

Informe 10: Modelos integrados

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Introducción

En el informe anterior vimos que los modelos de Expresión génica y metilación no lograban el overfitting. Se piensa que podría ser un problema referido al rango de datos que encontramos dentro de los datasets, por lo que vamos a volver a normalizar los datos crudos de estas dos ómicas.

$$(x - \min(\text{col})) / (\max(\text{col}) - \min(\text{col}))$$

donde x es el dato de una casilla del array y col es la columna de genes o sondas.

Tenemos que retomar los objetos de R:

- ExpGenTCGA_KIRC_Norm : Objeto de Expresión Génica antes de realizar el análisis diferencial. En este objeto utilizamos solo la función `TCGAanalyze_Normalization` que vimos que solo quitaba los decimales.
- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA
- ExpProtTCGA_KIRC_RawData_woNA

En este caso aún no hemos traspuesto los arrays por lo que las muestras se encuentran en las columnas y aún no hemos modificado el nombre de estas para que sean los nombres cortos.

Tenemos que:

- 1) Normalizar los datos correctamente
- 2) Hacer Filtrado no específico al 75%. Se puede hacer con la función `TCGAanalyze_Filtering`
- 3) Volver a hacer el PCA de los datos e intentar obtener las componentes principales
- 4) Hacer Análisis de Expresión diferencial y Análisis de metilación diferencial
- 5) Renombrar datasets y quedarnos con las muestras compartidas entre ómicas
- 6) Modelos de las ómicas independientes y ver si se comportan de otra manera (si memorizan o aprenden)
- 7) Modelo de ómicas integradas

1. Normalización de los datasets

Expresión génica

```
> dim(ExpGenTCGA_KIRC_RawData)
[1] 19662    606
ExpGenTCGA_KIRC_Norm01 <- ExpGenTCGA_KIRC_Norm
```

```

for (i in 1:dim(ExpGenTCGA_KIRC_Norm01)[1]){
min <- min(ExpGenTCGA_KIRC_Norm01[i,])
max <- max(ExpGenTCGA_KIRC_Norm01[i,])
for (j in 1:dim(ExpGenTCGA_KIRC_Norm01)[2]){
ExpGenTCGA_KIRC_Norm01[i,j] <- (ExpGenTCGA_KIRC_Norm01[i,j] - min)/(max - min)
print(c(i,j))
}}

```

Metilación

```

> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA)
[1] 373382 483
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm <- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA
x <- assay(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA)
for (i in 1:dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm)[1]){
min <- min(x[i,])
max <- max(x[i,])
print(i)
for (j in 1:dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm)[2]){
x[i,j] <- (x[i,j] - min)/(max - min)
}}
assay(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm) <- x

```

Proteomica

```

> dim(ExpProtTCGA_KIRC_RawData_woNA)
[1] 177 478
ExpProtTCGA_KIRC_RawData_woNA_Norm <- ExpProtTCGA_KIRC_RawData_woNA
for (i in 1:dim(ExpProtTCGA_KIRC_RawData_woNA_Norm)[1]){
min <- min(ExpProtTCGA_KIRC_RawData_woNA_Norm[i,])
max <- max(ExpProtTCGA_KIRC_RawData_woNA_Norm[i,])
print(i)
for (j in 1:dim(ExpProtTCGA_KIRC_RawData_woNA_Norm)[2]){
ExpProtTCGA_KIRC_RawData_woNA_Norm[i,j] <- (ExpProtTCGA_KIRC_RawData_woNA_Norm[i,j] - min)/(max - min)
}}

```

2. Filtrado no específico al 75%

Expresión génica

```

ExpGenTCGA_KIRC_Norm01_Filt75 <- TCGAanalyze_Filtering(tabDF = ExpGenTCGA_KIRC_Norm01, method = "quantile")
> dim(ExpGenTCGA_KIRC_Norm01)
[1] 19586 606
> dim(ExpGenTCGA_KIRC_Norm01_Filt75)
[1] 4897 606

```

Metilación

75%

```

x <- assay(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm)

```

```

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75 <- TCGAanalyze_Filtering(tabDF = x, method = "Filt75")
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm)
[1] 373382 483
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75)
[1] 93346 483

```

85%

```

x <- assay(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm)
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt85 <- TCGAanalyze_Filtering(tabDF = x, method = "Filt85")
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm)
[1] 373382 483
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt85)
[1] 56008 483

```

90%

```

x <- assay(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm)
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt90 <- TCGAanalyze_Filtering(tabDF = x, method = "Filt90")
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm)
[1] 373382 483
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt90)
[1] 37339 483

```

3. PCA

Expresión génica

```

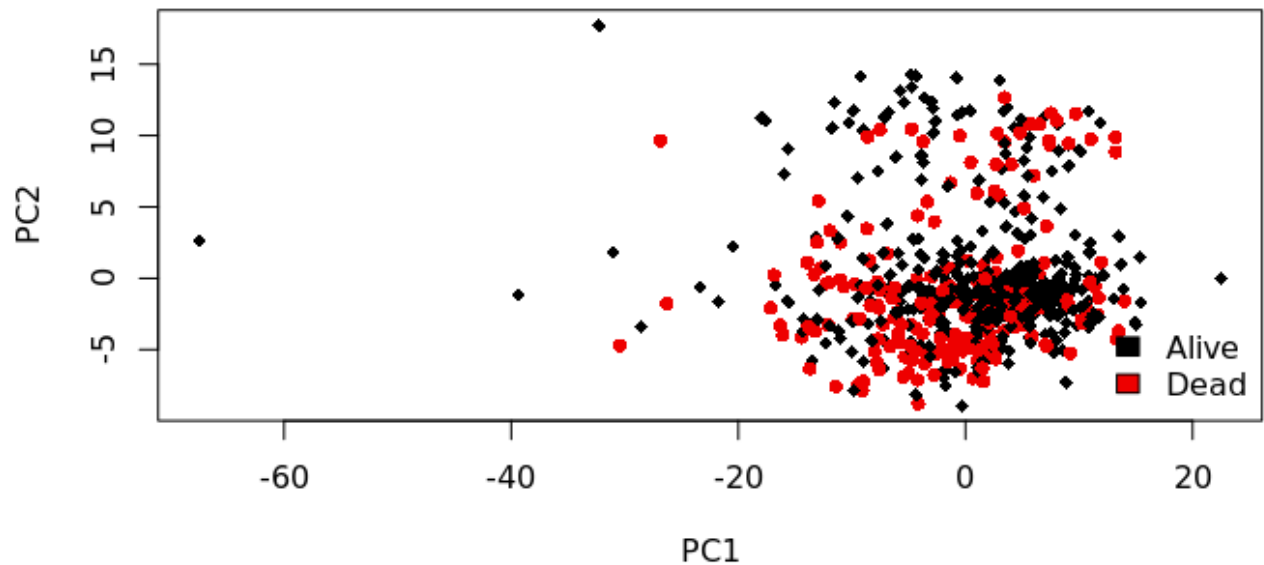
ExpGenTCGA_KIRC_Norm01_Filt75
> ExpGenTCGA_KIRC_Norm01_Filt75_PCA <- prcomp(t(ExpGenTCGA_KIRC_Norm01_Filt75))
> str(ExpGenTCGA_KIRC_Norm01_Filt75_PCA)
List of 5
 $ sdev      : num [1:606] 6.98 2.83 2.47 2.02 1.68 ...
 $ rotation: num [1:4897, 1:606] 0.0149 0.0102 0.0125 0.0168 0.0122 ...
 .. attr(*, "dimnames")=List of 2
 .. ..$ : chr [1:4897] "A2M" "NAT1" "AAMP" "ABCF1" ...
 .. ..$ : chr [1:606] "PC1" "PC2" "PC3" "PC4" ...
 $ center   : Named num [1:4897] 0.311 0.312 0.314 0.342 0.272 ...
 .. attr(*, "names")= chr [1:4897] "A2M" "NAT1" "AAMP" "ABCF1" ...
 $ scale     : logi FALSE
 $ x         : num [1:606, 1:606] -8.884 -1.439 2.618 -0.535 0.183 ...
 .. attr(*, "dimnames")=List of 2
 .. ..$ : chr [1:606] "TCGA-B0-5694-01A-11R-1541-07" "TCGA-CJ-4637-01A-02R-1325-07" "TCGA-CZ-4860-01A-02R-1325-07" ...
 .. ..$ : chr [1:606] "PC1" "PC2" "PC3" "PC4" ...
 - attr(*, "class")= chr "prcomp"
> type <- factor(ExpGenTCGA_KIRC_RawData$vital_status)
> c("black", "red2")[type]
> plot(
ExpGenTCGA_KIRC_Norm_Trans_Filt75_238DEG_Transposed_PCA$x,
col = c("black", "red2")[type],
pch = c(18, 16)[type],

```

```

cex = 1.0)
> legend(
  "bottomright",
  bty = "n",
  c("Alive", "Dead"),
  fill = c("black", "red2"),
  cex = 1.0)

```



Metilación

75%

```
#MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75
```

```
> MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_PCA <- prcomp(t(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_PCA))
```

```
> str(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_PCA)
```

```
List of 5
```

```
$ sdev      : num [1:483] 14.25 8.19 7.21 6.51 5.48 ...
```

```
$ rotation: num [1:93346, 1:483] 0.000263 0.000311 0.002017 0.000988 0.001926 ...
```

```
..- attr(*, "dimnames")=List of 2
```

```
.. ..$ : chr [1:93346] "cg00000236" "cg00000721" "cg00000948" "cg00001349" ...
```

```
.. ..$ : chr [1:483] "PC1" "PC2" "PC3" "PC4" ...
```

```
$ center   : Named num [1:93346] 0.887 0.952 0.872 0.841 0.886 ...
```

```
..- attr(*, "names")= chr [1:93346] "cg00000236" "cg00000721" "cg00000948" "cg00001349" ...
```

```
$ scale     : logi FALSE
```

```
$ x         : num [1:483, 1:483] -0.06359 -21.42776 -3.05577 -0.00718 16.83284 ...
```

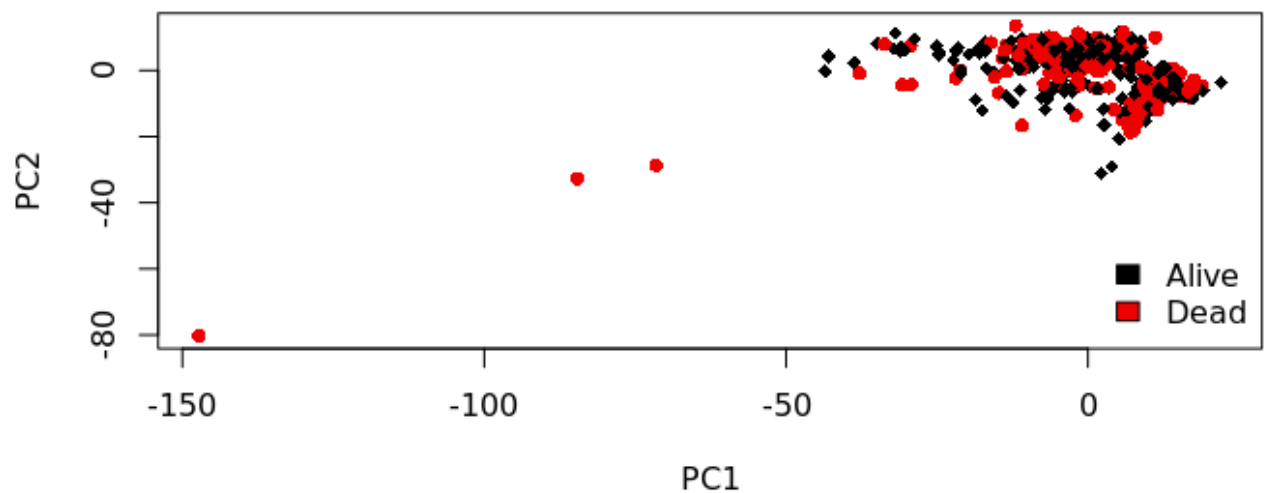
```
..- attr(*, "dimnames")=List of 2
```

```
.. ..$ : chr [1:483] "TCGA-BP-4993-01A-02D-1418-05" "TCGA-CZ-5982-01A-11D-1670-05" "TCGA-B0-4703-01A-02D-1418-05" ...
```

```

.. ..$ : chr [1:483] "PC1" "PC2" "PC3" "PC4" ...
- attr(*, "class")= chr "prcomp"
> type <- factor(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm$vital_status)
> c("black", "red2")[type]
> plot(
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_PCA$x,
col = c("black", "red2")[type],
pch = c(18, 16)[type],
cex = 1.0)
> legend(
"bottomright",
bty = "n",
c("Alive", "Dead"),
fill = c("black", "red2"),
cex = 1.0)

```



85%

```
#MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt85
```

```

> MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt85_PCA <- prcomp(t(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt85))
> str(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt85_PCA)

```

```
List of 5
```

```

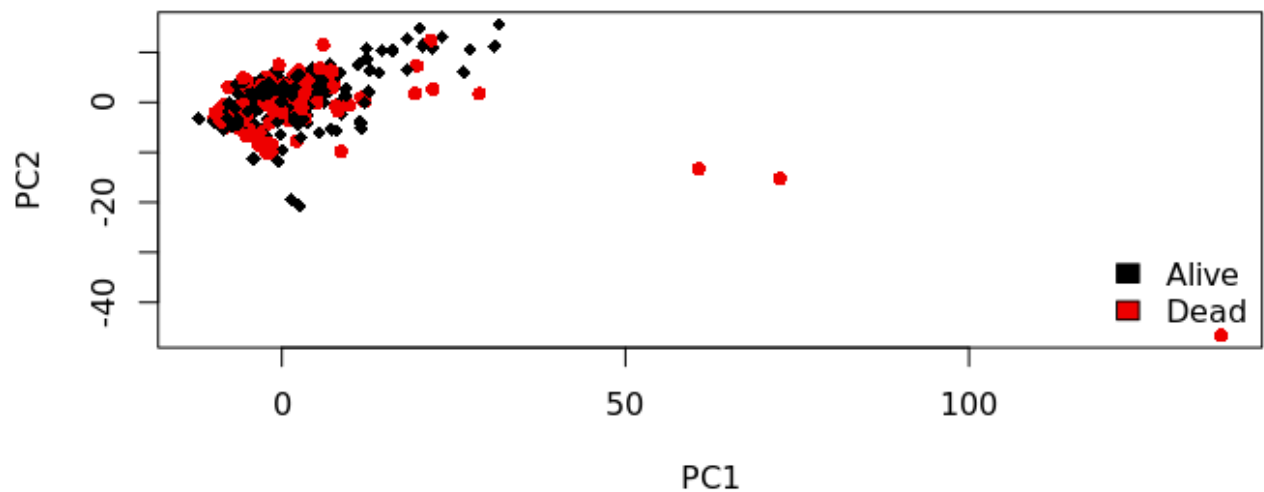
$ sdev      : num [1:483] 10.23 5.1 4.41 4.03 3.62 ...
$ rotation: num [1:56008, 1:483] -0.000417 -0.00052 -0.002611 -0.002566 -0.000308 ...
..- attr(*, "dimnames")=List of 2
.. ..$ : chr [1:56008] "cg00000236" "cg00000721" "cg00000948" "cg00001364" ...
.. ..$ : chr [1:483] "PC1" "PC2" "PC3" "PC4" ...
$ center   : Named num [1:56008] 0.887 0.952 0.872 0.886 0.977 ...
..- attr(*, "names")= chr [1:56008] "cg00000236" "cg00000721" "cg00000948" "cg00001364" ...
$ scale     : logi FALSE

```

```

$ x      : num [1:483, 1:483] -0.917 14.652 0.436 -1.506 -8.847 ...
.. attr(*, "dimnames")=List of 2
.. ..$ : chr [1:483] "TCGA-BP-4993-01A-02D-1418-05" "TCGA-CZ-5982-01A-11D-1670-05" "TCGA-B0-4703-01A-02D-1418-05" ...
.. ..$ : chr [1:483] "PC1" "PC2" "PC3" "PC4" ...
- attr(*, "class")= chr "prcomp"
> type <- factor(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm$vital_status)
> c("black", "red2")[type]
> plot(
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt85_PCA$x,
col = c("black", "red2")[type],
pch = c(18, 16)[type],
cex = 1.0)
> legend(
"bottomright",
bty = "n",
c("Alive", "Dead"),
fill = c("black", "red2"),
cex = 1.0)

```



90%

```

#MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt90

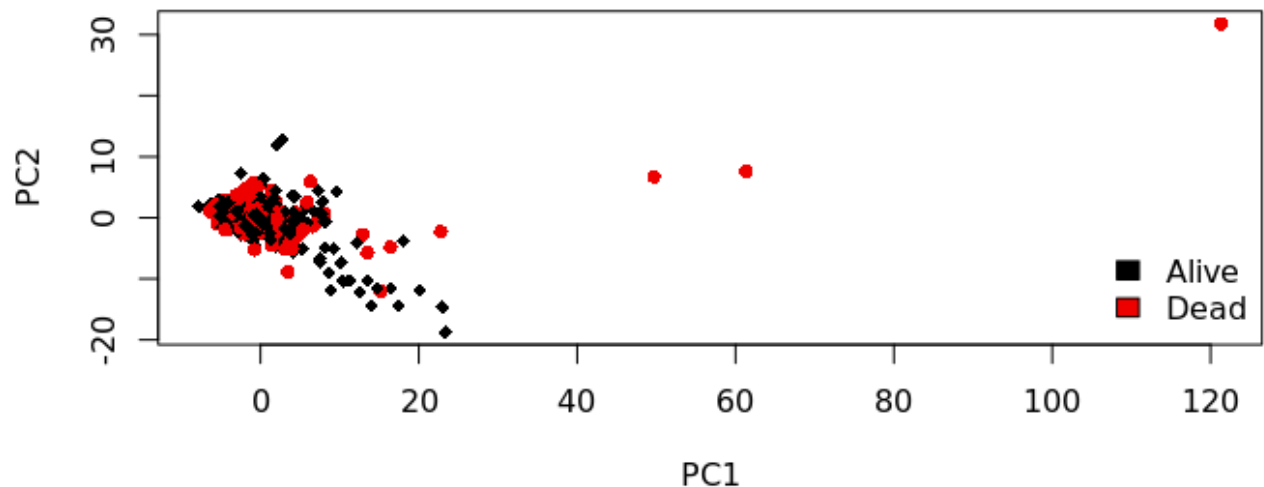
> MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt90_PCA <- prcomp(t(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt90))
> str(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt90_PCA)
List of 5
 $ sdev      : num [1:483] 8.11 3.64 3.06 2.83 2.55 ...
 $ rotation: num [1:37339, 1:483] -0.000662 -0.000262 -0.0066 -0.000648 -0.006593 ...
.. attr(*, "dimnames")=List of 2
.. ..$ : chr [1:37339] "cg00000721" "cg00001687" "cg00001791" "cg00001854" ...
.. ..$ : chr [1:483] "PC1" "PC2" "PC3" "PC4" ...

```

```

$ center : Named num [1:37339] 0.952 0.977 0.903 0.892 0.923 ...
..- attr(*, "names")= chr [1:37339] "cg00000721" "cg00001687" "cg00001791" "cg00001854" ...
$ scale : logi FALSE
$ x : num [1:483, 1:483] -1.01 10.4 -0.19 -1.6 -5.69 ...
..- attr(*, "dimnames")=List of 2
.. ..$ : chr [1:483] "TCGA-BP-4993-01A-02D-1418-05" "TCGA-CZ-5982-01A-11D-1670-05" "TCGA-B0-4703-01A-02D-1418-05" ...
.. ..$ : chr [1:483] "PC1" "PC2" "PC3" "PC4" ...
- attr(*, "class")= chr "prcomp"
> type <- factor(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm$vital_status)
> c("black", "red2")[type]
> plot(
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt90_PCA$x,
col = c("black", "red2")[type],
pch = c(18, 16)[type],
cex = 1.0)
> legend(
"bottomright",
bty = "n",
c("Alive", "Dead"),
fill = c("black", "red2"),
cex = 1.0)

```



Proteómica

No puedo hacer un PCA de los datos de proteómica sueltos (solo puedo si cojo las muestras que son iguales que transcriptómica), puesto que no se encuentran metadatos disponibles para descargar acerca de esta ómica.

4. Análisis de Expresión diferencial y Análisis de metilación diferencial

Análisis de Expresión diferencial

Normalizado (ExpGenTCGA_KIRC_Norm01)

Si realizamos el análisis sin el prefiltrado, tarda demasiado (intentar más adelante).

```
ExpGenTCGA_KIRC_SampleName_DeadStatus <- subset(ExpGenTCGA_KIRC_RawData$barcode, ExpGenTCGA_KIRC_RawData$barcode == "Dead")
ExpGenTCGA_KIRC_SampleName_AliveStatus <- subset(ExpGenTCGA_KIRC_RawData$barcode, ExpGenTCGA_KIRC_RawData$barcode == "Alive")
```

```
ExpGenTCGA_KIRC_Norm01_DEGs <- TCGAanalyze_DEA(mat1 = ExpGenTCGA_KIRC_Norm01[,ExpGenTCGA_KIRC_SampleName_AliveStatus], mat2 = ExpGenTCGA_KIRC_Norm01[,ExpGenTCGA_KIRC_SampleName_DeadStatus])
```

Normalizado y filtrado (ExpGenTCGA_KIRC_Norm01_Filt75)

Si realizamos un análisis de expresión diferencial de los datos tras haberlos normalizado y filtrado al 75% a valores entre 0-1 vemos que la función `TCGAanalyze_DEA` no encuentra ningún gen diferencialmente expresado entre las condiciones de vivo o muerto.

```
ExpGenTCGA_KIRC_SampleName_DeadStatus <- subset(ExpGenTCGA_KIRC_RawData$barcode, ExpGenTCGA_KIRC_RawData$barcode == "Dead")
ExpGenTCGA_KIRC_SampleName_AliveStatus <- subset(ExpGenTCGA_KIRC_RawData$barcode, ExpGenTCGA_KIRC_RawData$barcode == "Alive")
```

```
ExpGenTCGA_KIRC_Norm01_Filt75_DEGs <- TCGAanalyze_DEA(mat1 = ExpGenTCGA_KIRC_Norm01_Filt75[,ExpGenTCGA_KIRC_SampleName_AliveStatus], mat2 = ExpGenTCGA_KIRC_Norm01_Filt75[,ExpGenTCGA_KIRC_SampleName_DeadStatus])
```

```
> ExpGenTCGA_KIRC_Norm01_Filt75_DEGs
[1] logFC      logCPM      LR          PValue      FDR          start_position
[7] end_position
<0 rows> (or 0-length row.names)
```

Análisis de metilación diferencial

Por otro lado, vamos a realizar el análisis de metilación diferencial de sitios CpG para el objeto de metilacion normalizado y el objeto normalizado y filtrado con una variabilidad del 75%.

Normalizado (MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm)

```
Differentially_metylated_analysis <- TCGAanalyze_DMC(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm,
groupCol = "vital_status", # a column in the colData matrix
group1 = "Dead", # a type of the disease type column
group2 = "Alive", # a type of the disease column
p.cut = 0.05,
plot.filename = "survival_metvolcano_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm.png",
diffmean.cut = 0.15,
save = FALSE,
legend = "State",
cores = 1 # if set to 1 there will be a progress bar
)
```

Normalizado y filtrado (MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt

```
Differentially_metylated_analysis <- TCGAanalyze_DMC(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_
groupCol = "vital_status", # a column in the colData matrix
group1 = "Dead", # a type of the disease type column
group2 = "Alive", # a type of the disease column
p.cut = 0.05,
plot.filename = "survival_metvolcano_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75.png"
diffmean.cut = 0.15,
save = FALSE,
legend = "State",
cores = 1 # if set to 1 there will be a progress bar
)
```

5. Renombrar datasets y muestras compartidas

Expresión génica

Renombrar

```
ExpGenTCGA_KIRC_Norm01_Filt75_ColnamesShort <- c()
for (j in colnames(ExpGenTCGA_KIRC_Norm01_Filt75)){
ExpGenTCGA_KIRC_Norm01_Filt75_ColnamesShort <- c(ExpGenTCGA_KIRC_Norm01_Filt75_ColnamesShort, sub("(.*)",
})
```

```
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed <- ExpGenTCGA_KIRC_Norm01_Filt75
colnames(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed) <- ExpGenTCGA_KIRC_Norm01_Filt75_ColnamesShort
```

Muestras compartidas

Cuatro objetos distintos vamos a crear:

ExpGenTCGA_KIRC_Norm01_Filt75_Renamed. El objeto de Expresión génica con rango de datos entre 0-1, con variabilidad de genes al 75% pero sin haber realizado un análisis de expresión diferencial.

En este dataset hay 606 muestras entre las que encontramos 404 (66.67%) pacientes vivos y 202 (33.33%) muertos.

```
> dim(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed)
[1] 4897 606
> table(ExpGenTCGA_KIRC_RawData$vital_status)
```

Alive	Dead
404	202

ExpGenTCGA_KIRC_Norm01_Filt75_DEG_Renamed

ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed En este dataset hay 474 muestras entre las que encontramos 309 (65.19%) pacientes vivos y 165 (34.81%) muertos.

```
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed <- ExpGenTCGA_KIRC_Norm01_Filt75_Renamed[, -ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed]
> dim(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed)
[1] 4897 474

# Labels

x <- c()
for (i in colnames(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed)){
  x <- c(x, which(ExpGenTCGA_KIRC_RawData$sample %in% i))
}
> x
[1] 1 3 4 5 6 7 8 10 13 14 15 16 17 19 20 21 22 23 24 25 26 27 28 29
[25] 30 31 32 35 36 37 38 40 42 44 45 47 48 50 51 52 53 54 55 56 57 59 60 61
[49] 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86
[73] 90 91 92 93 96 97 98 99 100 101 102 103 104 105 106 109 110 112 113 114 116 117 118 119
[97] 120 121 122 123 124 125 127 128 129 130 132 133 135 136 137 139 143 146 147 148 149 150 151 153
[121] 154 155 156 157 158 159 160 161 162 163 164 165 166 167 168 171 173 174 175 176 178 179 180 182
[145] 183 184 185 186 187 189 190 193 195 196 197 198 199 200 201 202 205 206 207 208 209 211 213 216
[169] 217 218 219 220 222 224 227 228 229 230 231 232 233 234 235 236 237 238 239 240 242 244 245 248
[193] 249 250 251 252 254 255 256 257 259 260 261 263 264 265 266 267 268 269 270 272 273 274 275 276
[217] 277 279 280 281 282 283 285 286 289 290 293 294 295 296 299 300 302 303 304 305 307 308 309 311
[241] 312 313 314 315 319 320 321 322 323 324 325 326 327 328 329 330 331 332 333 335 336 337 338 339
[265] 340 343 344 345 346 347 348 349 350 351 352 353 354 356 357 358 360 361 362 363 364 365 366 367
[289] 368 369 370 371 372 375 377 378 379 380 381 382 383 384 385 386 387 388 389 390 392 394 395 396
[313] 397 398 401 402 403 405 406 407 408 409 411 413 414 415 417 418 420 421 422 423 424 425 427 428
[337] 429 431 432 433 434 435 436 437 438 439 440 441 442 443 444 445 446 448 449 450 451 452 453 454
[361] 455 456 458 459 460 461 463 464 465 466 467 468 469 470 471 472 475 476 477 478 480 482 483 484
[385] 486 487 488 490 491 492 493 495 496 497 499 500 502 503 504 505 506 507 508 509 510 511 512 514
[409] 515 517 519 520 522 523 525 527 528 529 531 532 533 534 535 537 538 539 540 542 543 545 546 547
[433] 548 549 550 551 553 555 556 557 558 559 560 563 564 565 566 567 568 571 572 573 574 577 579 580
[457] 581 582 583 586 587 591 593 594 595 596 597 598 599 600 601 602 603 605
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels <- ExpGenTCGA_KIRC_RawData$vital_status[x]
> table(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels)
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels
Alive Dead
309 165
```

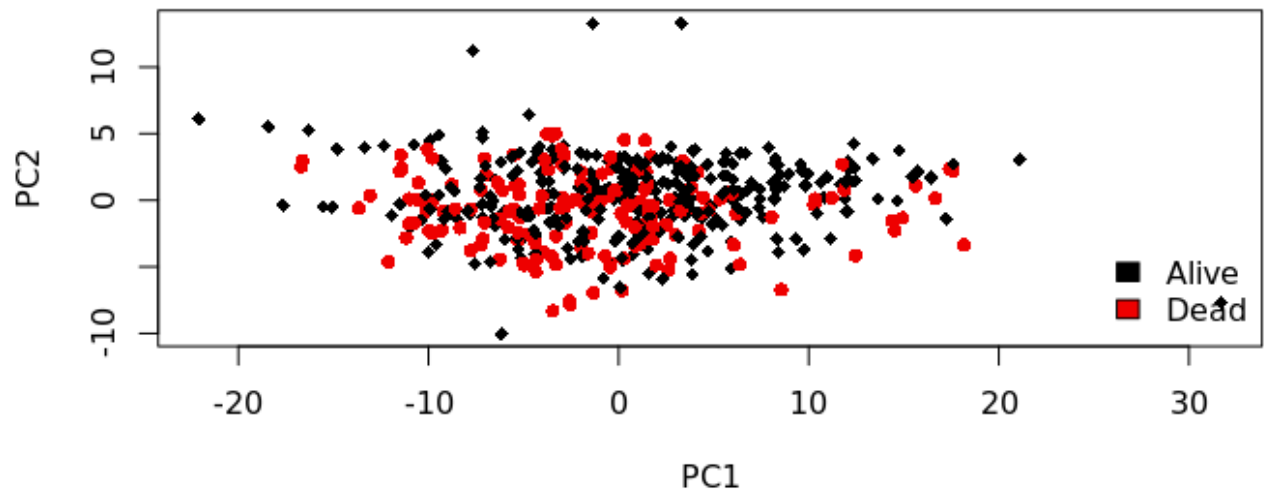
PCA

```
> ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_PCA <- prcomp(t(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed))
> str(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_PCA)
List of 5
 $ sdev      : num [1:474] 7.09 2.86 2.32 1.8 1.72 ...
 $ rotation: num [1:4897, 1:474] 0.01676 0.00963 0.01176 0.01563 0.01427 ...
 ..- attr(*, "dimnames")=List of 2
 .. ..$ : chr [1:4897] "A2M" "NAT1" "AAMP" "ABCF1" ...
 .. ..$ : chr [1:474] "PC1" "PC2" "PC3" "PC4" ...
 $ center   : Named num [1:4897] 0.323 0.295 0.309 0.327 0.296 ...
 ..- attr(*, "names")= chr [1:4897] "A2M" "NAT1" "AAMP" "ABCF1" ...
 $ scale    : logi FALSE
```

```

$ x      : num [1:474, 1:474] -8.764 2.806 -0.457 0.345 -5.104 ...
..- attr(*, "dimnames")=List of 2
.. ..$ : chr [1:474] "TCGA-B0-5694-01A" "TCGA-CZ-4860-01A" "TCGA-B0-4706-01A" "TCGA-B4-5844-01A" ...
.. ..$ : chr [1:474] "PC1" "PC2" "PC3" "PC4" ...
- attr(*, "class")= chr "prcomp"
> type <- factor(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels)
> plot(
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_PCA$x,
col = c("black", "red2")[type],
pch = c(18, 16)[type],
cex = 1.0)
> legend(
"bottomright",
bty = "n",
c("Alive", "Dead"),
fill = c("black", "red2"),
cex = 1.0)

```



ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed En este dataset hay 290 muestras entre las que encontramos 188 (64.83%) pacientes vivos y 102 (35.17%) muertos.

```

ExpGenSampleNumb_IN_Met01 <- which(match(colnames(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed), colnames(MetT
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed <- ExpGenTCGA_KIRC_Norm01_Filt75_Renar

> dim(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed)
[1] 4897 290

# Labels

```

```

x <- c()
for (i in colnames(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed)){
x <- c(x, which(ExpGenTCGA_KIRC_RawData$sample %in% i))
}
> x
  [1] 1 4 5 7 8 10 13 14 15 19 20 21 22 23 26 28 29 30 31 32 35 36 37 40
 [25] 42 44 47 48 50 52 53 55 57 63 64 65 66 67 69 72 73 74 75 76 77 78 80 82
 [49] 83 84 86 90 91 92 93 96 97 99 100 101 102 110 114 117 120 123 124 129 130 132 133 136
 [73] 139 143 146 147 148 149 150 153 156 157 158 160 162 163 164 165 166 168 173 175 179 180 182 185
 [97] 186 187 189 196 198 205 206 207 211 216 218 220 229 231 232 233 234 237 238 240 242 244 245 250
[121] 251 254 255 257 259 265 268 269 272 273 274 275 276 277 280 281 283 285 286 289 290 293 300 302
[145] 303 305 307 312 314 319 320 321 323 325 327 328 330 331 333 335 336 337 339 343 344 345 347 348
[169] 349 352 353 356 358 360 362 365 366 367 368 369 370 372 375 377 378 379 383 385 386 387 389 396
[193] 401 402 403 405 406 407 408 411 414 420 421 423 425 427 428 432 433 434 436 437 438 439 440 441
[217] 443 444 449 451 452 454 455 460 461 464 465 466 472 477 483 484 486 487 488 490 491 492 493 495
[241] 496 497 500 503 504 505 506 509 514 517 519 522 523 525 527 528 529 531 532 535 538 540 542 545
[265] 547 548 549 550 553 555 557 560 563 564 565 566 567 571 572 580 581 582 583 593 595 597 599 600
[289] 601 602
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels <- ExpGenTCGA_KIRC_RawData$vit
> table(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels)
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels
Alive Dead
  188  102

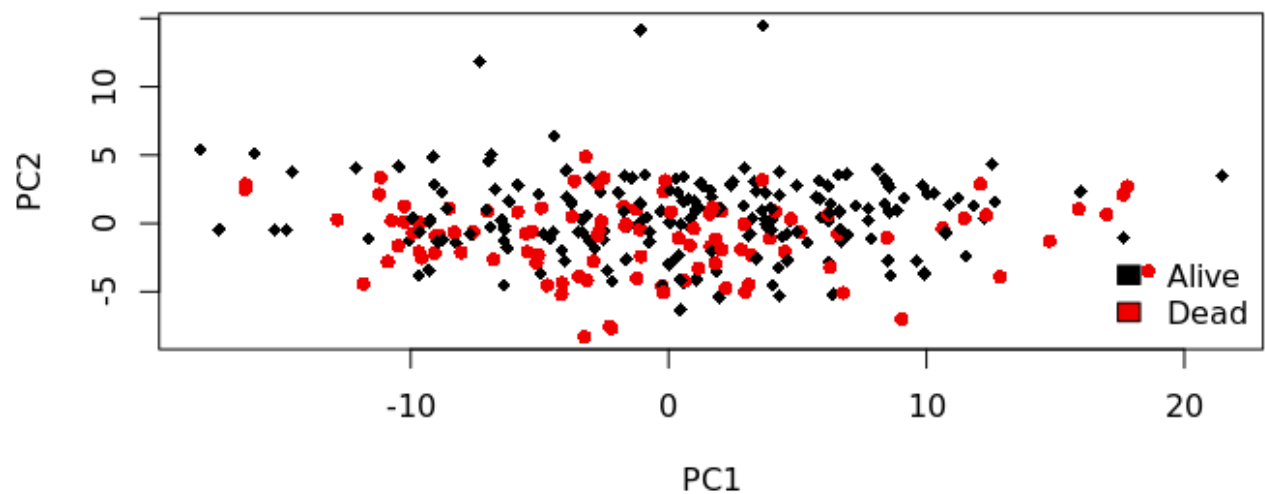
```

PCA

```

> ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_PCA <- prcomp(t(ExpGenTCGA_KIRC_Norm
> List of 5
 $ sdev      : num [1:290] 7.21 2.96 2.06 1.9 1.8 ...
 $ rotation: num [1:4897, 1:290] 0.01767 0.00995 0.01158 0.01642 0.01411 ...
 ..- attr(*, "dimnames")=List of 2
 .. ..$ : chr [1:4897] "A2M" "NAT1" "AAMP" "ABCF1" ...
 .. ..$ : chr [1:290] "PC1" "PC2" "PC3" "PC4" ...
 $ center   : Named num [1:4897] 0.341 0.296 0.315 0.339 0.295 ...
 ..- attr(*, "names")= chr [1:4897] "A2M" "NAT1" "AAMP" "ABCF1" ...
 $ scale     : logi FALSE
 $ x         : num [1:290, 1:290] -8.498 -0.266 0.578 -12.114 6.2 ...
 ..- attr(*, "dimnames")=List of 2
 .. ..$ : chr [1:290] "TCGA-B0-5694-01A" "TCGA-B0-4706-01A" "TCGA-B4-5844-01A" "TCGA-B8-A54F-01A" ...
 .. ..$ : chr [1:290] "PC1" "PC2" "PC3" "PC4" ...
 - attr(*, "class")= chr "prcomp"
> type <- factor(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels)
> plot(
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_PCA$x,
col = c("black", "red2")[type],
pch = c(18, 16)[type],
cex = 1.0)
> legend(
"bottomright",
bty = "n",
c("Alive", "Dead"),
fill = c("black", "red2"),
cex = 1.0)

```



Metilación

Renombrar

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed <- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed
colnames(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed) <- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed
```

Muestras compartidas

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed

En este dataset hay 483 muestras entre las que encontramos 299 (61.90%) pacientes vivos y 184 (38.10%) muertos.

```
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed)
[1] 93346 483
> table(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed$vital_status)
```

Alive	Dead
299	184

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_Renamed

En este dataset hay 291 muestras entre las que encontramos 188 (64.60%) pacientes vivos y 103 (35.39%) muertos.

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_Renamed <- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_Renamed
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_Renamed)
[1] 93346 291
```

```
# Labels
```

```
x <- c()
for (i in colnames(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed))
x <- c(x, which(ExpGenTCGA_KIRC_RawData$sample %in% i))
}

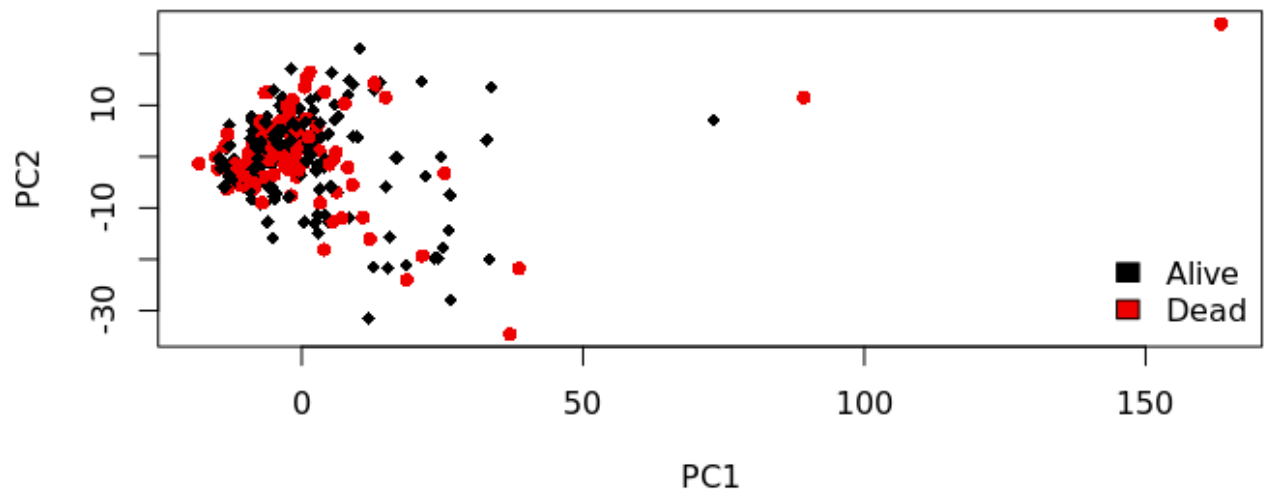
[1] 582 162 519 372 257 547 503 486 180 29 37 290 339 149 572 385 168 525 265 277 314 272 8 64
[25] 509 189 560 80 237 15 132 175 555 428 157 396 549 580 280 500 129 52 461 368 69 550 406 86
[49] 366 377 250 375 369 466 274 436 433 335 557 538 564 47 477 331 234 150 408 303 330 421 302 206
[73] 300 19 504 21 53 438 244 240 245 465 65 99 545 529 100 407 571 32 460 383 216 505 91 491
[97] 4 211 532 348 166 231 67 492 323 218 540 437 367 179 187 83 411 273 114 10 102 96 522 336
[121] 403 337 186 595 319 497 379 164 528 207 553 600 449 345 358 182 139 434 427 527 389 535 293 405
[145] 14 439 565 158 602 343 143 123 483 130 327 567 30 153 454 90 5 452 259 74 66 78 36 73
[169] 148 542 76 490 352 356 370 196 160 238 328 77 583 597 268 26 548 563 93 40 378 281 365 444
[193] 440 97 269 325 110 92 493 333 321 402 133 285 484 251 156 472 7 423 320 487 13 289 185 517
[217] 124 84 146 63 163 136 205 455 464 254 48 593 420 275 120 276 57 305 432 401 147 75 599 198
[241] 349 286 229 531 22 1 425 173 283 441 55 353 451 165 344 31 82 496 566 495 117 387 347 386
[265] 443 514 242 362 581 312 101 601 50 44 307 23 232 20 506 28 42 523 255 233 360 414 488 220
[289] 72 35
```

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels <- ExpGen
>
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels
Alive Dead
188 103
```

PCA

```
> MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_PCA <- prcomp(
> str(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_PCA)
List of 5
 $ sdev      : num [1:291] 15.35 8.46 6.97 6.55 6.41 ...
 $ rotation: num [1:93346, 1:291] -0.000169 -0.000345 -0.001552 -0.001045 -0.001783 ...
 .. attr(*, "dimnames")=List of 2
 .. ..$ : chr [1:93346] "cg00000236" "cg00000721" "cg00000948" "cg00001349" ...
 .. ..$ : chr [1:291] "PC1" "PC2" "PC3" "PC4" ...
 $ center   : Named num [1:93346] 0.887 0.954 0.857 0.834 0.879 ...
 .. attr(*, "names")= chr [1:93346] "cg00000236" "cg00000721" "cg00000948" "cg00001349" ...
 $ scale    : logi FALSE
 $ x        : num [1:291, 1:291] -5.23 15.22 -3.19 -6.15 -10.38 ...
 .. attr(*, "dimnames")=List of 2
 .. ..$ : chr [1:291] "TCGA-BP-4993-01A" "TCGA-CZ-5982-01A" "TCGA-B0-4703-01A" "TCGA-CJ-4908-01A" ...
 .. ..$ : chr [1:291] "PC1" "PC2" "PC3" "PC4" ...
 - attr(*, "class")= chr "prcomp"
> type <- factor(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_PCA,
> plot(
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_PCA$x,
col = c("black", "red2")[type],
pch = c(18, 16)[type],
cex = 1.0)
> legend(
"bottomright",
```

```
bty = "n",
c("Alive", "Dead"),
fill = c("black", "red2"),
cex = 1.0)
```



MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed

En este dataset hay 290 muestras entre las que encontramos 188 (64.83%) pacientes vivos y 102 (35.17%) muertos.

```
# Muestras de metilación que están en Expresión proteica
```

```
> MetSampleNumb_IN_ExpProt01 <- which(match(colnames(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed),
```

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed) != 0)
```

```
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed)
[1] 93346 290
```

```
# Labels
```

```
x <- c()
```

```
for (i in colnames(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed))
```

```
x <- c(x, which(ExpGenTCGA_KIRC_RawData$sample %in% i))
```

```
}
```

```
> x
```

```
[1] 582 162 519 372 257 547 503 486 180 29 37 290 339 149 572 385 168 525 265 277 314 272 8 64
[25] 509 189 560 80 237 15 132 175 555 428 157 396 549 580 280 500 129 52 461 368 69 550 406 86
[49] 366 377 250 375 369 466 274 436 433 335 557 538 564 47 477 331 234 150 408 303 330 421 302 206
[73] 300 19 504 21 53 438 244 240 245 465 65 99 545 529 100 407 571 32 460 383 216 505 91 491
[97] 4 211 532 348 166 231 67 492 323 218 540 437 367 179 187 83 411 273 114 10 102 96 522 336
[121] 403 337 186 595 319 497 379 164 528 207 553 600 449 345 358 182 139 434 427 527 389 535 293 405
```



```

[145] 14 439 565 158 602 343 143 123 483 130 327 567 30 153 454 90 5 452 259 74 66 78 36 73
[169] 148 542 76 490 352 356 370 196 160 238 328 77 583 597 268 26 548 563 93 40 378 281 365 444
[193] 440 97 269 325 110 92 493 333 321 402 133 285 484 251 156 472 7 423 320 487 13 289 185 517
[217] 124 84 146 63 163 136 205 455 464 254 48 593 420 275 120 276 57 305 432 401 147 75 599 198
[241] 349 286 229 531 22 1 425 173 283 441 55 353 451 165 344 31 82 496 566 495 117 387 347 386
[265] 443 514 242 362 581 312 101 601 50 44 307 23 232 20 506 28 42 523 255 233 360 414 488 220
[289] 72 35

```

```

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_La
> table(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Ren
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_La
Alive Dead
188 102

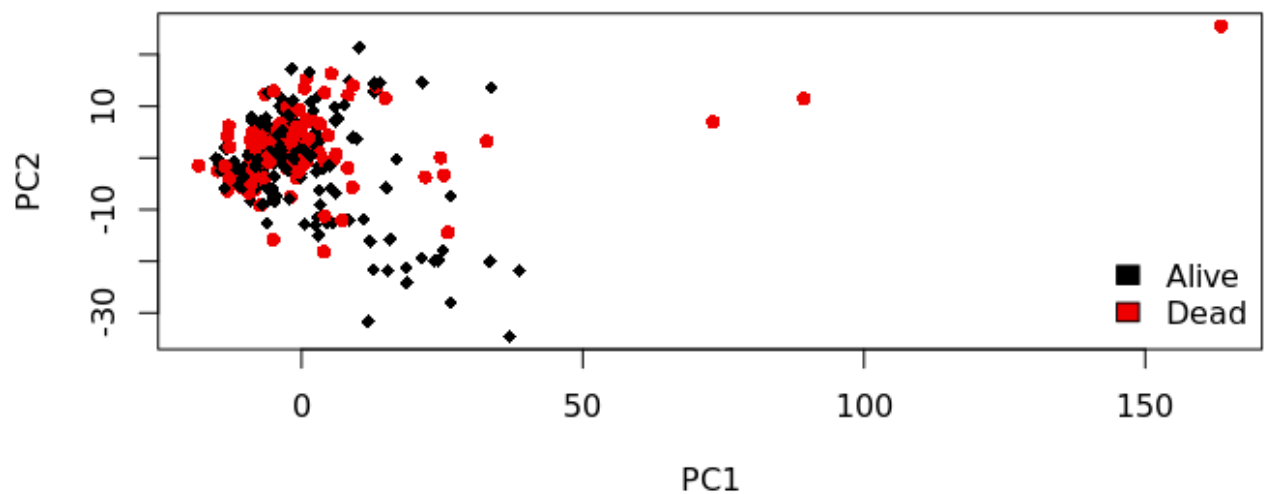
```

PCA

```

> MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_L
> str(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renan
List of 5
 $ sdev      : num [1:290] 15.37 8.46 6.97 6.56 6.42 ...
 $ rotation: num [1:93346, 1:290] -0.000172 -0.000347 -0.001557 -0.001049 -0.001783 ...
 ..- attr(*, "dimnames")=List of 2
 .. ..$ : chr [1:93346] "cg00000236" "cg00000721" "cg00000948" "cg00001349" ...
 .. ..$ : chr [1:290] "PC1" "PC2" "PC3" "PC4" ...
 $ center   : Named num [1:93346] 0.887 0.954 0.857 0.834 0.879 ...
 ..- attr(*, "names")= chr [1:93346] "cg00000236" "cg00000721" "cg00000948" "cg00001349" ...
 $ scale     : logi FALSE
 $ x         : num [1:290, 1:290] -5.21 15.23 -3.16 -6.13 -10.36 ...
 ..- attr(*, "dimnames")=List of 2
 .. ..$ : chr [1:290] "TCGA-BP-4993-01A" "TCGA-CZ-5982-01A" "TCGA-B0-4703-01A" "TCGA-CJ-4908-01A" ...
 .. ..$ : chr [1:290] "PC1" "PC2" "PC3" "PC4" ...
 - attr(*, "class")= chr "prcomp"
> type <- factor(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_PC
> plot(
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_PC
col = c("black", "red2")[type],
pch = c(18, 16)[type],
cex = 1.0)
> legend(
"bottomright",
bty = "n",
c("Alive", "Dead"),
fill = c("black", "red2"),
cex = 1.0)

```



Proteómica

Renombrar

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed <- ExpProtTCGA_KIRC_RawData_woNA_Norm
colnames(ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed) <- ExpProtTCGA_KIRC_RawData_woNA_ColNamesShort
```

Muestras compartidas

ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed No podemos conocer el porcentaje de vivos y muertos de este dataset puesto que no tenemos las etiquetas (metadatos) de las muestras.

ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen En este dataset hay 474 muestras entre las que encontramos 309 (65.19%) pacientes vivos y 165 (34.81%) muertos.

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen <- ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed
```

```
> dim(ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen)
[1] 177 474
```

Labels

```
x <- c()
for (i in colnames(ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen)){
  x <- c(x, which(ExpGenTCGA_KIRC_RawData$sample %in% i))
}
> x
[1] 161 546 202 114 235 595 25 52 38 593 539 429 504 476 232 254 187 183 151 582 37 490 418 69
[25] 211 153 449 601 465 238 282 97 79 600 299 149 510 242 573 139 440 45 136 531 420 255 220 264
```

```

[49] 154 375 17 113 495 119 422 356 360 540 269 3 162 15 109 484 311 6 63 165 441 591 456 558
[73] 471 478 509 366 446 602 91 603 201 146 200 280 285 227 230 557 65 566 53 460 30 304 314 128
[97] 486 330 454 487 389 315 362 122 323 173 433 14 55 286 237 428 129 547 251 125 379 367 586 512
[121] 22 390 290 24 178 432 105 42 64 244 385 413 213 333 7 239 369 338 199 553 427 174 16 206
[145] 249 450 163 361 90 209 303 472 378 67 497 80 60 402 599 451 434 54 208 339 96 358 184 277
[169] 159 19 488 71 605 166 555 372 581 156 545 261 514 523 233 312 344 78 388 8 167 305 506 340
[193] 363 343 324 27 185 21 147 240 574 415 597 519 23 386 551 143 29 475 309 470 528 435 123 228
[217] 234 587 565 307 224 403 308 431 458 384 257 81 405 336 348 508 28 382 364 59 461 189 351 563
[241] 580 477 444 560 443 533 326 325 252 583 168 567 98 70 371 483 164 73 507 517 421 522 260 491
[265] 396 535 266 293 349 559 468 321 300 245 354 525 104 130 198 133 205 51 36 48 157 377 72 500
[289] 135 289 150 482 345 395 392 320 467 197 448 193 101 549 265 302 110 1 281 414 256 529 84 92
[313] 452 83 322 207 222 527 329 267 117 505 248 502 594 332 492 61 116 40 93 438 409 543 86 295
[337] 127 176 283 480 121 572 13 331 137 219 425 106 77 250 365 408 180 26 411 196 328 577 459 171
[361] 182 370 564 218 76 453 160 158 347 469 296 335 57 319 571 270 346 10 44 4 195 532 437 496
[385] 550 82 503 102 100 120 56 383 542 596 279 537 466 337 493 75 112 186 568 47 439 455 350 190
[409] 276 464 66 387 534 103 548 99 50 380 353 397 231 313 499 511 74 148 259 423 352 598 179 236
[433] 424 229 445 273 217 124 520 417 394 463 436 85 327 68 357 407 381 20 35 32 538 5 556 442
[457] 268 401 398 294 175 515 274 579 263 155 406 368 216 132 118 272 31 275

```

```

ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen_Labels <- ExpGenTCGA_KIRC_RawData$vital_status
> table(ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen_Labels)
ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen_Labels
Alive Dead
  309   165

```

ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampMet En este dataset hay 291 muestras entre las que encontramos 188 (64.60%) pacientes vivos y 103 (35.39%) muertos.

```

ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampMet <- ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed[,E

```

```

# Labels

```

```

x <- c()
for (i in colnames(ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampMet)){
x <- c(x, which(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm$sample %in% i))
}
> x
[1] 195 207 64 384 129 463 382 190 1 15 287 70 168 261 220 457 143 297 328 219 23 449 226 327
[25] 376 413 386 473 481 78 436 293 475 183 329 2 45 346 372 426 422 37 75 247 163 369 61 345
[49] 92 144 432 134 158 260 32 11 114 263 358 234 453 180 418 88 241 423 407 44 52 63 8 349
[73] 212 186 415 17 396 468 36 137 26 339 355 79 218 230 119 374 264 109 354 320 177 210 43 342
[97] 402 425 229 18 199 223 31 125 477 175 51 4 454 352 150 447 472 474 455 427 275 35 395 465
[121] 248 365 130 399 141 310 3 462 444 249 13 216 251 106 244 460 203 6 240 202 174 466 66 39
[145] 317 60 102 326 42 446 330 306 27 258 252 215 278 366 116 200 165 55 236 239 406 341 120 142
[169] 28 255 403 343 377 276 383 53 76 482 62 363 107 222 357 456 56 30 118 334 416 322 476 151
[193] 368 335 268 191 217 232 439 162 179 157 319 318 136 73 419 25 359 105 417 305 77 325 108 12
[217] 314 193 295 300 225 294 95 182 284 296 246 443 89 392 209 154 196 459 167 169 184 431 71 429
[241] 9 197 152 388 160 283 82 204 338 400 205 99 242 378 389 380 274 442 316 148 458 424 176 273
[265] 280 270 356 290 188 409 194 367 84 256 153 464 483 156 93 266 311 397 50 83 72 68 161 46
[289] 33 428 387

```

```

ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampMet_Labels <- MetTCGA_KIRC_RawData_woDupSamples_woSNP
> table(ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampMet_Labels)

```

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampMet_Labels
Alive  Dead
    188   103
```

ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen_SameSampMet

En este dataset hay 290 muestras entre las que encontramos 188 (64.83%) pacientes vivos y 102 (35.17%) muertos.

Muestras de Expresión proteica que están en metilación

```
> ExpProt01SampleNumb_IN_Met <- which(match(colnames(ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampMet),
```

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen_SameSampMet <- ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampMet[,
```

Labels

```
x <- c()
```

```
for (i in colnames(ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen_SameSampMet)){
```

```
x <- c(x, which(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm$sample %in% i))
```

```
}
```

```
> x
```

```
 [1] 195 207  64 384 129 463 382 190   1  15 287  70 168 261 220 457 143 297 328 219  23 449 226 327
[25] 376 413 386 473 481  78 436 293 475 183 329   2  45 346 372 426 422  37  75 247 163 369  61 345
[49]  92 144 432 134 158 260  32  11 114 263 358 234 453 180 418  88 241 423 407  44  52  63   8 349
[73] 212 186 415  17 396 468  36 137  26 339 355  79 218 230 119 374 264 109 354 320 177 210  43 342
[97] 402 425 229  18 199 223  31 125 477 175  51   4 454 352 150 447 472 474 455 427 275  35 395 465
[121] 248 365 130 399 141 310   3 462 444 249  13 216 251 106 244 460 203   6 240 202 174 466  66  39
[145] 317  60 102 326  42 446 330 306  27 258 252 215 278 366 116 200 165  55 236 239 406 341 120 142
[169]  28 255 403 343 377 276 383  53  76 482  62 363 107 222 357 456  56  30 118 334 416 322 476 151
[193] 368 335 268 191 217 232 439 162 179 319 318 136  73 419  25 359 105 417 305  77 325 108  12 314
[217] 193 295 300 225 294  95 182 284 296 246 443  89 392 209 154 196 459 167 169 184 431  71 429   9
[241] 197 152 388 160 283  82 204 338 400 205  99 242 378 389 380 274 442 316 148 458 424 176 273 280
[265] 270 356 290 188 409 194 367  84 256 153 464 483 156  93 266 311 397  50  83  72  68 161  46  33
[289] 428 387
```

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen_SameSampMet_Labels <- MetTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen_SameSampMet[,
```

```
> table(ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen_SameSampMet_Labels)
```

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed_SameSampExpGen_SameSampMet_Labels
```

```
Alive  Dead
```

```
    188   102
```

6. Modelos independientes de ómicas

Expresión génica

Modelo de Expresión génica (ExpGenTCGA_KIRC_Norm01_Filt75_Renamed: genes = 4897, n = 606)

Usamos: ExpGenTCGA_KIRC_Norm01_Filt75_Renamed

```
> dim(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed)
[1] 4897 606
```

Creación de conjuntos test y train

```
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed <- t(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed)

set.seed(231)
```

```
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Index_Training <- sample(1:nrow(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed),
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Test <- ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed[Index_Training,]
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train <- ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed[-Index_Training,]
```

Obtención de etiquetas

```
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Test <- ExpGenTCGA_KIRC_RawData$vital_status[-ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Index_Training]
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Train <- ExpGenTCGA_KIRC_RawData$vital_status[ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Index_Training]

ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Test_FactorNumb <- as.integer(factor(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Test))
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Test_FactorNumb[ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Test == 0] <- NA

ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Train_FactorNumb <- as.integer(factor(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Train))
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Train_FactorNumb[ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Train == 0] <- NA
```

Guardar objetos importantes para modelos

Base de datos completa

```
save(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed, file = "ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed.Rsave")
```

Conjuntos Train y Test

```
# Train
save(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train, file = "ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train.Rsave")

# Test
save(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Test, file = "ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Test.Rsave")
```

Etiquetas

```
# Train
save(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Train_FactorNumb, file = "ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Train_FactorNumb.Rsave")

# Test
save(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Test_FactorNumb, file = "ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Test_FactorNumb.Rsave")
```

Creando script (ExpGenTCGA_KIRC_Norm01_Filt75modelscript.R)

```
# Cargando los archivos

# test_x
load("ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Test.rda")

# train_x
load("ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train.rda")

# test_y
load("ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Test_FactorNumb.rda")

# train_y
load("ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Train_FactorNumb.rda")

library(lattice)
library(ggplot2)
library(keras)
library(caret)

# Definición del modelo ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed: genes = 4897, n = 606
Model_ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed <- keras_model_sequential() %>%
  layer_dense(units = 16, activation = "relu", input_shape = c(4897)) %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(units = 1, activation = "sigmoid")

Model_ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed %>% compile(
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

# Entrenamiento y evaluación del modelo

history <- Model_ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed %>% fit(ExpGenTCGA_KIRC_Norm01_Filt75,
plot(history)

score <- Model_ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed %>% evaluate(
  ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Test, ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Test,
  verbose = 0
)

cat('Test loss:', score[[1]], '\n')
cat('Test accuracy:', score[[2]], '\n')
```

Resultados

Modelo 1 Resumen del modelo

```
> summary(Model_ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed)
```

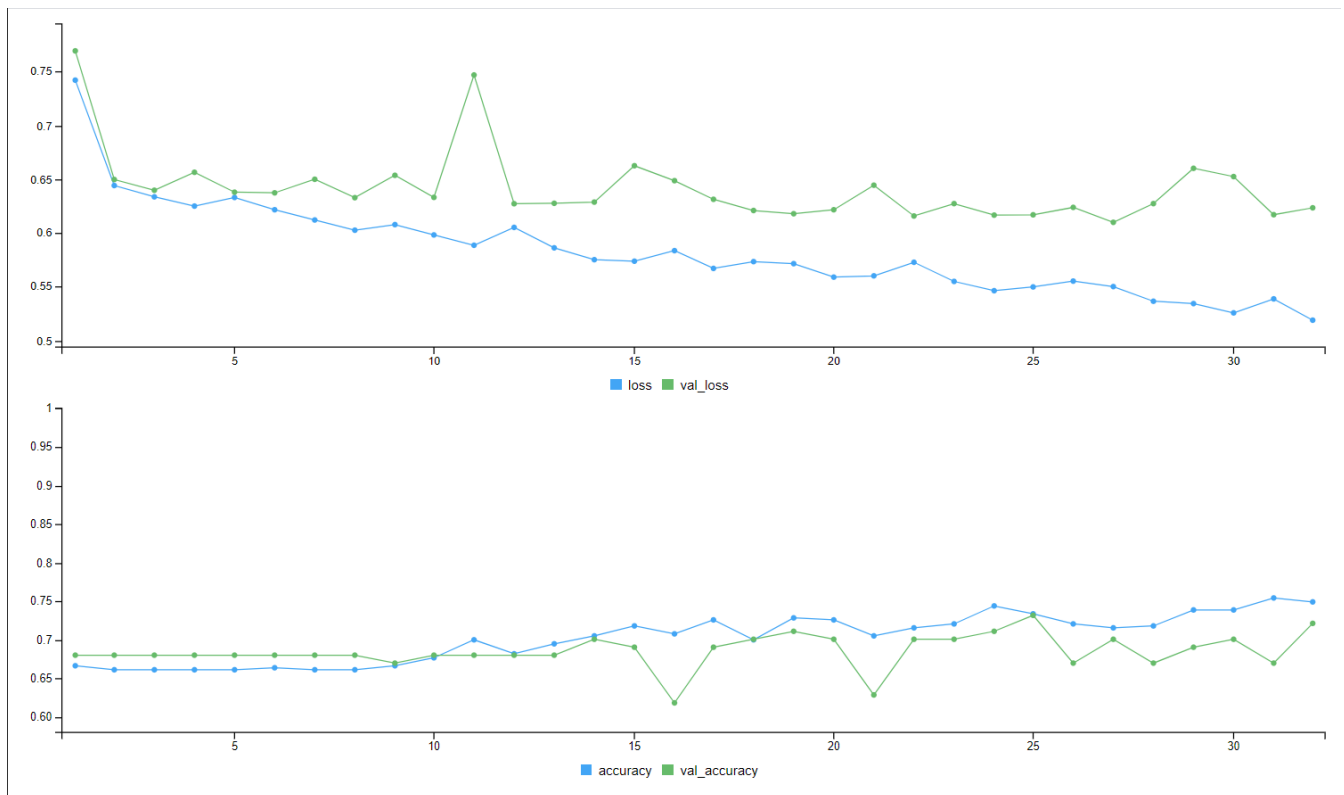
Model: "sequential_2"

Layer (type)	Output Shape	Param #
dense_8 (Dense)	(None, 16)	78368
dense_7 (Dense)	(None, 16)	272
dense_6 (Dense)	(None, 1)	17

Total params: 78,657
Trainable params: 78,657
Non-trainable params: 0

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.5348775 0.7049180
```

```
> history
```

```
Final epoch (plot to see history):
      loss: 0.519
      accuracy: 0.7494
```

```
val_loss: 0.6234
val_accuracy: 0.7216
```

```
> predict(Model_ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed, ExpGenTCGA_KIRC_Norm01_Filt75_Renamed,
          [,1]
[1,] 0.8697336
[2,] 0.8963979
[3,] 0.7891341
[4,] 0.9498302
[5,] 0.8369223
[6,] 0.6368501
[7,] 0.8639055
[8,] 0.6090716
[9,] 0.7070348
[10,] 0.9417554
[11,] 0.8116871
[12,] 0.6496152
[13,] 0.5939503
[14,] 0.9229082
[15,] 0.8405334
[16,] 0.5555996
[17,] 0.8322977
[18,] 0.6479468
[19,] 0.5068920
[20,] 0.5940652
[21,] 0.5033886
[22,] 0.9677508
[23,] 0.9109388
[24,] 0.9026528
[25,] 0.5398332
[26,] 0.6096040
[27,] 0.7442436
[28,] 0.4699266
```

Modelo 2 Resumen del modelo

Vamos a aumentar las epochs de 32 a 100, a ver si encontramos sobreajuste

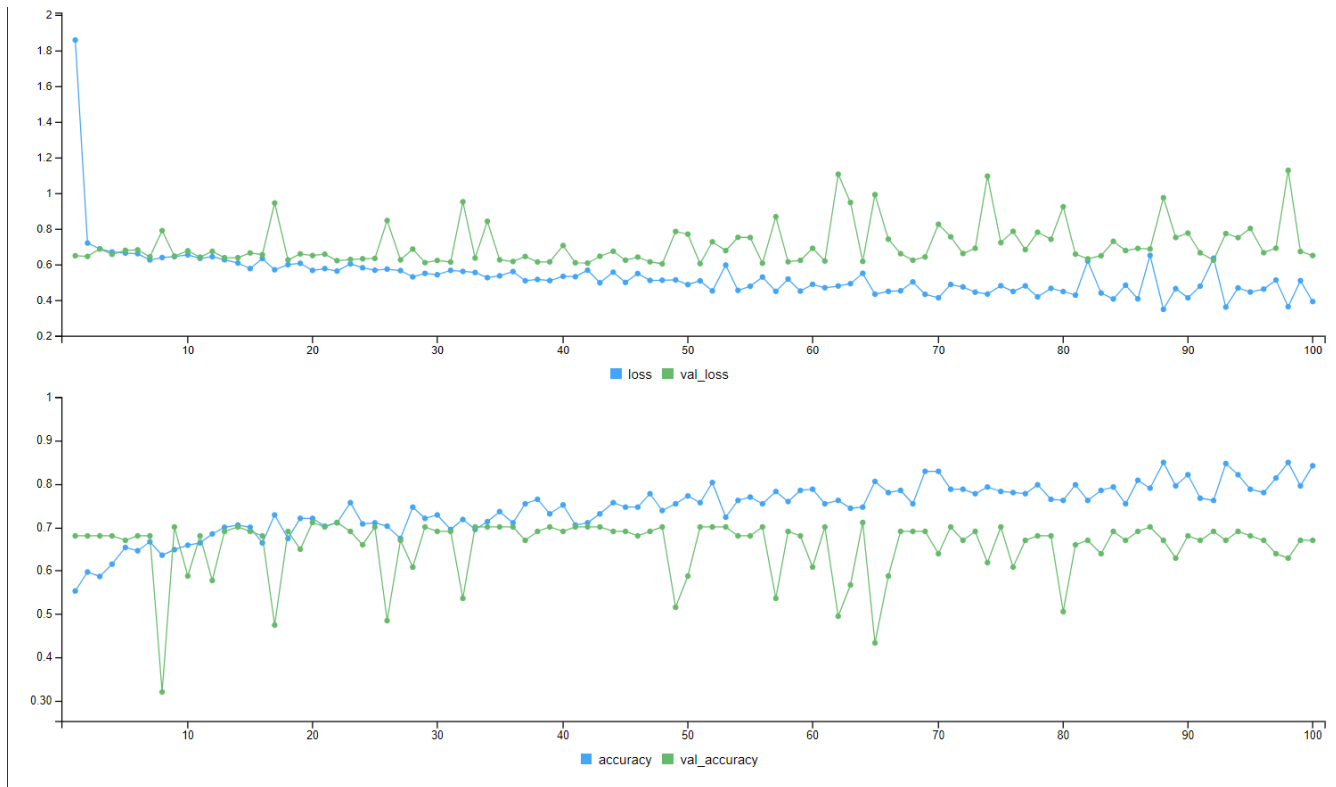
```
> summary(Model_ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed)
Model: "sequential_8"
```

Layer (type)	Output Shape	Param #
dense_30 (Dense)	(None, 400)	1959200
dense_29 (Dense)	(None, 200)	80200
dense_28 (Dense)	(None, 100)	20100
dense_27 (Dense)	(None, 50)	5050
dense_26 (Dense)	(None, 1)	51

Total params: 2,064,601
Trainable params: 2,064,601
Non-trainable params: 0

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.5257909 0.7295082
```

```
> history
```

Final epoch (plot to see history):

```
      loss: 0.3912
      accuracy: 0.8424
      val_loss: 0.6498
val_accuracy: 0.6701
```

```
> predict(Model_ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed, ExpGenTCGA_KIRC_Norm01_Filt75_Renamed,
          [,1]
[1,] 0.80715787
[2,] 0.90325236
[3,] 0.78039771
[4,] 0.95047009
[5,] 0.99955904
```

```

[6,] 0.55102897
[7,] 0.85213304
[8,] 0.67574543
[9,] 0.57154405
[10,] 0.95356965
[11,] 0.84602123
[12,] 0.73663223
[13,] 0.48719525
[14,] 0.94099689
[15,] 0.68009329
[16,] 0.64478403
[17,] 0.85300636
[18,] 0.57713234
[19,] 0.54804152
[20,] 0.59751326
[21,] 0.48638651
[22,] 0.97435153
[23,] 0.92414105
[24,] 0.92769742
[25,] 0.42746255
[26,] 0.57173383
[27,] 0.77193344

```

Conclusiones A pesar de que no conseguimos overfitting, ahora la red sí que parece aprender un poco más ya que en las predicts encontramos números más cercanos a 1 y más cercanos a 0.

Modelo de Expresión génica (ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed: genes = 4897, n = 474)

Usamos: ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed

```

> dim(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed)
[1] 4897 606

```

Creación de conjuntos test y train

```

ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed <- t(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed)

set.seed(231)

ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Index_Training <- sample(1:nrow(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed))

ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Test <- ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed[ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Index_Training,]

ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Train <- ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed[-ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Index_Training,]

```

Obtención de etiquetas

```

ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Labels_Test <- ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Labels[ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Index_Training,]

ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Labels_Train <- ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Labels[-ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Index_Training,]

```

```
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Test_FactorNumb <- as.integer(factor(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Test_FactorNumb[ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Test_FactorNumb]))
```

```
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Train_FactorNumb <- as.integer(factor(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Train_FactorNumb[ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Train_FactorNumb]))
```

Guardar objetos importantes para modelos

Base de datos completa

```
save(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed, file = "ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed.rda")
```

Conjuntos Train y Test

```
# Train
save(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Train, file = "ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Train.rda")
```

```
# Test
save(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Test, file = "ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Test.rda")
```

Etiquetas

```
# Train
save(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Train_FactorNumb, file = "ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Train_FactorNumb.rda")
```

```
# Test
save(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Test_FactorNumb, file = "ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Test_FactorNumb.rda")
```

Creando script (ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProtmodelscrip.R)

```
# Cargando los archivos
```

```
# test_x
load("ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Test.rda")
```

```
# train_x
load("ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Train.rda")
```

```
# test_y
load("ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Test_FactorNumb.rda")
```

```
# train_y
load("ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Train_FactorNumb.rda")
```

```
library(lattice)
library(ggplot2)
library(keras)
library(caret)
```

```
# Definición del modelo ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed: genes = 4897, n = 474
Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed <- keras_model_sequential() %>%
  layer_dense(units = 16, activation = "relu", input_shape = c(4897)) %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(units = 1, activation = "sigmoid")

Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed %>% compile(
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

# Entrenamiento y evaluación del modelo

history <- Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed %>% fit(ExpGenTCGA_KI

plot(history)

score <- Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed %>% evaluate(
  ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Test, ExpGenTCGA_KIRC_Norm01_Filt75_S
  verbose = 0
)

cat('Test loss:', score[[1]], '\n')
cat('Test accuracy:', score[[2]], '\n')
```

Resultados

Modelo 1 Resumen del modelo

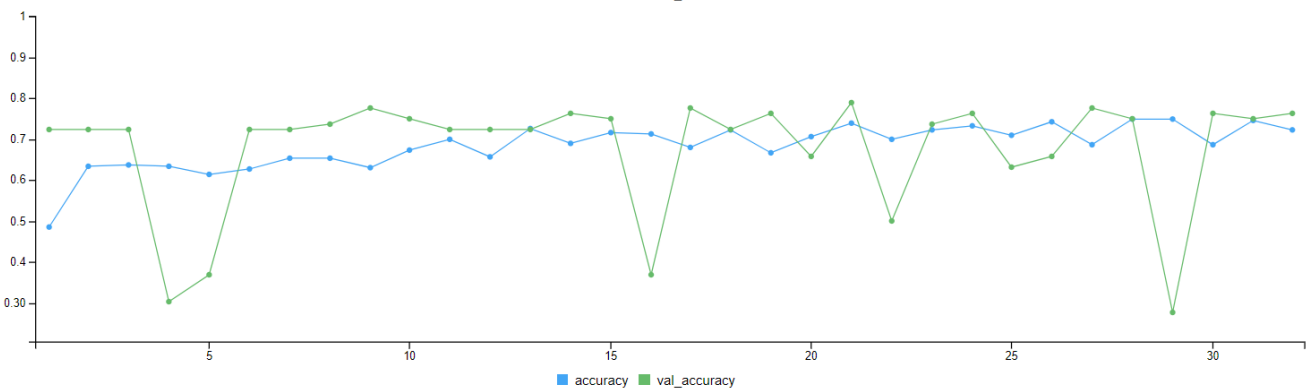
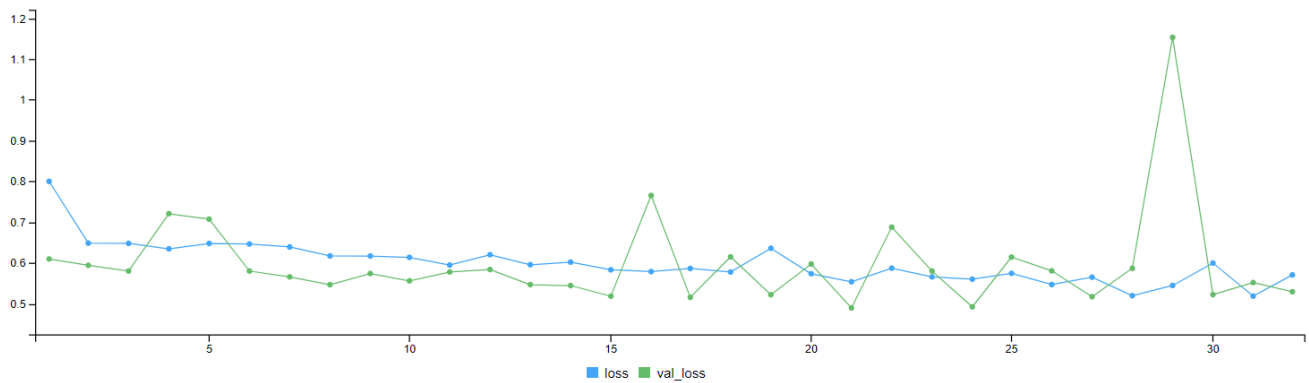
```
> summary(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed)
```

```
Model: "sequential_10"
```

Layer (type)	Output Shape	Param #
dense_36 (Dense)	(None, 16)	78368
dense_35 (Dense)	(None, 16)	272
dense_34 (Dense)	(None, 1)	17
Total params: 78,657		
Trainable params: 78,657		
Non-trainable params: 0		

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.7499498 0.6736842
```

```
> history
```

```
history
```

```
Final epoch (plot to see history):
```

```
      loss: 0.571
      accuracy: 0.7228
      val_loss: 0.5297
      val_accuracy: 0.7632
```

```
> predict(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed, ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed, ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed)
[1,]
[1,] 0.9568077
[2,] 0.8131423
[3,] 0.9724365
[4,] 0.8784594
[5,] 0.9493513
[6,] 0.6912041
[7,] 0.9366431
[8,] 0.9188679
[9,] 0.6161845
[10,] 0.6595472
[11,] 0.9713345
[12,] 0.7594427
```

```
[13,] 0.8381165
[14,] 0.6564200
[15,] 0.6075458
[16,] 0.9662790
[17,] 0.7718409
[18,] 0.8716229
[19,] 0.9890674
[20,] 0.9213936
[21,] 0.9744039
[22,] 0.8079967
[23,] 0.9582961
[24,] 0.9827141
[25,] 0.2664481
[26,] 0.7576817
[27,] 0.8992621
[28,] 0.4911505
[29,] 0.8541773
[30,] 0.7387527
[31,] 0.5711002
[32,] 0.8454475
[33,] 0.8391758
[34,] 0.8886519
```

Modelo 2 Resumen del modelo

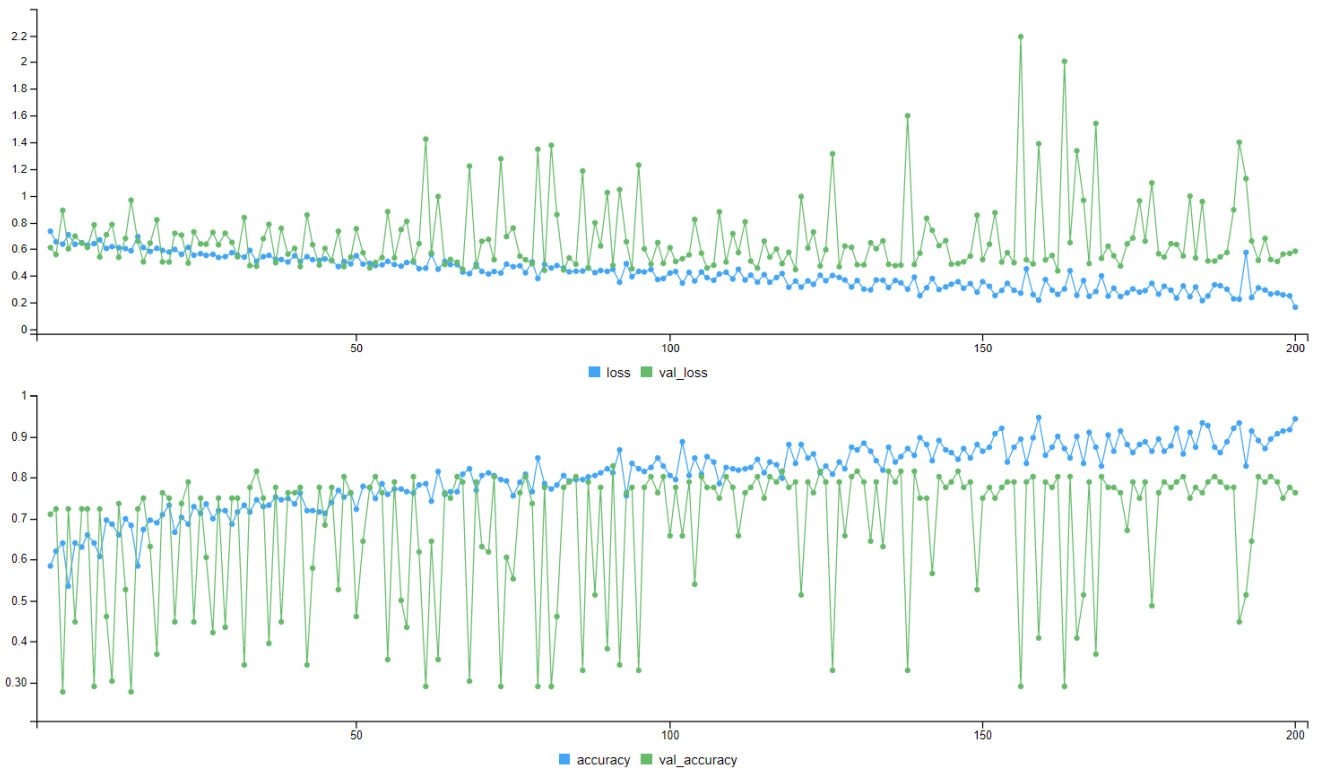
Vamos a aumentar las epochs de 32 a 200. Podemos observar un sobreajuste del modelo, y aunque vemos que la precision en el de validación y de prueba no es mala, en la gráfica de precisión observamos picos extraños en el conjunto de validación.

```
> summary(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed)
Model: "sequential_11"
```

Layer (type)	Output Shape	Param #
dense_39 (Dense)	(None, 16)	78368
dense_38 (Dense)	(None, 16)	272
dense_37 (Dense)	(None, 1)	17
Total params: 78,657		
Trainable params: 78,657		
Non-trainable params: 0		

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.9051554 0.6631579
> history

Final epoch (plot to see history):
      loss: 0.1643
      accuracy: 0.9439
      val_loss: 0.5839
      val_accuracy: 0.7632
> predict(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed, ExpGenTCGA_KIRC_Norm0
      [,1]
[1,] 9.025037e-01
[2,] 1.459529e-01
[3,] 9.691236e-01
[4,] 9.416673e-01
[5,] 9.207168e-01
[6,] 1.361501e-02
[7,] 1.049048e-01
[8,] 6.768511e-01
[9,] 8.850604e-03
[10,] 1.898098e-01
[11,] 9.774320e-01
[12,] 3.574330e-02
[13,] 2.186203e-02
[14,] 6.725825e-01
[15,] 6.669530e-01
[16,] 9.066889e-01
```

```
[17,] 1.798538e-01
[18,] 4.095941e-01
[19,] 9.837865e-01
[20,] 8.323203e-01
[21,] 9.902082e-01
[22,] 7.857132e-01
[23,] 9.524424e-01
[24,] 9.999757e-01
[25,] 5.250251e-05
[26,] 4.366115e-02
[27,] 1.661978e-01
[28,] 2.193150e-02
```

Modelo 3 Resumen del modelo

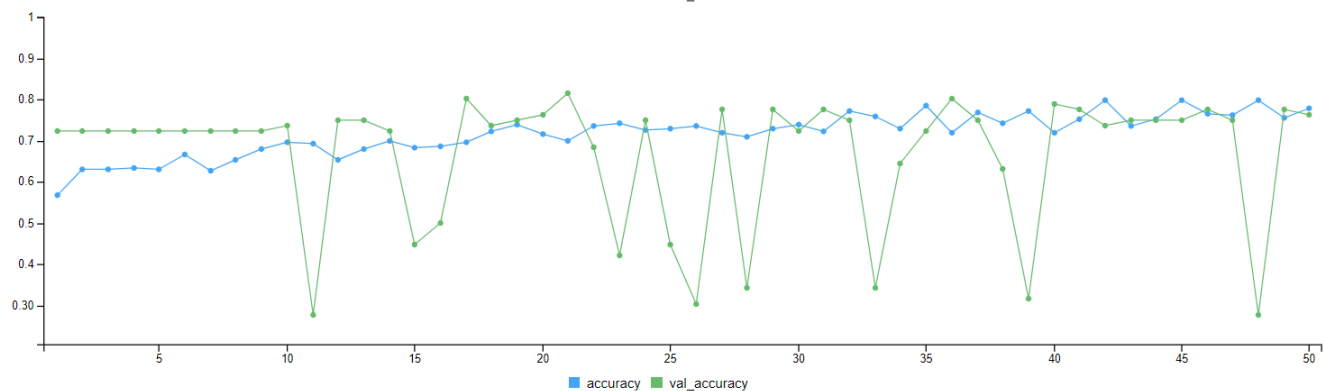
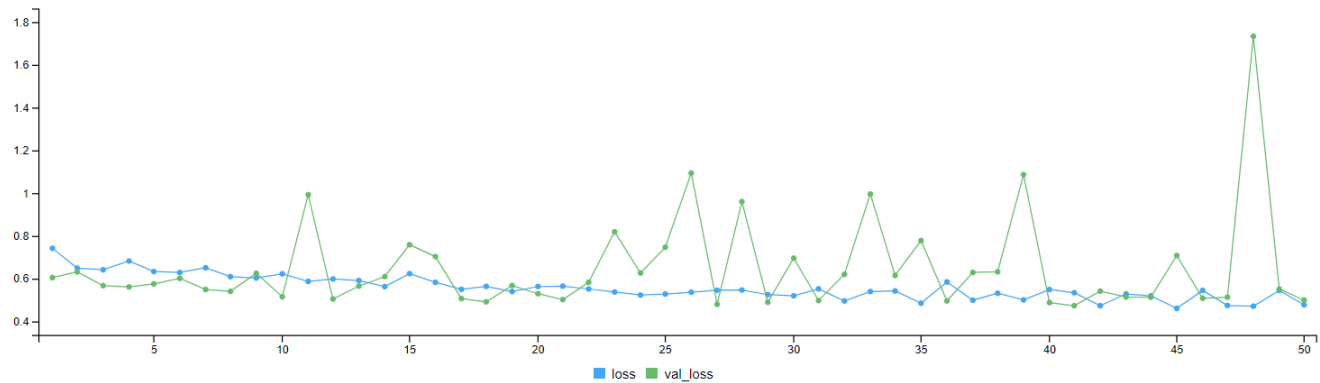
Hemos aumentado capas y las epochs a 50.

```
> summary(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed)
Model: "sequential_14"
```

Layer (type)	Output Shape	Param #
dense_51 (Dense)	(None, 20)	97960
dense_50 (Dense)	(None, 16)	336
dense_49 (Dense)	(None, 8)	136
dense_48 (Dense)	(None, 1)	9
Total params: 98,441		
Trainable params: 98,441		
Non-trainable params: 0		

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.6106607 0.7263158
> history
```

Final epoch (plot to see history):

```
      loss: 0.4787
      accuracy: 0.7789
      val_loss: 0.5008
      val_accuracy: 0.7632
```

```
> predict(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed, ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed, ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed, ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed)
[1,]
```

```
[1,] 0.83467633
[2,] 0.31380272
[3,] 0.89783919
[4,] 0.60204035
[5,] 0.86398113
[6,] 0.18751249
[7,] 0.65454161
[8,] 0.74137282
[9,] 0.17497104
[10,] 0.37883353
[11,] 0.85166055
[12,] 0.26118419
[13,] 0.31547427
[14,] 0.46910909
```

Modelo de Expresión génica (ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_genes = 4897, n = 290)

Usamos: ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed

```
> dim(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed)
[1] 4897 290
```

Creación de conjuntos test y train

```
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed <- t(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed)
set.seed(231)
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Index_Training <- sample(1:nrow(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed), 200)
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Test <- ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed[Index_Training, ]
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Train <- ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed[-Index_Training, ]
```

Obtención de etiquetas

```
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Labels_Test <- ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Labels[Index_Training, ]
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Labels_Train <- ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Labels[-Index_Training, ]
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Test_FactorNumb <- as.integer(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Test)
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Test_FactorNumb[ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Test == 0] <- 1
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Train_FactorNumb <- as.integer(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Train)
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Train_FactorNumb[ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Train == 0] <- 1
```

Guardar objetos importantes para modelos

Base de datos completa

```
save(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed, file = "ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed.RData")
```

Conjuntos Train y Test

```
# Train
save(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Train, file = "ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Train.RData")

# Test
save(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Test, file = "ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Test.RData")
```

Etiquetas

```
# Train
save(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Train_FactorNumb, file = "1")
```

```
# Test
save(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Test_FactorNumb, file = "2")
```

Creando script (ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMetmodelscrip.R)

```
# Cargando los archivos
```

```
# test_x
load("ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Test.rda")
```

```
# train_x
load("ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Train.rda")
```

```
# test_y
load("ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Test_FactorNumb.rda")
```

```
# train_y
load("ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Labels_Train_FactorNumb.rda")
```

```
library(lattice)
library(ggplot2)
library(keras)
library(caret)
```

```
# Definición del modelo ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed: genes = 4897
Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed <- keras_model_sequential(
  layer_dense(units = 16, activation = "relu", input_shape = c(4897)) %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(units = 1, activation = "sigmoid")
)
```

```
Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed %>% compile(
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)
```

```
# Entrenamiento y evaluación del modelo
```

```
history <- Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed %>% fit(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Test, ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Train,
  verbose = 0
)
```

```
score <- Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed %>% evaluate(
  ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Test, ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed_Train,
  verbose = 0
)
```

```
cat('Test loss:', score[[1]], '\n')
cat('Test accuracy:', score[[2]], '\n')
```

Resultados

Modelo 1 Resumen del modelo

```
> summary(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed)
Model: "sequential_15"
```

Layer (type)	Output Shape	Param #
dense_54 (Dense)	(None, 16)	78368
dense_53 (Dense)	(None, 16)	272
dense_52 (Dense)	(None, 1)	17

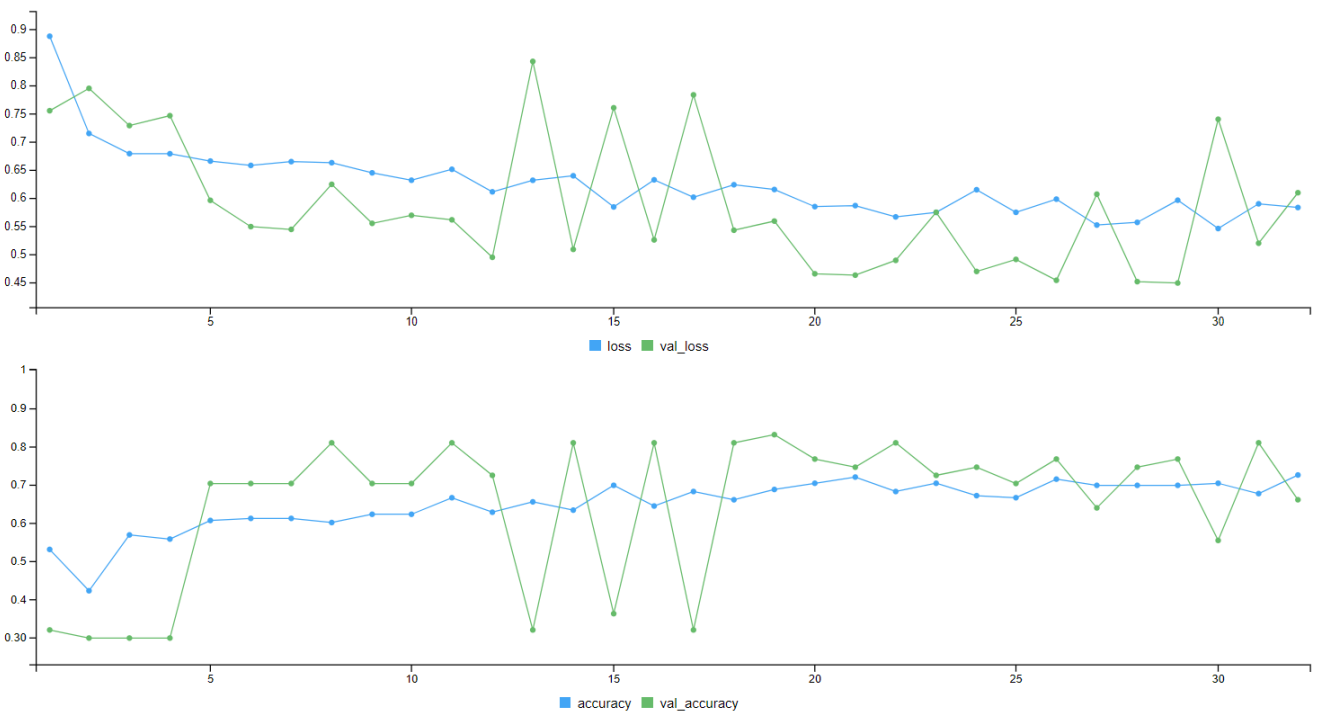
Total params: 78,657

Trainable params: 78,657

Non-trainable params: 0

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.5348775 0.7049180
```

```
> history
```

Final epoch (plot to see history):

```
    loss: 0.519
    accuracy: 0.7494
    val_loss: 0.6234
    val_accuracy: 0.7216
```

```
> predict(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed, ExpGenTCG
      [,1]
[1,] 0.58461225
[2,] 0.60310704
[3,] 0.67405194
[4,] 0.81585377
[5,] 0.31713414
[6,] 0.14554837
[7,] 0.34794801
[8,] 0.29168567
[9,] 0.58980548
[10,] 0.61459279
[11,] 0.48619995
[12,] 0.46376172
[13,] 0.24309367
[14,] 0.22715920
[15,] 0.49996880
[16,] 0.48184609
[17,] 0.20491400
[18,] 0.66487873
[19,] 0.28882766
[20,] 0.46932176
[21,] 0.42240679
[22,] 0.63178110
[23,] 0.34535626
[24,] 0.58418208
[25,] 0.15185118
[26,] 0.61035919
[27,] 0.53604364
[28,] 0.54063535
```

Modelo 2 Resumen del modelo

Vamos a aumentar las epochs de 32 a 100.

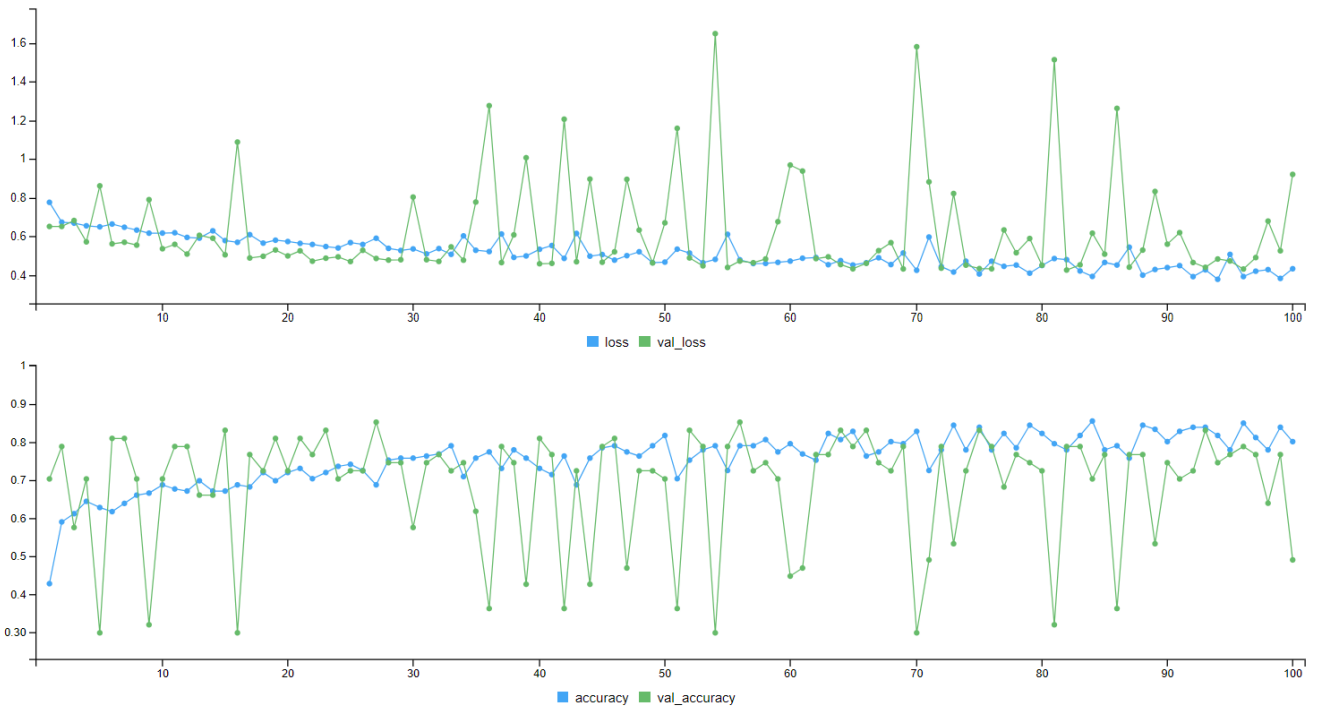
```
> summary(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed)
Model: "sequential_16"
```

Layer (type)	Output Shape	Param #
dense_57 (Dense)	(None, 16)	78368
dense_56 (Dense)	(None, 16)	272
dense_55 (Dense)	(None, 1)	17
Total params: 78,657		

Trainable params: 78,657
Non-trainable params: 0

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.9658350 0.5344828
> history

Final epoch (plot to see history):
      loss: 0.4316
      accuracy: 0.8
      val_loss: 0.9197
val_accuracy: 0.4894
> predict(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed, ExpGenTCG
      [,1]
[1,] 3.161165e-01
[2,] 4.803107e-01
[3,] 8.270217e-01
[4,] 7.530786e-01
[5,] 2.729392e-01
[6,] 9.059221e-03
[7,] 2.192812e-01
[8,] 2.647204e-01
[9,] 4.573123e-01
[10,] 7.129636e-01
[11,] 4.777987e-01
```

```
[12,] 5.553334e-01
[13,] 5.959237e-02
[14,] 3.188428e-02
[15,] 3.768789e-01
[16,] 2.820298e-01
[17,] 3.953472e-02
[18,] 7.984113e-01
[19,] 1.953096e-01
[20,] 1.101498e-01
[21,] 2.716530e-01
[22,] 5.827190e-01
[23,] 2.029104e-01
[24,] 3.827968e-01
[25,] 1.153731e-02
[26,] 7.944947e-01
[27,] 1.018376e-01
[28,] 9.481812e-02
```

Modelo 3 Resumen del modelo

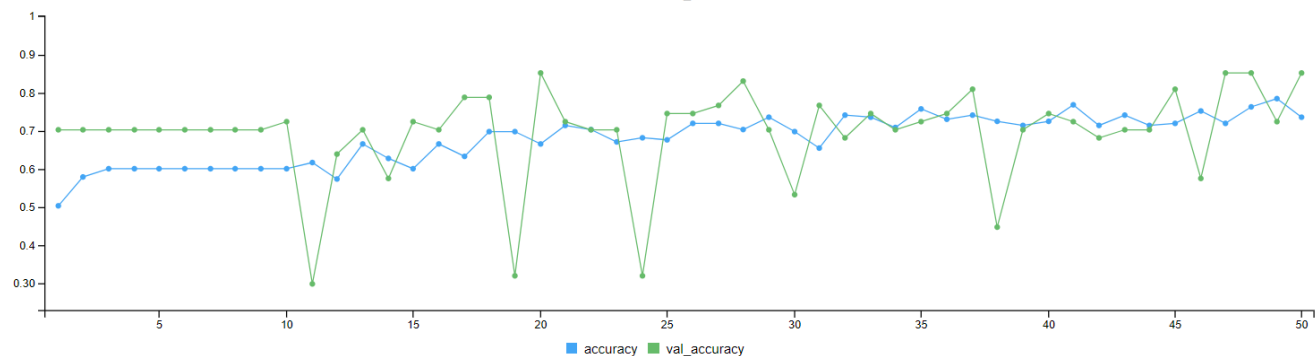
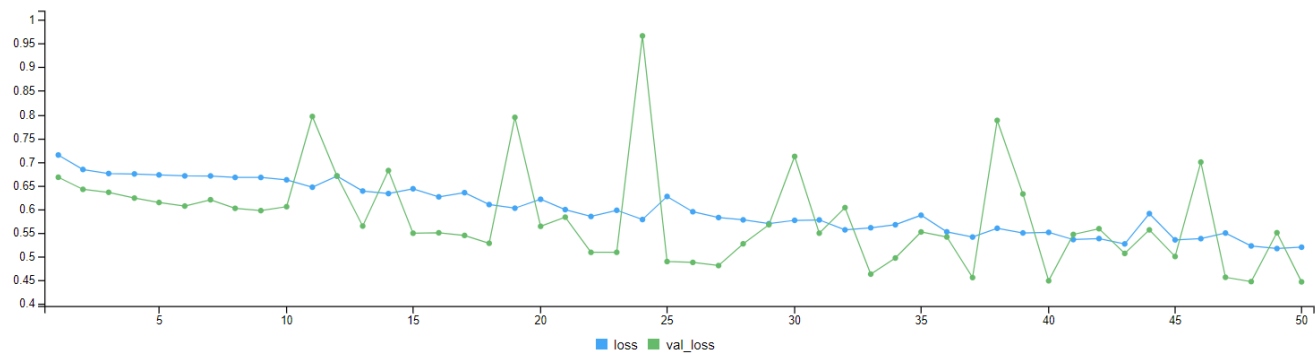
Vamos a cambiar las epochs= 50.

```
> summary(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed)
Model: "sequential_17"
```

Layer (type)	Output Shape	Param #
dense_61 (Dense)	(None, 20)	97960
dense_60 (Dense)	(None, 16)	336
dense_59 (Dense)	(None, 8)	136
dense_58 (Dense)	(None, 1)	9
Total params: 98,441		
Trainable params: 98,441		
Non-trainable params: 0		

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.5299286 0.7413793
> history

Final epoch (plot to see history):
      loss: 0.5191
      accuracy: 0.7351
      val_loss: 0.4457
      val_accuracy: 0.8511
> predict(Model_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_Transposed, ExpGenTCGA
      [,1]
[1,] 0.83764637
[2,] 0.77914727
[3,] 0.87687790
[4,] 0.96164382
[5,] 0.48738194
[6,] 0.19217414
[7,] 0.55559862
[8,] 0.53899276
[9,] 0.81982958
[10,] 0.90991068
[11,] 0.68609488
[12,] 0.67460680
[13,] 0.49418601
[14,] 0.40798798
[15,] 0.75500524
[16,] 0.72544819
[17,] 0.28343984
[18,] 0.92997670
```



```
[19,] 0.49273008
[20,] 0.69549948
[21,] 0.58153230
[22,] 0.90136254
[23,] 0.54840910
[24,] 0.83853483
[25,] 0.36407518
[26,] 0.87791800
[27,] 0.82587719
[28,] 0.60410601
```

Metilación

Modelo de metilación (MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_sondas = 93346, n = 483)

Usamos: MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed

```
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed)
[1] 93346 483
```

Creación de conjuntos test y train

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed <- t(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed)

set.seed(231)

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Index_Training <- sample(1:nrow(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed), 400)

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Test <- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed[MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Index_Training, ]
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Train <- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed[-MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Index_Training, ]
```

Obtención de etiquetas

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Test <- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels[MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Index_Training, ]
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Train <- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels[-MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Index_Training, ]

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Test_FactorNumb <- as.integer(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Test)
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Test_FactorNumb[MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Test_FactorNumb == 0] <- NA

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Train_FactorNumb <- as.integer(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Train)
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Train_FactorNumb[MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Train_FactorNumb == 0] <- NA
```

Guardar objetos importantes para modelos

Base de datos completa

```
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed, file = "MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed.Rsave")
```

Conjuntos Train y Test

```
# Train
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Train, file = "MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Train.rda")

# Test
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Test, file = "MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Test.rda")
```

Etiquetas

```
# Train
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Train_FactorNumb, file = "MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Train_FactorNumb.rda")

# Test
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Test_FactorNumb, file = "MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Test_FactorNumb.rda")
```

Creando script (MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75model.R)

```
# Cargando los archivos

# test_x
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Test.rda")

# train_x
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Train.rda")

# test_y
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Test_FactorNumb.rda")

# train_y
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Labels_Train_FactorNumb.rda")

library(lattice)
library(ggplot2)
library(keras)
library(caret)

# Definición del modelo MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed: sondas = 93346
Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed <- keras_model_sequential%>%
  layer_dense(units = 16, activation = "relu", input_shape = c(93346)) %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(units = 1, activation = "sigmoid")

Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed %>% compile(
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

# Entrenamiento y evaluación del modelo

history <- Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed %>% fit(
  test_x, test_y,
  validation_data = list(train_x, train_y),
  callbacks = list(
    EarlyStopping(monitor = "val_loss", patience = 10)
  ),
  verbose = 1
)
```

```

plot(history)

score <- Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed %>% eval
  MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed_Test, MetTCGA_KIRC_Raw
  verbose = 0
)

cat('Test loss:', score[[1]], '\n')
cat('Test accuracy:', score[[2]], '\n')

```

Resultados

Modelo 1 Resumen del modelo

```

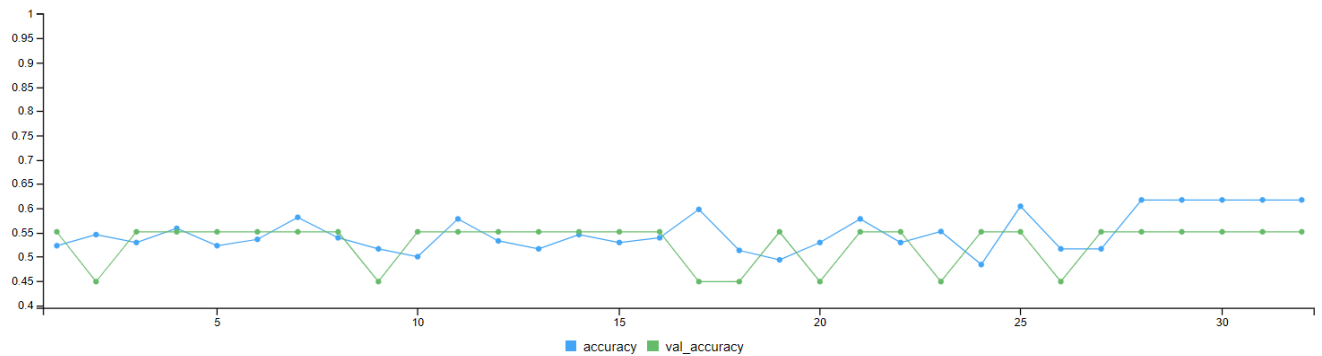
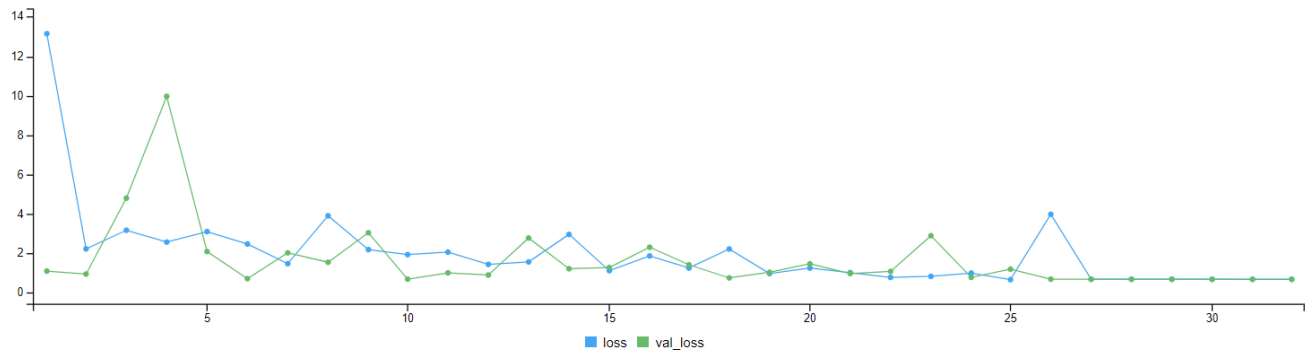
> summary(Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed)
Model: "sequential_18"

```

Layer (type)	Output Shape	Param #
dense_64 (Dense)	(None, 16)	1493552
dense_63 (Dense)	(None, 16)	272
dense_62 (Dense)	(None, 1)	17
Total params: 1,493,841		
Trainable params: 1,493,841		
Non-trainable params: 0		

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```

> score
      loss accuracy
0.6819232 0.6907216
> history

Final epoch (plot to see history):
      loss: 0.6848
      accuracy: 0.6169
      val_loss: 0.6905
      val_accuracy: 0.5513
> predict(Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed, MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed)
[1,]
[1,] 0.5153267
[2,] 0.5153267
[3,] 0.5153267
[4,] 0.5153267
[5,] 0.5153267
[6,] 0.5153267
[7,] 0.5153267
[8,] 0.5153267
[9,] 0.5153267
[10,] 0.5153267
[11,] 0.5153267
[12,] 0.5153267
[13,] 0.5153267
[14,] 0.5153267
[15,] 0.5153267
[16,] 0.5153267
[17,] 0.5153267
[18,] 0.5153267
[19,] 0.5153267

```

```
[20,] 0.5153267
[21,] 0.5153267
[22,] 0.5153267
[23,] 0.5153267
[24,] 0.5153267
[25,] 0.5153267
[26,] 0.5153267
[27,] 0.5153267
[28,] 0.5153267
```

Esta red parece ser muy pequeña, el modelo no aprende. Si bservamos los predicts son todos parecidos.

Modelo 2 Resumen del modelo

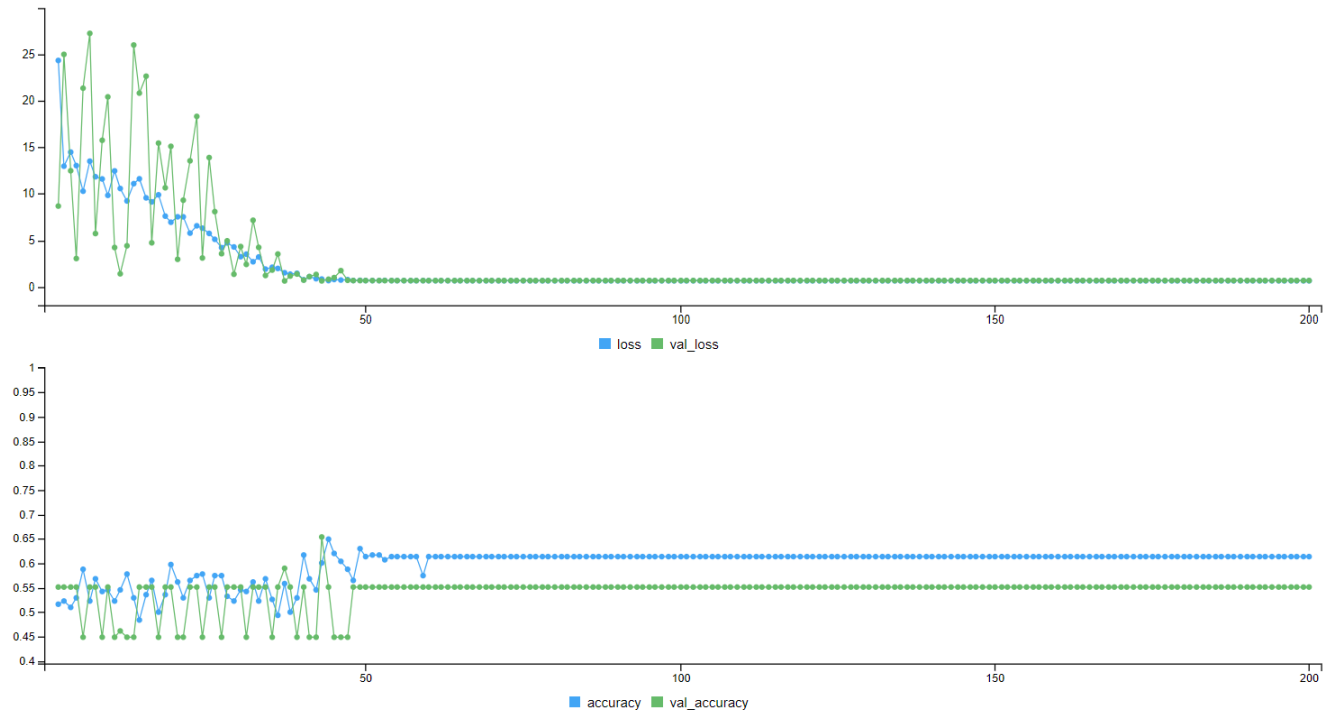
Vamos a aumentar las epochs de 32 a 200, a ver si encontramos sobreajuste.

```
> summary(Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed)
Model: "sequential_20"
```

Layer (type)	Output Shape	Param #
dense_70 (Dense)	(None, 16)	1493552
dense_69 (Dense)	(None, 8)	136
dense_68 (Dense)	(None, 1)	9
Total params: 1,493,697		
Trainable params: 1,493,697		
Non-trainable params: 0		
>		

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.6313332 0.6907216
> history

Final epoch (plot to see history):
      loss: 0.6671
      accuracy: 0.6136
      val_loss: 0.696
      val_accuracy: 0.5513
> predict(Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed, MetTCGA)
      [,1]
[1,] 0.6139413
[2,] 0.6139413
[3,] 0.6139413
[4,] 0.6139413
[5,] 0.6139413
[6,] 0.6139413
[7,] 0.6139413
[8,] 0.6139413
[9,] 0.6139413
[10,] 0.6139413
[11,] 0.6139413
[12,] 0.6139413
[13,] 0.6139413
[14,] 0.6139413
[15,] 0.6139413
[16,] 0.6139413
[17,] 0.6139413
[18,] 0.6139413
```

```
[19,] 0.6139413
[20,] 0.6139413
[21,] 0.6139413
[22,] 0.6139413
[23,] 0.6139413
```

Sigue sin aprender, vamos a hacer un modelo más grande.

Modelo 3 Resumen del modelo

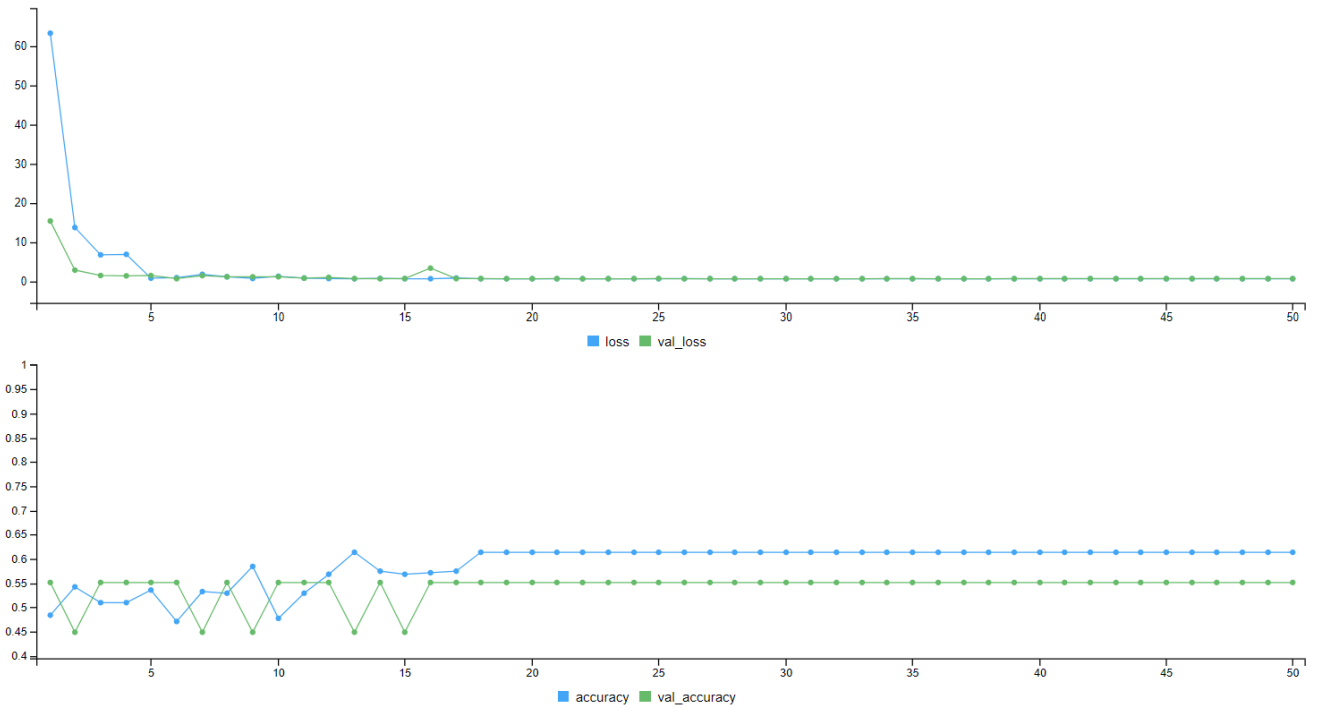
Vamos a aumentar las epochs de 32 a 200, a ver si encontramos sobreajuste.

```
> summary(Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed)
Model: "sequential_22"
```

Layer (type)	Output Shape	Param #
dense_81 (Dense)	(None, 500)	46673500
dense_80 (Dense)	(None, 200)	100200
dense_79 (Dense)	(None, 100)	20100
dense_78 (Dense)	(None, 50)	5050
dense_77 (Dense)	(None, 20)	1020
dense_76 (Dense)	(None, 1)	21
Total params: 46,799,891		
Trainable params: 46,799,891		
Non-trainable params: 0		

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.6286385 0.6907216
> history

Final epoch (plot to see history):
      loss: 0.6682
      accuracy: 0.6136
      val_loss: 0.6985
      val_accuracy: 0.5513
> predict(Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed, MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_Transposed)
[1,]
[1,] 0.6227190
[2,] 0.6227190
[3,] 0.6227190
[4,] 0.6227190
[5,] 0.6227190
[6,] 0.6227190
[7,] 0.6227190
[8,] 0.6227190
[9,] 0.6227190
[10,] 0.6227190
[11,] 0.6227190
[12,] 0.6227190
[13,] 0.6227190
[14,] 0.6227190
[15,] 0.6227190
[16,] 0.6227190
[17,] 0.6227190
[18,] 0.6227190
[19,] 0.6227190
```



```
[20,] 0.6227190
[21,] 0.6227190
[22,] 0.6227190
[23,] 0.6227190
[24,] 0.6227190
[25,] 0.6227190
[26,] 0.6227190
[27,] 0.6227190
[28,] 0.6227190
```

Sigue sin aprender.

Modelo de metilación (MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_ sondas = 93346, n = 291)

Usamos: MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed

```
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed)
[1] 93346    483
```

Creación de conjuntos test y train

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed <- t(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed)
set.seed(231)

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed_Index <- sample(1:nrow(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed), nrow(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed))
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed_Test <- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed[MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed_Index,]
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed_Train <- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed[-MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed_Index,]
```

Obtención de etiquetas

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Test <- M
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Train <- M

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Test_Factor <- factor(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Test)
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Test_Factor <- factor(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Test_Factor)

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Train_Factor <- factor(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Train)
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Train_Factor <- factor(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Train_Factor)
```

Guardar objetos importantes para modelos

Base de datos completa

```
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed,
```

Conjuntos Train y Test

```
# Train
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed_

# Test
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed_
```

Etiquetas

```
# Train
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Train

# Test
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Test
```

Creando script (MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Sam

```
# Cargando los archivos

# test_x
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed

# train_x
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed

# test_y
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Tes

# train_y
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Labels_Tra

library(lattice)
library(ggplot2)
library(keras)
library(caret)

# Definición del modelo MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_
Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed
  layer_dense(units = 16, activation = "relu", input_shape = c(93346)) %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(units = 1, activation = "sigmoid")

Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

# Entrenamiento y evaluación del modelo

history <- MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transp
```

```
plot(history)
```

```
score <- Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Test  
  MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Transposed_Test  
  verbose = 0  
)
```

```
cat('Test loss:', score[[1]], '\n')  
cat('Test accuracy:', score[[2]], '\n')
```

Modelo de metilación (MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75__SameSampExpProt_Renamed_Test, sondas = 93346, n = 290)

Usamos: MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Test

```
> dim(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Test)  
[1] 93346    290
```

Creación de conjuntos test y train

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Test

```
set.seed(231)
```

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Test

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Test
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Test

Obtención de etiquetas

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Labels
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Labels

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Labels
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Labels

MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Labels
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Labels

Guardar objetos importantes para modelos

Base de datos completa

```
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_Test, file = "base_datos_completa.Rsave")
```

Conjuntos Train y Test

```
# Train
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed, "train.Rsave")

# Test
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed, "test.Rsave")
```

Etiquetas

```
# Train
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed, "train.Rsave")

# Test
save(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed, "test.Rsave")
```

Creando script (MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed.R)

```
# Cargando los archivos

# test_x
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_x.Rsave")

# train_x
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_x.Rsave")

# test_y
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_y.Rsave")

# train_y
load("MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_y.Rsave")

library(lattice)
library(ggplot2)
library(keras)
library(caret)

# Definición del modelo MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed
Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed <-
  layer_dense(units = 16, activation = "relu", input_shape = c(93346)) %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(units = 1, activation = "sigmoid")

Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed <-
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

# Entrenamiento y evaluación del modelo

history <- Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed %>%
  fit(train_x, train_y, validation_data = c(test_x, test_y))
```

```

plot(history)

score <- Model_MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_T
  MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_T
  verbose = 0
)

cat('Test loss:', score[[1]], '\n')
cat('Test accuracy:', score[[2]], '\n')

```

Proteómica

Modelo de Expresión proteica (ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed: proteínas = 177, n = 478)

Usamos: ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed

```

> dim(ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed)
[1] 177 478

```

Dado que de este conjunto de datos no podemos obtener todas las etiquetas de vital_status para las 478 muestras, porque no se pueden descargar este tipo de metadatos, pasaremos al siguiente modelo en el que tenemos las muestras que coinciden entre expresión génica y expresión proteica. Así, podremos conocer las etiquetas de las muestras gracias a los datos de Expresión génica.

Modelo de Expresión proteica (ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed: proteínas = 177, n = 474)

Usamos: ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed

```

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed <- ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed
> dim(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed)
[1] 177 474

```

Creación de conjuntos test y train

```

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed <- t(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed)

set.seed(231)

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Index_Training<- sample(1:nrow(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed), nrow(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed)-1)

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Test <- ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed[ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Index_Training,]
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Train <- ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed[-ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Index_Training,]

```

Obtención de etiquetas

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels <- ExpProtTCGA_KIRC_RawData_woNA_Norm_L
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Test <- ExpProtTCGA_KIRC_RawData_woNA_N
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Train <- ExpProtTCGA_KIRC_RawData_woNA_N

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Test_FactorNumb <- as.integer(factor(E
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Test_FactorNumb[ExpProtTCGA_KIRC_RawD

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Train_FactorNumb <- as.integer(factor(E
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Train_FactorNumb[ExpProtTCGA_KIRC_RawD
```

Guardar objetos importantes para modelos

Base de datos completa

```
save(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed, file = "ExpProtTCGA_KIRC_RawD
```

Conjuntos Train y Test

```
# Train
save(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Train, file = "ExpProtTCGA_KIR

# Test
save(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Test, file = "ExpProtTCGA_KIR
```

Etiquetas

```
# Train
save(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Train_FactorNumb, file = "ExpProtT

# Test
save(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Test_FactorNumb, file = "ExpProtT
```

Creando script (ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGenmmmodelscrip.R)

```
# Cargando los archivos

# test_x
load("ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Test.rda")

# train_x
load("ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Train.rda")

# test_y
load("ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Test_FactorNumb.rda")

# train_y
load("ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Train_FactorNumb.rda")
```

```

library(lattice)
library(ggplot2)
library(keras)
library(caret)

# Definición del modelo ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed: proteínas = 177, n=
Model_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed <- keras_model_sequential() %>%
  layer_dense(units = 16, activation = "relu", input_shape = c(177)) %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(units = 1, activation = "sigmoid")

Model_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed %>% compile(
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

# Entrenamiento y evaluación del modelo

history <- Model_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed %>% fit(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Test, ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Val, verbose = 0)

plot(history)

score <- Model_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed %>% evaluate(
  ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Test, ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Val, verbose = 0
)

cat('Test loss:', score[[1]], '\n')
cat('Test accuracy:', score[[2]], '\n')

```

Resultados

Modelo 1 Resumen del modelo

```

> summary(Model_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed)
Model: "sequential_3"

```

Layer (type)	Output Shape	Param #
dense_11 (Dense)	(None, 16)	2848
dense_10 (Dense)	(None, 16)	272
dense_9 (Dense)	(None, 1)	17

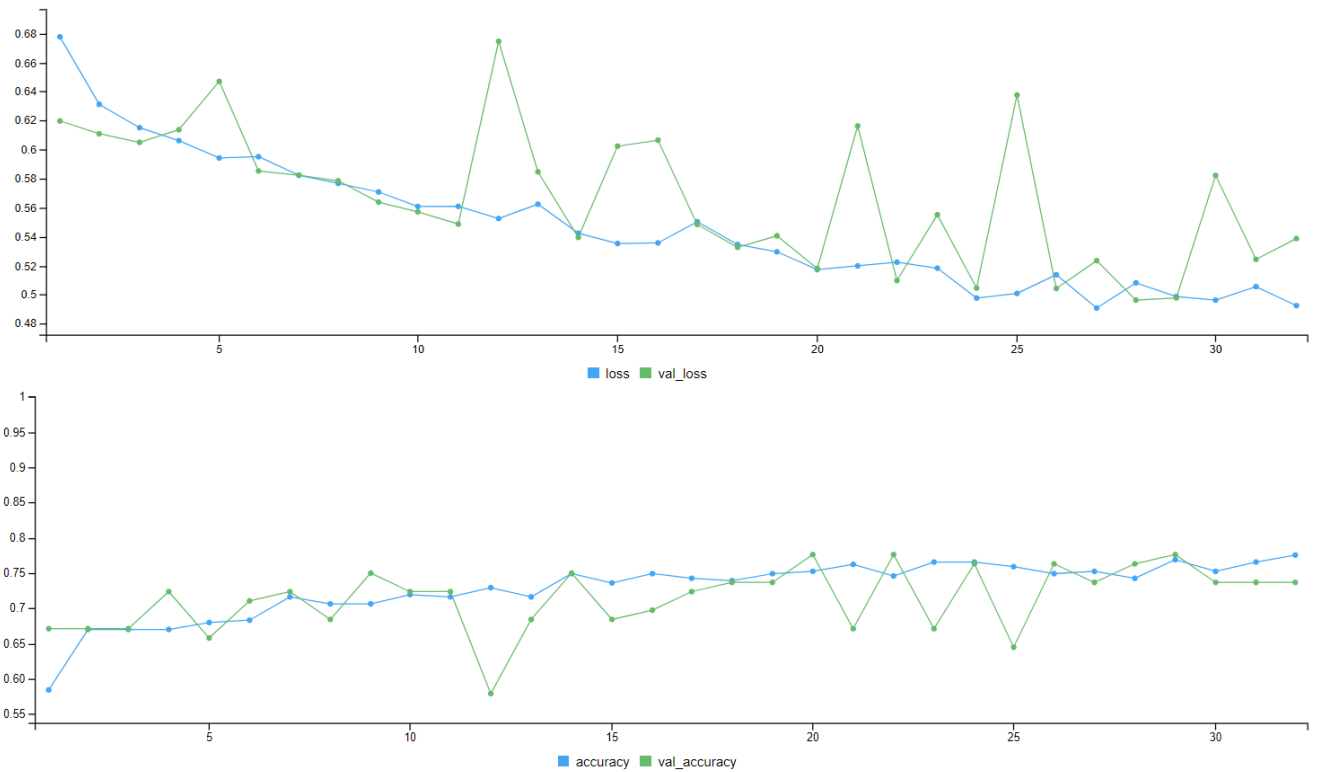
```

Total params: 3,137
Trainable params: 3,137
Non-trainable params: 0

```

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.7878002 0.6000000
> history
```

Final epoch (plot to see history):

```
      loss: 0.4925
      accuracy: 0.7756
      val_loss: 0.5387
val_accuracy: 0.7368
```

```
> predict(Model_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed, ExpProtTCGA_KIRC_
      [,1]
[1,] 0.8020363
[2,] 0.7002377
[3,] 0.8389700
[4,] 0.9240683
[5,] 0.6572965
[6,] 0.7046134
[7,] 0.5297390
[8,] 0.9204122
[9,] 0.5820349
[10,] 0.9205120
[11,] 0.9140373
[12,] 0.3199417
[13,] 0.9347509
[14,] 0.9449486
[15,] 0.6863053
```



```
[16,] 0.7290468
[17,] 0.6065519
[18,] 0.8446778
[19,] 0.7743371
[20,] 0.9493220
[21,] 0.9058605
[22,] 0.7501490
[23,] 0.6700755
[24,] 0.6719083
[25,] 0.8489730
[26,] 0.8599136
[27,] 0.9141070
[28,] 0.7553965
```

Parece que hay overfitting, vamos a poner dropout.

Modelo 2 Resumen del modelo

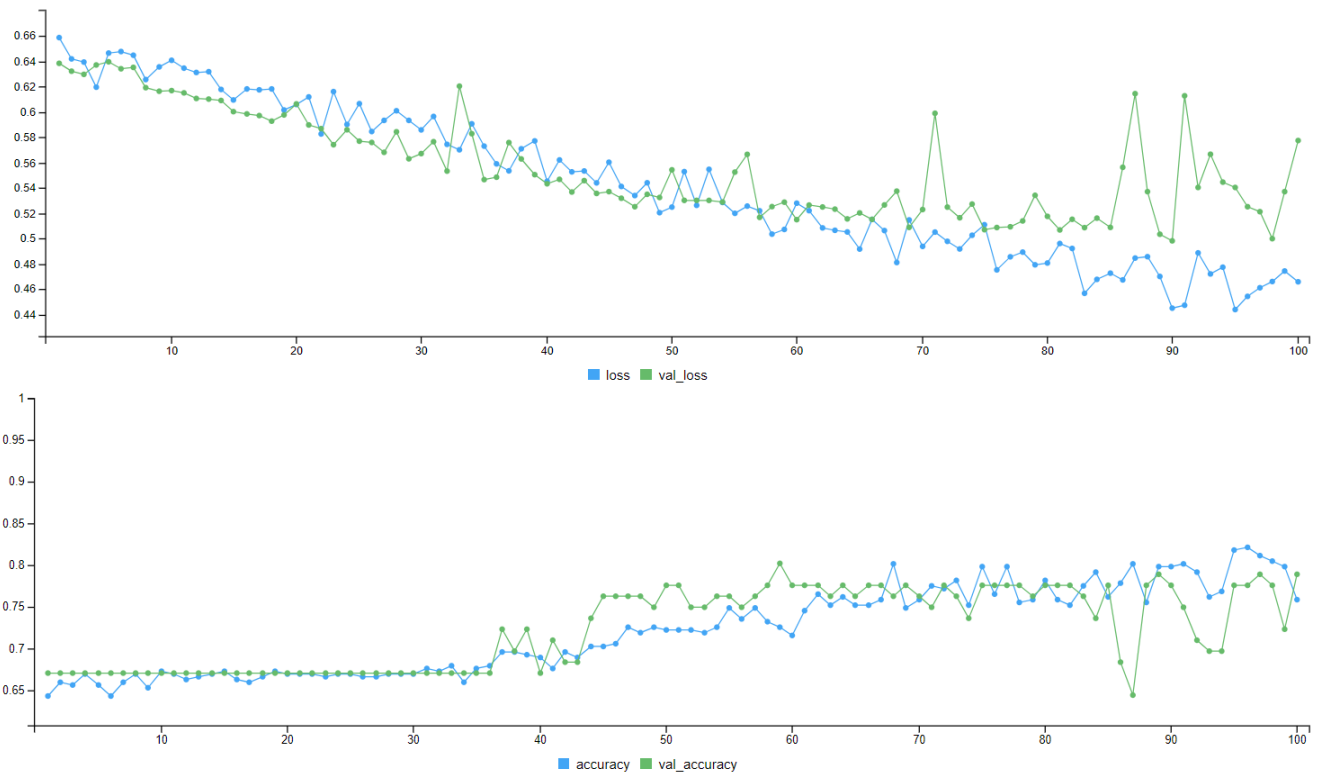
Aumentamos las capas y añadimos dropout.

```
> summary(Model_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed)
Model: "sequential"
```

Layer (type)	Output Shape	Param #
dense_3 (Dense)	(None, 20)	3560
dropout_2 (Dropout)	(None, 20)	0
dense_2 (Dense)	(None, 16)	336
dropout_1 (Dropout)	(None, 16)	0
dense_1 (Dense)	(None, 8)	136
dropout (Dropout)	(None, 8)	0
dense (Dense)	(None, 1)	9
Total params: 4,041		
Trainable params: 4,041		
Non-trainable params: 0		

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.8679943 0.6000000
> history

Final epoch (plot to see history):
      loss: 0.4659
      accuracy: 0.7591
      val_loss: 0.5773
      val_accuracy: 0.7895
> predict(Model_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed, ExpProtTCGA_KIRC_I
      [,1]
[1,] 0.7436856
[2,] 0.8600804
[3,] 0.8964235
[4,] 0.9579632
[5,] 0.5083777
[6,] 0.5475296
[7,] 0.3687240
[8,] 0.9250146
[9,] 0.4088703
[10,] 0.9768463
[11,] 0.9818953
[12,] 0.4274961
[13,] 0.9851228
[14,] 0.9495082
[15,] 0.9644765
[16,] 0.6614694
```

```
[17,] 0.7163674
[18,] 0.8811067
[19,] 0.7547270
[20,] 0.9704388
[21,] 0.9655876
[22,] 0.7541791
[23,] 0.5552937
[24,] 0.8054403
[25,] 0.9021704
[26,] 0.7542448
[27,] 0.9641717
[28,] 0.5106784
```

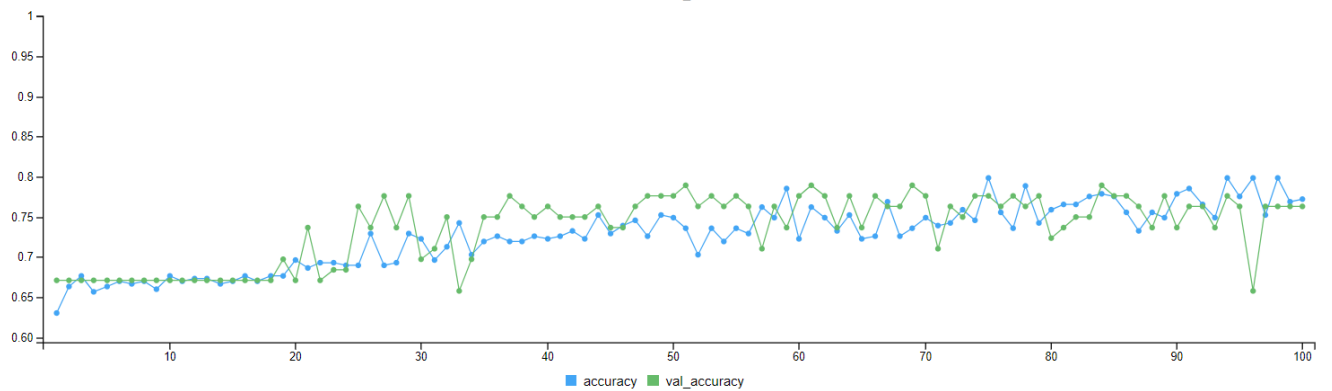
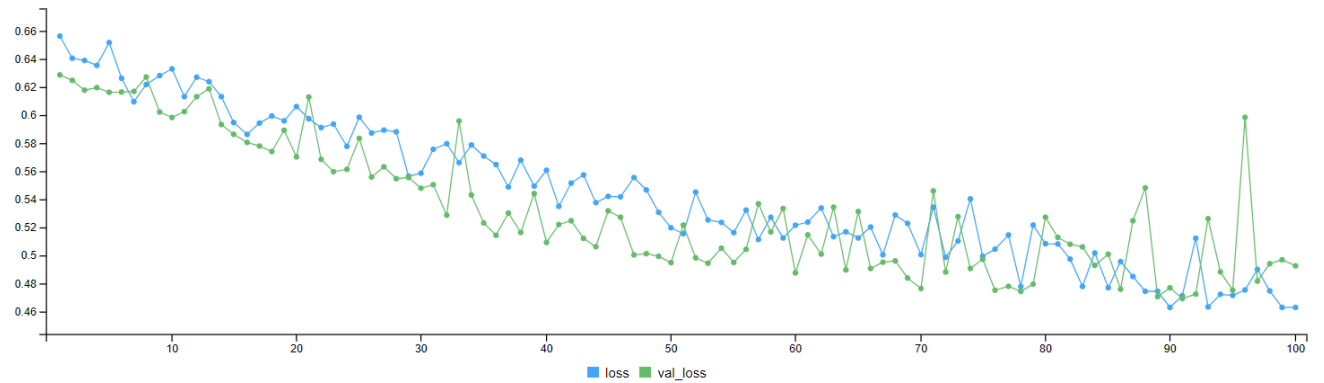
Modelo 3 Resumen del modelo

```
> summary(Model_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed)
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
dense_7 (Dense)	(None, 20)	3560
dropout_5 (Dropout)	(None, 20)	0
dense_6 (Dense)	(None, 16)	336
dropout_4 (Dropout)	(None, 16)	0
dense_5 (Dense)	(None, 8)	136
dropout_3 (Dropout)	(None, 8)	0
dense_4 (Dense)	(None, 1)	9
Total params: 4,041		
Trainable params: 4,041		
Non-trainable params: 0		

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```
> score
      loss accuracy
0.6850594 0.6631579
> history
```

Final epoch (plot to see history):

```
      loss: 0.4629
      accuracy: 0.7723
      val_loss: 0.4926
      val_accuracy: 0.7632
```

```
> predict(Model_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed, ExpProtTCGA_KIRC_
      [,1]
[1,] 0.7606218
[2,] 0.5897886
[3,] 0.7539814
[4,] 0.9038323
[5,] 0.5623838
[6,] 0.5429451
[7,] 0.2953670
[8,] 0.8428588
[9,] 0.3376764
[10,] 0.8447326
[11,] 0.9222915
[12,] 0.2503030
[13,] 0.9530908
[14,] 0.9092823
[15,] 0.7956692
[16,] 0.4327042
[17,] 0.6261219
```

```
[18,] 0.8463207
[19,] 0.4852300
[20,] 0.9246504
[21,] 0.8973757
[22,] 0.6761926
[23,] 0.6136307
[24,] 0.4704547
[25,] 0.7839123
[26,] 0.8087447
[27,] 0.9226632
[28,] 0.5500689
```

Modelo de Expresión proteica (ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed, n = 177, n = 290)

Usamos: ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed

```
ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed <- ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed
> dim(ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed)
[1] 177 290
```

Creación de conjuntos test y train

```
ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed <- t(ExpProtTCGA_KIRC_RawData_woNA_Norm_Renamed)
set.seed(231)

ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed_Index_Training <- sample(nrow(ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed), 177)
ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed_Test <- ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed[Index_Training, ]
ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed_Train <- ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed[-Index_Training, ]
```

Obtención de etiquetas

```
ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Test <- ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels[Test_Index, ]
ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Train <- ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels[Train_Index, ]

ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Test_FactorNumb <- as.integer(ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Test)
ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Test_FactorNumb[ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Test == 0] <- 1
ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Train_FactorNumb <- as.integer(ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Train)
ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Train_FactorNumb[ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Train == 0] <- 1
```

Guardar objetos importantes para modelos

Base de datos completa

```
save(ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed, file = "ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed.Rsave")
```

Conjuntos Train y Test

```
# Train
save(ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed_Train, file = "ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed_Train.rda")

# Test
save(ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed_Test, file = "ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed_Test.rda")
```

Etiquetas

```
# Train
save(ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Train_FactorNumb, file = "ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Train_FactorNumb.rda")

# Test
save(ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Test_FactorNumb, file = "ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Test_FactorNumb.rda")
```

Creando script (ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMetscrip

```
# Cargando los archivos

# test_x
load("ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed_Test.rda")

# train_x
load("ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed_Train.rda")

# test_y
load("ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Test_FactorNumb.rda")

# train_y
load("ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Train_FactorNumb.rda")

library(lattice)
library(ggplot2)
library(keras)
library(caret)

# Definición del modelo ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed: proteína
Model_ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed <- keras_model_sequential%>%
  layer_dense(units = 16, activation = "relu", input_shape = c(177)) %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(units = 1, activation = "sigmoid")

Model_ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed %>% compile(
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

# Entrenamiento y evaluación del modelo

history <- Model_ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed %>% fit(
```

```

plot(history)

score <- Model_ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed %>% ev
  ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed_Test, ExpProtTCGA_KI
  verbose = 0
)

cat('Test loss:', score[[1]], '\n')
cat('Test accuracy:', score[[2]], '\n')

```

Resultados

Modelo 1 Tenemos que superar el:

```

> score
      loss accuracy
0.5824013 0.7758621

```

del modelo

```

> summary(Model_ExpProtTCGA_KIRC_RawData_woNA_SameSampExpGen_SameSampMet_Renamed)
Model: "sequential_4"

```

Layer (type)	Output Shape	Param #
dense_14 (Dense)	(None, 8)	1424
dropout_1 (Dropout)	(None, 8)	0
dense_13 (Dense)	(None, 2)	18
dropout (Dropout)	(None, 2)	0
dense_12 (Dense)	(None, 1)	3

Total params: 1,445
 Trainable params: 1,445
 Non-trainable params: 0

que utilizaba los datos sin normalizar.

Resumen del modelo

```

> summary(Model_ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed)
Model: "sequential_8"

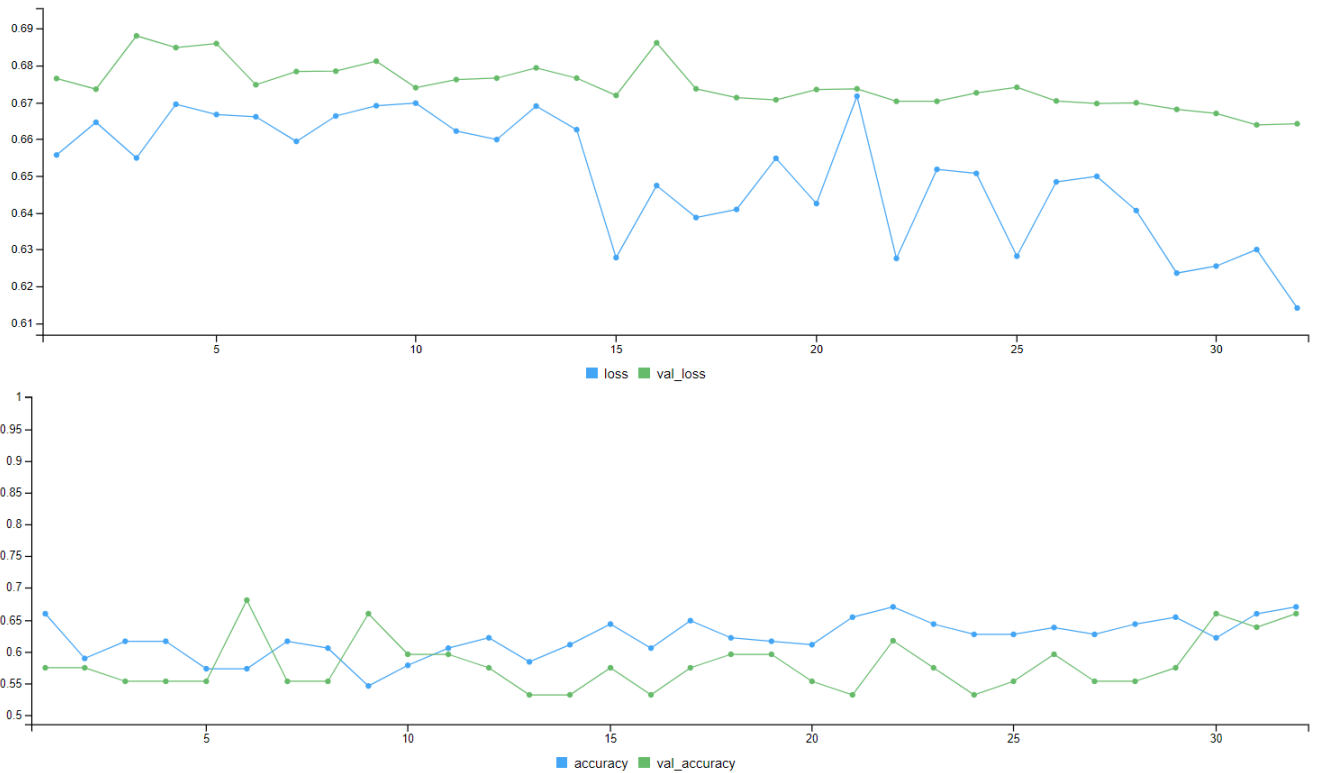
```

Layer (type)	Output Shape	Param #
dense_28 (Dense)	(None, 8)	1424

dropout_19 (Dropout)	(None, 8)	0
dense_27 (Dense)	(None, 2)	18
dropout_18 (Dropout)	(None, 2)	0
dense_26 (Dense)	(None, 1)	3
=====		
Total params: 1,445		
Trainable params: 1,445		
Non-trainable params: 0		

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```

> score
      loss accuracy
0.5836589 0.7413793
> history

Final epoch (plot to see history):
      loss: 0.6141
      accuracy: 0.6703
      val_loss: 0.6642
      val_accuracy: 0.6596
> predict(Model_ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed, ExpP
      [,1]

```


[1,] 0.6588583
[2,] 0.6685524
[3,] 0.6444975
[4,] 0.5781231
[5,] 0.4950803
[6,] 0.6356037
[7,] 0.6146865
[8,] 0.6851306
[9,] 0.6228296
[10,] 0.5840369
[11,] 0.6150343
[12,] 0.6080506
[13,] 0.6911544
[14,] 0.5064683
[15,] 0.6277201
[16,] 0.5299095
[17,] 0.6735159
[18,] 0.5453626
[19,] 0.5641113
[20,] 0.5420477
[21,] 0.6450393
[22,] 0.6378152
[23,] 0.5608349
[24,] 0.5863496
[25,] 0.5772927
[26,] 0.6212904
[27,] 0.6647993
[28,] 0.6734720
[29,] 0.5984204
[30,] 0.6461792
[31,] 0.5455145
[32,] 0.6058615
[33,] 0.6539574
[34,] 0.5648665
[35,] 0.6712549
[36,] 0.5809708
[37,] 0.6397321
[38,] 0.5093380
[39,] 0.5545826
[40,] 0.5814481
[41,] 0.5352771
[42,] 0.6896653
[43,] 0.5567027
[44,] 0.6017753
[45,] 0.5956193
[46,] 0.6171705
[47,] 0.6123638
[48,] 0.6179831
[49,] 0.6002995
[50,] 0.6846988
[51,] 0.5857004
[52,] 0.4995881
[53,] 0.6531309
[54,] 0.6165737

```
[55,] 0.6023639
[56,] 0.6046523
[57,] 0.5799499
[58,] 0.6944157
```

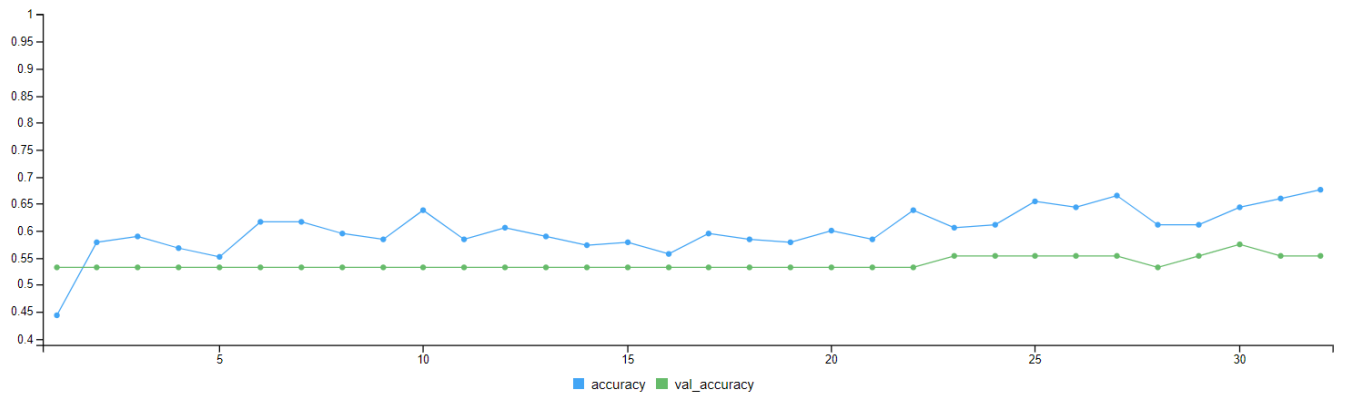
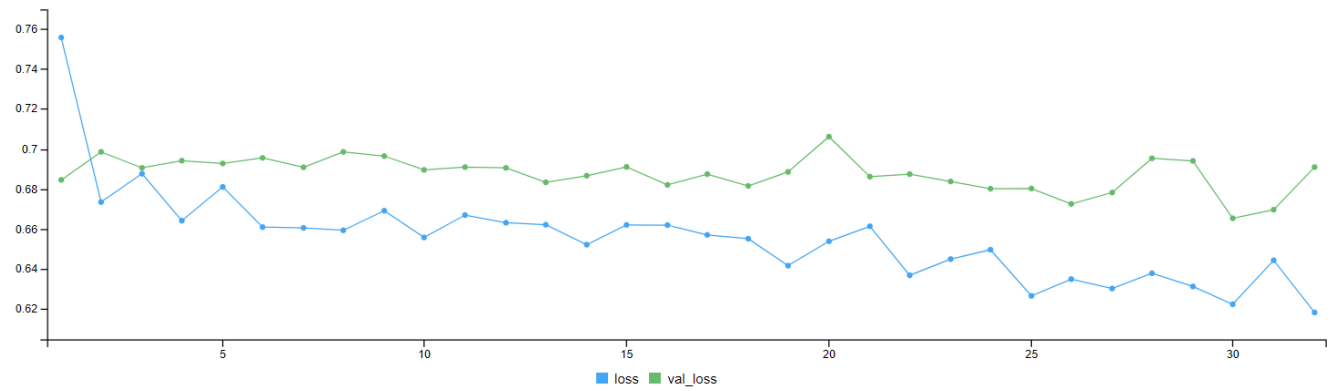
Modelo 2 Resumen del modelo

```
> summary(Model_ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed)
Model: "sequential_7"
```

Layer (type)	Output Shape	Param #
dense_25 (Dense)	(None, 10)	1780
dropout_17 (Dropout)	(None, 10)	0
dense_24 (Dense)	(None, 4)	44
dropout_16 (Dropout)	(None, 4)	0
dense_23 (Dense)	(None, 1)	5
Total params: 1,829		
Trainable params: 1,829		
Non-trainable params: 0		

Gráficas de pérdida y precisión

Ahora, presentamos las gráficas de pérdida y precisión:



```

> score
      loss accuracy
0.6397267 0.7758621
> history

Final epoch (plot to see history):
      loss: 0.6203
      accuracy: 0.7135
      val_loss: 0.6594
      val_accuracy: 0.6383
> predict(Model_ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed, ExpP
      [,1]
[1,] 0.5676859
[2,] 0.5676859
[3,] 0.5676859
[4,] 0.5676859
[5,] 0.5083192
[6,] 0.5676859
[7,] 0.5676859
[8,] 0.5676859
[9,] 0.5676859
[10,] 0.5662532
[11,] 0.5676859
[12,] 0.5676859
[13,] 0.5529552
[14,] 0.5415108
[15,] 0.5676859
[16,] 0.5676859

```

```

[17,] 0.5676859
[18,] 0.5676859
[19,] 0.2972086
[20,] 0.5367039
[21,] 0.5676859
[22,] 0.5676859
[23,] 0.5676859
[24,] 0.5439425
[25,] 0.5676859
[26,] 0.5676859
[27,] 0.5676859
[28,] 0.5676859
[29,] 0.4727215
[30,] 0.5676859
[31,] 0.3027540
[32,] 0.5676859
[33,] 0.5676859
[34,] 0.4062908
[35,] 0.5676859
[36,] 0.5676859
[37,] 0.5676859
[38,] 0.3041144
[39,] 0.5676859
[40,] 0.5565755
[41,] 0.4916607
[42,] 0.5676859
[43,] 0.4987919
[44,] 0.5589045
[45,] 0.5676859
[46,] 0.5661155
[47,] 0.5676859
[48,] 0.5676859
[49,] 0.5676859
[50,] 0.5676859
[51,] 0.5479358
[52,] 0.3945759
[53,] 0.5676859
[54,] 0.5676859
[55,] 0.5615835
[56,] 0.5355625
[57,] 0.5676859
[58,] 0.5676859

```

```

> which(predict(Model_ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Transposed
[1] 19 29 31 34 38 41 43 52
> ExpProtTCGA_KIRC_RawData_woNA_Norm__SameSampExpGen_SameSampMet_Renamed_Labels_Test[c(19,29,31,34,38,41,43,52)]
[1] "Dead" "Dead" "Alive" "Dead" "Alive" "Dead" "Alive" "Alive"

```

De las 8 muestras que el predict del modelo dice que son de pacientes muertos, solo en 4 está en lo cierto.

7. Support Vector Machine (SVM)

Para saber si estos modelos pueden mejorar su precisión podemos realizar un SVM con kernel radial basis function (rbf). Para esto necesitaremos modificar un poco los datasets de train y test que ya habíamos creado en el apartado **6. Modelo independientes de ómicas** añadiéndoles una columna llamada labels en una columna. Tendremos que instalar el paquete `e1071` y utilizar la función `svm()`.

```
install.packages("e1071")
library(e1071)
```

Expresión Génica

Modelo de Expresión génica (ExpGenTCGA_KIRC_Norm01_Filt75_Renamed: genes = 4897, n = 606)

Preparación de dataset El conjunto train de este modelo: ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed
Precisión final del SVM: 71.31%

```
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM <- cbind(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM,
colnames(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM)[1] <- "Labels"
```

Entrenamiento del modelo

```
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM_classifierR = svm(formula = Labels ~ .,
data = ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM,
type = 'C-classification', # this is because we want to make a regression classification
kernel = 'radial')
```

```
> ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM_classifierR
```

Call:

```
svm(formula = Labels ~ ., data = ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM,
type = "C-classification", kernel = "radial")
```

Parameters:

```
SVM-Type: C-classification
SVM-Kernel: radial
cost: 1
```

Number of Support Vectors: 386

Predicciones

```
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM_classifierR_predR = predict(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM_classifierR, newdata = ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Test_SVM)
```

Matriz de confusión

```

cmR_ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM_classifierR_predR = table(ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM_classifierR_predR)
> cmR_ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM_classifierR_predR
                                     ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM_classifierR_predR
ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Labels_Test_FactorNumb  0  1
                                                                0  8 32
                                                                1  3 79

> (79+8)/(8+32+3+79)
[1] 0.7131148

```

Modelo de Expresión génica (ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed: genes = 4897, n = 474)

Preparación de dataset El conjunto train de este modelo: ExpGenTCGA_KIRC_Norm01_Filt75_Renamed_Transposed_Train_SVM_classifierR_predR
Precisión final del SVM: 66.31%

```

ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM <- cbind(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM,
colnames(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM)[1] <- "Labels"

```

Entrenamiento del modelo

```

ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM_classifierR = svm(formula = Labels ~ .,
data = ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM,
type = 'C-classification', # this is because we want to make a regression classification
kernel = 'radial')

```

```

> ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM_classifierR

```

Call:

```

svm(formula = Labels ~ ., data = ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM,
type = "C-classification", kernel = "radial")

```

Parameters:

```

SVM-Type: C-classification
SVM-Kernel: radial
cost: 1

```

Number of Support Vectors: 299

Predicciones

```

ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM_classifierR_predR = predict(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM_classifierR_predR)

```

Matriz de confusión

```

cmR_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM_classifierR_predR = table(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM_classifierR_predR)
> cmR_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM_classifierR_predR
                                     ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM_classifierR_predR
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_SVM_classifierR_predR  0  1
                                                                0  6  5
                                                                1 27 57

> (57+6)/(57+6+5+27)
[1] 0.6631579

```

Modelo de Expresión génica (ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_genes = 4897, n = 290)

Preparación de dataset El conjunto train de este modelo: ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet
Precisión final del SVM: 77.58%

```
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM <- cbind(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM, 1)
colnames(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM)[1] <- "Labels"
```

Entrenamiento del modelo

```
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM_classifierR = svm(formula = Labels ~ ., data = ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM,
type = 'C-classification', # this is because we want to make a regression classification
kernel = 'radial')
```

```
> ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM_classifierR
```

Call:

```
svm(formula = Labels ~ ., data = ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM,
type = "C-classification", kernel = "radial")
```

Parameters:

```
SVM-Type: C-classification
SVM-Kernel: radial
cost: 1
```

Number of Support Vectors: 198

Predicciones

```
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM_classifierR_predR = predict(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM_classifierR, newdata = ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM)
```

Matriz de confusión

```
cmR_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM_classifierR_predR = table(ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM_classifierR_predR, newdata = ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM)
> cmR_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM_classifierR_predR
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_SameSampMet_Renamed_SVM_classifierR_predR 0 1
0 7 6
1 7 38
> (38+7)/(38+7+6+7)
[1] 0.7758621
```

Metilación

Modelo de metilación (MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_sondas = 93346, n = 483)

Preparación de dataset El conjunto train de este modelo: MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_sondas
Precisión final del SVM: No puedo crear el SVM porque no hay RAM suficiente

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_SVM <- cbind(MetTCGA_KIRC_RawData,
colnames(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_SVM)[1] <- "Labels"
```

Entrenamiento del modelo

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_SVM_classifierR = svm(formula = L
data = MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_SVM,
type = 'C-classification', # this is because we want to make a regression classification
kernel = 'radial')
```

****Error: cannot allocate vector of size 32.5 Gb****

Modelo de metilación (MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_SVM)
sondas = 93346, n = 291)

Preparación de dataset El conjunto train de este modelo: MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_Renamed_SVM
Precisión final del SVM: No puedo crear el SVM porque no hay RAM suficiente

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_Renamed_SVM <- cbind(MetTCGA_KIRC_RawData,
colnames(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_Renamed_SVM)[1] <- "Labels"
```

Entrenamiento del modelo

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_Renamed_SVM_classifierR = svm(formula = L
data = MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_Renamed_SVM,
type = 'C-classification', # this is because we want to make a regression classification
kernel = 'radial')
```

Error: cannot allocate vector of size 32.5 Gb

Modelo de metilación (MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_Renamed_SVM)
sondas = 93346, n = 290)

Preparación de dataset El conjunto train de este modelo: MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_Renamed_SVM
Precisión final del SVM: No puedo crear el SVM porque no hay RAM suficiente

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_SVM <- cbind(MetTCGA_KIRC_RawData,
colnames(MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_SVM)[1] <- "Labels"
```

Entrenamiento del modelo

```
MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_SVM_classifierR = svm(formula = L
data = MetTCGA_KIRC_RawData_woDupSamples_woSNP_woXY_woNA_Norm_Filt75_SameSampExpProt_SameSampExpGen_Renamed_SVM,
type = 'C-classification', # this is because we want to make a regression classification
kernel = 'radial')
```

Error: cannot allocate vector of size 32.5 Gb

Proteómica

Modelo de Expresión proteica (ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Rena
proteínas = 177, n = 474)

Preparación de dataset El conjunto train de este modelo: ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Rena
Precisión final del SVM: 77.58%

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM <- cbind(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM, Labels)
colnames(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM)[1] <- "Labels"
```

Entrenamiento del modelo

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM_classifierR = svm(formula = Labels ~ ., data = ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM,
  type = 'C-classification', # this is because we want to make a regression classification
  kernel = 'radial')
```

```
> ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM_classifierR
```

Call:

```
svm(formula = Labels ~ ., data = ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM,
  type = "C-classification", kernel = "radial")
```

Parameters:

```
SVM-Type: C-classification
SVM-Kernel: radial
cost: 1
```

Number of Support Vectors: 212

Predicciones

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM_classifierR_predR = predict(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM_classifierR, newdata = ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM)
```

Matriz de confusión

```
cmR_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM_classifierR_predR = table(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM_classifierR_predR, ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM)
```

```
> cmR_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM_classifierR_predR
      ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM_classifierR_predR  0  1
                                                                 0  5  5
                                                                 1  8  40
```

```
> (40+5)/(40+5+8+5)
[1] 0.7758621
```

Modelo de Expresión proteica (ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM)
proteínas = 177, n = 290)

Preparación de dataset El conjunto train de este modelo: ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_SameSampMet_Renamed_SVM
Precisión final del SVM: 63.16%

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM <- cbind(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM,
colnames(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM)[1] <- "Labels"
```

Entrenamiento del modelo

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM_classifierR = svm(formula = Labels ~ .,
data = ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM,
type = 'C-classification', # this is because we want to make a regression classification
kernel = 'radial')
```

```
> ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM_classifierR
```

Call:

```
svm(formula = Labels ~ ., data = ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM,
type = "C-classification", kernel = "radial")
```

Parameters:

```
SVM-Type: C-classification
SVM-Kernel: radial
cost: 1
```

Number of Support Vectors: 307

Predicciones

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM_classifierR_predR = predict(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM_classifierR,
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM)
```

Matriz de confusión

```
cmR_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM_classifierR_predR = table(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM_classifierR_predR,
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM_classifierR_predR)
cmR_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_SVM_classifierR_predR
```

	0	1	2
0	9	4	
1	31	51	

```
> (51+9)/(51+9+4+31)
[1] 0.6315789
```

8. Modelos de ómicas integradas

Modelo de dos ómicas

En este caso haremos dos modelos con los datos de proteómica y transcriptómica integrados. Los dos modelos se basan en que antes de pasar los datos por el clasificador serán el input de un autoencoder que reducirá la dimensionalidad (columnas/genes/proteínas) de los datasets. Los autoencoders están formados por un codificador, que comprime los datos y un decodificador que intenta descomprimir los datos lo mejor posible para que los datos de entrada y salida sean iguales. La mayor utilidad de los autoencoders se ha encontrado en la reducción de la dimensionalidad o en modelos de deep learning generativos. Tras comprobar que los datos de salida del autoencoder son similares o iguales a los datos de entrada podremos “desensamblar” el

autoencoder para quedarnos solo con el encoder, más concretamente con los el output del bottleneck del autoencoder.

Este bottleneck que tendrá la dimensionalidad reducida pero con la información más relevante de nuestro dataset de ómicas integradas se utilizará como entrada para nuestro clasificador.

En este caso queremos hacer dos tipos de autoencoder:

- 1) Autoencoder que tiene como input un dataset con la unión de los datos de proteómica y transcriptómica mediante un cbind()
- 2) Autoencoder que tiene como input los datasets de las ómicas por separado, se pasan por el autoencoder y el bottleneck de ambos se une con un cbind()

Reordenar datasets

Vamos a utilizar los siguientes datasets:

ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed y ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed

Expresión génica

```
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort <- ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed
```

Expresión proteica

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort <- ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed
```

Juntar datasets

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort <- cbind(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort, ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort)
> dim(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort)
[1] 474 5074
```

Modelo 1: Concatenación + Autoencoder + Clasificador

Sampling: Creación de conjuntos de Test y Train

```
set.seed(231)
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort <- ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort <- sample_n(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort, 474)
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort <- ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort[474:nrow(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort),]
```

Creación de etiquetas de test y train

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_SORTSample <- ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_SORTSample[474:nrow(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_SORTSample),]
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort <- ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort[474:nrow(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort),]
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort <- ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort[474:nrow(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_RowSort),]
```

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01

Creación del encoder

```
enc_input_ExpGenExpProtNorm_M1 <- layer_input(shape = 5074)
enc_output_ExpGenExpProtNorm_M1 = enc_input_ExpGenExpProtNorm_M1 %>%
  layer_dense(units=100, activation = "relu") %>%
  layer_dense(units=20)

encoder_ExpGenExpProtNorm_M1 = keras_model(enc_input_ExpGenExpProtNorm_M1, enc_output_ExpGenExpProtNorm_M1)
> summary(encoder_ExpGenExpProtNorm_M1)
Model: "model_6"
```

Layer (type)	Output Shape	Param #
input_7 (InputLayer)	[(None, 5074)]	0
dense_12 (Dense)	(None, 100)	507500
dense_11 (Dense)	(None, 20)	2020
Total params: 509,520		
Trainable params: 509,520		
Non-trainable params: 0		

Creación del decoder

```
dec_input_ExpGenExpProtNorm_M1 = layer_input(shape = 20)
dec_output_ExpGenExpProtNorm_M1 = dec_input_ExpGenExpProtNorm_M1 %>%
  layer_dense(units=100, activation = "relu") %>%
  layer_dense(units = 5074, activation = "relu")
decoder_ExpGenExpProtNorm_M1 = keras_model(dec_input_ExpGenExpProtNorm_M1, dec_output_ExpGenExpProtNorm_M1)
> summary(decoder_ExpGenExpProtNorm_M1)
Model: "model_7"
```

Layer (type)	Output Shape	Param #
input_8 (InputLayer)	[(None, 20)]	0
dense_14 (Dense)	(None, 100)	2100
dense_13 (Dense)	(None, 5074)	512474
Total params: 514,574		

```
Trainable params: 514,574
Non-trainable params: 0
```

Definiendo el autoencoder

```
aen_input_ExpGenExpProtNorm_M1 = layer_input(shape = 5074)
aen_output_ExpGenExpProtNorm_M1 = aen_input_ExpGenExpProtNorm_M1 %>%
  encoder_ExpGenExpProtNorm_M1() %>%
  decoder_ExpGenExpProtNorm_M1()

aen_ExpGenExpProtNorm_M1 = keras_model(aen_input_ExpGenExpProtNorm_M1, aen_output_ExpGenExpProtNorm_M1)

> summary(aen_ExpGenExpProtNorm_M1)
Model: "model_2"
```

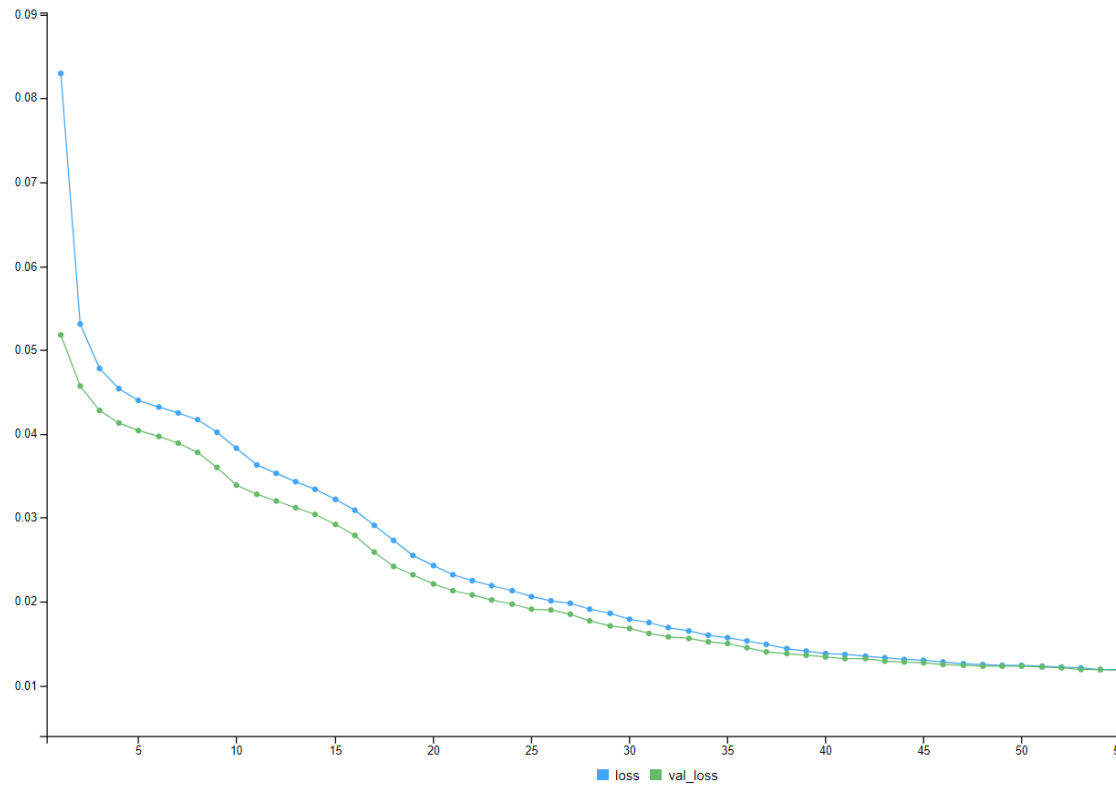
Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 5074)]	0
model (Model)	(None, 20)	509520
model_1 (Model)	(None, 5074)	514574

```
Total params: 1,024,094
Trainable params: 1,024,094
Non-trainable params: 0

aen_ExpGenExpProtNorm_M1 %>% compile(optimizer="adam", loss="mean_squared_error")
```

Entrenamiento del modelo

```
history <- aen_ExpGenExpProtNorm_M1 %>% fit(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_T-
```



Resultado autoencoder

```
> history
```

```
Final epoch (plot to see history):
```

```
    loss: 0.01106
```

```
val_loss: 0.01117
```

Vemos que el mse entre el input y el output es de 0.01117 para el conjunto test y 0.01106 para el conjunto train.

Obtener el bottleneck output del autoencodercoder

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01.
```

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm01.
```

Guardado de datos

Conjuntos Train y Test

```
# Train
```

```
save(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_N
```

```
# Test
```

```
save(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_N
```

Etiquetas

```
# Train
save(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_N
```

```
# Test
save(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_N
```

Clasificador con datos del bottleneck Haremos un script para utilizar el tfruns, asi será más sencillo encontrar el mejor modelo

Script: Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen

```
# test_x
load("ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_N
```

```
# train_x
load("ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_N
```

```
# test_y
load("ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_N
```

```
# train_y
load("ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_N
```

```
library(lattice)
library(ggplot2)
library(keras)
library(caret)
```

```
# Definición del modelo Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen: muestras: 474 dimensiones: 2
```

```
Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen <- keras_model_sequential() %>%
  layer_dense(units = 10, activation = "relu", input_shape = c(20)) %>%
  layer_dropout(0.2) %>%
  layer_dense(units = 4, activation = "relu") %>%
  layer_dropout(0.2) %>%
  layer_dense(units = 1, activation = "sigmoid")
```

```
Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen %>% compile(
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)
```

```
# Entrenamiento y evaluación del modelo
```

```
history <- Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen %>% fit(ExpProtTCGA_KIRC_RawData_woNA_Norm
plot(history)
```

```
score <- Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen %>% evaluate(
  ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTCGA_KIRC_Norm
  verbose = 0
```

```
)

cat('Test loss:', score[[1]], '\n')
cat('Test accuracy:', score[[2]], '\n')
```

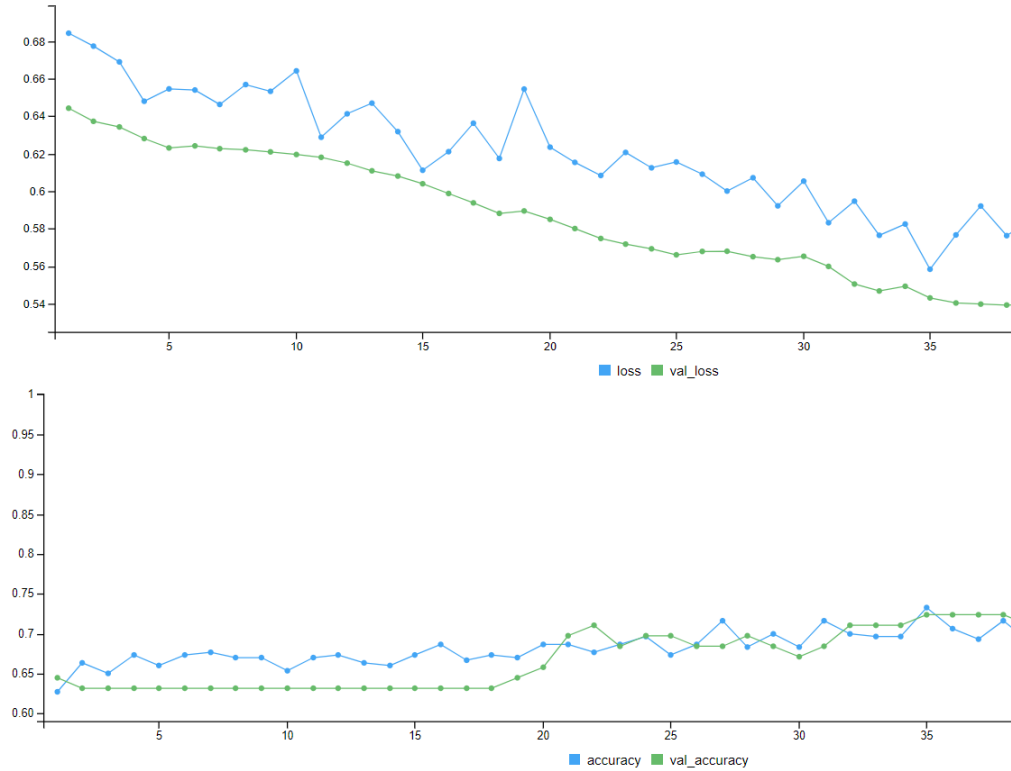
Resultados

Modelo 1

Resumen del modelo

```
> summary(Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen)
Model: "sequential"
```

Layer (type)	Output Shape	Param #
dense_41 (Dense)	(None, 10)	210
dropout_1 (Dropout)	(None, 10)	0
dense_40 (Dense)	(None, 4)	44
dropout (Dropout)	(None, 4)	0
dense_39 (Dense)	(None, 1)	5
Total params: 259		
Trainable params: 259		
Non-trainable params: 0		



Gráficas de pérdida y precisión

```
> history
```

Final epoch (plot to see history):

```
    loss: 0.5582
  accuracy: 0.7228
   val_loss: 0.5392
 val_accuracy: 0.7237
> score
      loss accuracy
0.6371682 0.6000000
```

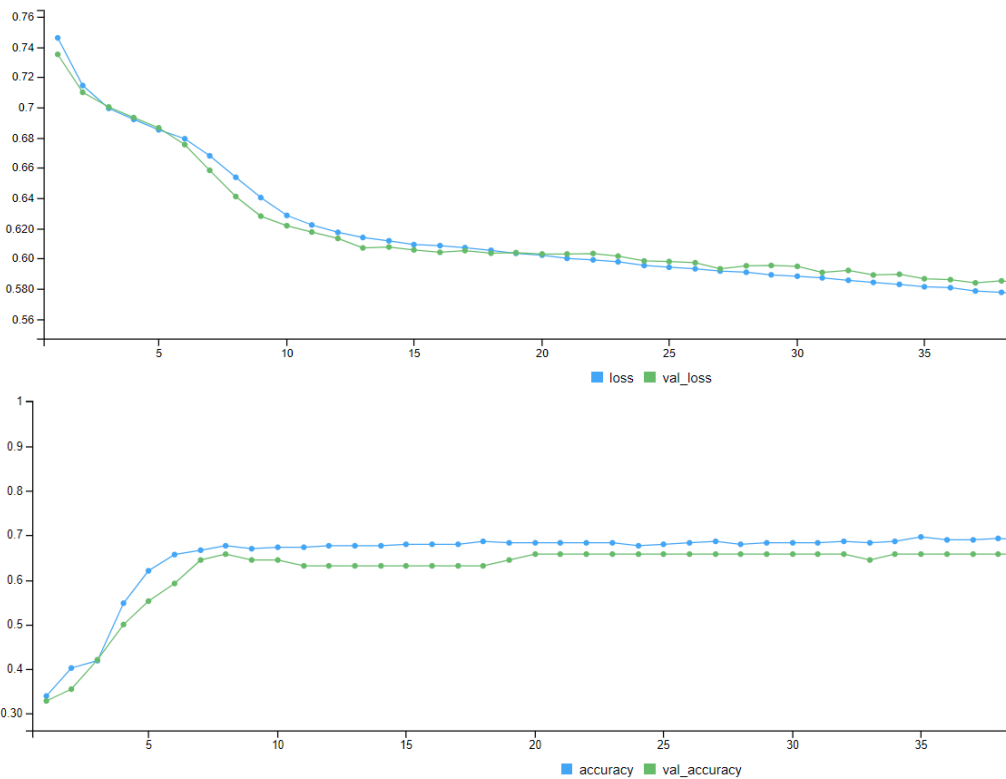
Modelo 2

Resumen del modelo

```
> summary(Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen)
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
dense_44 (Dense)	(None, 10)	210
dense_43 (Dense)	(None, 4)	44
dense_42 (Dense)	(None, 1)	5
Total params: 259		

Trainable params: 259
Non-trainable params: 0



Gráficas de pérdida y precisión

```
> score
      loss accuracy
0.6191577 0.6842105
> history
```

```
Final epoch (plot to see history):
      loss: 0.5648
      accuracy: 0.6964
      val_loss: 0.5737
      val_accuracy: 0.6974
```

Modelo 3

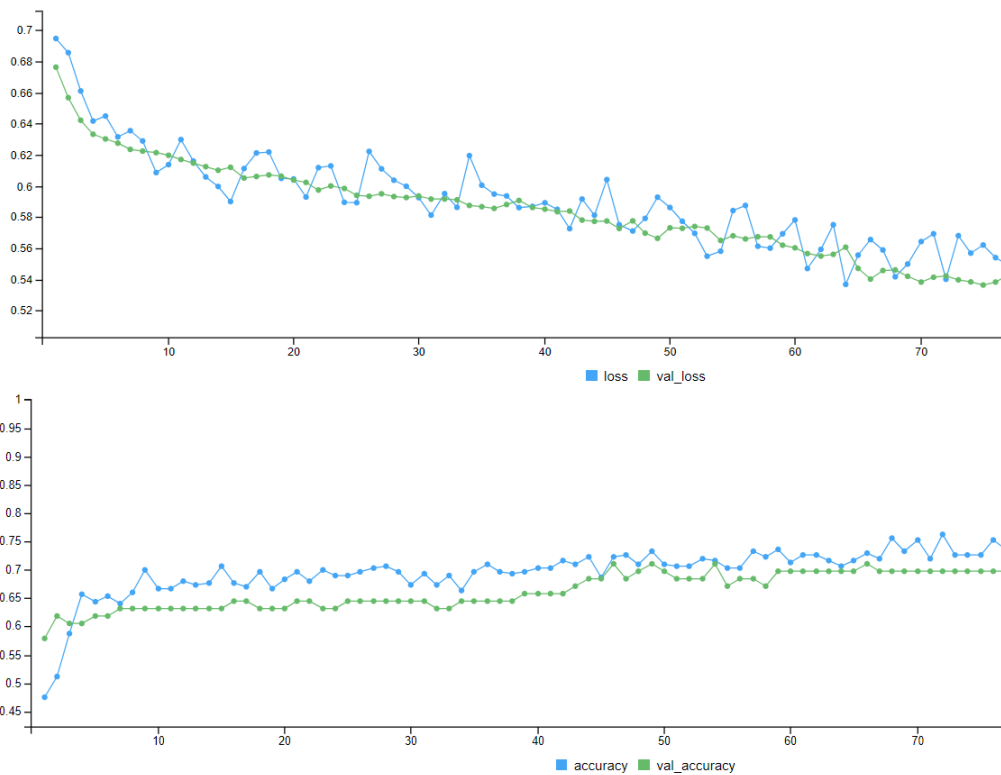
Resumen del modelo

```
> summary(Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen)
Model: "sequential_6"
```

Layer (type)	Output Shape	Param #
dense_62 (Dense)	(None, 16)	336

dropout_6 (Dropout)	(None, 16)	0
dense_61 (Dense)	(None, 8)	136
dropout_5 (Dropout)	(None, 8)	0
dense_60 (Dense)	(None, 4)	36
dense_59 (Dense)	(None, 1)	5

Total params: 513
 Trainable params: 513
 Non-trainable params: 0



Gráficas de pérdida y precisión

```

> score
      loss accuracy
0.6193671 0.6736842
> history

```

```

Final epoch (plot to see history):
      loss: 0.5376
      accuracy: 0.7492
      val_loss: 0.537
      val_accuracy: 0.6974

```

Modelo 4

Resumen del modelo

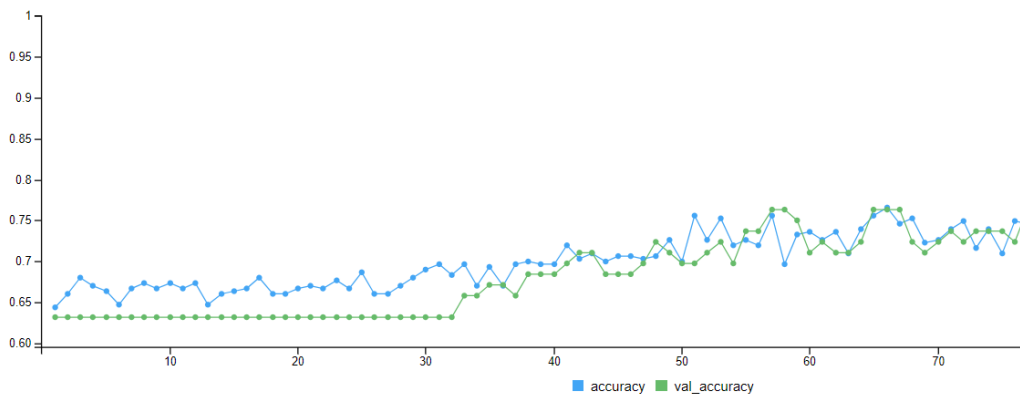
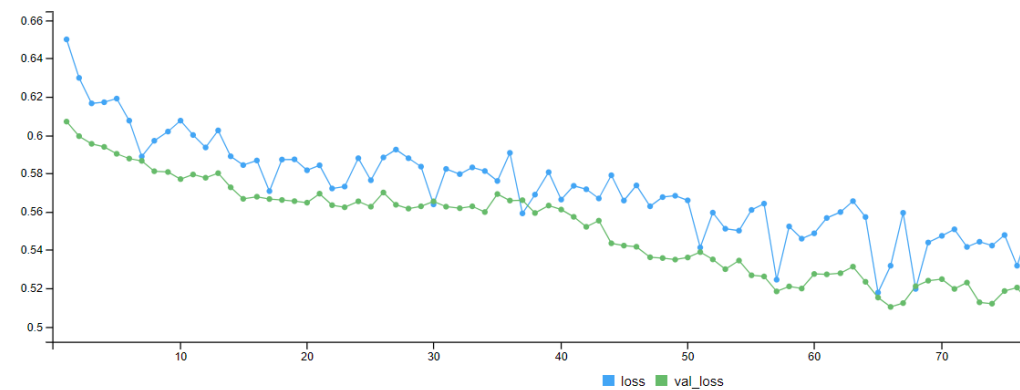
```
> summary(Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen)
Model: "sequential_12"
```

Layer (type)	Output Shape	Param #
dense_88 (Dense)	(None, 18)	378
dropout_16 (Dropout)	(None, 18)	0
dense_87 (Dense)	(None, 8)	152
dense_86 (Dense)	(None, 5)	45
dense_85 (Dense)	(None, 1)	6

Total params: 581

Trainable params: 581

Non-trainable params: 0



Gráficas de pérdida y precisión

```
> score
      loss  accuracy
0.6462954 0.6631579
> history
```

Final epoch (plot to see history):

```
    loss: 0.5299
    accuracy: 0.7624
    val_loss: 0.5198
    val_accuracy: 0.7237
```

SVM del modelo La precisión de este modelo como SVM es de 66.31%.

```
Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM <- cbind(ExpProtTCGA_KIRC_RawData_woNA_Norm_Same
colnames(Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM)[1] <- "Labels"
```

Entrenamiento del modelo

```
Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR = svm(formula = Labels ~ .,
    data = Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM,
    type = 'C-classification', # this is because we want to make a regression classification
    kernel = 'radial')
```

```
> str(Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR)
```

List of 30

```
$ call      : language svm(formula = Labels ~ ., data = Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM)
$ type      : num 0
$ kernel    : num 2
$ cost      : num 1
$ degree    : num 3
$ gamma     : num 0.05
$ coef0     : num 0
$ nu        : num 0.5
$ epsilon   : num 0.1
$ sparse     : logi FALSE
$ scaled    : logi [1:20] TRUE TRUE TRUE TRUE TRUE TRUE TRUE ...
$ x.scale    :List of 2
..$ scaled:center: Named num [1:20] -2.741 0.976 0.107 0.665 2.648 ...
.. ..- attr(*, "names")= chr [1:20] "V2" "V3" "V4" "V5" ...
..$ scaled:scale : Named num [1:20] 1.098 0.573 0.552 1.047 1.118 ...
.. ..- attr(*, "names")= chr [1:20] "V2" "V3" "V4" "V5" ...
$ y.scale    : NULL
$ nclasses   : int 2
$ levels     : chr [1:2] "0" "1"
$ tot.nSV    : int 270
$ nSV        : int [1:2] 149 121
$ labels     : int [1:2] 2 1
$ SV         : num [1:270, 1:20] 1.483 1.631 0.449 1.098 -4.437 ...
..- attr(*, "dimnames")=List of 2
.. ..$ : chr [1:270] "1" "2" "3" "4" ...
.. ..$ : chr [1:20] "V2" "V3" "V4" "V5" ...
$ index      : int [1:270] 1 2 3 4 9 10 14 16 18 20 ...
$ rho        : num -0.336
$ compprob   : logi FALSE
$ probA      : NULL
$ probB      : NULL
$ sigma      : NULL
$ coefs      : num [1:270, 1] 1 1 1 0.753 0.677 ...
$ na.action   : NULL
$ fitted     : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 1 2 2 2 ...
```

```

..- attr(*, "names")= chr [1:379] "1" "2" "3" "4" ...
$ decision.values: num [1:379, 1] 0.5448 0.0134 0.9554 0.9998 1.1077 ...
..- attr(*, "dimnames")=List of 2
.. ..$ : chr [1:379] "1" "2" "3" "4" ...
.. ..$ : chr "1/0"
$ terms :Classes 'terms', 'formula' language Labels ~ V2 + V3 + V4 + V5 + V6 + V7 + V8 + V9 +
.. ..- attr(*, "variables")= language list(Labels, V2, V3, V4, V5, V6, V7, V8, V9, V10, V11, V12, V13,
.. ..- attr(*, "factors")= int [1:21, 1:20] 0 1 0 0 0 0 0 0 0 0 ...
.. ..- attr(*, "dimnames")=List of 2
.. .. ..$ : chr [1:21] "Labels" "V2" "V3" "V4" ...
.. .. ..$ : chr [1:20] "V2" "V3" "V4" "V5" ...
.. ..- attr(*, "term.labels")= chr [1:20] "V2" "V3" "V4" "V5" ...
.. ..- attr(*, "order")= int [1:20] 1 1 1 1 1 1 1 1 1 1 ...
.. ..- attr(*, "intercept")= num 0
.. ..- attr(*, "response")= int 1
.. ..- attr(*, ".Environment")=<environment: R_GlobalEnv>
.. ..- attr(*, "predvars")= language list(Labels, V2, V3, V4, V5, V6, V7, V8, V9, V10, V11, V12, V13,
.. ..- attr(*, "dataClasses")= Named chr [1:21] "numeric" "numeric" "numeric" "numeric" ...
.. ..- attr(*, "names")= chr [1:21] "Labels" "V2" "V3" "V4" ...
- attr(*, "class")= chr [1:2] "svm.formula" "svm"

# Predicciones
Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR = predict(Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR,
ExpProtTCGA_KIRC_RawData_woNA_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Train)

# Matriz de confusión

cmR_Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR = table(Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR,
ExpProtTCGA_KIRC_RawData_woNA_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Train)
> cmR_Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR
               ExpProtTCGA_KIRC_RawData_woNA_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Train
Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR  0  1
                                                                           0 13  9
                                                                           1 23 50

> (50+13)/(50+13+23+9)
[1] 0.6631579

```

Modelo 2: Autoencoder + Concatenación + Clasificador

Tratamiento dataset Expresión génica x_train (Train de Expresión génica con las mismas muestras que Expresión proteica) ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Train

x_test (Test de Expresión génica con las mismas muestras que Expresión proteica) ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Test

y_train (Labels Train de Expresión génica con las mismas muestras que Expresión proteica) ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Train_FactorNumb

y_test (Labels Test de Expresión génica con las mismas muestras que Expresión proteica) ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Labels_Test_FactorNumb

Creación de encoder

```

enc_input_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 <- layer_input(shape = 4897)
enc_output_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 = enc_input_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 %>%
  layer_dense(units=100, activation = "relu") %>%
  layer_dense(units=20)

```

```
encoder_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 = keras_model(enc_input_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2)
```

```
> summary(encoder_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2)
```

```
Model: "model_24"
```

Layer (type)	Output Shape	Param #
input_26 (InputLayer)	[(None, 4897)]	0
dense_90 (Dense)	(None, 100)	489800
dense_89 (Dense)	(None, 20)	2020
Total params: 491,820		
Trainable params: 491,820		
Non-trainable params: 0		

Creación de decoder

```
dec_input_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 = layer_input(shape = 20)
```

```
dec_output_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 = dec_input_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2
```

```
layer_dense(units=100, activation = "relu") %>%
```

```
layer_dense(units = 4897, activation = "relu")
```

```
decoder_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 = keras_model(dec_input_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2)
```

```
> summary(decoder_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2)
```

```
Model: "model_26"
```

Layer (type)	Output Shape	Param #
input_28 (InputLayer)	[(None, 20)]	0
dense_94 (Dense)	(None, 100)	2100
dense_93 (Dense)	(None, 4897)	494597
Total params: 496,697		
Trainable params: 496,697		
Non-trainable params: 0		

Definiendo el autoencoder

```
aen_input_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 = layer_input(shape = 4897)
```

```
aen_output_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 = aen_input_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2
```

```
encoder_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2() %>%
```

```
decoder_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2()
```

```
aen_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 = keras_model(aen_input_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2)
```

```
> summary(aen_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2)
```

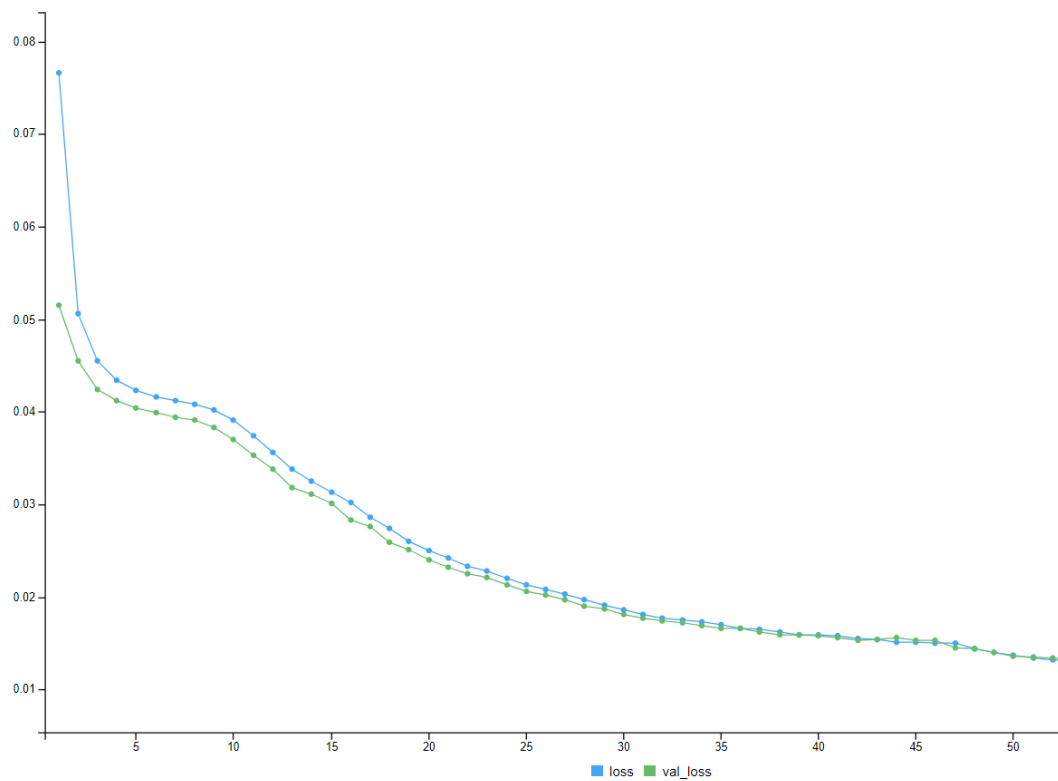
```
Model: "model_27"
```

Layer (type)	Output Shape	Param #
input_29 (InputLayer)	[(None, 4897)]	0
model_24 (Model)	(None, 20)	491820
model_26 (Model)	(None, 4897)	496697
Total params: 988,517		
Trainable params: 988,517		
Non-trainable params: 0		

```
aen_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 %>% compile(optimizer="adam", loss="mean_squared_e
```

Entrenamiento del modelo

```
history <- aen_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_M2 %>% fit(ExpGenTCGA_KIRC_Norm01_Filt75_S
```



Resultado del autoencoder

```
> history
```

```
Final epoch (plot to see history):
```

```
loss: 0.01184
```

```
val_loss: 0.01225
```


Obtener el bottleneck output del autoencoder

```
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Bottleneck <- predict(encoder_ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Bottleneck, ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Test_FactorNumb)
```

Tratamiento dataset Expresión proteica/proteómica x_train (Train de Expresión proteica con las mismas muestras que Expresión génica) ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Train_FactorNumb
x_test (Test de Expresión proteica con las mismas muestras que Expresión génica) ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Test_FactorNumb
y_train (Labels Train de Expresión proteica con las mismas muestras que Expresión génica) ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Train_FactorNumb
y_test (Labels Test de Expresión proteica con las mismas muestras que Expresión génica) ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Labels_Test_FactorNumb

Creación de encoder

```
enc_input_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 <- layer_input(shape = 177)
enc_output_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 = enc_input_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 >%
  layer_dense(units=100, activation = "relu") %>%
  layer_dense(units=20)

encoder_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 = keras_model(enc_input_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2, enc_output_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2)

> summary(encoder_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2)
Model: "model_32"
```

Layer (type)	Output Shape	Param #
input_34 (InputLayer)	[(None, 177)]	0
dense_102 (Dense)	(None, 100)	17800
dense_101 (Dense)	(None, 20)	2020

Total params: 19,820
Trainable params: 19,820
Non-trainable params: 0

Creación de decoder

```
dec_input_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 = layer_input(shape = 20)
dec_output_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 = dec_input_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 >%
  layer_dense(units=100, activation = "relu") %>%
  layer_dense(units = 177, activation = "relu")

decoder_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 = keras_model(dec_input_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2, dec_output_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2)

> summary(decoder_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2)
Model: "model_33"
```

Layer (type)	Output Shape	Param #
input_35 (InputLayer)	[(None, 20)]	0

dense_104 (Dense)	(None, 100)	2100
dense_103 (Dense)	(None, 177)	17877

=====

Total params: 19,977
Trainable params: 19,977
Non-trainable params: 0

Definiendo el autoencoder

```
aen_input_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 = layer_input(shape = 177)
aen_output_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 = aen_input_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2
encoder_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2() %>%
decoder_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2()

aen_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 = keras_model(aen_input_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2,
aen_output_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2)

> summary(aen_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2)
Model: "model_34"
```

Layer (type)	Output Shape	Param #
input_36 (InputLayer)	[(None, 177)]	0
model_32 (Model)	(None, 20)	19820
model_33 (Model)	(None, 177)	19977

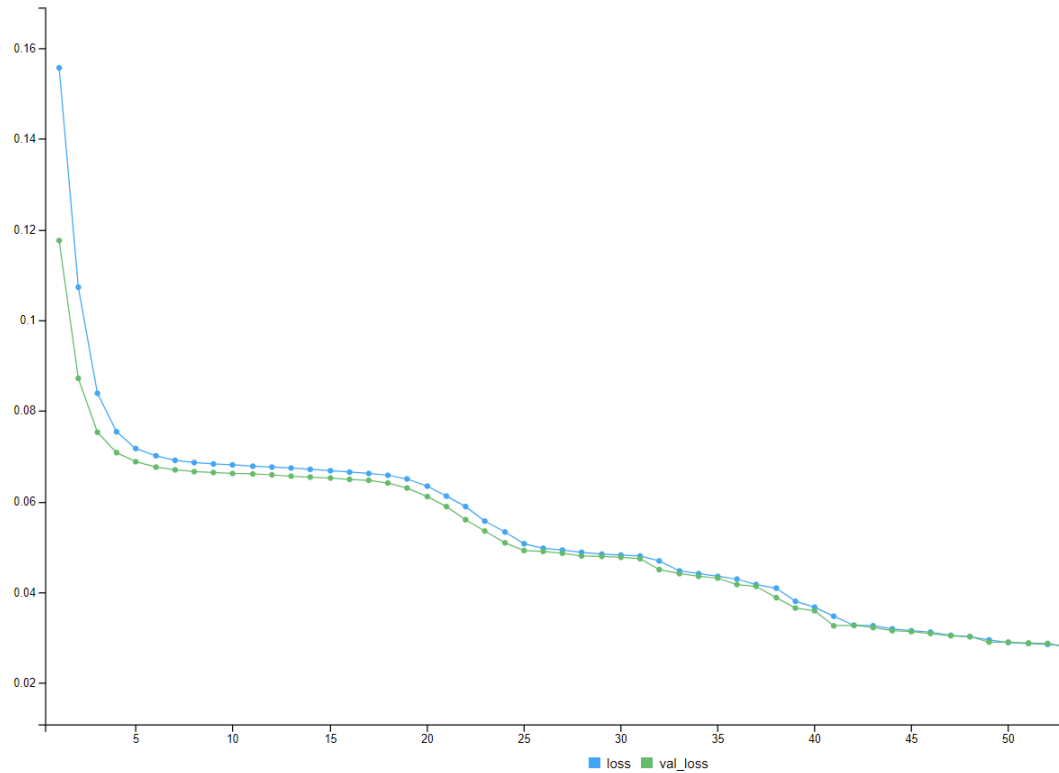
=====

Total params: 39,797
Trainable params: 39,797
Non-trainable params: 0

```
aen_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 %>% compile(optimizer="adam", loss="mean_squared_error")
```

Entrenamiento del modelo

```
history <- aen_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2 %>% fit(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2,
aen_output_ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_M2)
```



Resultado del autoencoder

```
> history
```

Final epoch (plot to see history):

loss: 0.02438

val_loss: 0.02391

Obtener el bottleneck output del autoencoder

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Bottleneck <- predict(encoder_ExpP
```

Concatenación de datasets

Ordenar datasets

```
# Expresión génica
```

```
ExpGenTCGA_KIRC_Norm01_Filt75_SameSampExpProt_Renamed_Transposed_Bottleneck_RowSort <- ExpGenTCGA_KIRC_L
```

```
# Proteomica
```

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Bottleneck_RowSort <- ExpProtTCGA_L
```

Concatenar

```
ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Bottleneck_RowSort_AND_ExpGenTCGA_L
```

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Bottleneck_RowSort_AND_ExpGenTCGA_1

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Bottleneck_RowSort_AND_ExpGenTCGA_1

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTC

ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_RowSort_AND_ExpGenTC

```
# Train
save(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Bottleneck_RowSort_AND_ExpGen'

# Test
save(ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Bottleneck_RowSort_AND_ExpGen'
```

Script: Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen

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```

    metrics = c("accuracy")
)

# Entrenamiento y evaluación del modelo

history <- Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen %>% fit(ExpProtTCGA_KIRC_RawData_woNA_Norm

plot(history)

score <- Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen %>% evaluate(
  ExpProtTCGA_KIRC_RawData_woNA_Norm_SameSampExpGen_Renamed_Transposed_Bottleneck_RowSort_AND_ExpGenTCG
  verbose = 0
)

cat('Test loss:', score[[1]], '\n')
cat('Test accuracy:', score[[2]], '\n')

```

Resultados

Modelo 1 Resumen del modelo

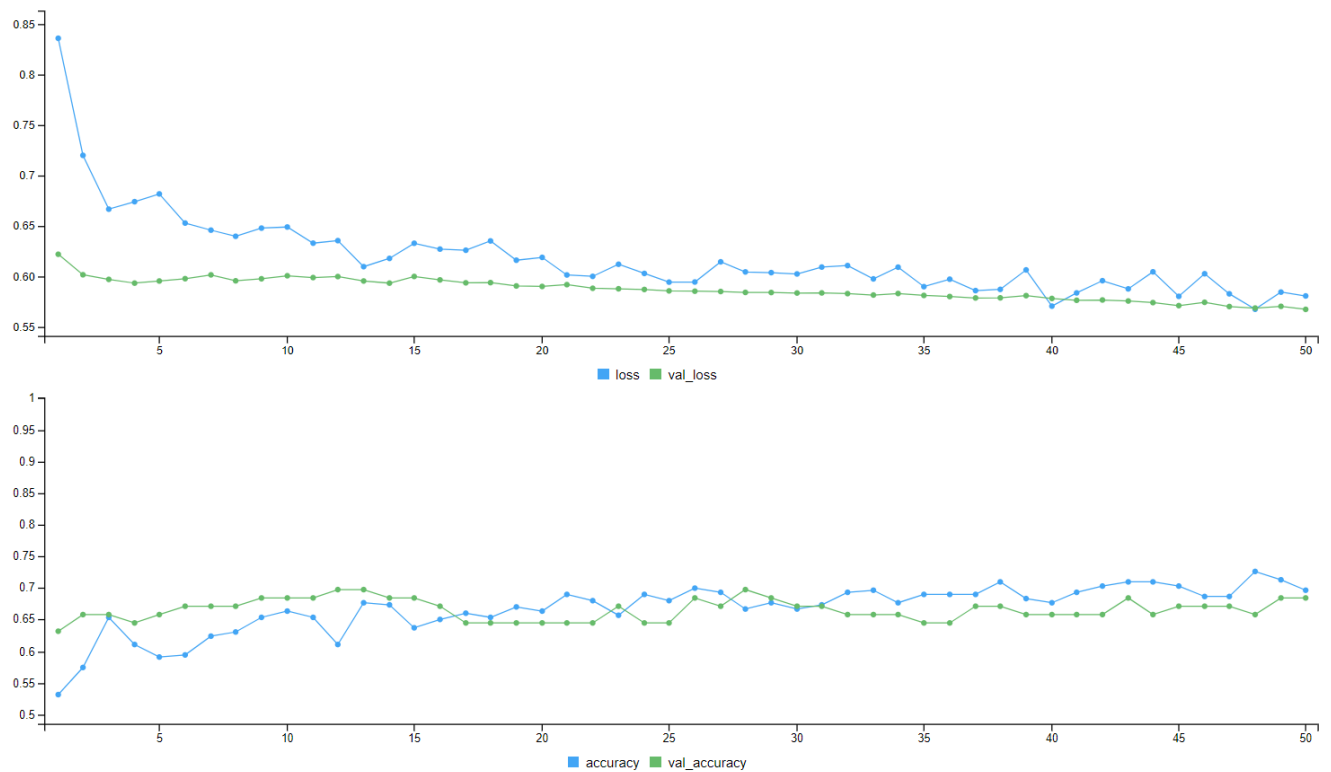
```

> summary(Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen)
Model: "sequential_13"

```

Layer (type)	Output Shape	Param #
dense_107 (Dense)	(None, 10)	410
dropout_18 (Dropout)	(None, 10)	0
dense_106 (Dense)	(None, 4)	44
dropout_17 (Dropout)	(None, 4)	0
dense_105 (Dense)	(None, 1)	5
Total params: 459		
Trainable params: 459		
Non-trainable params: 0		

Precisión y loss



```
> score
      loss accuracy
0.6364123 0.6210526
> history
```

```
Final epoch (plot to see history):
      loss: 0.581
      accuracy: 0.6964
      val_loss: 0.5677
      val_accuracy: 0.6842
```

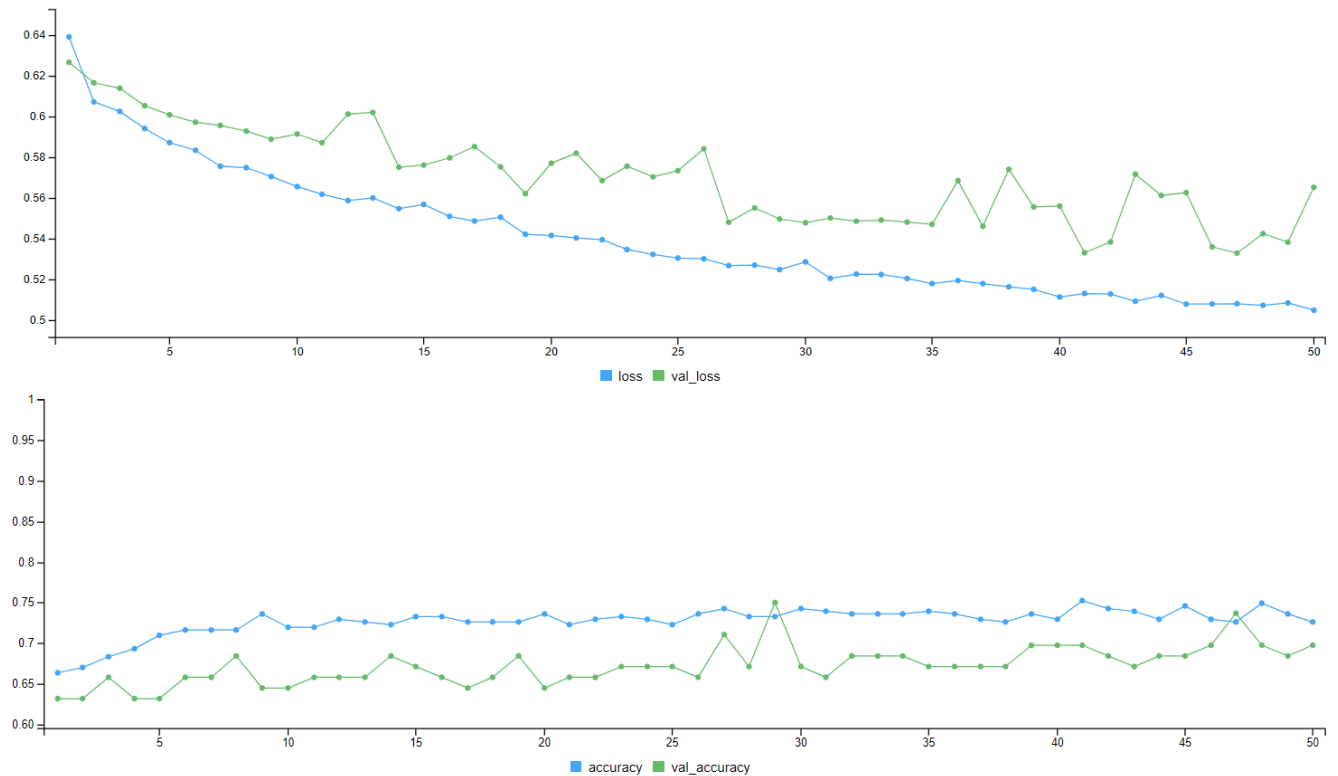
Modelo 2 Resumen del modelo

```
> summary(Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen)
Model: "sequential_14"
```

Layer (type)	Output Shape	Param #
dense_110 (Dense)	(None, 20)	820
dense_109 (Dense)	(None, 8)	168
dense_108 (Dense)	(None, 1)	9

```
Total params: 997
Trainable params: 997
Non-trainable params: 0
```

Precisión y loss



```
> score
      loss accuracy
0.6747756 0.6315789
> history
```

```
Final epoch (plot to see history):
      loss: 0.5046
      accuracy: 0.7261
      val_loss: 0.5651
      val_accuracy: 0.6974
```

Modelo 3 Resumen del modelo

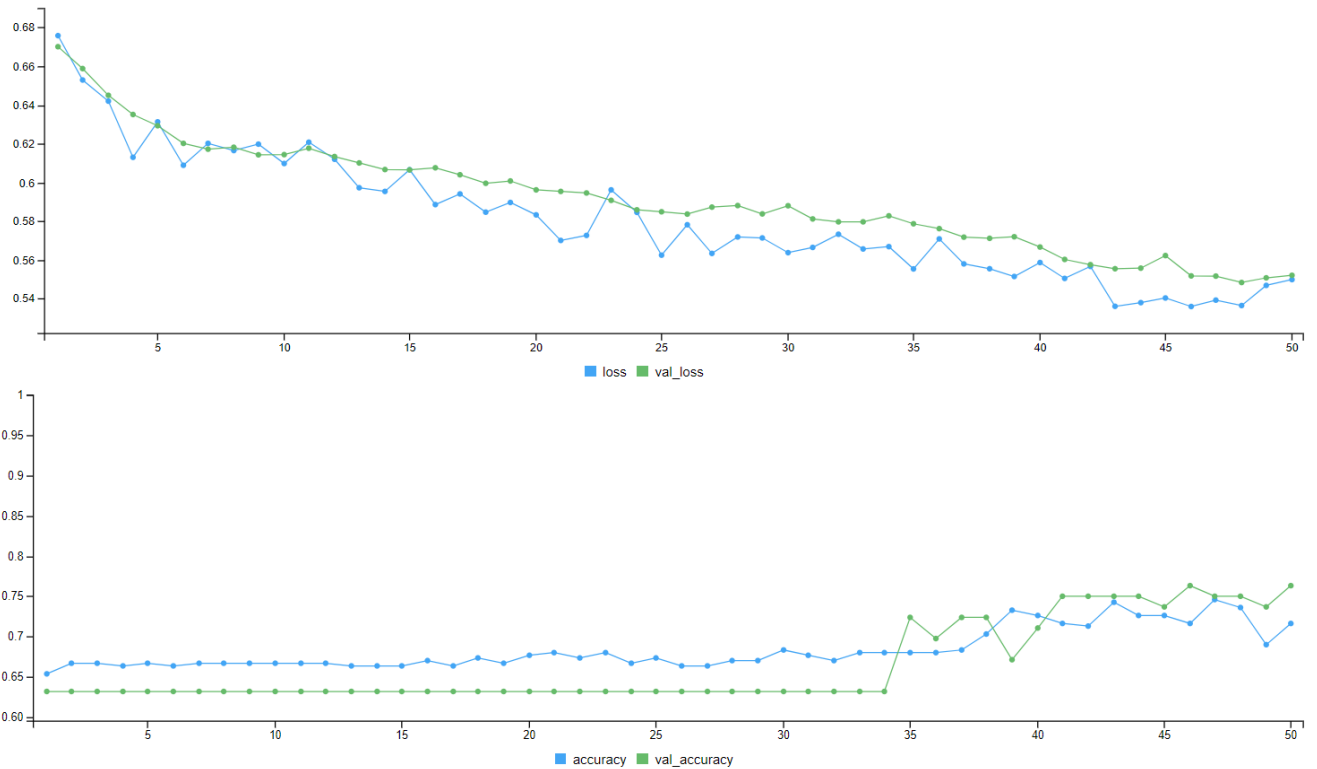
```
> summary(Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen)
Model: "sequential_15"
```

Layer (type)	Output Shape	Param #
dense_114 (Dense)	(None, 20)	820
dropout_20 (Dropout)	(None, 20)	0
dense_113 (Dense)	(None, 16)	336
dropout_19 (Dropout)	(None, 16)	0

dense_112 (Dense)	(None, 8)	136
dense_111 (Dense)	(None, 1)	9

Total params: 1,301
 Trainable params: 1,301
 Non-trainable params: 0

Precisión y loss



```

> score
      loss accuracy
0.6102709 0.6947368
> history

```

```

Final epoch (plot to see history):
      loss: 0.5499
      accuracy: 0.7162
      val_loss: 0.5521
      val_accuracy: 0.7632

```

Modelo 4 Resumen del modelo

```

> summary(Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen)
Model: "sequential_31"

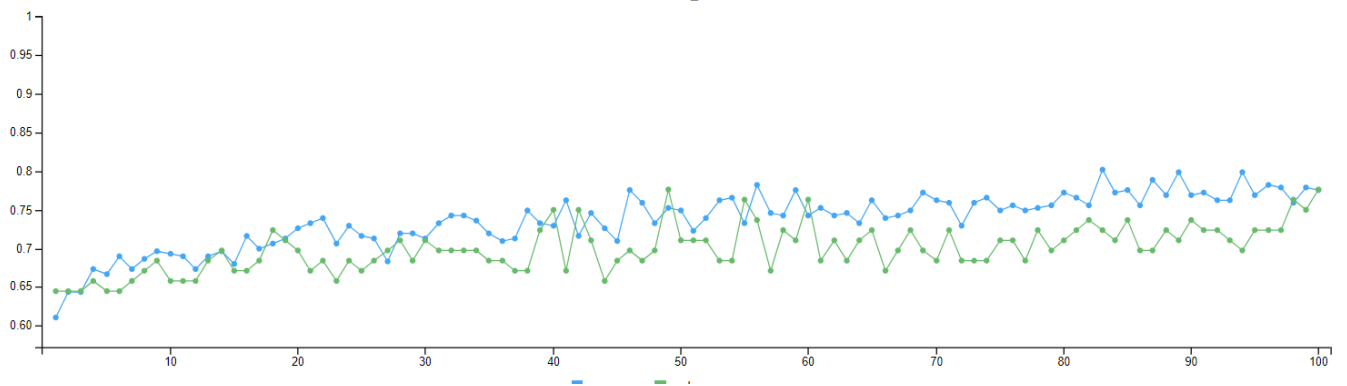
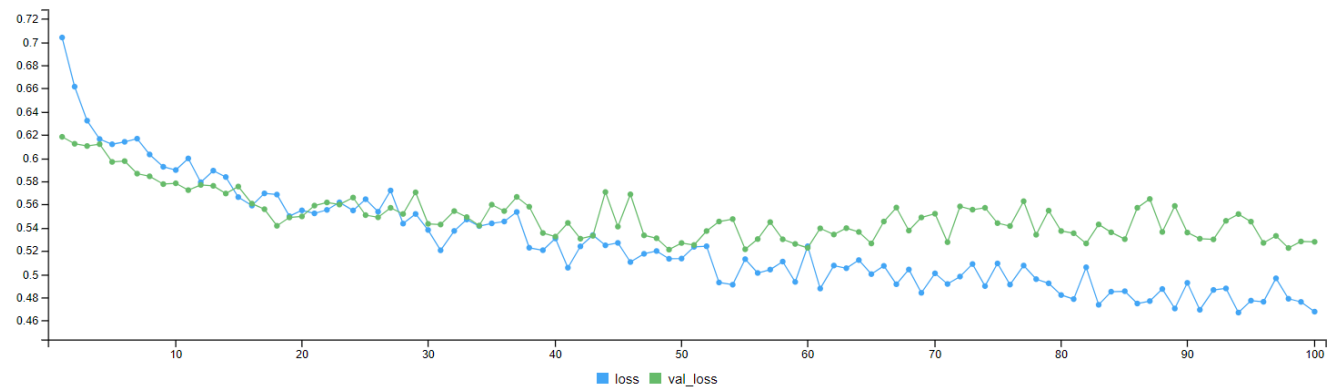
```

Layer (type)	Output Shape	Param #
--------------	--------------	---------

dense_175 (Dense)	(None, 35)	1435
dropout_44 (Dropout)	(None, 35)	0
dense_174 (Dense)	(None, 20)	720
dropout_43 (Dropout)	(None, 20)	0
dense_173 (Dense)	(None, 10)	210
dense_172 (Dense)	(None, 1)	11

Total params: 2,376
 Trainable params: 2,376
 Non-trainable params: 0

Precisión y loss



```
> score
      loss accuracy
0.6541336 0.6736842
> history
```

```
Final epoch (plot to see history):
      loss: 0.4678
      accuracy: 0.7756
      val_loss: 0.5279
```

val_accuracy: 0.7763

Modelo 5 Resumen del modelo

```
> summary(Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen)
```

Model: "sequential_71"

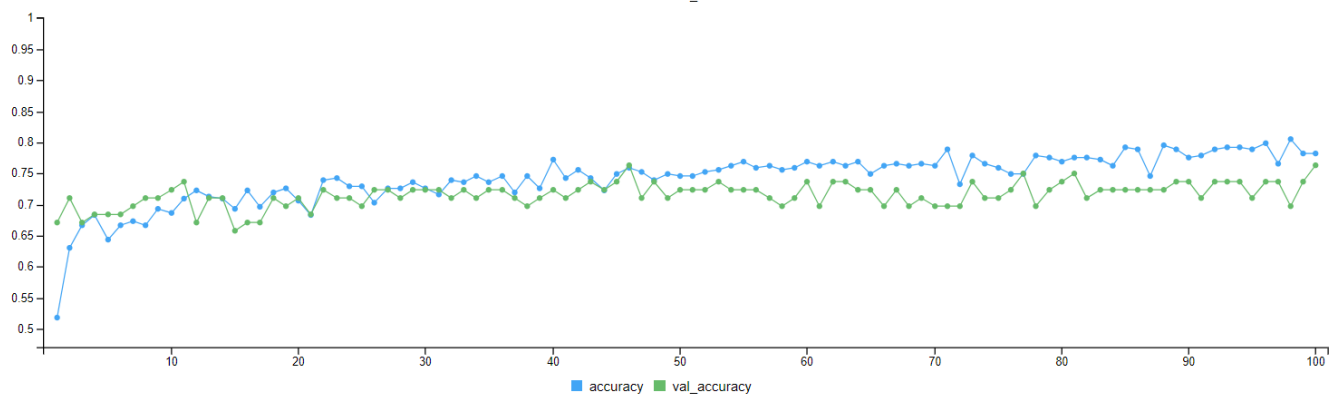
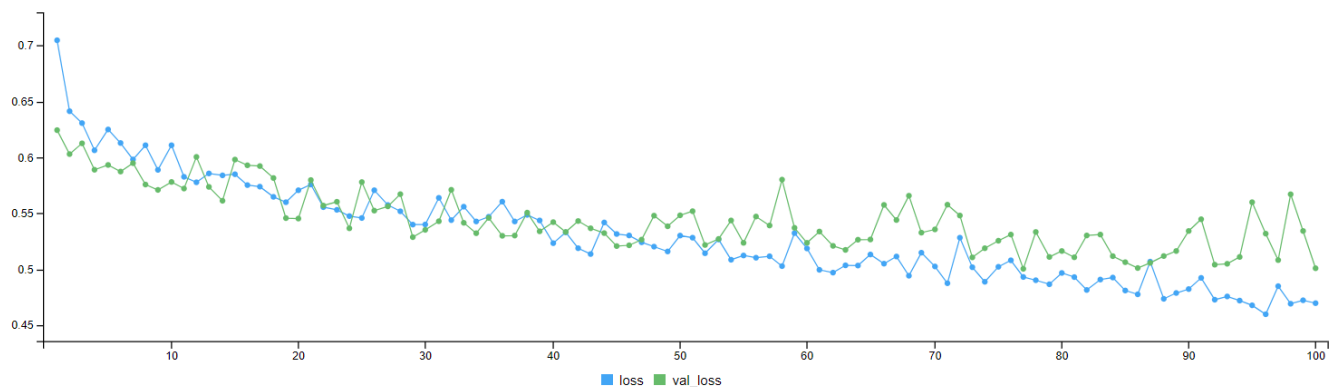
Layer (type)	Output Shape	Param #
dense_348 (Dense)	(None, 40)	1640
dropout_112 (Dropout)	(None, 40)	0
dense_347 (Dense)	(None, 20)	820
dense_346 (Dense)	(None, 8)	168
dense_345 (Dense)	(None, 4)	36
dense_344 (Dense)	(None, 1)	5

Total params: 2,669

Trainable params: 2,669

Non-trainable params: 0

Precisión y loss



```
> score
      loss accuracy
0.6559734 0.7263158
> history
```

```
Final epoch (plot to see history):
      loss: 0.4699
      accuracy: 0.7822
      val_loss: 0.5011
      val_accuracy: 0.7632
```

SVM del modelo La precisión de este modelo como SVM es de 65.26%.

```
Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen_SVM <- cbind(ExpProtTCGA_KIRC_RawData_woNA_Norm_Same,
colnames(Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen_SVM)[1] <- "Labels"
```

Entrenamiento del modelo

```
Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR = svm(formula = Labels ~ .,
      data = Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen_SVM,
      type = 'C-classification', # this is because we want to make a regression classification
      kernel = 'radial')
> str(Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR)
List of 30
 $ call      : language svm(formula = Labels ~ ., data = Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen_SVM, type = 'C-classification', kernel = 'radial')
 $ type      : num 0
 $ kernel    : num 2
 $ cost      : num 1
 $ degree    : num 3
 $ gamma     : num 0.025
 $ coef0     : num 0
 $ nu        : num 0.5
 $ epsilon   : num 0.1
 $ sparse    : logi FALSE
 $ scaled    : logi [1:40] TRUE TRUE TRUE TRUE TRUE TRUE TRUE ...
 $ x.scale   :List of 2
 ..$ scaled:center: Named num [1:40] 0.838 0.257 -0.601 -1.483 -0.575 ...
 .. ..- attr(*, "names")= chr [1:40] "V2" "V3" "V4" "V5" ...
 ..$ scaled:scale : Named num [1:40] 0.244 0.194 0.299 0.165 0.162 ...
 .. ..- attr(*, "names")= chr [1:40] "V2" "V3" "V4" "V5" ...
 $ y.scale   : NULL
 $ nclasses  : int 2
 $ levels    : chr [1:2] "0" "1"
 $ tot.nSV   : int 284
 $ nSV       : int [1:2] 161 123
 $ labels    : int [1:2] 2 1
 $ SV        : num [1:284, 1:40] -1.134 -0.669 -1.292 -0.408 -1.835 ...
 ..- attr(*, "dimnames")=List of 2
 .. ..$ : chr [1:284] "1" "2" "3" "4" ...
 .. ..$ : chr [1:40] "V2" "V3" "V4" "V5" ...
 $ index     : int [1:284] 1 2 3 4 5 9 10 14 16 18 ...
 $ rho       : num -0.351
```

```

$ compprob      : logi FALSE
$ probA        : NULL
$ probB        : NULL
$ sigma        : NULL
$ coefs        : num [1:284, 1] 1 1 0.674 1 0.565 ...
$ na.action    : NULL
$ fitted       : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 1 2 2 2 ...
..- attr(*, "names")= chr [1:379] "1" "2" "3" "4" ...
$ decision.values: num [1:379, 1] 0.906 0.219 1 0.534 1 ...
..- attr(*, "dimnames")=List of 2
.. ..$ : chr [1:379] "1" "2" "3" "4" ...
.. ..$ : chr "1/0"
$ terms        :Classes 'terms', 'formula' language Labels ~ V2 + V3 + V4 + V5 + V6 + V7 + V8 + V9 +
.. ..- attr(*, "variables")= language list(Labels, V2, V3, V4, V5, V6, V7, V8, V9, V10, V11, V12, V13,
.. ..- attr(*, "factors")= int [1:41, 1:40] 0 1 0 0 0 0 0 0 0 0 ...
.. ..- attr(*, "dimnames")=List of 2
.. .. ..$ : chr [1:41] "Labels" "V2" "V3" "V4" ...
.. .. ..$ : chr [1:40] "V2" "V3" "V4" "V5" ...
.. ..- attr(*, "term.labels")= chr [1:40] "V2" "V3" "V4" "V5" ...
.. ..- attr(*, "order")= int [1:40] 1 1 1 1 1 1 1 1 1 1 ...
.. ..- attr(*, "intercept")= num 0
.. ..- attr(*, "response")= int 1
.. ..- attr(*, ".Environment")=<environment: R_GlobalEnv>
.. ..- attr(*, "predvars")= language list(Labels, V2, V3, V4, V5, V6, V7, V8, V9, V10, V11, V12, V13,
.. ..- attr(*, "dataClasses")= Named chr [1:41] "numeric" "numeric" "numeric" "numeric" ...
.. ..- attr(*, "names")= chr [1:41] "Labels" "V2" "V3" "V4" ...
- attr(*, "class")= chr [1:2] "svm.formula" "svm"

# Predicciones
Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR = predict(Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR)

# Matriz de confusi3n

cmR_Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR = table(Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR,
> cmR_Clasificador_Modelo2Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR
ExpProtTCGA_KIRC_RawData_woNA_N
Clasificador_Modelo1Autoencoder_ExpProt_AND_ExpGen_SVM_classifierR_predR  0  1
                                0 13  9
                                1 23 50

> (53+9)/(53+9+27+6)
[1] 0.6526316

```