Ejemplos

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Paper: *Modelos ocultos de Markov:*

una aplicación de estimación Bayesiana para series de tiempo financieras

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https://github.com/lizbethna/HMMBayes.git

Este archivo muestra las instrucciones para correr los códigos de R y Stan.

Distribución Gamma-Poisson

```
library(ggplot2)
library(extraDistr)
library(rstan)
```

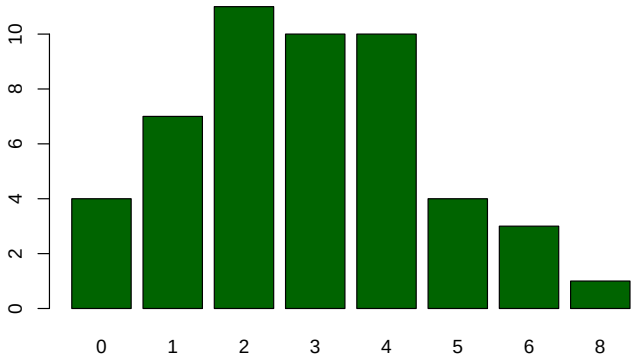
```
## Loading required package: StanHeaders
```

```
## rstan (Version 2.21.3, GitRev: 2e1f913d3ca3)
```

```
## For execution on a local, multicore CPU with excess RAM we recommend calling
## options(mc.cores = parallel::detectCores()).
## To avoid recompilation of unchanged Stan programs, we recommend calling
## rstan_options(auto_write = TRUE)
```

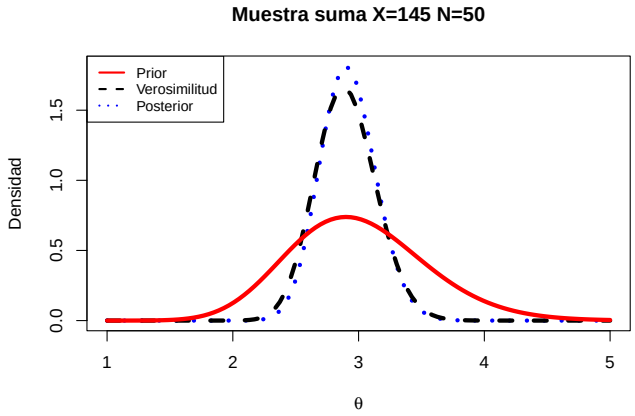
Simular datos

```
N = 50   # tamaño de muestra
theta = 3   # parametro de media
a0 = 30; b0 = 10 # hiperparametros de la distribucion inicial

set.seed(12345)
x = rpois(N,theta)   # x ~ Poisson(theta)
barplot(table(x), nclass=10, col="darkgreen")
```

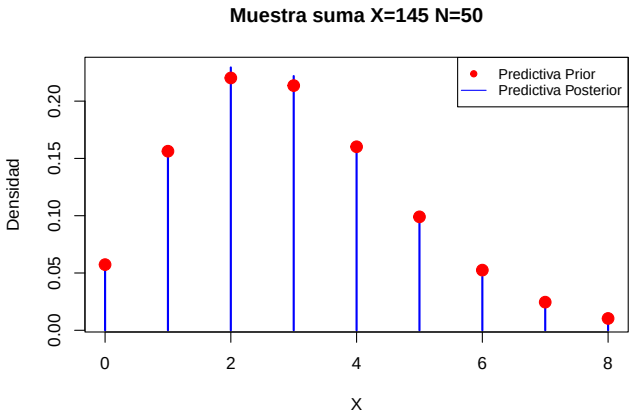


Graficas de las distribuciones final y predictiva final

```
### Posterior
a1 = a0+sum(x)
b1 = b0+N
the0 = seq(quantile(x,0.1),quantile(x,0.9),length.out=100)
plot(the0,  dgamma(the0,a1,b1), main=paste0("Muestra suma X=",sum(x)," N=",N),
     xlab=expression(theta), ylab="Densidad", lty=3, lwd=4, col="blue", type="l")
lines(the0, dgamma(the0,sum(x),N), lty=2, lwd=4)
lines(the0,dgamma(the0,a0,b0), lty=1, lwd=4,  col="red")
legend("topleft", legend=c("Prior","Verosimilitud","Posterior"),
       lty=c(1,2,3), col=c("red","black","blue"), lwd=2, cex=0.8)
```




```
### Predictiva  Prior & Posterior
x0 = (0:max(x))
plot(x0,dgpois(x0, a1, b1), main=paste0("Muestra suma X=",sum(x), " N=",N),
     xlab="X", ylab="Densidad", type="h", lwd=2, col="blue")
points(x0,dgpois(x0, a0, b0), col="red", pch=19, cex=1.5)
legend("topright", legend=c("Predictiva Prior","Predictiva Posterior"),
       lty=c(NA,1), col=c("red","blue"), pch=c(19,NA), cex=0.8)
```



Código Stan

```
datos <- list( "x"=x, "N"=N,  # muestra
               "a0"=a0,"b0"=b0)  # valores iniciales de la distribucion inicial
param  = c("theta","x_star") # parametros a estimar
fit_dist <- stan("dist_poisson_gamma.stan", data=datos,
            chains=2, warmup=1000, iter=2000, thin=2)
```

```
SAMPLING FOR MODEL 'dist_poisson_gamma' NOW (CHAIN 1).
Chain 1:
Chain 1: Gradient evaluation took 1.4e-05 seconds
Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0.14 seconds.
Chain 1: Adjust your expectations accordingly!
Chain 1:
Chain 1:
Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
Chain 1:
Chain 1:  Elapsed Time: 0.009714 seconds (Warm-up)
Chain 1:                0.009257 seconds (Sampling)
Chain 1:                0.018971 seconds (Total)
Chain 1:

SAMPLING FOR MODEL 'dist_poisson_gamma' NOW (CHAIN 2).
Chain 2:
Chain 2: Gradient evaluation took 3e-06 seconds
Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0.03 seconds.
Chain 2: Adjust your expectations accordingly!
```

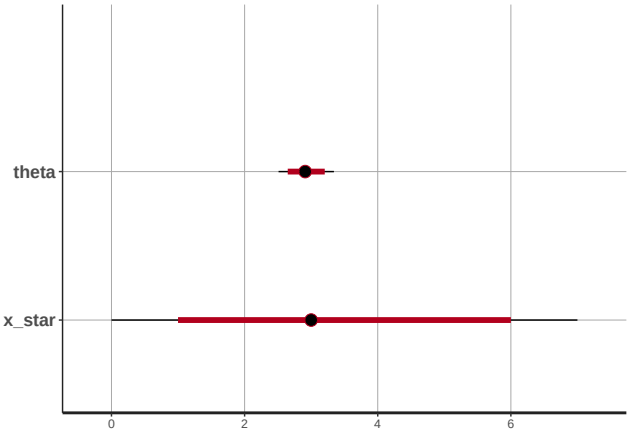
```
Chain 2:
Chain 2:
Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
Chain 2:
Chain 2:  Elapsed Time: 0.009798 seconds (Warm-up)
Chain 2:                0.009023 seconds (Sampling)
Chain 2:                0.018821 seconds (Total)
Chain 2:
```

Resultados

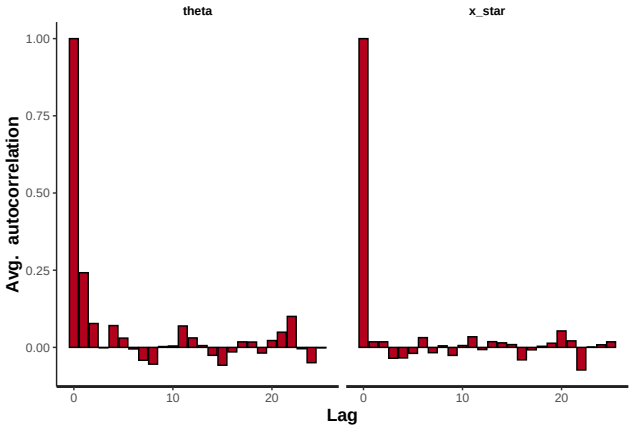
```
print(fit_dist, pars=param)
```

```
Inference for Stan model: dist_poisson_gamma.
2 chains, each with iter=2000; warmup=1000; thin=2;
post-warmup draws per chain=500, total post-warmup draws=1000.

       mean se_mean   sd 2.5%  25%  50%  75% 97.5% n_eff Rhat
theta  2.92    0.01 0.22 2.51 2.78 2.91 3.07  3.34   551    1
x_star 3.07    0.06 1.81 0.00 2.00 3.00 4.00  7.00   968    1

Samples were drawn using NUTS(diag_e) at Wed Apr 23 12:32:55 2025.
For each parameter, n_eff is a crude measure of effective sample size,
and Rhat is the potential scale reduction factor on split chains (at
convergence, Rhat=1).
```

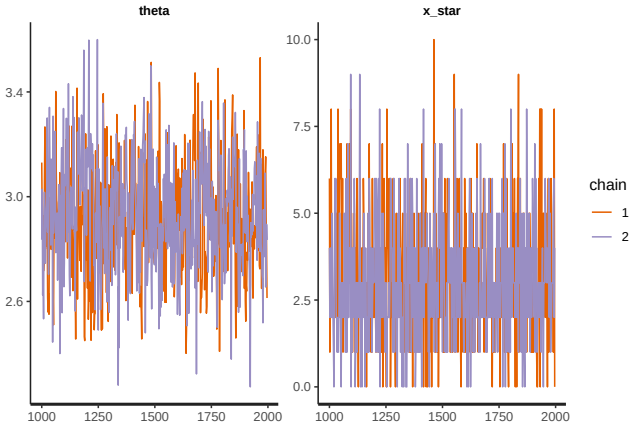
```
stan_plot(fit_dist,pars=param)
```



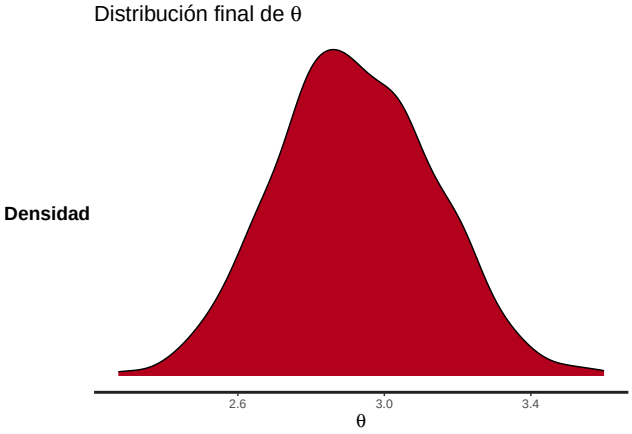
```
stan_ac(fit_dist,pars=param)
```




```
stan_trace(fit_dist,pars=param)
```




```
stan_dens(fit_dist,pars="theta", point_est = "mean", show_density = TRUE) +
  ggtitle(expression(paste("Distribución final de ",theta))) +
  ylab("Densidad") + xlab(expression(theta)) +
  theme(axis.title.x=element_text(size=14), axis.title.y=element_text(size=14),
        plot.title = element_text(size=16))
```



```
stan_hist(fit_dist,pars="x_star", point_est = "mean", show_density = TRUE) +
  ggtitle(expression(paste("Distribución predictiva final de ",x^{star}))) +
    ylab("Densidad") + xlab(expression(x^{star})) +
  theme(axis.title.x=element_text(size=14), axis.title.y=element_text(size=14),
        plot.title = element_text(size=16))
```