R Vignettes

Scatterplots

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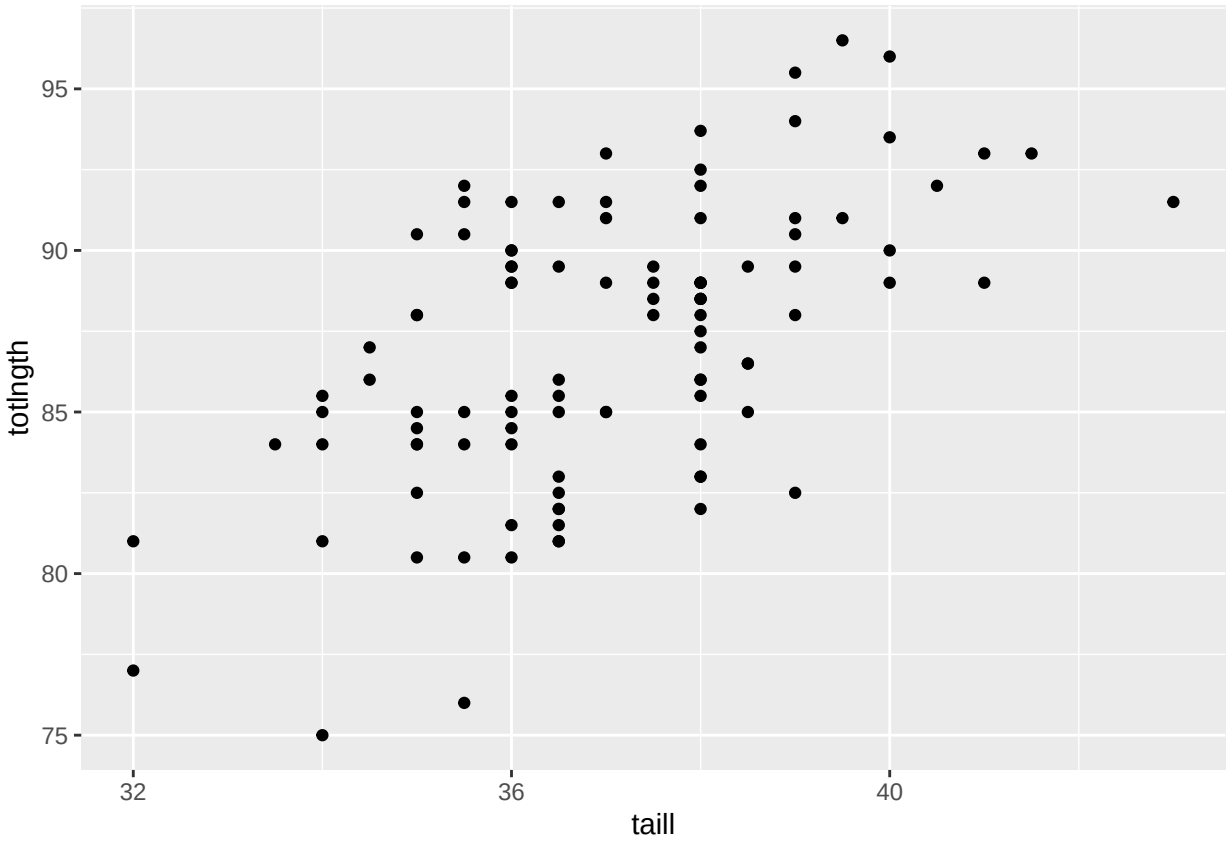
Scatter plot vignette

Reference Dr. Bharatendra https://www.youtube.com/watch?v=BPR_Dkll17Y&list=PL34t5iLfZddtUUABMikey6NtL05hP
index=8

Done here for learning purposes.

Basic

```
ggplot(possum, aes(x=taill, y=totlngth)) +
  geom_point()
```

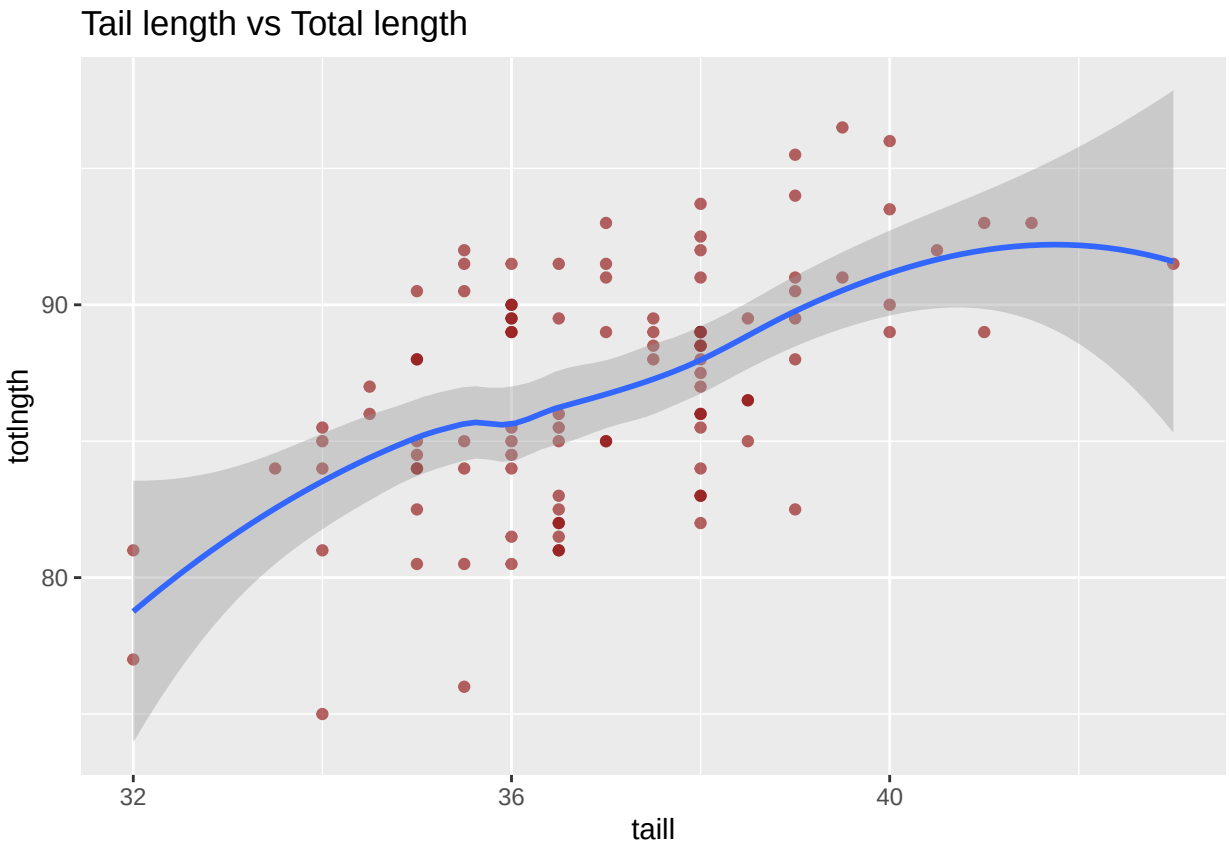


Trend line with default (LOESS and y ~ x)

- With geom_smooth() we get a trendline with confidence levels

```
ggplot(possum, aes(x=taill, y=totlngth)) +
  geom_point(color='darkred', alpha=0.6) +
  ggtitle('Tail length vs Total length') +
  geom_smooth()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

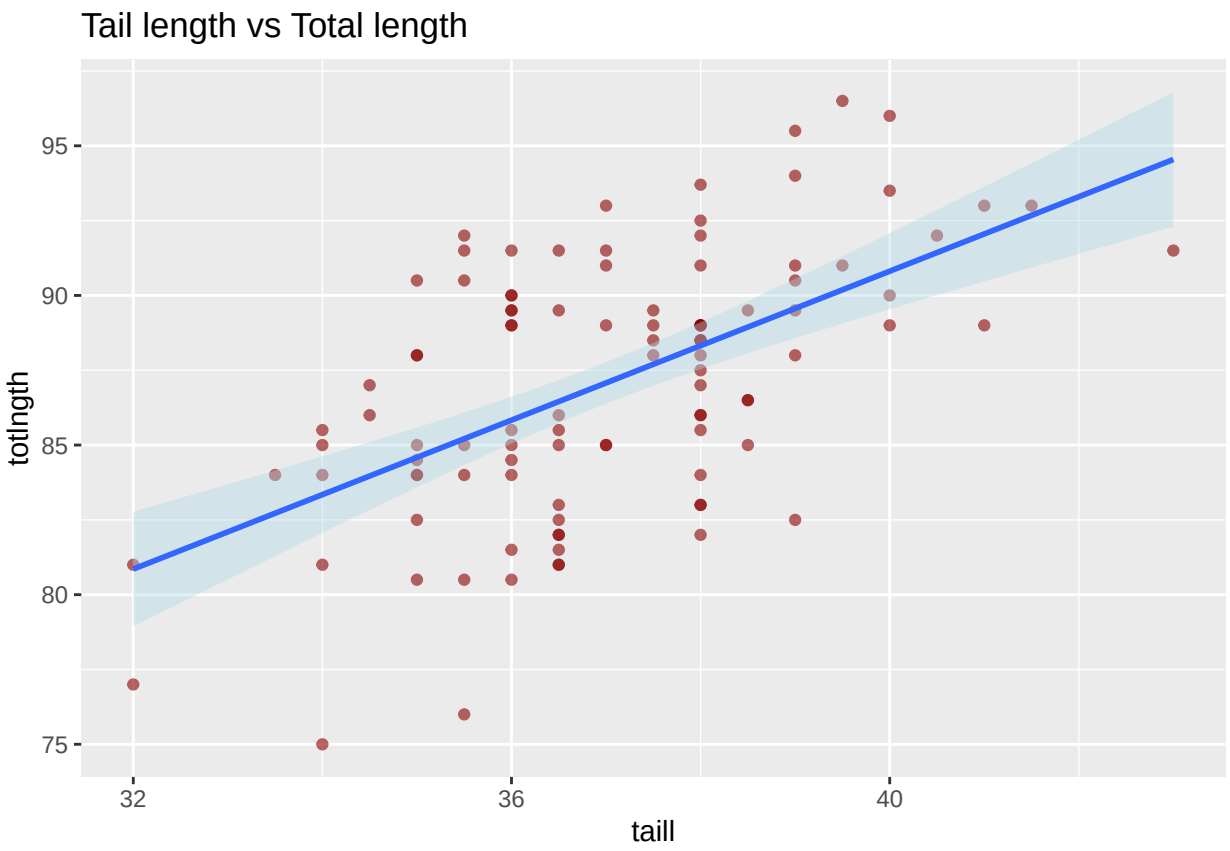


Trend line with 'lm' method

- Here the trendline uses linear regression.
- The command includes confidence levels
- The 'se' argument in geom_smooth() controls the trendline

```
ggplot(possum, aes(x=taill, y=totlngth)) +
  geom_point(color='darkred', alpha=0.6) +
  ggtitle('Tail length vs Total length') +
  geom_smooth(method='lm', fill="lightblue", se=TRUE)
```

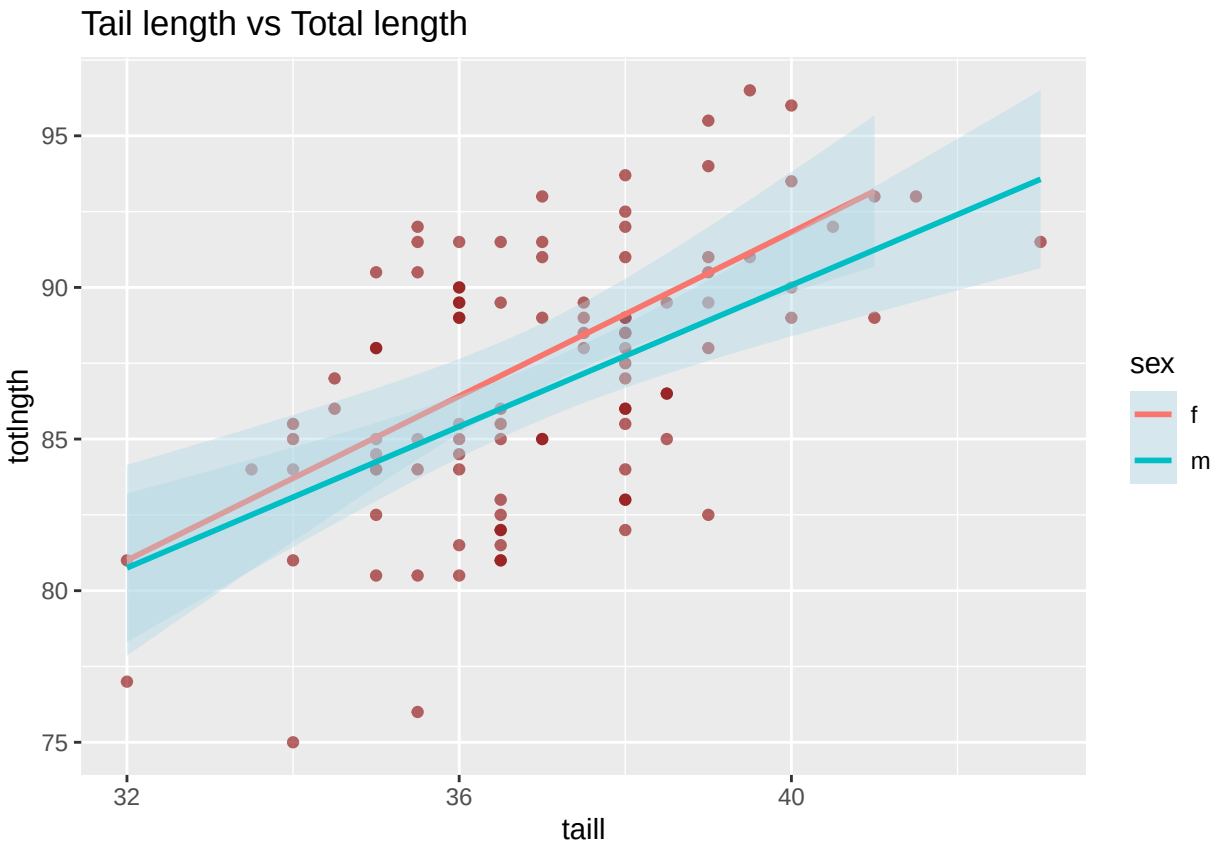
```
## `geom_smooth()` using formula 'y ~ x'
```



Two trend lines

```
ggplot(possum, aes(x=taill, y=totlngth, col=sex)) +
  geom_point(color='darkred', alpha=0.6) +
  ggtitle('Tail length vs Total length') +
  geom_smooth(method='lm', fill="lightblue", se=TRUE)
```

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

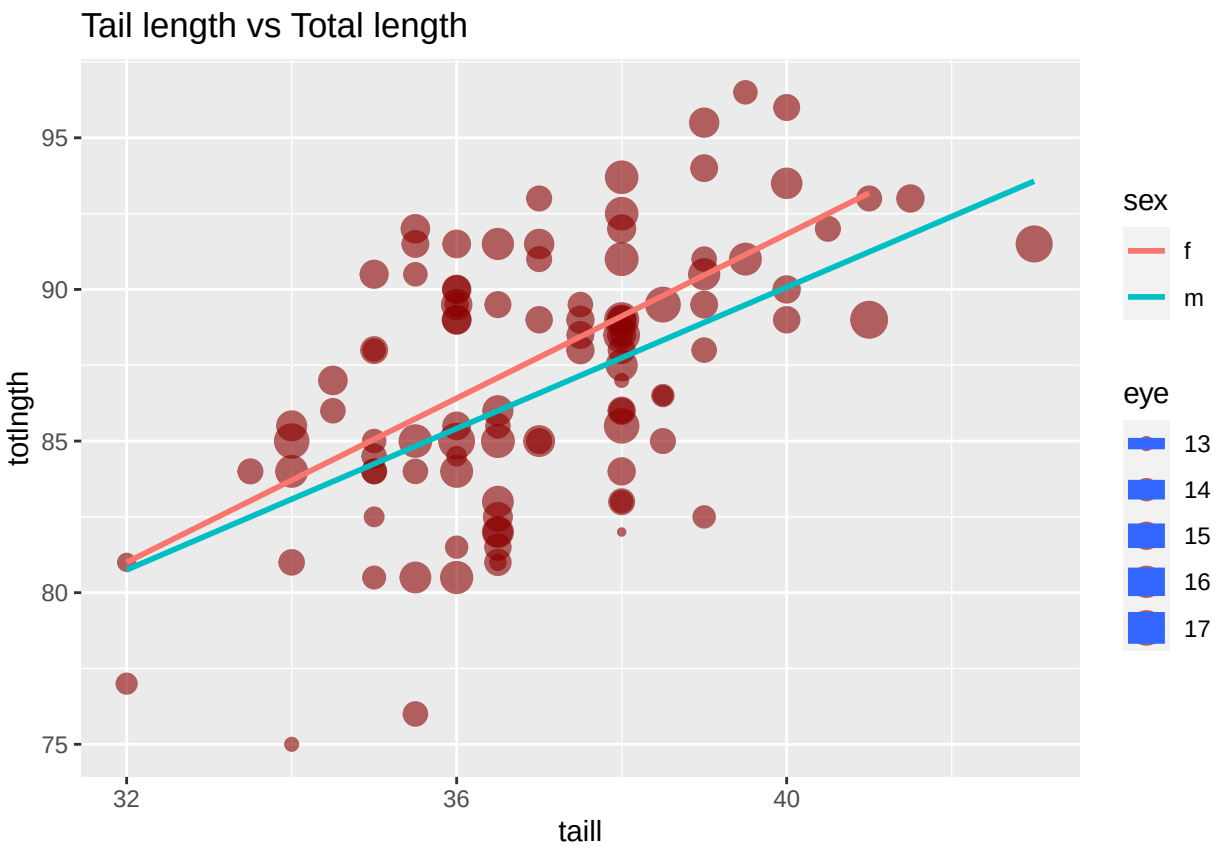


Two trend lines and bubble size

- Here I changed geom_smooth(... se=FALSE)

```
ggplot(possum, aes(x=taill, y=totlngth, col=sex, size=eye)) +
  geom_point(color='darkred', alpha=0.6) +
  ggtitle('Tail length vs Total length') +
  geom_smooth(method='lm', se=FALSE)
```

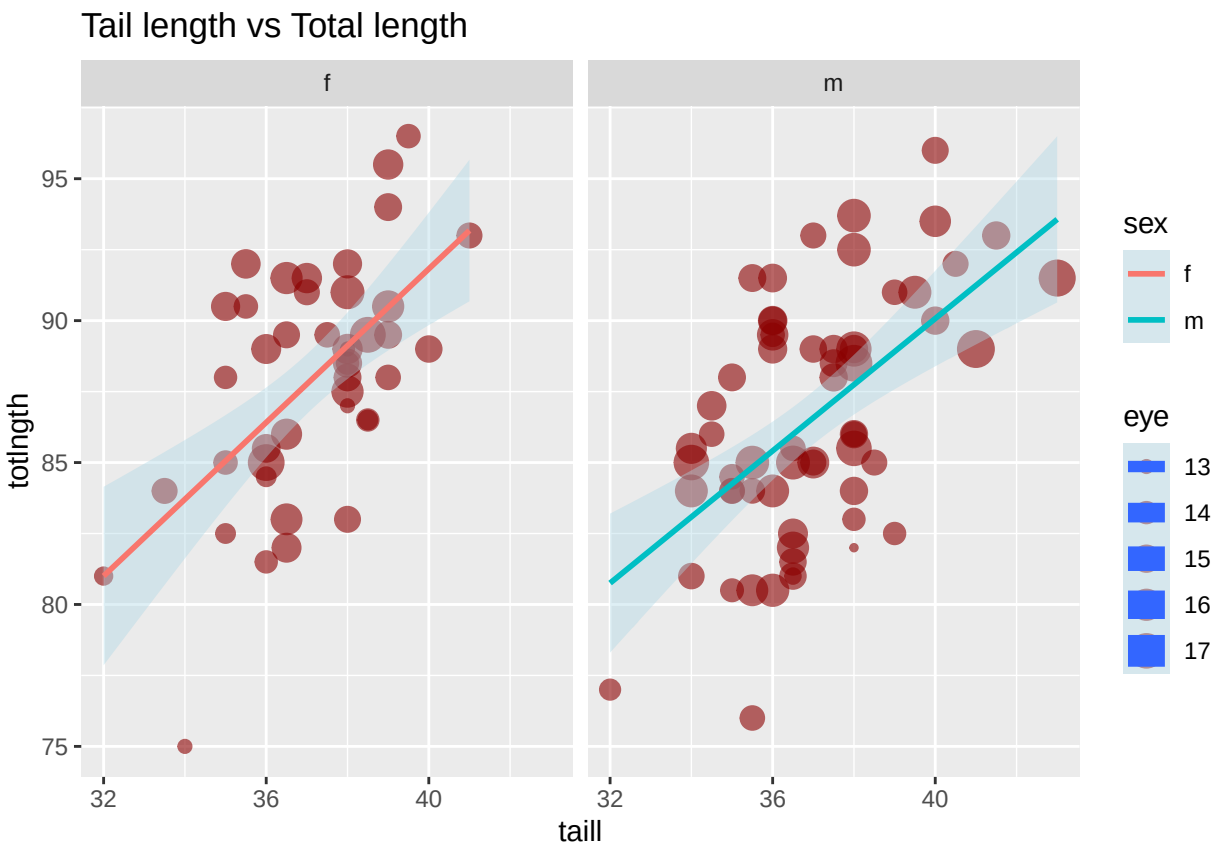
```
## `geom_smooth()` using formula 'y ~ x'
```



Add facet_wrap

```
ggplot(possum, aes(x=taill, y=totlngth, col=sex, size=eye)) +
  geom_point(color='darkred', alpha=0.6) +
  ggtitle('Tail length vs Total length') +
  geom_smooth(method='lm', fill="lightblue", se=TRUE) +
  facet_wrap(~sex)
```

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

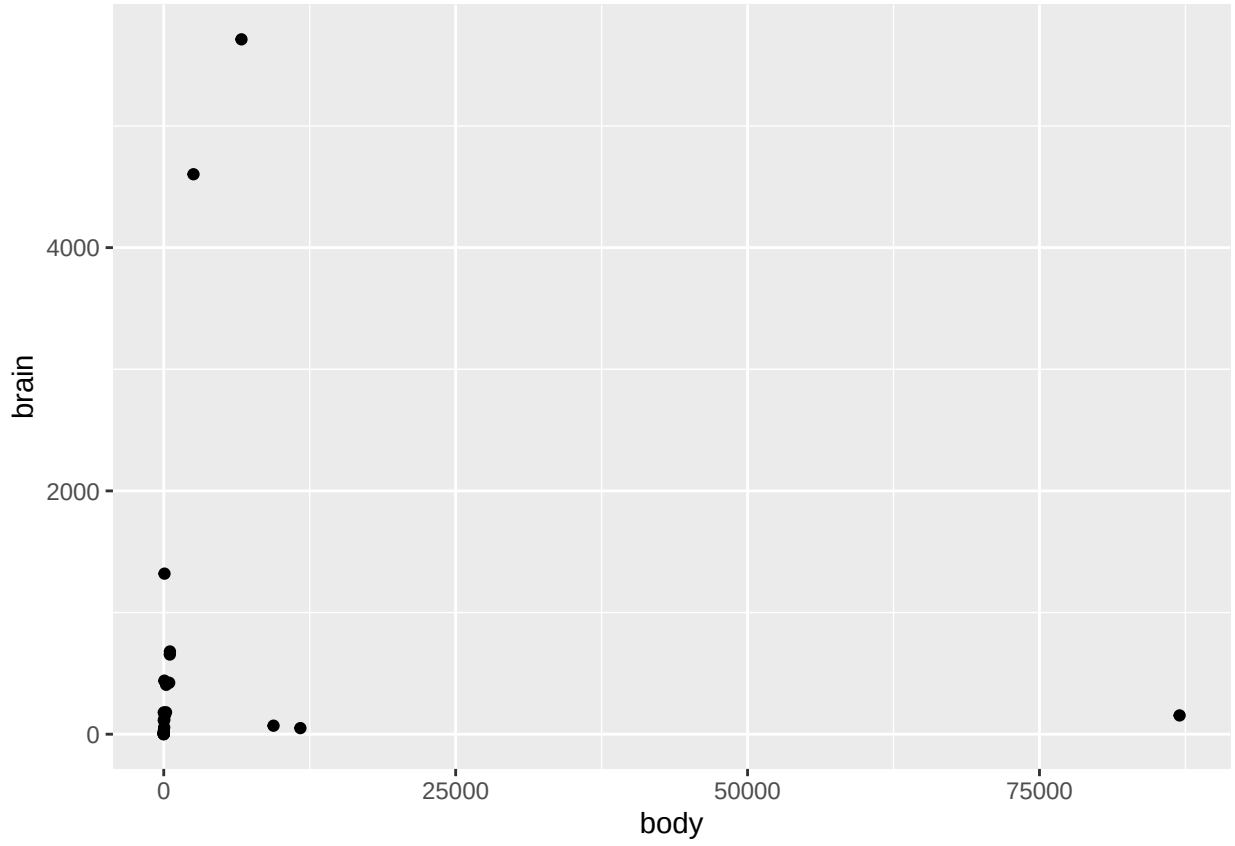


With log scale

Swtich to the Animals from the MASS dataset. It lends itself to demo the log feature.

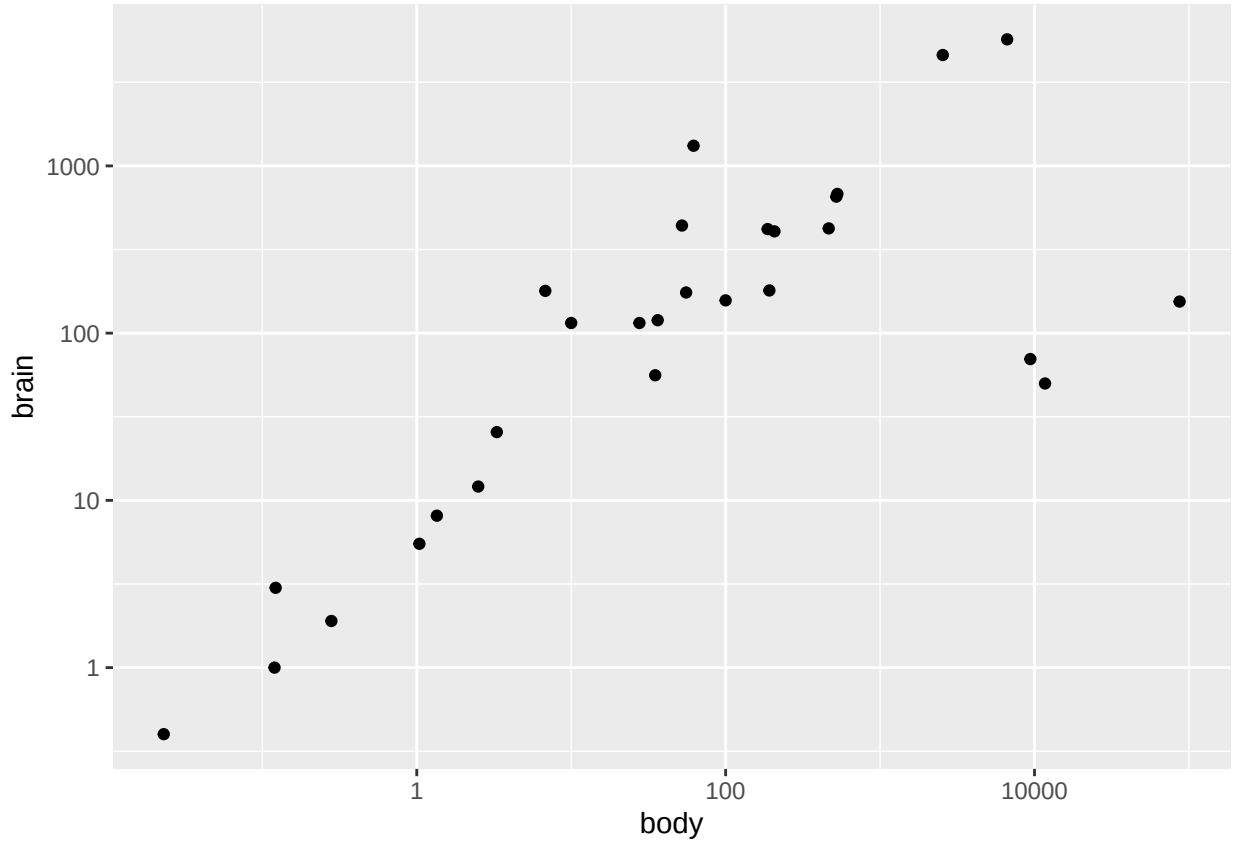
First demo without log

```
ggplot(Animals, aes(x=body, y=brain)) +
  geom_point()
```



Now with log

```
ggplot(Animals, aes(x=body, y=brain)) +
  geom_point() +
  scale_x_log10() +
  scale_y_log10()
```



Scatterplot for large file

- Here we will use a very large data.frame.
- If you knit to PDF, it will tend to create a very large PDF file as well with all the points.
- Therefore, we need to force it to create a png file instead and manage its size.

Load nycflights13

- Enter commands as indicated in the instructions above.

```
library(nycflights13)
data('flights')
str(flights)
```

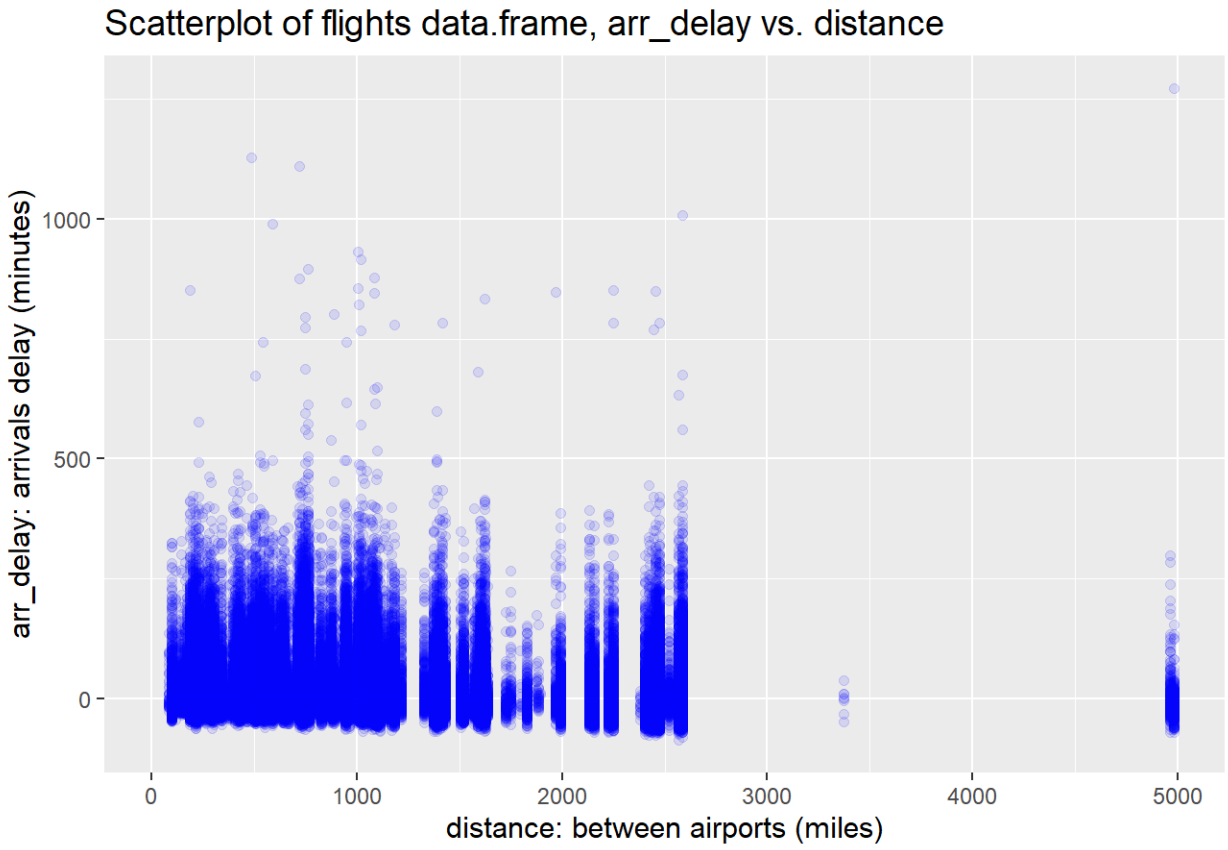
```
## tibble [336,776 x 19] (S3: tbl_df/tbl/data.frame)
##  $ year          : int [1:336776] 2013 2013 2013 2013 2013 2013 2013 2013 2013 2013 ...
##  $ month         : int [1:336776] 1 1 1 1 1 1 1 1 1 1 ...
##  $ day           : int [1:336776] 1 1 1 1 1 1 1 1 1 1 ...
##  $ dep_time      : int [1:336776] 517 533 542 544 554 554 555 557 557 558 ...
##  $ sched_dep_time: int [1:336776] 515 529 540 545 600 558 600 600 600 600 ...
##  $ dep_delay     : num [1:336776] 2 4 2 -1 -6 -4 -5 -3 -3 -2 ...
##  $ arr_time      : int [1:336776] 830 850 923 1004 812 740 913 709 838 753 ...
##  $ sched_arr_time: int [1:336776] 819 830 850 1022 837 728 854 723 846 745 ...
```

```
##  $ arr_delay     : num [1:336776] 11 20 33 -18 -25 12 19 -14 -8 8 ...
##  $ carrier       : chr [1:336776] "UA" "UA" "AA" "B6" ...
##  $ flight        : int [1:336776] 1545 1714 1141 725 461 1696 507 5708 79 301 ...
##  $ tailnum       : chr [1:336776] "N14228" "N24211" "N619AA" "N804JB" ...
##  $ origin        : chr [1:336776] "EWR" "LGA" "JFK" "JFK" ...
##  $ dest          : chr [1:336776] "IAH" "IAH" "MIA" "BQN" ...
##  $ air_time      : num [1:336776] 227 227 160 183 116 150 158 53 140 138 ...
##  $ distance      : num [1:336776] 1400 1416 1089 1576 762 ...
##  $ hour          : num [1:336776] 5 5 5 5 6 5 6 6 6 6 ...
##  $ minute        : num [1:336776] 15 29 40 45 0 58 0 0 0 0 ...
##  $ time_hour     : POSIXct[1:336776], format: "2013-01-01 05:00:00" "2013-01-01 05:00:00" ...
```

Plot arr_delay vs distance

- To reduce the size of the image, I am forcing the Rmd chunk to create a *png* image with specific resolution of 200 *dpi*. That is done by specifying $dev =' png'$, $dpi = 200'$ in the chunk command. I chose 200 for *dpi* after experimenting with *Knit* and and *PDF* file that it rendered.

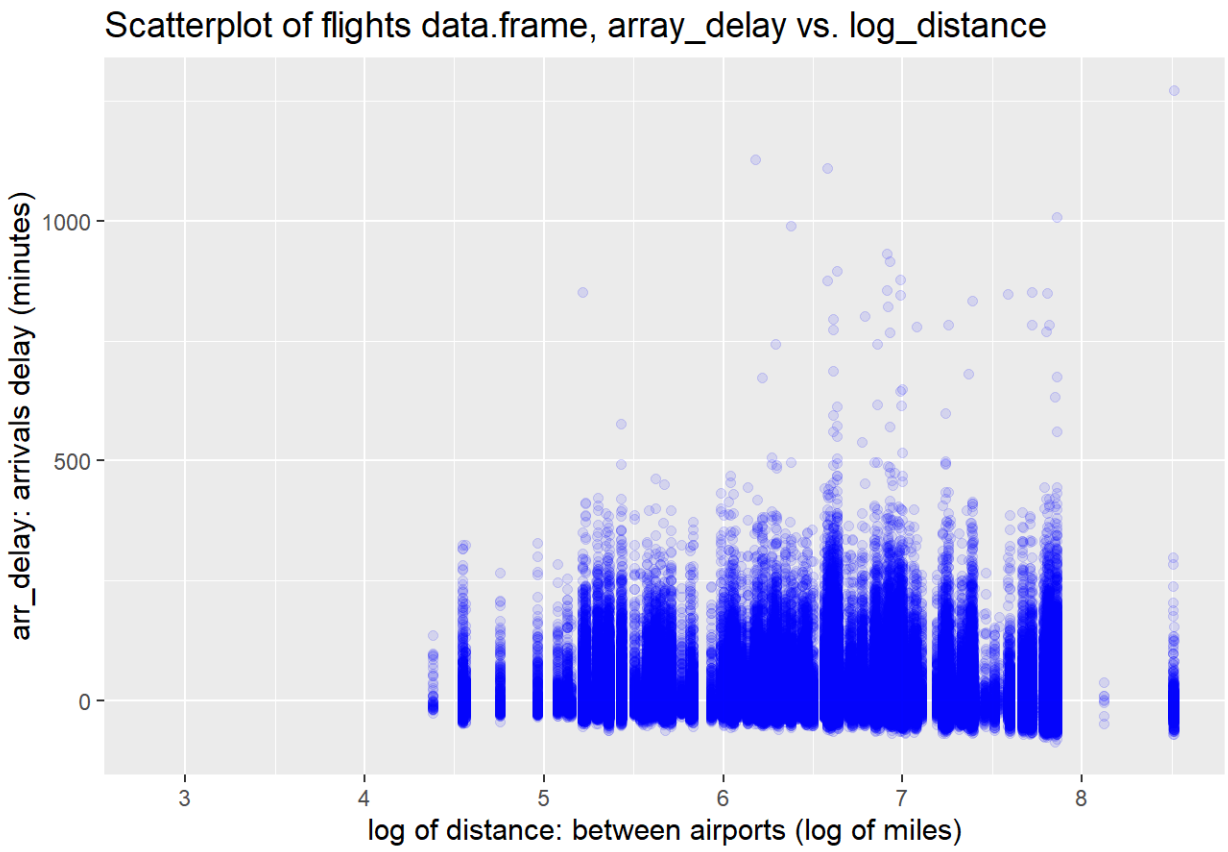
```
# Apply the ggplot() approach.
#
# There are many NA point. Remove them when plotting geom_point() using na.rm=TRUE.
#
ggplot(flights, aes(x=distance, y=arr_delay)) +
  geom_point(color='blue', alpha=0.1, na.rm=TRUE) +
  ggtitle('Scatterplot of flights data.frame, arr_delay vs. distance') +
  labs(y='arr_delay: arrivals delay (minutes)',
       x='distance: between airports (miles)')
```



Plot arr_delay vs log(distance)

- For this exercise, I will apply the natural log to *flights$distance*.
- I will apply the *log()* command directly within the *ggplot()* and *hist()* commands, for simplicity.
- Again, I will force Knit to render a *png* image as described previously to reduce the size of the *PDF* at the end.

```
# I will use thee natural log, base e, the default base.
#
ggplot(flights, aes(x=log(distance), y=arr_delay)) +
  geom_point(color='blue', alpha=0.1, na.rm=TRUE) +
  ggtitle('Scatterplot of flights data.frame, array_delay vs. log_distance') +
  labs(y='arr_delay: arrivals delay (minutes)',
       x='log of distance: between airports (log of miles)')
```



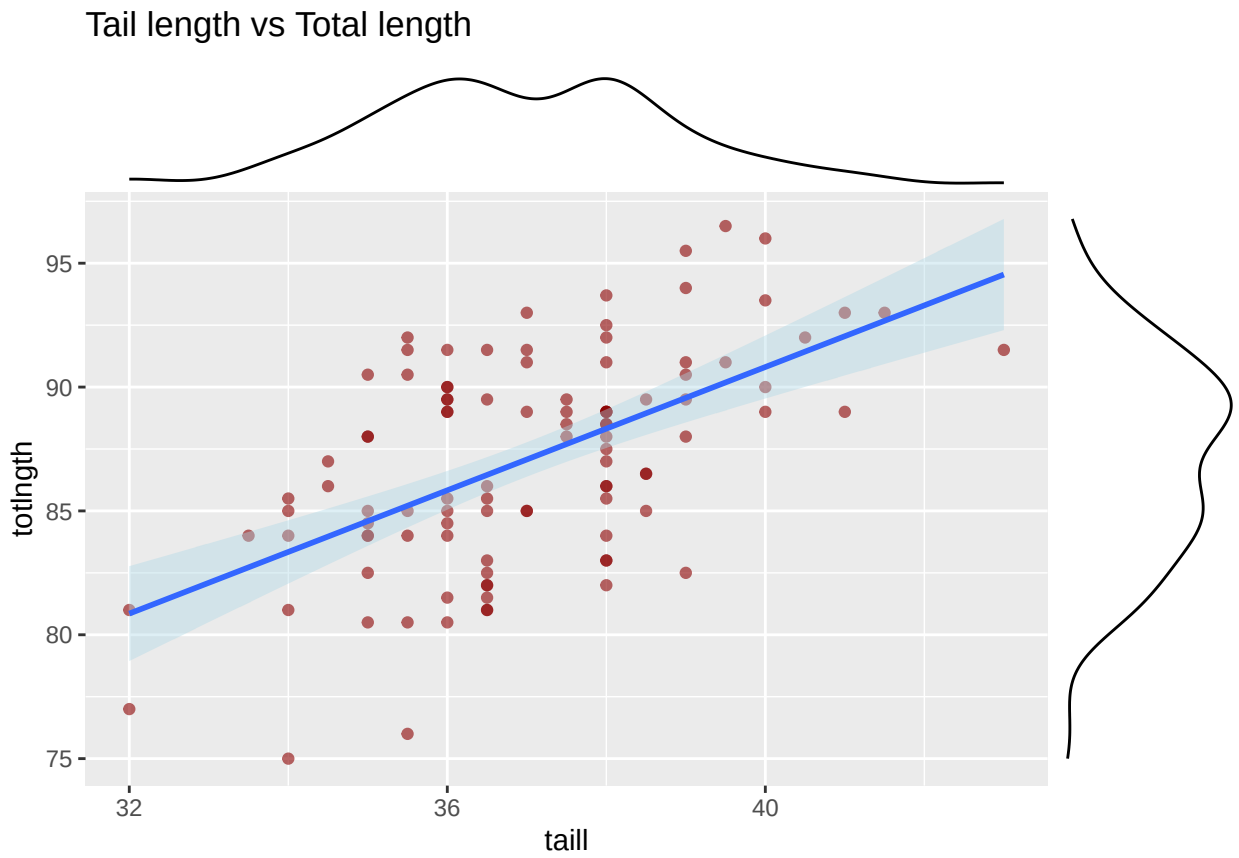
Marginal

Density plots (default)

```
# put the plot in p
p <- ggplot(possum, aes(x=taill, y=totlngth)) +
  geom_point(color='darkred', alpha=0.6) +
  ggtitle('Tail length vs Total length') +
  geom_smooth(method='lm', fill="lightblue", se=TRUE)

ggMarginal(p)
```

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

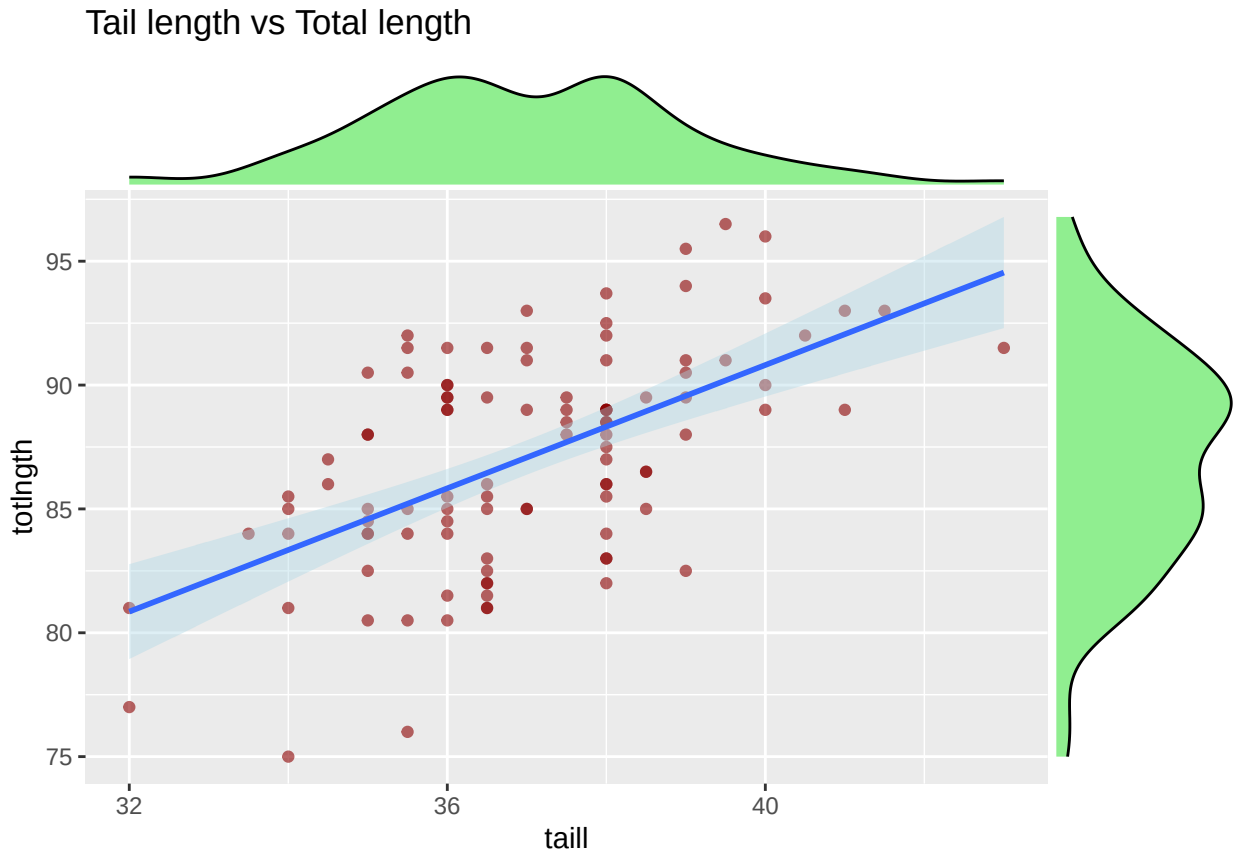


Add fill with ggmarginal()

```
# put the plot in p
p <- ggplot(possum, aes(x=taill, y=totlngth)) +
  geom_point(color='darkred', alpha=0.6) +
  ggtitle('Tail length vs Total length') +
  geom_smooth(method='lm', fill="lightblue", se=TRUE)

ggMarginal(p, fill='lightgreen')
```

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

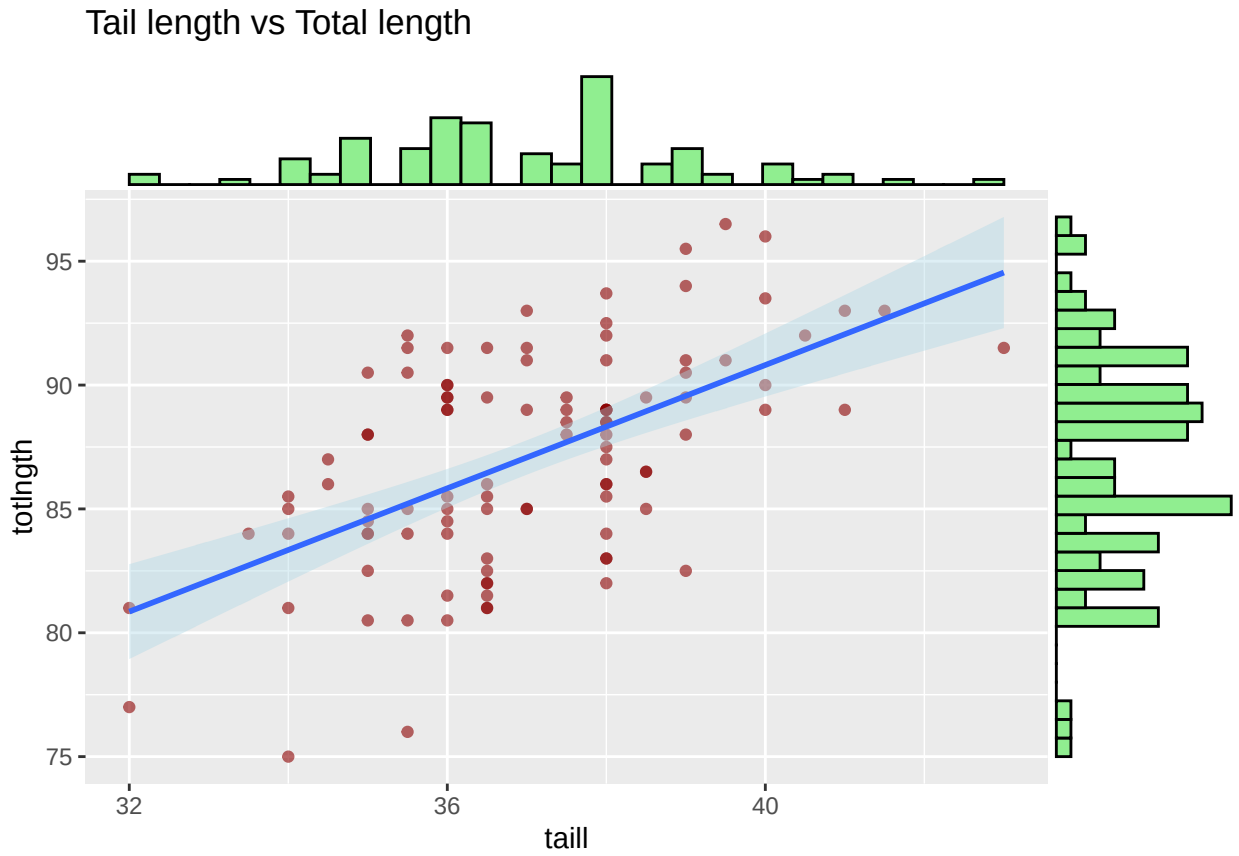


with histogram in ggMarginal

```
# put the plot in p
p <- ggplot(possum, aes(x=taill, y=totlngth)) +
  geom_point(color='darkred', alpha=0.6) +
  ggtitle('Tail length vs Total length') +
  geom_smooth(method='lm', fill="lightblue", se=TRUE)

ggMarginal(p, fill='lightgreen', type='histogram')
```

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

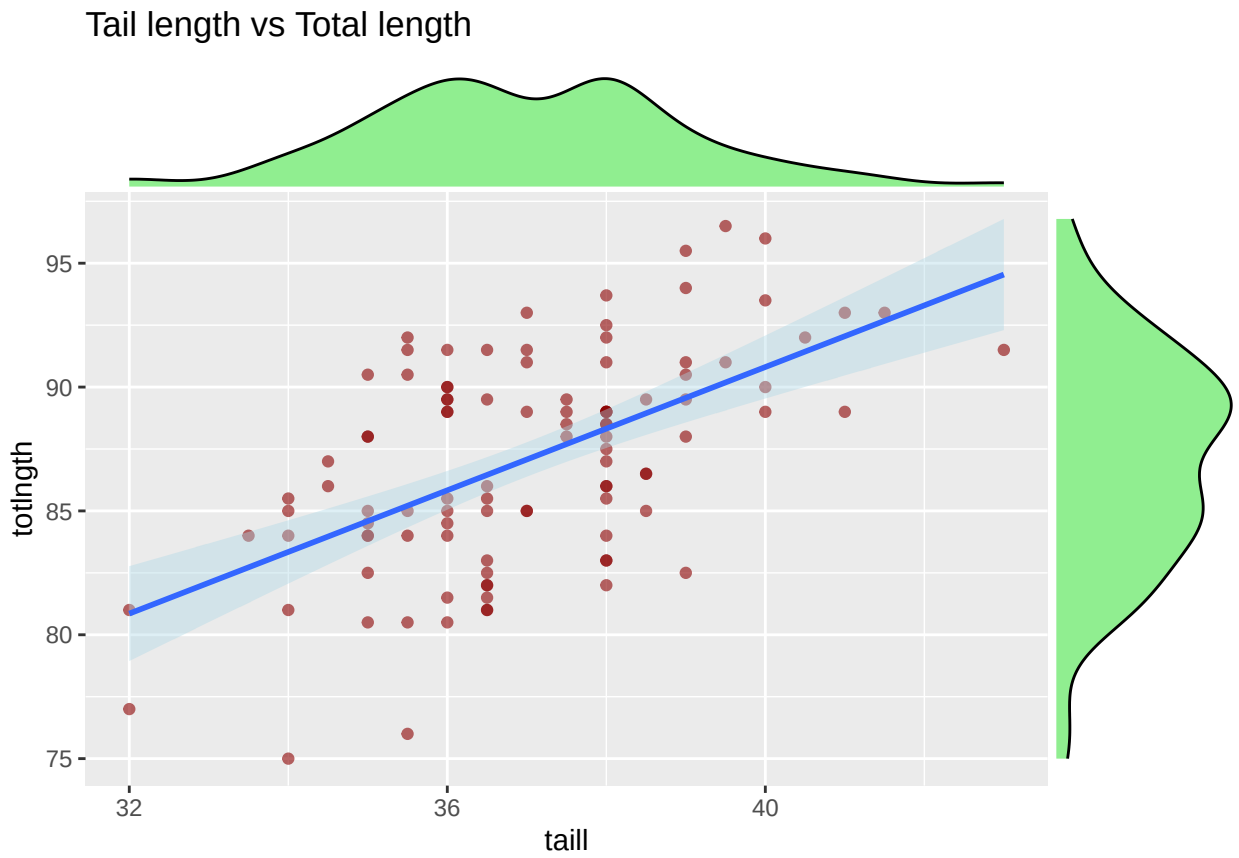


Specify density

```
# put the plot in p
p <- ggplot(possum, aes(x=taill, y=totlngth)) +
  geom_point(color='darkred', alpha=0.6) +
  ggtitle('Tail length vs Total length') +
  geom_smooth(method='lm', fill="lightblue", se=TRUE)

ggMarginal(p, fill='lightgreen', type='density')
```

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



Boston Example from MASS library

> library (MASS)

> dataset Boston

Get documentation for this library:

> ?Boston

Load MASS

- Firstly, *?Boston* gave us a complete documentation of the dataset, describing each variable.

```
# Load library MASS
#
# including warn.conflicts = FALSE to suppress a known warning.
# There was a conflict in a function name, but it does not impact this assignment.
library(MASS, warn.conflicts = FALSE)
```

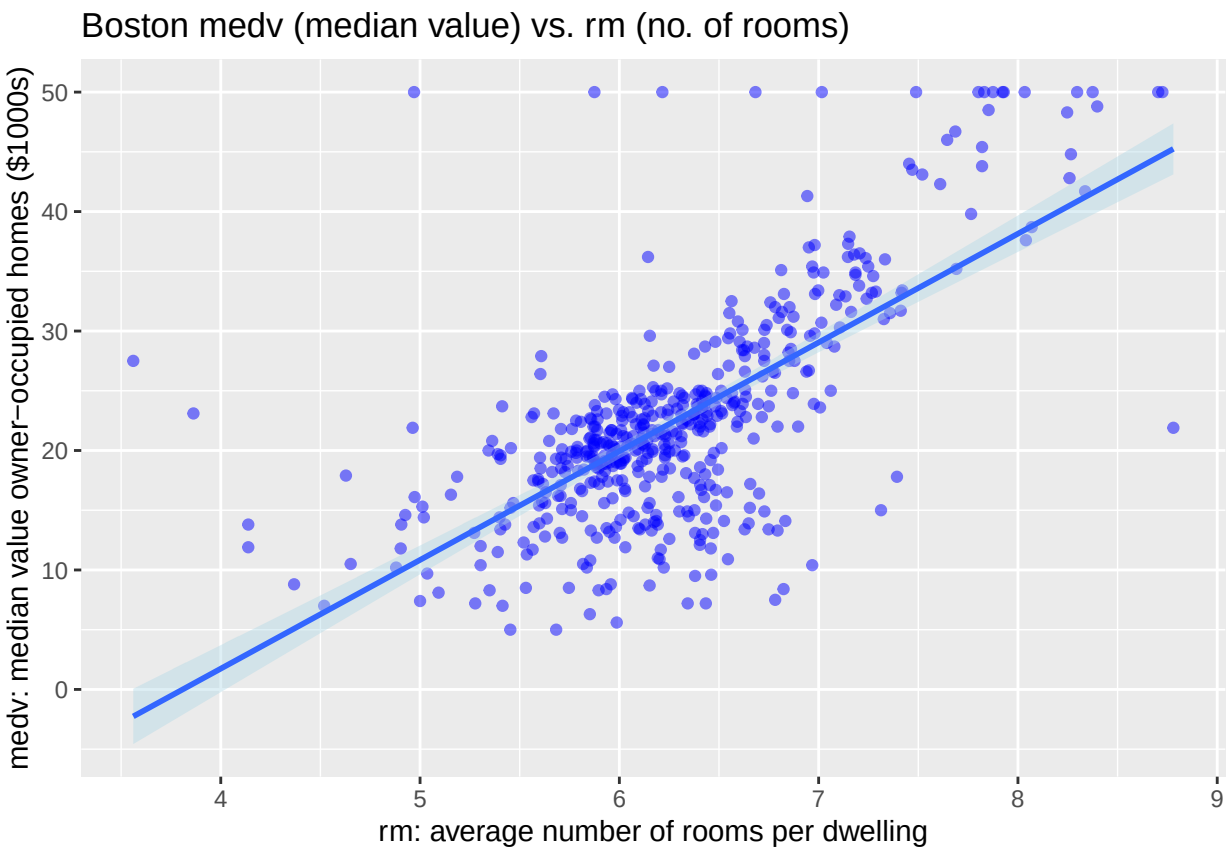
Boston example set 1. Scatterplots with trendline and 95% confidence levels

- This time I will run *ggplot* with *geom_point()* to create the two meaningful scatterplots for this problem quesiton.

- As stated above, two meaningful scatterplots to me, for this exercise, are:
- *medv* vs *rm*
- *medv* vs *lstat*

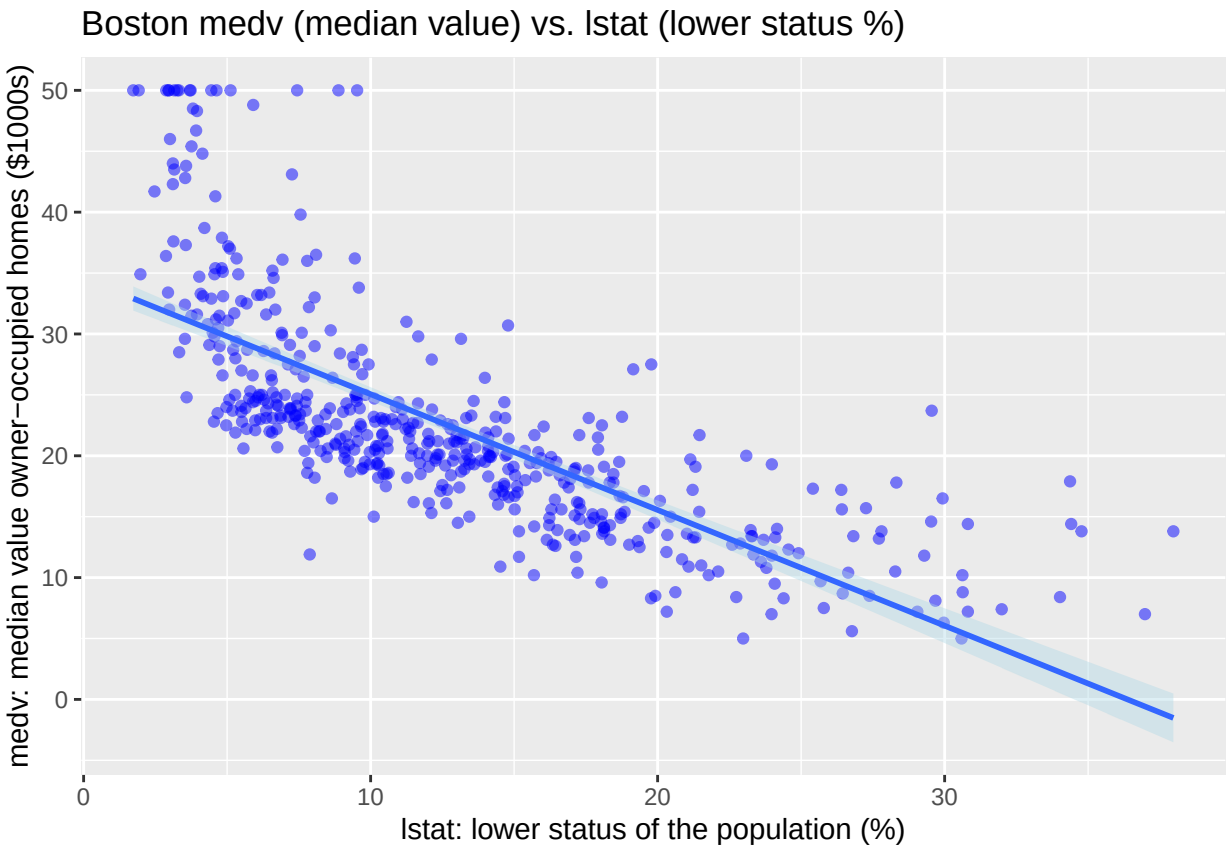
```
# Apply ggplot to create a scatterplot for medv ~ rm
#
ggplot(Boston, aes(x=rm, y=medv)) +
  geom_point(color='blue', alpha=0.5, na.rm=TRUE) +
  geom_smooth(method='lm', fill="lightblue", se=TRUE) +
  ggtitle('Boston medv (median value) vs. rm (no. of rooms)') +
  labs(y='medv: median value owner-occupied homes ($1000s)',
       x='rm: average number of rooms per dwelling')
```

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




```
# Apply ggplot to create a scatterplot for medv ~ lstat
#
ggplot(Boston, aes(x=lstat, y=medv)) +
  geom_point(color='blue', alpha=0.5, na.rm=TRUE) +
  geom_smooth(method='lm', fill="lightblue", se=TRUE) +
  ggtitle('Boston medv (median value) vs. lstat (lower status %)') +
  labs(y='medv: median value owner-occupied homes ($1000s)',
       x='lstat: lower status of the population (%)')
```

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



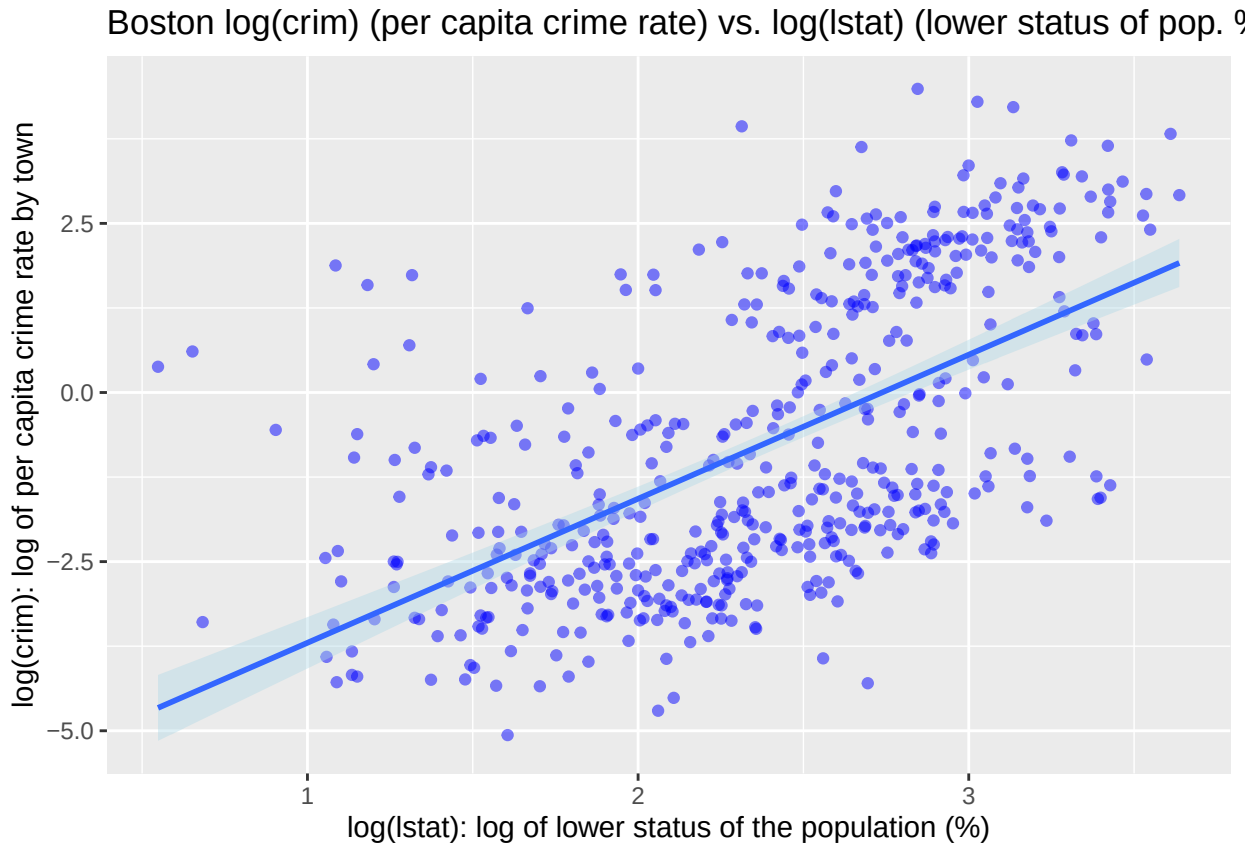
- *medv* vs *rm* exhibit a strong positive relationship: The median value of the home increases as the number of rooms per dwelling increases.
- *medv* vs *lstat* exhit a strong negative relationship: The median value of the home decreases as the percentage of lower status of the population increases.
- The charts include a linear regression line and 95% confidence levels.
- In the case of *lstat* the relation shows a tail. The visual from tail from *medv* vs *lstat* could be improved with a log transformation. It may straighten the line a bit more.
- Variable *lstat* deserves more research. The documentation does not describe exactly what determines *lower status of population*, nor how the percentage is calculated. These demographics are also very dynamic and change over timer. As far as this exercise goes, the chart is certainly meaningful.

Boston example set 2. Scatterplots with log() trendline and 95% confidence levels

- Focus on *crim* vs *lstat* and *crim* vs *medv*.
- *crim* is very skewed left. This chart would improve greatly by transforming its values, for example with a *log()* scale.
- *medv* and *lstat* are also skewed left and will benefit from a log transformation.
- *medv* shows some significant relationships, and that would be more obvious if we were to apply *log()* transformations.
- *lstat* may also benefit from log transformation. Its values may be a bit noisy, jumpy, more scattered. Those jumps could be tested with additional analysis (error rates for example). Nevertheless, the variable may offer value to predict *crim*.
- Therefore, apply a *log transformations to crim, lstat and mdev* in the following charts.

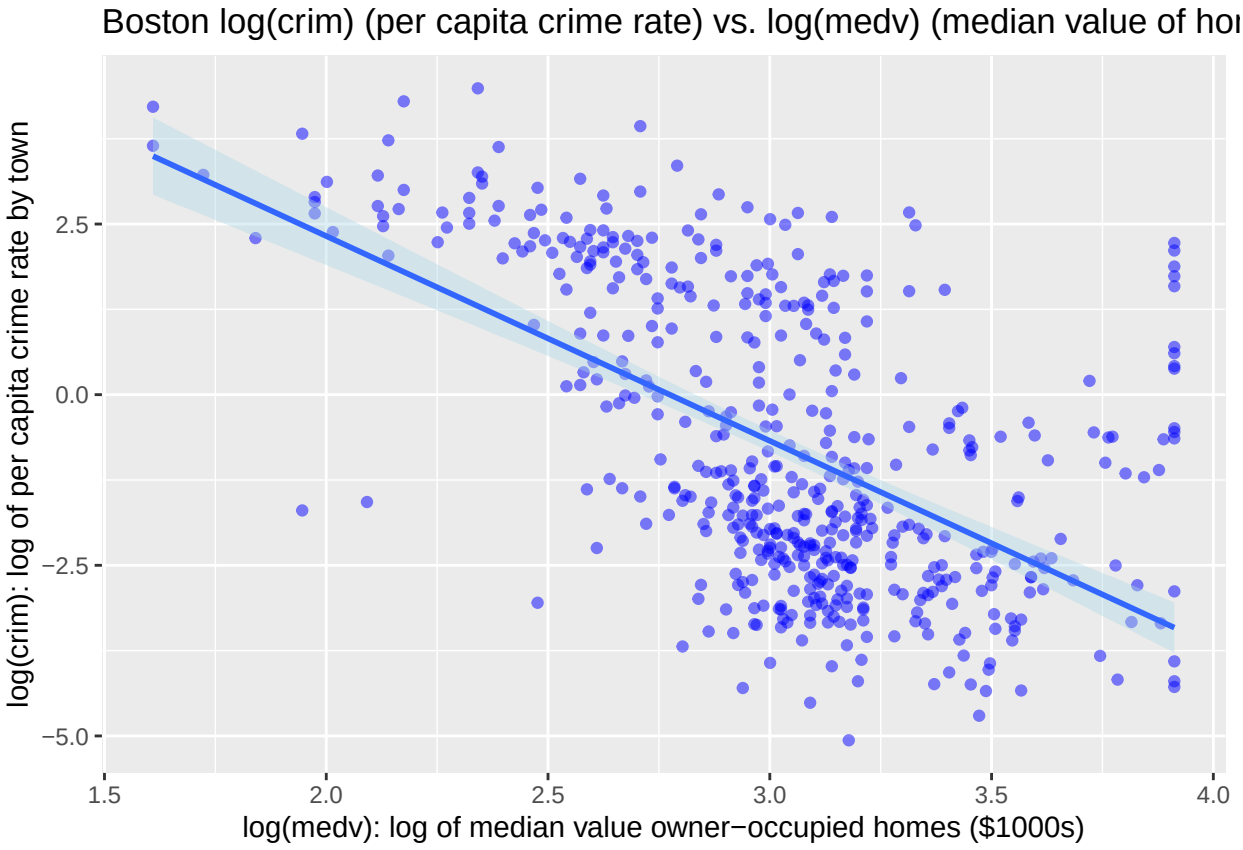
```
# Apply ggplot to create a scatterplot for log(crim) ~ log(lstat)
#
ggplot(Boston, aes(x=log(lstat), y=log(crim))) +
  geom_point(color='blue', alpha=0.5, na.rm=TRUE) +
  geom_smooth(method='lm', fill="lightblue", se=TRUE) +
  ggtitle('Boston log(crim) (per capita crime rate) vs. log(lstat) (lower status of pop. %)') +
  labs(y='log(crim): log of per capita crime rate by town',
       x='log(lstat): log of lower status of the population (%)')
```

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




```
# Apply ggplot to create a scatterplot for log(crim) ~ log(medv)
#
ggplot(Boston, aes(x=log(medv), y=log(crim))) +
  geom_point(color='blue', alpha=0.5, na.rm=TRUE) +
  geom_smooth(method='lm', fill="lightblue", se=TRUE) +
  ggtitle('Boston log(crim) (per capita crime rate) vs. log(medv) (median value of homes)') +
  labs(y='log(crim): log of per capita crime rate by town',
       x='log(medv): log of median value owner-occupied homes ($1000s)')
```

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



- For outcome *log_crim*, both predictors *lstat* and *medv* offer a good amount of information.
- The charts include a linear regression line and 95% confidence levels.
- Of the two predictors chosen here, *lstat* offers the nicest relationship, meaning, from the chart alone, the scatterplot.
- In the case of *log_lstat*, there is an interesting set of datapoints lined up vertically towards the higher end of the horizontal scale that will require further study.
- These two predictors of *log_crim* (i.e., *log_lstat* and *log_medv*) are not the only significant predictors from the dataset; other predictors may be very helpful to predict *crim*. Those are the two predictors that caught my attention from a regression perspective.