Sistema tidyverse: purrr, broom, tidyr

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Índice

Uso de la librería: purrr (map,...)

```
library(tidyverse)
#library(purrr)  # se carga con tidyverse
```

Uso de map()

```
(v_doub <- 1:4 * 1.2)
```

```
## [1] 1.2 2.4 3.6 4.8
```

```
l_doub = as.list(v_doub)
l_doub
```

```
## [[1]]
## [1] 1.2
##
## [[2]]
## [1] 2.4
##
## [[3]]
## [1] 3.6
##
## [[4]]
## [1] 4.8
```

```
map(l_doub,exp)
```

```
## [[1]]
## [1] 3.320117
```

```
##
## [[2]]
## [1] 11.02318
##
## [[3]]
## [1] 36.59823
##
## [[4]]
## [1] 121.5104
```

```
map_dbl(l_doub,exp)
```

```
## [1]   3.320117  11.023176  36.598234 121.510418
```

```
map_int(l_doub,exp)
```

```
## Error: Can't coerce element 1 from a double to a integer
```

Equivalentes:

```
lapply(l_doub,exp)
```

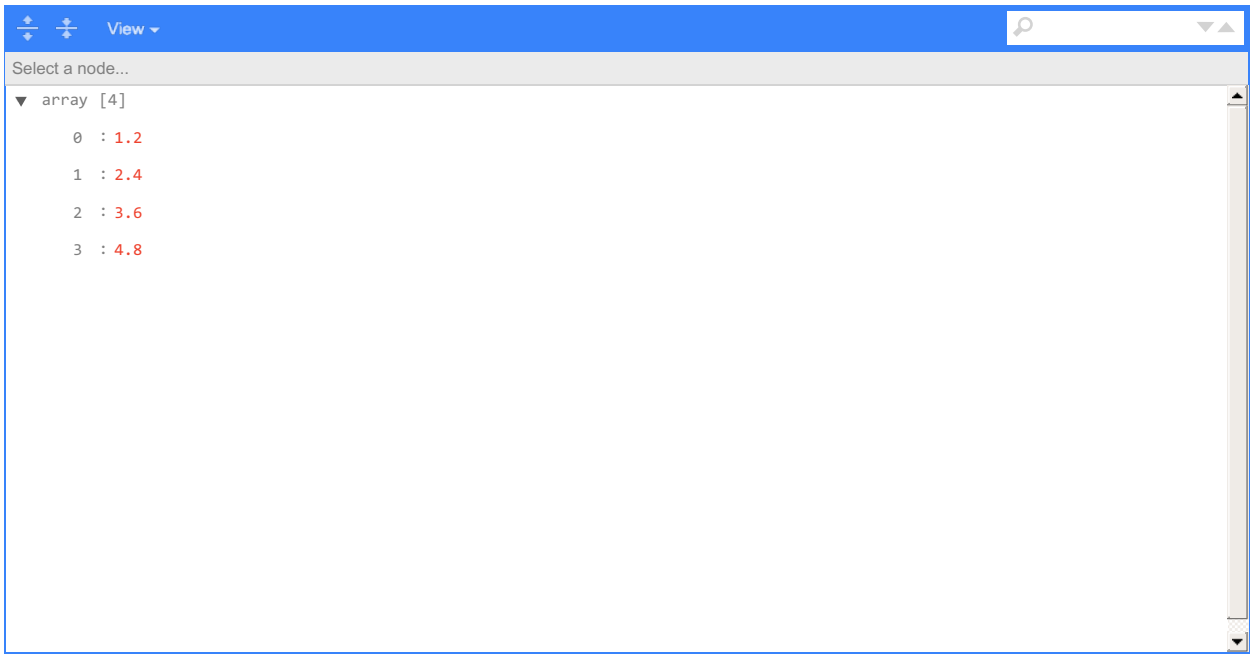
```
## [[1]]
## [1] 3.320117
##
## [[2]]
## [1] 11.02318
##
## [[3]]
## [1] 36.59823
##
## [[4]]
## [1] 121.5104
```

```
sapply(l_doub,exp)
```

```
## [1]   3.320117  11.023176  36.598234 121.510418
```

Ejemplo 2: map()

```
#listviewer::jsonedit(got_chars, mode = "view")
listviewer::jsonedit(l_doub, mode = "view")
```




```
map(v_doub,exp)
```

```
## [[1]]
## [1] 3.320117
##
## [[2]]
## [1] 11.02318
##
## [[3]]
## [1] 36.59823
##
## [[4]]
## [1] 121.5104
```

```
map_dbl(v_doub,exp)
```

```
## [1]   3.320117  11.023176  36.598234 121.510418
```

Ejemplo 3: map()

```
## Obtenido de: https://malco.io/slides/hs_purrr/#45
## Ver: https://malco.io/slides/
# library(tidyverse)
library(gapminder)
gapminder %>%
  dplyr::select_if(is.numeric) %>%
  map(sd)
```

```
## $year
## [1] 17.26533
##
## $lifeExp
## [1] 12.91711
##
```

```
## $pop
## [1] 106157897
##
## $gdpPercap
## [1] 9857.455
```

Las siguientes dos son equivalentes

```
gapminder %>%
  dplyr::select_if(is.numeric) %>%
  map(~mean(.,na.rm = T))     # map(~mean(.,na.rm = T))
```

```
## $year
## [1] 1979.5
##
## $lifeExp
## [1] 59.47444
##
## $pop
## [1] 29601212
##
## $gdpPercap
## [1] 7215.327
```

```
gapminder %>%
  dplyr::select_if(is.numeric) %>%
  map(mean,na.rm = T)
```

```
## $year
## [1] 1979.5
##
## $lifeExp
## [1] 59.47444
##
## $pop
## [1] 29601212
##
## $gdpPercap
## [1] 7215.327
```

Otro ejemplo:

```
map(gapminder, ~length(unique(.x)))
```

```
## $country
## [1] 142
##
## $continent
## [1] 5
##
## $year
## [1] 12
##
## $lifeExp
## [1] 1626
##
## $pop
```

```
## [1] 1704
##
## $gdpPercap
## [1] 1704
```

Tipos de valores que se devuelven con map()

map	returns
`map()`	list
`map_chr()`	character vector
`map_dbl()`	double vector (numeric)
`map_int()`	integer vector
`map_lgl()`	logical vector
`map_dfc()`	data frame (by column)
`map_dfr()`	data frame (by row)

Ejemplo 4: map()

```
gapminder %>%
  dplyr::select_if(is.numeric) %>%
  map(mean,na.rm = T)
```

```
## $year
## [1] 1979.5
##
## $lifeExp
## [1] 59.47444
##
## $pop
## [1] 29601212
##
## $gdpPercap
## [1] 7215.327
```

```
gapminder %>%
  dplyr::select_if(is.numeric) %>%
  map_dbl(mean,na.rm = T)
```

```
##         year      lifeExp          pop    gdpPercap
## 1.979500e+03 5.947444e+01 2.960121e+07 7.215327e+03
```

```
gapminder %>%
  dplyr::select_if(is.numeric) %>%
  map_dfc(mean,na.rm = T)
```

```
## # A tibble: 1 x 4
##    year lifeExp       pop gdpPercap
##   <dbl>   <dbl>     <dbl>     <dbl>
## 1 1980.    59.5 29601212.     7215.
```

```
gapminder %>%
  dplyr::select_if(is.numeric) %>%
  map_dfr(mean,na.rm = T)
```

```
## # A tibble: 1 x 4
```

```
##    year lifeExp       pop gdpPercap
##   <dbl>   <dbl>     <dbl>     <dbl>
## 1 1980.    59.5 29601212.     7215.
```

Uso de map2()

Sintaxis:

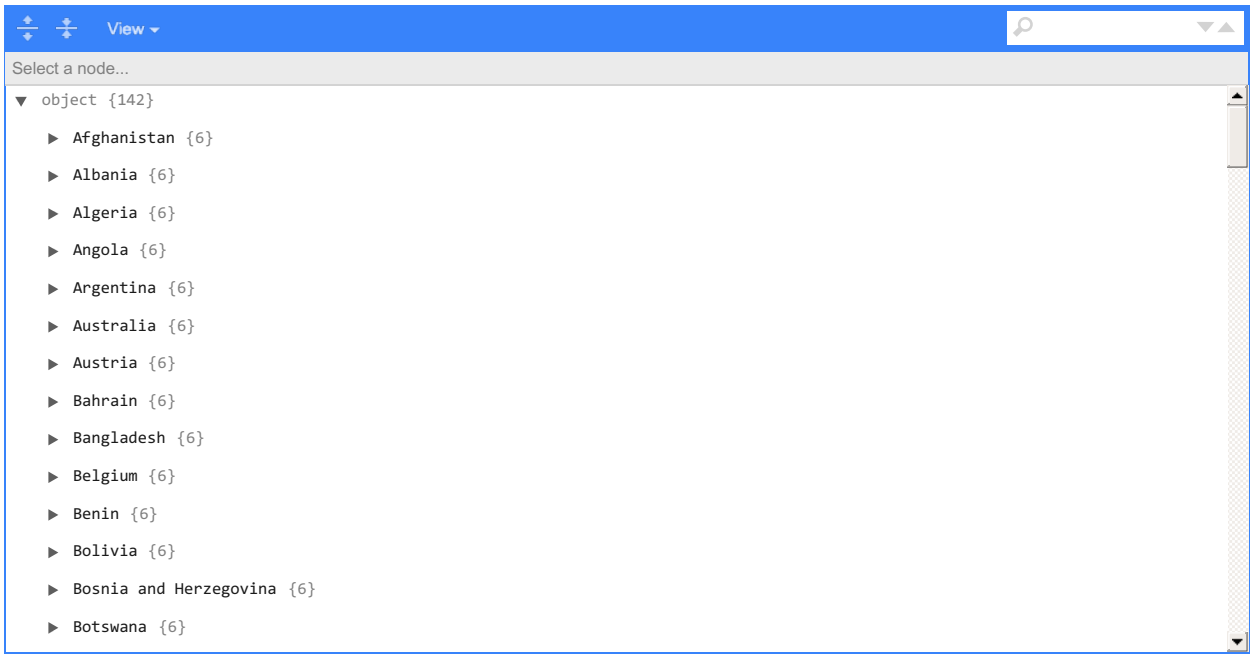
```
map2(.x, .y, .f)

.x, .y: a vector, list, or data frame

map2(.x, .y, ~.f(.x, .y))
```

Ejemplo 1: map2()

```
gapminder_countries <- split(gapminder, gapminder$country)
models <- map(gapminder_countries, ~ lm(lifeExp ~ year, data = .x))
preds <- map2(models, gapminder_countries, predict)
head(preds, 3)
```

```
## $Afghanistan
##        1        2        3        4        5        6        7        8
## 29.90729 31.28394 32.66058 34.03722 35.41387 36.79051 38.16716 39.54380
##        9       10       11       12
## 40.92044 42.29709 43.67373 45.05037
##
## $Albania
##        1        2        3        4        5        6        7        8
## 59.22913 60.90254 62.57596 64.24938 65.92279 67.59621 69.26962 70.94304
##        9       10       11       12
## 72.61646 74.28987 75.96329 77.63671
##
## $Algeria
##        1        2        3        4        5        6        7        8
## 43.37497 46.22137 49.06777 51.91417 54.76057 57.60697 60.45337 63.29976
##        9       10       11       12
## 66.14616 68.99256 71.83896 74.68536
```

```
listviewer::jsonedit(gapminder_countries, mode = "view")
```




```
preds_r <- map2_dfr(models, gapminder_countries, predict)
```

```
preds_c <- map2_dfc(models, gapminder_countries, predict)
```

Tipos de valores que se devuelven con map2()

input 1	input 2	returns
`map()`	`map2()`	list
`map_chr()`	`map2_chr()`	character vector
`map_dbl()`	`map2_dbl()`	double vector (numeric)
`map_int()`	`map2_int()`	integer vector
`map_lgl()`	`map2_lgl()`	logical vector
`map_dfc()`	`map2_dfc()`	data frame (by column)
`map_dfr()`	`map2_dfr()`	data frame (by row)

Otras funciones de mapping

- `pmap()` y amigas: coge n listas o data.frame con nombres de argumento.
- `walk()` y amigas: para producir otros elementos como gráficos; devuelven input invisibles.
- `imap()` y amigas: incluye contador `i`.
- `map_if()`, `map_at()`: se aplica solamente a ciertos elementos.

input 1	input 2		devuelve n entradas
`map()`	`map2()`	`pmap()`	list
`map_chr()`	`map2_chr()`	`pmap_chr()`	character vector
`map_dbl()`	`map2_dbl()`	`pmap_dbl()`	double vector (numeric)
`map_int()`	`map2_int()`	`pmap_int()`	integer vector
`map_lgl()`	`map2_lgl()`	`pmap_lgl()`	logical vector
`map_dfc()`	`map2_dfc()`	`pmap_dfc()`	data frame (by column)

input 1	input 2		devuelve n entradas
`map_dfr()`	`map2_dfr()`	`pmap_dfr()`	data frame (by row)
`walk()`	`walk2()`	`pwalk()`	input (side effects!)

Equivalentes a purrr en el sistema base

base R	purrr
`lapply()`	`map()`
`vapply()`	`map_*()`
`sapply()`	?
`x[] <- lapply()`	`map_dfc()`
`mapply()`	`map2(), pmap()`

```
#gapminder_countries <- split(gapminder, gapminder$country)
# models <- map(gapminder_countries, ~ lm(lifeExp ~ year, data = .x))
# models_b <- lapply(gapminder_countries, ~ lm(lifeExp ~ year, data = .x))
models_b <- lapply(gapminder_countries, function(.x) lm(lifeExp ~ year, data = .x))
```

Beneficios de purrr

1. Consistencia
2. Evita errores con tipos de datos (Type-safe)
3. Uso de: `~f(.x)`

Loops contra programación funcional

```
set.seed(123)
x <- map(1:20,~rnorm(10))
y <- map(x, mean)
```

```
set.seed(123)
x2 <- map(1:20,~rnorm(10))
y2 <- vector("list", length(x2))
for (i in seq_along(x2)) {
  y2[[i]] <- mean(x2[[i]])
}
```

Uso de la librería: tidyr (datos anidados)

```
df1 <- tibble(
  g = c(1, 2, 3),
  data = list(
    tibble(x = 1, y = 2),
    tibble(x = 4:5, y = 6:7),
    tibble(x = 10)
  )
)

df1
```

```
## # A tibble: 3 x 2
##       g data
##   <dbl> <list>
## 1     1 <tibble [1 x 2]>
## 2     2 <tibble [2 x 2]>
## 3     3 <tibble [1 x 1]>
```

```
df2 <- tribble(
  ~g, ~x, ~y,
  1,  1,  2,
  2,  4,  6,
  2,  5,  7,
  3, 10,  NA
)
df2 %>% nest(data = c(x, y))
```

```
## # A tibble: 3 x 2
##       g data
##   <dbl> <list>
## 1     1 <tibble [1 x 2]>
## 2     2 <tibble [2 x 2]>
## 3     3 <tibble [1 x 2]>
```

```
df2 %>% group_by(g) %>% nest()
```

```
## # A tibble: 3 x 2
## # Groups:   g [3]
##       g data
##   <dbl> <list>
## 1     1 <tibble [1 x 2]>
## 2     2 <tibble [2 x 2]>
## 3     3 <tibble [1 x 2]>
```

```
df1 %>% unnest(data)
```

```
## # A tibble: 4 x 3
##       g     x     y
##   <dbl> <dbl> <dbl>
## 1     1     1     2
## 2     2     4     6
## 3     2     5     7
## 4     3    10    NA
```

Modelos

```
mtcars_nested <- mtcars %>%
  group_by(cyl) %>%
  nest()

mtcars_nested
```

```
## # A tibble: 3 x 2
## # Groups:   cyl [3]
##     cyl data
##   <dbl> <list>
## 1     6 <tibble [7 x 10]>
```

```
## 2     4 <tibble [11 x 10]>
## 3     8 <tibble [14 x 10]>
```

```
mtcars_nested <- mtcars_nested %>%
  mutate(model = map(data, function(df) lm(mpg ~ wt, data = df)))
mtcars_nested
```

```
## # A tibble: 3 x 3
## # Groups:   cyl [3]
##     cyl data               model
##   <dbl> <list>             <list>
## 1     6 <tibble [7 x 10]>  <lm>
## 2     4 <tibble [11 x 10]> <lm>
## 3     8 <tibble [14 x 10]> <lm>
```

```
mtcars_nested <- mtcars_nested %>%
  mutate(predicciones = map(model, predict))
mtcars_nested
```

```
## # A tibble: 3 x 4
## # Groups:   cyl [3]
##     cyl data               model  predicciones
##   <dbl> <list>             <list> <list>
## 1     6 <tibble [7 x 10]>  <lm>   <dbl [7]>
## 2     4 <tibble [11 x 10]> <lm>   <dbl [11]>
## 3     8 <tibble [14 x 10]> <lm>   <dbl [14]>
```

Uso de tidyr y broom

Uso de map - tidyr - broom (data.frame nest (anidadados)):

```
diabetes = read_csv(file = "diabetes.csv")
diabetes_nested <- diabetes %>%
  group_by(location) %>%
  nest()
```

```
class(diabetes_nested)
```

```
## [1] "grouped_df" "tbl_df"     "tbl"        "data.frame"
```

```
model_lm <- function(.data) {
  mdl <- lm(chol ~ ratio, data = .data)
  # get model statistics
  broom::glance(mdl)
}
```

```
model_lm(diabetes)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
## 1     0.226         0.224  39.1      117. 4.51e-24     1 -2044. 4093. 4105.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
diabetes_nested
```

```
## # A tibble: 2 x 2
## # Groups:   location [2]
##   location   data
```

```
##   <chr>      <list>
## 1 Buckingham <tibble [200 x 18]>
## 2 Louisa     <tibble [203 x 18]>
```

```
nested_glance <- diabetes_nested %>%
  mutate(glance = map(data, model_lm))

nested_glance
```

```
## # A tibble: 2 x 3
## # Groups:   location [2]
##   location   data                glance
##   <chr>      <list>              <list>
## 1 Buckingham <tibble [200 x 18]> <tibble [1 x 12]>
## 2 Louisa     <tibble [203 x 18]> <tibble [1 x 12]>
```

```
nested_glance_unnest = unnest(nested_glance, glance)
```

Uso de la librería: broom (resultados maquetados)

El paquete "broom" toma las salidas que devuelven las funciones del sistema base R, tales como `lm`, `nls`, o `t.test`, y las devuelve en formato objetos tibbles.

Más información sobre broom en:

- https://cran.r-project.org/web/packages/broom/index.html
- https://cran.r-project.org/web/packages/broom/vignettes/broom.html
- https://cran.r-project.org/web/packages/broom/vignettes/broom_and_dplyr.html
- https://www.tidymodels.org/learn/statistics/bootstrap/

funciones: tidy(), augment(), glance()

Ejemplo 1 (modelo lineal)

```
lmfit <- lm(mpg ~ wt, mtcars)
lmfit
```

```
##
## Call:
## lm(formula = mpg ~ wt, data = mtcars)
##
## Coefficients:
## (Intercept)           wt
##      37.285       -5.344
```

```
summary(lmfit)
```

```
##
## Call:
## lm(formula = mpg ~ wt, data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5432 -2.3647 -0.1252  1.4096  6.8727
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)  37.2851     1.8776  19.858  < 2e-16 ***
## wt           -5.3445     0.5591  -9.559 1.29e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.046 on 30 degrees of freedom
## Multiple R-squared:  0.7528, Adjusted R-squared:  0.7446
## F-statistic: 91.38 on 1 and 30 DF,  p-value: 1.294e-10
```

```
library(broom)  # se carga con tidyverse
tidy(lmfit)
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)    37.3      1.88      19.9  8.24e-19
## 2 wt             -5.34     0.559     -9.56 1.29e-10
```

```
augment(lmfit)
```

```
## # A tibble: 32 x 9
##    .rownames          mpg    wt .fitted .resid   .hat .sigma  .cooksd .std.resid
##    <chr>            <dbl> <dbl>   <dbl>  <dbl>  <dbl>  <dbl>    <dbl>      <dbl>
##  1 Mazda RX4         21    2.62    23.3 -2.28  0.0433   3.07  1.33e-2    -0.766
##  2 Mazda RX4 Wag     21    2.88    21.9 -0.920 0.0352   3.09  1.72e-3    -0.307
##  3 Datsun 710        22.8  2.32    24.9 -2.09  0.0584   3.07  1.54e-2    -0.706
##  4 Hornet 4 Drive    21.4  3.22    20.1  1.30  0.0313   3.09  3.02e-3     0.433
##  5 Hornet Sportabo~  18.7  3.44    18.9 -0.200 0.0329   3.10  7.60e-5    -0.0668
##  6 Valiant           18.1  3.46    18.8 -0.693 0.0332   3.10  9.21e-4    -0.231
##  7 Duster 360        14.3  3.57    18.2 -3.91  0.0354   3.01  3.13e-2    -1.31
##  8 Merc 240D         24.4  3.19    20.2  4.16  0.0313   3.00  3.11e-2     1.39
##  9 Merc 230          22.8  3.15    20.5  2.35  0.0314   3.07  9.96e-3     0.784
## 10 Merc 280          19.2  3.44    18.9  0.300 0.0329   3.10  1.71e-4     0.100
## # ... with 22 more rows
```

```
glance(lmfit)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
## 1     0.753         0.745  3.05      91.4 1.29e-10     1  -80.0  166.  170.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

Ejemplo 2 (contrastes)

```
tt <- t.test(wt ~ am, mtcars)
tidy(tt)
```

```
## # A tibble: 1 x 10
##   estimate estimate1 estimate2 statistic    p.value parameter conf.low conf.high
##      <dbl>     <dbl>     <dbl>     <dbl>      <dbl>     <dbl>    <dbl>     <dbl>
## 1     1.36      3.77      2.41      5.49 0.00000627      29.2    0.853      1.86
## # ... with 2 more variables: method <chr>, alternative <chr>
```

```
glance(tt) # misma salida
```

```
## # A tibble: 1 x 10
```

```
##   estimate estimate1 estimate2 statistic    p.value parameter conf.low conf.high
##      <dbl>     <dbl>     <dbl>     <dbl>      <dbl>     <dbl>    <dbl>     <dbl>
## 1     1.36      3.77      2.41      5.49 0.00000627      29.2    0.853      1.86
## # ... with 2 more variables: method <chr>, alternative <chr>
```

```
#augment(tt)
```

Ejemplo 3 (contrastes)

```
chit <- chisq.test(xtabs(Freq ~ Sex + Class,
                         data = as.data.frame(Titanic)))
tidy(chit)
```

```
## # A tibble: 1 x 4
##   statistic  p.value parameter method
##       <dbl>    <dbl>     <int> <chr>
## 1      350. 1.56e-75         3 Pearson's Chi-squared test
```

```
augment(chit)
```

```
## # A tibble: 8 x 9
##   Sex    Class .observed  .prop .row.prop .col.prop .expected .resid .std.resid
##   <fct>  <fct>     <dbl>  <dbl>     <dbl>     <dbl>     <dbl>  <dbl>      <dbl>
## 1 Male   1st         180 0.0818    0.104     0.554      256.   -4.73     -11.1
## 2 Female 1st         145 0.0659    0.309     0.446       69.4   9.07      11.1
## 3 Male   2nd         179 0.0813    0.103     0.628      224.   -3.02      -6.99
## 4 Female 2nd         106 0.0482    0.226     0.372       60.9   5.79       6.99
## 5 Male   3rd         510 0.232     0.295     0.722      555.   -1.92      -5.04
## 6 Female 3rd         196 0.0891    0.417     0.278      151.    3.68       5.04
## 7 Male   Crew        862 0.392     0.498     0.974      696.    6.29      17.6
## 8 Female Crew         23 0.0104    0.0489    0.0260     189.  -12.1      -17.6
```