Modeling

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Variable pre-selection

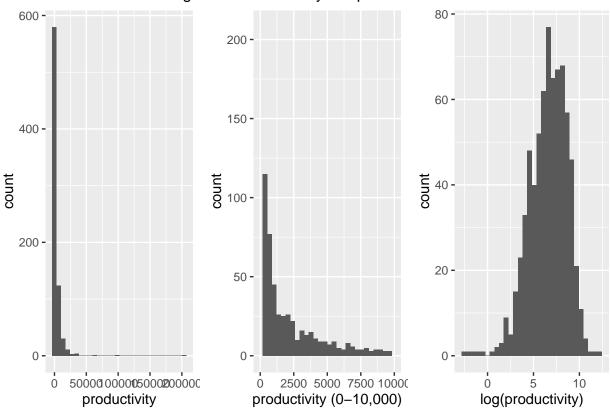
Check for highly correlated variables. Variables that have perfect or very high correlation will have one of the pair removed (marked as a "C" in the Variables spreadsheet).

```
##
                                           Var1
                                                        Var2
                                                                 value
## 16319
                                            t10
                                                          t8 0.9066941
## 25385 produccion en libras producto vendido
                                                       ad11 0.9381219
                                                       a16_b 0.9130902
## 31087
                                          a24_f
## 44556
                                         tp52_g
                                                      tp48_g 0.9778341
## 44820
                                         to57_e
                                                      to53_e 0.9143210
## 48441
                                      percperm2
                                                   percperm 0.9274772
## 49477
                                   percpasture2 percpasture 0.9737279
## 49996
                                     percother2
                                                  percother 0.9465343
```

UPA Production

```
zero_prod <- reduced_data[reduced_data$productivity ==0,]</pre>
summary(zero_prod$netincome)
##
      Min. 1st Qu.
                    Median
                               Mean 3rd Qu.
                                               Max.
##
   -84380
             -7020
                     -1490
                              -8633
                                       -283
                                               9399
par(mfrow = c(2,1))
raw_prod_hist <- ggplot(data = reduced_data) + geom_histogram(mapping = aes(x = productivity))</pre>
log_prod_hist <- ggplot(data = reduced_data) + geom_histogram(mapping = aes(x = log(productivity)))</pre>
lower_prod_hist <- ggplot(data = reduced_data) + geom_histogram(mapping = aes(x = productivity)) +</pre>
  xlim(0, 10000) + xlab("productivity (0-10,000)")
grid.arrange(raw_prod_hist, lower_prod_hist, log_prod_hist, nrow = 1, top = "Histogram of Productivity")
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat bin()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 56 rows containing non-finite values (stat_bin).
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 38 rows containing non-finite values (stat_bin).
```

Histogram of Productivity Response Variable

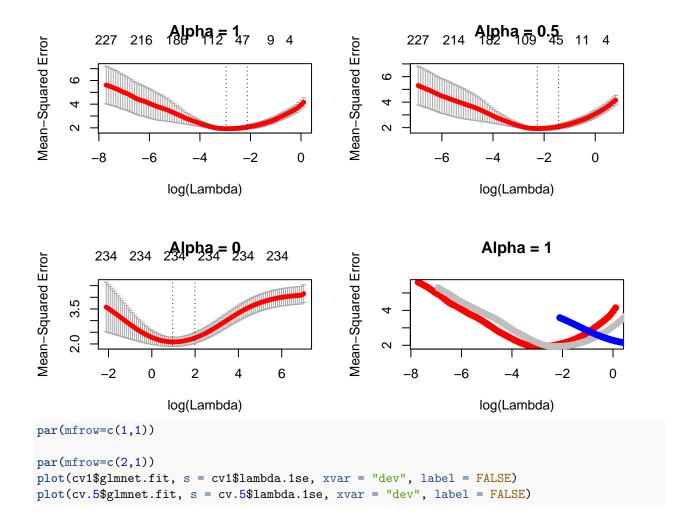


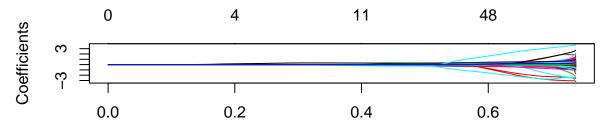
```
production_include <- vars[which(is.na(vars$`UPA Production`)),1]$`Variable Name`
production_x <- subset(reduced_data[reduced_data$productivity > 0,], select = production_include)
production_x <- model.matrix(~., production_x)[,-1]

log_productivity <- log(reduced_data[reduced_data$productivity > 0, 'productivity'])

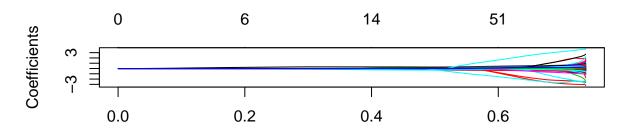
foldid=sample(1:10,size=length(log_productivity),replace=TRUE)
cv1=cv.glmnet(production_x,log_productivity,foldid=foldid,alpha=1)
cv.5=cv.glmnet(production_x,log_productivity,foldid=foldid,alpha=.5)
cv0=cv.glmnet(production_x,log_productivity,foldid=foldid,alpha=0)

par(mfrow=c(2,2))
plot(cv1,main="Alpha = 1");plot(cv.5,main="Alpha = 0.5");plot(cv0,main="Alpha = 0");
plot(log(cv1$lambda),cv1$cvm,pch=19,col="red",xlab="log(Lambda)",ylab=cv1$name, main="Alpha = 1")
points(log(cv.5$lambda),cv.5$cvm,pch=19,col="grey", main="Alpha = 0.5")
points(log(cv0$lambda),cv0$cvm,pch=19,col="blue", main="Alpha = 0")
```





Fraction Deviance Explained 0.119131121247271



Fraction Deviance Explained 0.238262242494542

lasso.coef <- predict(cv1,type="coefficients",s=cv1\$lambda.1se)[1:227,]
lasso.coef[lasso.coef!=0]</pre>

```
##
                               (Intercept)
##
                              6.209901e+00
##
             `CPermanentes_OTROS BANANOS`
##
                              3.878382e-01
##
                     CPermanentes_PLATANO
                              2.893157e-01
##
##
             `CTransitorios_TOMATE RINON`
                              2.507306e-01
##
                       CTransitorios_YUCA
##
##
                              1.857631e-02
                              num cultivo
##
##
                              1.529339e-05
##
                        Pastos_BRACHIARIA
##
                             -3.499138e-01
##
                          Pastos_ELEFANTE
##
                             -1.473814e-01
##
                      `Pastos_KING GRASS`
##
                             -4.483688e-02
                                   pc4None
##
##
                              1.223847e-01
##
                                       pc6
##
                             -3.876450e-03
##
                             Arboles_GUABA
##
                              1.515741e-01
                            Arboles_GUINEO
##
##
                              1.136355e-01
##
                `Arboles_LIMON MANDARINA`
```

##	9.626446e-02
##	Arboles_NARANJA
##	5.683590e-03
##	ad11
##	3.213144e-05
##	produccion_en_libras_producto_vendido
##	1.798939e-05
##	v30_a
##	-2.997173e-03
##	c12
##	2.018429e-06
##	ga9Si
##	5.476493e-02
##	ga15_cualADECUACION UPA -1.711513e-02
##	ga15_cualPACHETE
##	1.028400e+00
##	percperm
##	1.439874e-02
##	perctemp
##	1.857261e-02
##	percfallow
##	9.513629e-05
##	percpasture
##	-6.248586e-03
##	percbrush
##	-1.020253e-03
##	percother
##	1.646750e-02
##	perctemp2
##	1.147495e-03
##	percinv2
##	-1.209785e-03
##	d3Si
##	-4.102828e-02
##	ReclassCONSERVACION
##	-3.415214e-01
##	ReclassPECUARIO
##	-1.772193e-01
##	ABANDONEDTRUE
##	-1.378821e-01 CONSERVATIONTRUE
##	-5.645474e-02
##	-5.645474e-02 FORESTRYTRUE
##	-1.399897e-01
##	LODGINGTRUE
##	-2.307416e-02
##	`ENERGIA_ELENERGIA SOLAR PRIVADA`
##	-1.152407e+00
	1.1021070.00