

Ejercicio 3.3

Silvia Pineda

Carga de Datos y Librerías

```
library(naniar)
library(tidyverse)
```

```
-- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
v dplyr      1.1.4      v readr      2.1.5
v forcats    1.0.1      v stringr    1.5.2
v ggplot2    4.0.0      v tibble     3.3.0
v lubridate  1.9.4      v tidyr      1.3.1
v purrr      1.1.0
-- Conflicts ----- tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()     masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become
```

```
library(rio)

data <- read.csv("students_FP.csv",
  na.strings = c("", "NA", "NaN", "NULL"),
  stringsAsFactors = TRUE
)
```

Imputación múltiple

```
library(mice)
```

Attaching package: 'mice'

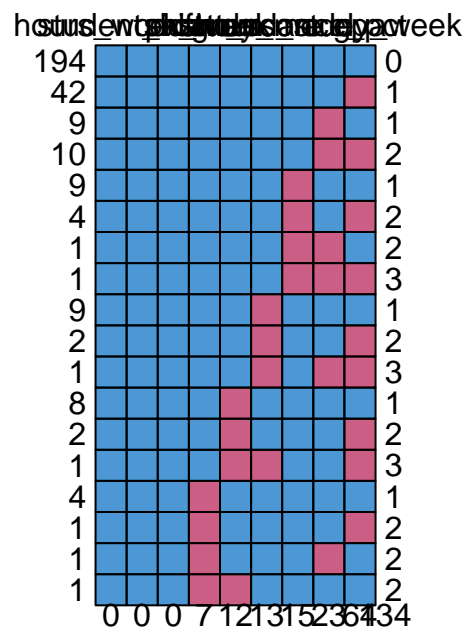
The following object is masked from 'package:stats':

filter

The following objects are masked from 'package:base':

cbind, rbind

```
md.pattern(data)
```



student_id	hours_work_week	shift	program	exam_score	study_mode
194	1	1	1	1	1
42	1	1	1	1	1
9	1	1	1	1	1
10	1	1	1	1	1
9	1	1	1	1	1
4	1	1	1	1	1
1	1	1	1	1	1

1	1	1	1	1	1	1
9	1	1	1	1	1	0
2	1	1	1	1	1	0
1	1	1	1	1	1	0
8	1	1	1	1	0	1
2	1	1	1	1	0	1
1	1	1	1	1	0	0
4	1	1	1	0	1	1
1	1	1	1	0	1	1
1	1	1	1	0	1	1
1	1	1	1	0	0	1
	0	0	0	7	12	13
	attendance_pct	hours_study_week	gpa			
194	1	1	1	0		
42	1	1	0	1		
9	1	0	1	1		
10	1	0	0	2		
9	0	1	1	1		
4	0	1	0	2		
1	0	0	1	2		
1	0	0	0	3		
9	1	1	1	1		
2	1	1	0	2		
1	1	0	0	3		
8	1	1	1	1		
2	1	1	0	2		
1	1	1	0	3		
4	1	1	1	1		
1	1	1	0	2		
1	1	0	1	2		
1	1	1	1	2		
	15	23	64	134		

No hay ninguna observación con todas las variables missing.

```
impData <- mice(select(data,-student_id),m=5,maxit=50,seed=500)
```

iter	imp	variable
1	1	hours_study_week attendance_pct gpa exam_score program study_mode
1	2	hours_study_week attendance_pct gpa exam_score program study_mode
1	3	hours_study_week attendance_pct gpa exam_score program study_mode

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]


```

44 4 hours_study_week attendance_pct gpa exam_score program study_mode
44 5 hours_study_week attendance_pct gpa exam_score program study_mode
45 1 hours_study_week attendance_pct gpa exam_score program study_mode
45 2 hours_study_week attendance_pct gpa exam_score program study_mode
45 3 hours_study_week attendance_pct gpa exam_score program study_mode
45 4 hours_study_week attendance_pct gpa exam_score program study_mode
45 5 hours_study_week attendance_pct gpa exam_score program study_mode
46 1 hours_study_week attendance_pct gpa exam_score program study_mode
46 2 hours_study_week attendance_pct gpa exam_score program study_mode
46 3 hours_study_week attendance_pct gpa exam_score program study_mode
46 4 hours_study_week attendance_pct gpa exam_score program study_mode
46 5 hours_study_week attendance_pct gpa exam_score program study_mode
47 1 hours_study_week attendance_pct gpa exam_score program study_mode
47 2 hours_study_week attendance_pct gpa exam_score program study_mode
47 3 hours_study_week attendance_pct gpa exam_score program study_mode
47 4 hours_study_week attendance_pct gpa exam_score program study_mode
47 5 hours_study_week attendance_pct gpa exam_score program study_mode
48 1 hours_study_week attendance_pct gpa exam_score program study_mode
48 2 hours_study_week attendance_pct gpa exam_score program study_mode
48 3 hours_study_week attendance_pct gpa exam_score program study_mode
48 4 hours_study_week attendance_pct gpa exam_score program study_mode
48 5 hours_study_week attendance_pct gpa exam_score program study_mode
49 1 hours_study_week attendance_pct gpa exam_score program study_mode
49 2 hours_study_week attendance_pct gpa exam_score program study_mode
49 3 hours_study_week attendance_pct gpa exam_score program study_mode
49 4 hours_study_week attendance_pct gpa exam_score program study_mode
49 5 hours_study_week attendance_pct gpa exam_score program study_mode
50 1 hours_study_week attendance_pct gpa exam_score program study_mode
50 2 hours_study_week attendance_pct gpa exam_score program study_mode
50 3 hours_study_week attendance_pct gpa exam_score program study_mode
50 4 hours_study_week attendance_pct gpa exam_score program study_mode
50 5 hours_study_week attendance_pct gpa exam_score program study_mode

```

```
summary(impData)
```

Class: mids

Number of multiple imputations: 5

Imputation methods:

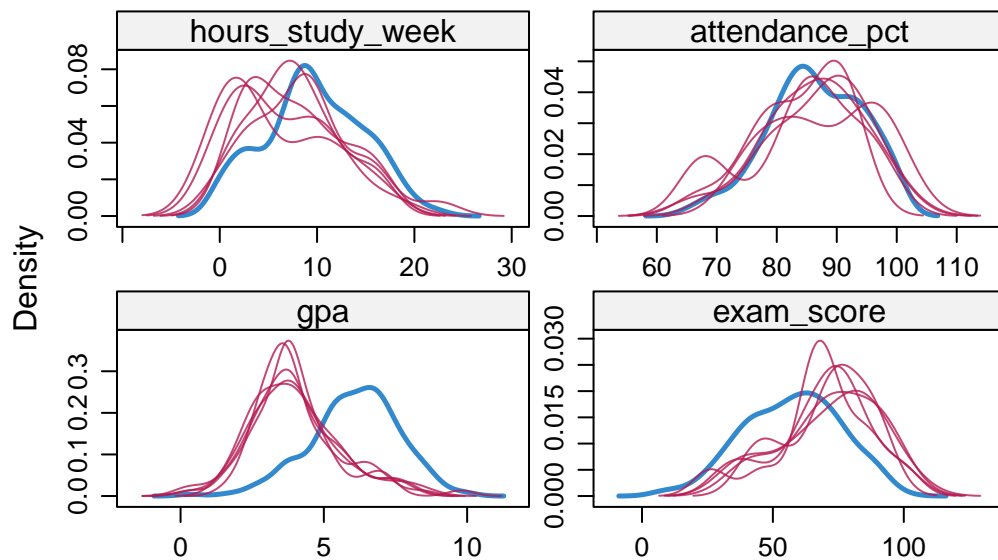
hours_work_week	hours_study_week	attendance_pct	gpa
" "	"pmm"	"pmm"	"pmm"
exam_score	program	study_mode	shift
"pmm"	"polyreg"	"polyreg"	" "

PredictorMatrix:

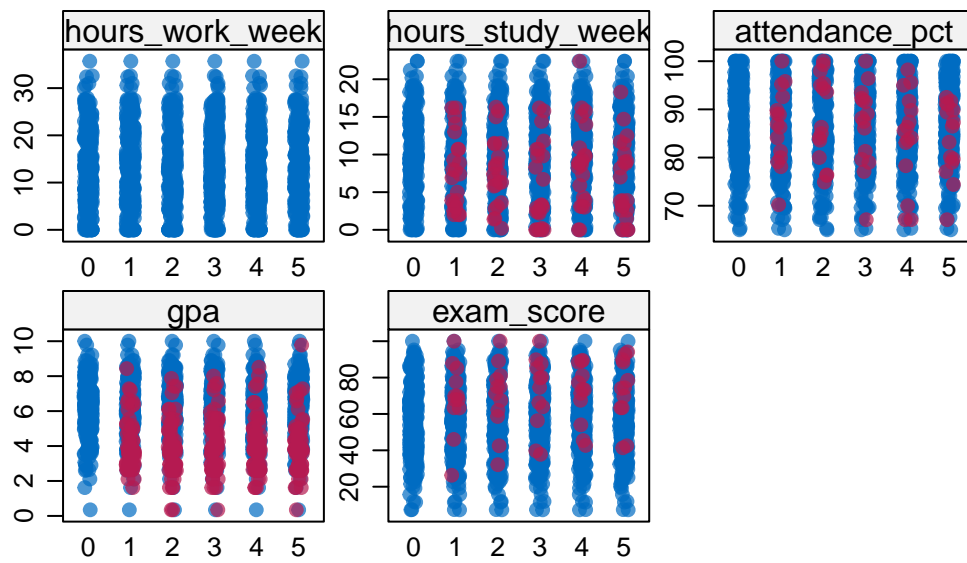
	hours_work_week	hours_study_week	attendance_pct	gpa	exam_score
hours_work_week	0	1	1	1	1
hours_study_week	1	0	1	1	1
attendance_pct	1	1	0	1	1
gpa	1	1	1	0	1
exam_score	1	1	1	1	0
program	1	1	1	1	1

	program	study_mode	shift
hours_work_week	1	1	1
hours_study_week	1	1	1
attendance_pct	1	1	1
gpa	1	1	1
exam_score	1	1	1
program	0	1	1

```
###Visualizar las variables cuantitativas
densityplot(impData)
```

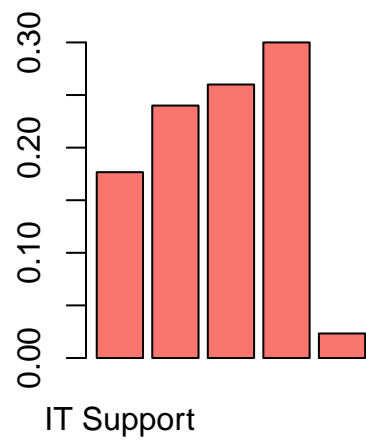


```
stripplot(impData, pch = 20, cex = 1.2)
```

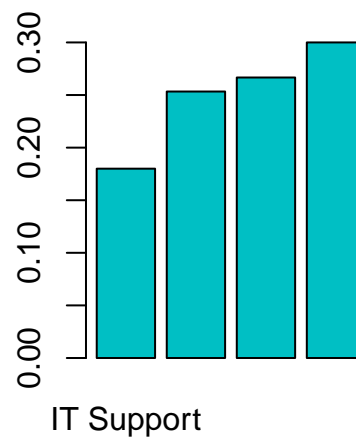


```
###Visualizar las variables cualitativas
completedData <- complete(impData,1)
par(mfrow = c(1, 2))
barplot(prop.table(table(data$program, useNA = "ifany")),
        main = "Antes de la imputación", col = "#F8766D" )
barplot(prop.table(table(completedData$program)),
        main = "Después de la imputación",col = "#00BFC4")
```

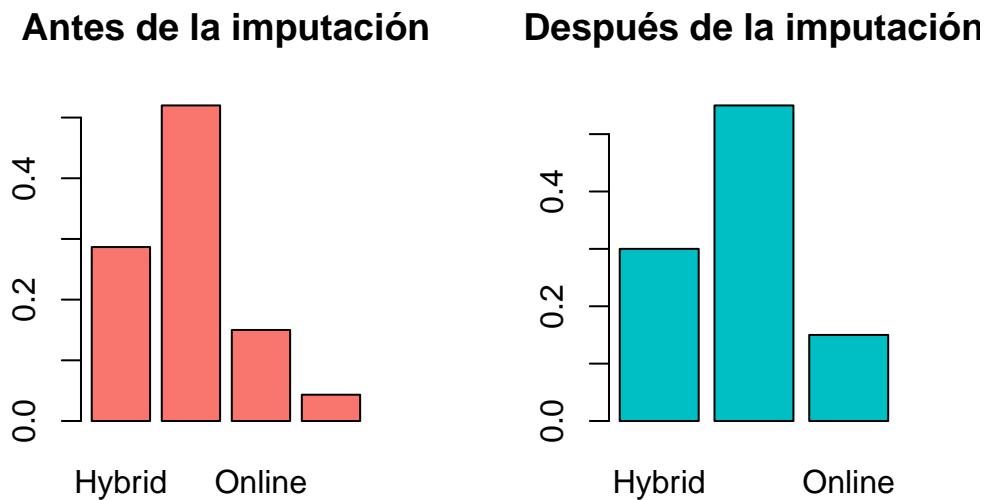
Antes de la imputación



Después de la imputación



```
par(mfrow = c(1, 2))
barplot(prop.table(table(data$study_mode, useNA = "ifany")),
        main = "Antes de la imputación", col = "#F8766D" )
barplot(prop.table(table(completedData$study_mode)),
        main = "Después de la imputación", col = "#00BFC4")
```



Excepto la variable `attendance_pct`, ninguna variable se ha imputado demasiado bien, pero la que se ha imputado muy mal es la de `gpa` que todos los valores se han imputado por debajo del resto de la distribución, esto no necesariamente está mal, precisamente una hipótesis era que los datos faltantes de `gpa` era MNAR porque podrías estar relacionados con valores bajos de `gpa`, pero no explicado por el resto de variables. En este caso, al tener en cuenta de forma multivariante toda la base de datos, ha imputado los valores de la variable como bajos desplazando así toda la distribución.

Por otro lado las dos variables cualitativas parece que se imputa de forma correcta.

Imputación con `missForest`

```
library(missForest)

set.seed(123)
data_missForest<-select(data,-student_id)
imp <- missForest(data_missForest)
imp$OOBError
```

NRMSE	PFC
0.1441779	0.4063217

```
set.seed(123)
imp <- missForest(data_missForest, variablewise = TRUE)
imp$OOBError
```

```

      MSE      MSE      MSE      MSE      MSE      PFC      PFC
0.0000000 13.1874025 52.6990576 0.4157744 51.1884986 0.6928328 0.5261324
      PFC
0.0000000
```

```
# Calcular la Standard Deviation para normalizar solo en las cuantitativas
num_vars <- names(data_missForest)[sapply(data_missForest, is.numeric)]
id<-match(num_vars,names(data_missForest))

mse_num <- imp$OOBError[id]
sd_num <- sapply(data_missForest[id], sd, na.rm = TRUE)

# Calcular el NRMSE
NRMSE <- sqrt(mse_num) / sd_num
names(NRMSE)<-colnames(data_missForest[id])
NRMSE
```

```

hours_work_week hours_study_week  attendance_pct      gpa
0.0000000      0.7111160      0.9260997      0.4147127
exam_score
0.3855255
```

De forma global los dos errores tanto para las cuantitativas como para las cualitativas, los errores son pequeños:

NRMSE = 0.14

PFC = 0.41

Si lo sacamos de forma individual por variable, para las cualitativas tenemos:

program (PFC = 0.69)

study_mode (PFC = 0.53)

hours_study_week (NRMSE = 0.71)

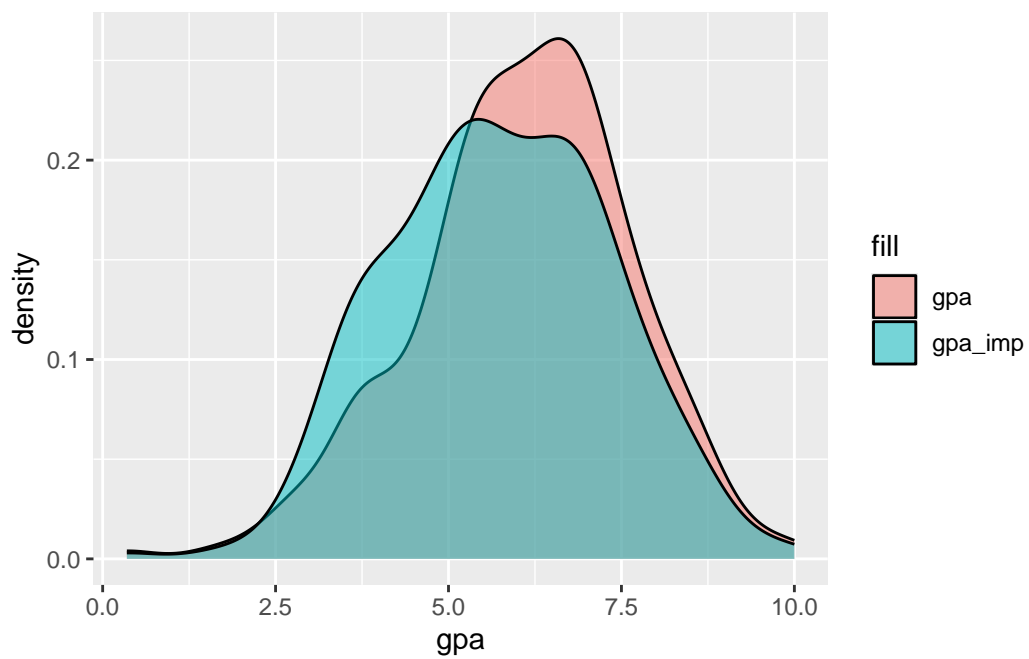
attendance_pct (NRMSE = 0.93)

gpa (NRMSE = 0.41)

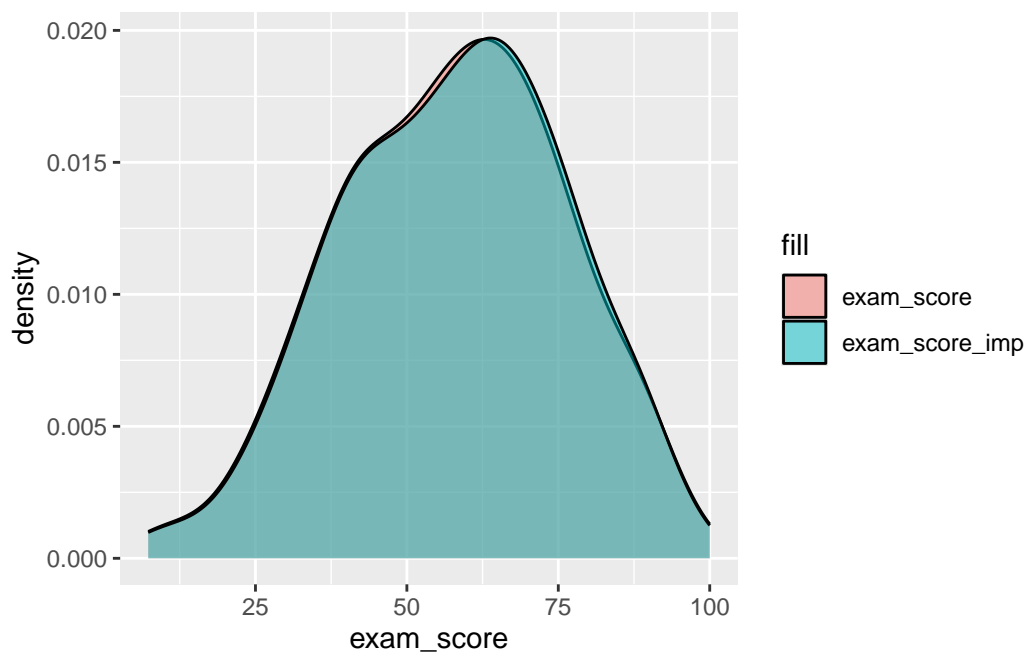
exam_score (NRMSE = 0.38)

Ninguno parece demasiado alto, pero es curioso que gpa sea uno de los más bajos a diferencia del resto de imputaciones.

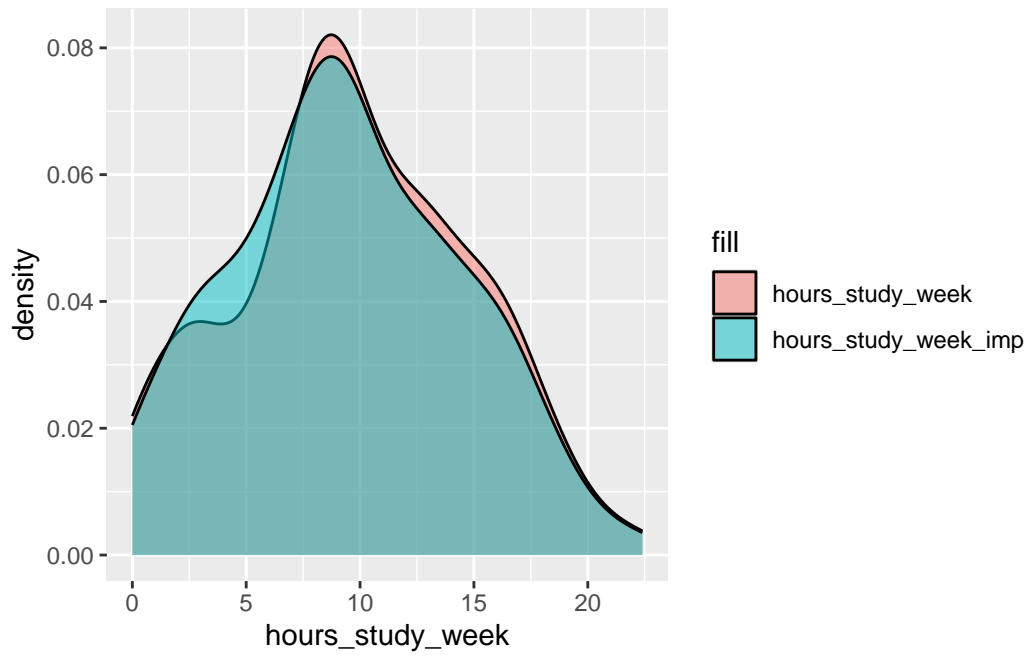
```
g1<-ggplot(data, aes(x =gpa, fill = "gpa")) +  
  geom_density(alpha = 0.5, na.rm = TRUE) +  
  geom_density(aes(x = imp$rimp$gpa,  
    fill = "gpa_imp"), alpha = 0.5)  
  
g2<-ggplot(data, aes(x = exam_score, fill = "exam_score")) +  
  geom_density(alpha = 0.5, na.rm = TRUE) +  
  geom_density(aes(x = imp$rimp$exam_score,  
    fill = "exam_score_imp"),alpha = 0.5)  
  
g3<-ggplot(data, aes(x = hours_study_week,  
    fill = "hours_study_week")) +  
  geom_density(alpha = 0.5, na.rm = TRUE) +  
  geom_density(aes(x = imp$rimp$hours_study_week,  
    fill = "hours_study_week_imp"), alpha = 0.5)  
  
g4<-ggplot(data, aes(x = attendance_pct,  
    fill = "attendance_pct")) +  
  geom_density(alpha = 0.5, na.rm = TRUE) +  
  geom_density(aes(x = imp$rimp$attendance_pct,  
    fill = "attendance_pct_imp"), alpha = 0.5)  
  
g1
```



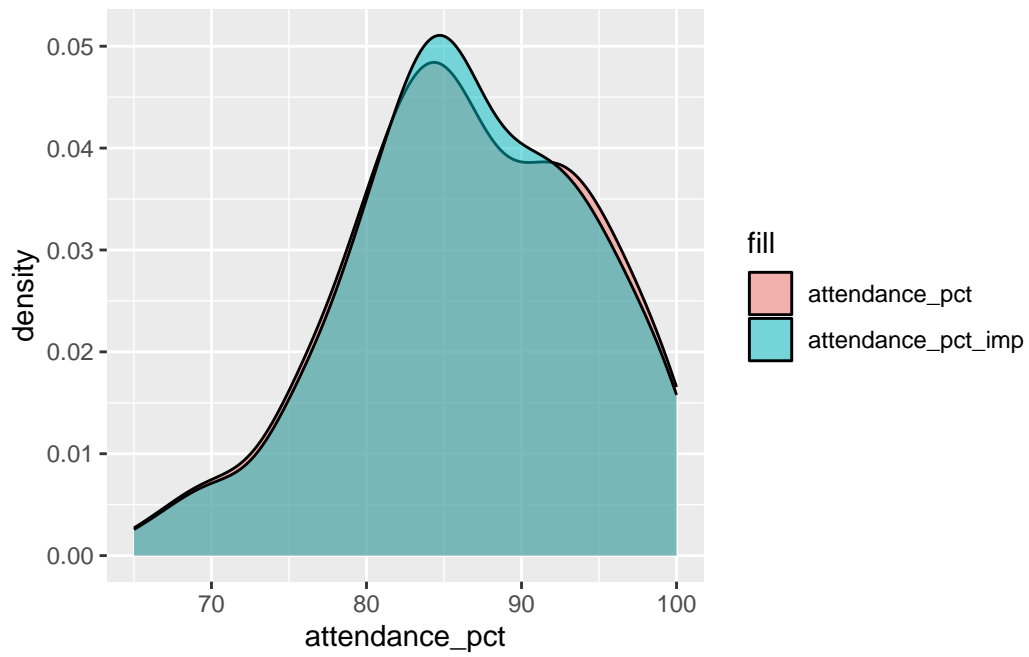
g2



g3



g4



El gráfico de gpa es el que peor se ajusta a su distribución, pero mejora mucho a lo que veíamos con el resto de imputaciones.