

Exercise Solutions

Linear model with an interaction between a continuous and a categorical variable

This exercise builds on the previous exercises where you fitted a linear model with either a single continuous explanatory variable or a single categorical explanatory variable. In this exercise you will fit a model with both a continuous and categorical explanatory variable and allow their effects to interact (i.e. the effect of one explanatory changes with the value of the other explanatory variable). This is the third of four complementary exercises, based on the `loyn` data set.

1. As in previous exercises, either create a new R script (perhaps call it `linear_model_3`) or continue with your previous R script in your RStudio Project. Again, make sure you include any metadata you feel is appropriate (title, description of task, date of creation etc) and don't forget to comment out your metadata with a `#` at the beginning of the line.
2. Import the data file 'loyn.txt' into R and take a look at the structure of this dataframe using the `str()` function. We know that the abundance of birds `ABUND` increases quickly with the area of the patch `LOGAREA`, and more slowly for the larger patches (a saturating "log-linear relationship"). We now also know that bird abundance changes with the grazing intensity (`FGRAZE` variable). But how do these effects combine together? Would a small patch with low grazing intensity have more birds than a larger patch with high grazing intensity? Could the fit of the `ABUND ~ LOGAREA` model for the large patches be improved, if we accounted for grazing intensity in the patches?
3. As previously we want to treat `AREA` as a log-transformed area to limit the influence of the couple of disproportionately large patches, and `GRAZE` as a categorical variable with five levels. So the first thing we need to do is create the corresponding variables in the `loyn` dataframe, called `LOGAREA` and `FGRAZE`.
4. Explore the relationship between bird abundance and log transformed forest patch area for each level of grazing. You could manually create a separate plot for each graze level but it's more efficient to use a conditional scatter plot (aka coplot, see section 4.2.6 of the R book or the help page for the function `coplot()`). A coplot lets you visualise the relationship between `ABUND` and `LOGAREA` for each level of `FGRAZE`, with `FGRAZE` levels increasing from the bottom-left panel (Graze level 1) to the top-right panel (Graze level 5). What patterns do you see? Is it okay to assume that the relationship between `ABUND` and `LOGAREA` is the same for all grazing levels or does the relationship change? This is effectively asking if the slopes of the relationship between `LOGAREA` and `FGRAZE` are different for each `FGRAZE` level - this is called an interaction.

5. Fit an appropriate linear model in R to explain the variation in the response variable **ABUND** with the explanatory variables **LOGAREA** and **FGRAZE**. Also include the interaction between **LOGAREA** and **FGRAZE**. Hint: **:** is the interaction symbol! Remember to use the **data =** argument. Assign this linear model to an appropriately named object, like **birds.inter.1**. Optional: Can you remember how to specify the model using the ‘shortcut’ version (with *****) instead?

6. As conscientious modellers, let’s first check the assumptions of our linear model by creating plots of the residuals. Remember, that you can split your plotting device into 2 rows and 2 columns using the **par()** function before you create the plots. Check each of the assumptions using these plots and report whether your model meets these assumptions.

7. Use the **anova()** function to produce the ANOVA table of your linear model. Remember, this ANOVA table is based on sequential sums of squares (the order of the explanatory variables matters). The only P value that we should interpret is the one that occurs in the second to last row of the table (the one above ‘Residuals’). This is the interaction term between **FGRAZE** and **LOGAREA** (**FGRAZE:LOGAREA**). What is the null hypothesis associated with this interaction term? Do we reject or fail to reject this hypothesis? What is the biological interpretation of this interaction term? Can we say anything about the hypotheses for the main effects of **FGRAZE** or **LOGAREA**?

8. OK, now for the part you all know and love! Use the **summary()** function on your model object to produce the table of parameter estimates. Using this output, take each line in turn and answer the following questions: (A) what does this parameter estimate? (B) What is the biological interpretation of the corresponding estimate? (C) What is the null hypothesis associated with it? (D) Do you reject or fail to reject this hypothesis? (E) compare the multiple R^2 from this model to your previous two models. I encourage you to get someone to discuss your answers with you.

9. Right, now hang onto your hat. Let’s plot the predictions from your model to figure out how it really fits the data (and help us understand the output from the **summary()** function :). Here’s a recipe, using the **predict()** function.

- plot the raw data, using a different colour for points from each **FGRAZE** level
- for each **FGRAZE** level in turn,
- create a sequence of **LOGAREA** from the minimum value to the maximum within the grazing level (unless you wish to predict outside the range of observed values, probably best not too!).
- store it in a data frame (e.g. **dat4pred**) containing the variables **FGRAZE** and **LOGAREA**. Remember that **FGRAZE** is a factor, so its values require double quotes.
- add a predicted column containing the predictions of the model for the new data frame, using **predict()**
- plot the predictions with the appropriate colours

See the script below, for one of many ways of doing this. Now this might seem like a huge amount of code just to plot your predicted values (and admittedly it is!) but most of the code is just repeated for each level of graze. Just work through it slowly and logically and hopefully it will make sense (please ask if you are confused). I will also show you some alternative (easier?) ways to do this below.

```

par(mfrow= c(1, 1))
plot(ABUND ~ LOGAREA, data = loyn, col = GRAZE, pch = 16)
# Note: # colour 1 means black in R
# colour 2 means red in R
# colour 3 means green in R
# colour 4 means blue in R
# colour 5 means cyan in R

# FGRAZE1
# create a sequence of increasing Biomass within the observed range
LOGAREA.seq <- seq(from = min(loyn$LOGAREA[loyn$FGRAZE == 1]),
                  to = max(loyn$LOGAREA[loyn$FGRAZE == 1]),
                  length = 20)
# create data frame for prediction
dat4pred <- data.frame(FGRAZE = "1", LOGAREA = LOGAREA.seq)
# predict for new data
dat4pred$predicted <- predict(birds.inter.1, newdata = dat4pred)
# add the predictions to the plot of the data
lines(predicted ~ LOGAREA, data = dat4pred, col = 1, lwd = 2)

# FGRAZE2
LOGAREA.seq <- seq(from = min(loyn$LOGAREA[loyn$FGRAZE == 2]),
                  to = max(loyn$LOGAREA[loyn$FGRAZE == 2]),
                  length = 20)
dat4pred <- data.frame(FGRAZE = "2", LOGAREA = LOGAREA.seq)
dat4pred$predicted <- predict(birds.inter.1, newdata = dat4pred)
lines(predicted ~ LOGAREA, data = dat4pred, col = 2, lwd = 2)

# FGRAZE3
LOGAREA.seq <- seq(from = min(loyn$LOGAREA[loyn$FGRAZE == 3]),
                  to = max(loyn$LOGAREA[loyn$FGRAZE == 3]),
                  length = 20)
dat4pred <- data.frame(FGRAZE = "3", LOGAREA = LOGAREA.seq)
dat4pred$predicted <- predict(birds.inter.1, newdata = dat4pred)
lines(predicted ~ LOGAREA, data = dat4pred, col = 3, lwd = 2)

# FGRAZE4
LOGAREA.seq <- seq(from = min(loyn$LOGAREA[loyn$FGRAZE == 4]),
                  to = max(loyn$LOGAREA[loyn$FGRAZE == 4]),
                  length = 20)
dat4pred <- data.frame(FGRAZE = "4", LOGAREA = LOGAREA.seq)
dat4pred$predicted <- predict(birds.inter.1, newdata = dat4pred)
lines(predicted ~ LOGAREA, data = dat4pred, col = 4, lwd = 2)

# FGRAZE5
LOGAREA.seq <- seq(from = min(loyn$LOGAREA[loyn$FGRAZE == 5]),
                  to = max(loyn$LOGAREA[loyn$FGRAZE == 5]),
                  length = 20)
dat4pred <- data.frame(FGRAZE = "5", LOGAREA = LOGAREA.seq)
dat4pred$predicted <- predict(birds.inter.1, newdata = dat4pred)
lines(predicted ~ LOGAREA, data = dat4pred, col = 5, lwd = 2)

legend("topleft",

```

```

legend = paste("Graze = ", 5:1),
col = c(5:1), bty = "n",
lty = c(1, 1, 1),
lwd = c(1, 1, 1))

```



(Optional, for the geeks) Alternative method, using a loop. Just keep this code in case you ever want to do something like this in the future.

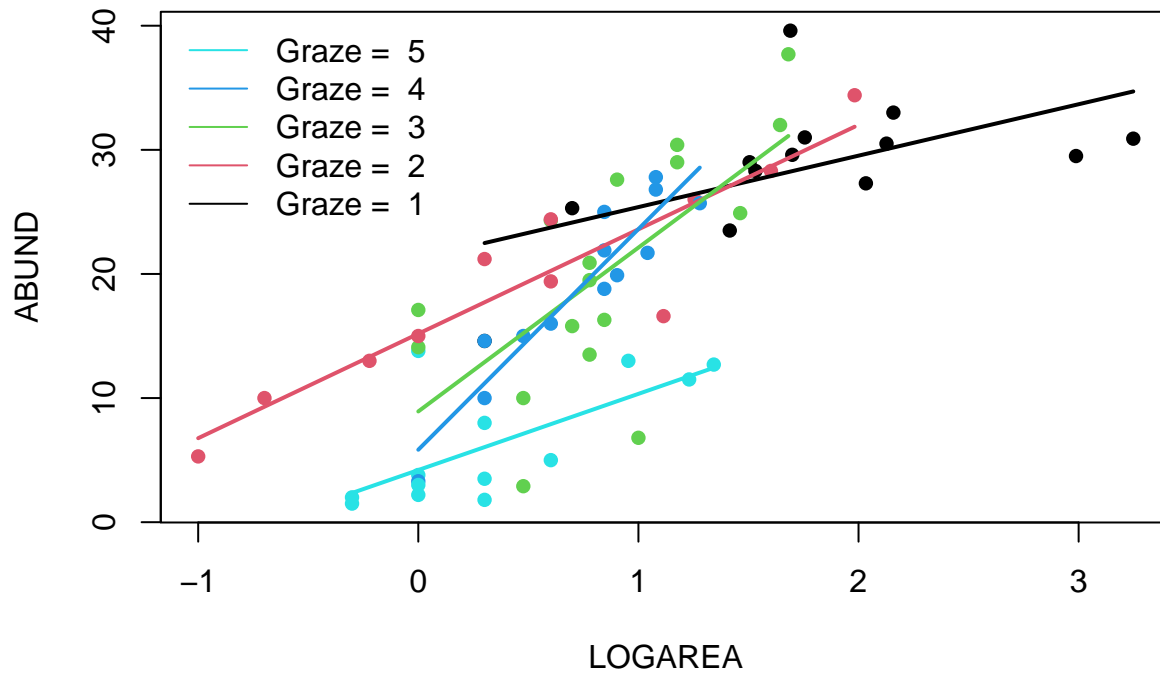
```

# Okay, that was a long-winded way of doing this.
# If, like me, you prefer more compact code and less risks of errors,
# you can use a loop, to save repeating the sequence 5 times:
par(mfrow = c(1, 1))
plot(ABUND ~ LOGAREA, data = loyn, col = GRAZE, pch = 16)

for(g in levels(loyn$FGRAZE)){ # g will take the values "1", "2", ..., "5" in turn
  LOGAREA.seq <- seq(from = min(loyn$LOGAREA[loyn$FGRAZE == g]),
                    to = max(loyn$LOGAREA[loyn$FGRAZE == g]),
                    length = 20)

  dat4pred <- data.frame(FGRAZE = g, LOGAREA = LOGAREA.seq)
  dat4pred$predicted <- predict(birds.inter.1, newdata = dat4pred)
  lines(predicted ~ LOGAREA, data = dat4pred, col = as.numeric(g), lwd = 2)
}
legend("topleft",
  legend = paste("Graze = ", 5:1),
  col = c(5:1), bty = "n",
  lty = c(1, 1, 1),
  lwd = c(1, 1, 1))

```



(Optional, for the lazy!) And, if you want an even easier way, then we can use the `ggplot2` package.

```
library(ggplot2)

ggplot(loyn, aes(x = LOGAREA, y = ABUND, color = FGRAZE)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)
```



End of the Linear model with interactive continuous and categorical predictors exercise