



UNAM
POSGRADO

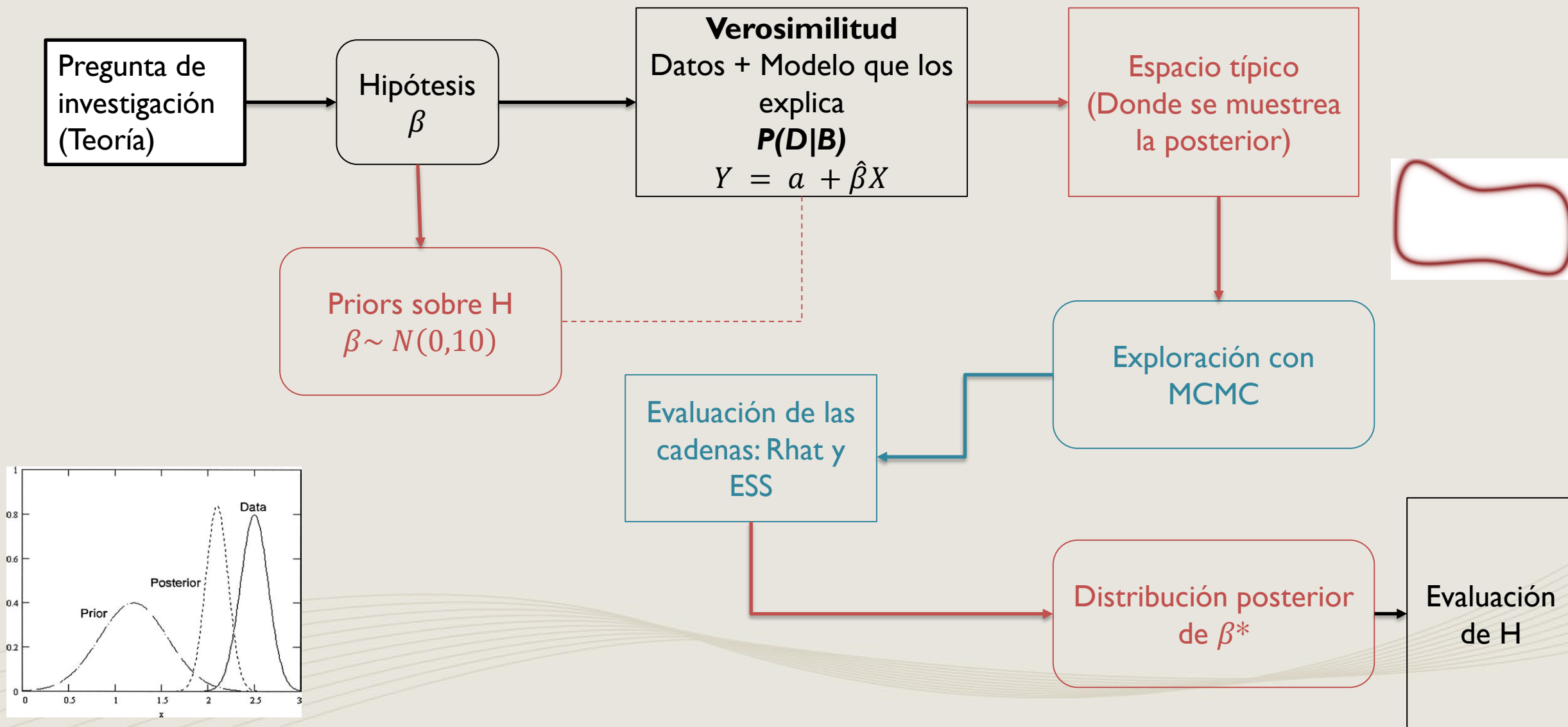


Programa
Universitario
de Estudios
del Desarrollo
UNAM

Clase I I: Estimación en R-Stan

Dr. Héctor Nájera
Dr. Curtis Huffman

Pasos en inferencia bayesiana



Stan: Diferentes plataformas



RStan

The R interface to Stan

Stan está escrito
en C++

Programas

rstan

PyStan

Stan.jl

CmdStan

Rstan (crudo)

rstan
(interfaces
para rstan)

rstanarm

rethinking

brms

cmdstanr

Tidybayes

bayesplot

Avanzado: mayor potencia y flexibilidad

Intermedio: menor flexibilidad

Intermediarios: brms y rstanarm

Además brms conecta con cmdstanr y puede ser multicore y multithread –y ahora se puede usar con las tarjetas gráficas- dentro de cada cadena!

Noten las combinaciones posibles:

- Modelo espacio/temporal (AR y CAR) inflado de ceros!!!!

brms offers more modeling capabilities, flexibility with priors, and more³

	brms	rstanarm
Supported model types:		
Linear models	yes	yes
Robust linear models	yes	yes ¹
Binomial models	yes	yes
Categorical models	yes	no
Multinomial models	no	no
Count data models	yes	yes
Survival models	yes ²	yes
Ordinal models	various	cumulative ³
Zero-inflated and hurdle models	yes	no
Generalized additive models	yes	yes
Non-linear models	yes	no
Additional modeling options:		
Variable link functions	various	various
Weights	yes	yes
Offset	yes	yes
Multivariate responses	limited	no
Autocorrelation effects	yes	no
Category specific effects	yes	no
Standard errors for meta-analysis	yes	no
Censored data	yes	no
Truncated data	yes	no
Customized covariances	yes	no
Missing value imputation	no	no
Bayesian specifics:		
parallelization	yes	yes
population-level priors	flexible	normal, Student-t
group-level priors	normal	normal
covariance priors	flexible	restricted ⁵
Other:		
Estimator	HMC, NUTS	HMC, NUTS
Information criterion	WAIC, LOO	AIC, LOO
C++ compiler required	yes	no
Modularized	no	no

Spatial models

Si no se puede hay que usar rstan

¿Intermediario?

- Brms:

```
MI.I<-brm(ins_ali_mo_3 ~ ed_jefe_2 + ed_jefe_3 + ed_jefe_4 + ed_jefe_5
+ sexo_jefe_1 + edad_jefe + niv_ed_prom + tv + compu +
refri + lavad + tvpaga + hablaind + tinaco + internet + tot_integ +
salario_mun +
i_nolav + i_nostvp + i_noref + salario_ent + rural + (1|id_mun) +
(1|clave_ent),
data=DI, family = bernoulli(),
prior = c(set_prior("normal(0,1)", class = "b"),
set_prior("normal(0,5)", class= "sd")),
warmup = 400, iter = 1800, control = list(adapt_delta = .96),
chains = 2, cores=14, threads = threading(14, grainsize = 100),backend =
"cmdstanr")
```

STAN:

```
functions {
  /* integer sequence of values
  * Args:
  * start: starting integer
  * end: ending integer
  * Returns:
  * an integer sequence from start to end
  */
  int[] sequence(int start, int end) {
    int seq[end - start + 1];
    for (n in 1:num_elements(seq)) {
      seq[n] = n + start - 1;
    }
    return seq;
  }
  // compute partial sums of the log-likelihood
  real partial_log_lik_lpmf(int[] seq, int start, int end, data int[] Y, data matrix Xc, vector b, real Intercept, data int[] J_1, data vector
  Z_1_1, vector r_1_1, data int[] J_2, data vector Z_2_1, vector r_2_1) {
    real ptarget = 0;
    int N = end - start + 1;
    // initialize linear predictor term
    vector[N] mu = Intercept + rep_vector(0.0, N);
    for (n in 1:N) {
      // add more terms to the linear predictor
      int nn = n + start - 1;
      mu[nn] += r_1_1[J_1[nn]] * Z_1_1[nn] + r_2_1[J_2[nn]] * Z_2_1[nn];
    }
    ptarget += bernoulli_logit_glm_lpmf(Y[start:end] | Xc[start:end], mu, b);
    return ptarget;
  }
}
data {
  int<lower=1> N; // total number of observations
  int Y[N]; // response variable
  int<lower=1> K; // number of population-level effects
  matrix[N, K] X; // population-level design matrix
  int grainsize; // grainsize for threading
  // data for group-level effects of ID 1
  int<lower=1> N_1; // number of grouping levels
  int<lower=1> M_1; // number of coefficients per level
  int<lower=1> J_1[N]; // grouping indicator per observation
```



STAN Cont.

```
• STAN
• // group-level predictor values
• vector[N] Z_1_1;
• // data for group-level effects of ID 2
• int<lower=1> N_2; // number of grouping levels
• int<lower=1> M_2; // number of coefficients per level
• int<lower=1> J_2[N]; // grouping indicator per observation
• // group-level predictor values
• vector[N] Z_2_1;
• int prior_only; // should the likelihood be ignored?
• }
• transformed data {
•   int Kc = K - 1;
•   matrix[N, Kc] Xc; // centered version of X without an intercept
•   vector[Kc] means_X; // column means of X before centering
•   int seq[N] = sequence(1, N);
•   for (i in 2:K) {
•     means_X[i - 1] = mean(X[, i]);
•     Xc[, i - 1] = X[, i] - means_X[i - 1];
•   }
• }
• parameters {
•   vector[Kc] b; // population-level effects
•   real Intercept; // temporary intercept for centered predictors
•   vector<lower=0>[M_1] sd_1; // group-level standard deviations
•   vector[N_1] z_1[M_1]; // standardized group-level effects
•   vector<lower=0>[M_2] sd_2; // group-level standard deviations
•   vector[N_2] z_2[M_2]; // standardized group-level effects
• }
• transformed parameters {
•   vector[N_1] r_1_1; // actual group-level effects
•   vector[N_2] r_2_1; // actual group-level effects
•   r_1_1 = (sd_1[1] * (z_1[1]));
•   r_2_1 = (sd_2[1] * (z_2[1]));
• }
• model {
•   // likelihood including constants
•   if (!prior_only) {
•     target += reduce_sum(partial_log_lik_lpmf, seq, grainsize, Y, Xc, b, Intercept, J_1, Z_1_1, r_1_1, J_2, Z_2_1, r_2_1);
•   }
•   // priors including constants
•   target += normal_lpdf(b | 0, 1);
•   target += student_t_lpdf(Intercept | 3, 0, 2.5);
•   target += normal_lpdf(sd_1 | 0, 5)
```




Estructura de modelo bayesiano

Estructura de un modelo Bayesiano:

$\text{outcome}_i \sim \text{Normal}(\mu_i, \sigma)$
 $\mu_i = \beta \times \text{predictor}_i$
 $\beta \sim \text{Normal}(0, 10)$
 $\sigma \sim \text{HalfCauchy}(0, 1)$

$D_i \sim \text{Normal}(\mu_i, \sigma)$
 $\mu_i = \alpha + \beta_A A_i$
 $\alpha \sim \text{Normal}(10, 10)$
 $\beta_A \sim \text{Normal}(0, 1)$
 $\sigma \sim \text{Uniform}(0, 10)$

$D_i \sim \text{Normal}(\mu_i, \sigma)$	[likelihood]
$\mu_i = \alpha + \beta_R R_i + \beta_A A_i$	[linear model]
$\alpha \sim \text{Normal}(10, 10)$	[prior for α]
$\beta_R \sim \text{Normal}(0, 1)$	[prior for β_R]
$\beta_A \sim \text{Normal}(0, 1)$	[prior for β_A]
$\sigma \sim \text{Uniform}(0, 10)$	[prior for σ]

<https://mc-stan.org/docs/stan-users-guide/linear-regression.html>

Pasos para la modelación



RStan

The R interface to Stan

- Programa: R + Rstudio
- Algoritmo HMC: Rstan
- Interface: brms + cmdstan



CmdStanR



Paso I

- Instalar (asegurarse) R version 4 o superior:

<https://cran.r-project.org/bin/windows/base/>



Paso 2

- Instalar Rstudio

<https://www.rstudio.com/products/rstudio/download/#download>



- Instalar Rtools 4.0 o superior

<https://cran.r-project.org/bin/windows/Rtools/>



Paso 4

- Instalar Rstan

Seguir estos pasos

<https://github.com/stan-dev/rstan/wiki/RStan-Getting-Started>

Asegurarse que el ejemplo “corre”





Paso 5

- Instalar en Rstudio

Brms, tidybayes, bayesplot, posterior, tidyverse



Paso 6

- Instalar cmdstanr –mayor rapidez-

<https://mc-stan.org/cmdstanr/>



Introducción –refrescando- R Software

- Algunas guías
 - https://www.youtube.com/watch?v=_V8eKsto3Ug