Marah Notes.

A good start is with the data display.

```
data = read.csv("module2_exo5_shuttle.csv",header=T)
data
```

```
##        Date Count Temperature Pressure Malfunction
## 1   4/12/81     6          66       50           0
## 2  11/12/81     6          70       50           1
## 3   3/22/82     6          69       50           0
## 4  11/11/82     6          68       50           0
## 5   4/04/83     6          67       50           0
## 6   6/18/82     6          72       50           0
## 7   8/30/83     6          73      100           0
## 8  11/28/83     6          70      100           0
## 9   2/03/84     6          57      200           1
## 10  4/06/84     6          63      200           1
## 11  8/30/84     6          70      200           1
## 12 10/05/84     6          78      200           0
## 13 11/08/84     6          67      200           0
## 14  1/24/85     6          53      200           2
## 15  4/12/85     6          67      200           0
## 16  4/29/85     6          75      200           0
## 17  6/17/85     6          70      200           0
## 18  7/29/85     6          81      200           0
## 19  8/27/85     6          76      200           0
## 20 10/03/85     6          79      200           0
## 21 10/30/85     6          75      200           2
## 22 11/26/85     6          76      200           0
## 23  1/12/86     6          58      200           1
```

The data is too small, which will affect the results.

I think we shouldn't remove the 0 malfuntion , that will be missing some good information about the data.

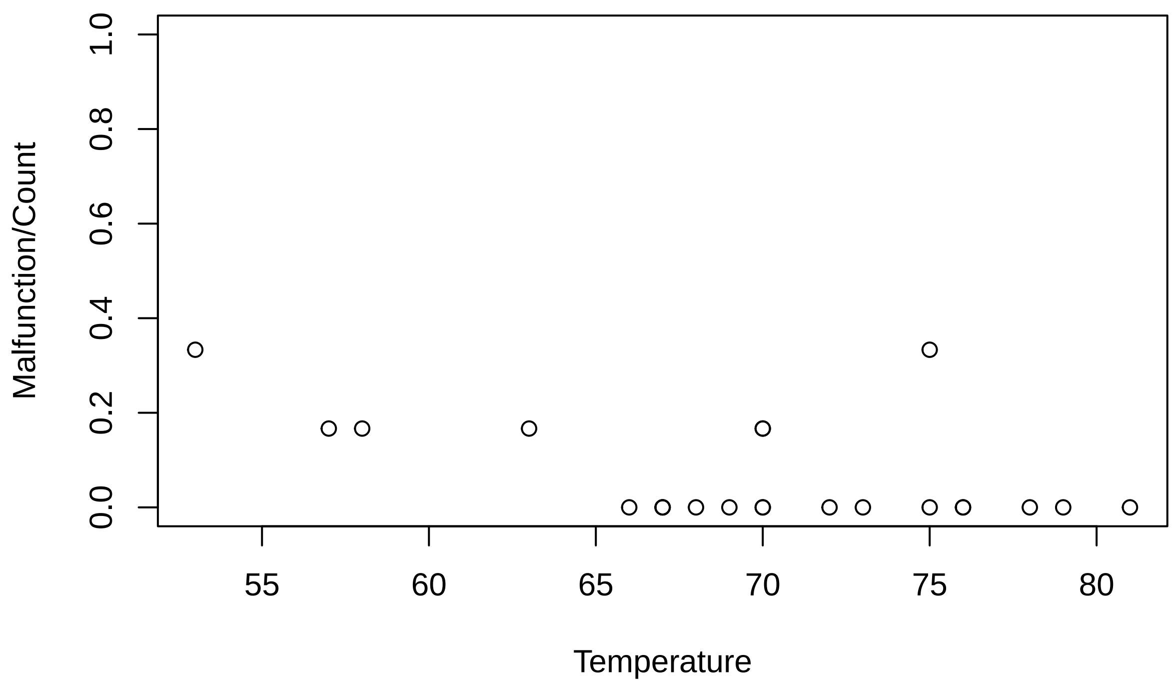
```
logistic_reg = glm(data=data, Malfunction/Count ~ Temperature, weights=Count,
                   family=binomial(link='logit'))
summary(logistic_reg)
```

```
##
## Call:
## glm(formula = Malfunction/Count ~ Temperature, family = binomial(link = "logit"),
##     data = data, weights = Count)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  5.08498    3.05247   1.666   0.0957 .
```

```
## Temperature -0.11560    0.04702  -2.458   0.0140 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 24.230  on 22  degrees of freedom
## Residual deviance: 18.086  on 21  degrees of freedom
## AIC: 35.647
##
## Number of Fisher Scoring iterations: 5
```

I don't like how there is output without a good explanation.

```
plot(data=data, Malfunction/Count ~ Temperature, ylim=c(0,1))
```



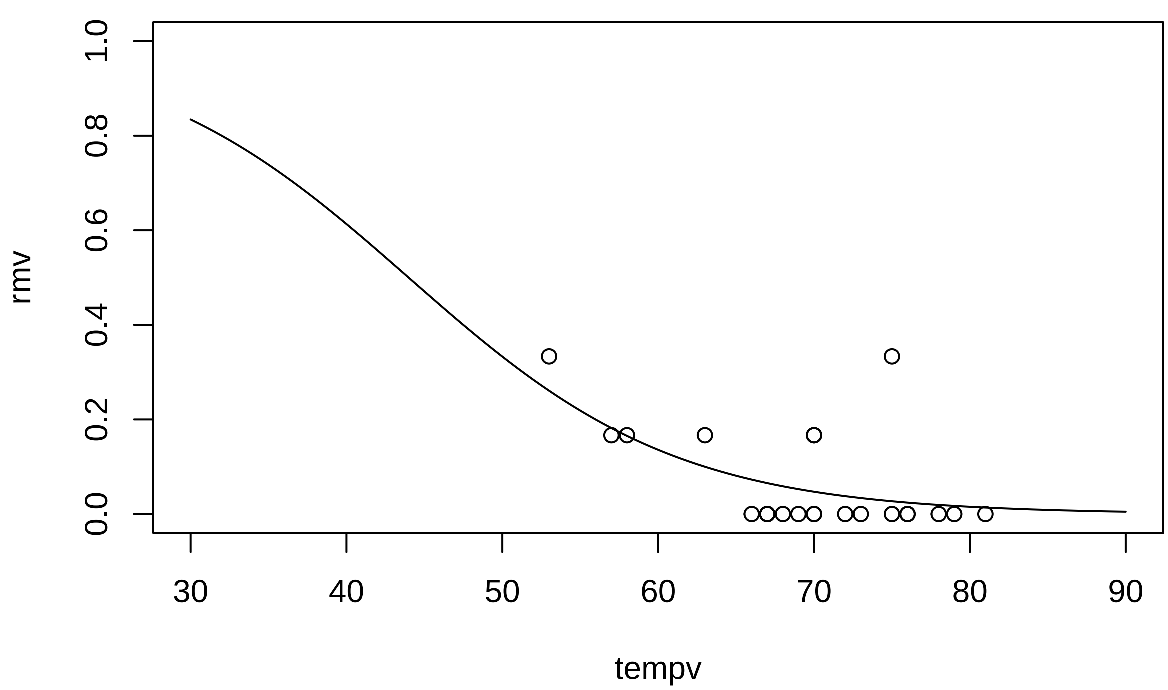
Also, I think the graph from above was enough to understand that there is not a significant impact between temperature and the malfunction.

Here also not a very good explanation(if your audience is not familiar with this kind of output). It is a little complex.

Suppose that each of the six O-rings is damaged with the same probability and independently of the others and that this probability depends only on the temperature. If $p(t)$ is this probability, the number D of malfunctioning O-rings during a flight at temperature t follows a binomial law with parameters $n = 6$ and $p = p(t)$. To link $p(t)$ to t, we will therefore perform a logistic regression.

Why are we doing this if there is no impact between temp and malfunction? , after the lecture, I got the answer, we should make it by numbers not just visualizing.

```
# shuttle=shuttle[shuttle$r!=0,]
tempv = seq(from=30, to=90, by = .5)
rmv <- predict(logistic_reg,list(Temperature=tempv),type="response")
plot(tempv,rmv,type="l",ylim=c(0,1))
points(data=data, Malfunction/Count ~ Temperature)
```



Note: I should determine the audience for my computational document to know what I should explain and what I shouldn't.