

# Risk Analysis of the Space Shuttle: Pre-Challenger Prediction of Failure

Arnaud Legrand

23 September 2018

In this document we reperform some of the analysis provided in *Risk Analysis of the Space Shuttle: Pre-Challenger Prediction of Failure* by Siddhartha R. Dalal, Edward B. Fowlkes, Bruce Hoadley published in *Journal of the American Statistical Association*, Vol. 84, No. 408 (Dec., 1989), pp. 945-957 and available at <http://www.jstor.org/stable/2290069>.

On the fourth page of this article, they indicate that the maximum likelihood estimates of the logistic regression using only temperature are:  $\hat{\alpha} = 5.085$  and  $\hat{\beta} = -0.1156$  and their asymptotic standard errors are  $s_{\hat{\alpha}} = 3.052$  and  $s_{\hat{\beta}} = 0.047$ . The Goodness of fit indicated for this model was  $G^2 = 18.086$  with 21 degrees of freedom. Our goal is to reproduce the computation behind these values and the Figure 4 of this article, possibly in a nicer looking way.

## Technical information on the computer on which the analysis is run

We will be using the R language using the ggplot2 library.

```
library(ggplot2)
sessionInfo()

## R version 3.5.1 (2018-07-02)
## Platform: x86_64-pc-linux-gnu (64-bit)
## Running under: Debian GNU/Linux buster/sid
##
## Matrix products: default
## BLAS: /usr/lib/x86_64-linux-gnublas/libblas.so.3.8.0
## LAPACK: /usr/lib/x86_64-linux-gnulapack/liblapack.so.3.8.0
##
## locale:
## [1] LC_CTYPE=fr_FR.UTF-8          LC_NUMERIC=C
## [3] LC_TIME=fr_FR.UTF-8          LC_COLLATE=fr_FR.UTF-8
## [5] LC_MONETARY=fr_FR.UTF-8       LC_MESSAGES=fr_FR.UTF-8
## [7] LC_PAPER=fr_FR.UTF-8          LC_NAME=C
## [9] LC_ADDRESS=C                  LC_TELEPHONE=C
## [11] LC_MEASUREMENT=fr_FR.UTF-8   LC_IDENTIFICATION=C
##
## attached base packages:
## [1] stats      graphics   grDevices  utils      datasets   methods    base
##
## other attached packages:
## [1] ggplot2_3.0.0
##
## loaded via a namespace (and not attached):
## [1] Rcpp_0.12.17     bindr_0.1.1      knitr_1.20      magrittr_1.5
## [5] tidyselect_0.2.4  munsell_0.5.0    colorspace_1.3-2 R6_2.2.2
## [9] rlang_0.2.1      stringr_1.3.1    plyr_1.8.4      dplyr_0.7.6
## [13] tools_3.5.1     grid_3.5.1      gtable_0.2.0    withr_2.1.2
```

```

## [17] htmltools_0.3.6    yaml_2.2.0        lazyeval_0.2.1   rprojroot_1.3-2
## [21] digest_0.6.15      assertthat_0.2.0 tibble_1.4.2     bindrcpp_0.2.2
## [25] purrrr_0.2.5       glue_1.2.0        evaluate_0.10.1  rmarkdown_1.10
## [29] stringi_1.2.3      compiler_3.5.1   pillar_1.2.3    scales_0.5.0
## [33] backports_1.1.2    pkgconfig_2.0.1

```

Here are the available libraries

```
devtools::session_info()
```

```

## Session info -----
## setting  value
## version  R version 3.5.1 (2018-07-02)
## system   x86_64, linux-gnu
## ui        X11
## language (EN)
## collate   fr_FR.UTF-8
## tz        Europe/Paris
## date     2018-09-23

## Packages -----
## package * version date      source
## assertthat 0.2.0  2017-04-11 CRAN (R 3.5.0)
## backports  1.1.2  2017-12-13 CRAN (R 3.5.1)
## base       * 3.5.1  2018-07-02 local
## bindr      0.1.1  2018-03-13 CRAN (R 3.5.0)
## bindrcpp   0.2.2  2018-03-29 CRAN (R 3.5.0)
## colorspace 1.3-2  2016-12-14 CRAN (R 3.5.0)
## compiler   3.5.1  2018-07-02 local
## datasets   * 3.5.1  2018-07-02 local
## devtools   1.13.6 2018-06-27 CRAN (R 3.5.1)
## digest     0.6.15  2018-01-28 CRAN (R 3.5.0)
## dplyr      0.7.6  2018-06-29 CRAN (R 3.5.1)
## evaluate   0.10.1 2017-06-24 CRAN (R 3.5.0)
## ggplot2    * 3.0.0  2018-07-03 CRAN (R 3.5.1)
## glue       1.2.0  2017-10-29 CRAN (R 3.5.0)
## graphics   * 3.5.1  2018-07-02 local
## grDevices  * 3.5.1  2018-07-02 local
## grid       3.5.1  2018-07-02 local
## gtable     0.2.0  2016-02-26 CRAN (R 3.5.0)
## htmltools  0.3.6  2017-04-28 CRAN (R 3.5.0)
## knitr      1.20   2018-02-20 CRAN (R 3.5.0)
## lazyeval    0.2.1  2017-10-29 CRAN (R 3.5.0)
## magrittr   1.5    2014-11-22 CRAN (R 3.5.0)
## memoise    1.1.0  2017-04-21 CRAN (R 3.5.1)
## methods    * 3.5.1  2018-07-02 local
## munsell    0.5.0  2018-06-12 CRAN (R 3.5.0)
## pillar     1.2.3  2018-05-25 CRAN (R 3.5.0)
## pkgconfig  2.0.1  2017-03-21 CRAN (R 3.5.0)
## plyr      1.8.4  2016-06-08 CRAN (R 3.5.0)
## purrrr    0.2.5  2018-05-29 CRAN (R 3.5.0)
## R6         2.2.2  2017-06-17 CRAN (R 3.5.0)
## Rcpp      0.12.17 2018-05-18 CRAN (R 3.5.0)
## rlang      0.2.1  2018-05-30 CRAN (R 3.5.0)
## rmarkdown  1.10   2018-06-11 CRAN (R 3.5.1)

```

```

## rprojroot     1.3-2   2018-01-03 CRAN (R 3.5.1)
## scales        0.5.0   2017-08-24 CRAN (R 3.5.0)
## stats         * 3.5.1   2018-07-02 local
## stringi       1.2.3   2018-06-12 CRAN (R 3.5.0)
## stringr       1.3.1   2018-05-10 CRAN (R 3.5.0)
## tibble        1.4.2   2018-01-22 CRAN (R 3.5.0)
## tidyselect    0.2.4   2018-02-26 CRAN (R 3.5.0)
## tools         3.5.1   2018-07-02 local
## utils         * 3.5.1   2018-07-02 local
## withr         2.1.2   2018-03-15 CRAN (R 3.5.0)
## yaml          2.2.0   2018-07-25 cran (@2.2.0)

```

## Loading and inspecting data

Let's start by reading data:

```

data = read.csv("../data/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

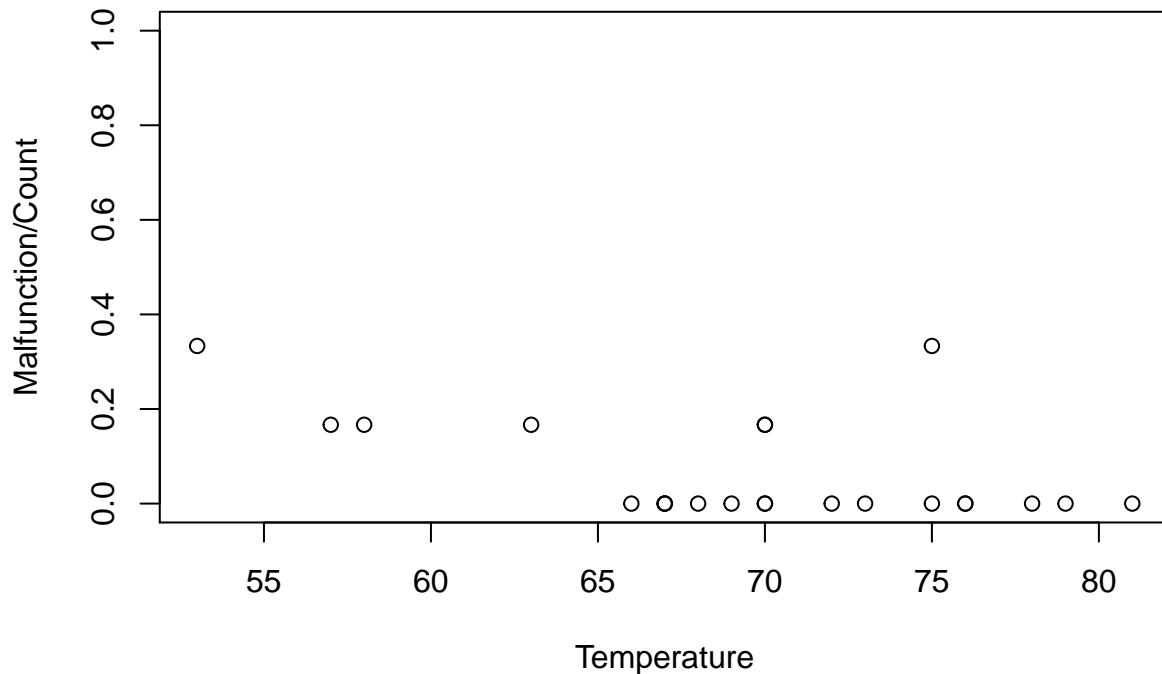
We know from our previous experience on this data set that filtering data is a really bad idea. We will therefore process it as such.

Let's visually inspect how temperature affects malfunction:

```

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

```



## Logistic regression

Let's assume O-rings independently fail with the same probability which solely depends on temperature. A logistic regression should allow us to estimate the influence of temperature.

```
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)
##
## Deviance Residuals:
##       Min        1Q        Median         3Q        Max
## -0.95227 -0.78299 -0.54117 -0.04379  2.65152
##
## 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
##
```

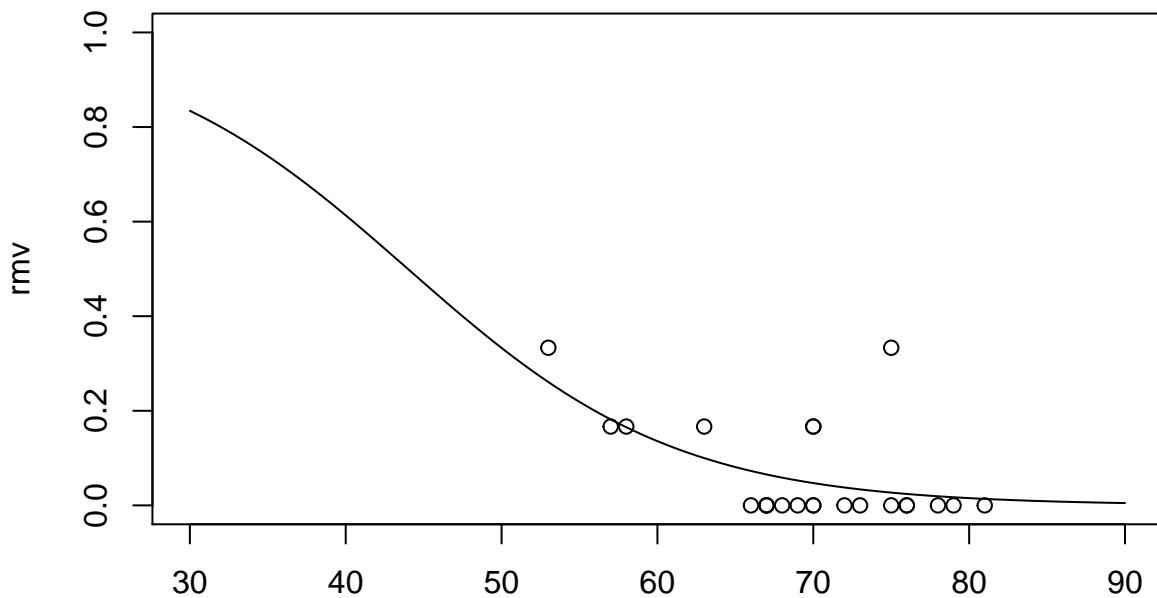
```
## Number of Fisher Scoring iterations: 5
```

The maximum likelihood estimator of the intercept and of Temperature are thus  $\hat{\alpha} = 5.0849$  and  $\hat{\beta} = -0.1156$  and their standard errors are  $s_{\hat{\alpha}} = 3.052$  and  $s_{\hat{\beta}} = 0.04702$ . The Residual deviance corresponds to the Goodness of fit  $G^2 = 18.086$  with 21 degrees of freedom. I have therefore managed to replicate the results of the Dalal et. al. article.

## Predicting failure probability

The temperature when launching the shuttle was 31°F. Let's try to estimate the failure probability for such temperature using our model.:

```
# 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)
```



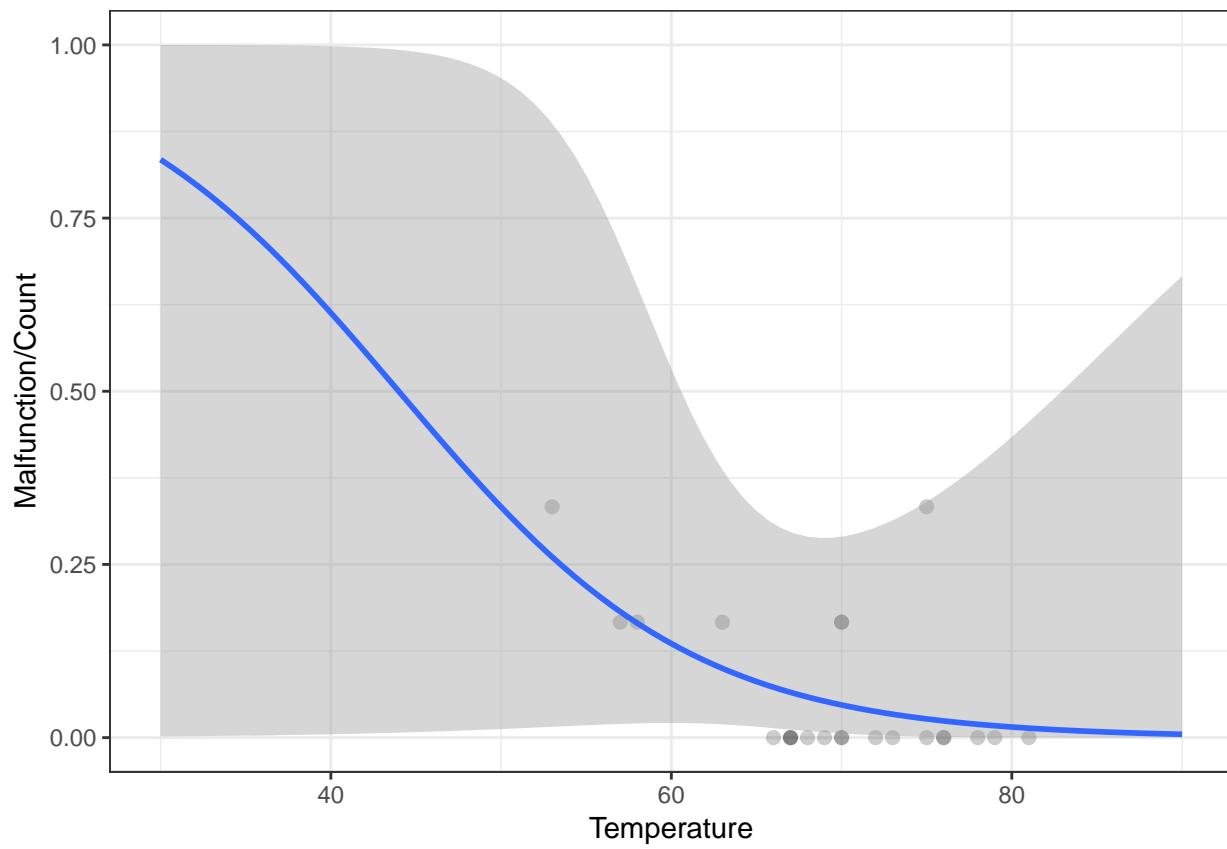
This figure is very similar to the Figure 4 of Dalal et al. I have managed to replicate the Figure 4 of the Dalal et al. article.

Let's try to plot confidence intervals although I am not sure exactly how they are computed.

```
ggplot(data, aes(y=Malfunction/Count, x=Temperature)) + geom_point(alpha=.2, size = 2) +
  geom_smooth(method = "glm", method.args = list(family = "binomial"), fullrange=T) +
  xlim(30,90) + ylim(0,1) + theme_bw()
```

```
## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!
```



No confidence region was given in the original article. **Let's hope this confidence region estimation is correct.**