

# Tutorial 07

ENVX2001 – Applied Statistical Methods

Semester 1

## Bird abundance

This is the *same* dataset used in the lecture.

Fragmentation of forest habitat has an impact of wildlife abundance. This study looked at the relationship between bird abundance (bird ha<sup>-1</sup>) and the characteristics of forest patches at 56 locations in SE Victoria.

The predictor variables are:

- ALT Altitude (m)
- YR.ISOL Year when the patch was isolated (years)
- GRAZE Grazing (coded 1-5 which is light to heavy)
- AREA Patch area (ha)
- DIST Distance to nearest patch (km)
- LDIST Distance to largest patch (km)

Import the data from the “Loyn” tab in the MS Excel file.

```
CODE
library(readxl)
loyn ← read_xlsx("data/mlr.xlsx", "Loyn")
```

Often, the first step in model development is to examine the data. This is a good way to get a feel for the data and to identify any issues that may need to be addressed. In this case, we will examine the data using histograms and a correlation matrix.

## Histograms

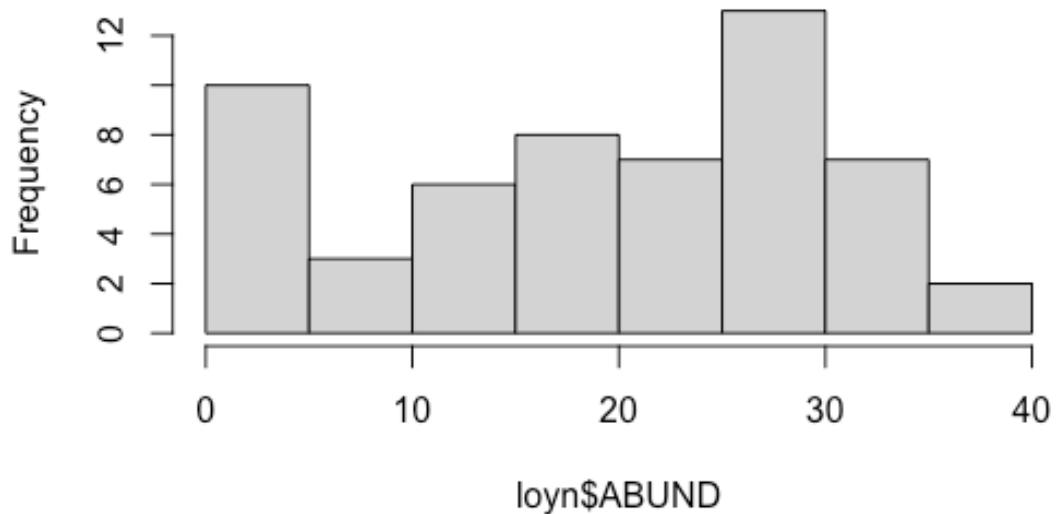
There are a breadth of ways to create histograms in R. In each tab below you will find some different ways to create the same plot outputs.

## hist()

This is a straightforward way to create multiple histograms with `hist()`. The `par()` function is used to arrange the plots on the page. The `mfrow` argument specifies the number of rows and columns of plots.

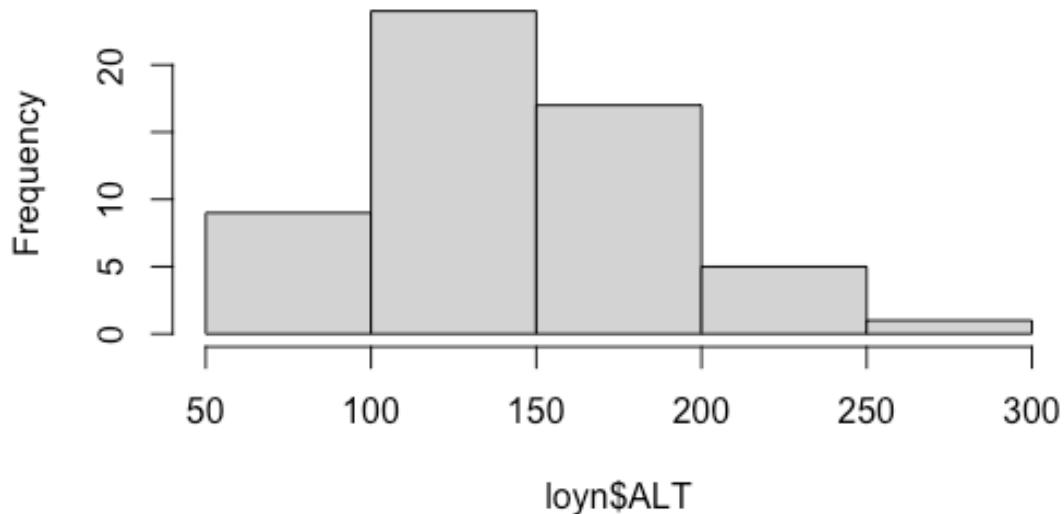
```
CODE  
# par(mfrow=c(3,3))  
hist(loyn$ABUND)
```

**Histogram of loyn\$ABUND**



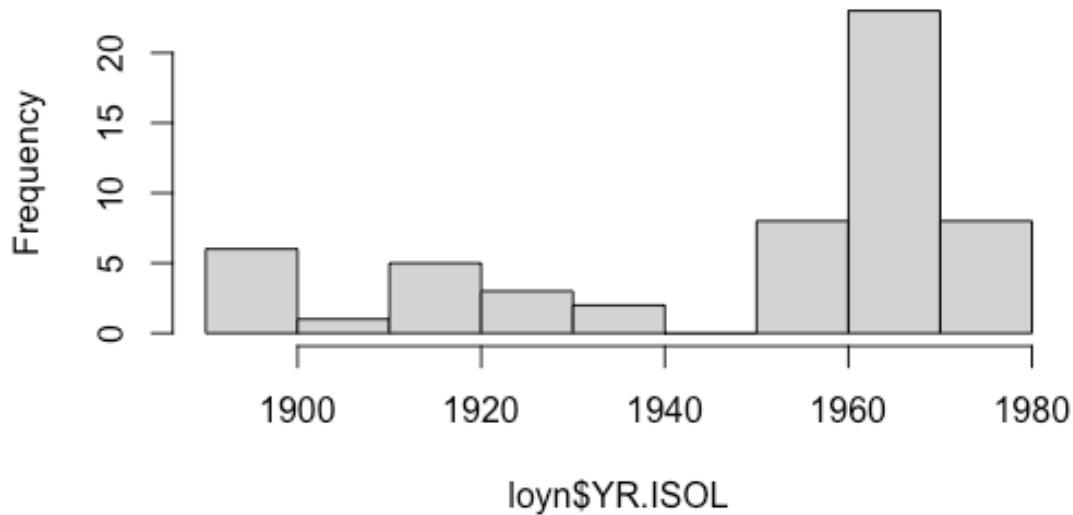
```
CODE  
hist(loyn$ALT)
```

### Histogram of loyn\$ALT



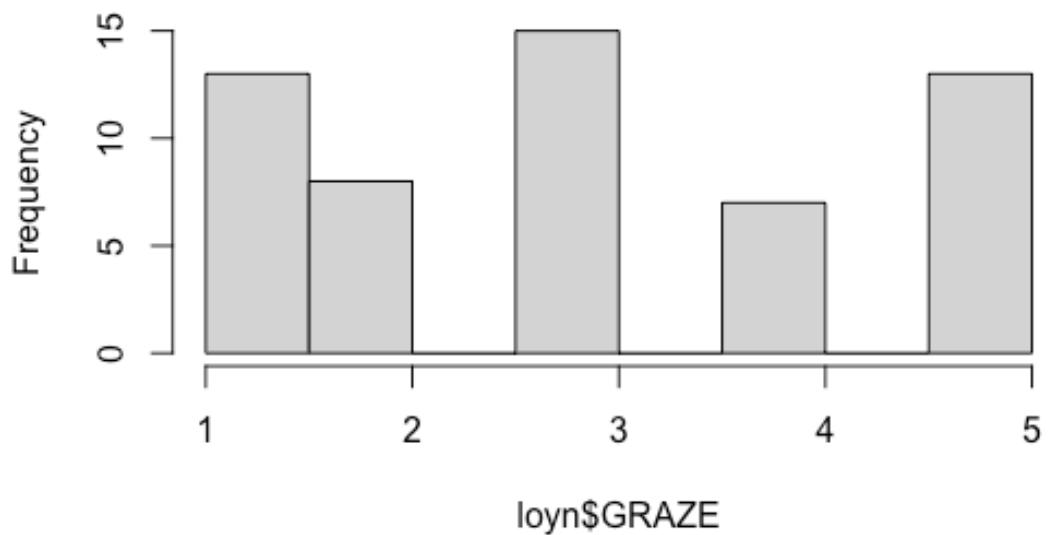
```
CODE  
hist(loyn$YR.ISOL)
```

### Histogram of loyn\$YR.ISOL



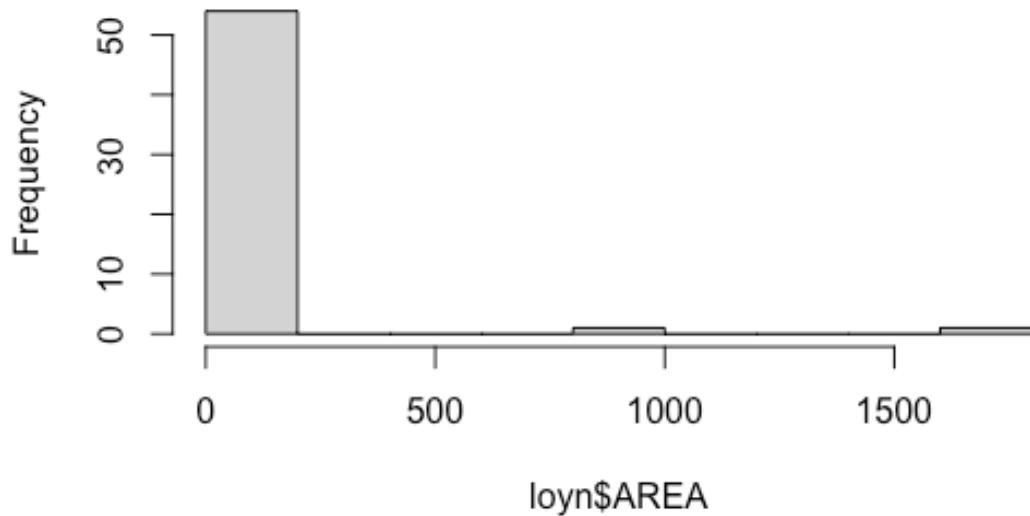
```
CODE  
hist(loyn$GRAZE)
```

**Histogram of loyn\$GRAZE**



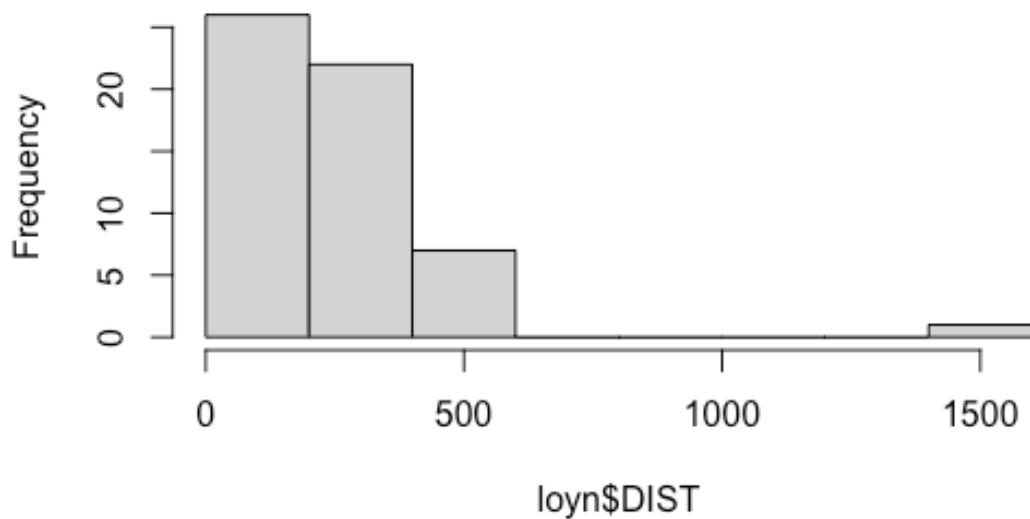
```
CODE  
hist(loyn$AREA)
```

### Histogram of loyn\$AREA



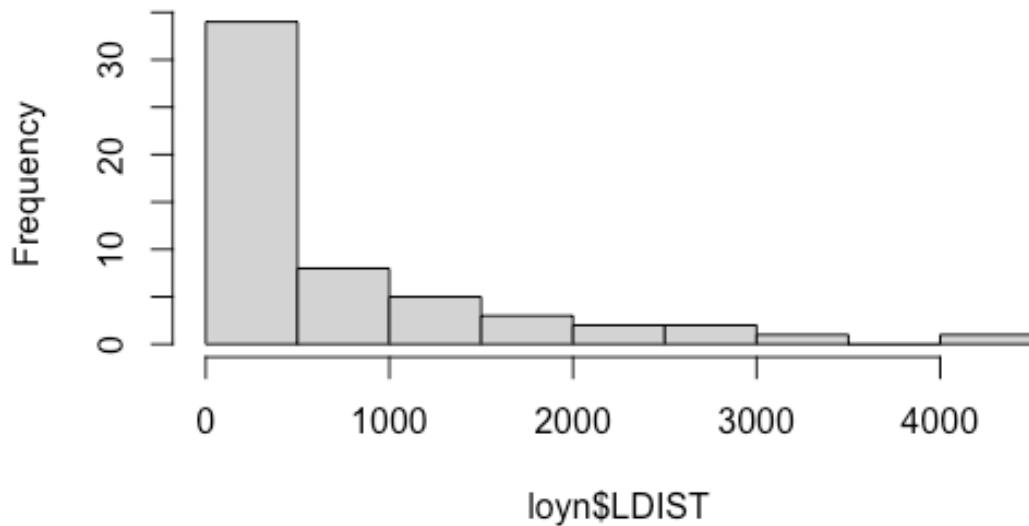
```
CODE  
hist(loyn$DIST)
```

### Histogram of loyn\$DIST



```
CODE  
hist(loyn$LDIST)
```

## Histogram of loyn\$LDIST



```
CODE  
# par(mfrow=c(1,1))
```

## hist.data.frame() from Hmisc

The `Hmisc` package provides a function `hist.data.frame()` that can be used to create multiple histograms, which can be called by simply using `hist()`. You may need to tweak the `nclass` argument to get the desired number of bins, as the default may not look appropriate.

```
CODE  
# install.packages("Hmisc")  
library(Hmisc)  
hist(loyn, nclass = 50)
```

## ggplot()

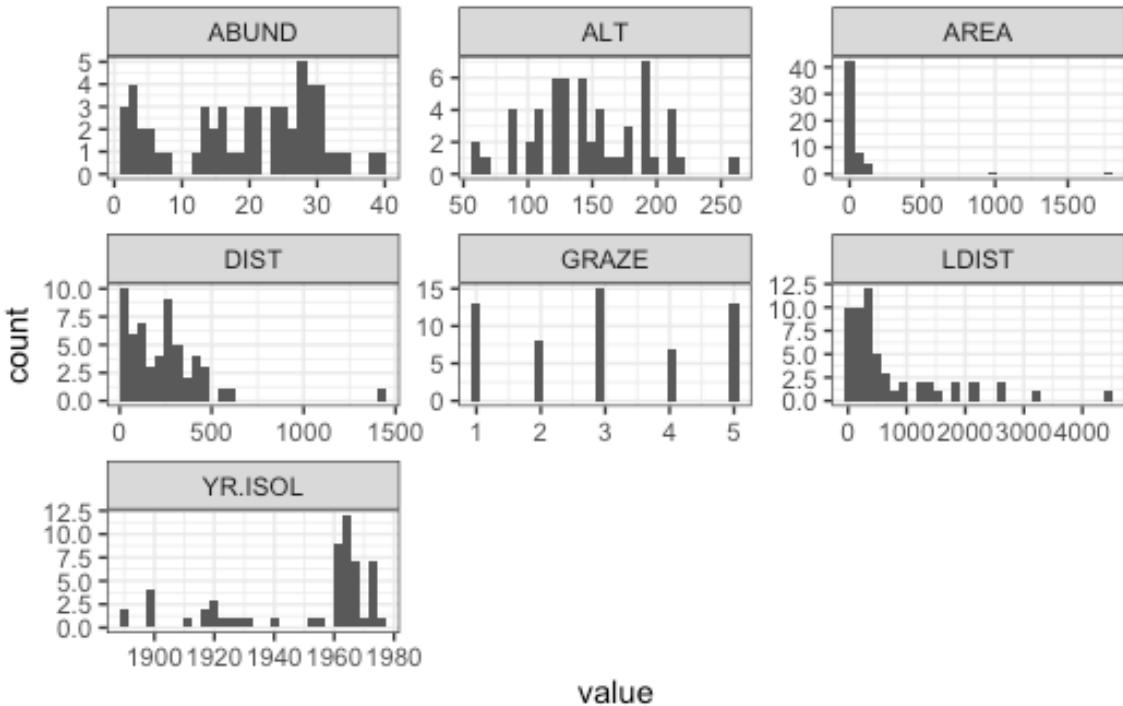
A more modern approach is to use `ggplot()` with `facet_wrap()` to arrange multiple plots on a single page. To do this, the `pivot_longer()` function from the `tidyverse` package is used to reshape the data into a tidy format.

```

CODE
# tidy the data
loyn_tidy ← pivot_longer(loyn, cols = everything())

# plot
ggplot(loyn_tidy, aes(x = value)) +
  geom_histogram() +
  facet_wrap(~name, scales = "free") +
  theme_bw()

```



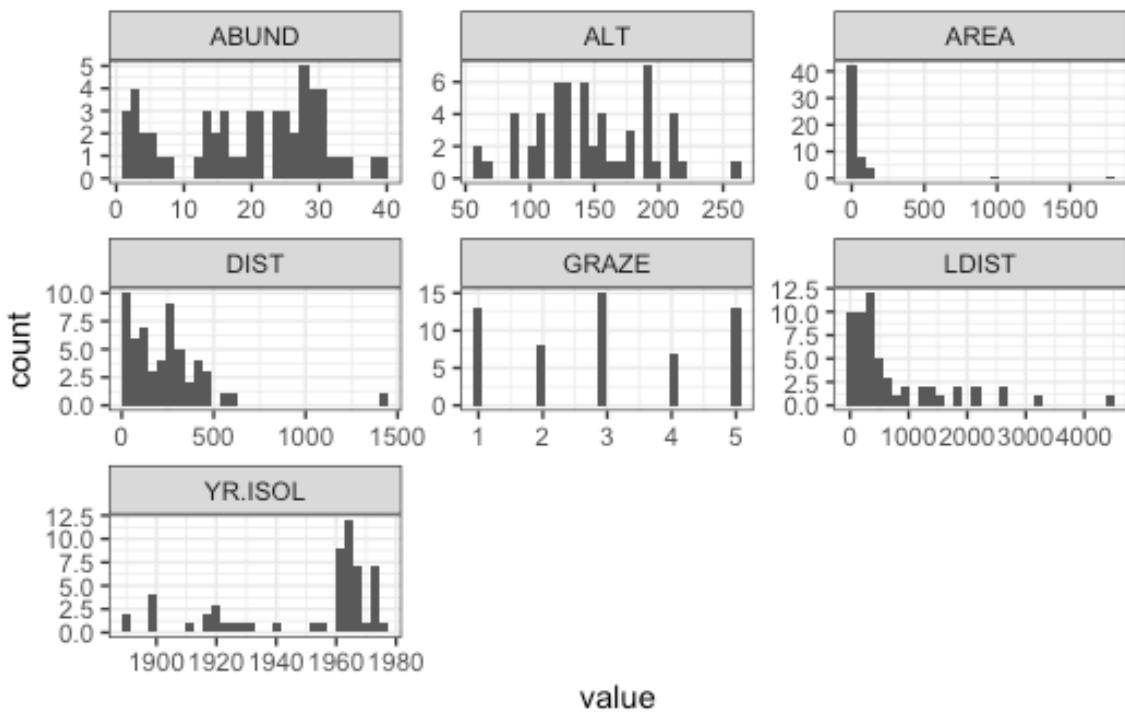
## ggplot() with dplyr

Here we use the pipe operator `%>%` from `dplyr` to chain together a series of commands. The pipe operator takes the output of the command on the left and passes it to the command on the right (or below) the pipe. This means that we can create a series of commands that are executed in order.

```

CODE
loyn %>%
  pivot_longer(cols = everything()) %>%
  ggplot(aes(x = value)) +
  geom_histogram() +
  facet_wrap(~name, scales = "free") +
  theme_bw()

```



## Question 1

Comment on the histograms in terms of leverage. Hint: what is the relationship between leverage and skewness?

## Correlation matrix

Calculate the correlation matrix using `cor(Loyn)`.

```
CODE
cor(Loyn)
```

OUTPUT

	ABUND	AREA	YR.ISOL	DIST	LDIST
ABUND	1.0000000	0.255970206	0.503357741	0.2361125	0.08715258
AREA	0.25597021	1.000000000	-0.001494192	0.1083429	0.03458035
YR.ISOL	0.50335774	-0.001494192	1.000000000	0.1132175	-0.08331686
DIST	0.23611248	0.108342870	0.113217524	1.0000000	0.31717234
LDIST	0.08715258	0.034580346	-0.083316857	0.3171723	1.00000000
GRAZE	-0.68251138	-0.310402417	-0.635567104	-0.2558418	-0.02800944
ALT	0.38583617	0.387753885	0.232715406	-0.1101125	-0.30602220
	GRAZE	ALT			
ABUND	-0.68251138	0.3858362			
AREA	-0.31040242	0.3877539			
YR.ISOL	-0.63556710	0.2327154			
DIST	-0.25584182	-0.1101125			
LDIST	-0.02800944	-0.3060222			

```
GRAZE    1.00000000 -0.4071671
ALT      -0.40716705 1.0000000
```

## Question 2

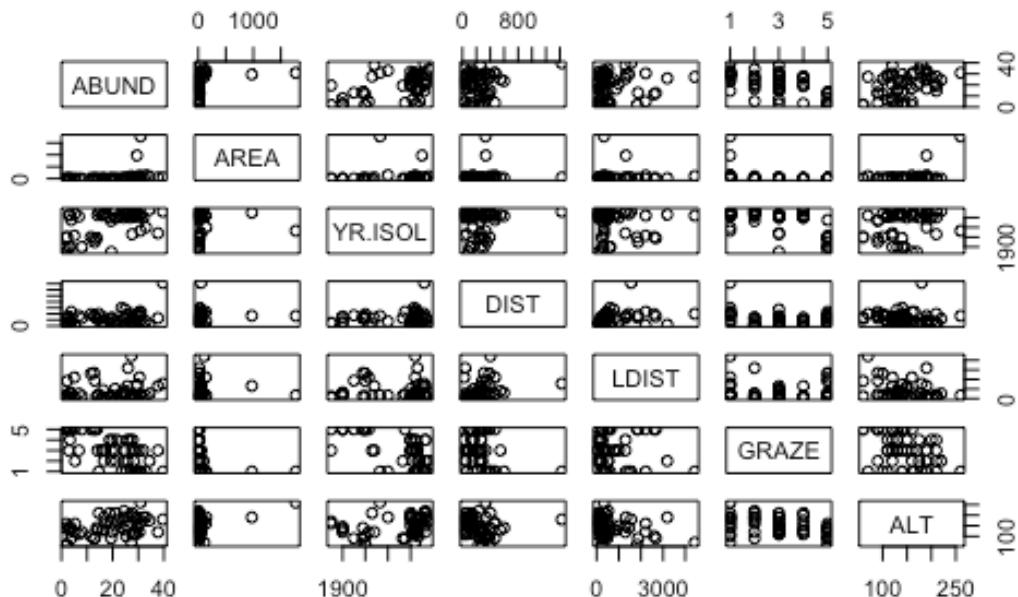
Which independent variables are useful for predicting the dependent variable abundance? Is there evidence for multi-collinearity?

## Plotting correlation

Examine correlations visually using `pairs()` or `corrplot()` from the `corrplot` package.

## Scatterplot matrix

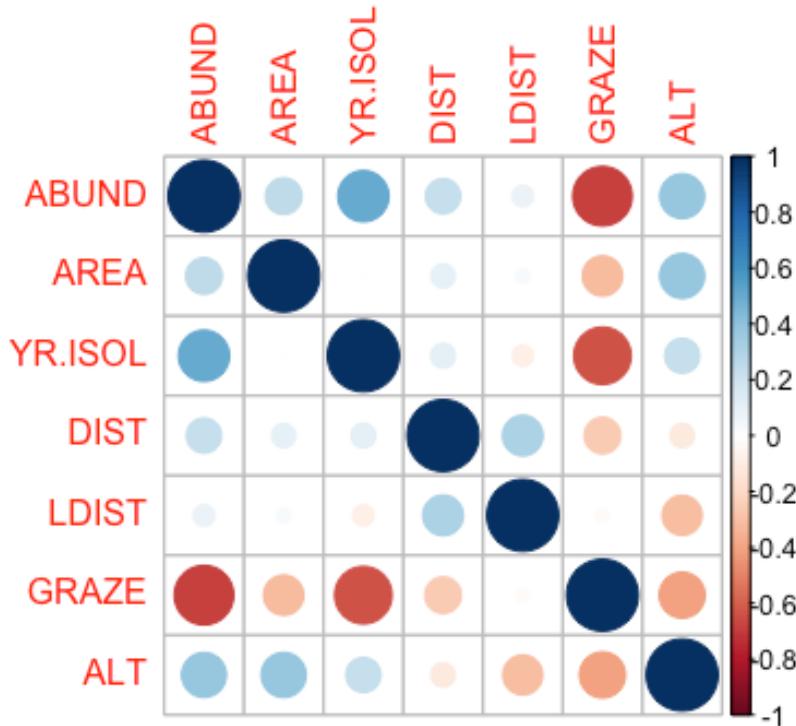
```
CODE
pairs(lyn)
```



## Correlation matrix

```
CODE
```

```
library(corrplot)
corrplot(cor(lyn))
```



### Question 3

Are there any trends visible from the plots?



Tip

We can also bring in variance inflation factors (VIF) to help us identify multi-collinearity, but that is done only after we have selected a model.

## Transformations

The AREA predictor has a small number of observations with very large values. Apply a  $\log_{10}$  transformation and label the new variable `Loyn$L10AREA`.

```
CODE
Loyn$L10AREA ← log10(Loyn$AREA)
```

### Question 4

Why are we transforming AREA?

## Question 5

Re-run `pairs(Loyn)` and create a histogram using the transformed value of AREA, how do the plots look?

```
CODE  
hist(Loyn$L10AREA)  
pairs(Loyn)
```

## Question 6

In preparation for modelling, transform the remaining skewed variables, DIST and LDIST the same way you did for AREA and examine the histogram and pairs plots using these new variables.

Make sure you end up with two new variables labelled `Loyn$L10DIST` and `Loyn$L10LDIST`.