Prognostic of NASA Turbofan Jet Engine

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| Contribuciones | Firma |
|-----------------------------|-----------------|
| Investigación previa | Fernando Chafim |
| Redacción de las respuestas | Fernando Chafim |
| Desarrollo código | Fernando Chafim |

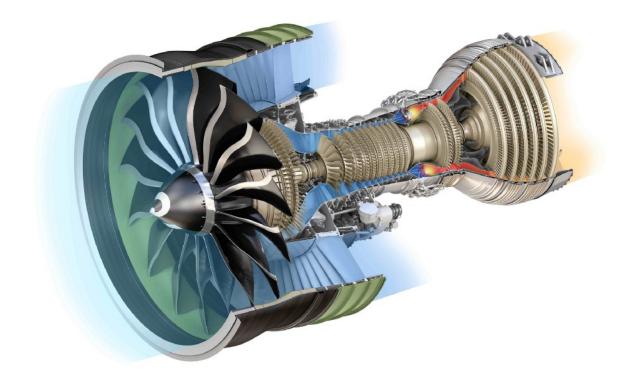
NASA TURBOFAN JET ENGINE

We define prognostics here exclusively as the estimation of remaining useful component life. The remaining useful life (RUL) estimates are in units of time (e.g., hours or cycles).

End-of-life can be subjectively determined as a function of operational thresholds that can be measured. These thresholds depend on user specifications to determine safe operational limits.

Prognostics is currently at the core of systems health management. Reliably estimating remaining life holds the promise for considerable cost savings (for example by avoiding unscheduled maintenance and by increasing equipment usage) and operational safety improvements. Remaining life estimates provide decision makers with information that allows them to change operational characteristics (such as load) which in turn may prolong the life of the component. It also allows planners to account for upcoming maintenance and set in motion a logistics process that supports a smooth transition from faulty equipment to fully functional.

knitr::include_graphics("img/turbofan1.jpeg")



2. Dataset

Los pronósticos y la gestión de la salud son un tema importante en la industria para predecir el estado de los activos para evitar tiempos de inactividad y fallas. Este conjunto de datos es la versión de Kaggle del muy conocido conjunto de datos públicos para el modelado de degradación de activos de la NASA. Incluye datos simulados Run-to-Failure de motores a reacción con turboventilador.

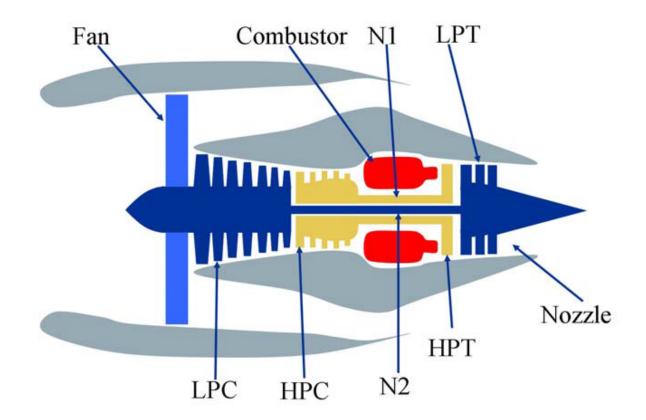
La simulación de la degradación del motor se llevó a cabo utilizando C-MAPSS. Se simularon cuatro conjuntos diferentes bajo diferentes combinaciones de condiciones operativas y modos de falla. Registra varios canales de sensores para caracterizar la evolución de la falla. El conjunto de datos fue proporcionado por el CoE de Pronósticos de NASA Ames.

Descripción

| Symbol | Description | Units |
|----------|--|------------------------|
| Unit | - | - |
| Time | - | t |
| Altitude | Altitude | ft |
| $Mach_N$ | Mach Number | ${ m M}$ |
| SeaTemp | Sea Level temperature | $^{\circ}\mathrm{F}$ |
| T2 | Total temperature at fan inlet | ${}^{\circ}\mathrm{R}$ |
| T2 | Total temperature at fan inlet | ${}^{\circ}\mathrm{R}$ |
| T24 | Total temperature at LPC outlet | ${}^{\circ}\mathrm{R}$ |
| T30 | Total temperature at HPC outlet | ${}^{\circ}\mathrm{R}$ |
| T50 | Total temperature at LPT outlet | ${}^{\circ}\mathrm{R}$ |
| P2 | Pressure at fan inlet | psia |
| P15 | Total pressure in bypass-duct | psia |
| P30 | Total pressure at HPC outlet | psia |

| Symbol | Description | Units |
|--------------|---------------------------------------|----------------------|
| Nf | Physical fan speed | rpm |
| Nc | Physical core speed | rpm |
| epr | Engine pressure ratio (P50/P2) | _ |
| Ps30 | Static pressure at HPC outlet | psia |
| phi | Ratio of fuel flow to Ps30 | pps/psi |
| NRf | Corrected fan speed | rpm |
| NRc | Corrected core speed | rpm |
| BPR | Bypass Ratio | _ |
| farB | Burner fuel-air ratio | _ |
| htBleed | Bleed Enthalpy | _ |
| Nf_dmd | Demanded fan speed | rpm |
| $PCNfR_dmd$ | Demanded corrected fan speed | rpm |
| W31 | HPT coolant bleed | lbm/s |
| W32 | LPT coolant bleed | lbm/s |
| T48 | (EGT) Total temperature at HPT outlet | $^{\circ}\mathrm{R}$ |
| SmFan | Fan stall margin | _ |
| SmLPC | LPC stall margin | _ |
| SmHPC | HPC stall margin | _ |

knitr::include_graphics("img/turbofan2.png")



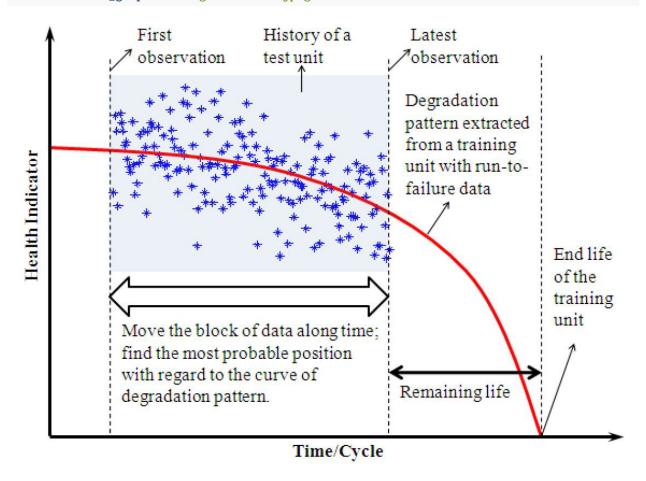
Importancia y objetivos de los análisis

Los pronósticos y la gestión de la salud son un tema importante en la industria para predecir el estado de los activos y evitar tiempos de inactividad y fallas. Este conjunto de datos es la versión de Kaggle del conjunto de datos públicos para el modelado de degradación de activos de la NASA. Incluye datos simulados Run-to-Failure de motores a reacción con turboventilador.

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En este conjunto de datos, el objetivo es predecir la **vida útil restante (RUL)** de cada motor. La vida útil restante (RUL) es el período de tiempo que es probable que funcione una máquina antes de que requiera reparación o reemplazo. Al tener en cuenta RUL, los ingenieros pueden programar el mantenimiento, optimizar la eficiencia operativa y evitar tiempos de inactividad no planificados. Por esta razón, estimar el RUL es una prioridad máxima en los programas de mantenimiento predictivo.





2. Integración y selección de los datos de interés a analizar.

Integración

La integración o fusión de los datos consiste en la combinación de datos procedentes de múltiples fuentes, con el fin de crear una estructura de datos coherente y única que contenga mayor cantidad de información.

```
library(dplyr)
library(e1071)
library(zeallot)
library(stringr)
library(data.table)
library(DT)
library(DataExplorer)
library(ggcorrplot)
library(plotly)
library(anomalize)
library(zoo)
library(tibbletime)
library(h2o)
library(isofor)
library(boot)
library(mice)
library(ggpubr)
library(MASS)
library(TTR)
library(caret)
library(FNN)
library(dbscan)
library(outliers)
library(car)
```

```
trainset <- fread("D:/UOC/Tipología y ciclo de vida de los datos/PRA2/CMaps/train_FD001.txt")
names(trainset) <- c('unit_number', 'time_in_cycles', 'altitude', 'mach_number', 'TRA', 'T2', 'T24', 'T</pre>
testset <- fread("D:/UOC/Tipología y ciclo de vida de los datos/PRA2/CMaps/test_FD001.txt")
names(testset) <- c('unit_number', 'time_in_cycles', 'altitude', 'mach_number', 'TRA', 'T2', 'T24', 'T3</pre>
y_testset <- fread("D:/UOC/Tipología y ciclo de vida de los datos/PRA2/CMaps/RUL_FD001.txt") %>% pull()
read_logs <- function(path = "D:/UOC/Tipología y ciclo de vida de los datos/PRA2/CMaps"){</pre>
  files <- c("FD001.txt", "FD002.txt", "FD003.txt", "FD004.txt")
  sets <- c("train", "test")</pre>
  files <- apply(expand.grid(sets, files), 1, paste, collapse="_")
  f <- file.path(path, files)</pre>
  d <- lapply(f, fread)</pre>
  names(d) <- str_remove(files, ".txt")</pre>
  columns = c('unit_number','time_in_cycles','altitude','mach_number','TRA','T2','T24','T30','T50','P2'
           'Nc','epr','Ps30','phi','NRf','NRc','BPR','farB','htBleed','Nf_dmd','PCNfR_dmd','W31','W32')
  temp_func = function(df){
    names(df) <- columns</pre>
    return(df)
    }
  d <- lapply(d, temp_func)</pre>
```

```
return(d)
}

#dfs <- read_logs()

#trainset <- bind_rows(

# dfs$train_FD001#,
    #dfs$train_FD002,
    #dfs$train_FD003,
    #dfs$train_FD004

# )

#testset <- bind_rows(

# dfs$test_FD001#,
    #dfs$test_FD002,
    #dfs$test_FD003,
    #dfs$test_FD004

# )

#trainset$set <- "train"
#testset$set <- "train"
#testset$set <- "test"</pre>
df <- trainset</pre>
```

Selección

Features Selection 1

```
FindOutliers <- function(x) {</pre>
  if(class(x)%in% c("numeric", "integer")){
    lowerq = quantile(x, na.rm = TRUE)[2]
    upperq = quantile(x, na.rm = TRUE)[4]
    iqr = upperq - lowerq #Or use IQR(data)
    # we identify extreme outliers
    extreme.threshold.upper = (iqr * 3) + upperq
    extreme.threshold.lower = lowerq - (iqr * 3)
    result <- which(x > extreme.threshold.upper | x < extreme.threshold.lower)
    output <- length(result)</pre>
  } else {
    output <- 0
    }
 return(output)
DataProfiling <- function(df){</pre>
  column_names <- colnames(df)</pre>
  column_classes <- as.vector(sapply(df, function(x) class(x)))</pre>
  column_mean <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){mean(x, na.re</pre>
  column_sd <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){sd(x, na.rm = "</pre>
  column_median <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){median(x, :
  column_max <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){max(x, na.rm =
```

```
column_min <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){min(x, na.rm =
  column_nunique <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){length(un
  column_quantile0 <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){quant
  column_quantile25 <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){quant</pre>
  column_quantile50 <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){quant</pre>
  column_quantile75 <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){quant
  column_quantile100 <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){quant</pre>
  column_interquartile_range <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer"
  column_skewness <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){skewness</pre>
  column_kurtosis <- as.vector(sapply(df, function(x) if(class(x)%in% c("numeric", "integer")){kurtosis</pre>
  column_na <- as.vector(sapply(df, function(x) sum(is.na(x))))</pre>
  column_zero <- as.vector(sapply(df, function(x) sum(x==0)))</pre>
  column_outliers <- as.vector(sapply(df, FindOutliers))</pre>
  df_table <- tibble(</pre>
    names = column_names,
    classes = column_classes,
    min = column_min,
    max = column_max,
    n_unique = column_nunique,
    mean = column_mean,
    sd = column_sd,
    median = column median,
    quantile_0 = column_quantile0,
    quantile_25 = column_quantile25,
    quantile_50 = column_quantile50,
    quantile_75 = column_quantile75,
    quantile_100 = column_quantile100,
    interquantile_range = column_interquartile_range,
    skewness = column_skewness,
    kurtosis = column_kurtosis,
    MissingValues = column_na,
    n_zero = column_zero,
    Outliers = column_outliers
    )
 return(df_table)
}
temp <- DataProfiling(df)</pre>
unique_columns <- temp$names[temp$n_unique == 1 & !is.na(temp$n_unique)]
print(unique columns)
                    "T2"
## [1] "TRA"
                                "P2"
                                                                     "Nf dmd"
                                            "epr"
                                                         "farB"
## [7] "PCNfR dmd"
df <- df %>% dplyr::select(-one_of(unique_columns))
trainset <- trainset %>% dplyr::select(-one_of(unique_columns))
testset <- testset %>% dplyr::select(-one_of(unique_columns))
```

Preprocesado de los datos

Feature Engineering 1

Remaining Useful Life

```
add_remaining_useful_life <- function(df){

df <- df %>%
   group_by(unit_number) %>%
   mutate(max_time_in_cycles = max(time_in_cycles)) %>%
   ungroup() %>%
   mutate(
    RUL = max_time_in_cycles - time_in_cycles
   ) %>%
   dplyr::select(-max_time_in_cycles)

return(df)
}
```

Cumulative terms

```
add_cumulative_features <- function(df, columns){
    df <- df %>%
        as_tibble() %>%
        group_by(unit_number) %>%
mutate(
        across(
        all_of(columns),
        list(
            cumsum = cumsum,
            cummin = cummin,
            cummax = cummax
        ),
        .names = "{.fn}_{.col}"
    )
    return(df)
}
```

Lag terms

```
add_lag <- function(df, columns, num = 1){

for (i in 1:length(num)) {
   num_temp <- num[i]
   df <- df %>%
        as_tibble() %>%
        group_by(unit_number) %>%
        mutate(
        across(all_of(columns), ~lag(.x, n = num_temp, default = NA), .names = paste0("lag", num_temp,
```

```
)
}
return(df)
}
```

Moving Average terms

```
add_moving_avg_features <- function(df, columns, num = 5){</pre>
 for (i in 1:length(num)) {
    num temp <- num[i]</pre>
    df <- df %>%
      as_tibble() %>%
      group_by(unit_number) %>%
      mutate(
        across(
          all_of(columns),
          list(
         rollmean = ~rollapplyr(.x, num_temp, FUN = mean, fill=NA),
         rollsd = ~rollapplyr(.x, num_temp, FUN = sd, fill=NA),
         rolliqr = ~rollapplyr(.x, num_temp, FUN = IQR, fill=NA)
         ),
         .names = paste0("{.fn}", num_temp, "_{.col}")
        )
 }
 return(df)
}
```

Interaction terms

```
add_interaction_terms <- function(df, columns){
    df_1 <- df %>% dplyr::select(all_of(columns))
    df_2 <- df %>% dplyr::select(!all_of(columns))
    df_interaction <- as.data.frame(model.matrix(~ .^2-1,df_1))
    df_output <- bind_cols(df_2, df_interaction)
    names(df_output) <- gsub(x = names(df_output), pattern = ":", replacement = "_")
    return(df_output)
}</pre>
```

Todos juntos

```
columns <- c("altitude", "mach_number","T24", "T30", "T50", "P15", "P30", "Nf", "Nc", "Ps30", "phi", "N
trainset2 <- trainset %>%
   add_remaining_useful_life() %>%
   add_interaction_terms(columns) %>%
   add_lag(columns=columns, num = 1:5) %>%
   add_moving_avg_features(columns = columns, num = c(3, 5)) %>%
   add_cumulative_features(columns=columns)
```

```
y_trainset <- trainset2$RUL

testset2 <- testset %>%
   add_interaction_terms(columns) %>%
   add_lag(columns=columns, num = 1:5) %>%
   add_moving_avg_features(columns = columns, num = c(3, 5)) %>%
   add_cumulative_features(columns=columns)
```

Benchmark

```
## RMSE Rsquared MAE
## 31.7404750 0.6525414 26.1234550
```

Análisis estadístico descriptivo

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| 4 h | tBleec248942.5756806080262709.1477.925925777.4394925685920257724334925886008080080804088765 0 | 0 | 0 |
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| 4 V | V32melr4734.D2D2920722143967.6212422149751.7478341.60292794673755758411.60976D2807.82323665 - 0 | 0 | 0 |
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| T50_NRmel:125255868736807370648569203333302523704684350397370803336374020360743128 T50_BRRel:1589.723112365532694.680.21738766892824708052905728809672423884762.4820.5253798 0 | 0 | 18 0 |
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| 1/11_DHUM1en967924 xxx299 H3292400039x929239H32.5H8B33444xxx20H3223025846622222H392025690025 0 | U | U |
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| BPR_ W.62 et 93 .83 D06.8822186 96.61 2.2235D06 .61 E73.63D068.11218.24E77.68D08.7322186 5046 0.008 2 . | - 0 106131 7047 | 0 | 0 |
| htBleed <u>u</u> ttvat6027.1154870 56 800 050 62.578. 59.33523 53.5560270 052 2200 032 2660 052 200 0755 0870 75 64800 00.00 66. | 7046 61336 | 0 | 0 |
| htBleed <u>u</u> hv3nd 7.892790.70211700 05 7.633.842817372.728870896370.038870712870.90277907041.6903 000 0. 0.0065 | | 0 | 0 |
| W31_ W32 6877.4392505053666904.033 0732 59340.789745263979.6009 7.78 97452641278571536407015 0.4464 | - 0 255 7494 | 0 | 0 |
| lag1_altimedeie 0.00870509 - 0.00210866000000 - 0.0000000015000087000030000 | - 100 D89 5190 | NA | 0 |
| lag1 macheriemba0006D40 0.0000026022938000000 - 0.00000000300000600005000081 | | NA | 0 |
| 0.0006000 0.000 60.00 02000 1. | 1307571 | | |
| | 1201506 | NA | |
| $ m lag1_Ti30meli571.046D69299200590.464783793870.045670.04586624590.065994306D698.06000002945$ | 601 100 0045267 | NA | 0 |
| lag1_Ti50mel382.2546695400020408.8 26827947 7.9 736224540234407394 4D44 64689542042000 04084 0. | 580 100 1978799 | NA | 0 |
| ${\rm lag1_Pit5me2ric6002D60100300021.609802332923102D6002D60102D60102D60102D60102D6010000000000$ | | NA | 406 |
| lag1_P60m649.855560065090053.377. 87 54753.45549.855552025560455504005560600000000 | - 100 0036383 | NA | 0 |
| 0.57 a.1 lag1 Nfum@387.9266604500002888.09.572238158.02667.92666026660236602466024660266026602660266026602660266 | | NA | 2 |
| lag1 Ngum 4021.73226.6665049065.0267632\$1037.6902D.73056.04060.6606060602266606250025057. | | NA | |
| ${\rm lag1_Psilone46c8504804800500047.5380.276385251046085047650470500470700480480065000004481}$ | | NA | |
| lag1_phitme518.6952503842200521.421.572865724.485D806952009652D48512D965126C8D00000000 | - 100 9 78 7752 | NA | 0 |
| lag1 NRfm&387.8236604940002888.09539423388.023670823660023660023660023660400000004191. | | NA | 2 |
| lag1_NRum&699.92266.260268943.68469481440.58099.98126028D40.58D4825268.264.9900215228. | | NA | 660 |
| ${\rm lag1} \\ {\rm _BRRne8:} \\ {\rm i324980584800048.44170163713338780624980404880438780465135084800503506741} \\$ | | NA | |
| lag1_htmlres%.00400000D400893.194.5 3253 97.00 880.00892.00898.00894.00400.00210000 000000.6308 | 324 100 0703201 | NA | 0 |
| $ m lag1_Waime3sc140604301200038.818237873388306004060700603306095060950004300025000000$ | - 100 17.9 04595 | NA | 0 |
| lag1_Wi3i2ne22c8942206084700023.2903.56471250.2987208042202232020873056723060840439000 | - 100 9 2 53772 | NA | 0 |
| lag2_altimedeie 0.00870569 - 0.0021865500000 - 0.0000000015000087000030000 | - 200 | NA | 0 |
| ${\rm lag2} \\ \underline{\ \ } \\ {\rm lag2} \\ \underline{\ \ } \\ {\rm mach} \\ \underline{\ \ } \\ {\rm eriemb} \\ \underline{\ \ } \\ {\rm 0.0000000000000000000000000000000000$ | | NA | 0 |
| ${\rm lag 2_Ti24m64d}. 216000506060642.670.77992542.64601020602232602260429960050006700002855$ | | NA | 0 |
| ${\rm lag 2_Ti30mel} \\ 1.0460609297700590.4673234590.08570.04586.22590.0857942460698.02000002819$ | 1325772 420 200 0106444 | NA | 0 |

| | | | | _ | - | | | | | | | | | - · · | | |
|-------------------|---|-------------------|---------------------|---------------------|----------------------------|---|---------------------|--------------------------|--------------------------------|--|-------------------------|--|-----------------------------|-----------|-------|-------------------|
| | classemin | | | | | | | | | _ | | | | | ngVz | e Ono tsli |
| lag2_T | D 50 melr 3 82 | .254060 | 589 651 | 0408.78 | 28987 | 2174907 7. | 9066202 | 64002 .0 | 304007).0 | 900000.3 | B4B8.50 | 2.0200 000 | 0.208 0.208 | | NA | 0 |
| 0. T | 215 01 00 | റത്താരവ | 000000 | 1 000 | തമാവ | റമ ാന ″ 1 | വരു വരു വരു വ | തന അവ | റത്താ അവ | റത്താ അവ | തന അവ | | | | TAT A | 100 |
| ag2_F | Pil 5 me2r1c6(|) (JR)TY(Q)(J | 10000002 | 21.609 | XUU3. | 329D.00 I | | RITIOU | OKUNOU | OKULIOU O | RITIOO CO | | | 822111210 | NΑ | 406 |
| о т | 200 510 (| | | 350.00 | ህ መው ታ ፣ | arrena 1 | FFO 6000 0000 | | ത്രാഹത വ | ~~~~ | ernervan ananer | | 8801151 | 200 | NT A | 0 |
| ag2_F | PBOme549.8 | S SORROY W | |)53.3 8 | ાજ્યા | 55025 .4 | | OWEND | POPPRIA | 300AUU2 | EDIDIOIOL | | | 200 | NA | U |
| 0.3 | TC 000 | (ADAYAYA) | 0 27000 | 2000 | ao ⊭oa⊛-o c | N#00#200 | O30303050 €0 | 280/20 /20/20/20/ | (D)(D)(D)(D)(D)(D) | @@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@ | 0 40000000000 | | 35 79.627 0 | | 37.4 | 0 |
| | Vafume 2:3 87 | | | | | | | | | | | | | | NA | |
| _ | Vicum @ 1021 | | | | | | | | | | | | | | NA | |
| ag2_F | Pasionetocs: | 50408.408 | 80 10506 004 | 17.5340 | 9.62650 | 545541 | .0406.8650 | 4070.03(4) | 04070.6501 | 04070.07000 | 48.4800 | 1 36 0000000 | $1272748 \\ 0.223$ | | NA | 0 |
| 0 | .1.: £10 (| ാവസത്തെത | രഹതാ | 101 400 | ስ <i>ር</i> ብጠና | 00739T14 A | വസത്ത | | യ ാതവ | തന്ത്രന തര | ന്നത്തെ തത്ത | | | | NA | 0 |
| ıg∠_p | ohimer18.0 |) HORTON D | MATTANOR |)21.4 2) | 9.9 <i>4</i> W3 | XXXX 14.4 | : SOLPOOR | OKIUIGI | | SWATTISW | IOTATION CONT | | ' - 101 07.312987 | 200 | INA | U |
| | ViRufme 2:3 87 | ത്തത്ത | മ്മ ത്വറെ | 10 00 m | ስ <i>ሰረታ</i> ውና | 2000 (2000) | ത്തുത്ത | TO TO TO TO TO | നവത്തെ | നമാ ത്തെ വ | വതാതാത്ര | | | | NA | 0 |
| | | | | | | | | | | | | | | | | |
| ~ — | ViRume 1099 | | | | | | | | | | | | | | NA | |
| ig2_E | BiRikneri324 | 19619184 | FSTRAIT S | 5.4413 | RO RO | 185.4558 | 46.50249 | 81444 | (8).4 5 8 | 481.41048 | &198 480 | MOOTUME | | | NA | U |
| | | | | | | | | | | | | | 0.139 | | | |
| ig2_h | nta Bhaeils 8.0 |)()410101010 | IODA OOE | 3 93.171 | 9.5886.E | £3953 .0 | CRRRIOO | BHHLLOO | ORBIBIRION | ORBANOO | 41010101002 | 1000000000 | | | NA | 0 |
| | | | | | | | | | | | | | 0.084 | | | |
| $g2_V$ | M3:1me3:8c 14 | 40 89 0.43 | 80DDD003 | 38.820 | 1.367(| B8.8 3 | 6 0808.04 0 | BB.070 | 088.83 | O BB.95 0 | BD 43 00 | | | 200 | NA | 0 |
| | | | | | | | | | | | | | 3178.054 | | | |
| $g2_V$ | M312 ne212c89 | 94239.60 | 84600002 | 23.2910 | 9.626 | 1 253.4 9 | 92420.894 | 20.00 | 423.09 | 9 2431.36 7 | 243)60 89 | | | 200 | NA | 0 |
| | | | | | | | | | | | | 0.3 | 31702.41420 | 3220 | | |
| g3_a | a ltitmde ie | 0.008 | | | | 18.64 0 | 00000 | - | 0.000 | 0 0.00 15 | 0.00 870 | 0 00 30000 | - | 300 | NA | 0 |
| | 0.008 | 37000 | (| 0.0000 | 073 | | 0.0087 | 0.001 | 5000 | | | 0.0 |)29 5.3512 | 4056 | | |
| g3_n | n ach erien | nb @ :000 | 06 D4 00 (| 0.0000 | 0.26 02 | 29.88 0 | 0000 | - | 0.000 | 00.0003 | 0.00 060 | 0 00 050000 | 087298 | 300 | NA | 0 |
| | 0.000 | 06000 | | | | | 0.0006 | 0.000 | 2000 | | | | 1.134 | 0397 | | |
| g3_Т | D24me64d. | 216000.5 | 608004 06 | 342.66 | 5.4961 | 66)4127 .6 | 46400.20 | 6400.30 | 2642 .60 | 464Q.98 | 644.500 | .6600 C | 711679 | 300 | NA | 0 |
| | | | | | | | | | | | | | 0.139 | 1064 | | |
| д3 Т | D 30 me lr57 1 | .046006. | .921.935601 | 16 90.3 | 4935 9 | 1 2 590. | 0.000000 | A5080 6.0 | O O O O O O O | 0.0466400 | 0 606.97 | L965000.0 | 698408 | 300 | NA | 0 |
| | | | | | | | | | | | | | 0.012 | | | |
| g3 Т | D50metr382 | .254060 | . 589 861 | 0008.68 | 3.7429 | 50 549007. | 8BBBD0 | 6 4002.0 | 20 4007.0 | 8B 4000.2 | Q4088.50 | 11.930000.6 | 8 96036 | 300 | NA | 0 |
| 0 — | | | | | | | | | | | | | 0.209 | | | |
| g3 F | Pil 5 me 2 1c60 | 0201.60 | 0000002 | 21.6093 | 80033 | 32919.66 1 | O 2 010.6600 | 2 00.60 | 02010.660 | O 2 010.6601.0 | 2010.60 0.00 | 00000000 | 45.09 | 130998 | NA | 406 |
| 0 — | | | | | | | | | | | | | 8621995 | | | |
| g3 F | P 30 m ejr49 .8 | 856660 | 1641919) OF | 3 53.390 | 6.8567 | 55502 .4 | 654490.895 | 616121.6W | 456B.4 6 | 65BA.002 | T600.60EE | | | 300 | NA | 0 |
| 0 | | | | | | | | | | | | | 34102.22654 | | | - |
| g3 N | Vafume 2:3 87 | .921818B) | 357 000 | 288.0 9 | 9.0681 | 88 13818. | 0288719 | POGRESSE).(| 021388).0 | 00208880 | 2 1308080.030 | 6,0000000 | 18508.80284 | 330300 | NA | 0 |
| ~ — | Vicum 902 1 | | | | | | | | | | | | | | NA | |
| ~ — | Pa:30ne46c8 | | | | | | | | | | | | | | NA | |
| 50 <u>-</u> - | 11011101010 | | .02000 | 11.001 | 2.20 0 (| 741101 | | | | | | ,,,, ,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,, | 0.249 | | | Ü |
| σ3 n | himeri8.9 | 25KMR/R | SADOMOF | 921 430 | KUSEUK | SMOUR 4 | | KIPIMOC | RESTRICTION OF | | TOTAL CHARGE | | | 300 | NA | 0 |
| 80—P | ,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,, | | | 21.10 | 200 | .,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,, | | <u> </u> | 0020 | 0041.00 | 020.000 | | 380 7.7224 | | 1111 | O |
| σ3 N | ViRufme 2:3 87 | STREE | 35 11000 | വ | oaro | AND PLANS | (1998)F) (A | (DKR)KR)KI | MOLENER I | nggreen a | <u> </u> | | | | NA | 0 |
| | ViRume 1099 | | | | | | | | | | | | | | NA | |
| _ | SiRikneri&24 | | | | | | | | | | | | | | NA | |
| გ ⊍ _∟ | личнительн 24 | 1 701.01094 | CINDIDIO C |). 44 UX | ≖வன∪ெ | JAHOO | 20. 014 43 | wat 41 | WHOO. | 4W44 | ന്നെവാറുക | JUUUGEOUUL | 0.141 | | IVA | U |
| _ຕ 9 1₋ | +Dilmedico | വഹത്ത | MTALL |) NO 164 | и ш _{ото} ч | ഗമാത്ര മാഹ | പ്രത്യത്ത്രത്ത്രത്ത | മ ന്നു പ്ര | നമാനതാ സ | ጠወንጠ ብ ጠጣ | ഹസ്തമ്മ | വക്കുന്നുകൾ | | | NT A | 0 |
| go_n | ntaBaleneal\$8.0 | | MTAPOOL |)93.10 <u>1</u> | H-0)K) ((1 | J ULZ Ø. () | Maranan | | Mrannar | MARKAGA | PETATA MANAGARA | | | | NA | U |
| ~9 τ | W949.0-1 | 4 നത്തെവര | വസമാഹ | 00 0016 | ስ <i>ለ ም</i> ም ፣ | ലുത തി | വരുതുവുവ | തത <i>്</i> പ | ന്ത്രത്തത്ത്യ സ്ത്രത്തത്ത്യ | ന്ത്രത്തെ അഭ്ര | ത്തവരാഗ | . ച വത്രവാവം | 0.084 | | NT A | 0 |
| go_V | Willime3% c14 | +000001413 | OUUUU | 08.8210 | #U49 5 | ാവമ്മു 👸 3 | | DNIGG | | COPPOSITE CONTRACTOR (C) | PANCAP ((() | | | 300 | NA | U |
| 0. * | 1700 00 0 | വ ഷത്രമാശായ | 0.4465555 | | መብጥ ታ ረ | വരുടെ കുറ | ഗത്തെത്തെ | തമ തര | ⊭∂⊞ @ @@ | റത്തത അത | onon one ~ | | 306 7.7253 | | 3.T.4 | 0 |
| g3_\ | M32ne22c89 | 94281.60 | 8446JBJL)2 | 23.2930 | W3 D42 | 233 30 | ULLL)(3994 | <i>22</i> 61.CAC2 | 523030 | OLUSIONS | KRIQU 8 3 | | | 300 | NA | U |
| | | | | | | | | | | | | 0.3 | 3050.51422 | 4219 | | |

| | <u> </u> |
|--|----------------|
| 0 = | NA 0 |
| | NA 0 |
| 0.0006000 0.000600000000000000000000000 | NA U |
| | NA 0 |
| 0.1473674 | 111 0 |
| | NA 0 |
| 0.0065031 | |
| $ m lag4_Ti50metr382.2546804688604008.53.66865497.788820264020264070784040426804608600003673928~400$ N | NA 0 |
| 0.2363099 | |
| $ m lag4_P115me2r1c6002D60100300021.6097.99342D45102D6002D6002D6002D6002D6000D00000000000$ | VA 406 |
| 6.8442371 | |
| | NA 0 |
| 0.3236.2272780 | 7.1 0 |
| 0 = | NA 0 |
| 0.0067720 | T A 700 |
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| $\begin{array}{cccccccccccccccccccccccccccccccccccc$ | NA U |
| | NA 0 |
| 1.3636.223.2518 | VA U |
| *************************************** | NA 0 |
| ▽ <u>−</u> | NA 575 |
| © — | NA 0 |
| 0.1428007 | |
| lag4_htBlacd58.00699.00000000893.150.49733353.00668.00692.00693.00694.00699.0002.00000002.912279 400 N | NA 0 |
| 0.1017056 | |
| ${\rm lag4_Wikimeisc1406004300007038.8237.4438387.8306800406807006808306809506004300024000000} - 400 {\rm New Constraints of the Constraints of t$ | NA 0 |
| 0.289 7.683 4606 | |
| | NA 0 |
| 0.2890.6826221 | T.A. O. |
| | NA 0 |
| 0.0087000 0.0000068 0.008700015000 0.03003046354 lag5 macheriembee006D40 0.0000270293300000 - 0.0000000030000600005000079244 500 N | NA 0 |
| $\begin{array}{cccccccccccccccccccccccccccccccccccc$ | NA U |
| $\frac{0.00000000}{1.1348525} = 0.00000000000000000000000000000000000$ | JA O |
| 0.1430997 | 111 0 |
| | NA 0 |
| 0.0186507 | 0 |
| lag5_Ti50met;382.2546804894404088.48.720484297.72882026402024070704080948804607700003495435 500 N | NA 0 |
| 0.2555627 | |
| ${\rm lag5_Pit5me2ric6002D6010000021.6097.983.4255102D6002D6002D6002D6002D6000000000000000$ | VA 406 |
| 6.8262275 | |
| 0 = | NA 0 |
| 0.310 3.230 6295 | |
| 0 = | NA 0 |
| 0.0240081 | TA 070 |
| 0 = | NA 676 |
| | NA 0 |
| 0.2672464 lag5 phium &19.1452803840 60 05 21.4 53839885 38550 5000045520000520.90520.9055283909700 0000 - 500 N | NA 0 |
| 1ag5_pmtmerre.14akasao4wwooz1.43saboaszabsowszabsowakaswowakasowkasowkowooo | 1A U |
| U.33U@22%0 (304 | |

| names class es in max n <u>uniquae</u> n sd mediaquantid <u>etatitidetat</u> | ngVz | — Chots liers |
|---|------|-------------------------|
| lag5_NRfme2387.8238835500002988.09.276552328.023871.8233881023881023881023881023881000000013365176 500 | NA | 0 |
| 0.0101762 | | |
| ${\rm lag} 5_{\rm NRm} - 8099.92268.03582808043.178633824466.480000.921033.0310400425048.007268.09407300200417.52831638$ | NA | |
| lag5_BiRineri22490567806498.44020.08578.4B7780502498040438403778046348056780.04905013177248 500 | NA | 0 |
| 0.1434169 | | |
| ${\rm lag 5_ht} {\rm Binedis} 8.0069900000000993.1354830197.00668000692006930069400699000200000002808471~500$ | NA | 0 |
| 0.0992936 | | |
| ${\rm lag5_Whitneisc14060400000038.8254672335.\$4060140607006084060950604300024000000} \ \ - \ \ 500$ | NA | 0 |
| 0.27 798479 2075 | | |
| ${\rm lag5_Wi32n4268942306084547023.2951.62532320122089423022823300123036873060840402500} - 500$ | NA | 0 |
| 0.2763.79747333 | 37.4 | |
| rollmeamusmartictude.004687070 - 0.0012626000000 - 0.0000000008383846660717000 - 200 | NA | 1 |
| 0.0063000 0.0000087 0.0063 0.00 008667 0.026 2.5019 3285 | 37.4 | |
| rollsd3_nahtidid000000642531 0.00194.00100706181.480000000117.90181.480259.42647.381415.2083.84342258 | NA | |
| rolliqr3 <u>maltidriade</u> 00000635007 0.00185394096671750000000011000017500025000635001400619305202024 | NA | |
| rollmeamu3m_emisch_0h00054993 0.0000002050107.08000000 - 0.0000000001033805338026667263494 200 | NA | U |
| 0.0005333 | NT A | 0 |
| $ {\rm rollsd3} \underline{{\bf numehio000000005774}} \ \ 0.00026460012000264600000001732026460350205770017380245260 \ \ 200 \\ {\rm rollsd3} \underline{{\bf numehio000000005774}} \ \ 0.00026460012000264600000001732026460350205770017380245260 \ \ 200 \\ {\rm rollsd3} \underline{{\bf numehio0000000005774}} \ \ 0.00026460012000264600000001732026460350205770017380245260 \ \ 200 \\ {\rm rollsd3} \underline{{\bf numehio000000005774}} \ \ \ 0.00026460012000264600000000173200264600350205770017380245260 \ \ 200 \\ {\rm rollsd3} {\bf numehio000000000000000000000000000000000000$ | NA | U |
| 0.7656307 | NT A | 0 |
| $ \text{rolliqr3} \underline{\text{num}} \underline{\text{adia0}} \text{00000000000000000000000000000000000$ | NA | U |
| 0.014 3.798 8741 rollmea mi3m&44 .50 348.39128564 2.67 7.4298242 .63 600.50342.38642.676042.99383.36676666 4466393 200 | NA | 0 |
| 10111111111111111111111111111111111111 | INA | U |
| $ \begin{array}{c} \text{0.1397773} \\ \text{rollsd3} \\ \underline{\text{n}} \\ \text{1} \\ \text{2} \\ \text{2} \\ \text{1} \\ \text{2} \\ \text{3} \\ \text{3} \\ \text{3} \\ \text{2} \\ \text{3} $ | NA | 0 |
| rolligr3nuF2@10000087508500 0.25626824212400000000005500240008750008500067143386200 | NA | |
| rollmeam3m45504.3D3D3339206590.4832835780.8P57465753333538550565753333726607005099247 200 | NA | |
| 0.0140140 | 11/1 | U |
| | NA | 0 |
| rolliqr3m4F3QriQ000DDQ40BQDD3.38495.78773.18000000020Q0030B0045050DDQ4024950000646622233286 | NA | |
| rollmeamu3maF367.3D43764TBBB33308.864282938407.85333338402.65407080583335435044B23333005263619 200 | NA | |
| 0.2474249 | 1111 | O |
| | NA | 3 |
| rolligr3mi li50 :i0200 D28 70 B05 D3.4133 5 4 7 93 7.28 500 .02 00 2 00 2 0 07 00 8 1 20 50 4 50 D2 8 7 0 D407 5000 6 34 6.287 8 B32 | NA | |
| rollmeamsm2156002D600000021.609804D82L5102D6002D6002D6002D6002D6000D00000000000 | | |
| - 4.7133815 | | |
| rollsd3 <u>n</u> Prh#ri@000@0057735 0.0003 1.00 13@8D00@000@0000@0000@0000@00577.85000&953 23.7528201 9 | NA | 1100 |
| ${\rm rolliqr3} \underline{{\rm nuPri45:}} \underline{{\rm i6000000050030}} \hspace{0.1cm} 0.0002692112850000000000000000000000000000000000$ | NA | 1100 |
| rollmea m3<u>m</u>#550 .675550 3072 6556553.374 \$0108886 .445566 67 550 2089533.344 5556 98 5555 67 6. 6967 3333 - 200 | NA | 0 |
| 0.4732224442 | | |
| ${\rm rollsd3} \underline{\mathbf{n}} \mathbf{\overline{h}3601} \mathbf{\overline{h}00000004448883} 0.359630\mathbf{\overline{h}07088364520000020509636452479611.734448.284521.6430.224762033}$ | NA | |
| ${\rm rolliqr3}\underline{{\rm m}}\mathbf{R300000035004820} \ \ 0.3433448291.42200000000000000004550035000025000026606.23812397$ | NA | |
| ${\rm rollmeam3}\underline{m}\underline{\text{A}587.926866246662388.0906272388.02383.3268662788662288662288662666070952746881295}$ | NA | |
| ${\rm rollsd3}\underline{{\rm m}}{\rm N}{\rm fn}{\rm drig}0000002214827 - 0.02678414280251660000000527.52516608510.22143347984860050148520414347861616161616161616161616161616161616161$ | NA | |
| ${\rm rolliqr3}\underline{\rm m}\mathbf{M}\mathbf{f}\mathbf{\Phi}\mathbf{i}0000002050490 \ \ 0.0254871377.4250000000000050002500005000000000000$ | NA | |
| ${\rm roll meass} \underline{\mathbf{m}} \underline{44027}. \underline{\mathbf{032346.6B32239965}}. \underline{120.4393033}. \underline{\mathbf{440270.020556670160664506807723466B33.733829973.767392007}}$ | NA | |
| rollsd3 <u>m</u> Nm4ri02516680429988B.69991L96002238057.92512622147.148054.9149623-804289984826497.228902004 | NA | |
| ${\rm rolliqr3}\underline{{\rm nu}}{\rm Nor4}; \underline{{\rm 025012390359003.533311.48033.72000.02502000.0352004.6950123.9023985000.6673.27812009}$ | NA | |
| rollmeamsim_P4639634833308620047.5390.2905475813483363473330470503473586486730033666667167147 200 0.2594036 | NA | 0 |
| rollsd3 nPs30i0000029671279 0.090037046967085049000000550750850490 9303296704064227.82595250542004 | NA | 0 |
| rolligr3nuPsaBii00000Q950DB4 0.0858650449586000000000500008000001500029500065000636221445298 | NA | |
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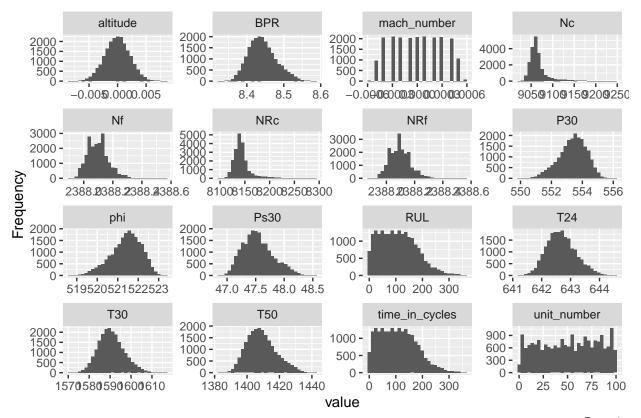
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| 0.49 7922197 44 rollsd3 <u>n</u> phid2id000D0602373950.26632.118896.25006.670000.06093.42\$006.67232.566023.5913908560357492 rolliqr3 <u>nuphid2id</u> 000D00503640.25440.48350.2400000000005500.240000350D005000050006798.45302 | |
| ollsd3 <u>nphi@i@000D@60237</u> \$50.26632.1B89&2500&6700@06093.4\$500&67232.56023.591390&56@57479 olliqr3 <u>nphi@i@000D@05086#</u> 0.2544@4\$35@2400@@000@055@2400@ G3 50D 00 50@04800@679&45302 | |
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| ollsd3 nNR@:i02081065801798342.8221226702366477.02081.67197266473.64401107.48027.02422005007.33312 | |
| olliqr3 <u>m</u> NR Q: iQ200 087 00 8002 1 2.6969D 45 92 7:24 50 0.02 00D 03 50 2154 50 8157 50 087 00D 94 00 006 72 4.478 902 | |
| ollmea m3mBBB58333 13 647 58.441 85.76 33 8.149 82 333 58 8.33 69 8.33 82 336 18 5.65 13 667 4491 6 75144393 2 | |
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| - 0.09951 | |
| ollsd3 <u>nhtnAbi@d00n0055050</u> 5_0.82446.116829.417735.00000007735.637735.034731.055056577350.3640.400472 | 800 NA 6 |
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| llmea m5<u>m</u>&170 3.462800 | | | | | | NA | |
| ollsd5 <u>n</u> NnRa c i2:1859.7779 | | | | | | NA | |
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| | | | | | 0.2350833 | | |
| ollsd5 <u>n</u> Barati 001 10.82 3 | | | | | | NA | |
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| ollsd5 <u>n</u> hthB0cie00020489 | | | | | | NA | |
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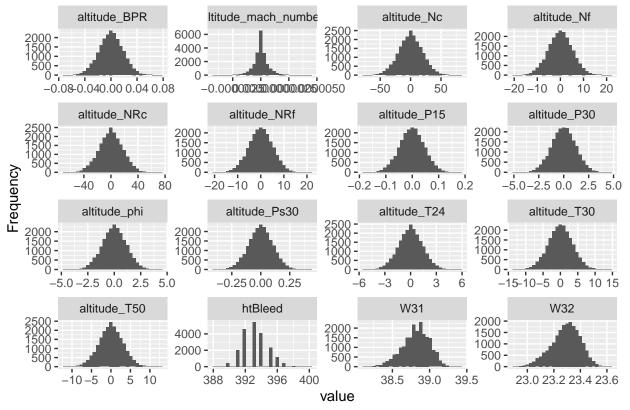
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| mmim <u>u</u> p | nle5r18.6950202086 | 8886 00 6 20.87 | 75.69408512 (1.8951)& | 1 6952 00.48520 | .8951211.3 7 51212.880.8900 | | - | 0 | 0 | 0 |
| | | | | | | | 93.293 | 5410 | | |
| | പൂടാക വെത്തുക | ROMONO 52 57 | 75.6LR 205L22 9.606020 | DROSTOPPOORTO | .6052B.0052B.380.780 | 0000 | _ | 0 | 0 | 0 |
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|---|----------------------------|---------------|-----|----------------------|
| umsum <u>ur</u> N &3 87.936040049451 2 59840.68447 34123512357 0.9 6200171246235121275142666404.99 666006 | 199837 6 | 0 | 0 | 0 |
| | 0.2190 | 301 | | |
| ummim <u>u</u> iN A\$ 87.8 8388.05 000 29 87.98 8475413 7.9 2687.82387.92387.92688.023388.05.090 0000 | 1876883 | 0 | 0 | 0 |
| | 0.9052 | 2250 | | |
| ummax <u>ur</u> N#3587.9238889560000 <u>20</u> 88.152753423648.1238799238890268890238880226889560900000 | 555.086 9 | 0047 | 0 | 4 |
| ımsum <u>ur</u> N&tid 6. 8200450020072399570 5.233.33347438.8376.8 02062739. 4330402 97 13529 90 5303 94372 813040 | 000785 6 | 0 | 0 | 0 |
| | 0.2185 | 192 | | |
| ummim <u>u</u> iN R69 9.98115188921008029.82 276492 1811.03000098112819811810091185022151889103100004 | 0 - | 0 | 0 | 0 |
| 0.3 | 309 5.386 5 | 5097 | | |
| ımmax <u>ur</u> N FRid 6.8 82010.0717116090 50.7 129.12381459 .420106 88 00411 09 104914 2 105044 322010.07120.3 4001210 | 12 259 .26 5 | 39229 | 0 | 721 |
| imsum <u>ur</u> B &R 3038055.729d0 9 06.91583.5782 29.693.73034 68.128750.09B718930755.0 9 81.9800.5 | 600 2753 | 0 | 0 | 0 |
| | 0.2170 | 9711 | | |
| | 919331 | 0 | 0 | 3 |
| | 0.1382 | 2855 | | |
| | 2170000 | 0 | 0 | 0 |
| | 0.1640 | 0209 | | |
| ımsum <u>ur</u> ht :Bil e:dDD42B20.5488 4 2709 2749611. \$5 7532 2B 00.00 20 4D44677B9 00 B98 150 2B2 400 984.0 00 | 00029 09 | 0 | 0 | 0 |
| | 0.2169 | | | |
| mmim <u>u</u> ht# 3% edC8960000000890.220.84723398.0C88800890000890000891000896000100000000 | 136.628294 | -0900 | 0 | 2 |
| mmax <u>ur</u> h tBle&D4 000.001D00 B 94.92 5.423339 \$.00890.00894.008950089600400.002.0000000 |)4 70.78 71 | 0802 | 0 | 0 |
| ımsum <u>ur</u> Ne 33 :610D40048.£94997 02 01.3 2: 67 2.524 2336 .\$9 89.600 02 0279.640036. 96 008D. 96 40048 .9 2456. 920 0 | !980 709 | 0 | 0 | 0 |
| | 0.2219 | 0665 | | |
| mmim <u>u</u> NA 33 c140 59.27 0105038.6255 .743 7 3%4 3058040580540580630580 72 05 9.27 00 03 00000 | | 637 | 0 | 1 |
| *** | 934173 | | | |
| mmax <u>ur</u> N VBE :610B94306B0039.156 7.09\$83953 50B96 0 0B9 09 0B90 5 0B9 23 0B9430004400000 | 0.2365 | 9 7 01 | 0 | 3 |
| *** | 0677189 | | | |
| ımsum <u>ur</u> HNEBB:201574BB:22007DB:538.8H2H8:4D452210B59.200072DB:338221.0B694905885621.0D4474.0Q468 | 1983 058 | 0 | 0 | 0 |
| | 0.2211 | .579 | | |
| mmim <u>u</u> NA 32 :894 23,53 49160023.177 7.6872634 81 22,89423,02126,08123,04323,5349,020 2004 | - | 0 | 0 | 0 |
| | 20 79.1102 5 | 366 | | |
| .mmax <u>un</u> N 4332 201 273.60 84275023.4938 563 52334952 3.201273.44 9223.4 9 523 .53 52336 0 84 085 9004 | - | 0 | 0 | 0 |
| 0.7 | 9 34.2512)4 | 125 | | |

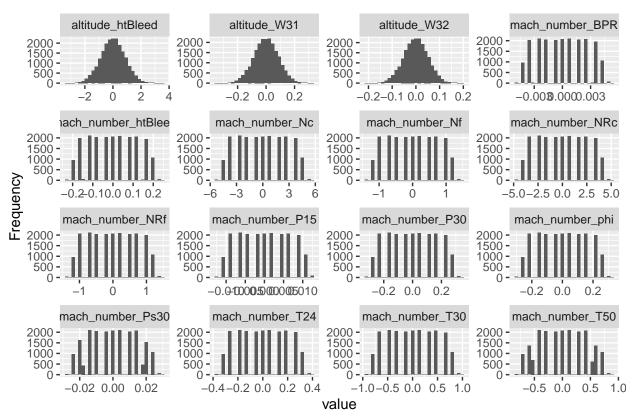
plot_histogram(trainset2)



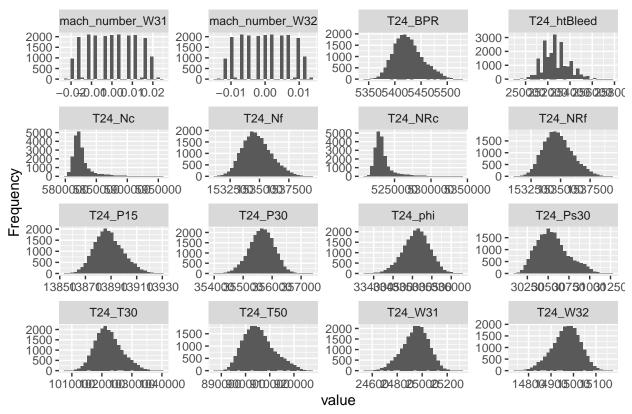
Page 1



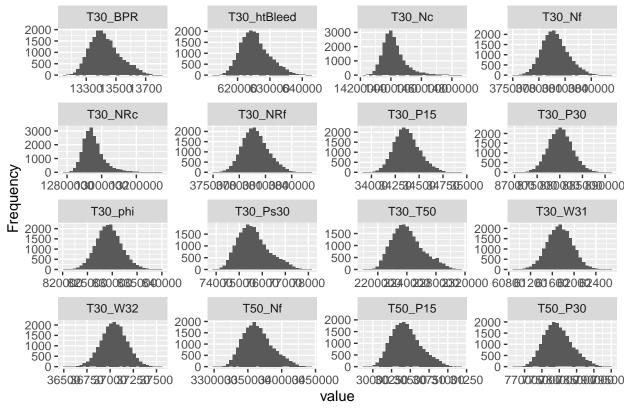
Page 2



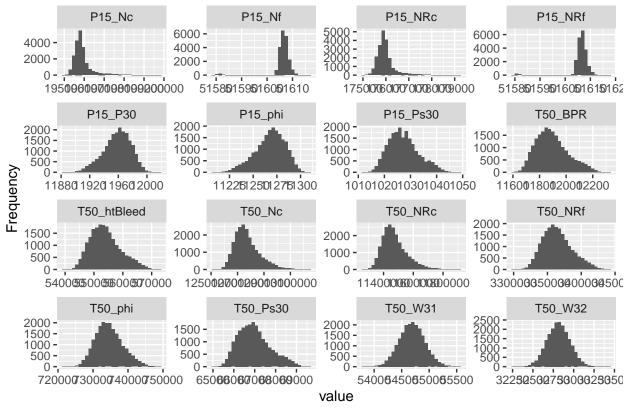
Page 3



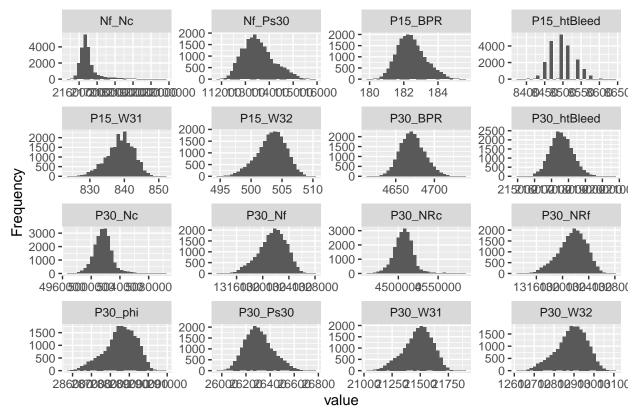
Page 4



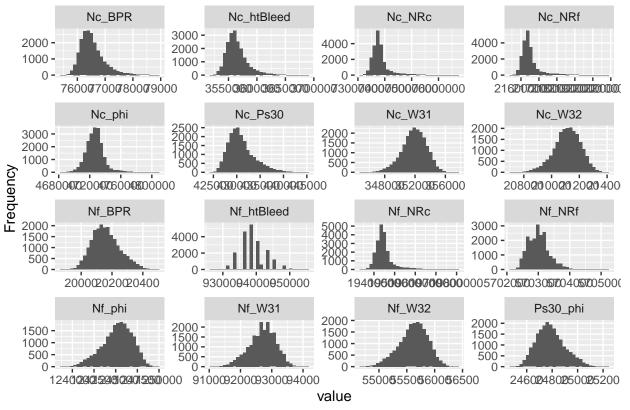
Page 5



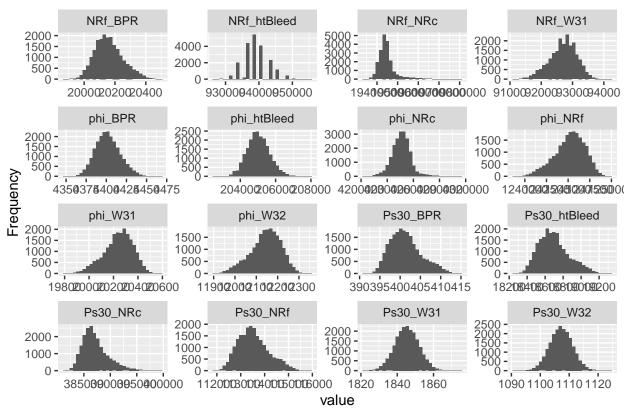
Page 6



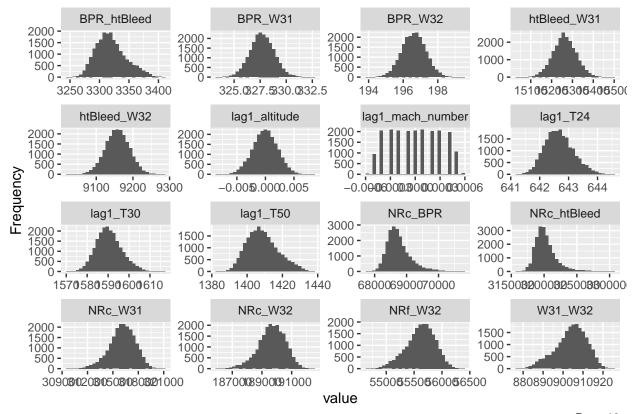
Page 7



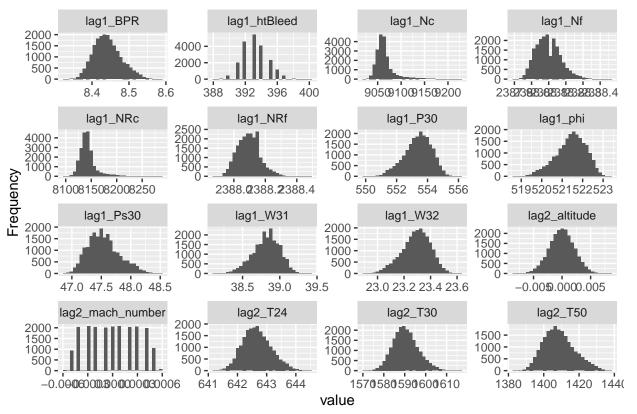
Page 8



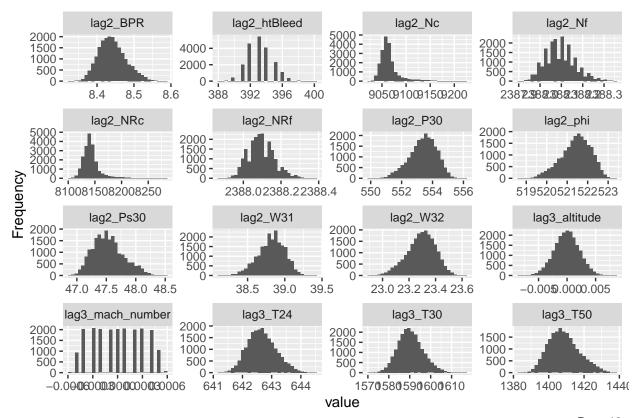
Page 9



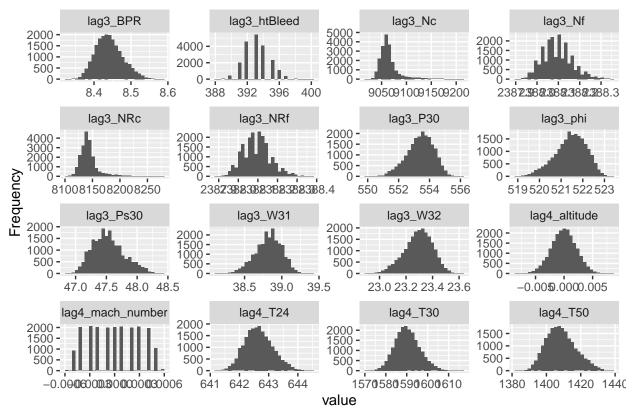
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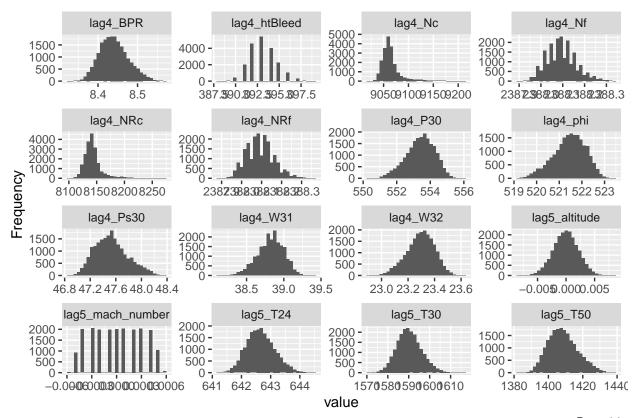
Page 11



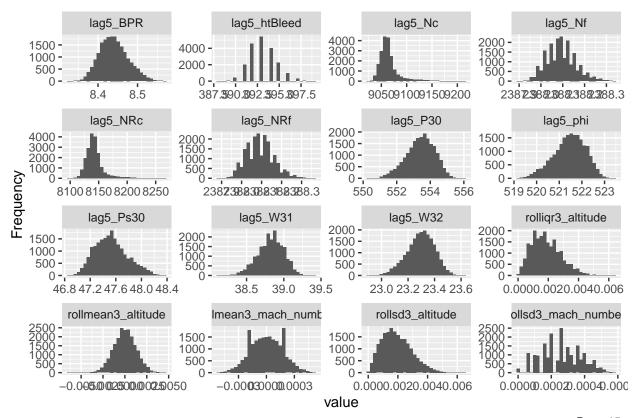
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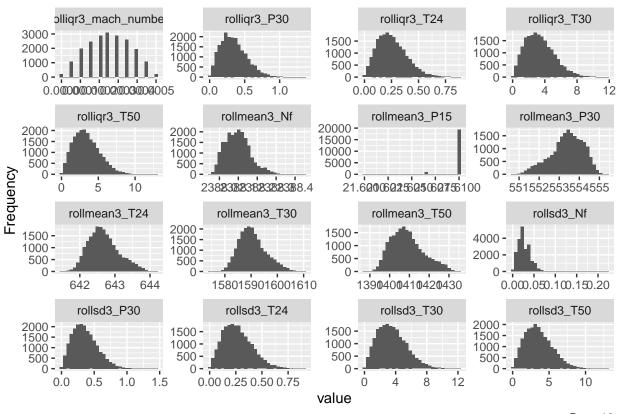
Page 13



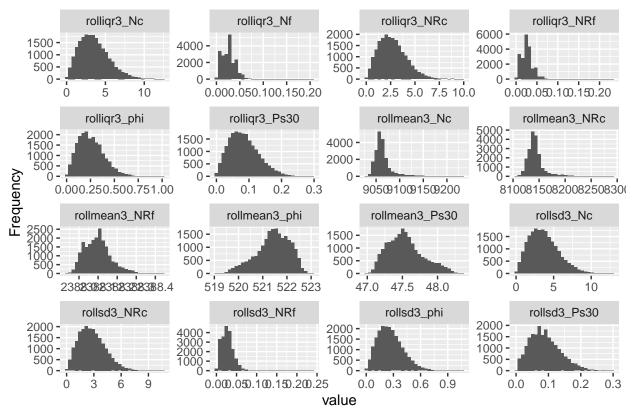
Page 14



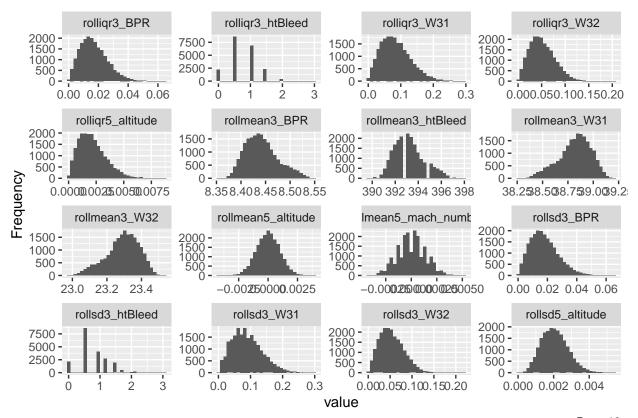
Page 15



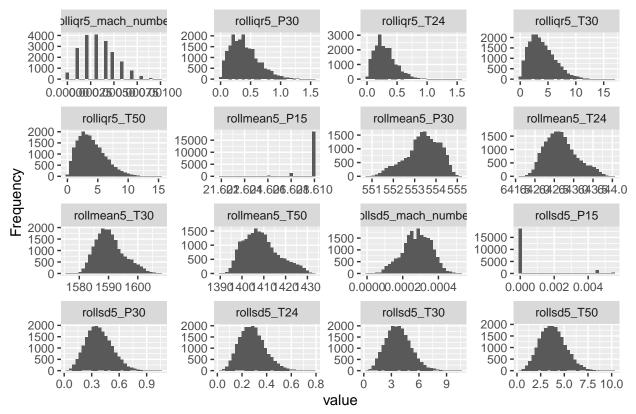
Page 16



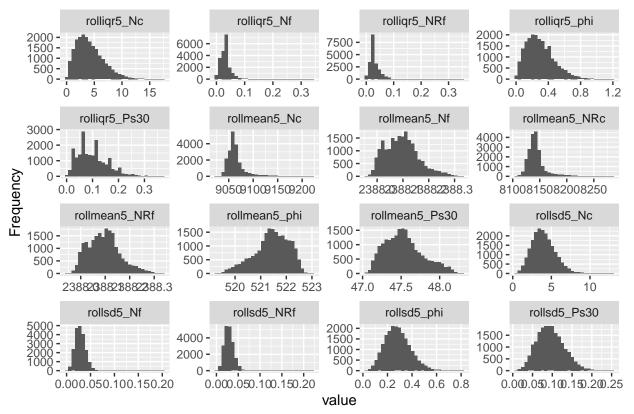
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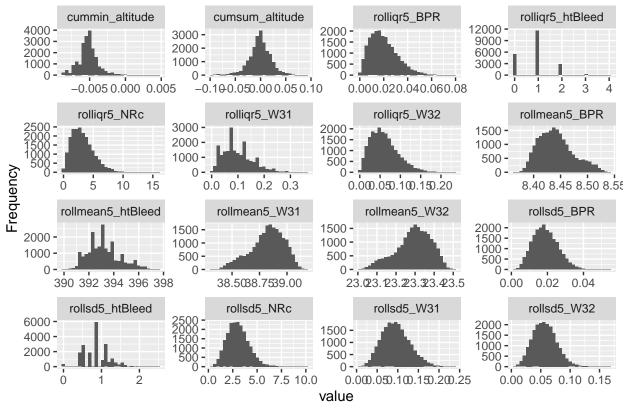
Page 18



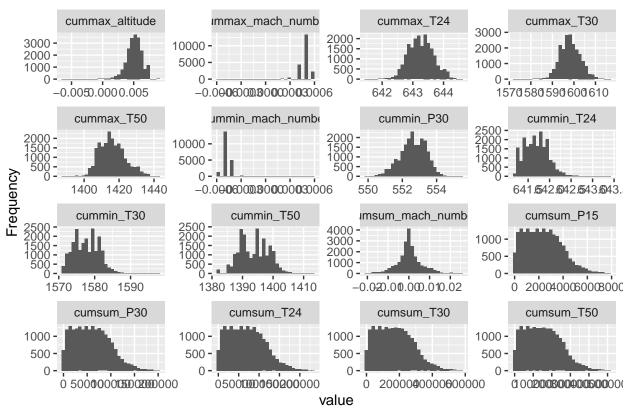
Page 19



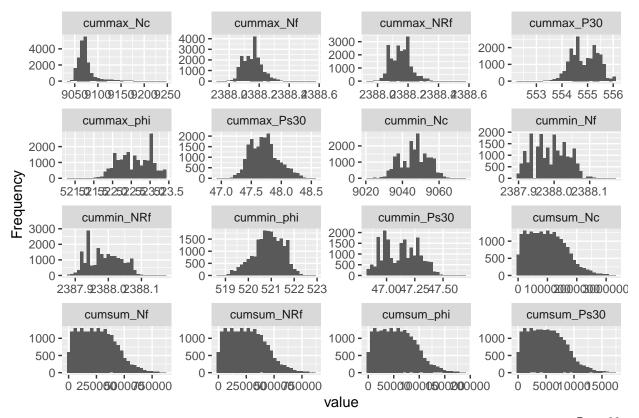
Page 20



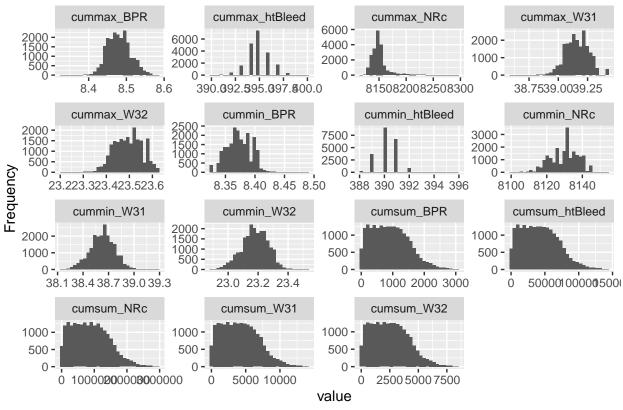
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Page 24

3. Limpieza de los datos

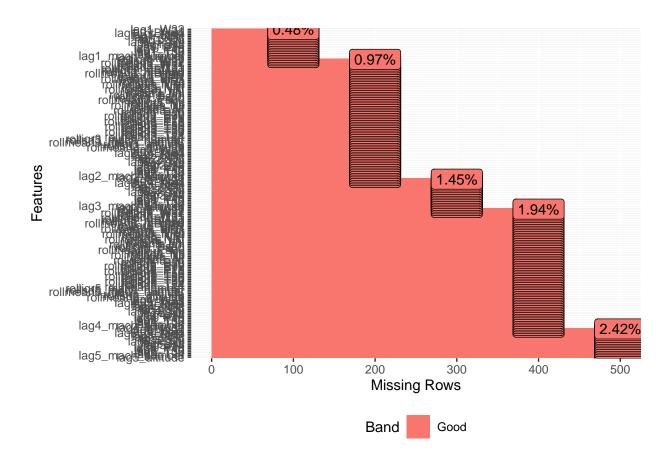
3.2. Identificación y tratamiento de valores extremos.

Nuestro dataset no tiene Missing values, pero hay valores extremos. Para

3.1. Missing Values o Ceros

Como tenemos muchas variables, filtramos las variables sin na y generamos un gráfica para conocer las columnas con NA y sus patrones.

```
columns_without_na <- colnames(trainset2[, sapply(trainset2, Negate(anyNA)), drop = FALSE])
df_columns_with_na <- trainset2[ , -which(names(trainset2) %in% columns_without_na)]
plot_missing(df_columns_with_na)</pre>
```



Como se esperaba, las columnas con lag y roll contienen NAs. Pero esto tiene que ser hasta un time_in_cycles máximo de 5. Vamos a confirmar esto:

```
df_columns_with_na$time_in_cycles <- trainset2$time_in_cycles
borra <- df_columns_with_na %>% filter_all(any_vars(is.na(.)))
table(borra$time_in_cycles)
```

Merece la pena hacer algún tipo de imputación de valor?

Para contestar a esta pregunta, vamos a ver si hay alguna máquina en nuestros datos que tenga fallado en este período:

```
trainset2 %>% filter(RUL == 0) %>% pull(time_in_cycles) %>% sort() %>% unique()

## [1] 128 135 137 147 150 153 154 155 156 158 163 165 166 168 170 172 174 178 179

## [20] 180 181 185 188 189 191 192 193 194 195 196 198 199 200 201 202 207 208 209

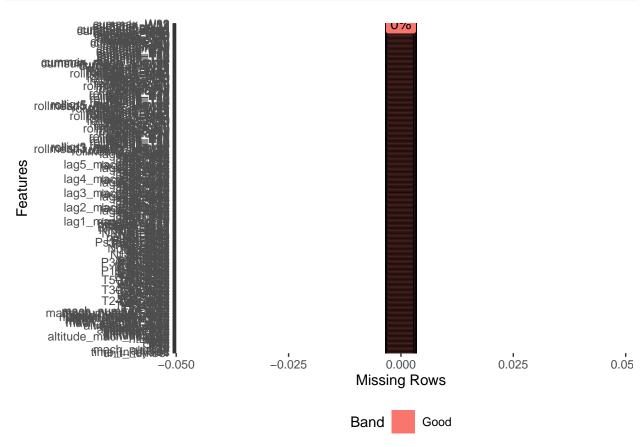
## [39] 210 213 214 215 216 217 222 229 230 231 234 240 256 257 258 259 267 269 275

## [58] 276 278 283 287 293 313 336 341 362
```

```
testset2 %>%
  group_by(unit_number) %>%
  filter(time_in_cycles == max(time_in_cycles)) %>%
  pull(time_in_cycles) %>%
  sort() %>%
  unique()
    [1]
                 37
                     39
                         46
                             48
                                 49
                                      50
                                         54
                                             55
                                                  56
                                                      68
                                                          71
                                                              72
                                                                  73
                                                                      74
  [20]
         88
                 94
                     97
                         98 101 105 106 110 112 113 121 123 125 126 130 131 133 134
       135 136 137 140 143 144 145 146 147 148 150 152 155 156 158 159 160 162 164
       165 166 168 171 172 176 177 184 186 187 189 192 195 196 198 203 205 213 217
   [58]
       232 234 244 303
```

Como se puede ver no existe ninguna necesidad de usar las observaciones de 1 a 5. Por lo tanto, vamos a eliminar estas observaciones con NA sin perder ninguna información importante para nuestro proyecto.

```
trainset2 <- trainset2 %>% na.omit()
testset2 <- testset2 %>% na.omit()
plot_missing(trainset2)
```



3.2. Identificación y tratamiento de valores extremos

El tratamiento de valores extremos es importante porque estos pueden sesgar / cambiar drásticamente las estimaciones y predicciones de ajuste. Estos datos se encuentran muy alejados de la distribución normal de

una variable o población.

Nuestros datos son basados en simulación de sensores. Esto significa a priori que no hay sospechas de que las observaciones que se desvían tanto del resto fueron generadas mediante un mecanismo distinto.

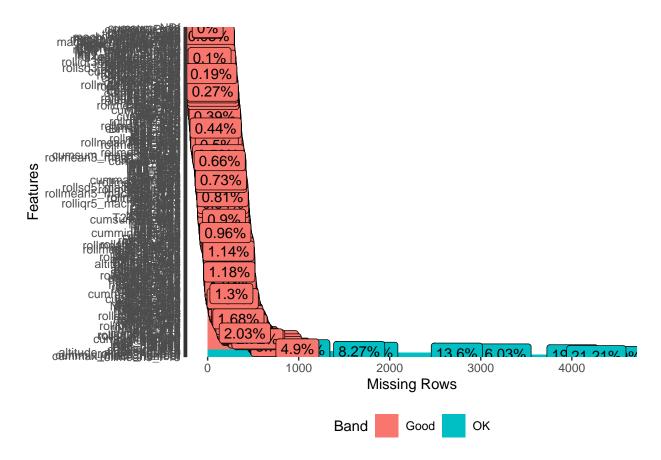
Estos datos son legítimos y en princípio no hace falta quitar de nuestra muestra. Pero podemos generar un algorítimo para quitar outliers basada en un criterio univariable y otros multivariable.

Nc numeric NRc numeric P15 numeric Nf numeric NRf numeric T30 numeric

```
remove_outliers <- function(x, na.rm = TRUE, ...) {
   qnt <- quantile(x, probs=c(.25, .75), na.rm = na.rm, ...)
   H <- 1.5 * IQR(x, na.rm = na.rm)
   y <- x
   y[x < (qnt[1] - H)] <- NA
   y[x > (qnt[2] + H)] <- NA
   y
}

temp <- trainset2 %>%
   group_by(time_in_cycles) %>%
   mutate_at(vars(-group_cols()), remove_outliers)

plot_missing(temp)
```



```
columns = c("altitude", "mach_number", "T24", "T30", "T50", "P15", "P30", "Nf", "Nc", "Ps30", "phi", "N
OutlierAnomalyDetection <- function(df, columns = "all", method = "all"){
  if(any(class(df) == "grouped_df")){
    df <- df %>% ungroup()
  if(any(columns == "all")){
    df_temp <- df
  } else {
    df_temp <- df %>% dplyr::select(one_of(columns))
  if(method %in% c("all", "cook")){
    mod \leftarrow lm(RUL \sim ., data = df)
    cooksd <- cooks.distance(mod)</pre>
    #influential <- as.numeric(names(cooksd)[(cooksd > (4/sample_size))])
    #df <- df[-influential, ]</pre>
    df$cook_score <- as.vector(cooksd)</pre>
  }
  if(method %in% c("all", "mahalanobis")){
    score <- as.vector(mahalanobis(df_temp, colMeans(df_temp)), cov(df_temp)))</pre>
    df$mahalanobis_score <- score</pre>
  if(method %in% c("all", "PCA")){
    # Cálculo de PCA
    pca <- prcomp(</pre>
         x = df_{temp}
         center = TRUE,
         scale. = TRUE
    comp <- seq_along(pca$sdev)</pre>
    recon <- as.matrix(pca$x[, comp]) %*% t(as.matrix(pca$rotation[, comp]))</pre>
    # Se revierte la trasformación centrado y escalado.
    recon <- scale(recon , center = FALSE, scale = 1/pca$scale)</pre>
    recon <- scale(recon , center = -1*pca$center, scale = FALSE)
    # Cálculo del error cuadrático medio de recostrucción
    reconstruction_error <- apply(X = (recon - df_temp)^2, MARGIN = 1, FUN = mean)
    # Se añade el error de reconstrucción al dataframe original.
    df$reconstruction_error_pca <- reconstruction_error</pre>
  if(method %in% c("all", "knn")){
    df scaled <- scale(df temp)</pre>
    df_knn <- get.knn(data = df_scaled, k = 5)</pre>
    # Averagedistancetonearestneighbors
    df_score <- rowMeans(df_knn$nn.dist)</pre>
    df$knn_score <- df_score</pre>
  if(method %in% c("all", "dbscan")){
    df$dbscan_score <- lof(scale(df_temp), k = 5)</pre>
```

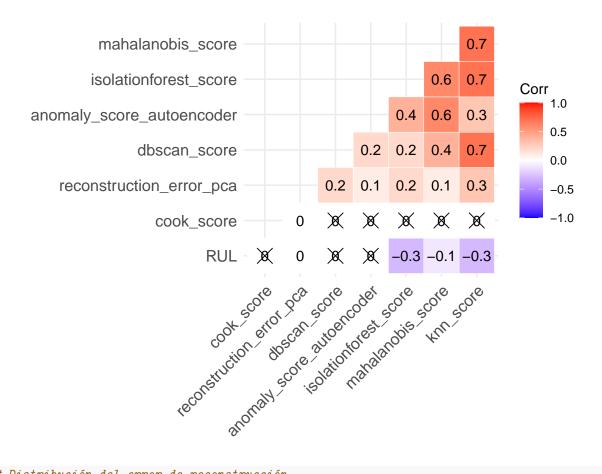
```
#if(method %in% c("all", "oneclasssum")){
# replications = 5
# # function to obtain R-Squared from the data
# oneclasssum <- function(data, indices) {</pre>
    x <- data[indices,] # allows boot to select sample</pre>
   y \leftarrow rep("oneclass", nrow(x))
#
  model \leftarrow svm(x, type='one-classification') #train an one-classification model
   # the output is Boolean
    pred <- predict(model, x) #create predictions</pre>
   return(pred)
#
   7-
# # bootstrapping
# results <- boot(</pre>
  data=df_temp,
#
  statistic=oneclasssum,
   R=replications,
   parallel = "multicore",
#
\# ncpus = 5
# temp <- as.data.frame(results$t)</pre>
# df$oneclasssvm_score <- as.vector(colSums(temp))/replications</pre>
if(method %in% c("all", "isolationforest")){
 df_tree <- iForest(X=df_temp, nt = 100)</pre>
  # Scores near 1 indicate anomalies (small path length)
 df_score <- predict(df_tree, newdata = df_temp)</pre>
 df$isolationforest_score <- df_score</pre>
if(method %in% c("all", "autoencoder")){
 h2o.init(ip = "localhost",
       # Si emplea un único core los resultados son reproducibles.
       # Si se dispone de muchos datos, mejor emplear varios cores.
       nthreads = 1
  # Se eliminan los datos del cluster por si ya había sido iniciado.
 h2o.removeAll()
 h2o.no_progress()
 df_h2o <- as.h2o(</pre>
              x = df_{temp}
              destination_frame = "df_h2o"
  # División de las observaciones en conjunto de entrenamiento y validación.
 df_h2o_split <- h2o.splitFrame(data = df_h2o, ratios = 0.8, seed = 123)</pre>
 df_h2o_train <- df_h2o_split[[1]]</pre>
 df_h2o_validacion <- df_h2o_split[[2]]</pre>
  # Se define la variables empleadas por el autoencoder
 predictores <- setdiff(h2o.colnames(df_h2o), "y")</pre>
  # Entrenamiento del modelo autoencoder con 2 neuronas en la capa oculta.
 autoencoder <- h2o.deeplearning(</pre>
   x = predictores,
```

```
training_frame = df_h2o_train,
      validation_frame = df_h2o_validacion,
      activation = "Tanh",
      autoencoder = TRUE,
                   = c(2),
     hidden
      epochs
                   = 50,
     ignore_const_cols
                          = FALSE,
     score_each_iteration = TRUE,
      # Seed solo válido cuando se emplea un único core
      seed = 999
   reconstruction_error <- h2o.anomaly(</pre>
                         object = autoencoder,
                         data = df_h2o[, predictores],
                         per_feature = FALSE
   reconstruction_error <- as.data.frame(reconstruction_error)</pre>
   reconstruction_error <- reconstruction_error[, 1]</pre>
   # Se añade el error de reconstrucción al dataframe original.
   df$anomaly_score_autoencoder <- reconstruction_error</pre>
 }
 return(df)
}
temp <- OutlierAnomalyDetection(df = trainset2, columns, method = "all")</pre>
## Connection successful!
##
## R is connected to the H2O cluster:
      H2O cluster uptime:
                              47 minutes 11 seconds
      H2O cluster timezone:
##
                                  Europe/Paris
##
      H2O data parsing timezone: UTC
##
      H2O cluster version:
                                  3.32.0.1
##
      H2O cluster version age: 2 months and 28 days
##
      H2O cluster name:
                                  H20_started_from_R_ferna_wkw207
##
      H2O cluster total nodes:
                                  1
##
      H2O cluster total memory: 7.07 GB
##
      H2O cluster total cores:
##
      H2O cluster allowed cores: 1
##
      H2O cluster healthy:
                                  TRUE
##
      H2O Connection ip:
                                  localhost
                                  54321
##
      H2O Connection port:
##
      H20 Connection proxy:
                                  NA
##
      H20 Internal Security:
                                  FALSE
##
      H20 API Extensions:
                                   Amazon S3, Algos, AutoML, Core V3, TargetEncoder, Core V4
##
      R Version:
                                   R version 4.0.3 (2020-10-10)
df_temp <- temp %>% ungroup() %>% dplyr::select(cook_score, mahalanobis_score, reconstruction_error_pca
```

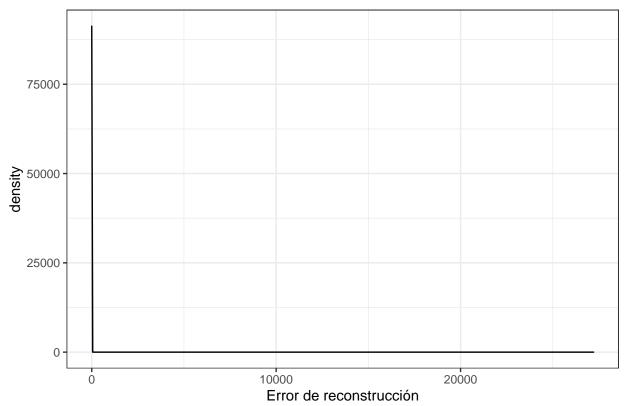
```
# Compute a correlation matrix
corr <- round(cor(df_temp), 1)
# Compute a matrix of correlation p-values
p.mat <- cor_pmat(df_temp)

# Visualize the lower triangle of the correlation matrix
# Barring the no significant coefficient
corr.plot <- ggcorrplot(
    corr, hc.order = TRUE, type = "lower", lab = TRUE, outline.col = "white",
    p.mat = p.mat
    )

corr.plot</pre>
```

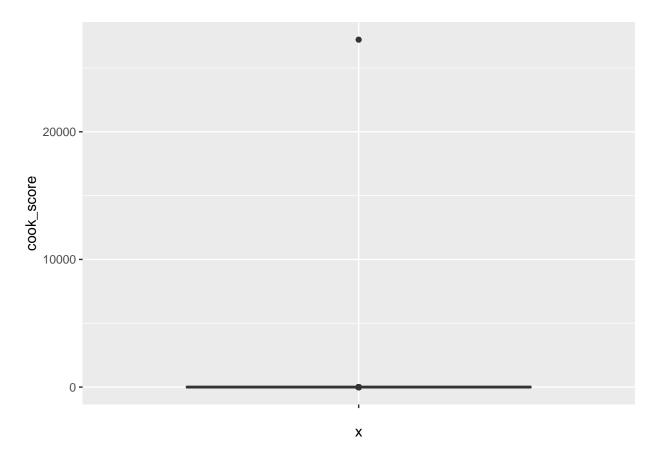






Según la distribución de la distancia de Cook, podemos ver claramente que existen outliers en los valores más grandes.

```
ggplot(data = df_temp, aes(x = "", y = cook_score)) +
  geom_boxplot() #+
```



```
# coord\_cartesian(ylim = c(0, 150)) # I set the y axis scale so the plot looks better.
```

Podemos aplicar la prueba de Grubbs. La prueba de Grubbs detecta un valor atípico a la vez (valor más alto o más bajo), por lo que las hipótesis nula y alternativa son las siguientes:

- H_0 : El valor más alto **no** es un outlier
- H_1 : El valor más alto es un outlier

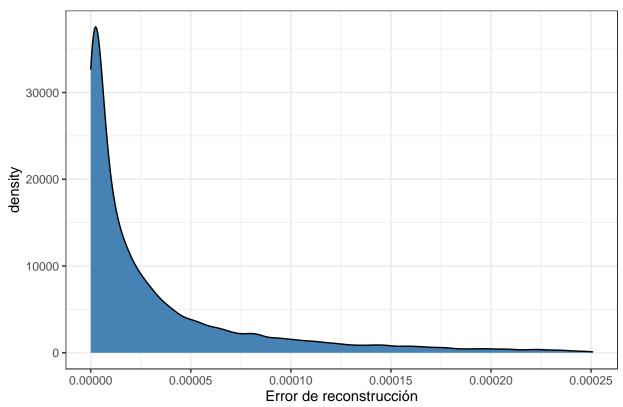
El valor de p<0,05 significa que al nivel de significancia del 5%, rechazamos la hipótesis de que el valor más no es un valor atípico.

Abajo generamos un loop dónde evaluamos en cada turno el valor más grande, si es outliers, se lo eliminamos y aplicamos otra vez la prueba hasta que no exista ningún outlier según Grubbs.

```
actual_p_value <- 0
p_value <- 0.05
outliers <- c()
df_no_cook_outlier <- df_temp

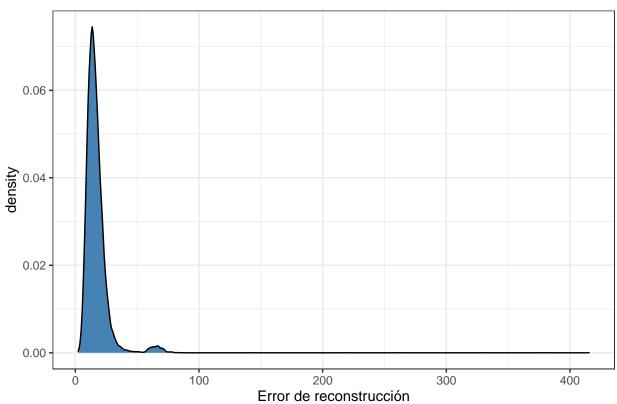
while (actual_p_value < p_value) {
   grubbs_test <- grubbs.test(df_no_cook_outlier$cook_score)
   actual_p_value <- grubbs_test$p.value
   value <- gsub(pattern = "highest value ", "", x = grubbs_test$alternative)
   value <- as.numeric(gsub(pattern = " is an outlier", "", x = value))</pre>
```

Distribución de las medidas de la Distancia de Cook

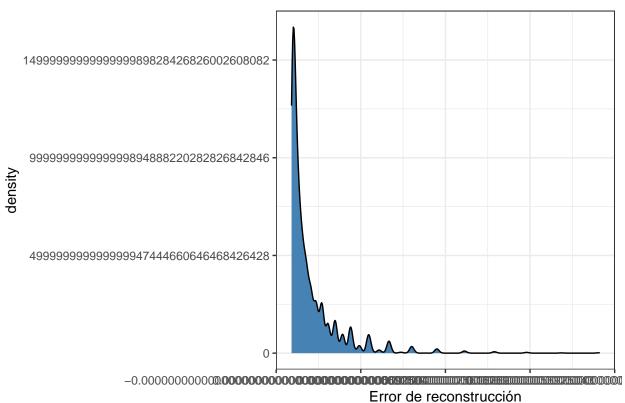


```
# Distribución del error de reconstrucción.
tibble(df_temp) %>%
    ggplot(aes(x = mahalanobis_score)) +
    geom_density(fill = "steelblue") +
    labs(title = "Distribución de las medidas de la Distancia de Mahalanobis",
        x = "Error de reconstrucción") +
```

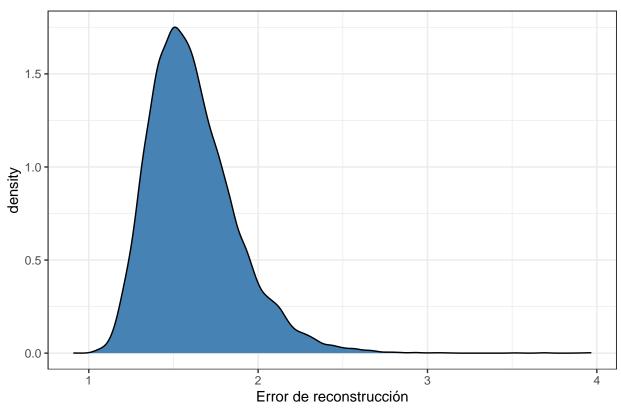
Distribución de las medidas de la Distancia de Mahalanobis



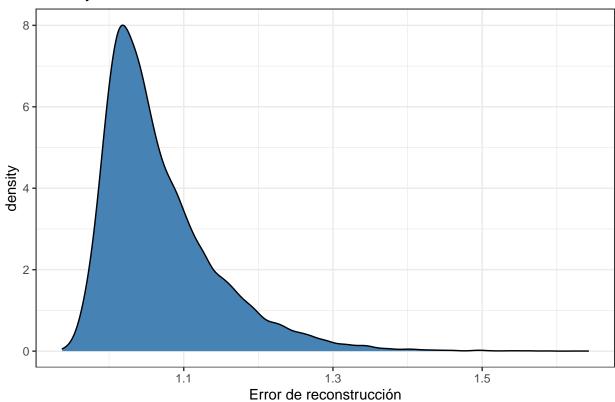
Distribución del error de reconstrucción de PC



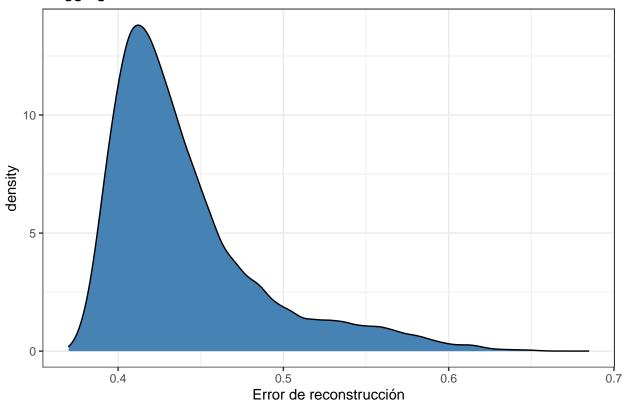
Distance based Outlier Detection



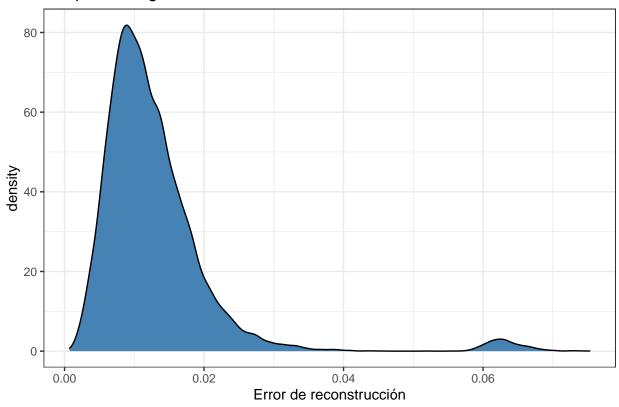
Density based Outlier Detection



Bagging of trees based Outlier Detection







4. Análisis de los datos

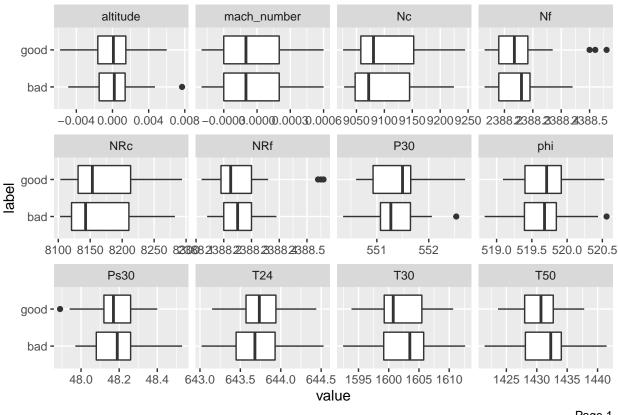
4.1. Selección de los grupos de datos que se quieren analizar/comparar (planificación de los análisis a aplicar).

Nuestro análisis se centrará en las máquinas cuando estas fallaron (RUL = 0). Además vamos a examinar dos grupos distintos, uno son las máquinas que fallaron con menos de 200 vuelos y el otro grupo son las máquinas con 200 o más vuelos.

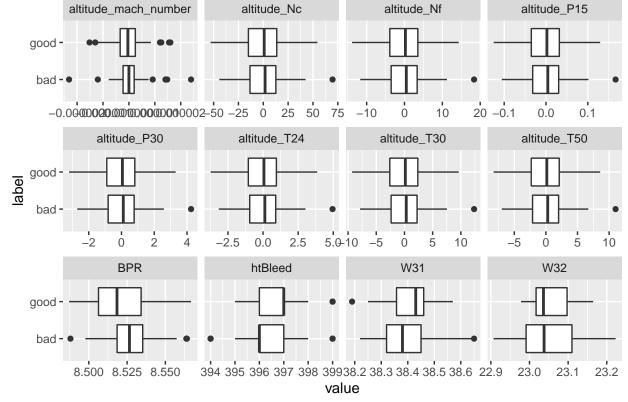
```
df <- trainset2 %>%
  ungroup() %>%
  filter(RUL == 0) %>%
  mutate(
    label = if_else(time_in_cycles < 200, "bad", "good")
) %>%
  dplyr::select(-RUL, -time_in_cycles, -unit_number)
```

```
## bad good
## 52 48
```

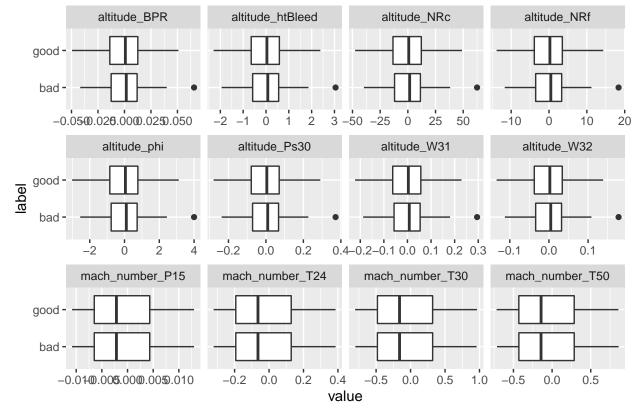
```
temp <- DataProfiling(df)</pre>
unique_columns <- temp$names[temp$n_unique == 1 & !is.na(temp$n_unique)]
print(unique_columns)
    [1] "P15"
                        "lag1_P15"
                                       "lag2_P15"
                                                                       "lag4_P15"
##
                                                       "lag3_P15"
##
    [6] "lag5_P15"
                        "rollsd3_P15"
                                       "rolliqr3_P15" "rollsd5_P15"
                                                                       "rolliqr5_P15"
## [11] "cummax_P15"
df <- df %>% dplyr::select(-one_of(unique_columns))
plot_boxplot(df, by = "label")
```



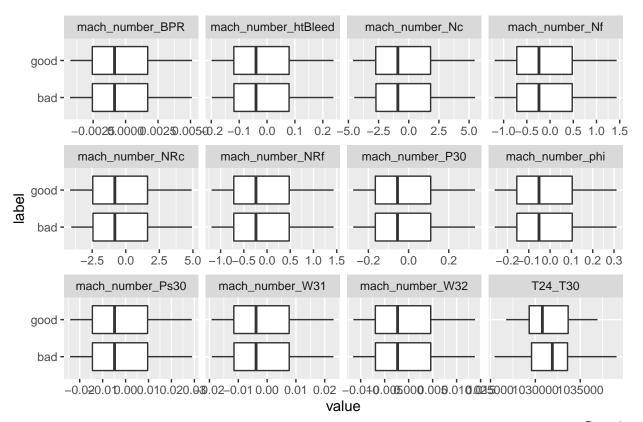
Page 1



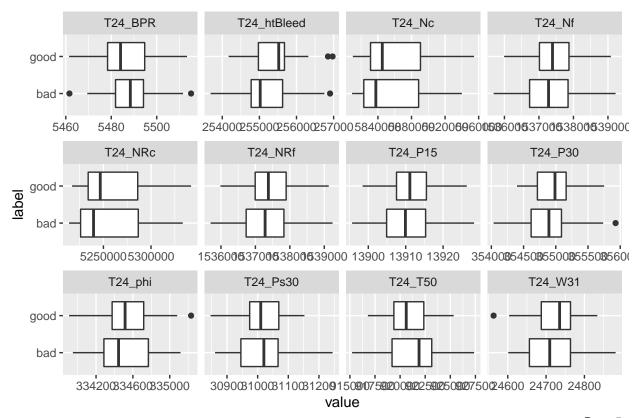
Page 2



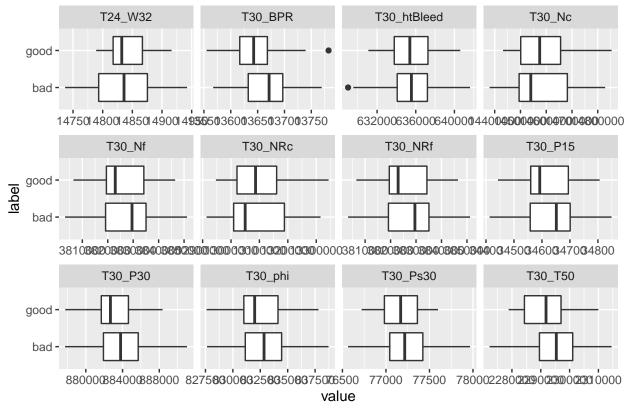
Page 3



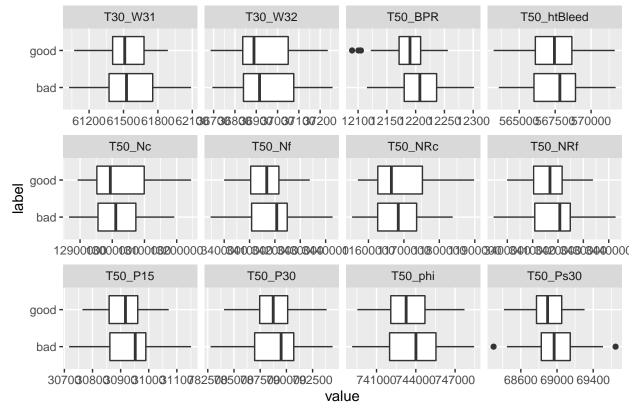
Page 4



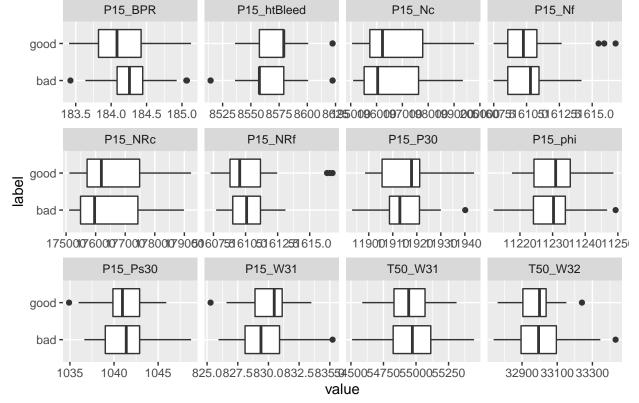
Page 5



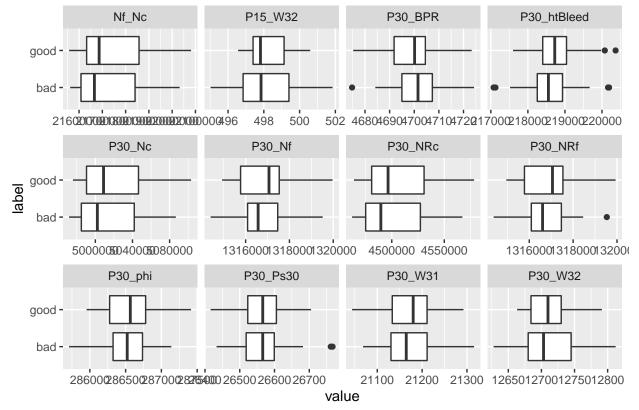
Page 6



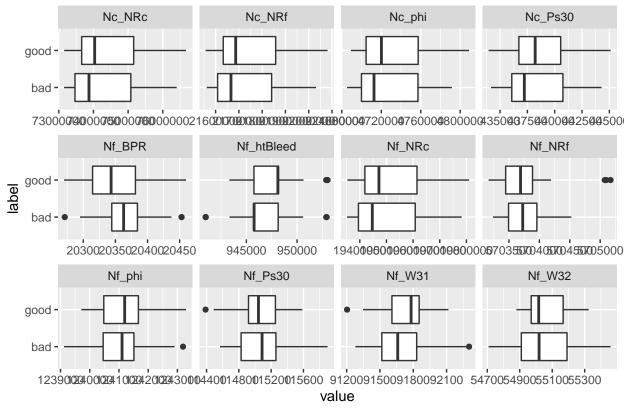
Page 7



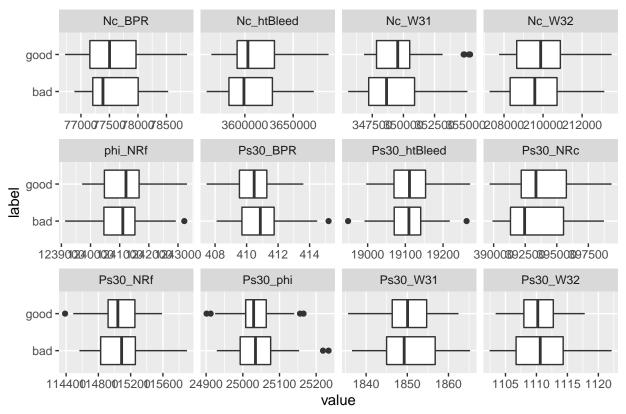
Page 8



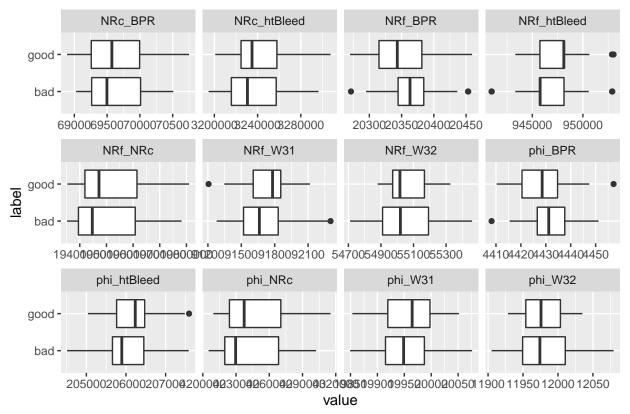
Page 9



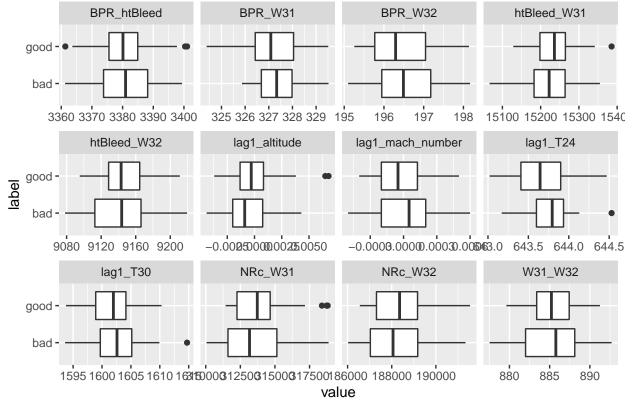
Page 10



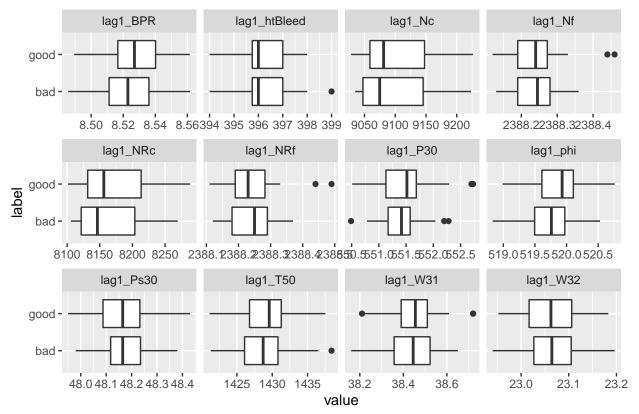
Page 11



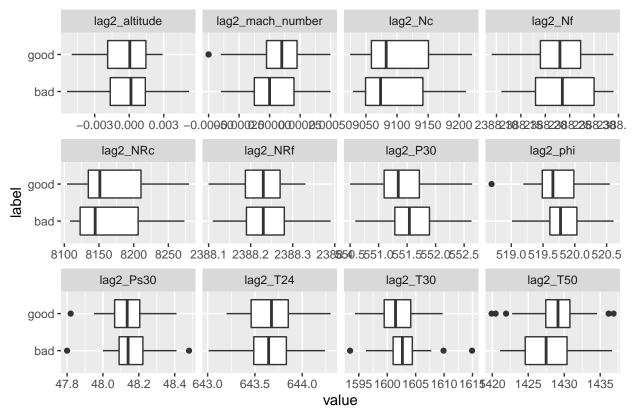
Page 12



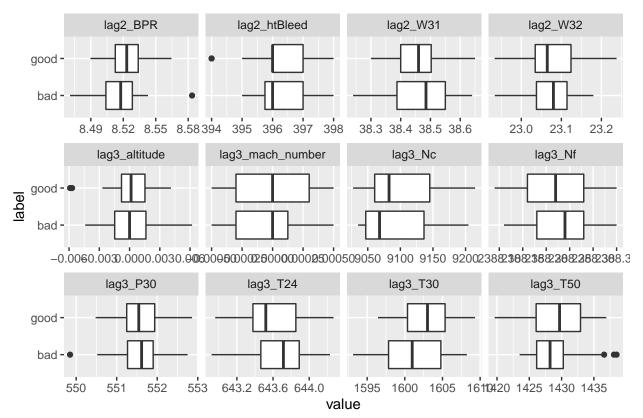
Page 13



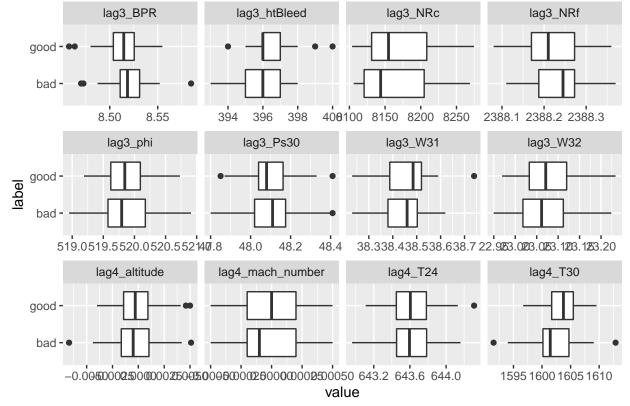
Page 14



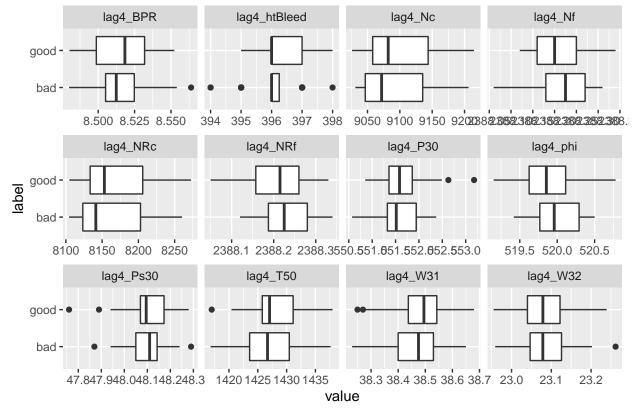
Page 15



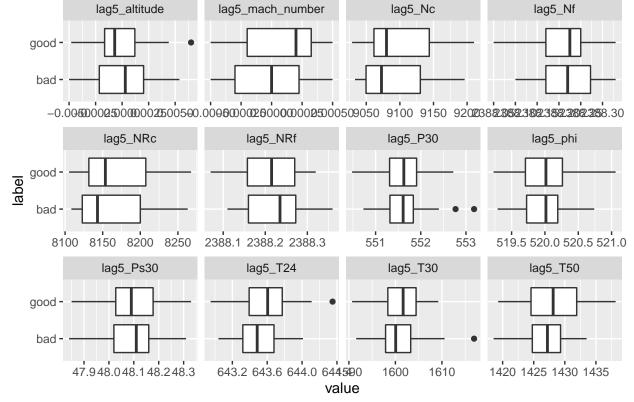
Page 16



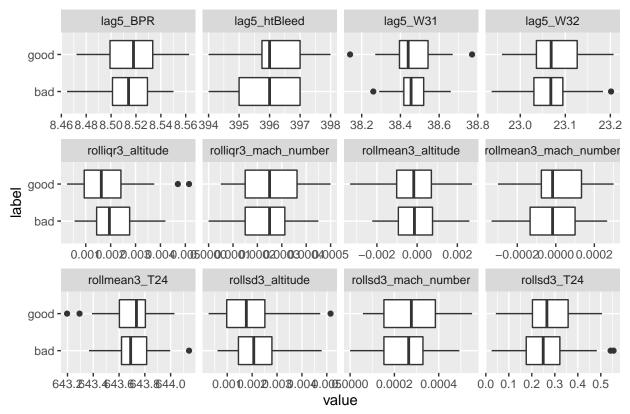
Page 17



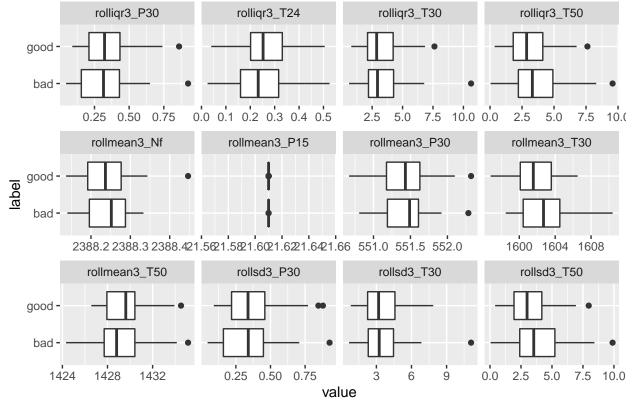
Page 18



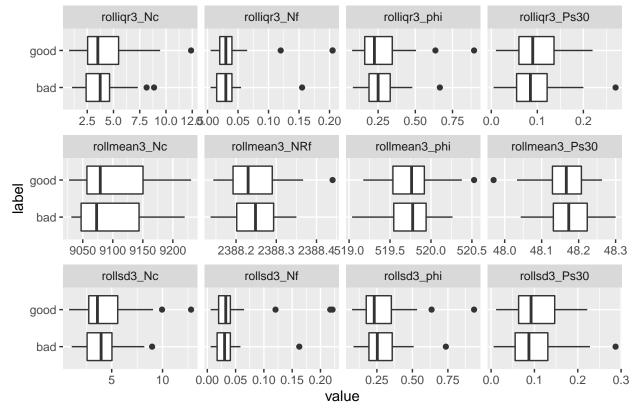
Page 19



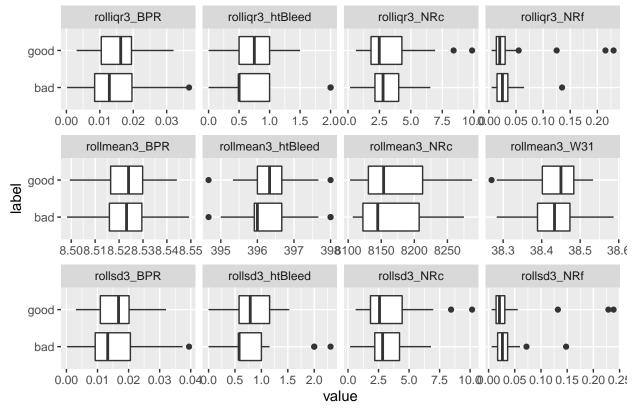
Page 20



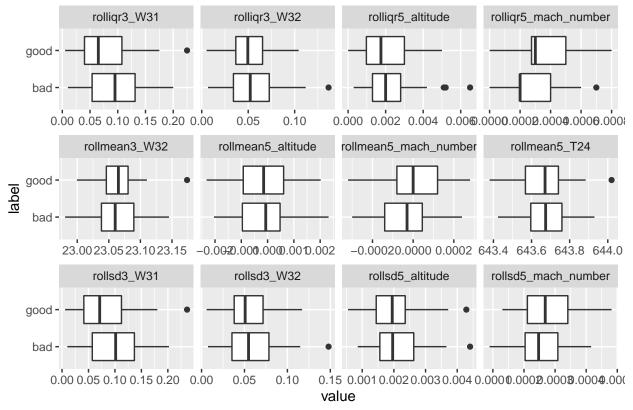
Page 21



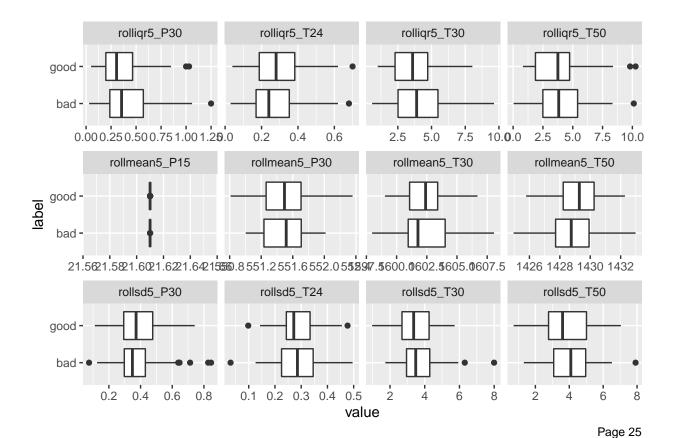
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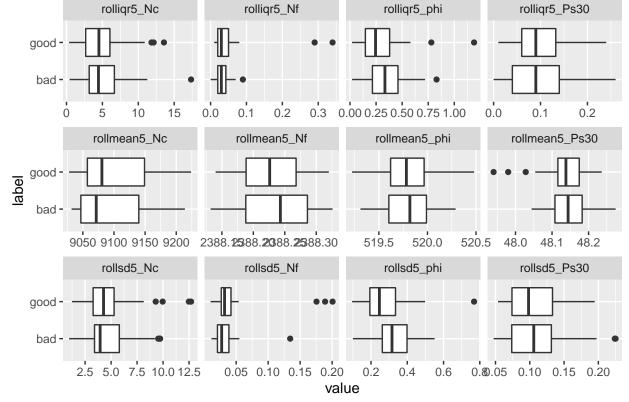


Page 23

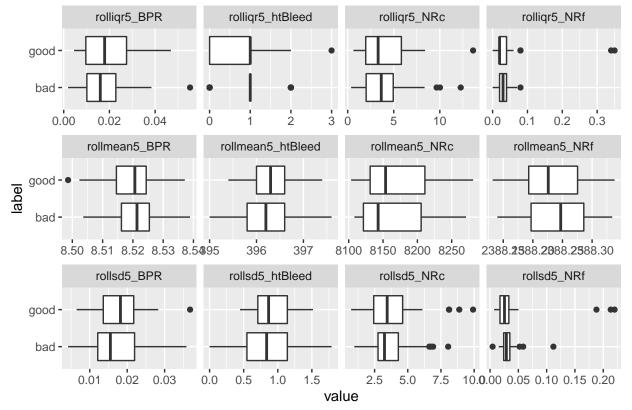


Page 24

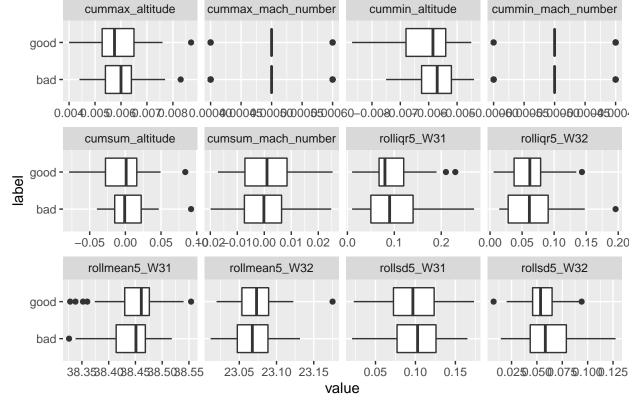




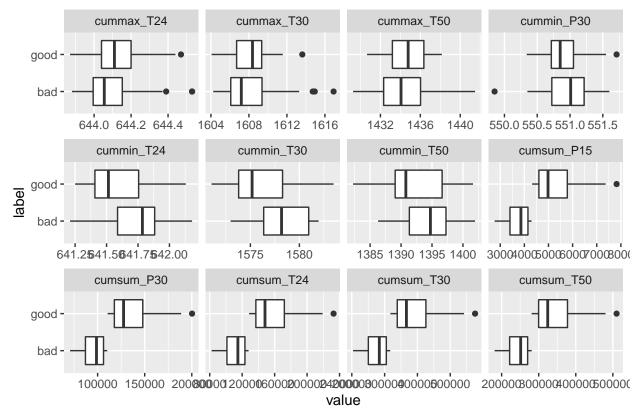
Page 26



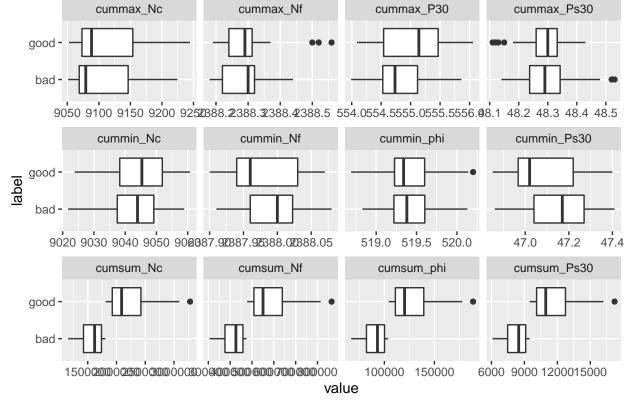
Page 27



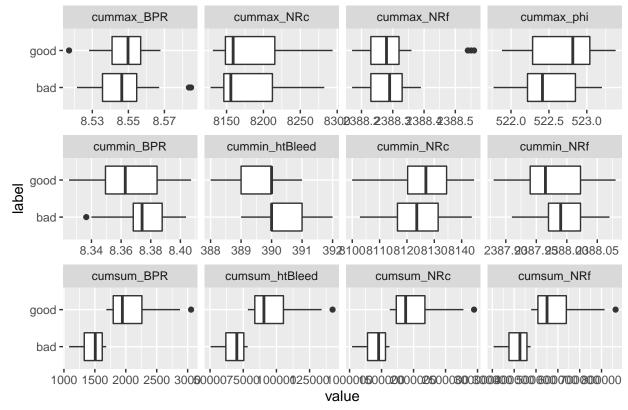
Page 28



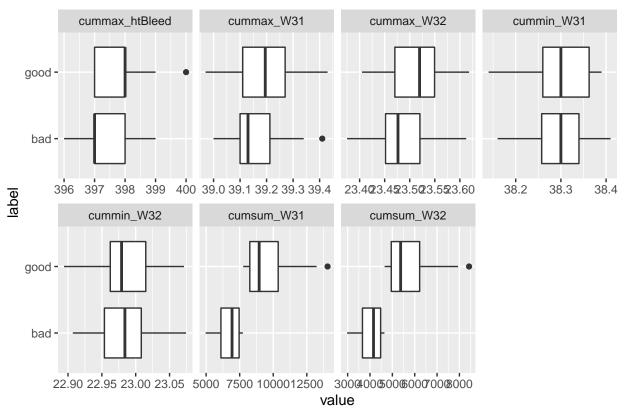
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4.2 Comprobación de la normalidad y homogeneidad de la varianza.

Primero, vamos a examinar si los datos siguen una distribución normal,

```
normalityChecker <- function(df){
    df$label = NULL
    result <- data.frame(variables = names(df), p_value = NA, result = NA)

for (i in 1:nrow(result)) {
    variable <- df[,i]
    prueba <- shapiro.test(pull(variable))
    result$p_value[i] <- prueba$p.value
    result$result[i] <- if_else(prueba$p.value >= 0.05, "normally distributed", "not normally distribut
    }

    return(result)
}

pruebas <- normalityChecker(df)

table(pruebas$result)</pre>
```

##
normally distributed not normally distributed

193 187

Ahora vamos a examinar la homocedasticidad.

Para las variables que siguen una distribución normal usaremos el test de Levene y el test de Fligner-Killeen para las columnas que no cumplen con la condición de normalidad.

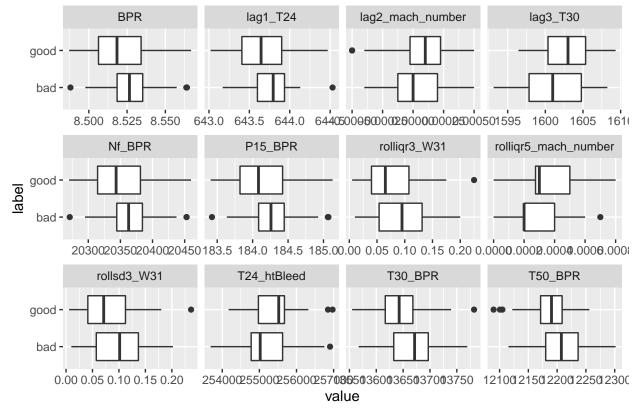
```
homoscedasticityChecker <- function(df_in, normalitychecker_table){
  group = as.factor(df_in$label)
  df_in$label = NULL
  names(normalitychecker_table) <- c("variables", "normal_p_value", "normal_result")</pre>
  normalitychecker_table$homoscedasticity_p_value = NA
  normalitychecker_table$homoscedasticity_result = NA
  for (i in 1:nrow(normalitychecker_table)) {
    y <- pull(df_in[,i])
    temp_df <- data.frame(y = y, group = group)</pre>
    if(normalitychecker_table[i,3] == "normally distributed"){
      result_test <- leveneTest(y = y, group = group, data = temp_df)</pre>
      p_value = result_test$'Pr(>F)'[1]
    } else {
      result_test <- fligner.test(x = y, g = group, data = temp_df)
      p_value = result_test$p.value
    normalitychecker_table$homoscedasticity_p_value[i] = p_value
    normalitychecker_table$homoscedasticity_result[i] = if_else(p_value < 0.05, "statistically differen
  return(normalitychecker_table)
}
pruebas2 <- homoscedasticityChecker(df = df, normalitychecker_table = pruebas)</pre>
table(pruebas2$homoscedasticity result)
##
## not statistically different variances
                                              statistically different variances
                                                                               37
table(pruebas2$normal_result, pruebas2$homoscedasticity_result)
##
##
                               not statistically different variances
##
     normally distributed
                                                                  179
##
     not normally distributed
                                                                  164
##
##
                               statistically different variances
##
     normally distributed
                                                               23
##
     not normally distributed
```

4.3 Aplicación de pruebas estadísticas para comparar los grupos de datos.

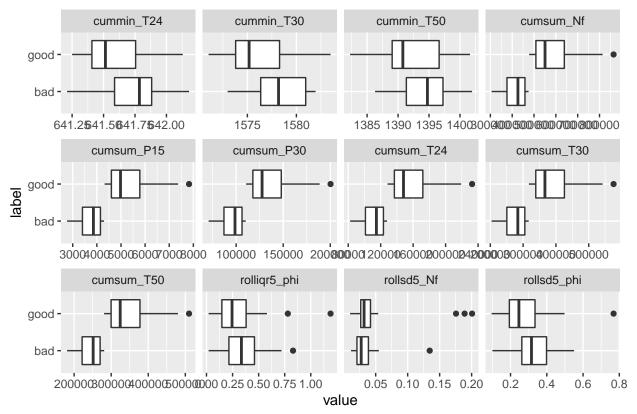
Queremos saber si el promedio de nuestra variables para el grupo de máquinas buenas (m_A) es significativamente diferente al de las máquinas malas (m_B) .

En este caso, tenemos dos grupos de muestras no relacionados (es decir, independientes o no apareados). Por lo tanto, es posible utilizar una prueba t independiente para evaluar si las medias son diferentes.

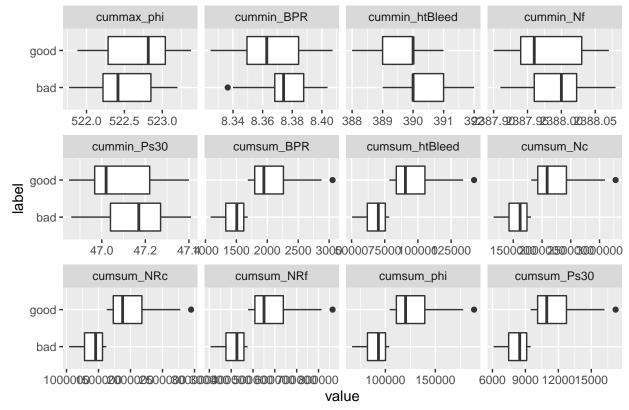
```
significantDifferenceChecker <- function(df_in, normalitychecker_table){</pre>
  group = as.factor(df in$label)
  df in$label = NULL
  normalitychecker_table$mean_difference_p_value = NA
  normalitychecker_table$mean_difference_result = NA
  for (i in 1:nrow(normalitychecker_table)) {
   y <- pull(df_in[,i])
   temp_df <- data.frame(y = y, group = group)</pre>
   if(normalitychecker_table[i,3] == "normally distributed" & normalitychecker_table[i,5] == "statisti
      result_test <- t.test(x = temp_df\$y[group == "good"], y = temp_df\$y[group == "bad"])
   } else {
      result test <- wilcox.test(x = temp df$y[group == "good"], y = temp df$y[group == "bad"])
   normalitychecker_table$mean_difference_p_value[i] = result_test$p.value
   normalitychecker_table$mean_difference_result[i] = if_else(result_test$p.value < 0.05, "statistical
  }
  return(normalitychecker_table)
pruebas3 <- significantDifferenceChecker(df_in = df, normalitychecker_table = pruebas2)</pre>
table(pruebas3$mean_difference_result)
##
## not statistically different means
                                          statistically different means
##
                                 339
columns_significant <- pruebas3 %>% filter(mean_difference_result == "statistically different means") %
plot_boxplot(df[,c(columns_significant,"label")], by = "label")
```



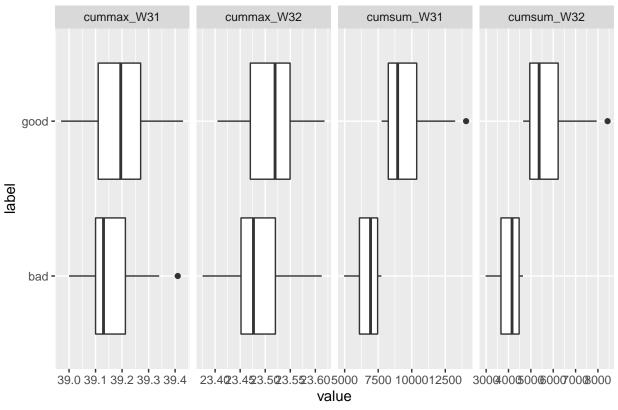
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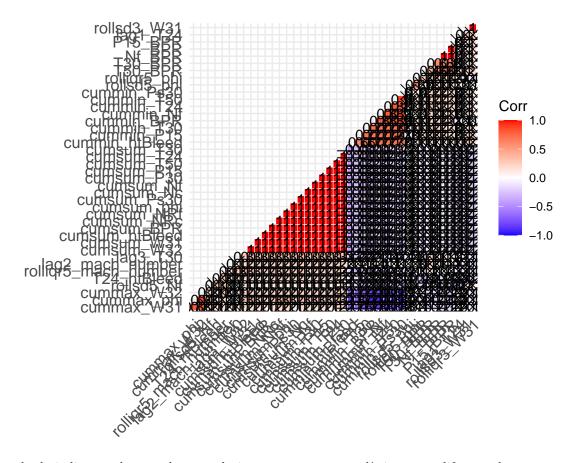
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Ahora vamos a estudiar el problema de multicolinealidad o de cuando dos variables son altamente correlacionadas, al punto de ser una combinación lineal. Además, examinaremos si la correlación es significativamente diferente de cero. Usaremos la prueba de Spearman porque gran parte de las variables no son normalmente distribuídas.

```
# Compute a correlation matrix
corr <- round(cor(df_temp), 1)
# Compute a matrix of correlation p-values
p.mat <- cor_pmat(df_temp, method="spearman")

# Visualize the lower triangle of the correlation matrix
# Barring the no significant coefficient
corr.plot <- ggcorrplot(
    corr, hc.order = TRUE, type = "lower", lab = TRUE, outline.col = "white",
    p.mat = p.mat
    )

corr.plot</pre>
```



El resultado indica que hay muchas correlaciones que no son estadísticamente diferente de cero y, por otro lado, algunas variables son combinación lineales. Este última condición sería un problema en un modelo de regresión lineal.

```
df_temp <- df[,c(columns_significant[!grepl('cumsum', columns_significant)], "label")]</pre>
df_temp$label <- as.factor(df_temp$label)</pre>
model <- glm(label ~., data = df_temp, family = binomial) %>%
  stepAIC(trace = FALSE)
# Summarize the final selected model
summary(model)
##
## Call:
   glm(formula = label ~ T30_BPR + lag2_mach_number + lag3_T30 +
       rollsd3_W31 + rolliqr3_W31 + rollsd5_Nf + rollsd5_phi + cummin_T30 +
##
##
       cummax_phi + cummin_htBleed, family = binomial, data = df_temp)
##
## Deviance Residuals:
                 1Q
                      Median
                                            Max
       Min
## -1.9656 -0.7588 -0.1976
                                         2.3426
                                0.6786
##
## Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
```

2.683 0.00730 **

2785.571308 1038.209952

(Intercept)

```
## T30 BPR
                      -0.017296
                                   0.006311
                                             -2.741 0.00613 **
                                                     0.00459 **
## lag2_mach_number 3426.358515 1208.903800
                                              2.834
## lag3 T30
                       0.114932
                                   0.082391
                                              1.395
                                                     0.16303
## rollsd3_W31
                    -126.389551
                                             -1.939
                                                     0.05252
                                  65.188692
## rolligr3_W31
                     125.561192
                                  67.570453
                                              1.858
                                                     0.06314
## rollsd5 Nf
                                                     0.09357
                      20.661018
                                  12.321427
                                              1.677
## rollsd5_phi
                      -5.280365
                                   2.381735
                                             -2.217
                                                     0.02662 *
## cummin_T30
                      -0.315528
                                   0.146278
                                             -2.157
                                                     0.03100 *
                                             -2.380
## cummax_phi
                      -3.105803
                                   1.304948
                                                     0.01731 *
## cummin_htBleed
                      -1.567459
                                   0.629747 -2.489
                                                     0.01281 *
                  0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
## Signif. codes:
##
  (Dispersion parameter for binomial family taken to be 1)
##
##
##
       Null deviance: 138.469
                               on 99
                                      degrees of freedom
## Residual deviance: 92.621
                               on 89
                                     degrees of freedom
## AIC: 114.62
##
## Number of Fisher Scoring iterations: 5
```

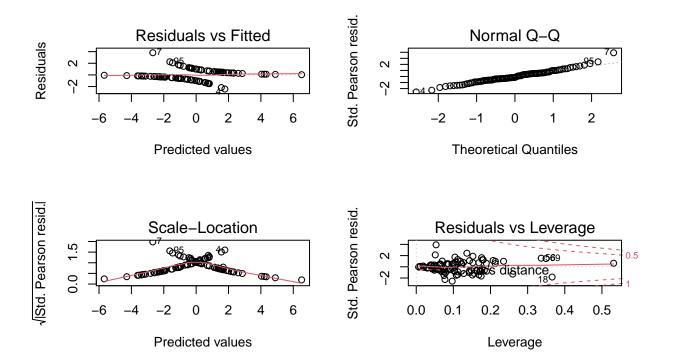
Hemos usado una selección de variable paso a paso basada en el criterio de información de akaike. Un modelo con un AIC bajo se caracteriza por una baja complejidad (minimiza p) y un buen ajuste. Las variables más importantes para explicar si una máquina tiene buen o malo rendimiento son:

- T30 BPR
- \bullet lag2_mach_number
- lag3_T30
- rollsd3_W31
- rolliqr3_W31
- rollsd5_Nf
- rollsd5_phi
- cummin_T30
- cummax_phi
- \bullet cummin_htBleed

5. Representación de los resultados a partir de tablas y gráficas.

```
oldpar <- par(oma = c(0, 0, 3, 0), mfrow = c(2, 2))
plot(model)
```

pel ~ T30_BPR + lag2_mach_number + lag3_T30 + rollsd3_W31 + rolling



Vemos el intervalo de confianza de los parametros.

```
confint(model, level = 0.95)
```

```
##
                             2.5 %
                                            97.5 %
## (Intercept)
                      839.08652419 4960.568982273
## T30_BPR
                       -0.03058919
                                      -0.005583626
## lag2_mach_number 1176.20980745 5977.450565982
## lag3_T30
                       -0.04353586
                                       0.283654081
## rollsd3_W31
                     -261.98460973
                                      -3.264000799
## rolliqr3_W31
                                    265.908040671
                       -2.31786819
## rollsd5_Nf
                       -0.22533057
                                      51.641153057
## rollsd5_phi
                      -10.24300577
                                      -0.756712201
## cummin_T30
                       -0.61570085
                                      -0.036416478
                                      -0.650232964
## cummax_phi
                       -5.82876638
## cummin_htBleed
                       -2.88617946
                                      -0.386898867
pred <- as.factor(round(predict(model, newdata = df_temp, type="response"),0))</pre>
observaciones <- as.factor(if_else(df$label=="bad", 0, 1))
matriz <- confusionMatrix(observaciones, pred)</pre>
matriz
```

Confusion Matrix and Statistics

```
##
##
             Reference
  Prediction
##
              0 1
            0 39 13
##
##
            1 13 35
##
##
                  Accuracy: 0.74
                    95% CI: (0.6427, 0.8226)
##
##
       No Information Rate: 0.52
##
       P-Value [Acc > NIR] : 0.000005478
##
                     Kappa: 0.4792
##
##
    Mcnemar's Test P-Value: 1
##
##
##
               Sensitivity: 0.7500
##
               Specificity: 0.7292
##
            Pos Pred Value: 0.7500
##
            Neg Pred Value: 0.7292
##
                Prevalence: 0.5200
##
            Detection Rate: 0.3900
##
      Detection Prevalence: 0.5200
         Balanced Accuracy: 0.7396
##
##
##
          'Positive' Class: 0
##
```

6. Resolución del problema. A partir de los resultados obtenidos, ¿cuáles son las

conclusiones? ¿Los resultados permiten responder al problema?

```
Nuestra conclusión es que la información contenida en las variables: lag2_mach_number lag3_T30 rollsd3_W31 rollsd5_W31 rollsd5_Nf rollsd5_phi cummin_T30 cummax_phi cummin_htBleed
```

Consigue explicar un 75% sobre cuando una máquina tendrá una vida larga o corta. Nuestro sample size es de 100 máquinas, nuestro modelo es lineal y predecimos sobre el mismo dato usado en el entrenamiento, lo que puede causar overfitting (parcialmente ignorado porque regresión logistica es bastante limitada en generar overfitting).

Este resultado no responde realmente el problema sobre los factores que determinan una vida larga en las máquinas, pero sirve para indicar factores importantes que pueden ser explorados con nuevas variables, modelos más potentes y diferentes "problem framings".

Futuramente continuaremos esta investigación con los otros datasets y tres "problem framings" distintos:

- (1) Como un problema de clasificación para predecir el riesgo de la máquina fallar en su siguiente ciclo;
- (2) Un análisis de supervivencia;