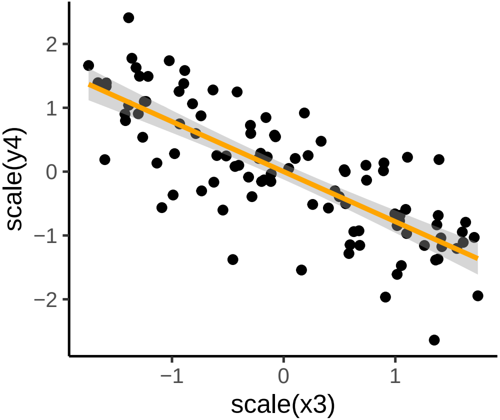


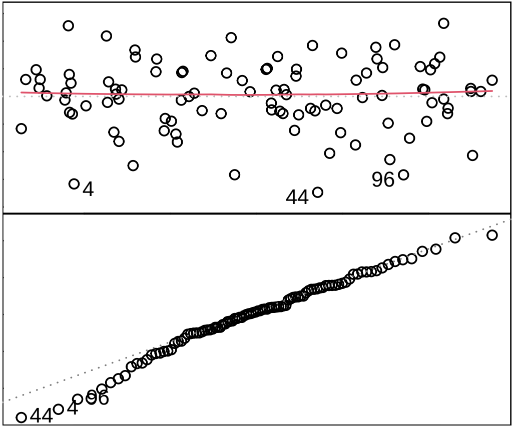


Model: `lm(y4~x3,data=d1)`

- $y4$ is tiny, while $x3$ is huge
- OK for now, but can cause problems when fitting other models

Solution: scale data/predictors before fitting






```r
#Subtracts mean, divides by SD
d1$s.y4 <- scale(y4)
d1$s.x3 <- scale(x3)
lm(s.y4~s.x3,data=d1) #Refit
```

- Residuals are the same as before

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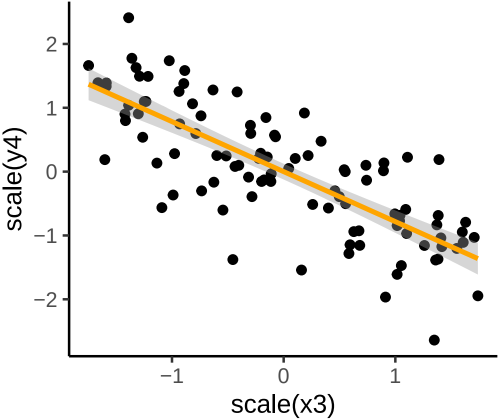

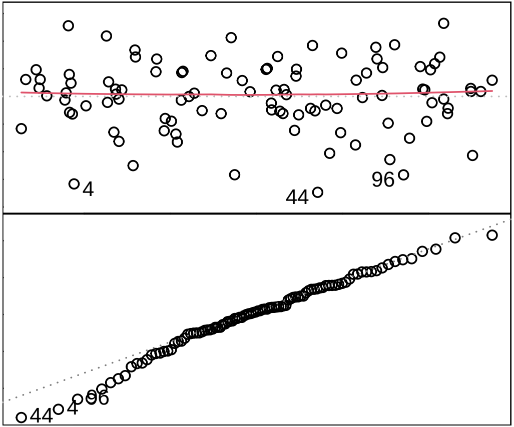


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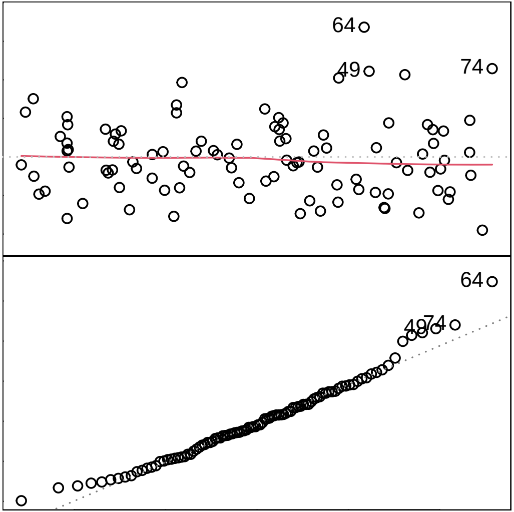
- Residuals are the same as before
- Coefficients are now related to *scaled* data and predictor

But wait... there's more (assumptions)!

One more assumption:

4. If you have 2+ predictors in your model, the predictors are not related to each other



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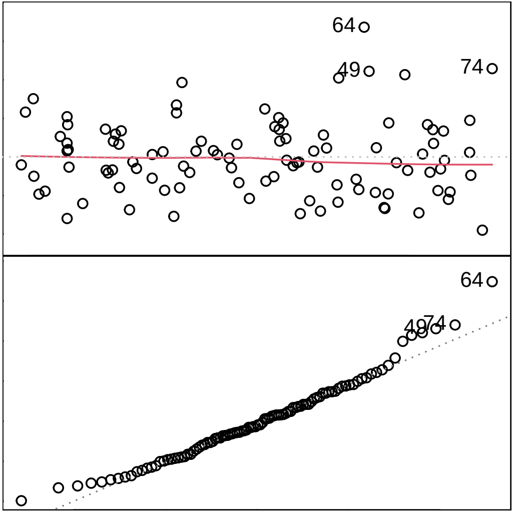
- Say we have 2 predictors, x and $x2$: `lm(y0~x+x2,data=d1)`



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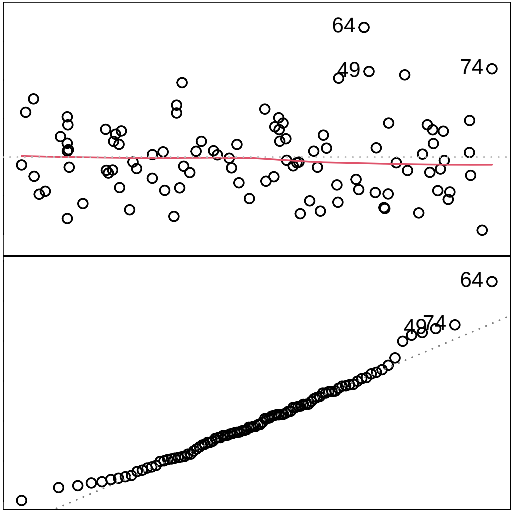
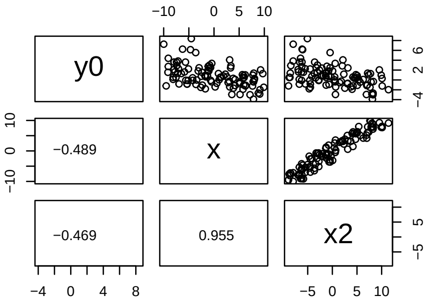
- Say we have 2 predictors, x and $x2$: `lm(y0~x+x2,data=d1)`
- Model fits, and residuals look OK, but there's trouble ahead!



Uh oh! Collinearity!

```r
#Function to print correlation (r) value
corText <- function(x,y){
  text(0.5,0.5,round(cor(x,y),3))}
#Pairplot of y0, x, and x2
pairs(d1[,c('y0','x','x2')],
      lower.panel=corText)
```



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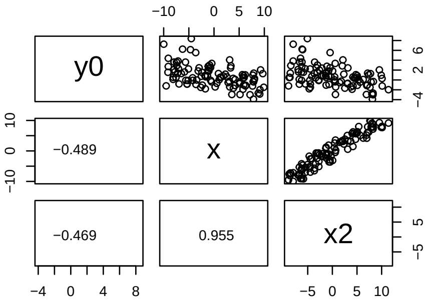

- x and $x2$ mean basically the same thing!

Uh oh! Collinearity!

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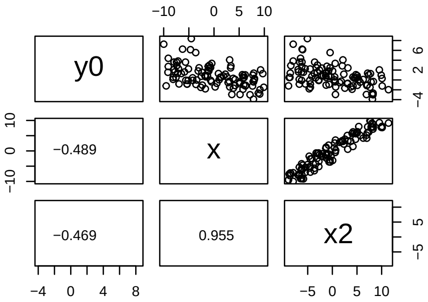

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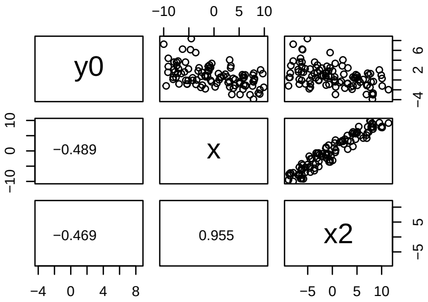

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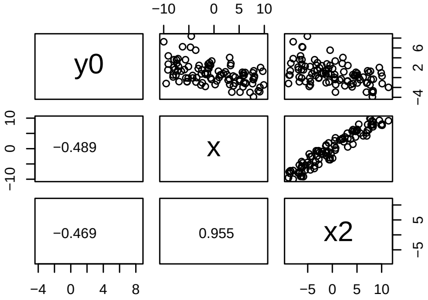

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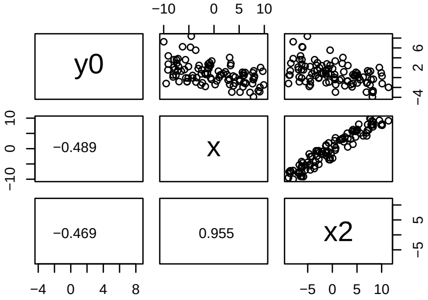

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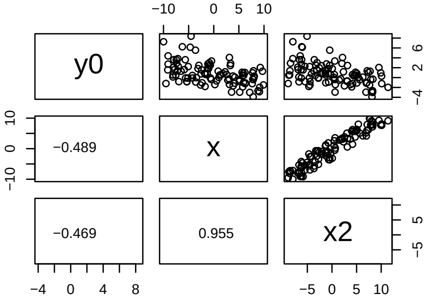

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#Correct model
m1 <- lm(y0~x,data=d1)
```

	Estimate	Std. Error	Pr(>|t|)
(Intercept)	0.7851936	0.1943002	0.0001059
x	-0.1900346	0.0342596	0.0000002

```r
#Incorrect model
m2 <- lm(y0~x+x2,data=d1)
```

	Estimate	Std. Error	Pr(>|t|)
(Intercept)	0.7860300	0.1955770	0.0001155
x	-0.1812556	0.1158464	0.1209288
x2	-0.0094931	0.1196074	0.9369028

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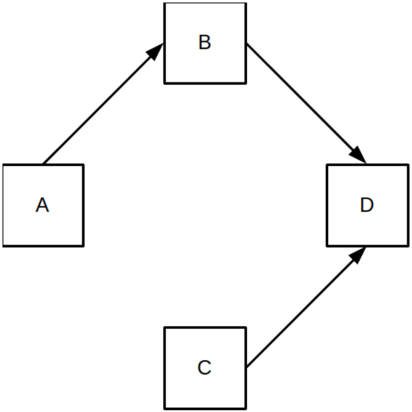

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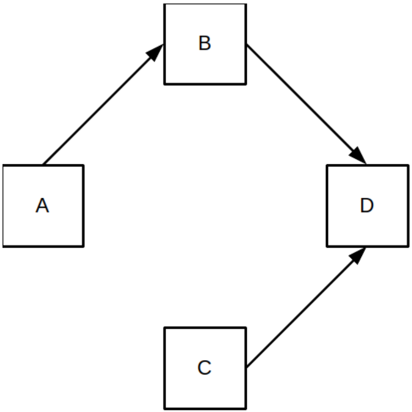

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- "Correct" `lm` model of D: `lm(D ~ B + C)`

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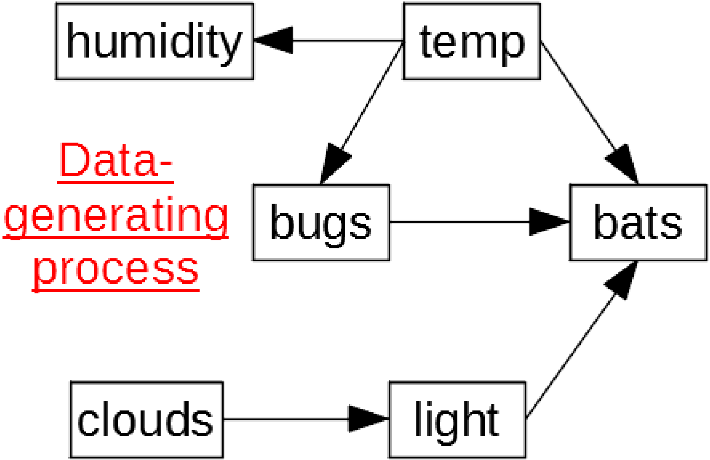
  - Draw it out on paper/in PowerPoint using flow diagrams
- Fit an `lm` model of `bats` from your causal model, check the assumptions, and update as necessary

Here's the answer



This is the **true** process that generated the data. Model for `bats` should look like:

```
lm(log(bats+0.1)~poly(temp,2)+light+bugs,data=dat)
```

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3. If a relationship is unclear, use a *double-headed arrow*