

Regresión logística de Bridge y Lasso

```
set.seed(123456789)
```

Primero se cargan las librerías

```
library(ggplot2)
library(ggpubr)
library(dplyr)
```

Attaching package: 'dplyr'

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

filter, lag

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

intersect, setdiff, setequal, union

```
library(glmnet) ## regresiones logisitcas
```

Loading required package: Matrix

Loaded glmnet 4.1-7

```
library(caret) ### bayes y knn
```

Loading required package: lattice

```
library(e1071) ## bayes
```

Cargamos los datos

```
datos <- read.table("./yeast.data",header = F)[-1]
```

Creamos las funciones que vamos a necesitar, es decir las funciones de transformación

```
min.max.mean <- function(X) apply(X,2,function(x) (x-mean(x))/(max(x)-min(x)))
min.max.median <- function(X) apply(X,2,function(x) (x-median(x))/(max(x)-min(x)))
min.max <- function(X) apply(X,2,function(x) (x-min(x))/(max(x)-min(x)))
zscore <- function(X) apply(X,2,function(x) (x-mean(x))/sd(x))
l2 <- function(X) apply(X,2,function(x) x/sqrt(sum(x^2)))
```

Para hacer las transformaciones, solamente necesitamos las variables numéricas.

```
datos <- as.data.frame(datos)
datos.numericos <- datos[, which(unlist(lapply(datos, is.numeric)))]
clase <- datos$V10 <- as.factor(datos$V10)
colnames(datos.numericos) <- paste0("Var", rep(1:8))
```

procedemos a crear una lista con todas las transformaciones

```
datos.lista <- list(
  raw = bind_cols(datos.numericos,clase=clase),
  zscore = bind_cols(zscore(datos.numericos),
                     clase = clase),
  l2 = bind_cols(l2(datos.numericos), clase = clase),
  media = bind_cols(min.max.mean(datos.numericos), clase = clase),
  mediana = bind_cols(min.max.median(datos.numericos), clase = clase),
  min_max = bind_cols(min.max(datos.numericos),
                      clase = clase))
```

Descriptiva Gráfica

Al ser demasiadas variables, podemos realizar un melt

```
lista_graficos <- vector("list",length=length(datos.lista))
datos.melt <- lapply(datos.lista,reshape2::melt)
```

Using clase as id variables
Using clase as id variables
Using clase as id variables
Using clase as id variables
Using clase as id variables
Using clase as id variables

Podemos ver la cabecera de alguna transformacion para ver el nombre nuevo de las variables

```
head(datos.melt$zscore)
```

	clase	variable	value
1	MIT	Var1	0.58178524
2	MIT	Var1	-0.51071851
3	MIT	Var1	1.01878674
4	NUC	Var1	0.58178524
5	MIT	Var1	-0.58355209
6	CYT	Var1	0.07195016

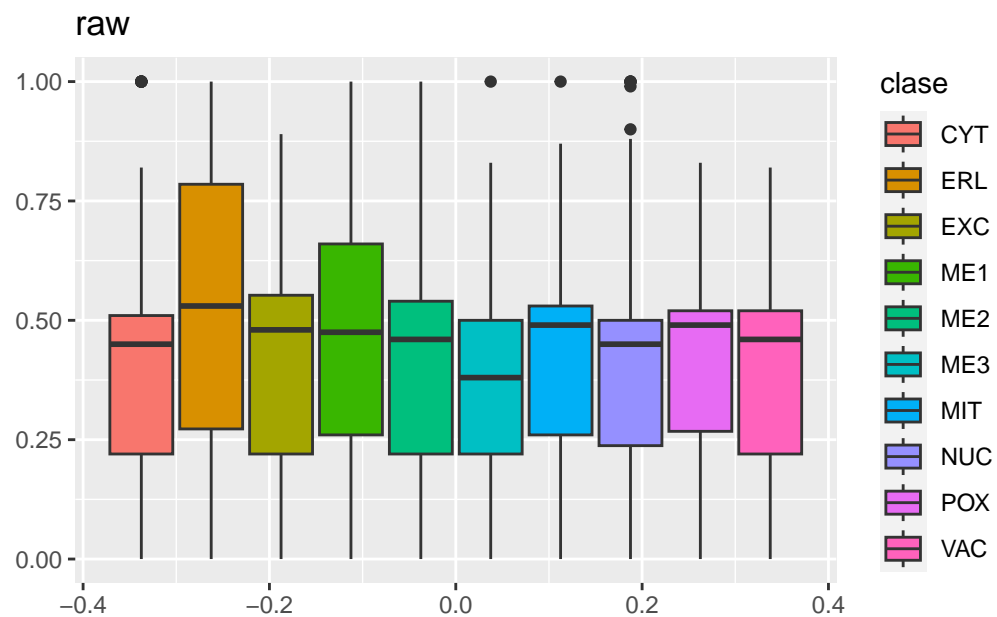
```
for(l in 1:length(datos.melt)){

  X <- datos.melt[[l]]
  nombre <- names(datos.melt)[l]
  lista_graficos[[l]] <- ggplot(X,aes(y=value,fill=clase))+geom_boxplot()+ggtitle(nombre)+

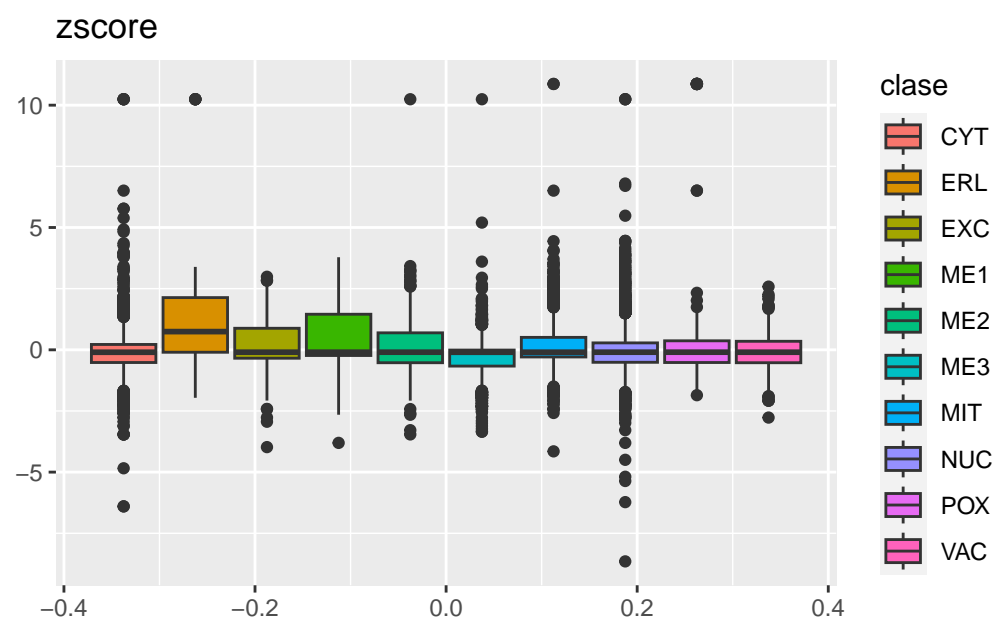
}

names(lista_graficos) <- paste0("plot",1:length(datos.lista))

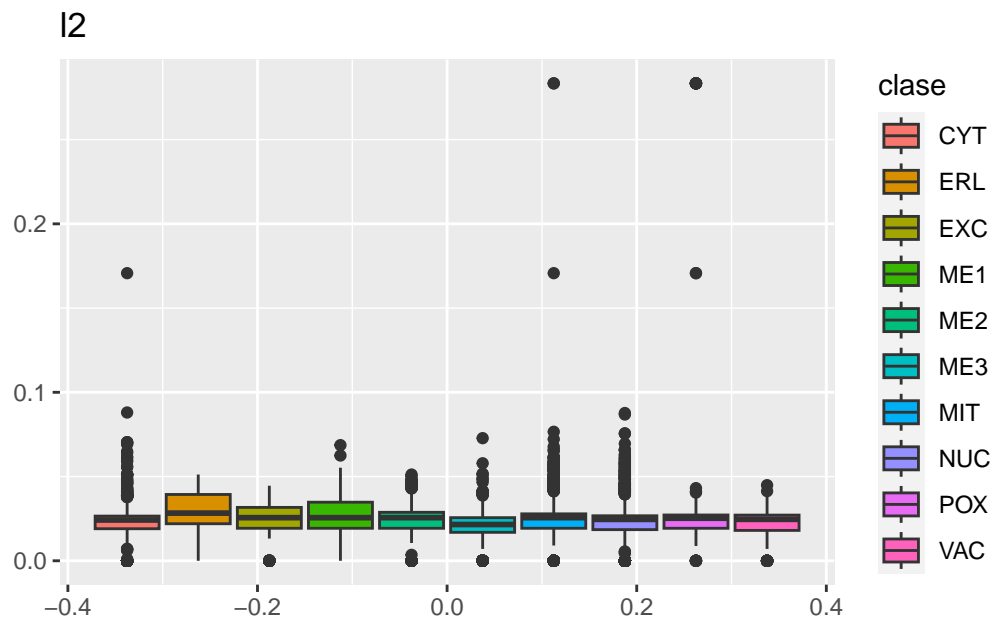
lista_graficos$plot1
```



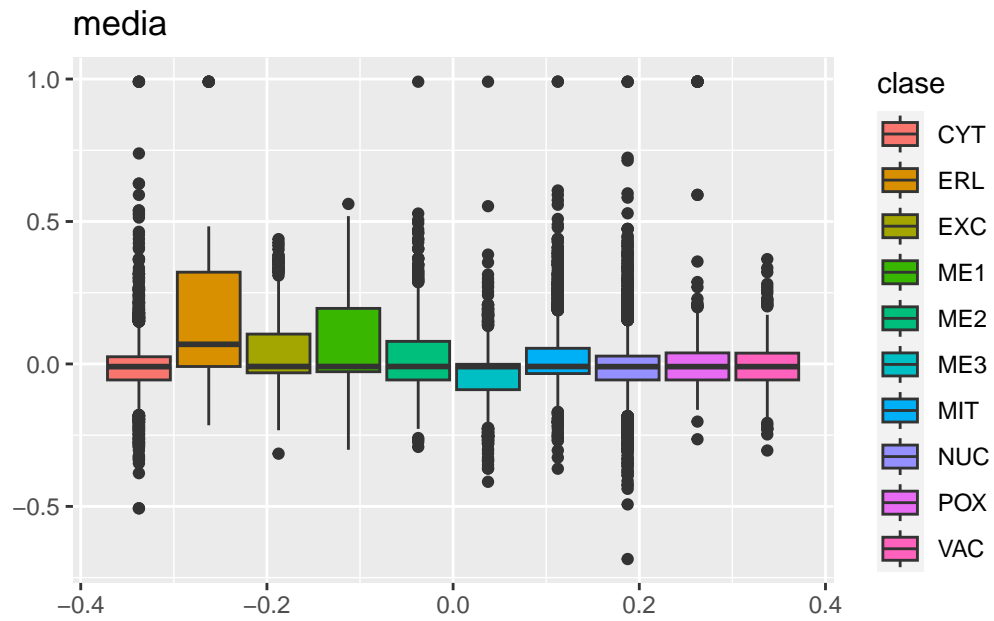
```
lista_graficos$plot2
```



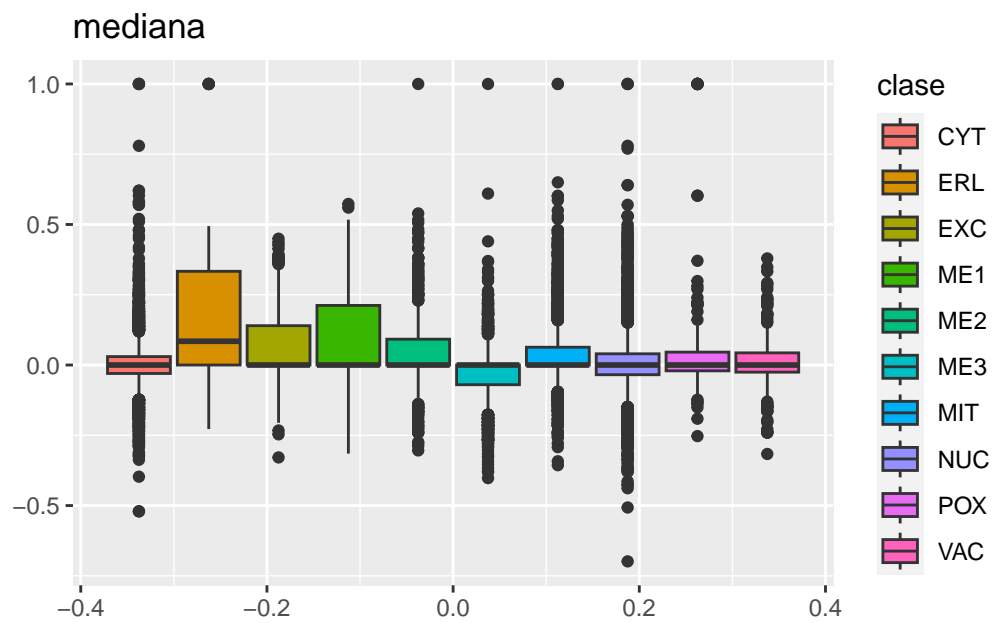
```
lista_graficos$plot3
```



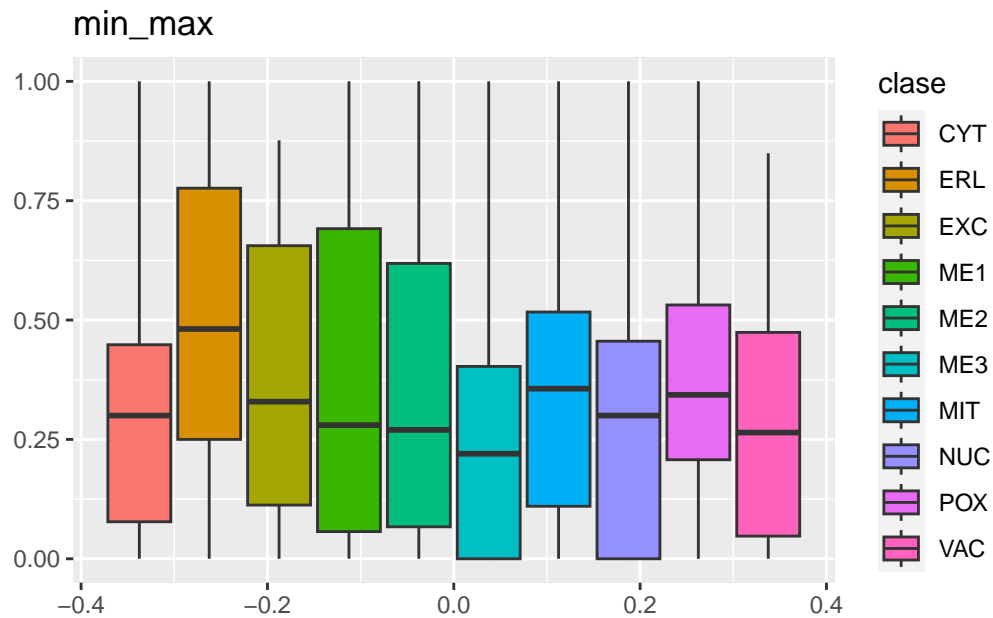
```
lista_graficos$plot4
```



```
lista_graficos$plot5
```



```
lista_graficos$plot6
```



Así por ejemplo la normalización min-max es la mejor, puesto que no tenemos outliers

Otra forma de ver la transformación es mediante gráficos de densidad

```
for(l in 1:length(datos.melt)){

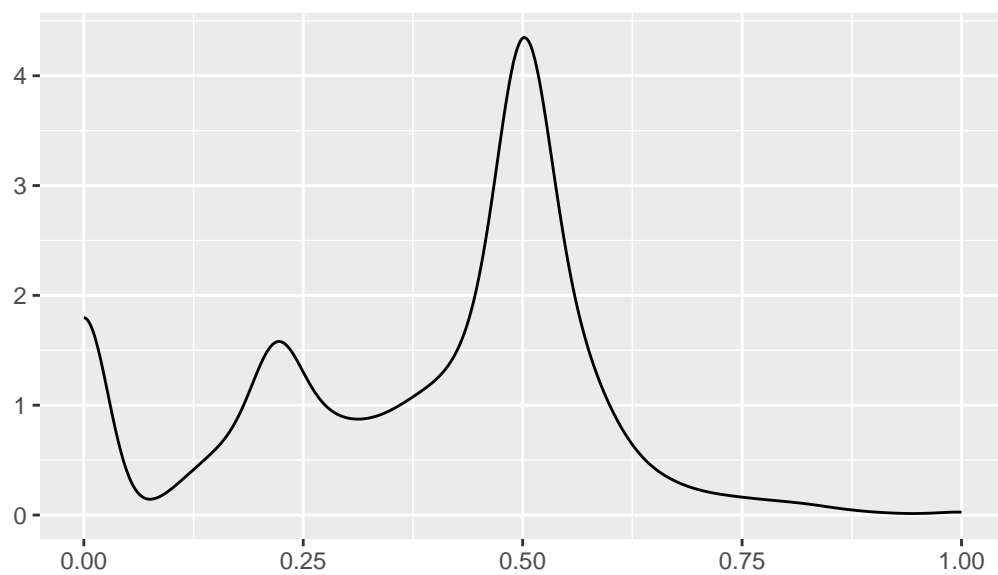
  X <- datos.melt[[l]]
  nombre <- names(datos.melt)[l]
  lista_graficos[[l]] <- ggplot(X,aes(x=value))+geom_density()+ggtitle(nombre)+xlab("")+ylab("")

}

names(lista_graficos) <- paste0("plot",1:length(datos.lista))

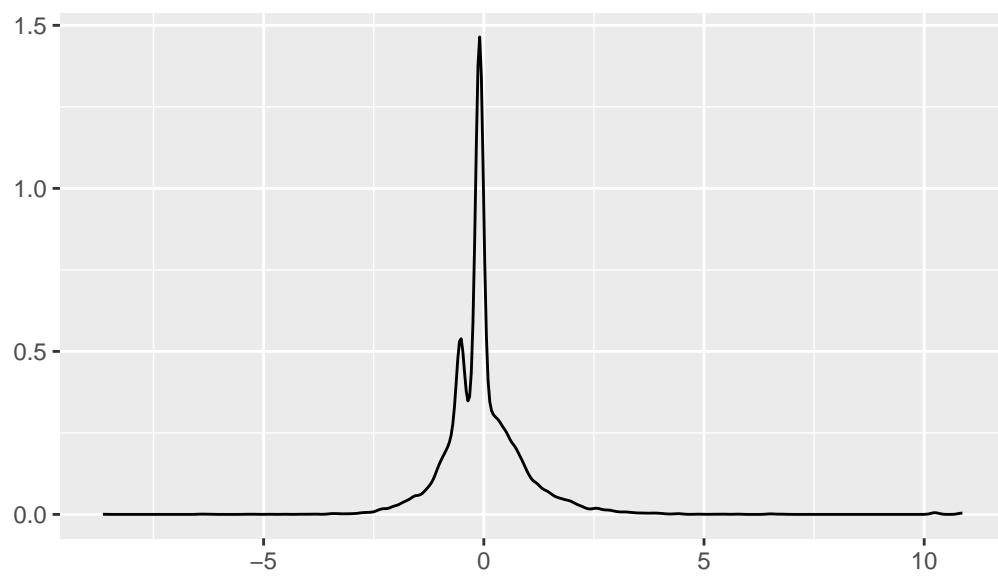
lista_graficos$plot1
```

raw

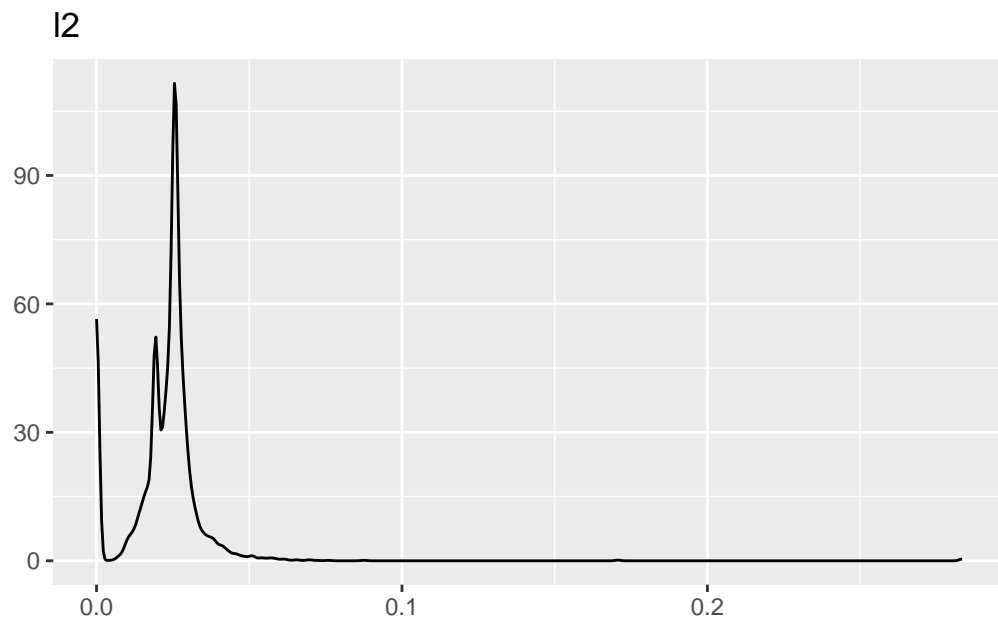


```
lista_graficos$plot2
```

zscore

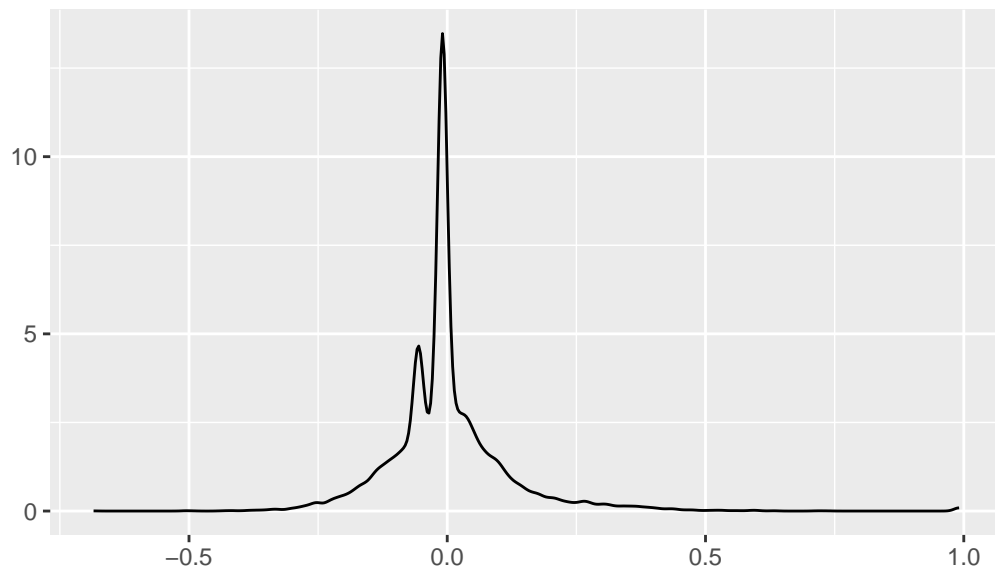



```
lista_graficos$plot3
```



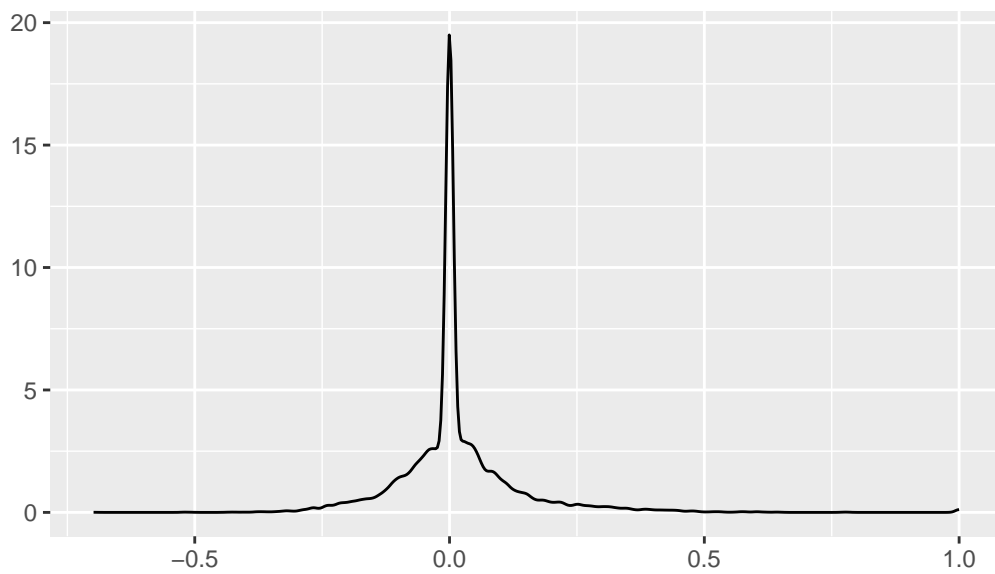
```
lista_graficos$plot4
```

media

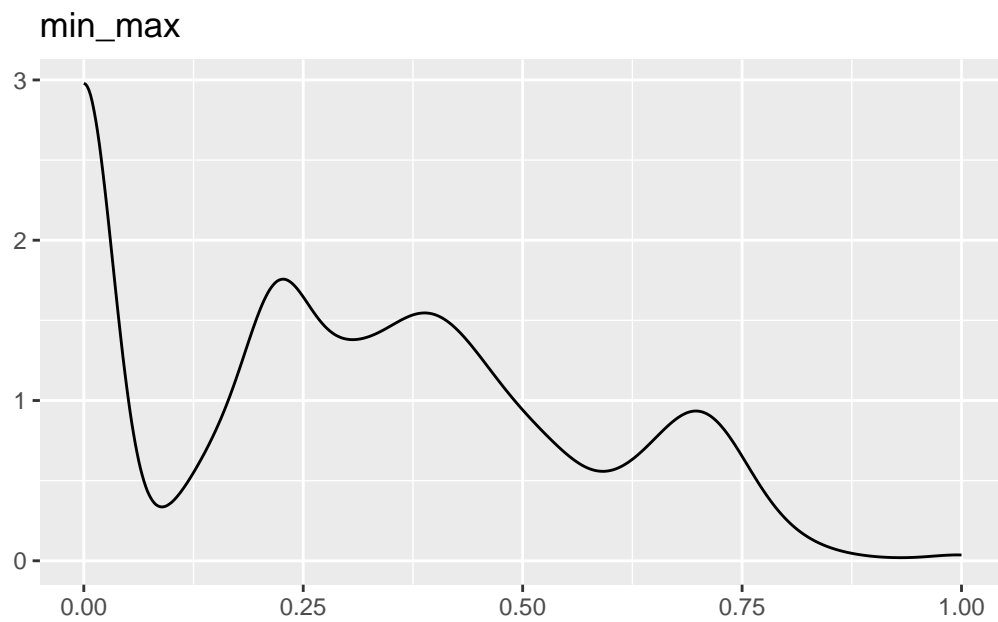


```
lista_graficos$plot5
```

mediana

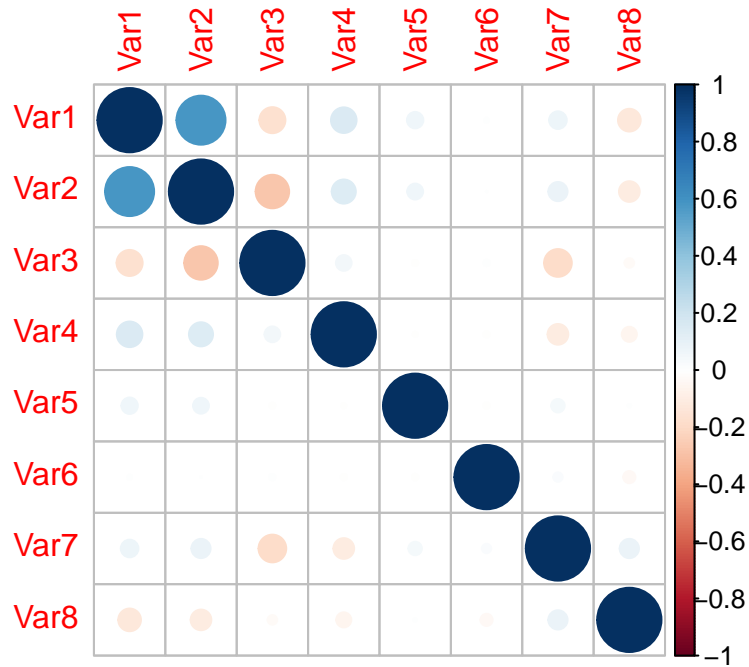


```
lista_graficos$plot6
```

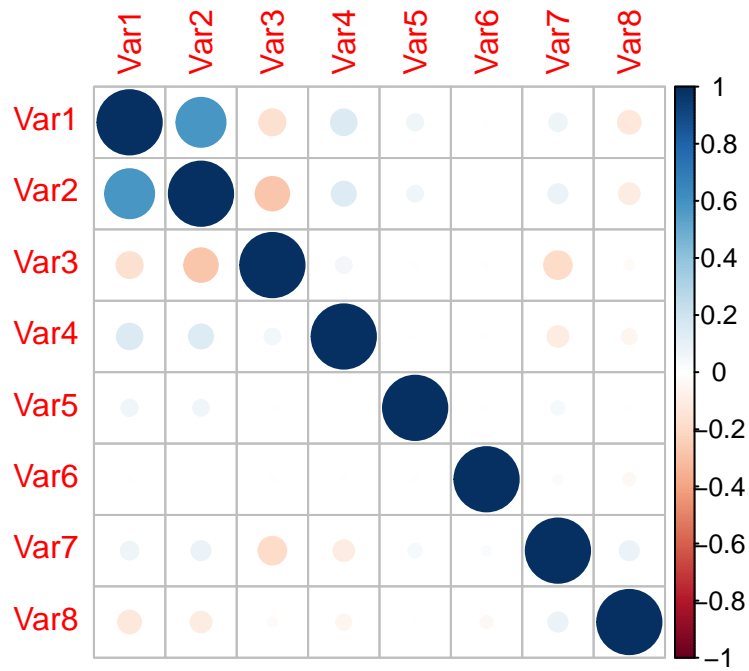


Sin embargo, al ver la densidad, no tenemos una transformacion uniforme.

```
corrplot::corrplot(cor(datos.numericos))
```



```
corrplot::corrplot(cor(datos.lista$media[, -ncol(datos)]))
```



Partición de datos

para conjunto de datos podemos realizar el split

```
set.seed(123456789)
n <- nrow(datos)
idx <- sample(1:n,n*0.7)
datos.train.lista <- lapply(datos.lista, function(x) x[idx,])
datos.test.lista <- lapply(datos.lista, function(x) x[-idx,])
```

Ejemplo regresión logística

https://rstudio-pubs-static.s3.amazonaws.com/38437_18a39a6487134d67b5f5e0d47221ec8d.html

https://rpubs.com/jkylearmstrong/logit_w_caret

alpha=1 es lasso y 0 es ridge

```
set.seed(123456789)
trControl <- trainControl(method = 'cv',
                           number = 5)
myfnlog <- function(x) train(clase ~ ., data = x, method = "multinom", trControl = trControl)

logistica.lista <- lapply(datos.train.lista,myfnlog)

logisita.pred <- vector("list",length = length(datos.lista))

for(l in 1:length(datos.lista)){

  logisita.pred[[l]] <- predict(logistica.lista[[l]],datos.test.lista[[l]])

}

names(logisita.pred) <- names(datos.lista)
accuracy <- vector("numeric",length = length(datos.lista))

for(l in 1:length(datos.lista)){
```

```

    accuracy[1] <- confusionMatrix(datos.test.lista$raw$clase,logisita.pred[[1]])$overall[1]
  }

  names(accuracy) <- names(datos.lista)

  ### Este valor lo tienen que guardar solamente haremos por accuracy y kappa
  ### tenemos que mirar el objeto matconf

  set.seed(123456789)

  ### para conjunto de datos podemos realizar el split
  ### lasso 1 ridge 0
  datos.train.lista <- lapply(datos.lista, function(x) x[idx,])
  datos.test.lista <- lapply(datos.lista, function(x) x[-idx,])

  cvfit_lasso <- cv.glmnet(as.matrix(datos.train.lista$raw[, -ncol(datos)]), as.numeric(datos.

```

Regresión logística de Ridge

```

set.seed(123456789)
trControl <- trainControl(method = 'cv',
                           number = 5)
myfnlog <- function(x) train(clase ~ ., data = x, method = "glmnet", trControl = trControl)

ridge.lista <- lapply(datos.train.lista, myfnlog)

```

Warning in lognet(xd, is.sparse, ix, jx, y, weights, offset, alpha, nobs, : one multinomial or binomial class has fewer than 8 observations; dangerous ground

Warning in lognet(xd, is.sparse, ix, jx, y, weights, offset, alpha, nobs, : one multinomial or binomial class has fewer than 8 observations; dangerous ground

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```
ridge.pred <- vector("list",length = length(ridge.lista))

for(l in 1:length(ridge.lista)){

  ridge.pred[[l]] <- predict(ridge.lista[[l]],datos.test.lista[[l]])

}

names(ridge.pred) <- names(ridge.lista)
ridge.accuracy <- vector("numeric",length = length(datos.lista))

for(l in 1:length(ridge.lista)){

  ridge.accuracy[l] <- confusionMatrix(datos.test.lista$raw$clase,ridge.pred[[l]])$overall

}

names(ridge.accuracy) <- names(datos.lista)

### Este valor lo tienen que guardar solamente haremos por accuracy y kappa
### tenemos que mirar el objeto matconf
```

Regresión de Lasso

```
set.seed(123456789)
trControl <- trainControl(method = 'cv',
                           number = 5)
myfnlasso <- function(x) train(clase ~ ., data = x, method = "glmnet", trControl = trControl)

lasso.lista <- lapply(datos.train.lista, myfnlasso)
```

Warning in lognet(xd, is.sparse, ix, jx, y, weights, offset, alpha, nobs, : one multinomial or binomial class has fewer than 8 observations; dangerous ground

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Warning in lognet(xd, is.sparse, ix, jx, y, weights, offset, alpha, nobs, : one multinomial or binomial class has fewer than 8 observations; dangerous ground

Warning: from glmnet C++ code (error code -22); Convergence for 22th lambda value not reached after maxit=100000 iterations; solutions for larger lambdas returned

Warning in lognet(xd, is.sparse, ix, jx, y, weights, offset, alpha, nobs, : one multinomial or binomial class has fewer than 8 observations; dangerous ground

Warning in lognet(xd, is.sparse, ix, jx, y, weights, offset, alpha, nobs, : one multinomial or binomial class has fewer than 8 observations; dangerous ground

```
lasso.pred <- vector("list",length = length(lasso.lista))  
  
for(l in 1:length(lasso.lista)){
```

```

lasso.pred[[l]] <- predict(lasso.lista[[l]],datos.test.lista[[l]])

}

names(lasso.pred) <- names(lasso.lista)
lasso.accuracy <- vector("numeric",length = length(datos.lista))

for(l in 1:length(lasso.lista)){

  lasso.accuracy[l] <- confusionMatrix(datos.test.lista$raw$clase,lasso.pred[[l]])$overall

}

names(lasso.accuracy) <- names(datos.lista)

### Este valor lo tienen que guardar solamente haremos por accuracy y kappa
### tenemos que mirar el objeto matconf

```

Knn

```

set.seed(123456789)
k_value=c(1:20)
kControl<- trainControl(method = 'repeatedcv',
                        number = 5,repeats = 15)
myfnknn <- function(x) train(clase ~ ., data = x, method = "knn", trControl = kControl,tun

knn.lista <- lapply(datos.train.lista,myfnknn)

knn.pred <- vector("list",length = length(knn.lista))

for(l in 1:length(knn.lista)){

  knn.pred[[l]] <- predict(knn.lista[[l]],datos.test.lista[[l]])

}

names(knn.pred) <- names(knn.lista)

```

```

knn.accuracy <- vector("numeric",length = length(datos.lista))

for(l in 1:length(knn.lista)){

  knn.accuracy[l] <- confusionMatrix(datos.test.lista$raw$clase,knn.pred[[l]])$overall[1]

}

names(knn.accuracy) <- names(datos.lista)

### Este valor lo tienen que guardar solamente haremos por accuracy y kappa
### tenemos que mirar el objeto matconf

```

Bayes

```

set.seed(123456789)
trControl <- trainControl(method = 'cv',
                           number = 5)
myfnbayes <- function(x) train(clase ~ ., data = x, method = "naive_bayes", trControl = trControl)

bayes.lista <- lapply(datos.train.lista,myfnbayes)

bayes.pred <- vector("list",length = length(bayes.lista))

for(l in 1:length(bayes.lista)){

  bayes.pred[[l]] <- predict(bayes.lista[[l]],datos.test.lista[[l]])

}

names(bayes.pred) <- names(bayes.lista)
bayes.accuracy <- vector("numeric",length = length(datos.lista))

for(l in 1:length(bayes.lista)){

  bayes.accuracy[l] <- confusionMatrix(datos.test.lista$raw$clase,bayes.pred[[l]])$overall

```

```
}
```

```
names(bayes.accuracy) <- names(datos.lista)
```

```
### Este valor lo tienen que guardar solamente haremos por accuracy y kappa  
### tenemos que mirar el objeto matconf
```

Matriz

```
m <- cbind(accuracy,ridge.accuracy,lasso.accuracy,knn.accuracy,bayes.accuracy )  
print(m)
```

	accuracy	ridge.accuracy	lasso.accuracy	knn.accuracy	bayes.accuracy
raw	0.5919283	0.5852018	0.5986547	0.5941704	0.4080717
zscore	0.5919283	0.5919283	0.5986547	0.5919283	0.5336323
l2	0.5964126	0.5919283	0.5964126	0.5896861	0.4596413
media	0.5941704	0.5941704	0.5941704	0.5964126	0.5336323
mediana	0.5941704	0.5896861	0.5964126	0.5784753	0.4125561
min_max	0.5941704	0.5919283	0.5986547	0.5964126	0.4125561