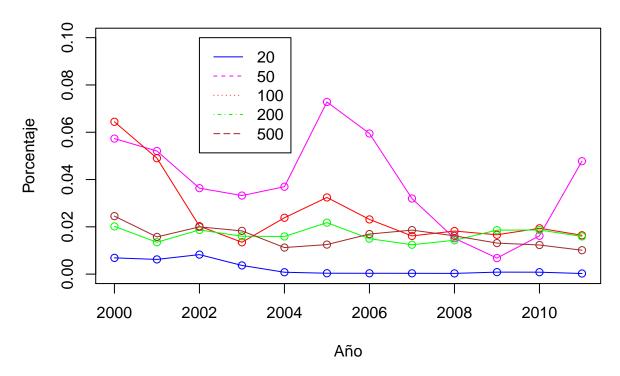
# Tarea 2018/11/07

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### Carga de Datos

Estos son los datos cargados en R y los que manipularemos para presentar los resultados del siguiente documento.

# Porcentaje de falsos por billete



## Modelo Original del Examen

```
## model {
##
    for(i in 1:n) {
        y[i] ~ dbin(p[i], ne[i])
##
        #mu[i] <- ne[i]*p[i]</pre>
##
##
        #Liga logistica
        #logit(p[i])<-beta[1]+beta[2]*x2+beta[3]*x3+beta[4]*x4+beta[5]*x5
##
##
        eta[i] \leftarrow beta[1] + beta[2]*x2[i] + beta[3]*x3[i] + beta[4]*x4[i] + beta[5]*x5[i]
        p[i] <- exp(eta[i])/(1+exp(eta[i]))</pre>
##
##
    }
```

```
##
    for (j in 1:5) {
        beta[j] ~ dnorm(0, 0.001)
##
##
   }
  #Preds 1
##
##
   for (i in 1:n) {
##
        yf1[i] ~ dbin(p[i], ne[i])
## }
## }
## Compiling model graph
##
      Resolving undeclared variables
##
      Allocating nodes
  Graph information:
##
      Observed stochastic nodes: 60
##
      Unobserved stochastic nodes: 65
##
      Total graph size: 584
## Initializing model
DIC
## [1] 1359
## [1] 1296.645
Pseudo R^2
## [1] 0.5460108
## [1] 0.5547716
```

#### Modelo A

Utilicé la siguiente fórmula:

```
\alpha^{\star} = \alpha + \overline{\beta}_1 + \overline{\beta}_2 + \overline{\beta}_3 + \overline{\beta}_4 + \overline{\beta}_5
## model {
##
     for(i in 1:n) {
##
          y[i] ~ dbin(p[i], ne[i])
          #mu[i] <- ne[i]*p[i]</pre>
##
##
          #Liga logistica
##
          \#logit(p[i] \leftarrow beta[1] + beta[2] *x2 + beta[3] *x3 + beta[4] *x4 + beta[5] *x5
##
          eta[i] \leftarrow alpha + beta[1]*x1[i] + beta[2]*x2[i] + beta[3]*x3[i] + beta[4]*x4[i] + beta[5]*x5[i]
##
          p[i] <- exp(eta[i])/(1+exp(eta[i]))</pre>
##
     alpha ~ dnorm(0, 0.001)
##
     for (j in 1:5) {
##
          beta[j] ~ dnorm(0, 0.001)
##
##
    }
##
    # Las primeras 4 betas
##
   for (j in 1:5) {
```

beta\_star[j] <- beta[j] - mean(beta[])</pre>

```
## }
## alpha_star <- alpha + mean(beta[])</pre>
## #Preds 1
  for (i in 1:n) {
##
##
      etaf[i] <- alpha_star + beta_star[1]*x1[i] + beta_star[2]*x2[i] + beta_star[3]*x3[i] + beta_star[
      pf[i] <- exp(etaf[i])/(1+exp(etaf[i]))</pre>
##
##
        yf1[i] ~ dbin(pf[i], ne[i])
##
## }
## Compiling model graph
      Resolving undeclared variables
##
##
      Allocating nodes
## Graph information:
##
      Observed stochastic nodes: 60
      Unobserved stochastic nodes: 66
##
      Total graph size: 927
##
##
## Initializing model
DIC
## [1] 1297
## [1] 1296.795
Pseudo R^2
## [1] 0.5544088
## [1] 0.5546933
Modelo B
## model {
   for(i in 1:n) {
        y[i] ~ dbin(p[i], ne[i])
##
##
        #mu[i] <- ne[i]*p[i]</pre>
##
        #Liga logistica
##
        \#logit(p[i] < -alpha+beta[1] *x1+beta[2] *x2+beta[3] *x3+beta[4] *x4+beta[5] *x5
        eta[i] \leftarrow alpha + beta[1]*x1[i] + beta[2]*x2[i] + beta[3]*x3[i] + beta[4]*x4[i] + beta[5]*x5[i]
##
        p[i] <- exp(eta[i])/(1+exp(eta[i]))</pre>
##
##
   beta[1] ~ dnorm(0, 0.001)
##
##
    tau.b ~ dgamma(0.001,0.001)
  #mu.b[1] <- 0
   #tau.y ~ dgamma(0.001,0.001)
##
##
    g ~ dnorm(0,0.001)
##
   for (j in 2:5) {
##
      beta[j] ~ dnorm(mu.b[j],tau.b)
##
      mu.b[j] \leftarrow g*beta[j-1]
## }
  alpha ~ dnorm(0, 0.001)
```

```
#Preds 1
##
    for (i in 1:n) {
##
        yf1[i] ~ dbin(p[i], ne[i])
##
##
        #yf1[i] ~ dnorm(mu[i],tau.y)
      #mu[i] <- beta[i]</pre>
##
##
      #beta[i] ~ dnorm(mu.b[i],tau.b)
       #mu.b[i] <- g*beta[i-1]</pre>
##
##
## }
## Compiling model graph
##
      Resolving undeclared variables
      Allocating nodes
##
##
  Graph information:
##
      Observed stochastic nodes: 60
##
      Unobserved stochastic nodes: 68
##
      Total graph size: 711
##
## Initializing model
DIC
## [1] 1297
## [1] 1297.065
Pseudo R^2
## [1] 0.5540039
## [1] 0.5550149
```

#### Conclusión

No noté gran diferencia, sobretodo que tarda mucho más en converger, puesto que hay mucha variación en la pseudo-R² para el modelo A. Además propongo el modelo B, basándome en su ejercicio 7 "O". Este tiene una mejora menor, pero al menos constante.

Modelo	DIC	Pseudo $\mathbb{R}^2$
Examen (BUGS)	1359	0.5460108
Examen (Jags)	1299.438	0.5535071
Modelo A (BUGS)	1307	0.5531456
Modelo A (Jags)	1296.844	0.5516561
Modelo B (BUGS)	1297	0.5540039
Modelo B (Jags)	1296.625	0.5539002