Ejercicio 3.2: Imputación de datos perdidos (simple)

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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   1.6.0
v ggplot2   4.0.0     v tibble    3.3.0
v lubridate 1.9.4     v tidyr     1.3.1
v purrr     1.2.0
-- 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 becor
```

```
library(rio)

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

1.Imputación de las variables MCAR

La variable `program` y `study_mode` tienen $< 5\%$ y ambas son cualitativas, por tanto la forma más simple de imputarlas sería por la moda.

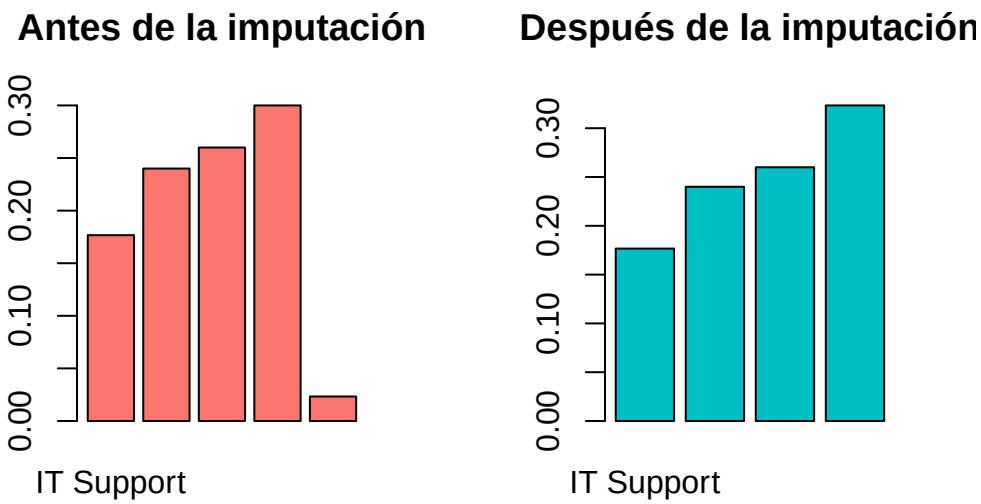
```r
#Comprobar la categoría más frecuente
prop.table(table(data$program,useNA = "always"))
```

```
             IT Support Network Administration   Software Engineering
             0.17666667             0.24000000             0.26000000
        Web Development                    <NA>
             0.30000000             0.02333333
```

```r
## Sustituir los NA con la categoría más frecuente
data$program_imp <-data$program
data$program_imp[is.na(data$program_imp)] <- "Web Development"

## Volvemos a comprobar
prop.table(table(data$program_imp,useNA = "always"))
```

```
             IT Support Network Administration   Software Engineering
              0.1766667              0.2400000              0.2600000
        Web Development                    <NA>
              0.3233333              0.0000000
```

```r
# Graficar la distribución de la variable categórica antes y después de la imputación
par(mfrow = c(1, 2)) # Organizar las gráficas en una fila de 2 columnas
barplot(prop.table(table(data$program, useNA = "ifany")),
        main = "Antes de la imputación", col = "#F8766D" )
barplot(prop.table(table(data$program_imp)),
        main = "Después de la imputación",col = "#00BFC4")
```



El % de datos missing de la variable program es muy bajo y al imputar por la moda, no cambia la distribución en absoluto, por tanto, lo asumiremos como una buena imputación

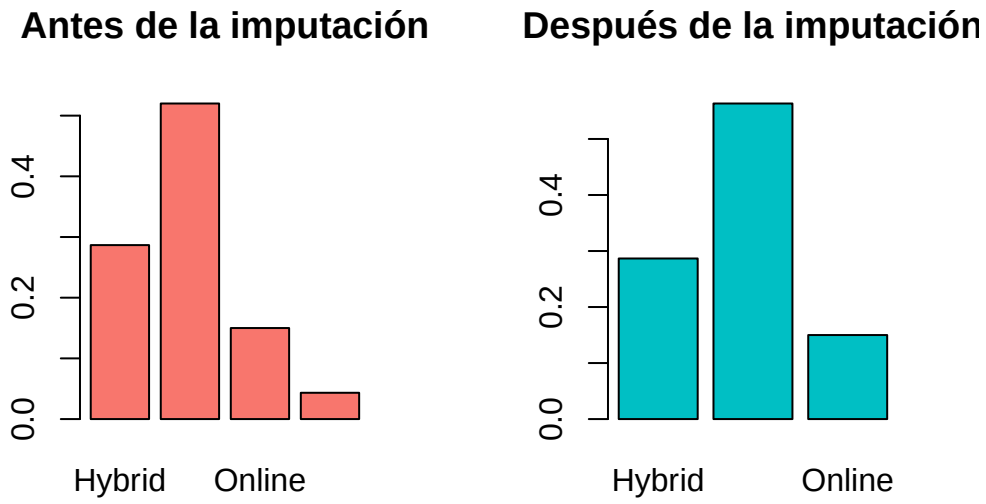
```
#Comprobar la categoría más frecuente
prop.table(table(data$study_mode,useNA = "always"))
```

```
    Hybrid  On-campus     Online       <NA>
0.28666667 0.52000000 0.15000000 0.04333333
```

```
## Sustituir los NA con la categoría más frecuente
data$study_mode_imp <-data$study_mode
data$study_mode_imp[is.na(data$study_mode_imp)] <- "On-campus"

## Volvemos a comprobar
prop.table(table(data$study_mode_imp,useNA = "always"))
```

```
   Hybrid On-campus    Online      <NA>
0.2866667 0.5633333 0.1500000 0.0000000
```

```r
# Graficar la distribución de la variable categórica antes y después de la imputación
par(mfrow = c(1, 2)) # Organizar las gráficas en una fila de 2 columnas
barplot(prop.table(table(data$study_mode, useNA = "ifany")),
        main = "Antes de la imputación", col = "#F8766D" )
barplot(prop.table(table(data$study_mode_imp)),
        main = "Después de la imputación",col = "#00BFC4")
```



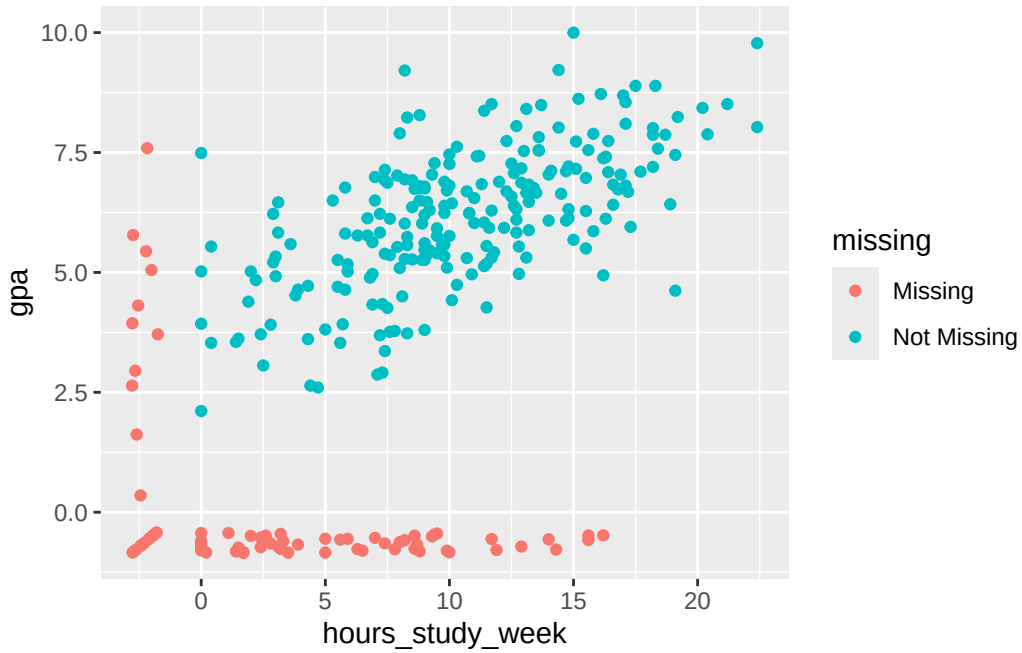
El % de datos missing de la variable `study_program` es muy bajo y al imputar por la moda, no cambia la distribución en absoluto, por tanto, lo asumiremos como una buena imputación

2.Imputación de las variables MAR/MNAR

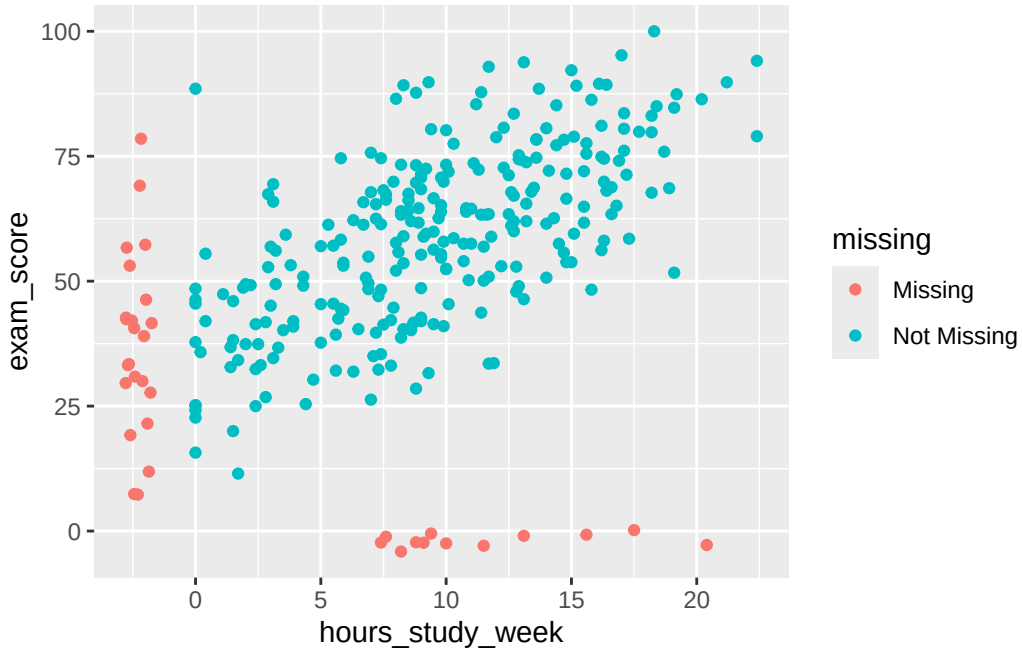
- Variable `hours_study_week`

Los NA de esta variable son MAR y corresponden a un 8%, además la variable está asociada con gpa y exam_score:

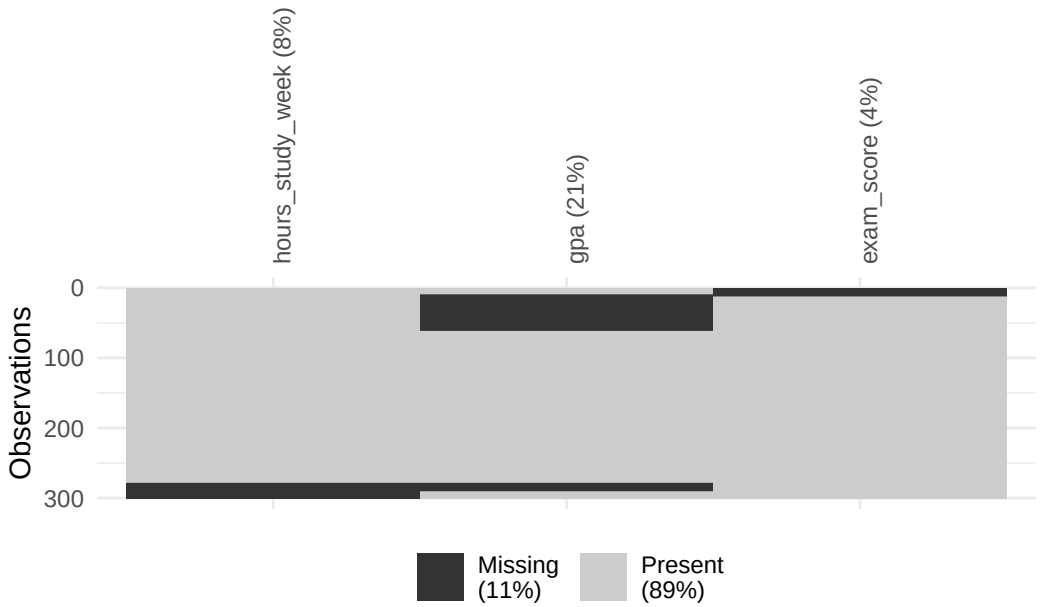
```r
ggplot(data = data, aes (x = hours_study_week ,
                         y =gpa )) + geom_miss_point()
```




```
ggplot(data = data, aes (x = hours_study_week ,
                         y =exam_score )) + geom_miss_point()
```



```
vis_miss(select(data,hours_study_week,gpa,exam_score),cluster=TRUE)  +
  theme(axis.text.x = element_text(angle = 90))
```



Como solo están completos los datos de `exam_score` para los NA de `hours_study_week`, la imputaremos mediante una regresión:

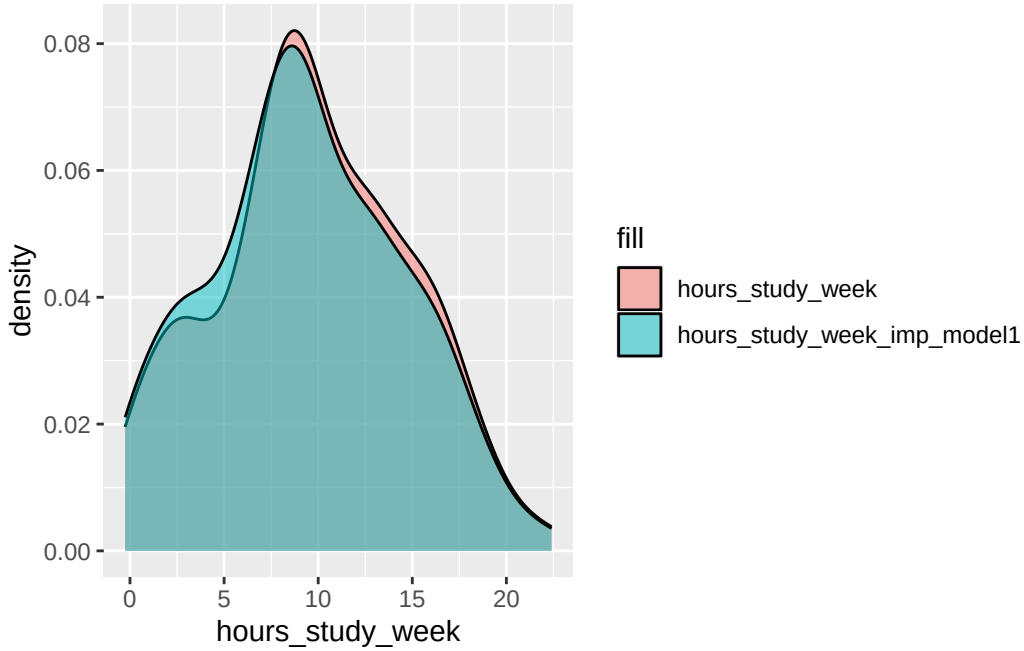
```
#Ajustar un modelo de regresión lineal
model1 <- lm(hours_study_week ~ exam_score, data = data)

#Predecir los valores solo para las observaciones faltantes
predictions <- predict(model1,newdata = data [is.na(data$hours_study_week),])

##Crear una nueva variable imputada
data$hours_study_week_imp_model1 <- data$hours_study_week
data$hours_study_week_imp_model1[is.na(data$hours_study_week)]<- predictions

summary(model1)
```

```
Call:
lm(formula = hours_study_week ~ exam_score, data = data)
```

```
Residuals:
    Min      1Q  Median      3Q     Max
-15.154  -2.908   0.145   2.647  10.931

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.64250    0.84511  -1.944    0.053 .
exam_score   0.18979    0.01368  13.871   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.908 on 263 degrees of freedom
  (35 observations deleted due to missingness)
Multiple R-squared:  0.4225,    Adjusted R-squared:  0.4203
F-statistic: 192.4 on 1 and 263 DF,  p-value: < 2.2e-16
```

```r
#Hacer un gráfico para comparar las observaciones
ggplot(data, aes(x = hours_study_week, fill = "hours_study_week")) +
  geom_density(alpha = 0.5) +

geom_density(aes(x = hours_study_week_imp_model1, fill = "hours_study_week_imp_model1"), alp
```

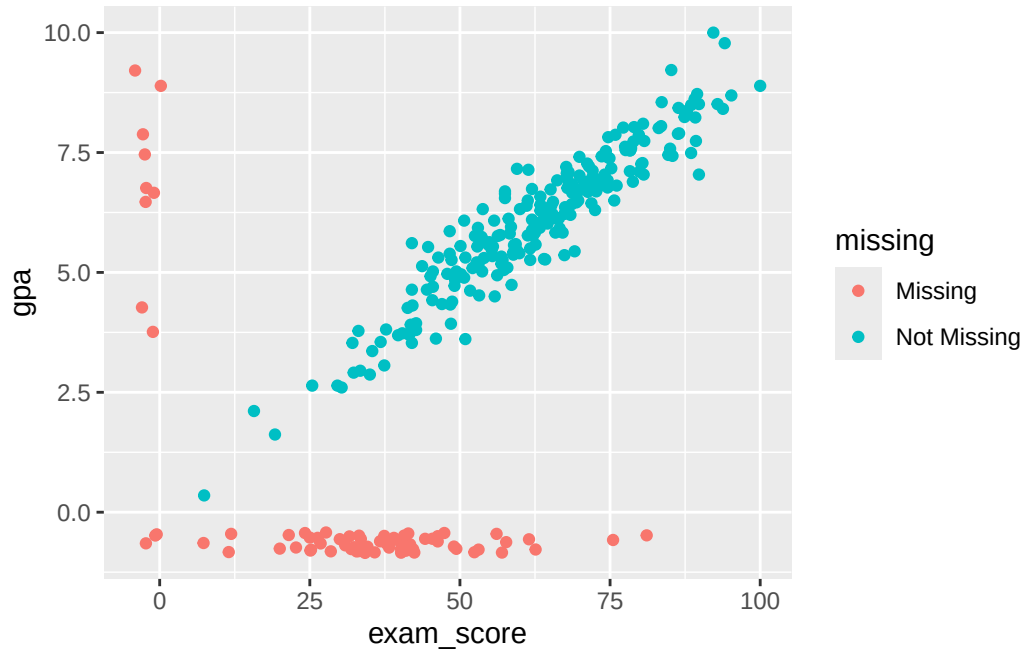
```
Warning: Removed 23 rows containing non-finite outside the scale range
(`stat_density()`).
```



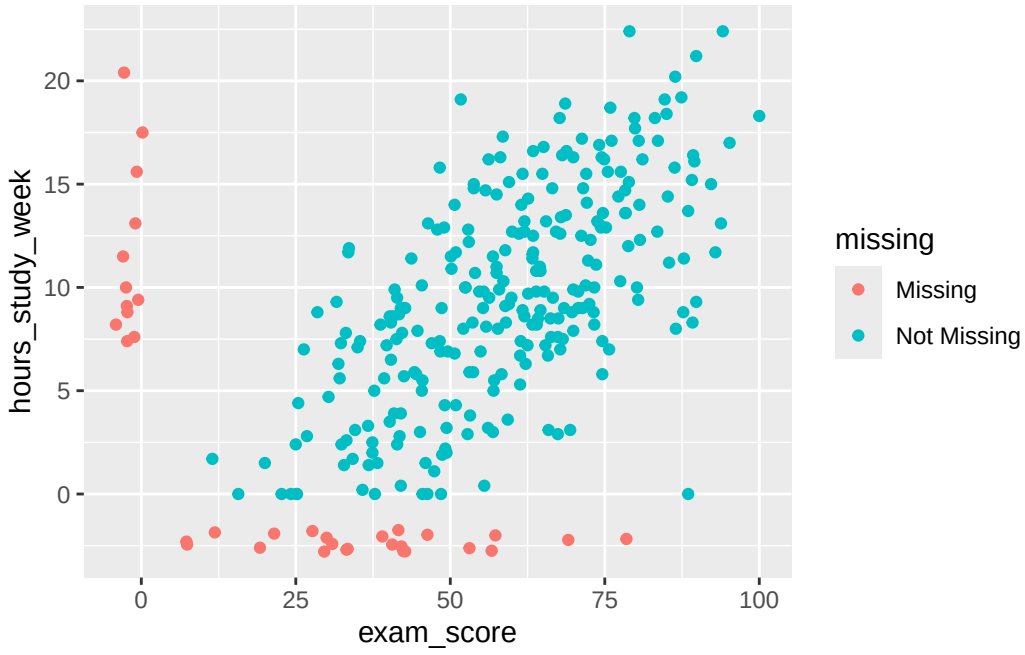
- **Variable `exam_score`**

Los `NA` de esta variable podrían ser MAR si corresponden a un profesor que no ha subido las notas o MNAR si correspondieran a aquellos que han suspendido.

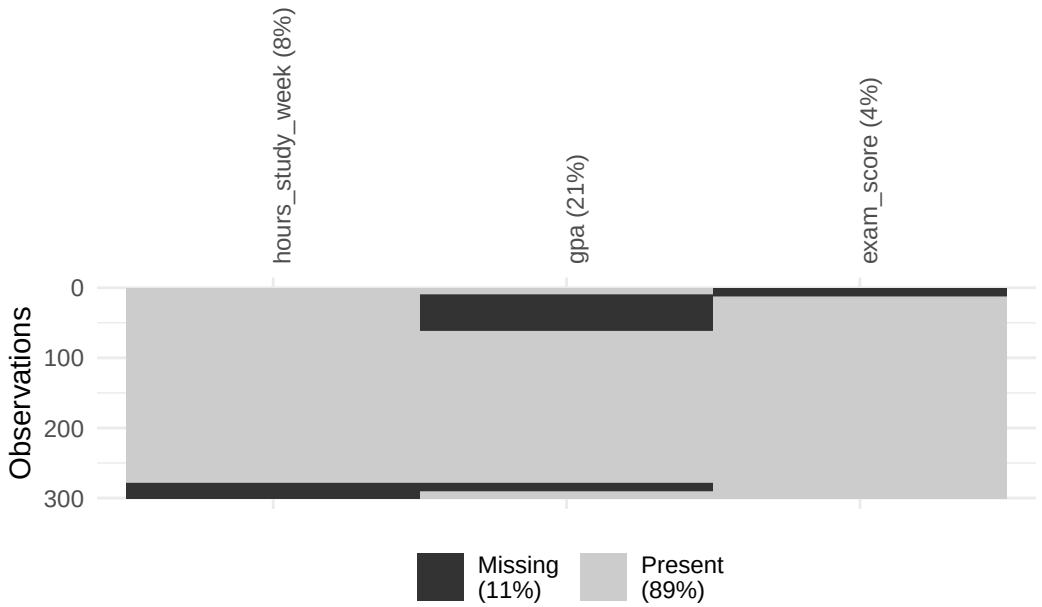
```
ggplot(data = data, aes (x = exam_score ,
                         y =gpa )) + geom_miss_point()
```




```
ggplot(data = data, aes (x = exam_score ,
                         y =hours_study_week )) + geom_miss_point()
```



```
vis_miss(select(data,hours_study_week,gpa,exam_score),cluster=TRUE)  +
  theme(axis.text.x = element_text(angle = 90))
```



Como solo están completos los datos de `hours_study_week` para los NA de `exam_score`, la imputaremos mediante una regresión:

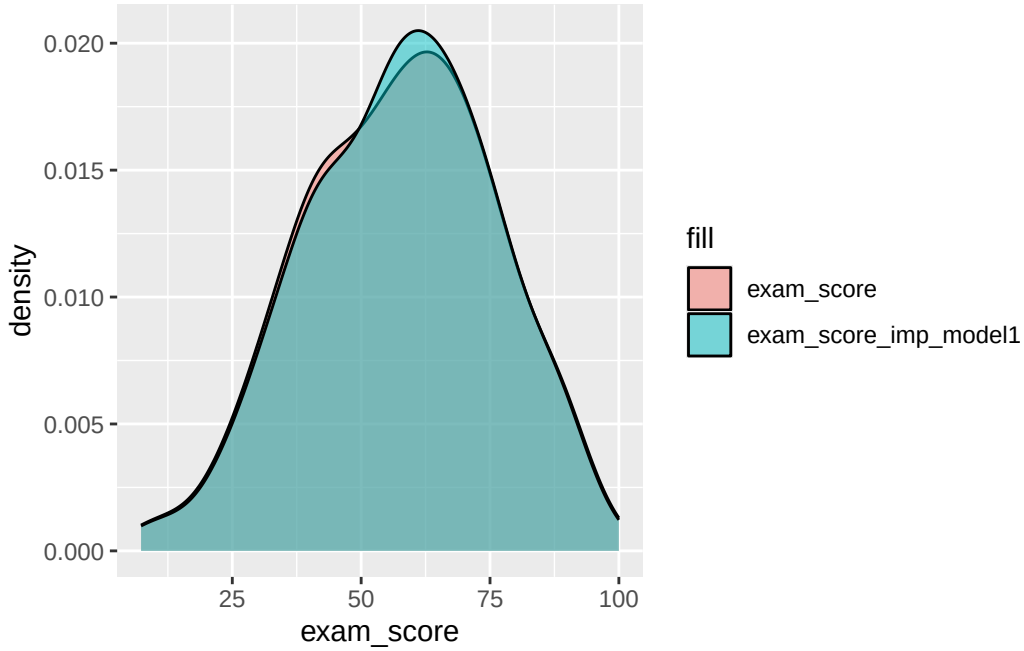
```
#Ajustar un modelo de regresión lineal
model1 <- lm(exam_score ~ hours_study_week, data = data)

#Predecir los valores solo para las observaciones faltantes
predictions <- predict(model1,newdata = data [is.na(data$exam_score),])

##Crear una nueva variable imputada
data$exam_score_imp_model1 <- data$exam_score
data$exam_score_imp_model1[is.na(data$exam_score_imp_model1)]<- predictions

summary(model1)
```

```
Call:
lm(formula = exam_score ~ hours_study_week, data = data)
```

```
Residuals:
    Min      1Q  Median      3Q     Max
-30.748 -10.156   0.564   8.443  50.643

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)       37.8574     1.7460   21.68   <2e-16 ***
hours_study_week   2.2261     0.1605   13.87   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 13.39 on 263 degrees of freedom
  (35 observations deleted due to missingness)
Multiple R-squared:  0.4225,    Adjusted R-squared:  0.4203
F-statistic: 192.4 on 1 and 263 DF,  p-value: < 2.2e-16
```

```r
#Hacer un gráfico para comparar las observaciones
ggplot(data, aes(x = exam_score, fill = "exam_score")) +
  geom_density(alpha = 0.5) +

geom_density(aes(x = exam_score_imp_model1,
                 fill = "exam_score_imp_model1"), alpha = 0.5)
```

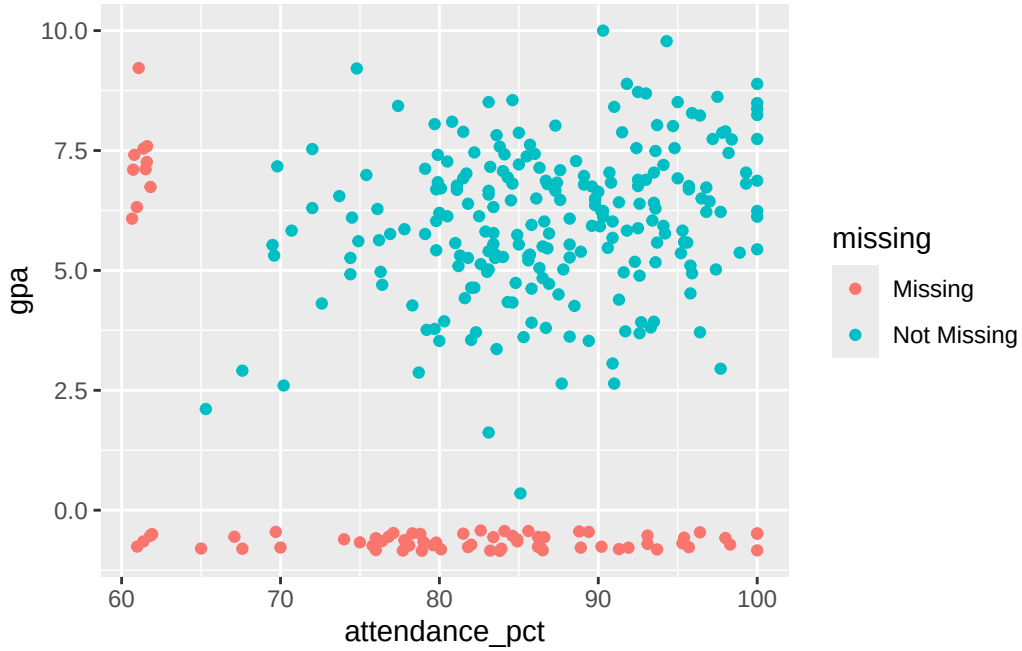
```
Warning: Removed 12 rows containing non-finite outside the scale range
(`stat_density()`).
```



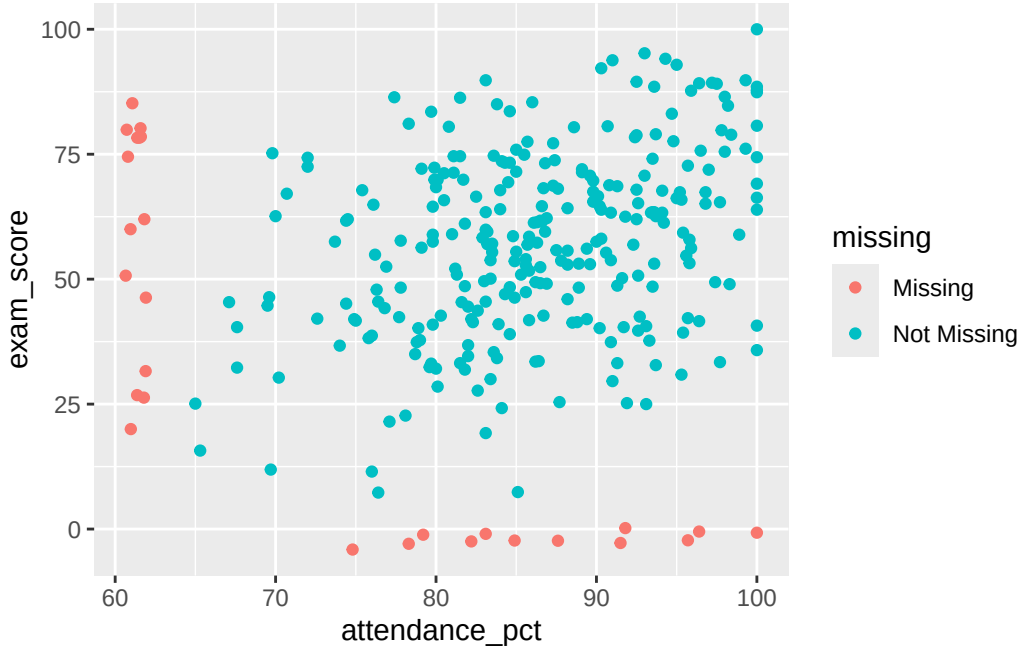
- **Variable** `attendance_pct`

Los `NA` de `attendance_pct` son MNAR, pero con un % pequeño y asociados a valores altos de `gpa`, además esta variable está asociada a exam_score y todos sus missing están completos

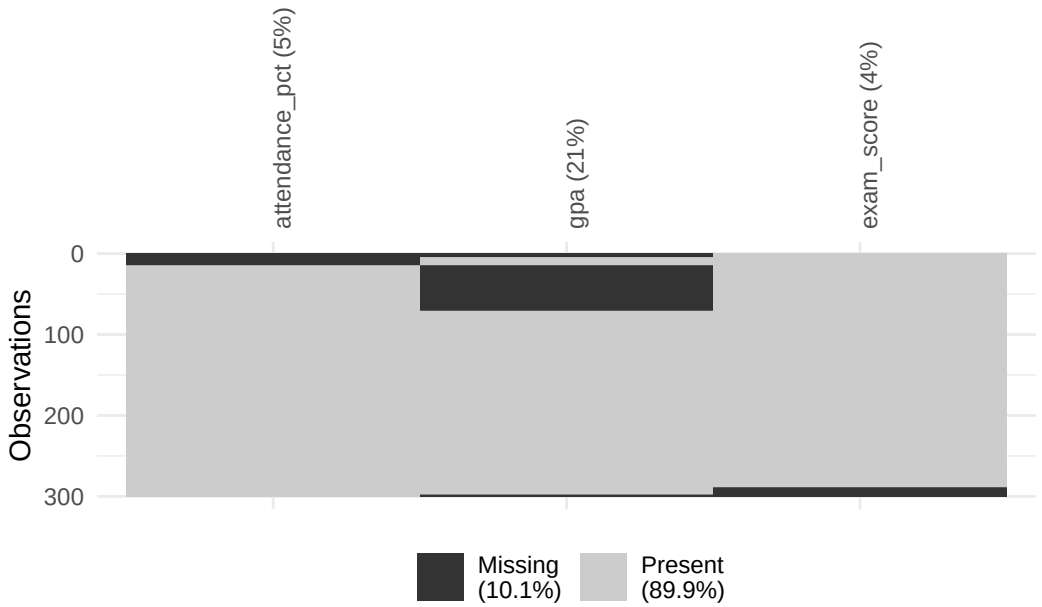
```
ggplot(data = data, aes (x = attendance_pct ,
                         y =gpa )) + geom_miss_point()
```




```
ggplot(data = data, aes (x = attendance_pct ,
                         y =exam_score )) + geom_miss_point()
```



```r
vis_miss(select(data,attendance_pct,gpa,exam_score),cluster=TRUE)  +
  theme(axis.text.x = element_text(angle = 90))
```



Como solo están completos los datos de `exam_score` para los NA de `attendance_pct`, la imputaremos mediante una regresión:

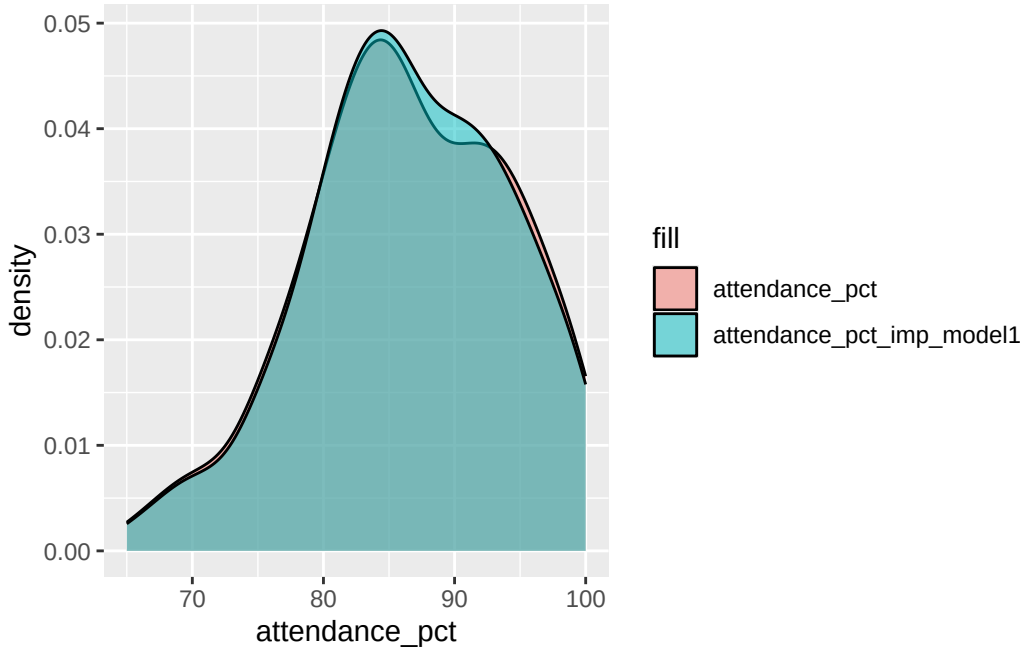
```r
#Ajustar un modelo de regresión lineal
model1 <- lm(attendance_pct ~ exam_score, data = data)
summary(model1)
```

```
Call:
lm(formula = attendance_pct ~ exam_score, data = data)

Residuals:
     Min       1Q   Median       3Q      Max
-19.4057  -4.3153   0.0505   5.7861  16.9649

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 77.42832    1.45920  53.062  < 2e-16 ***
exam_score   0.15661    0.02421   6.468 4.61e-10 ***
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 7.315 on 271 degrees of freedom
  (27 observations deleted due to missingness)
Multiple R-squared:  0.1337,    Adjusted R-squared:  0.1305
F-statistic: 41.84 on 1 and 271 DF,  p-value: 4.614e-10
```

```r
#Predecir los valores solo para las observaciones faltantes
predictions <- predict(model1,newdata = data [is.na(data$attendance_pct),])

##Crear una nueva variable imputada
data$attendance_pct_imp_model1 <- data$attendance_pct
data$attendance_pct_imp_model1[is.na(data$attendance_pct_imp_model1)]<- predictions



#Hacer un gráfico para comparar las observaciones
ggplot(data, aes(x = attendance_pct, fill = "attendance_pct")) +
  geom_density(alpha = 0.5) +

geom_density(aes(x = attendance_pct_imp_model1,
                 fill = "attendance_pct_imp_model1"), alpha = 0.5)
```

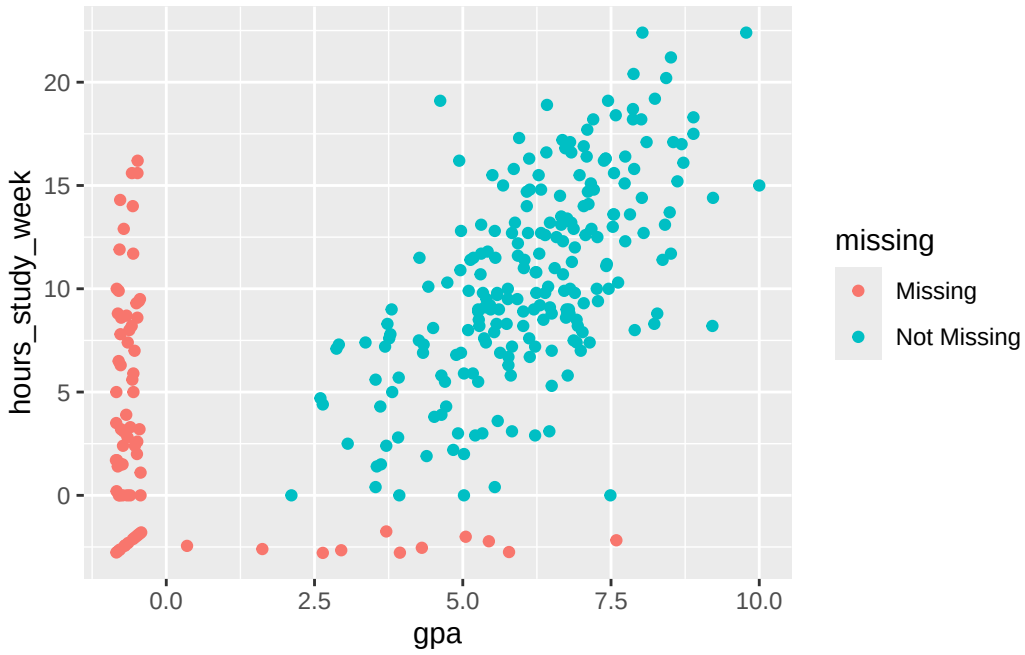
```
Warning: Removed 15 rows containing non-finite outside the scale range
(`stat_density()`).
```



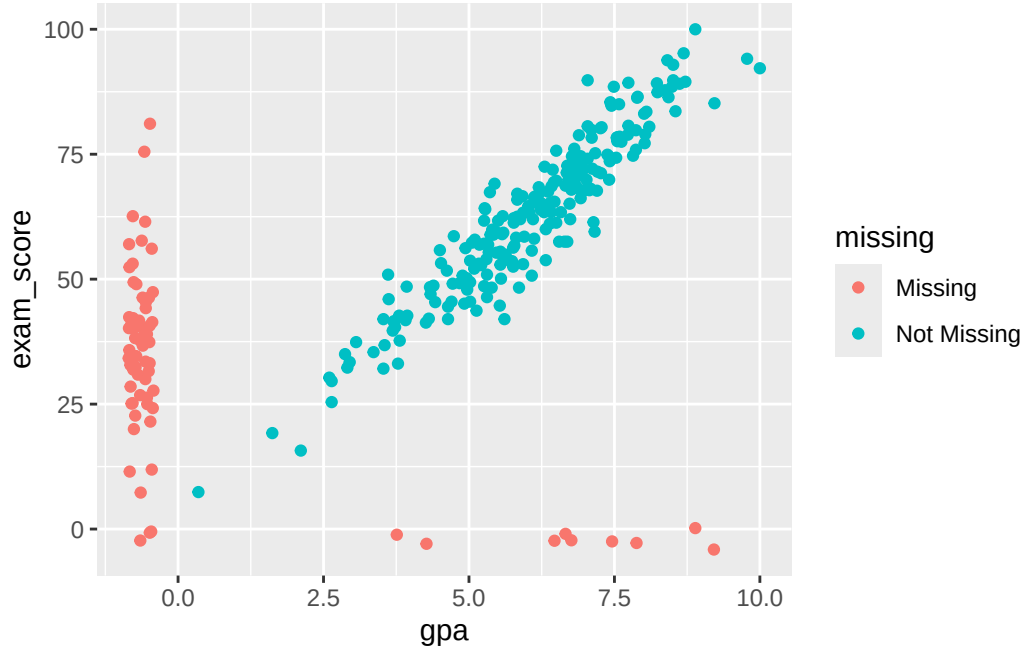
- **Variable** `gpa`

Los `NA` de `gpa` corresponden mayoritariamente a valores con datos inferiores de `hours_study_week` y con datos menores de `exam_score`. Por tanto, este patrón podría correnponder a un patrón **MNAR** ya que quizás corresponda a valores bajos de `gpa`.

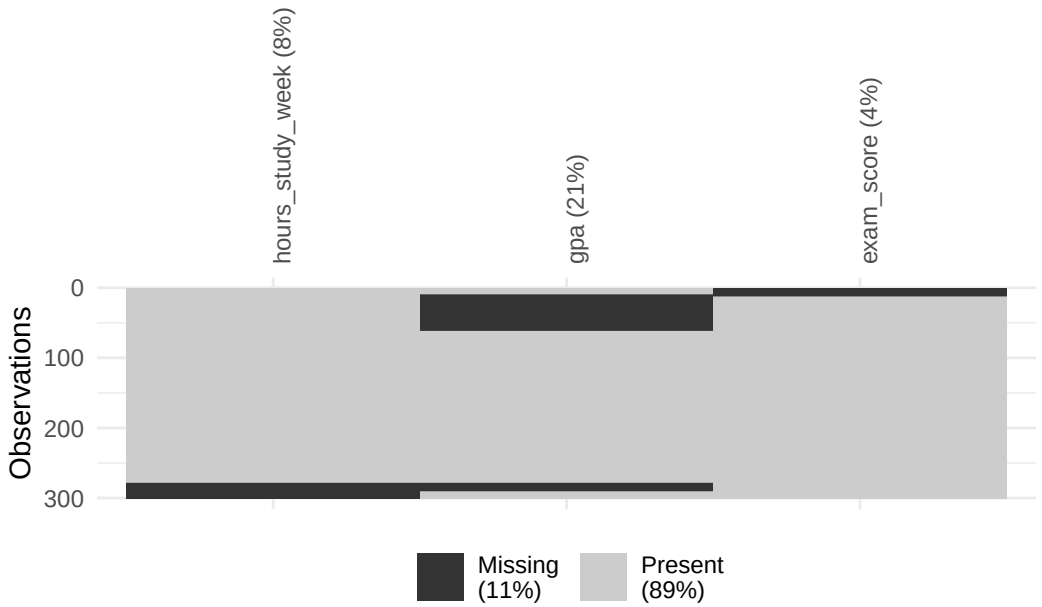
```
ggplot(data = data, aes (x = gpa ,
                         y =hours_study_week )) + geom_miss_point()
```




```
ggplot(data = data, aes (x = gpa ,
                         y =exam_score )) + geom_miss_point()
```



```r
vis_miss(select(data,hours_study_week,gpa,exam_score),cluster=TRUE)  +
  theme(axis.text.x = element_text(angle = 90))
```



En este caso, no tenemos ninguna de las dos variables asociadas como completas. Por tanto una opción es usar una de las ya imputadas. En este caso, usaremos exam_score que tiene el menor número de datos faltantes y una asociación muy clara

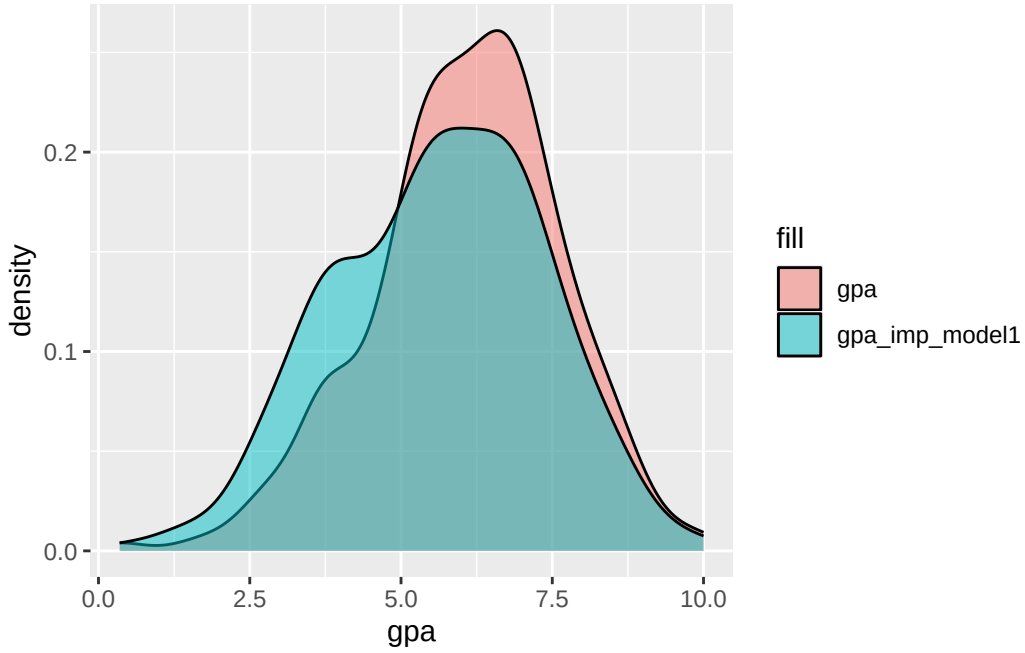
```r
#Ajustar un modelo de regresión lineal
model1 <- lm(gpa ~ exam_score_imp_model1, data = data)
summary(model1)
```

```
Call:
lm(formula = gpa ~ exam_score_imp_model1, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-1.8735 -0.3485 -0.0369  0.2798  3.7261

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.445945   0.160162   2.784   0.0058 **
```

```
exam_score_imp_model1 0.089785   0.002476  36.264   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6056 on 234 degrees of freedom
  (64 observations deleted due to missingness)
Multiple R-squared:  0.8489,    Adjusted R-squared:  0.8483
F-statistic:  1315 on 1 and 234 DF,  p-value: < 2.2e-16
```

```r
#Predecir los valores solo para las observaciones faltantes
predictions <- predict(model1,newdata = data [is.na(data$gpa),])

##Crear una nueva variable imputada
data$gpa_imp_model1 <- data$gpa
data$gpa_imp_model1[is.na(data$gpa_imp_model1)]<- predictions



#Hacer un gráfico para comparar las observaciones
ggplot(data, aes(x = gpa, fill = "gpa")) +
  geom_density(alpha = 0.5) +

geom_density(aes(x = gpa_imp_model1, fill = "gpa_imp_model1"),
             alpha = 0.5)
```

```
Warning: Removed 64 rows containing non-finite outside the scale range
(`stat_density()`).
```



En este caso vemos que la imputación no es tan buena como en las anteriores, se puede ver si añadiendo incertidumbre mejora

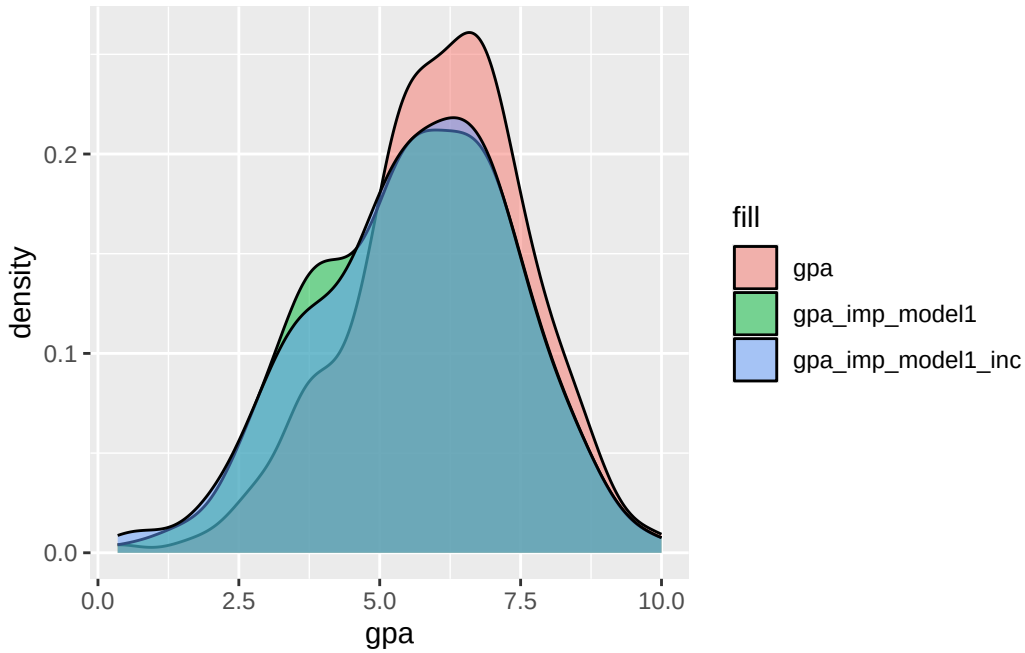
```
summary(model1) ##Cogemos el residual standard error
```

```
Call:
lm(formula = gpa ~ exam_score_imp_model1, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-1.8735 -0.3485 -0.0369  0.2798  3.7261

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.445945   0.160162   2.784   0.0058 **
exam_score_imp_model1 0.089785   0.002476  36.264   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6056 on 234 degrees of freedom
  (64 observations deleted due to missingness)
Multiple R-squared:  0.8489,    Adjusted R-squared:  0.8483
```

```
F-statistic:  1315 on 1 and 234 DF,  p-value: < 2.2e-16
```

```r
set.seed(3)
inc<-rnorm(sum(is.na(data$gpa)), 0, sd = 0.6056)

data$gpa_imp_model1_inc <- data$gpa
data$gpa_imp_model1_inc[is.na(data$gpa)]<- predictions + inc

#Hacer un gráfico para comparar las observaciones con la media y la regresión
ggplot(data, aes(x = gpa, fill = "gpa")) +
  geom_density(alpha = 0.5) +
  geom_density(aes(x = gpa_imp_model1, fill = "gpa_imp_model1"),
               alpha = 0.5) +
  geom_density(aes(x = gpa_imp_model1_inc, fill = "gpa_imp_model1_inc"),
               alpha = 0.5)
```

```
Warning: Removed 64 rows containing non-finite outside the scale range
(`stat_density()`).
```



tampoco parece muy acertado, las razones son que el % de faltantes es muy elevado y que estamos bajo el suspuesto de MNAR, así que habrá que ver imputaciones más sofitiscadas.