

# Hoops Longwing Sample Data Visualization

*Zane Billings*

*15 November 2019*

In order to start analyzing the Hoops' Longwing sample data, we will first load the **tidyverse** package suite. After loading the packages we need, we can use `readr::read_csv()` to load in the data. But, notice the imported data frame has a useless column at the beginning, which we can easily remove manually.

```
library(tidyverse)

butterfly <- read_csv("hoops_longwing_study.csv")
butterfly <- butterfly[, -1]
```

Now that we have the data imported, we can go ahead and take a quick look at the summary and structure.

```
summary(butterfly)
```

##	wing_length	wing_width	age	num_offspring
##	Min. : 7.46	Min. : 2.730	Min. : 2.00	Min. : 8.00
##	1st Qu.:14.19	1st Qu.: 6.670	1st Qu.:12.00	1st Qu.:24.00
##	Median :16.78	Median : 8.135	Median :19.00	Median :28.00
##	Mean :20.24	Mean : 8.748	Mean :22.68	Mean :27.84
##	3rd Qu.:26.74	3rd Qu.:10.910	3rd Qu.:31.00	3rd Qu.:32.00
##	Max. :42.18	Max. :17.390	Max. :61.00	Max. :39.00
##	feeding_range	color_peak	num_mates	avg_scale_size
##	Min. : -0.250	Min. :357.9	Min. : -2.000	Min. :18.27
##	1st Qu.: 2.640	1st Qu.:385.9	1st Qu.: 3.000	1st Qu.:28.02
##	Median : 3.510	Median :392.0	Median : 5.000	Median :32.39
##	Mean : 5.997	Mean :392.0	Mean : 6.212	Mean :38.43
##	3rd Qu.: 5.990	3rd Qu.:398.1	3rd Qu.: 9.000	3rd Qu.:48.60
##	Max. :69.880	Max. :428.3	Max. :21.000	Max. :89.43
##	antenna_length	num_spots	population	dispersal_distance
##	Min. :0.350	Min. : 2.000	Length:10000	Min. :21.84
##	1st Qu.:3.140	1st Qu.: 4.000	Class :character	1st Qu.:24.15
##	Median :3.850	Median : 6.000	Mode :character	Median :24.67
##	Mean :4.375	Mean : 5.755		Mean :24.67
##	3rd Qu.:5.800	3rd Qu.: 7.000		3rd Qu.:25.19
##	Max. :7.670	Max. :18.000		Max. :27.79
##	body_length	sample_id		
##	Min. : 1.000	Length:10000		
##	1st Qu.: 5.100	Class :character		
##	Median : 6.450	Mode :character		
##	Mean : 6.773			
##	3rd Qu.: 8.480			
##	Max. :14.590			

```
str(butterfly)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    10000 obs. of  14 variables:
## $ wing_length      : num  14.1 24.5 21.3 16.2 15.5 ...
## $ wing_width       : num   6.56 11 8.15 5.84 6.72 ...
## $ age              : num   40 38 25 13 43 9 36 23 37 26 ...
## $ num_offspring    : num   33 33 29 23 35 20 35 29 33 30 ...
## $ feeding_range    : num  10.78 8.58 3.86 3.14 13.07 ...
## $ color_peak       : num  402 387 373 407 399 ...
## $ num_mates        : num    4 8 8 4 3 8 11 3 0 7 ...
## $ avg_scale_size   : num  27.7 41.6 36.2 34.1 29.8 ...
## $ antenna_length   : num   3.05 5.48 4.85 3.68 3.57 5.76 6.29 2.05 2.49 5.54 ...
## $ num_spots        : num    7 4 6 8 7 4 4 9 10 4 ...
## $ population       : chr   "Ternate" "Tidore" "Kayoa" "Ternate" ...
## $ dispersal_distance: num  25.7 24.3 23.1 25.9 25.2 ...
## $ body_length      : num   6.91 8.16 7.03 3.56 7.12 8.42 8.19 5.02 4.36 9.86 ...
## $ sample_id        : chr   "Ter_00001_ZW" "Tid_00002_ZW" "Kay_00003_ZB" "Ter_00004_ZW" ...
```

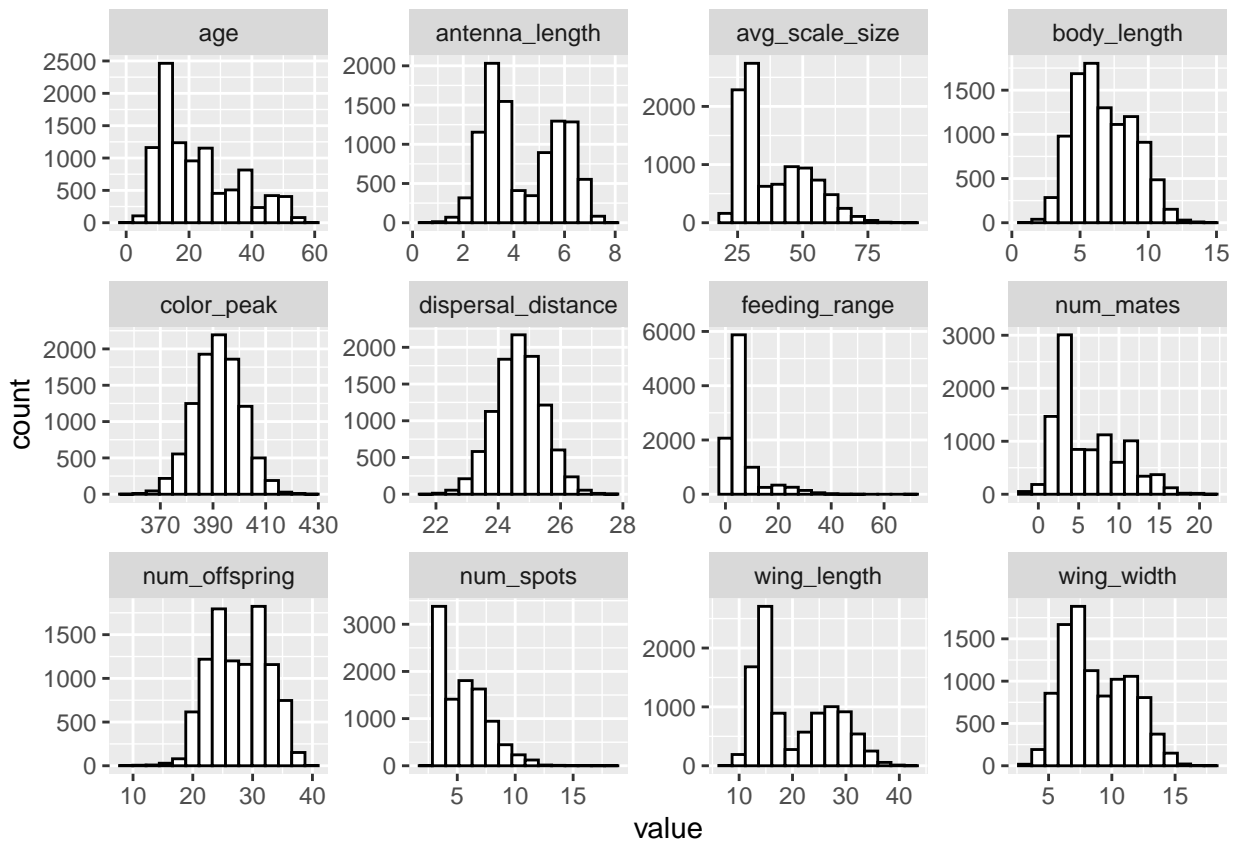
The only real change we need to make is to convert the `population` variable into a factor, since the functions provided in `readr` do not coerce strings to factors by default.

```
butterfly$population <- as.factor(butterfly$population)
summary(butterfly$population)
```

```
##   Kayoa Ternate  Tidore
##   1322   5486   3192
```

So, now we can start exploring our data. Let's start by making histograms of all the numeric data.

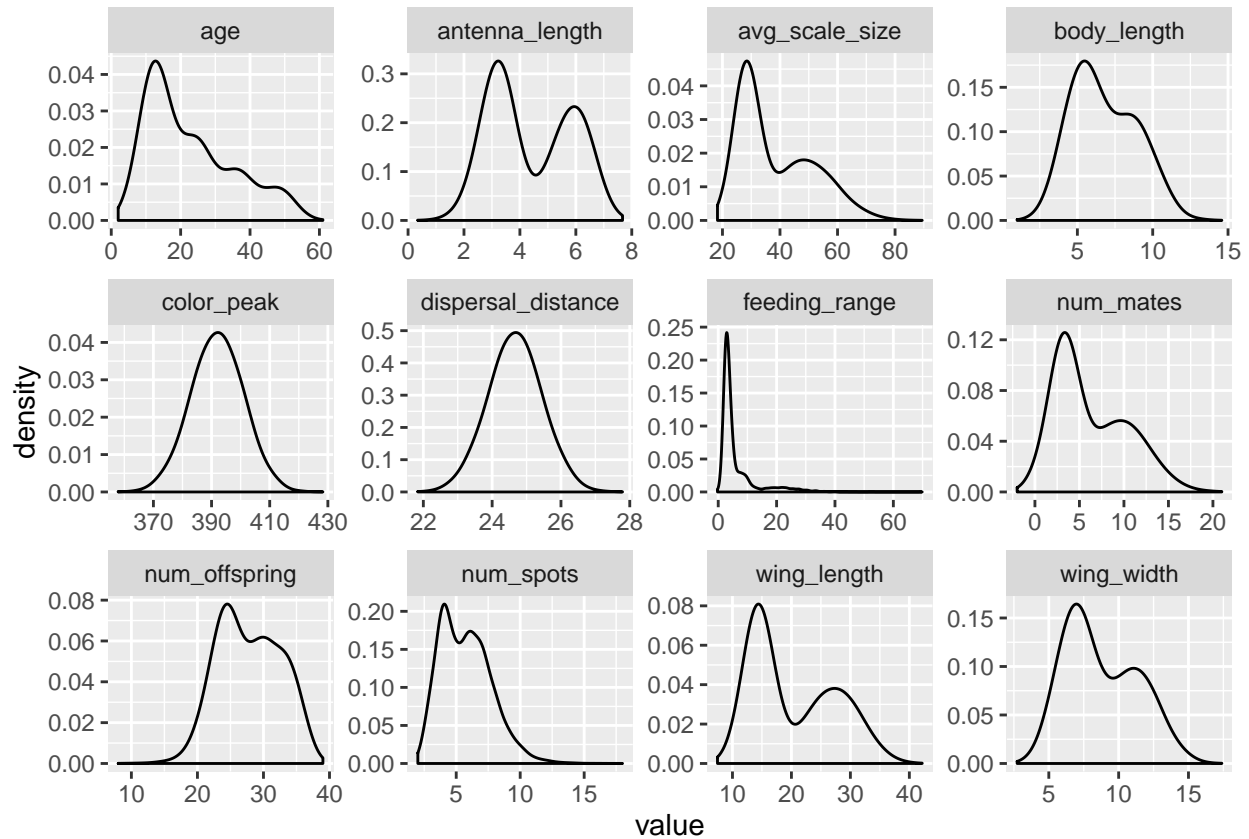
```
num_bins <- ceiling(log2(nrow(butterfly))) + 1
butterfly %>%
  select(-population) %>%
  gather(key = "field", value = "value", -"sample_id") %>%
  ggplot(aes(x = value)) +
  geom_histogram(col = "black",
                 fill = "white",
                 position = "identity",
                 bins = num_bins) +
  facet_wrap(~field, scales = "free")
```



We can also visualize the distributions of the data using density curves, although we have to adjust the interpolation settings because part of our data is integers.

```
# An alternative way to view the data
```

```
butterfly %>%
  select(-population) %>%
  gather(key = "field", value = "value", -"sample_id") %>%
  ggplot(aes(x = value)) +
  geom_density(adjust = 2) +
  facet_wrap(~field, scales = "free")
```

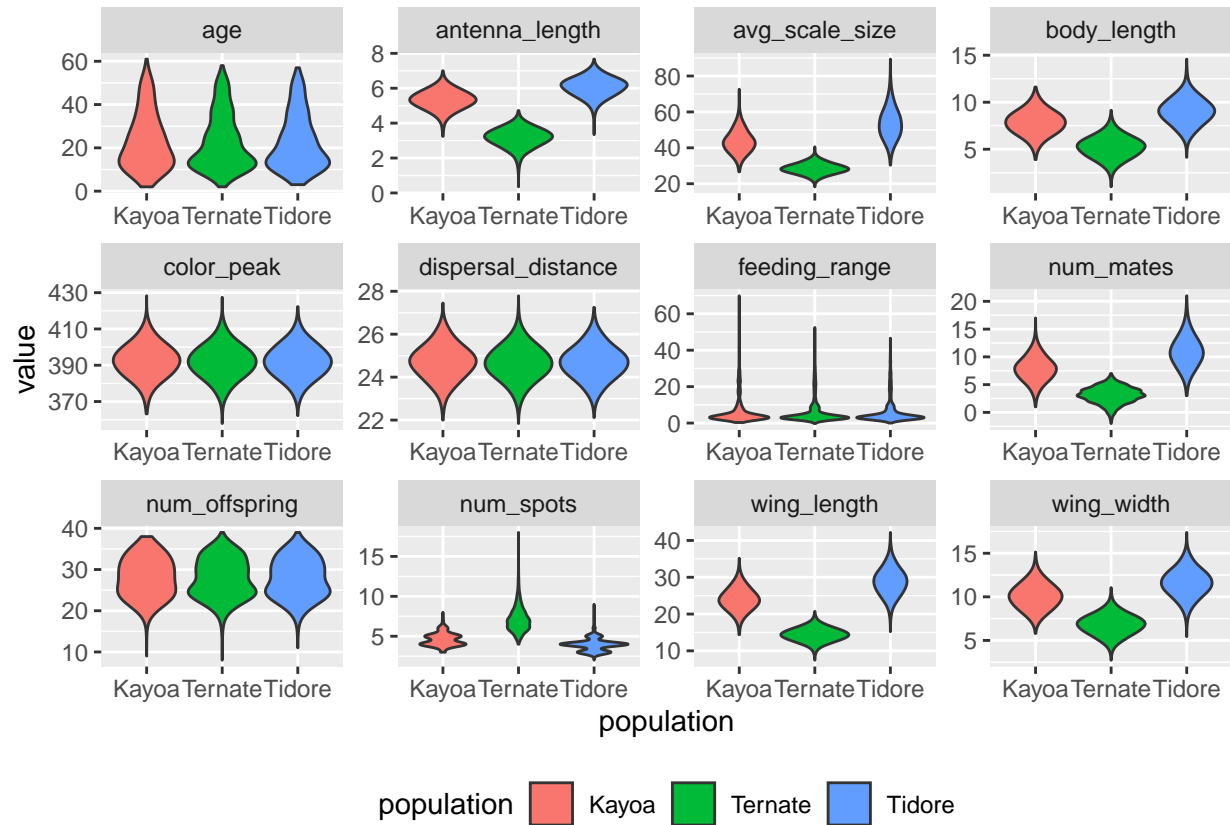


Now we have one categorical variable, so let's look at all of our data stratified by the `population` value.

```

butterfly %>%
  gather(key = "field", value = "value", -c(sample_id, population)) %>%
  ggplot(aes(x = population, y = value, fill = population)) +
  geom_violin(adjust = 2) +
  facet_wrap(~field, scales = "free") +
  theme(legend.position = "bottom")

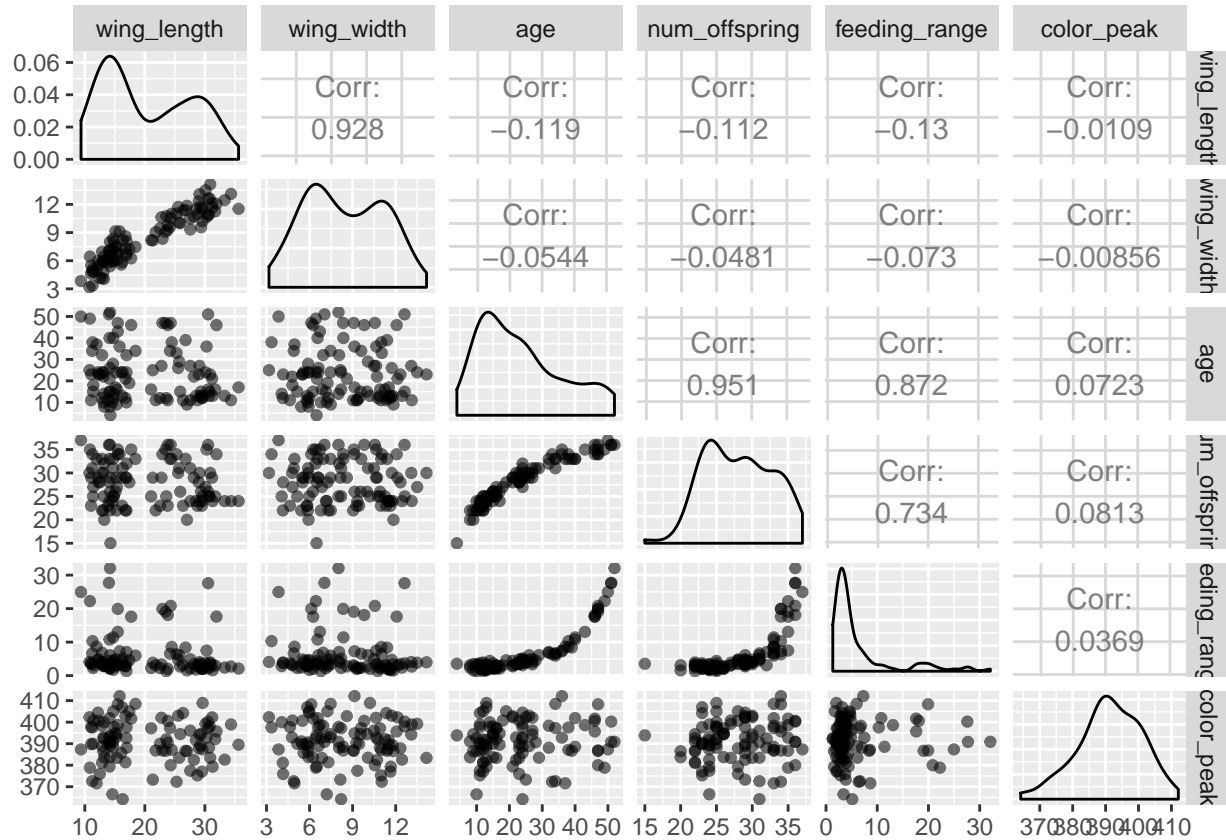
```



Now, using the `GGally` package, we can also make a scatterplot matrix like we did with `graphics::pairs()`. In order to get this to be visible, we'll need to split up the data.

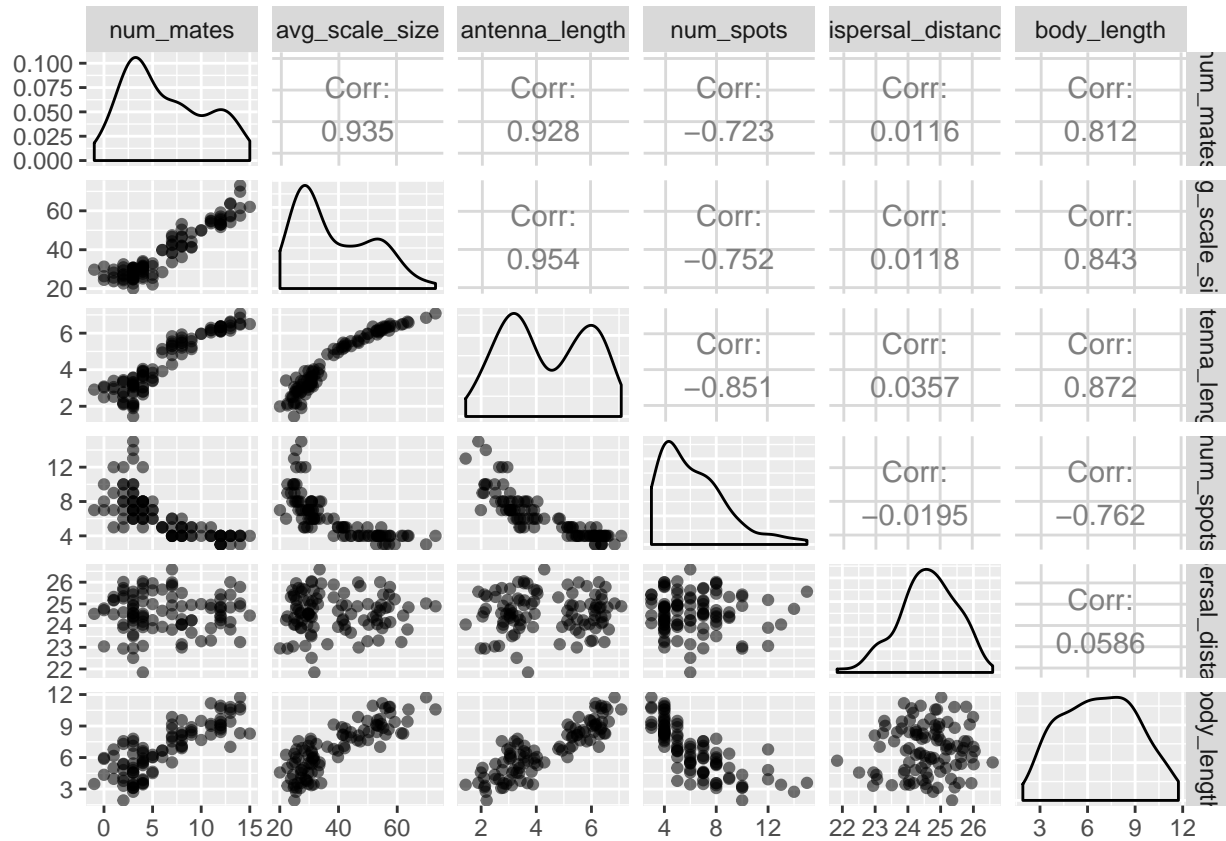
```
library(GGally)
```

```
butterfly[1:100, 1:6] %>%  
  ggpairs(aes(alpha = 0.2))
```



For the second half of the data, we also need to exclude our non-numeric variables.

```
butterfly[1:100, 7:14] %>%
  select(-c(sample_id, population)) %>%
  ggpairs(aes(alpha = 0.2))
```



As you can probably see, this visualization is not ideal when we have a lot of data.

Let's try a correlation table as well. However, note that while a correlation table can give us a good sense of linear relationships, we lose any information we had about nonlinear relationships, which we have to examine visually if we don't have a hypothesis about their existence.

```
library(pander)
butterfly %>%
  select(-c(sample_id, population)) %>%
  cor() %>%
  pander()
```

Table 1: Table continues below

	wing_length	wing_width	age	num_offspring
wing_length	1	0.9226	-0.001907	-0.002996
wing_width	0.9226	1	0.001328	-0.001489
age	-0.001907	0.001328	1	0.9413
num_offspring	-0.002996	-0.001489	0.9413	1
feeding_range	-0.004469	-0.00217	0.8559	0.7075
color_peak	0.01542	0.02052	0.00448	0.0009257
num_mates	0.9495	0.8747	-0.002376	-0.003543
avg_scale_size	0.9799	0.903	0.000683	-0.0002265
antenna_length	0.9906	0.9143	-0.002996	-0.00398
num_spots	-0.8294	-0.9372	0.00375	0.005168
dispersal_distance	0.01612	0.02096	0.0007418	-0.003065
body_length	0.8823	0.8511	-0.0002991	-0.002555

Table 2: Table continues below

	feeding_range	color_peak	num_mates
wing_length	-0.004469	0.01542	0.9495
wing_width	-0.00217	0.02052	0.8747
age	0.8559	0.00448	-0.002376
num_offspring	0.7075	0.0009257	-0.003543
feeding_range	1	0.01034	-0.004402
color_peak	0.01034	1	0.009925
num_mates	-0.004402	0.009925	1
avg_scale_size	-0.001537	0.01469	0.942
antenna_length	-0.005578	0.01548	0.9281
num_spots	0.005558	-0.01968	-0.769
dispersal_distance	0.006433	0.9468	0.01057
body_length	-0.0007702	0.01103	0.837

Table 3: Table continues below

	avg_scale_size	antenna_length	num_spots
wing_length	0.9799	0.9906	-0.8294
wing_width	0.903	0.9143	-0.9372
age	0.000683	-0.002996	0.00375
num_offspring	-0.0002265	-0.00398	0.005168
feeding_range	-0.001537	-0.005578	0.005558



	avg_scale_size	antenna_length	num_spots
color_peak	0.01469	0.01548	-0.01968
num_mates	0.942	0.9281	-0.769
avg_scale_size	1	0.9554	-0.7921
antenna_length	0.9554	1	-0.8447
num_spots	-0.7921	-0.8447	1
dispersal_distance	0.01492	0.01626	-0.02037
body_length	0.8639	0.875	-0.7775

	dispersal_distance	body_length
wing_length	0.01612	0.8823
wing_width	0.02096	0.8511
age	0.0007418	-0.0002991
num_offspring	-0.003065	-0.002555
feeding_range	0.006433	-0.0007702
color_peak	0.9468	0.01103
num_mates	0.01057	0.837
avg_scale_size	0.01492	0.8639
antenna_length	0.01626	0.875
num_spots	-0.02037	-0.7775
dispersal_distance	1	0.01044
body_length	0.01044	1

Or, we can use a function from the `ggcorrplot` library to make a visual representation of the same data.

```
library(ggcorrplot)
butterfly %>%
  select(-c(sample_id, population)) %>%
  cor() %>%
  ggcorrplot()
```

