

Regression Analysis Application in R

```
library(car)
library(ggplot2)
library(mosaicData)
library(dplyr)
library(psych)
```

Simple Regression

The data set for the reported vs. measured weights is called `Davis` and it is contained in the `car` package.

```
dim(Davis) # dim() gives the number of rows and columns
```

```
## [1] 200   5
head(Davis) # default is to show first 6 rows
```

```
##   sex weight height repwt rept
## 1   M     77    182     77   180
## 2   F     58    161     51   159
## 3   F     53    161     54   158
## 4   M     68    177     70   175
## 5   F     59    157     59   155
## 6   M     76    170     76   165
```

```
head(Davis, 15)
```

```
##   sex weight height repwt rept
## 1   M     77    182     77   180
## 2   F     58    161     51   159
## 3   F     53    161     54   158
## 4   M     68    177     70   175
## 5   F     59    157     59   155
## 6   M     76    170     76   165
## 7   M     76    167     77   165
## 8   M     69    186     73   180
## 9   M     71    178     71   175
## 10  M     65    171     64   170
## 11  M     70    175     75   174
## 12  F    166     57     56   163
## 13  F     51    161     52   158
## 14  F     64    168     64   165
## 15  F     52    163     57   160
```

```
cDavis <- Davis
cDavis[12, c(2, 3)] <- Davis[12, c(3, 2)] # correct the recording error
head(cDavis, 15)
```

```
##   sex weight height repwt rept
## 1   M     77    182     77   180
```

```

## 2   F    58   161   51   159
## 3   F    53   161   54   158
## 4   M    68   177   70   175
## 5   F    59   157   59   155
## 6   M    76   170   76   165
## 7   M    76   167   77   165
## 8   M    69   186   73   180
## 9   M    71   178   71   175
## 10  M   65   171   64   170
## 11  M   70   175   75   174
## 12  F   57   166   56   163
## 13  F   51   161   52   158
## 14  F   64   168   64   165
## 15  F   52   163   57   160

mod <- lm(weight ~ repwt, subset = sex == "F", data=cDavis)
#regression for women

```

Formulas look like $Y \sim X_1$, which `lm()` will translate to a regression equation: $Y = b_0 + b_1 X_1 + \epsilon$.

How to get the results from the model object

```

mod

##
## Call:
## lm(formula = weight ~ repwt, data = cDavis, subset = sex == "F")
##
## Coefficients:
## (Intercept)      repwt
##       1.7775          0.9772

```

If you type the name of your model object, you get only the coefficients. You can also obtain them using `coef()`

```

coef(mod)

## (Intercept)      repwt
##       1.7775034    0.9772242

```

You get more information if you use `summary()`

```

summary(mod)

##
## Call:
## lm(formula = weight ~ repwt, data = cDavis, subset = sex == "F")
##
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -5.5248 -0.7526 -0.3654  0.6118  6.3841 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 1.77750    1.74441   1.019    0.311    
## repwt       0.97722    0.03053  32.009   <2e-16 ***  
## ---        
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

## 
## Residual standard error: 2.057 on 99 degrees of freedom
##   (11 observations deleted due to missingness)
## Multiple R-squared:  0.9119, Adjusted R-squared:  0.911 
## F-statistic:  1025 on 1 and 99 DF,  p-value: < 2.2e-16

```

For a 1 kg increase in reported weight, the measured weight increases by 0.977, which is statistically significantly different from 0, $t(99) = 32.009, p < .001$. In other words, there is nearly a 1-to-1 relationship. The intercept means that the predicted measured weight is 1.78 kg for those who report a weight of 0 kg. But no one reported a weight of 0 kg and even if they did, it would not make sense. Nevertheless, the intercept is not significantly different from 0, $t(99) = 1.019, p = 0.311$. Note that in the case of simple regression, the overall (or omnibus) F statistic is equal to t^2 .

```
32.009^2
```

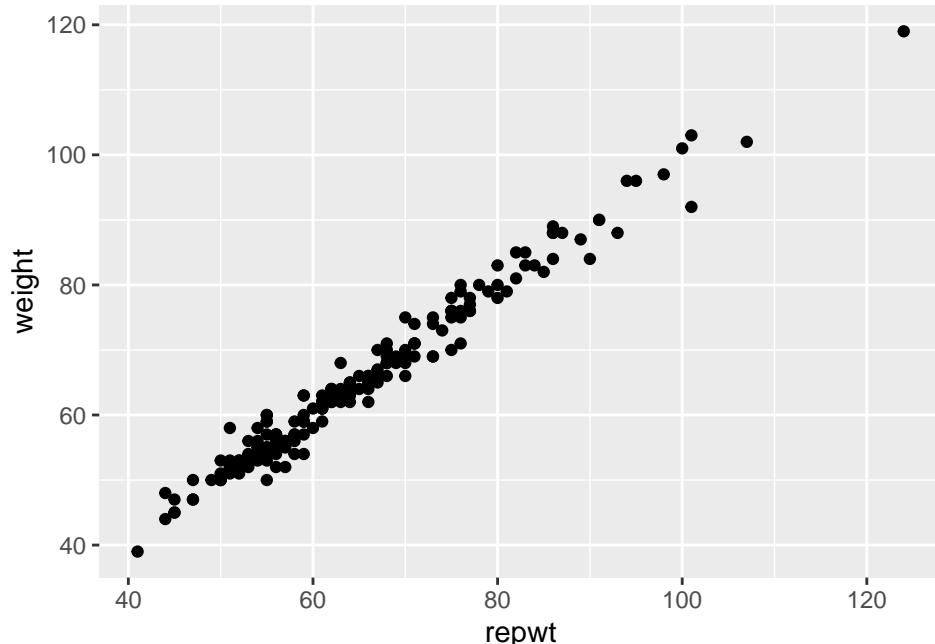
```
## [1] 1024.576
```

Finally, R^2 indicates that 91% of the variability in measured weight can be explained by reported weight.

Let's create a scatterplot.

```
ggplot(data=cDavis, aes(x=repwt, y=weight)) +
  geom_point()
```

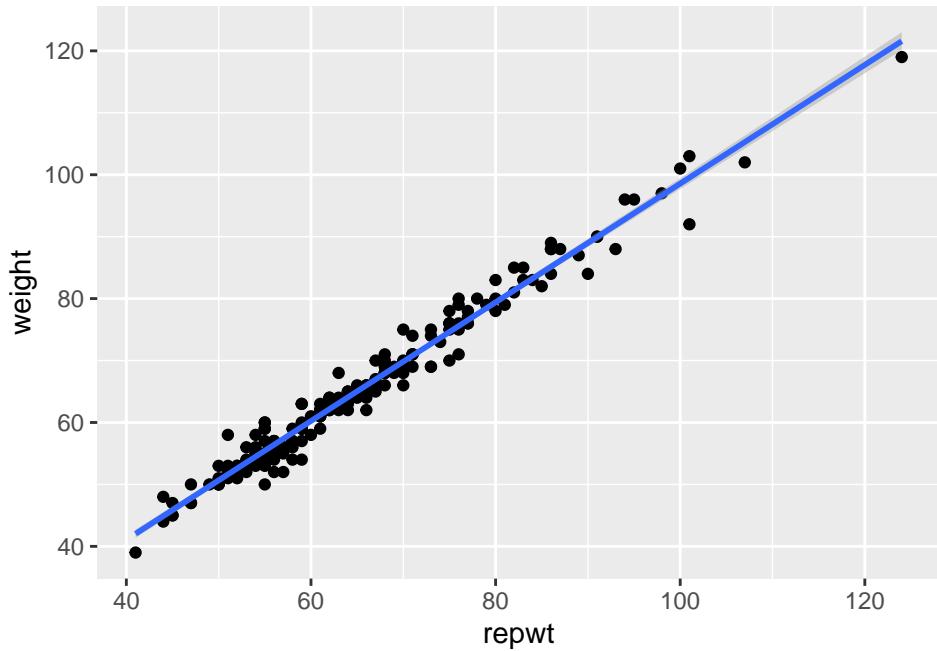
```
## Warning: Removed 17 rows containing missing values (`geom_point()`).
```



You can add the regression line to the plot.

```
ggplot(data=cDavis, aes(x=repwt, y=weight)) +
  geom_point() +
  geom_smooth(method="lm")

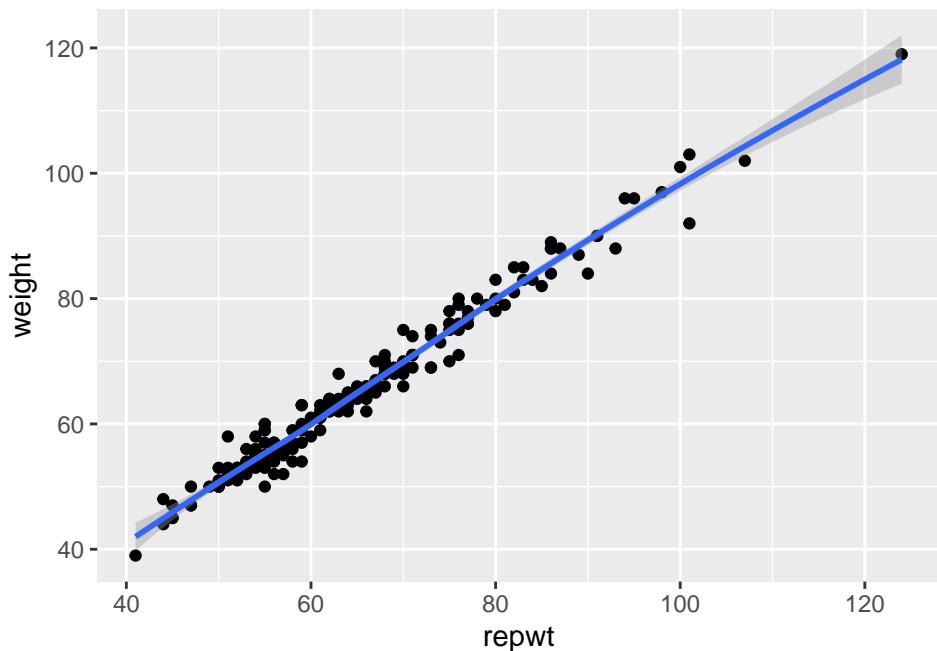
## `geom_smooth()` using formula = 'y ~ x'
## Warning: Removed 17 rows containing non-finite values (`stat_smooth()`).
## Warning: Removed 17 rows containing missing values (`geom_point()`).
```



There are other options for `geom_smooth()`, for example `method="loess"`, which gives a local linear regression smoother.

```
ggplot(data=cDavis, aes(x=repwt, y=weight)) +
  geom_point() +
  geom_smooth(method="loess")

## `geom_smooth()` using formula = 'y ~ x'
## Warning: Removed 17 rows containing non-finite values (`stat_smooth()`).
## Warning: Removed 17 rows containing missing values (`geom_point()`).
```



How about with the original “uncorrected” data:

```

ggplot(data=Davis, aes(x=repwt, y=weight)) +
  geom_point() +
  geom_smooth(method="loess")

## `geom_smooth()` using formula = 'y ~ x'
## Warning: Removed 17 rows containing non-finite values (`stat_smooth()`).
## Warning: Removed 17 rows containing missing values (`geom_point()`).

```

