Chapter 6 Sample Answers

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This page provides sample answers to the assignment at the end of Chapter 6 of Applied Statistics with R: A Practical Guide for the Life Sciences by Justin Touchon. Chapter 6 introduces you to *More Linear Models*, which is to say models like *linear regression*, *two-way ANOVA*, and *Analysis of Covariance*. We also continued practicing using the ***tidyverse*** to explore and manipulate our data. We saw how to do fun things like plot confidence intervals around non-linear regression lines and how to use the **predict()** function. There was **a lot** in this chapter.

There are three assignments to do to continue working on the skills you are building. As always, my hope is that you are here either because 1) you want to check the answers you got to make sure you completed the assignments correctly, or 2) you got stumped and need some help. Either way, you will learn much more if you have already spent some time working through the assignments on your own. If you haven't done that, close this page and go work on it! :) The first assignment at the end of Chapter 6 is straightforward, but the second and third are very open ended. I have tried to reasonably show some different options for what you might have come up with, but understand that your choices might have been different that what I show here.

Question 1

At the end of the Chapter 5, you analyzed the log of final mass by each of the three categorical predictors independently. What happens if you include all three predictors in the model at the same time? Does the significance of any of the individual predictors change when you include more variables? If so, what does that tell you about how your interpretation of one variable might change when you include other variables in the model?

As I did in Chapter 5, I'm going to load any packages I will need and create the "byTank" version of the data.

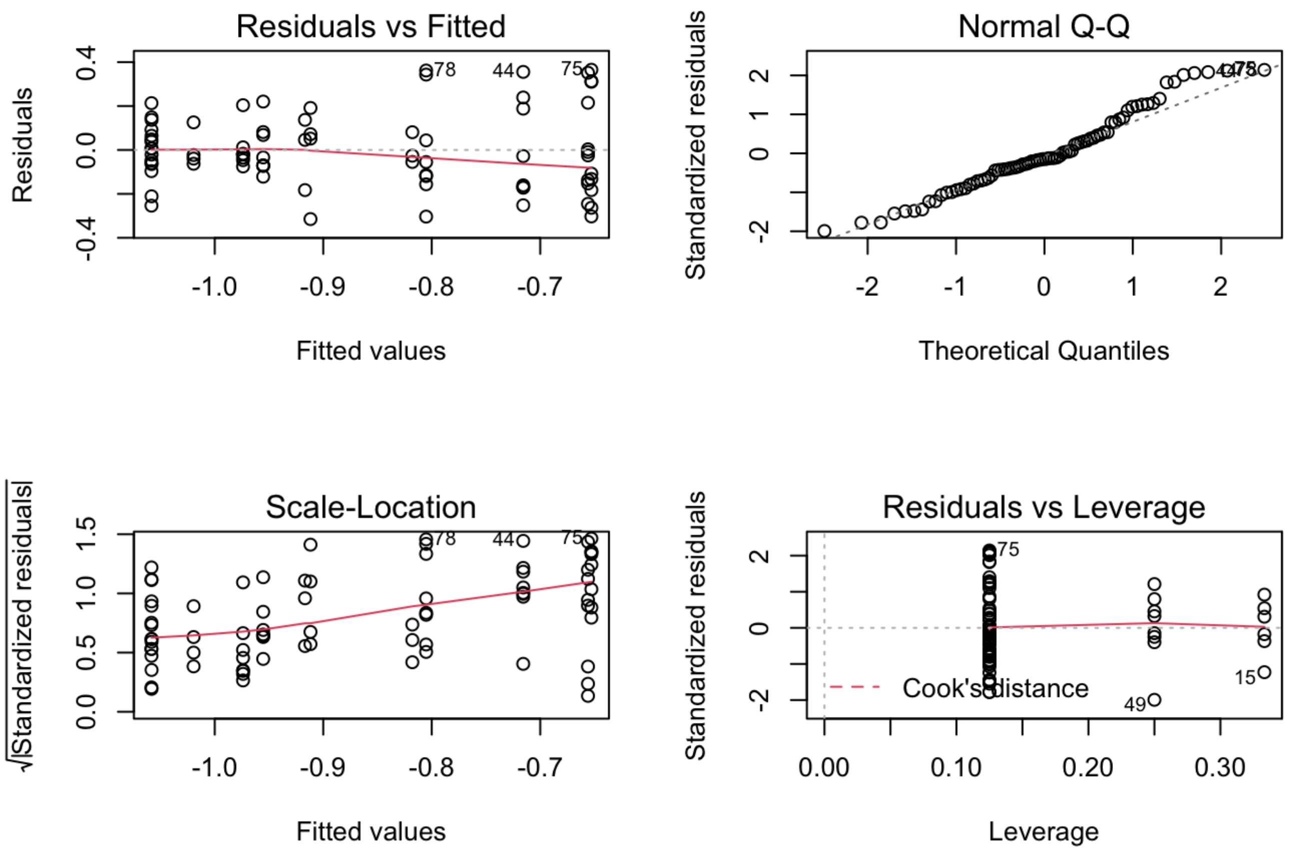
```
library(MASS)
library(car)
library(emmeans)
library(cowplot)
library(tidyverse)
```

```
## 'data.frame':    78 obs. of  16 variables:
##  $ Tank.Unique          : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ Block                : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ Pred                 : Factor w/ 3 levels "C","NL","L": 2 1 1 3 2 3 2 1 3 1 ...
##  $ Hatch                : Factor w/ 2 levels "E","L": 2 1 2 2 1 1 2 1 2 2 ...
##  $ Res                  : Factor w/ 2 levels "Hi","Lo": 1 1 1 2 1 1 2 2 1 2 ...
##  $ Age.DPO              : num  47.2 45.4 53.8 56.9 64.8 ...
##  $ Age.FromEmergence    : num  13.2 11.4 19.8 22.9 30.8 ...
##  $ SVL.initial          : num  19.4 18.4 18.9 18.8 19.7 ...
##  $ Tail.initial         : num  4.83 5.37 4.8 4.63 5.43 ...
##  $ SVL.final            : num  19.7 19 19.1 19.1 20.1 ...
##  $ Mass.final           : num  0.418 0.382 0.412 0.382 0.486 ...
##  $ Resorb.days          : num  3.49 3.79 3.51 3.65 4.22 ...
##  $ log.SVL.final        : num  2.98 2.94 2.95 2.95 3 ...
##  $ log.Age.FromEmergence: num  2.58 2.43 2.99 3.13 3.43 ...
##  $ log.Age.DPO          : num  3.85 3.82 3.99 4.04 4.17 ...
##  $ log.Mass.final       : num  -0.873 -0.962 -0.887 -0.962 -0.721 ...
```

The model we need to create is hopefully straightforward to you. Instead of having just one predictor, such as *Pred* or *Res*, we will have all three of our predictors: Pred, Hatch, and Res. We will then use the **Anova()** function from the ***car*** package to assess statistical significance.

Before we make the model, recall that when we analyzed the variables individually there was a highly significant effect of predators, but no significant effect of resources or hatching age. What will happen when all three predictors are in the model together?

```
lm.PHR<-lm(log.Mass.final~Pred*Hatch*Res, data=RxP.byTank)
par(mfrow=c(2,2));plot(lm.PHR)
```



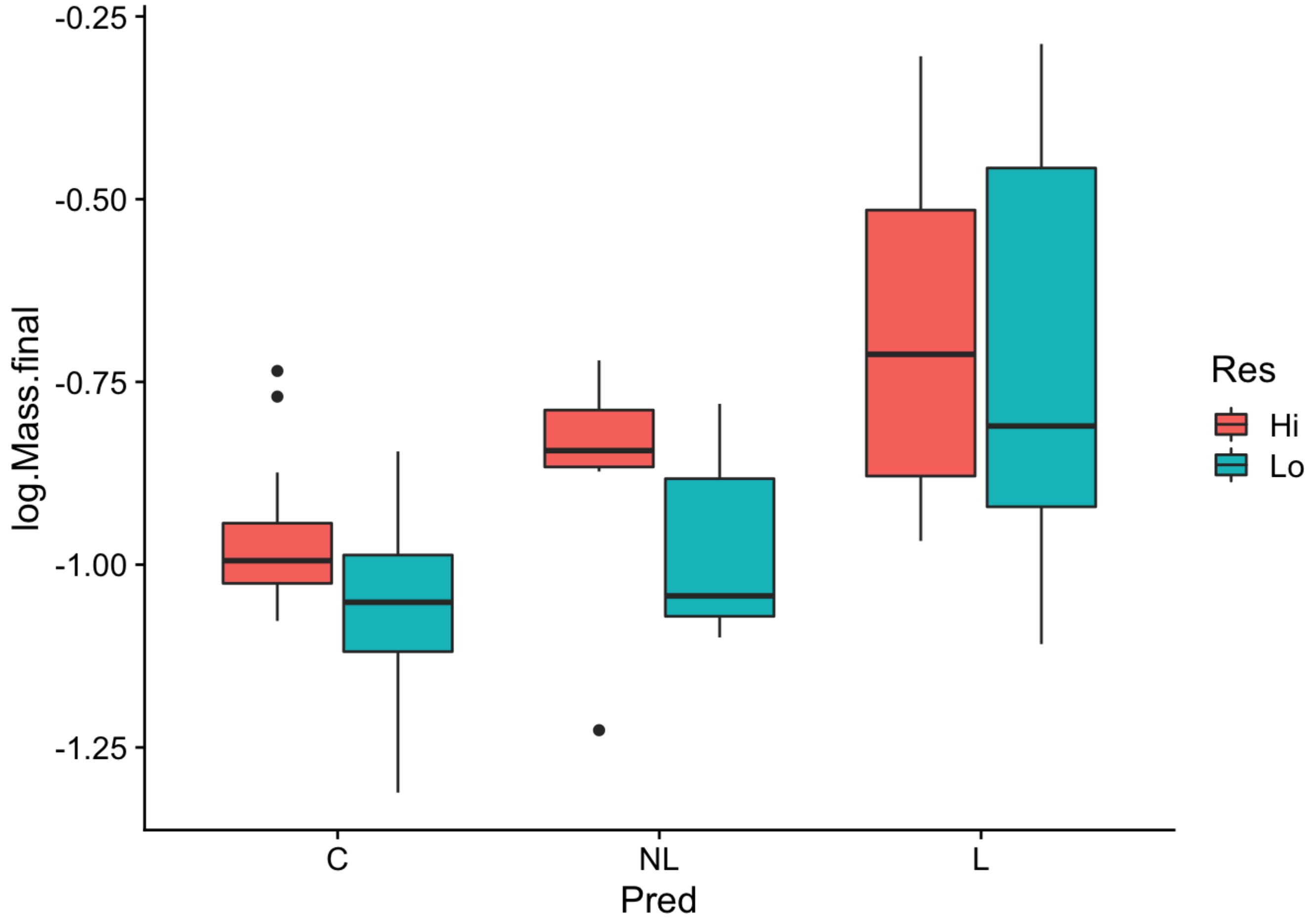
Notice that the QQ-plot looks particularly great now that we have more predictors in the model!

```
Anova(lm.PHR)
```

```
## Anova Table (Type II tests)
##
## Response: log.Mass.final
##                 Sum Sq Df F value    Pr(>F)
## Pred           1.52168  2 22.9030 2.79e-08 ***
## Hatch          0.03198  1  0.9628  0.33006
## Res            0.10805  1  3.2527  0.07587 .
## Pred:Hatch     0.05866  2  0.8829  0.41843
## Pred:Res       0.01362  2  0.2051  0.81511
## Hatch:Res      0.03142  1  0.9457  0.33437
## Pred:Hatch:Res 0.01953  2  0.2939  0.74629
## Residuals      2.19252 66
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

So this is really interesting. Now that we have more predictors in the model, the estimate of statistical significance for our Resource treatment has gone from 0.14 when it was analyzed alone to 0.076. It's not below the generally accepted threshold of 0.05, but it is close enough that I think you could argue that *something* is going on. Resources are not having as big of an effect as predators, but they are clearly have some impact on final mass at metamorphosis. We can see this effect if we create a box-and-whisker plot of the data.

```
qplot(data=RxP.byTank, x=Pred, y=log.Mass.final, fill=Res, geom="boxplot")+theme_cowplot()
```



This clearly shows us that metamorphs emerging from the High resource treatment were generally larger than those emerging from the Low resource treatment, and that this effect is pretty consistent across the three predator treatments (although it is less pronounced in the Lethal predator treatment).

Question 2

Combine your knowledge of predict() **and** ggplot() **to plot an ANCOVA different than that represented by lm5. Make sure it is plotted on the original scale of whatever variables you choose and that it has confidence intervals. Make sure to add interesting colors and useful axes, etc.**

Okay, this is a very open ended question. You can pick whichever variables you want! As a reminder, the lm5 was a model that evaluated the effect of Predators on final SVL while controlling for variation in age at metamorphosis. This is known as an Analysis of Covariance, or ANCOVA for short.

```
lm5<-lm(log.SVL.final~log.Age.DPO*Pred, data=RxP.byTank)
```

The assignment has two steps.

1. You need to pick a pair of continuous variables, one to use as a response variable and one to use as your covariate, and one categorical variable. Now, you can't just pick any pair of continuous variables. You need to make sure that the pair make sense together. For example, it would not make much sense to use SVL as

a covariate for age at metamorphosis, since we would generally expect the relationship to go in the other direction (age should effect size, but size would not effect age).

2. You use **predict()** to plot it, like we did while working through the chapter.

I will provide one examples of a possible answer you might get and hopefully that will illuminate how to think about making a figure like this.

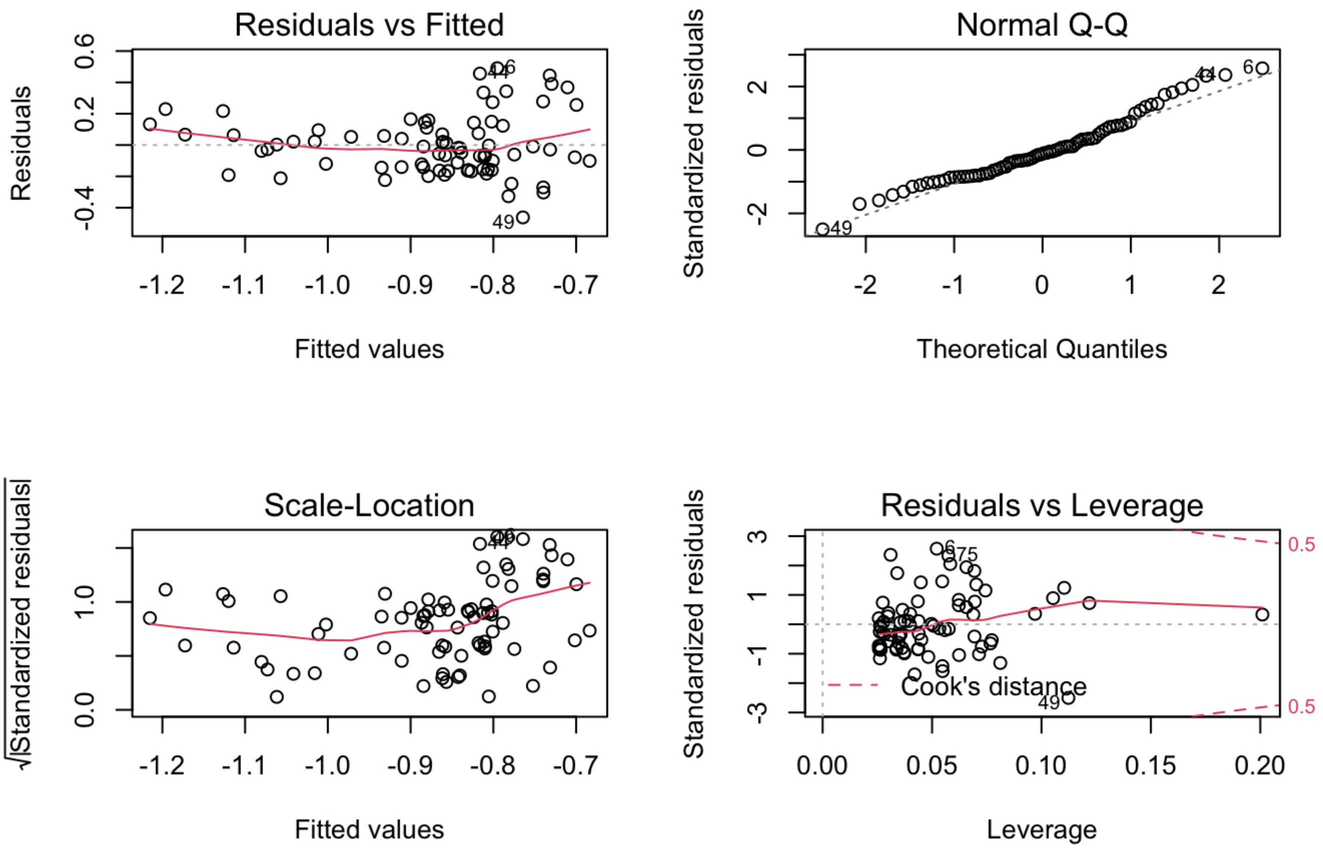
The effect of resources on final mass at metamorphosis, controlling for variation in age at metamorphosis

Perhaps the simplest thing you could do is just to change the response variable. Instead of looking at snout-vent length, let's examine mass. But, to make the example a little more interesting let's use *Res* as our categorical variable instead of *Pred*. The model would look like this. Recall that it is good practice to have your covariate coded before the categorical variable.

```
lm.Age_Res<-lm(log.Mass.final~log.Age.DPO*Res, data=RxP.byTank)
```

Let's look at the diagnostic plots to make sure everything looks okay.

```
par(mfrow=c(2,2));plot(lm.Age_Res)
```



Overall these look great. Next, let's look at the summary of the model and assess significance.

```
summary(lm.Age_Res)
```

```
## 
## Call:
## lm(formula = log.Mass.final ~ log.Age.DPO * Res, data = RxP.byTank)
## 
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -0.46215 -0.14395 -0.02316  0.10666  0.49077 
## 
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        0.02029    0.71186   0.029    0.977
## log.Age.DPO       -0.21551    0.17950  -1.201    0.234
## ResLo              0.99534    0.80811   1.232    0.222
## log.Age.DPO:ResLo -0.23531    0.20050  -1.174    0.244
## 
## Residual standard error: 0.1959 on 74 degrees of freedom
## Multiple R-squared:  0.2868, Adjusted R-squared:  0.2579 
## F-statistic: 9.918 on 3 and 74 DF,  p-value: 1.421e-05
```

```
Anova(lm.Age_Res)
```

```
## Anova Table (Type II tests)
## 
## Response: log.Mass.final
##                  Sum Sq Df F value    Pr(>F)    
## log.Age.DPO     0.98025  1 25.5352 3.037e-06 ***
## Res             0.03562  1  0.9279    0.3385    
## log.Age.DPO:Res 0.05287  1  1.3773    0.2443    
## Residuals       2.84073 74                      
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

This is really interesting. First, the summary output shows us that our adjusted R^2 is quite high, 0.2579. That tells us that our predictors collectively explain 25.79% of the variation in metamorph mass. That's not bad, but not nearly as high as when we included *Pred* in the model. Our model as a whole is also highly significant, with a p-value of 0.00001421. We could of course use the model coefficients (under the *Estimate* column) to figure out the intercepts and slopes for the regressions for each resource level, but we are going to use predict to do that for us. Let's do that, shall we?

First, let's figure out what the range should be for our x-variable. Recall that, as we did in Chapter 6, we can log-transform the values directly in next step where we create our blank data frame, so we want to know the range of the *raw* data values here.

```
range(RxP.byTank$Age.DPO)
```

```
## [1]  38.11111 140.90244
```

Okay, so the smallest average age at metamorphosis was 38.1 days and the largest was 140.9 days. We'll thus declare our x-axis range as 35–145 days (no harm in putting a little buffer around the data, right?). Next we need to make our "newdata" object for predict to use. We can use **expand.grid()** to make our lives easier.

```
lm.Age_Res.newdata<-expand.grid("log.Age.DPO"=log(35:145), Res=c("Lo","Hi"))
```

Next, use **predict()** to calculate the predicted values and their confidence intervals.

```
lm.Age_Res.predicted<-predict(lm.Age_Res, newdata=lm.Age_Res.newdata, se.fit=T)
str(lm.Age_Res.predicted)
```

```
## List of 4
##  $ fit           : Named num [1:222] -0.587 -0.6 -0.612 -0.624 -0.636 ...
##   ..- attr(*, "names")= chr [1:222] "1" "2" "3" "4" ...
##  $ se.fit        : Named num [1:222] 0.0709 0.0687 0.0665 0.0644 0.0624 ...
##   ..- attr(*, "names")= chr [1:222] "1" "2" "3" "4" ...
##  $ df            : int 74
##  $ residual.scale: num 0.196
```

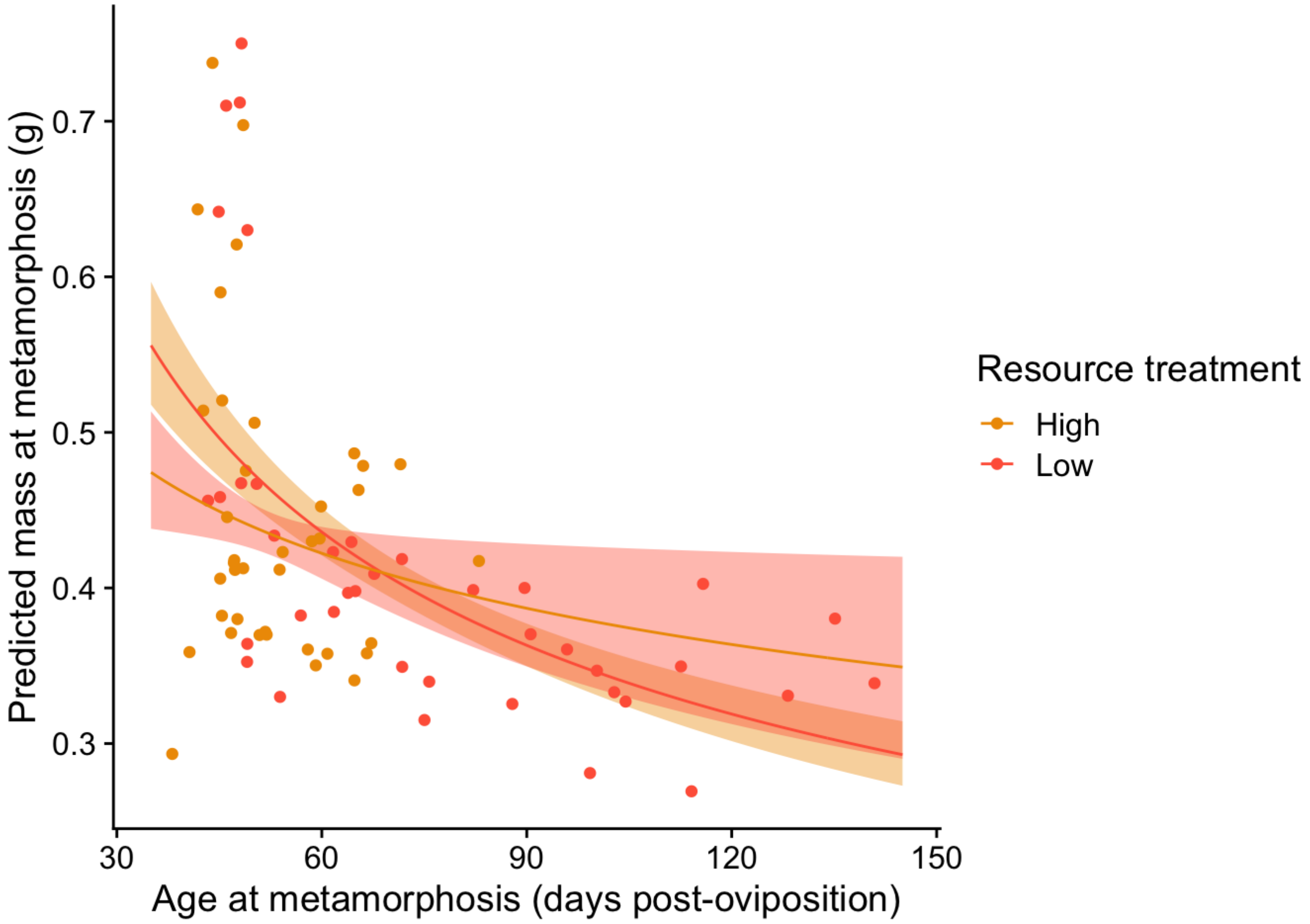
Recall that since the variables in our model were log-transformed, the predicted fits we just generated are also on a log-scale. Since our goal here is to plot them on the original scale, we need to expontentiate them.

```
#First, exponentiate the fitted values
lm.Age_Res.newdata$predict.SVL<-exp(lm.Age_Res.predicted$fit)
#Next, calculate the upper and lower bounds of the CIs
lm.Age_Res.newdata$predict.SVL.CIupper<-exp(lm.Age_Res.predicted$fit+lm.Age_Res.predicted$se.fit)
lm.Age_Res.newdata$predict.SVL.CIlower<-exp(lm.Age_Res.predicted$fit-lm.Age_Res.predicted$se.fit)
#Lastly, exponentiate the age data so it is back on the original scale
lm.Age_Res.newdata$Age.DPO<-exp(lm.Age_Res.newdata$log.Age.DPO)
lm.Age_Res.newdata
```

```
##    log.Age.DPO Res predict.SVL predict.SVL.CIupper predict.SVL.CIlower Age.DPO
## 1     3.555348  Lo   0.5558793           0.5967481           0.5178094      35
## 2     3.583519  Lo   0.5488642           0.5878942           0.5124254      36
## 3     3.610918  Lo   0.5421263           0.5794197           0.5072333      37
## 4     3.637586  Lo   0.5356476           0.5712995           0.5022205      38
## 5     3.663562  Lo   0.5294115           0.5635109           0.4973756      39
## 6     3.688879  Lo   0.5234033           0.5560334           0.4926880      40
## 7     3.713572  Lo   0.5176091           0.5488482           0.4881480      41
## 8     3.737670  Lo   0.5120163           0.5419381           0.4837466      42
## 9     3.761200  Lo   0.5066135           0.5352874           0.4794756      43
## 10    3.784190  Lo   0.5013900           0.5288818           0.4753272      44
## 11    3.806662  Lo   0.4963359           0.5227080           0.4712944      45
## 12    3.828641  Lo   0.4914422           0.5167540           0.4673703      46
## 13    3.850148  Lo   0.4867005           0.5110084           0.4635489      47
## 14    3.871201  Lo   0.4821029           0.5054611           0.4598241      48
## 15    3.891820  Lo   0.4776422           0.5001024           0.4561907      49
## 16    3.912023  Lo   0.4733117           0.4949237           0.4526434      50
## 17    3.931826  Lo   0.4691050           0.4899167           0.4491774      51
## 18    3.951244  Lo   0.4650163           0.4850738           0.4457882      52
## 19    3.970292  Lo   0.4610402           0.4803881           0.4424715      53
## 20    3.988984  Lo   0.4571714           0.4758529           0.4392233      54
## 21    4.007333  Lo   0.4534052           0.4714622           0.4360398      55
## 22    4.025352  Lo   0.4497370           0.4672102           0.4329173      56
## 23    4.043051  Lo   0.4461627           0.4630915           0.4298527      57
## 24    4.060443  Lo   0.4426782           0.4591012           0.4268426      58
## 25    4.077537  Lo   0.4392798           0.4552344           0.4238843      59
## 26    4.094345  Lo   0.4359639           0.4514865           0.4209750      60
## 27    4.110874  Lo   0.4327273           0.4478534           0.4181121      61
## 28    4.127134  Lo   0.4295667           0.4443307           0.4152933      62
## 29    4.143135  Lo   0.4264793           0.4409147           0.4125165      63
## 30    4.158883  Lo   0.4234621           0.4376013           0.4097797      64
## 31    4.174387  Lo   0.4205126           0.4343870           0.4070813      65
## 32    4.189655  Lo   0.4176282           0.4312681           0.4044196      66
## 33    4.204693  Lo   0.4148065           0.4282410           0.4017934      67
## 34    4.219508  Lo   0.4120452           0.4253024           0.3992013      68
## 35    4.234107  Lo   0.4093423           0.4224488           0.3966423      69
## 36    4.248495  Lo   0.4066956           0.4196770           0.3941156      70
## 37    4.262680  Lo   0.4041031           0.4169837           0.3916205      71
## 38    4.276666  Lo   0.4015632           0.4143657           0.3891562      72
## 39    4.290459  Lo   0.3990738           0.4118199           0.3867223      73
## 40    4.304065  Lo   0.3966335           0.4093434           0.3843183      74
## 41    4.317488  Lo   0.3942406           0.4069332           0.3819438      75
## 42    4.330733  Lo   0.3918935           0.4045865           0.3795987      76
## 43    4.343805  Lo   0.3895908           0.4023005           0.3772826      77
## 44    4.356709  Lo   0.3873311           0.4000726           0.3749953      78
## 45    4.369448  Lo   0.3851130           0.3979002           0.3727367      79
## 46    4.382027  Lo   0.3829353           0.3957809           0.3705065      80
## 47    4.394449  Lo   0.3807967           0.3937124           0.3683047      81
## 48    4.406719  Lo   0.3786961           0.3916924           0.3661309      82
## 49    4.418841  Lo   0.3766323           0.3897189           0.3639851      83
## 50    4.430817  Lo   0.3746043           0.3877898           0.3618671      84
## 51    4.442651  Lo   0.3726110           0.3859033           0.3597766      85
## 52    4.454347  Lo   0.3706515           0.3840574           0.3577135      86
## 53     4.465908  Lo   0.3687247           0.3822506           0.3556774       87
## 54     4.477337  Lo   0.3668298           0.3804812           0.3536682       88
## 55     4.488636  Lo   0.3649659           0.3787476           0.3516856       89
## 56     4.499810  Lo   0.3631321           0.3770485           0.3497293       90
## 57     4.510860  Lo   0.3613277           0.3753825           0.3477990       91
## 58     4.521789  Lo   0.3595517           0.3737483           0.3458945       92
## 59     4.532599  Lo   0.3578036           0.3721446           0.3440153       93
## 60     4.543295  Lo   0.3560826           0.3705704           0.3421611       94
## 61     4.553877  Lo   0.3543879           0.3690246           0.3403317       95
## 62     4.564348  Lo   0.3527189           0.3675061           0.3385266       96
## 63     4.574711  Lo   0.3510749           0.3660139           0.3367456       97
## 64     4.584967  Lo   0.3494553           0.3645472           0.3349881       98
## 65     4.595120  Lo   0.3478595           0.3631051           0.3332540       99
## 66     4.605170  Lo   0.3462870           0.3616868           0.3315428      100
## 67     4.615121  Lo   0.3447371           0.3602915           0.3298542      101
## 68     4.624973  Lo   0.3432093           0.3589184           0.3281877      102
## 69     4.634729  Lo   0.3417030           0.3575669           0.3265430      103
## 70     4.644391  Lo   0.3402179           0.3562362           0.3249198      104
## 71     4.653960  Lo   0.3387533           0.3549258           0.3233177      105
## 72     4.663439  Lo   0.3373088           0.3536350           0.3217363      106
## 73     4.672829  Lo   0.3358840           0.3523633           0.3201753      107
## 74     4.682131  Lo   0.3344783           0.3511102           0.3186343      108
## 75     4.691348  Lo   0.3330914           0.3498750           0.3171129      109
## 76     4.700480  Lo   0.3317229           0.3486573           0.3156109      110
## 77     4.709530  Lo   0.3303722           0.3474567           0.3141278      111
## 78     4.718499  Lo   0.3290391           0.3462726           0.3126634      112
## 79     4.727388  Lo   0.3277232           0.3451046           0.3112172      113
## 80     4.736198  Lo   0.3264241           0.3439524           0.3097890      114
## 81     4.744932  Lo   0.3251413           0.3428154           0.3083785      115
## 82     4.753590  Lo   0.3238747           0.3416934           0.3069853      116
## 83     4.762174  Lo   0.3226238           0.3405859           0.3056091      117
## 84     4.770685  Lo   0.3213883           0.3394926           0.3042496      118
## 85     4.779123  Lo   0.3201680           0.3384131           0.3029065      119
## 86     4.787492  Lo   0.3189624           0.3373472           0.3015795      120
## 87     4.795791  Lo   0.3177713           0.3362944           0.3002684      121
## 88     4.804021  Lo   0.3165944           0.3352546           0.2989728      122
## 89     4.812184  Lo   0.3154314           0.3342273           0.2976925      123
## 90     4.820282  Lo   0.3142820           0.3332124           0.2964271      124
## 91     4.828314  Lo   0.3131461           0.3322095           0.2951765      125
## 92     4.836282  Lo   0.3120232           0.3312184           0.2939404      126
## 93     4.844187  Lo   0.3109132           0.3302388           0.2927184      127
## 94     4.852030  Lo   0.3098157           0.3292705           0.2915105      128
## 95     4.859812  Lo   0.3087307           0.3283132           0.2903162      129
## 96     4.867534  Lo   0.3076578           0.3273668           0.2891354      130
## 97     4.875197  Lo   0.3065968           0.3264309           0.2879679      131
## 98     4.882802  Lo   0.3055475           0.3255053           0.2868133      132
## 99     4.890349  Lo   0.3045096           0.3245900           0.2856716      133
## 100    4.897840  Lo   0.3034831           0.3236845           0.2845424      134
## 101    4.905275  Lo   0.3024675           0.3227889           0.2834255      135
## 102    4.912655  Lo   0.3014629           0.3219028           0.2823208      136
## 103    4.919981  Lo   0.3004688           0.3210261           0.2812280      137
## 104    4.927254  Lo   0.2994853           0.3201585           0.2801470      138
## 105    4.934474  Lo   0.2985121           0.3193000           0.2790775      139
## 106    4.941642  Lo   0.2975489           0.3184504           0.2780193      140
## 107     4.948760  Lo   0.2965957            0.3176094            0.2769722     141
## 108     4.955827  Lo   0.2956522            0.3167770            0.2759362     142
## 109     4.962845  Lo   0.2947184            0.3159530            0.2749109     143
## 110     4.969813  Lo   0.2937939            0.3151371            0.2738962     144
## 111     4.976734  Lo   0.2928787            0.3143294            0.2728919     145
## 112     3.555348  Hi   0.4742884            0.5134944            0.4380758      35
## 113     3.583519  Hi   0.4714176            0.5080343            0.4374400      36
## 114     3.610918  Hi   0.4686421            0.5028086            0.4367973      37
## 115     3.637586  Hi   0.4659564            0.4978067            0.4361439      38
## 116     3.663562  Hi   0.4633552            0.4930195            0.4354757      39
## 117     3.688879  Hi   0.4608338            0.4884401            0.4347879      40
## 118     3.713572  Hi   0.4583880            0.4840629            0.4340749      41
## 119     3.737670  Hi   0.4560136            0.4798845            0.4333301      42
## 120     3.761200  Hi   0.4537069            0.4759029            0.4325461      43
## 121     3.784190  Hi   0.4514645            0.4721185            0.4317142      44
## 122     3.806662  Hi   0.4492833            0.4685331            0.4308243      45
## 123     3.828641  Hi   0.4471602            0.4651506            0.4298655      46
## 124     3.850148  Hi   0.4450924            0.4619762            0.4288257      47
## 125     3.871201  Hi   0.4430775            0.4590160            0.4276924      48
## 126     3.891820  Hi   0.4411129            0.4562759            0.4264538      49
## 127     3.912023  Hi   0.4391965            0.4537605            0.4251000      50
## 128     3.931826  Hi   0.4373261            0.4514713            0.4236241      51
## 129     3.951244  Hi   0.4354998            0.4494055            0.4220244      52
## 130     3.970292  Hi   0.4337156            0.4475551            0.4203041      53
## 131     3.988984  Hi   0.4319720            0.4459072            0.4184722      54
## 132     4.007333  Hi   0.4302671            0.4444448            0.4165416      55
## 133     4.025352  Hi   0.4285995            0.4431484            0.4145283      56
## 134     4.043051  Hi   0.4269677            0.4419977            0.4124489      57
## 135     4.060443  Hi   0.4253704            0.4409730            0.4103198      58
## 136     4.077537  Hi   0.4238062            0.4400562            0.4081562      59
## 137     4.094345  Hi   0.4222738            0.4392313            0.4059711      60
## 138     4.110874  Hi   0.4207722            0.4384844            0.4037755      61
## 139     4.127134  Hi   0.4193003            0.4378039            0.4015787      62
## 140     4.143135  Hi   0.4178569            0.4371798            0.3993881      63
## 141     4.158883  Hi   0.4164411            0.4366039            0.3972094      64
## 142     4.174387  Hi   0.4150519            0.4360695            0.3950474      65
## 143     4.189655  Hi   0.4136885            0.4355709            0.3929055      66
## 144     4.204693  Hi   0.4123500            0.4351033            0.3907865      67
## 145     4.219508  Hi   0.4110355            0.4346629            0.3886924      68
## 146     4.234107  Hi   0.4097443            0.4342463            0.3866248      69
## 147     4.248495  Hi   0.4084757            0.4338508            0.3845847      70
## 148     4.262680  Hi   0.4072289            0.4334739            0.3825728      71
## 149     4.276666  Hi   0.4060032            0.4331138            0.3805896      72
## 150     4.290459  Hi   0.4047981            0.4327687            0.3786353      73
## 151     4.304065  Hi   0.4036129            0.4324372            0.3767099      74
## 152     4.317488  Hi   0.4024470            0.4321179            0.3748134      75
## 153     4.330733  Hi   0.4012998            0.4318099            0.3729455      76
## 154     4.343805  Hi   0.4001709            0.4315120            0.3711060      77
## 155     4.356709  Hi   0.3990596            0.4312236            0.3692946      78
## 156     4.369448  Hi   0.3979655            0.4309438            0.3675109      79
## 157     4.382027  Hi   0.3968881            0.4306720            0.3657544      80
## 158     4.394449  Hi   0.3958270            0.4304077            0.3640246      81
## 159     4.406719  Hi   0.3947816            0.4301503            0.3623211      82
## 160     4.418841  Hi   0.3937517            0.4298993            0.3606435      83
## 161    4.430817  Hi   0.3927367              0.4296544              0.3589911       84
## 162    4.442651  Hi   0.3917363              0.4294152              0.3573635       85
## 163    4.454347  Hi   0.3907501              0.4291813              0.3557602       86
## 164    4.465908  Hi   0.3897778              0.4289525              0.3541807       87
## 165    4.477337  Hi   0.3888189              0.4287285              0.3526244       88
## 166    4.488636  Hi   0.3878732              0.4285090              0.3510909       89
## 167    4.499810  Hi   0.3869403              0.4282937              0.3495797       90
## 168    4.510860  Hi   0.3860199              0.4280826              0.3480903       91
## 169    4.521789  Hi   0.3851118              0.4278753              0.3466223       92
## 170    4.532599  Hi   0.3842156              0.4276717              0.3451750       93
## 171    4.543295  Hi   0.3833310              0.4274717              0.3437482       94
## 172    4.553877  Hi   0.3824577              0.4272750              0.3423414       95
## 173    4.564348  Hi   0.3815956              0.4270816              0.3409541       96
## 174    4.574711  Hi   0.3807443              0.4268914              0.3395858       97
## 175    4.584967  Hi   0.3799037              0.4267041              0.3382363       98
## 176    4.595120  Hi   0.3790734              0.4265196              0.3369050       99
## 177    4.605170  Hi   0.3782532              0.4263380              0.3355916      100
## 178    4.615121  Hi   0.3774429              0.4261590              0.3342957      101
## 179    4.624973  Hi   0.3766423              0.4259826              0.3330170      102
## 180    4.634729  Hi   0.3758512              0.4258087              0.3317549      103
## 181    4.644391  Hi   0.3750694              0.4256372              0.3305093      104
## 182    4.653960  Hi   0.3742967              0.4254680              0.3292798      105
## 183    4.663439  Hi   0.3735329              0.4253011              0.3280659      106
## 184    4.672829  Hi   0.3727777              0.4251363              0.3268675      107
## 185    4.682131  Hi   0.3720311              0.4249736              0.3256841      108
## 186    4.691348  Hi   0.3712929              0.4248130              0.3245155      109
## 187    4.700480  Hi   0.3705628              0.4246544              0.3233613      110
## 188    4.709530  Hi   0.3698408              0.4244977              0.3222213      111
## 189    4.718499  Hi   0.3691266              0.4243429              0.3210952      112
## 190    4.727388  Hi   0.3684202              0.4241900              0.3199827      113
## 191    4.736198  Hi   0.3677213              0.4240388              0.3188835      114
## 192    4.744932  Hi   0.3670298              0.4238893              0.3177973      115
## 193    4.753590  Hi   0.3663456              0.4237415              0.3167240      116
## 194    4.762174  Hi   0.3656685              0.4235954              0.3156632      117
## 195    4.770685  Hi   0.3649984              0.4234508              0.3146147      118
## 196    4.779123  Hi   0.3643352              0.4233078              0.3135783      119
## 197    4.787492  Hi   0.3636787              0.4231664              0.3125537      120
## 198    4.795791  Hi   0.3630289              0.4230264              0.3115407      121
## 199    4.804021  Hi   0.3623855              0.4228879              0.3105391      122
## 200    4.812184  Hi   0.3617485              0.4227508              0.3095488      123
## 201    4.820282  Hi   0.3611178              0.4226151              0.3085693      124
## 202    4.828314  Hi   0.3604932              0.4224807              0.3076007      125
## 203    4.836282  Hi   0.3598747              0.4223477              0.3066426      126
## 204    4.844187  Hi   0.3592621              0.4222159              0.3056949      127
## 205    4.852030  Hi   0.3586553              0.4220855              0.3047573      128
## 206    4.859812  Hi   0.3580543              0.4219563              0.3038298      129
## 207    4.867534  Hi   0.3574589              0.4218283              0.3029121      130
## 208    4.875197  Hi   0.3568691              0.4217015              0.3020040      131
## 209    4.882802  Hi   0.3562847              0.4215758              0.3011055      132
## 210    4.890349  Hi   0.3557057              0.4214513              0.3002162      133
## 211    4.897840  Hi   0.3551319              0.4213280              0.2993361      134
## 212    4.905275  Hi   0.3545633              0.4212057              0.2984649      135
## 213    4.912655  Hi   0.3539998              0.4210845              0.2976026      136
## 214    4.919981  Hi   0.3534413              0.4209644              0.2967490      137
## 215    4.927254  Hi   0.3528878           0.4208453           0.2959040     138
## 216    4.934474  Hi   0.3523391           0.4207272           0.2950673     139
## 217    4.941642  Hi   0.3517952           0.4206102           0.2942389     140
## 218    4.948760  Hi   0.3512560           0.4204941           0.2934185     141
## 219    4.955827  Hi   0.3507214           0.4203790           0.2926062     142
## 220    4.962845  Hi   0.3501914           0.4202648           0.2918017     143
## 221    4.969813  Hi   0.3496658           0.4201516           0.2910049     144
## 222    4.976734  Hi   0.3491447           0.4200393           0.2902158     145
```

Okay, now we are ready to plot these data and visualize the effects (or lack thereof) of resources and age on mass at metamorphosis. We will use ***ggplot2*** here, specifically plotting with the **ggplot()** function. The code below follows the exact same logic as that from Chapter 6. We first define the basic aesthetics of the figure with the **ggplot()** function, then customize what all we want to add to the figure (the ribbon, the points, the lines, the fills and colors, the x-axis and y-axis labels, and that we want to apply the cowplot theme). Easy peasy!

```
ggplot(data=RxP.byTank, aes(x=Age.DPO, y=Mass.final, col=Res))+
  geom_ribbon(data=lm.Age_Res.newdata, inherit.aes=F, aes(x=Age.DPO, ymax=predict.SVL.CI
upper, ymin=predict.SVL.CIlower, fill=Res), alpha=0.4)+
  geom_point()+
  geom_line(data=lm.Age_Res.newdata, inherit.aes=F, aes(x=Age.DPO, y=predict.SVL, col=Re
s))+
  scale_fill_manual(values=c("orange2","tomato1"), guide="none")+
  scale_color_manual(values=c("orange2","tomato1"), labels=c("High","Low"), name="Resour
ce treatment")+
  ylab("Predicted mass at metamorphosis (g)")+
  xlab("Age at metamorphosis (days post-oviposition)")+
  theme_cowplot()
```



Doesn’t that figure look nice! I think so.

Question 3

Explore the statistical analyses shown here but with different interactions. Pick two different questions to ask. There are lots of questions you can ask! Just make sure that you are clear about what question you are asking and then conduct the analysis to answer it.

There are many different questions you could ask here, so this is once again a very open ended assignment. Here are just two possibilities.

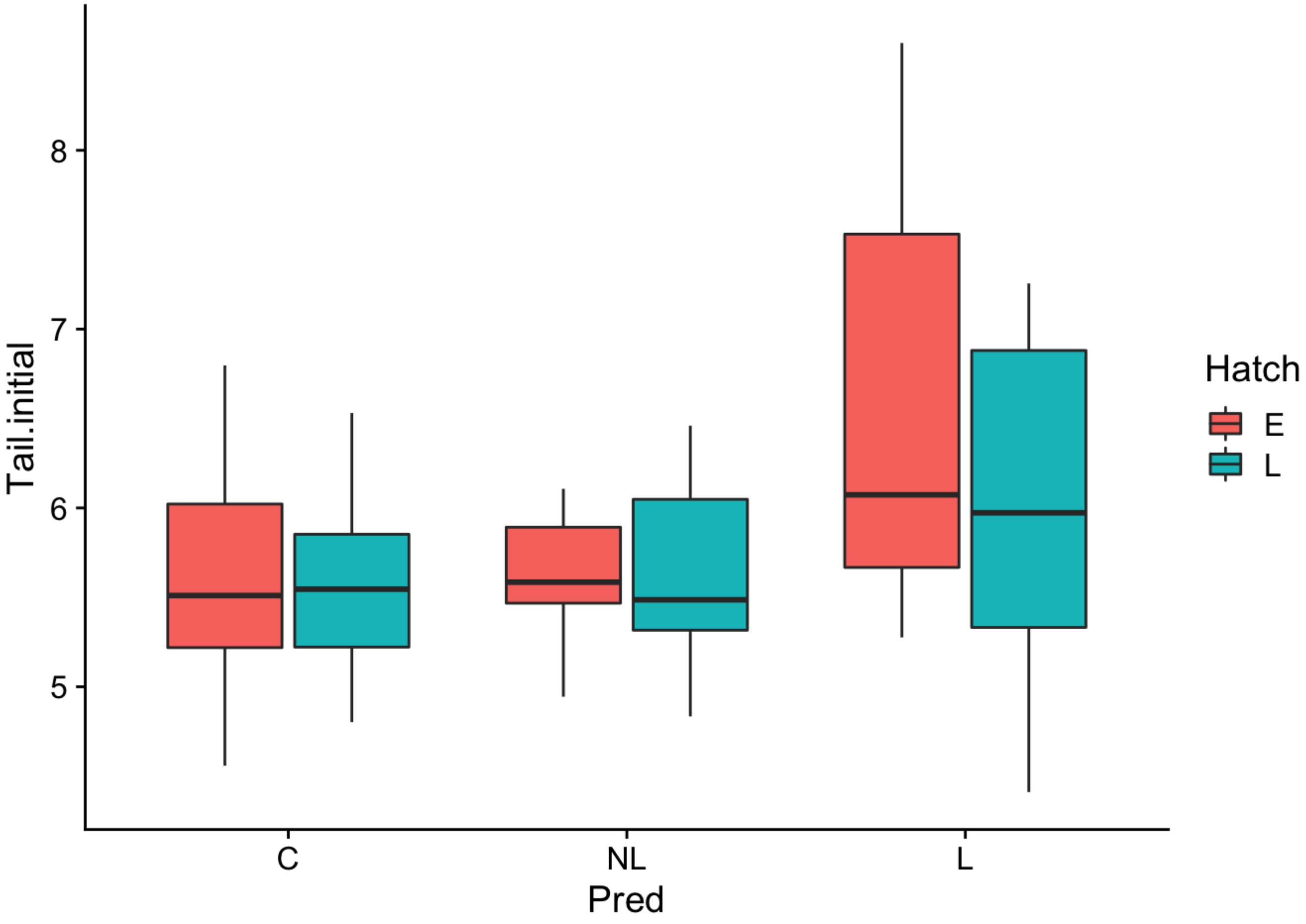
Do Hatching age and Predator treatment effect the length of the tail remaining when froglets crawl out of the water?

To understand this question, let’s think a little bit about the biology of an amphibian. When a tadpole is turning into a frog (what we call metamorphosis) one of the changes it goes through is that it resorbs the tail into the body. The tail essentially serves as energy for completing all of the morphological changes that are occurring during this time. Since the tail is generally long, it takes a little while for the froglet to resorb it and the transforming froglet can make a choice (to a certain degree) about when to crawl out of the water. As soon as the tadpole develops arms, its ability to swim is greatly hampered. Thus, staying in the water is a dangerous proposition. However, having a long tail on land is also dangerous, because it means the new little froglet will be less able to jump and avoid predators. Thus, you might predict that if the water is safe, you should stay put as long as possible and complete as much of metamorphosis as possible before entering the scary new terrestrial world. On the flip side, if there is eminent danger in the water, you probably want to get out and take your chances on land. Let's see how the different predator treatments (remember, one of the treatments is a real live lethal predator swimming around in the tank) and hatching age might affect the size of the tail when we collected froglets the morning after they had crawled out of the water. Longer tails would imply that they left the water earlier in the window of metamorphosis, whereas shorter tails would imply they stayed put longer.

```
lm.tail<-lm(Tail.initial~Hatch*Pred, data=RxP.byTank)
Anova(lm.tail)
```

```
## Anova Table (Type II tests)
##
## Response: Tail.initial
##             Sum Sq Df F value    Pr(>F)
## Hatch        0.920  1  1.5241 0.2210101
## Pred         9.298  2  7.7018 0.0009309 ***
## Hatch:Pred   1.334  2  1.1054 0.3366458
## Residuals   43.459 72
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
qplot(data=RxP.byTank, x=Pred, y=Tail.initial, fill=Hatch, geom="boxplot")+theme_cowplot
()
```



Very interesting. The **Anova()** results show us that there is a highly significant effect of predator treatment, but no effect of hatching age, on tail length at metamorphosis. By looking at the boxplots, we can see (even without running the necessary post-hoc tests) that this is being driven by the lethal predator treatment. As we might have expected, froglets collected from tanks with lethal predators had longer tails than froglets from either control tanks or tanks with caged, nonlethal predators. That last point is also particularly interesting, since it implies that the metamorphosing froglets in the tank are not sensing the nonlethal predators to be as big a risk as the lethal predators.

Is the amount of time needed to resorb the tail influenced by how long the tail was when froglets crawled out of the water and the Predator or Resource treatment?

We certainly might expect that there would be a positive relationship between how long a froglets tail is when it leaves the water and how long it takes to resorb that tail into the body. But is there an effect of predators or resources? We might imagine that an animal that is "skinnier" or has fewer fat reserves would resorb the tail faster, whereas an animal that is more robust would resorb it more slowly. We know that predators affect the size of froglets at metamorphosis (presumabely because they eat some of the tadpoles in the tank, thereby leaving more food for the survivors) and so it is possible that they might affect the energy reserves of the animals too.

Below I've made an ANCOVA with two categorical predictors, which allows us to see if there are effects of predators, resources, or if they interact, as well if any of them interact with the size of the tail when we first caught the froglets.

```
lm.resorb<-lm(Resorb.days~Tail.initial*Pred*Res, data=RxP.byTank)
Anova(lm.resorb)
```

```
## Anova Table (Type II tests)
## 
## Response: Resorb.days
##                        Sum Sq Df F value    Pr(>F)    
## Tail.initial          11.1528  1 78.2841 8.106e-13 ***
## Pred                   0.3255  2  1.1423 0.3253039    
## Res                    2.3333  1 16.3783 0.0001386 ***
## Tail.initial:Pred      0.5246  2  1.8411 0.1667014    
## Tail.initial:Res       0.7083  1  4.9719 0.0291689 *  
## Pred:Res               0.2546  2  0.8936 0.4140563    
## Tail.initial:Pred:Res  0.0279  2  0.0981 0.9067010    
## Residuals              9.4027 66                      
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The **Anova()** results demonstrate that the time needed to resorb the tail is affected by the size of the tail at emergence, the resource treatment of the tadpoles, and the interaction between them. There is clearly no effect of predator treatment, so if we wanted we could reduce the model to what is known as the *minimal adequate model*, an idea popularized by Michael Crawley in his excellent book, The R Book. This will give us the most accurate estimates of predictor significance. To do so, we would remove the nonsignificant predictor (in this case, *Pred*) from the model, like so.

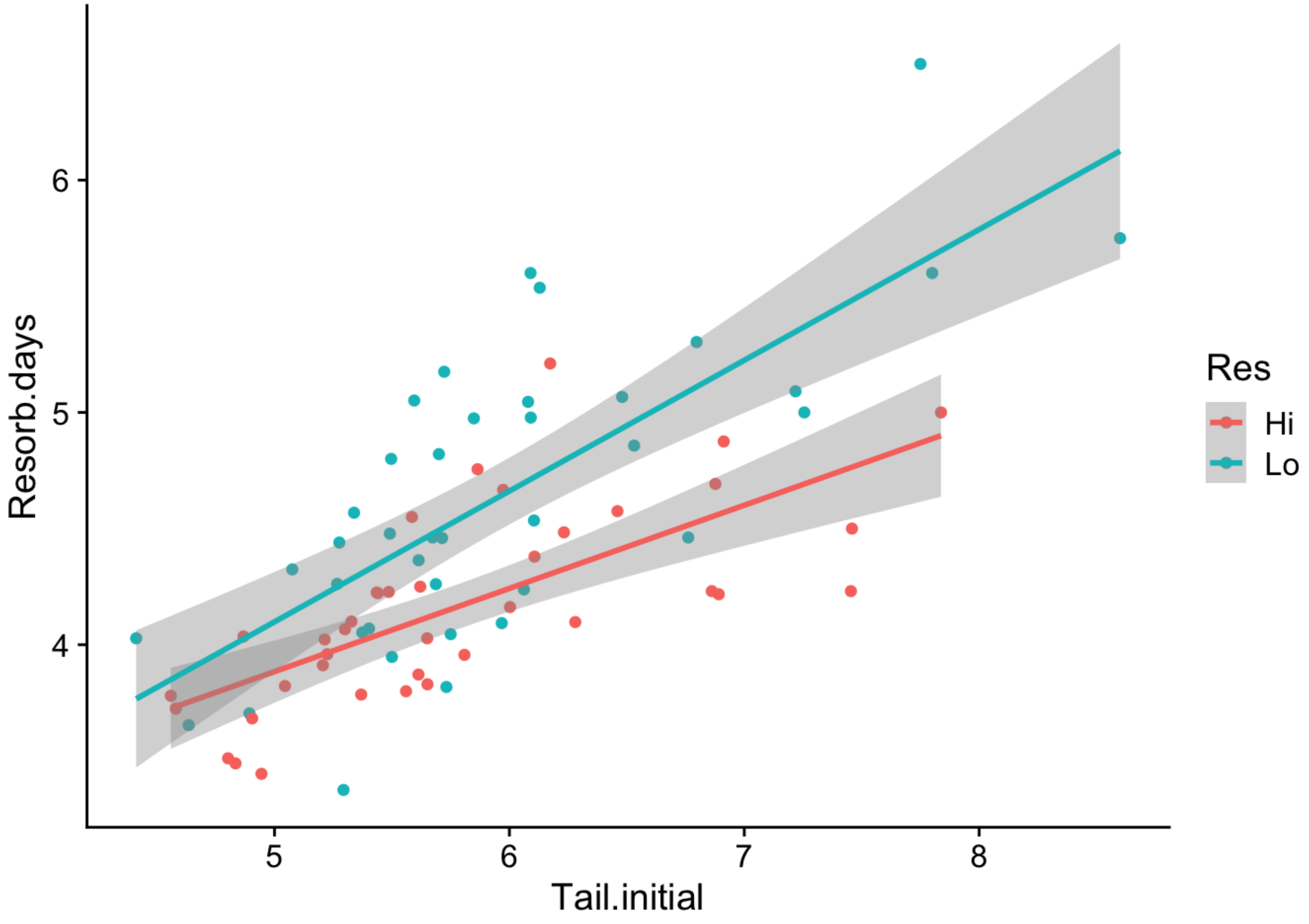
```
lm.resorb<-lm(Resorb.days~Tail.initial*Res, data=RxP.byTank)
Anova(lm.resorb)
```

```
## Anova Table (Type II tests)
##
## Response: Resorb.days
##                   Sum Sq Df F value    Pr(>F)
## Tail.initial     11.8299  1 83.2142 9.782e-14 ***
## Res               2.9483  1 20.7391 2.029e-05 ***
## Tail.initial:Res  0.5698  1  4.0082   0.04894 *
## Residuals        10.5200 74
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We can see that all three effects are still significant, and that the p-value for the interaction has increased a bit. FYI, these are the numbers you would want to publish if you were doing so. Now, let's visualize these effects!

```
qplot(data=RxP.byTank, x=Tail.initial, y=Resorb.days, col=Res, geom="point")+geom_smooth
(method="lm")+theme_cowplot()
```

```
## `geom_smooth()` using formula 'y ~ x'
```



So this implies that as expected, longer initial tails take more days to resorb but that frogs from Low resource treatments resorb them more slowly than do froglets from High resource treatments, and that the slopes of the regressions are not the same (which is what the interaction tells us). How interesting!

But wait! Oh no, we never checked our variables *Tail.initial* and *Resorb.days* for normality!! We better do so before we draw any hard conclusions about our data.

```
#Check normality of Tail.initial with a Shapiro-Wilks test
shapiro.test(RxP.byTank$Tail.initial)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  RxP.byTank$Tail.initial
## W = 0.93824, p-value = 0.0009202
```

```
shapiro.test(log(RxP.byTank$Tail.initial))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  log(RxP.byTank$Tail.initial)
## W = 0.96978, p-value = 0.06045
```

```
#Check normality of Resorb.days with a Shapiro-Wilks test
shapiro.test(RxP.byTank$Resorb.days)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  RxP.byTank$Resorb.days
## W = 0.95378, p-value = 0.006556
```

```
shapiro.test(log(RxP.byTank$Resorb.days))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  log(RxP.byTank$Resorb.days)
## W = 0.98023, p-value = 0.2668
```

In both cases, the data are significantly not normal and log-transforming the data makes them normal. Let's see what effect that has on our model and interpretation. Remember that you can just log-transform a variable directly in the model without actually coding it into the data frame.

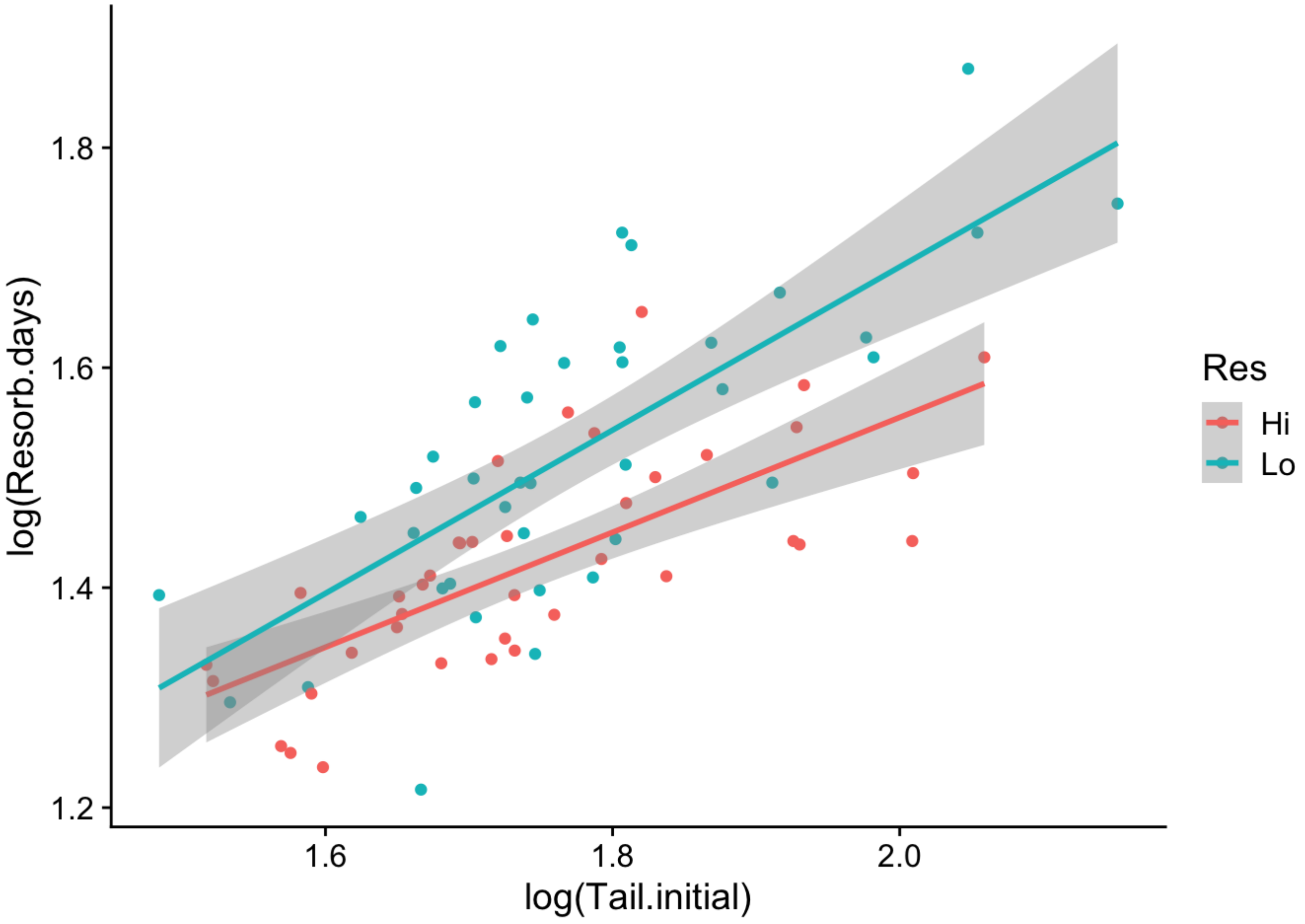
```
lm.resorb2<-lm(log(Resorb.days)~log(Tail.initial)*Res, data=RxP.byTank)
Anova(lm.resorb2)
```

```
## Anova Table (Type II tests)
##
## Response: log(Resorb.days)
##                        Sum Sq Df F value    Pr(>F)
## log(Tail.initial)     0.58309  1 84.7679 6.771e-14 ***
## Res                   0.13602  1 19.7735 3.014e-05 ***
## log(Tail.initial):Res 0.01754  1  2.5504    0.1145
## Residuals             0.50903 74
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Log-transforming the continuous variables clearly had effect. The interaction between initial tail length and resource treatment is no longer significant. We can visualize these effects quite easily.

```
qplot(data=RxP.byTank, x=log(Tail.initial), y=log(Resorb.days), col=Res, geom="point")+g
eom_smooth(method="lm")+theme_cowplot()
```

```
## `geom_smooth()` using formula 'y ~ x'
```



Taking together the statistical results and the figure, we can interpret this to mean that there is an effect of initial tail length on tail to resorb the tail (longer tails take longer to resorb) and that froglets from low resource tanks resorb their tails more slowly across the board (the slopes are not significantly different between the low and high resource animals).