

# INTRODUCCIÓN A LA INFERENCIA BAYESIANA CON R

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# Instalación OpenBugs

 [www.openbugs.net/w/Downloads](http://www.openbugs.net/w/Downloads)

## Linux Download

### ■ Source package

Should be usable on any x86 (PC) Linux platform. On 64 bit Linux, the necessary 32-bit C development packages are required. Compilation has been successful on 64-bit Ubuntu using the g++-multilib package,

Download:  [OpenBUGS-3.2.3.tar.gz](http://www.openbugs.net/w/Downloads#source)

To install this, unpack by typing

```
tar zxvf OpenBUGS-3.2.3.tar.gz
cd OpenBUGS-3.2.3
```

then compile and install by typing

```
./configure
make
sudo make install
```

# Instalación JAGS

 <https://launchpad.net/ubuntu/+source/jags>

To install this, unpack by typing

```
tar zxvf OpenBUGS-3.2.3.tar.gz  
cd OpenBUGS-3.2.3
```

then compile and install by typing

```
./configure  
make  
sudo make install
```

# Instalación RSTAN

Dentro de Rstudio, en la consola de R:

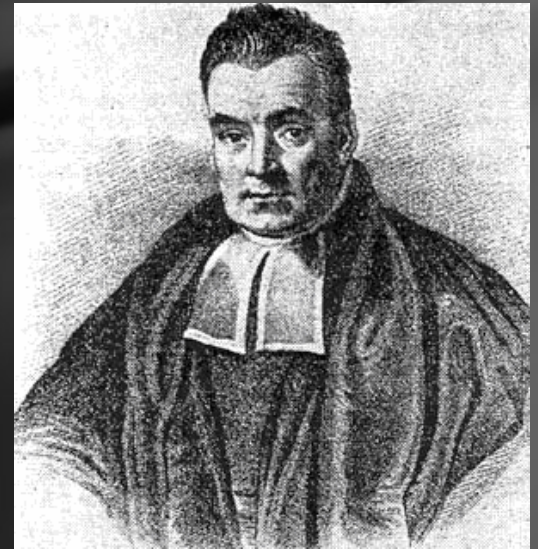
```
source('http://mc-stan.org/rstan/install.R', echo = TRUE, max.deparse.length = 2000)  
install_rstan()
```

# Índice

- Teorema de Bayes. Inferencia Bayesiana
- Posterior y Prior Conjugados
- MCMC
  - BUGS
  - JAGS
  - STAN
  - MCMCPACK
- Diagnósis de Convergencia

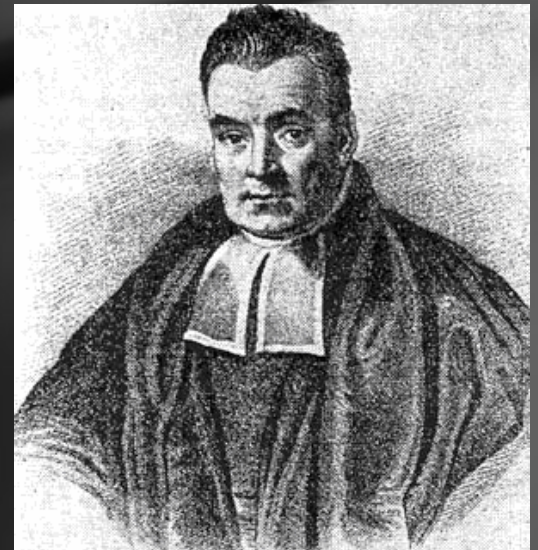
# El Origen

Un matemático visita a Bayes con dos gemelos recién nacidos



# El Origen

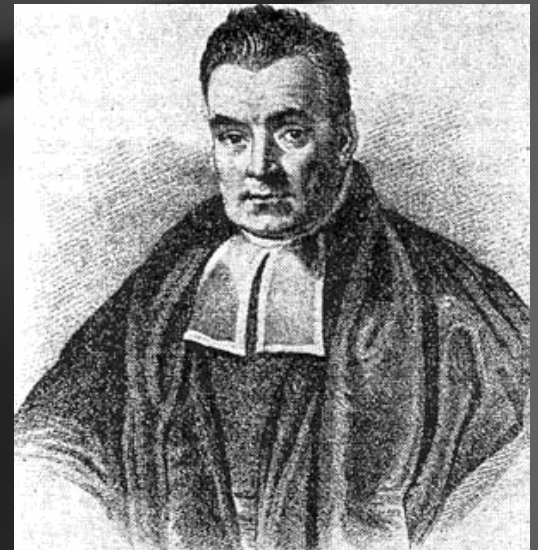
¿Vienes a bautizar a los gemelos?





# El Origen

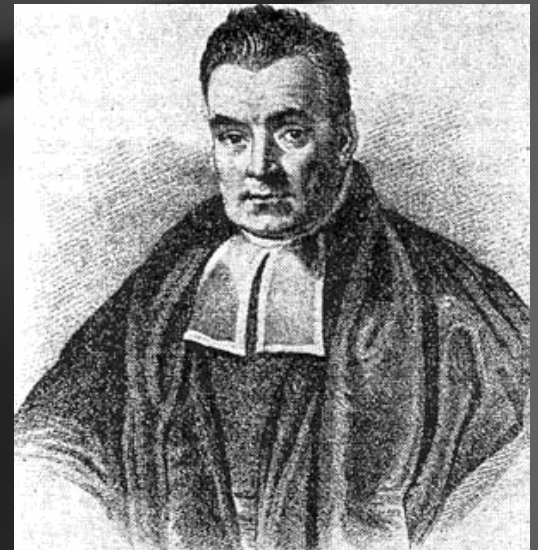
No, sólo quiero bautizar a uno.  
El otro servirá como grupo de control.  
Cuando sean mayores les haré un test,  
calcularé el p-valor y ...





# El Origen

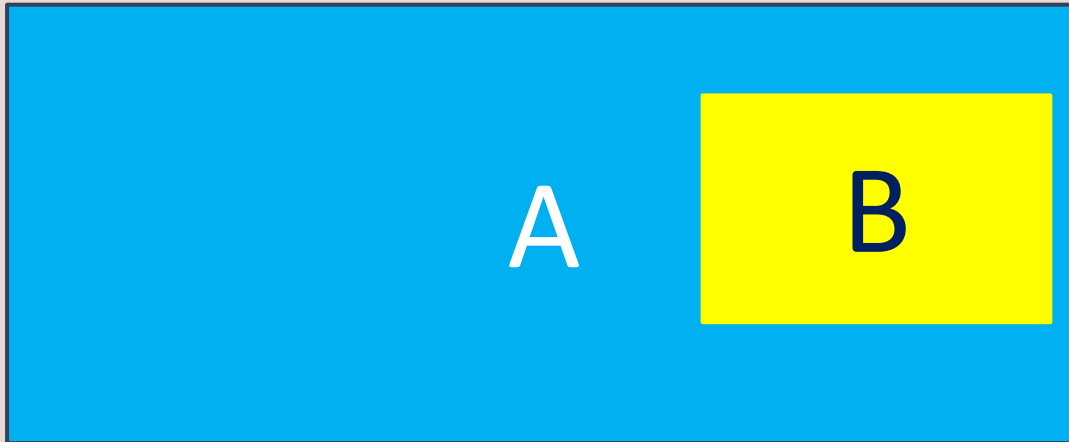
Me @#\*% en los p valores ...



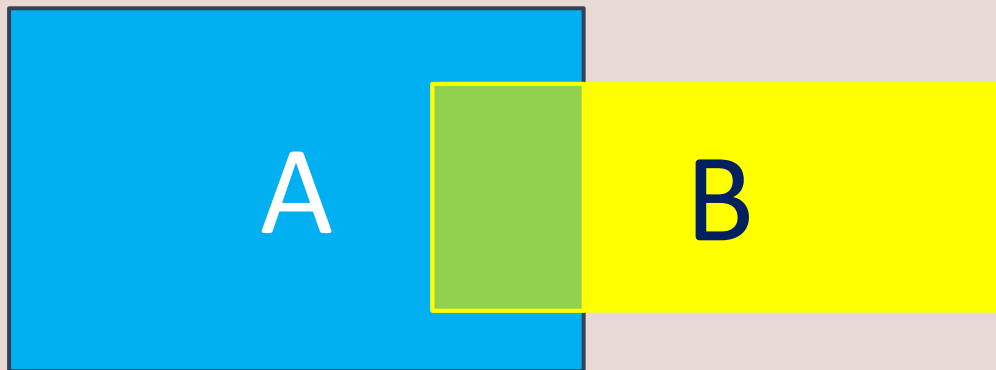
# Probabilidades Condicionadas



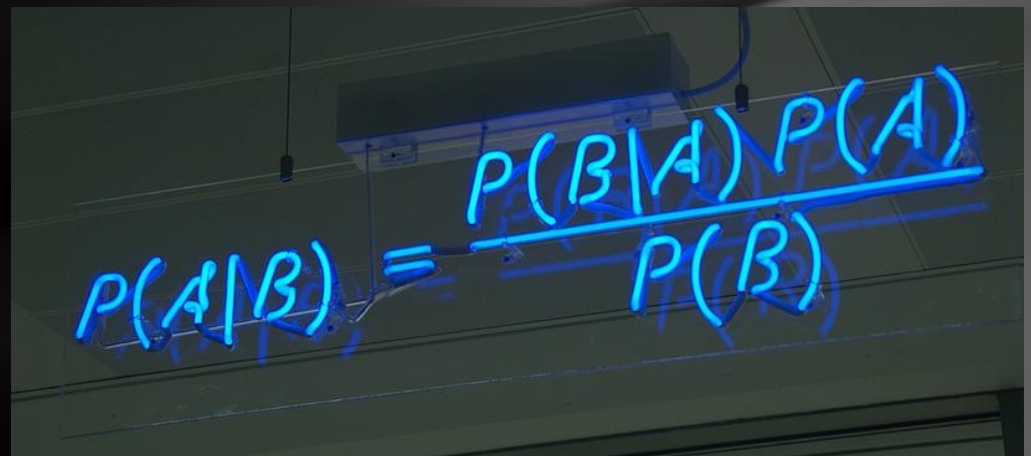
# Probabilidades Condicionadas



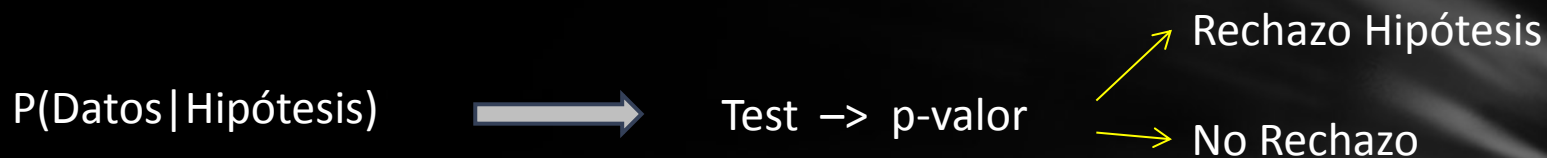
# Probabilidades Condicionadas



# Teorema de Bayes



# Inferencia Frecuentista vs Bayesiana



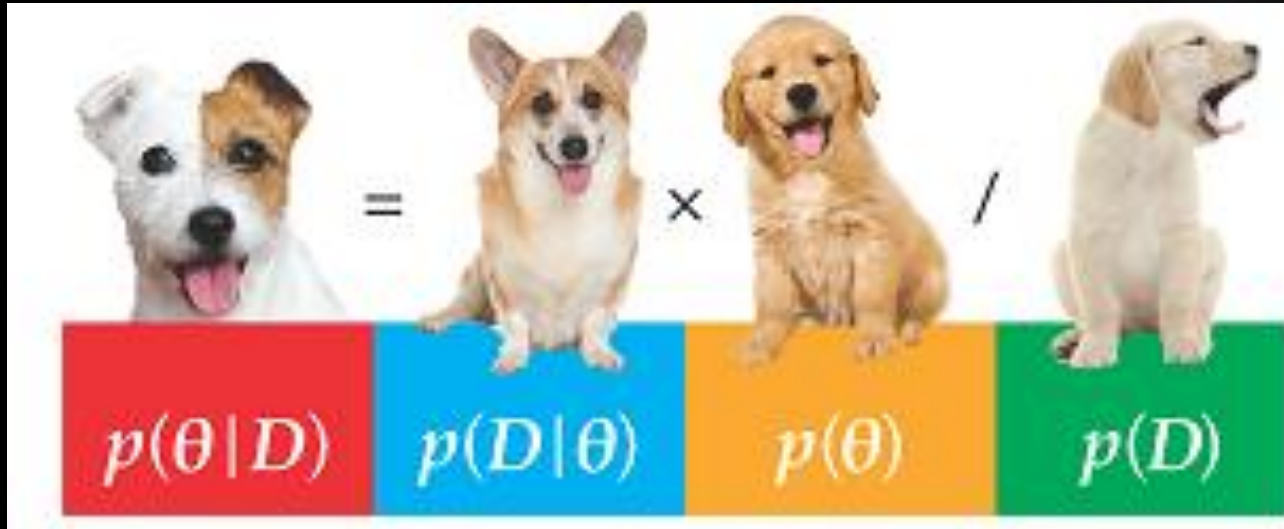
$$P(\text{Hipótesis} | \text{Datos}) = \frac{P(\text{Datos} | \text{Hipótesis}) \times P(\text{Hipótesis})}{P(\text{Datos})}$$

$$P(\text{Hipótesis} | \text{Datos}) \rightarrow P(\text{Datos} | \text{Hipótesis}) \times P(\text{Hipótesis})$$

$$\text{Posterior} \rightarrow \text{Verosimilitud} \times \text{Priori}$$

$$\text{Creencia después Datos} \rightarrow \text{Datos} \times \text{Creencia antes Datos}$$

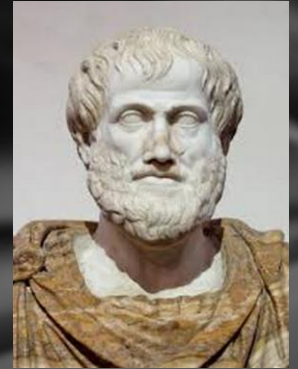
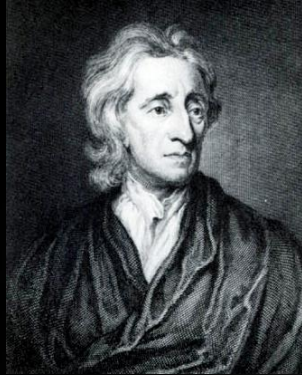
# Inferencia Bayesiana



Portada del próximo libro de Kruschke que saldrá en noviembre de 2014



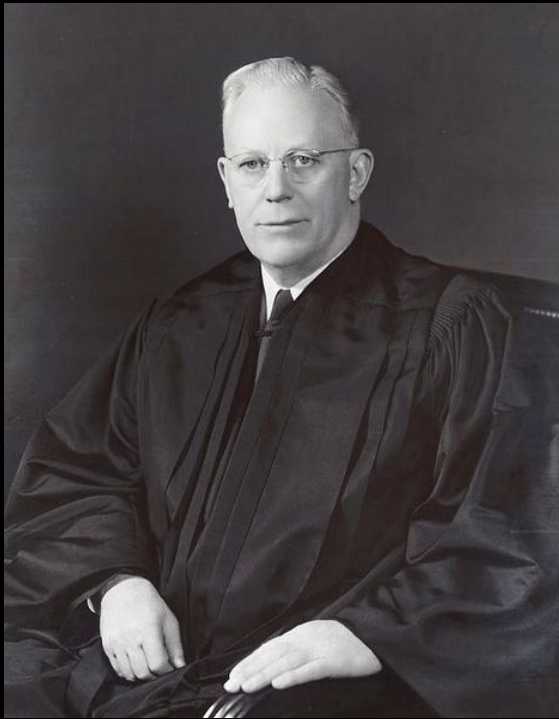
# Inducción - Deducción



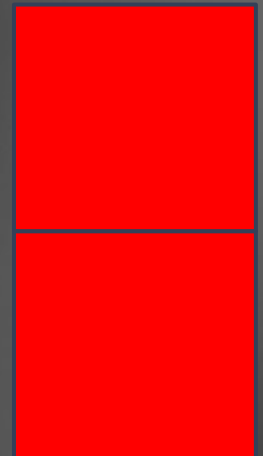
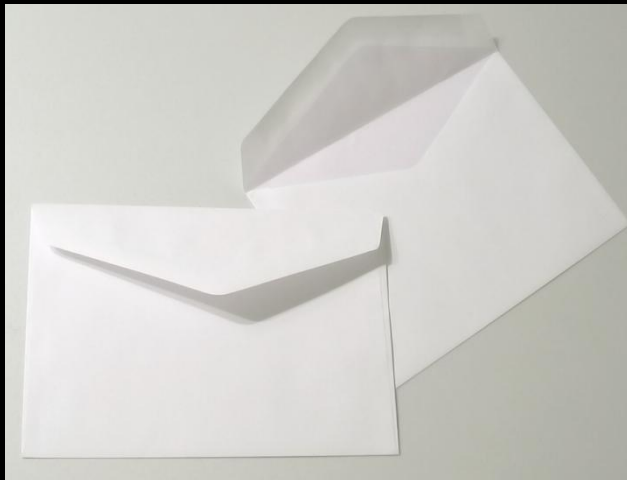
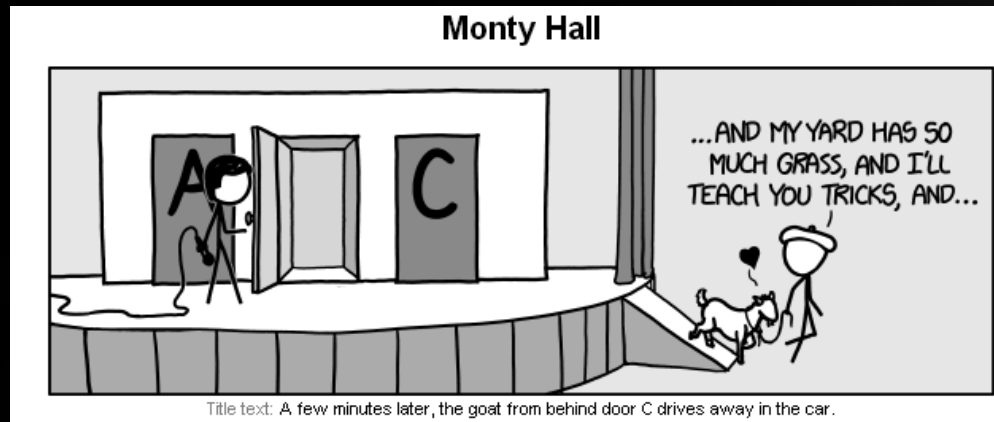
# Regla de Cromwell



# Earl Warren. Gobernador de California



# Monty Hall – Paradoja de los dos sobres – Tres cartas





# Teorema de Bayes

LET'S SEE...  
WE DID IT 5 TIMES THIS PAST MONTH.  
YOU COUNTED?!

SO THAT MEANS I HAVE A  $16.\bar{6}\%$  CHANCE OF HAVING SEX TONIGHT.  
YOU'RE FORGETTING ABOUT BAYESIAN INFERENCE.

LET "A" BE THE EVENT THAT YOU GET LAID. LET "B" BE THE EVENT THAT YOU COMPLIMENT HER EYES.  
OUT OF THE FIVE TIMES YOU GOT LAID, HOW MANY TIMES DID YOU COMPLIMENT HER EYES?

HMM...  
FROM THOSE 5 TIMES, I COMPLIMENTED HER EYES 3 TIMES.  
BUT I COMPLIMENT HER EYES ONCE A WEEK.

SO...  
 $P(B|A) = 3/5$   
 $P(A) = 5/30$   
 $P(B) = 4/30$   
THUS,  
$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$
  
$$= 3/4$$

SO, GIVEN THAT YOU COMPLIMENT HER EYES, YOU HAVE A 75% CHANCE OF GETTING SEX TONIGHT.

SWEET!  
BAYESIAN INFERENCE IS GETTING ME SEX TONIGHT!

PROBABLY.

spikedmath.com  
© 2010

# XKCD

< PREV COMIC #1132 (NOVEMBER 9, 2012) NEXT >

## Frequentists vs. Bayesians

**DID THE SUN JUST EXPLODE?**  
(IT'S NIGHT, SO WE'RE NOT SURE.)

THIS NEUTRINO DETECTOR MEASURES WHETHER THE SUN HAS GONE NOVA.

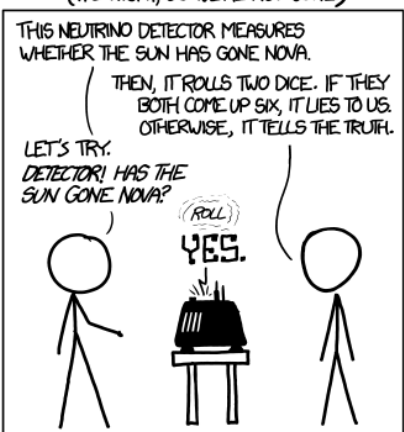
THEN, IT ROLLS TWO DICE. IF THEY BOTH COME UP SIX, IT LIES TO US. OTHERWISE, IT TELLS THE TRUTH.

LET'S TRY.  
DETECTOR! HAS THE SUN GONE NOVA?

ROLL  
YES.

**FREQUENTIST STATISTICIAN:**  
THE PROBABILITY OF THIS RESULT HAPPENING BY CHANCE IS  $\frac{1}{36} = 0.027$ .  
SINCE  $p < 0.05$ , I CONCLUDE THAT THE SUN HAS EXPLODED.

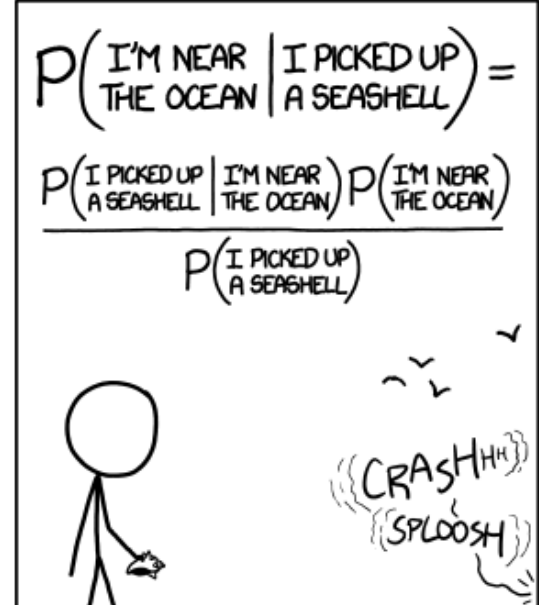
**BAYESIAN STATISTICIAN:**  
BET YOU \$50 IT HASN'T.



The comic shows two stick figures standing next to a neutrino detector. One figure asks the detector if the sun has exploded. The detector rolls two dice and says 'YES.' The frequentist statistician then calculates the probability of this result happening by chance and concludes that the sun has exploded because the p-value is less than 0.05. The Bayesian statistician, on the other hand, bets \$50 that the sun has not exploded.

## SEASHELL

< PREV RANDOM NEXT >

$$P(\text{I'M NEAR THE OCEAN} \mid \text{I PICKED UP A SEASHELL}) = \frac{P(\text{I PICKED UP A SEASHELL} \mid \text{I'M NEAR THE OCEAN}) P(\text{I'M NEAR THE OCEAN})}{P(\text{I PICKED UP A SEASHELL})}$$


STATISTICALLY SPEAKING, IF YOU PICK UP A SEASHELL AND DON'T HOLD IT TO YOUR EAR, YOU CAN PROBABLY HEAR THE OCEAN.

The comic features a stick figure holding a seashell. Above the figure, there are sound effects 'CRASHHH' and 'SPLOOSH' with arrows pointing towards the figure, suggesting a crash and a splash. Below the figure, the text reads: 'STATISTICALLY SPEAKING, IF YOU PICK UP A SEASHELL AND DON'T HOLD IT TO YOUR EAR, YOU CAN PROBABLY HEAR THE OCEAN.'

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# Stanislaw (Stan) Ulam

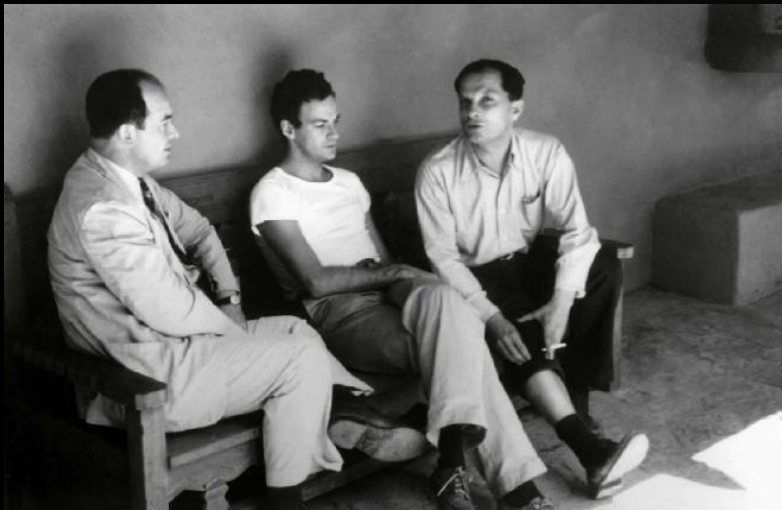
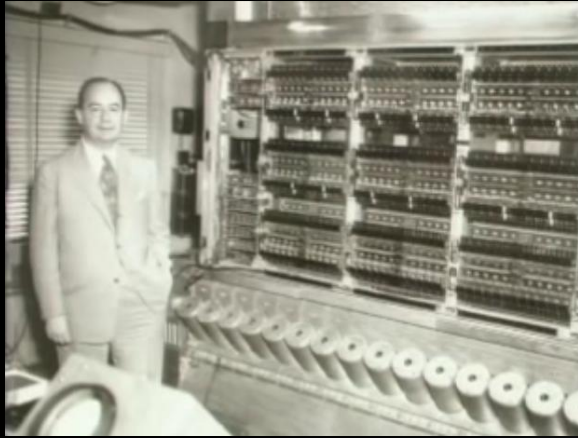
*Once in my life I had a mathematical dream which proved correct. I was twenty years old. I thought, my God, this is wonderful, I won't have to work, it will all come in dreams. But it never happened again. . .*



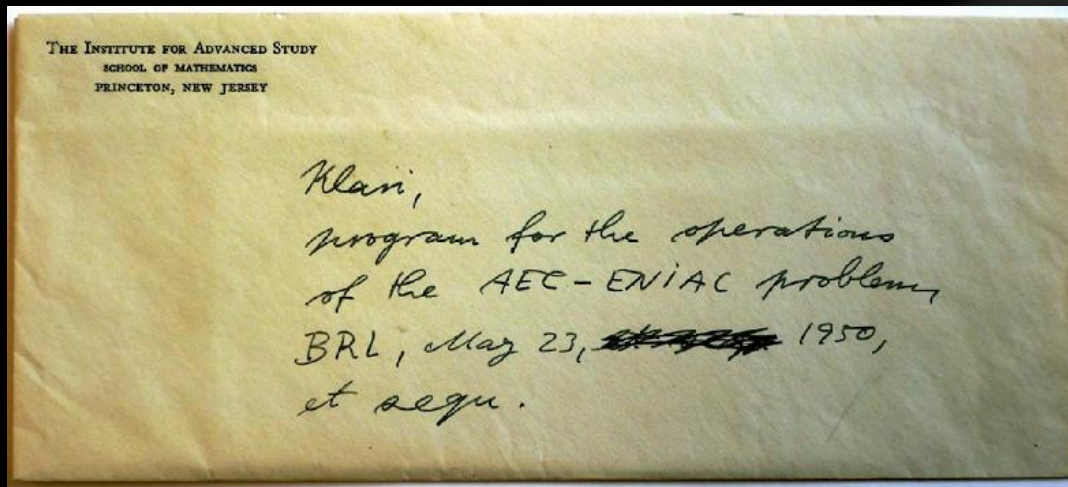
*All my father does is think, think, think . . .*

— Claire Ulam

# John von Neumann



# Klara von Neumann (Dan Eckart)



## WOMAN SCIENTIST REPORTED A SUICIDE

SAN DIEGO, Calif., Nov. 11 (UPI)—Coroner's deputies listed as probable suicide today the drowning of Mrs. Klara Dan Eckart, 52 years old, who helped develop the atomic bomb.

Authorities said that Mrs. Eckart, a native of Budapest, waded into the surf off San Diego yesterday.

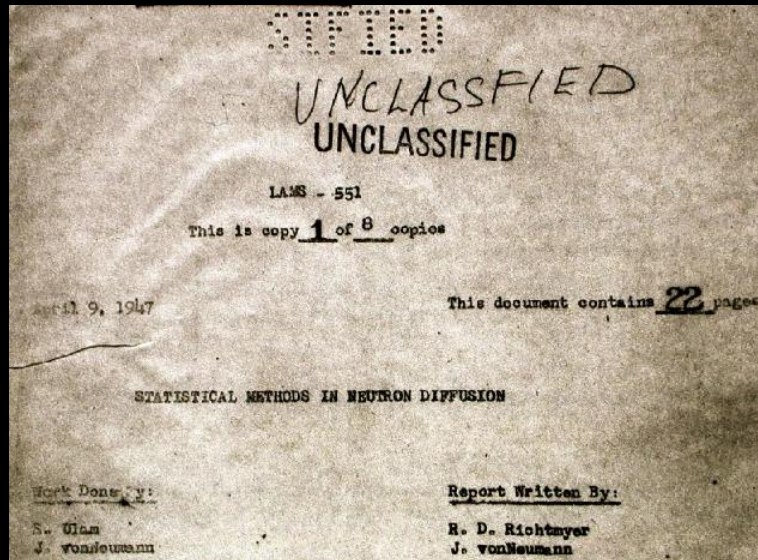
Mrs. Eckart was the widow of John Von Neumann and the wife of Dr. Carl H. Eckart, physics professor at the University of California at San Diego.

Dr. Von Neumann and Mrs. Eckart worked on theoretical problems at the Aberdeen, Md., Proving Grounds and at the Los Alamos, N. M., atomic laboratory in World War II.

Klara Dan Eckart's education did not extend beyond the standard secondary school of Europe. However, through diligent self-

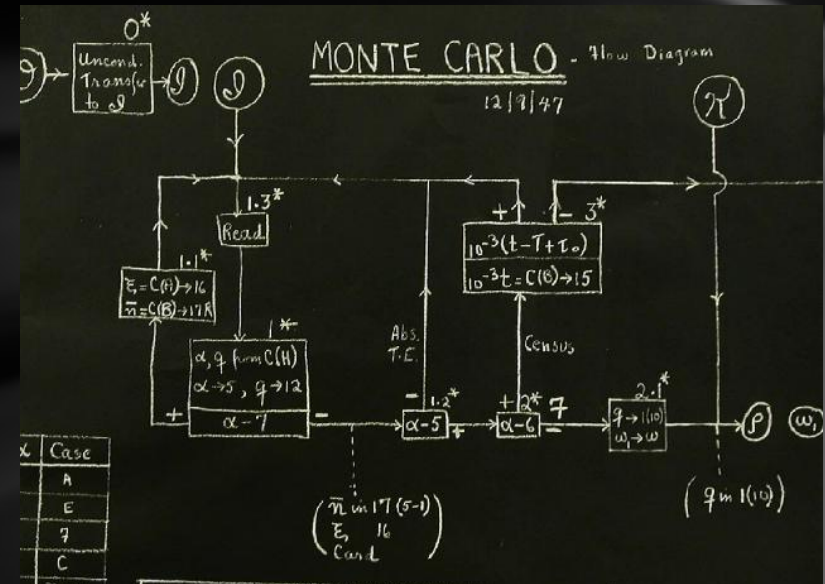



# Statistical Methods in Neutron Diffusion



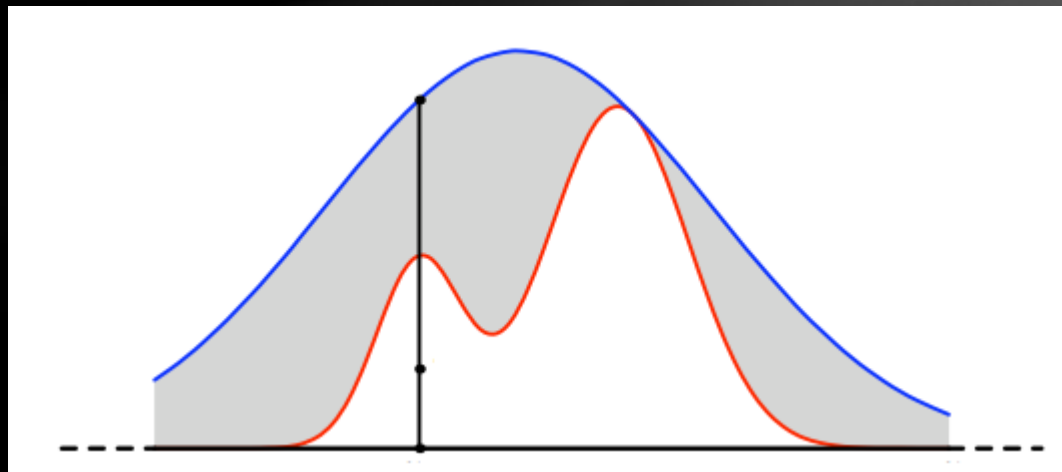
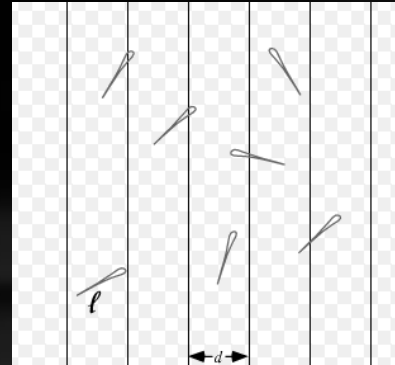
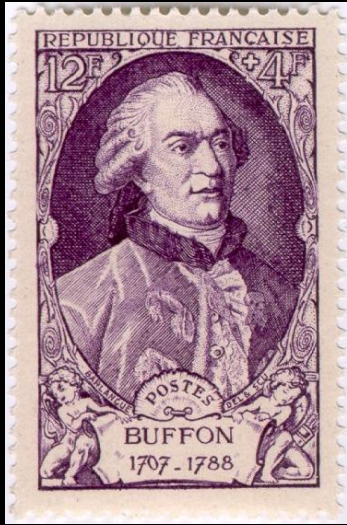
stop at (18, 8)

over to





# Aguja de Bufón - Método GRID





# Metropolis



Metropolis, Rosenbluth, Rosenbluth, Teller, and Teller (1953) Equations of State Calculations by Fast Computing Machines. *J. Chem. Phys.*, **21**, 1087–1092.

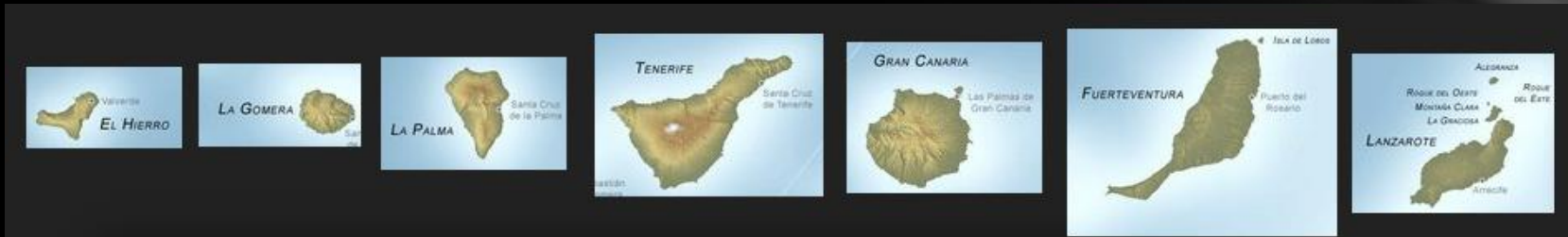


# Paseo Aleatorio por las Canarias

- Unos políticos quieren hacer campaña en las islas Canarias.
- Quieren dedicar a cada isla un tiempo proporcional a su población
- Sin embargo, estudiaron estadística en un par de tardes y no les dio tiempo a aprender a normalizar
- ¿Qué pueden hacer?

Idea de John Kruschke

# Paseo Aleatorio por las Canarias



# Paseo Aleatorio por las Canarias



Empezamos en una isla cualquiera. Por ejemplo: La Palma.



# Paseo Aleatorio por las Canarias



Elegimos al azar una de las islas adyacentes. Por ejemplo: Tenerife

La población de Tenerife es mayor que la de La Palma → Nos movemos a Tenerife

# Paseo Aleatorio por las Canarias



De nuevo, elegimos al azar una de las islas adyacentes.  
Por ejemplo: Gran Canaria

La población de Tenerife es mayor que la de Gran Canaria →

$$\frac{\text{Población de Gran Canaria}}{\text{Población de Tenerife}} = 0.9$$

# Paseo Aleatorio por las Canarias



Elegimos un número aleatorio entre 0 y 1  $\rightarrow$  0.7

Población de Gran Canaria

Población de Tenerife

$= 0.9 > 0.7 \rightarrow$  Nos movemos a Gran Canaria

# Paseo Aleatorio por las Canarias



Elegimos una isla adyacente al azar → Fuerteventura

De nuevo, la población de Gran Canaria es mayor que la de Fuerteventura →



# Paseo Aleatorio por las Canarias



Elegimos un número aleatorio entre 0 y 1  $\rightarrow$  0.4

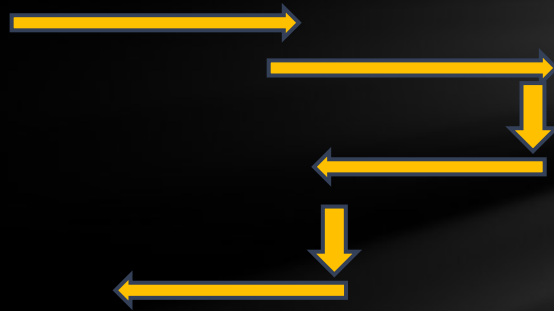
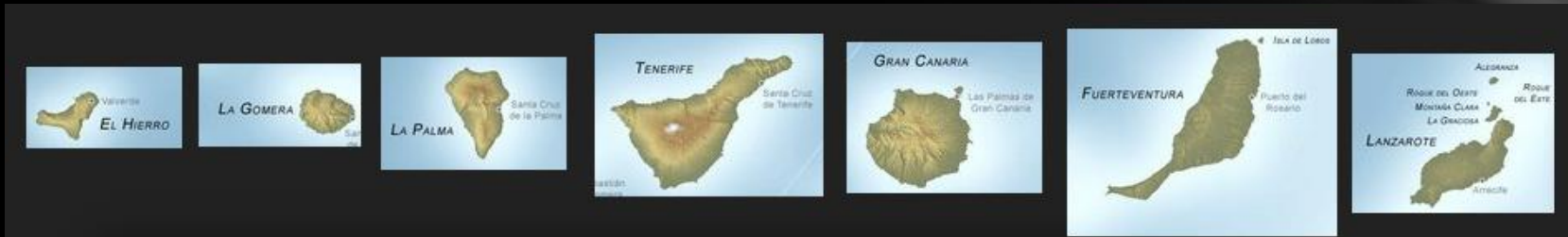
Población de Gran Canaria

Población de Tenerife

$= 0.9 > 0.7 \rightarrow$  Nos quedamos en Gran Canaria

¡Rechazamos el movimiento a Fuerteventura!

# Paseo Aleatorio por las Canarias



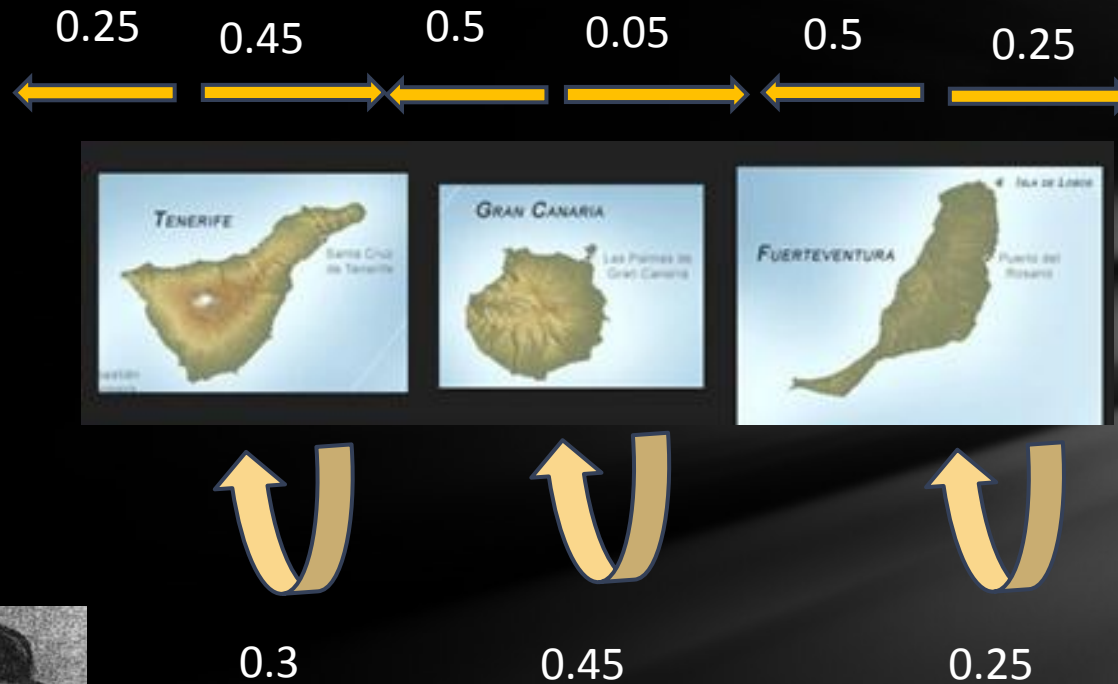
# Paseo Aleatorio por las Canarias



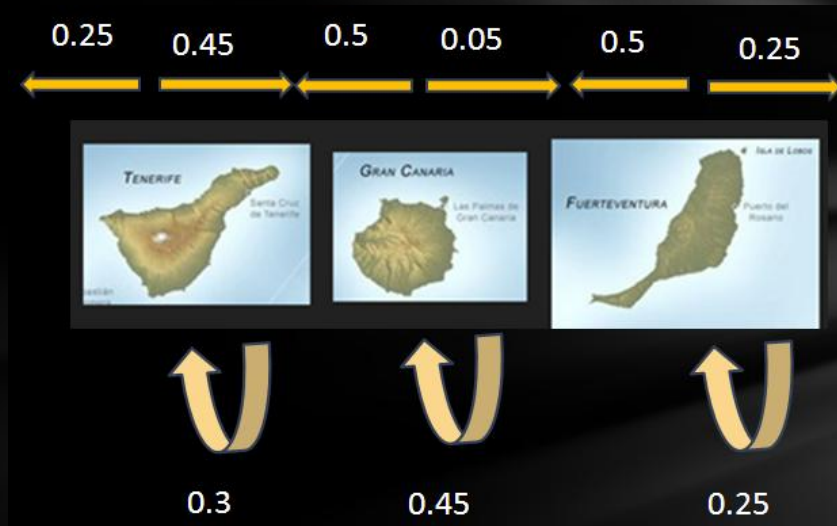
Si el paseo es lo suficientemente largo, al final el tiempo que pasan en cada isla es proporcional a su población relativa



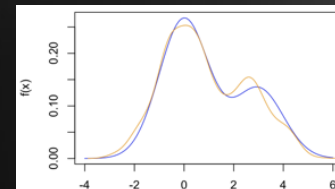
# Cadena de Markov



# Ergodicidad

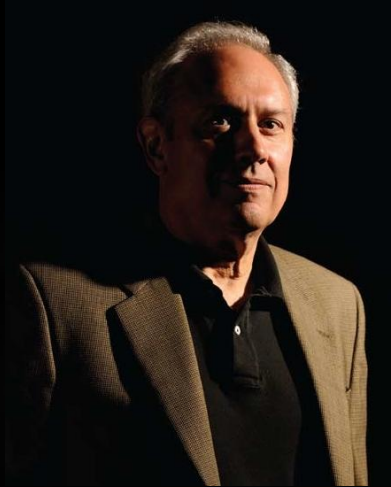
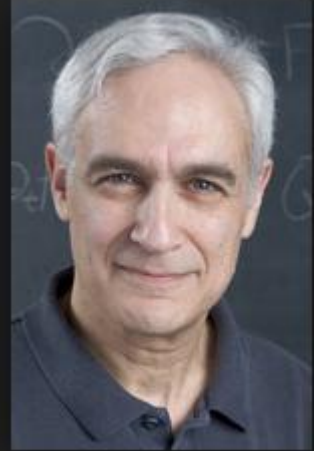


$$\frac{1}{n} \sum_{j=1}^n f \circ T^j(x) \rightarrow \int f \, d m$$

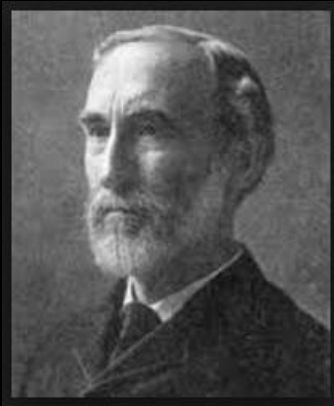




# Gibbs Sampling



Geman and Geman (1984) Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images. *IEEE Trans. Pattern Anal. Machine Intelligence*, 6, 721–741.\*



$$\begin{aligned}\theta_1^{(j)} &\sim \pi(\theta_1 | \theta_2^{(j-1)}, \theta_3^{(j-1)}, \dots, \theta_k^{(j-1)}) \\ \theta_2^{(j)} &\sim \pi(\theta_2 | \theta_1^{(j)}, \theta_3^{(j-1)}, \dots, \theta_k^{(j-1)}) \\ \theta_3^{(j)} &\sim \pi(\theta_3 | \theta_1^{(j)}, \theta_2^{(j)}, \theta_3^{(j-1)}, \dots, \theta_k^{(j-1)}) \\ &\vdots \\ \theta_k^{(j)} &\sim \pi(\theta_k | \theta_1^{(j)}, \theta_2^{(j)}, \dots, \theta_{k-1}^{(j)})\end{aligned}$$

## TOUR OF ACCOUNTING

OVER HERE  
WE HAVE OUR  
RANDOM NUMBER  
GENERATOR.



www.dilbert.com  
scottadamis@aol.com

NINE NINE  
NINE NINE  
NINE NINE



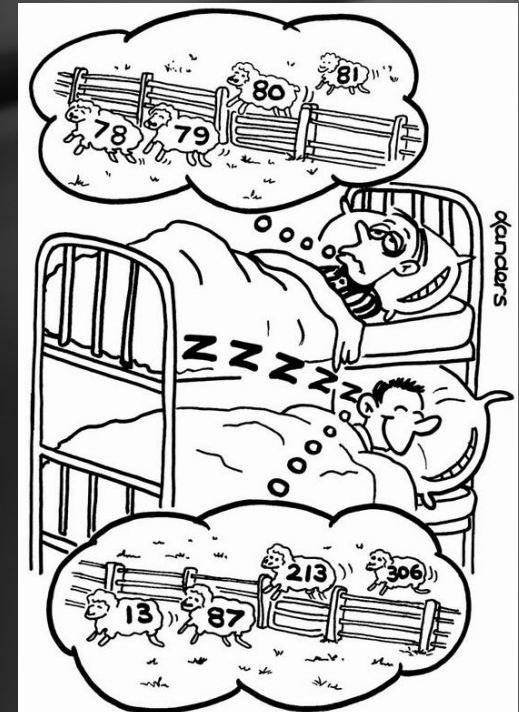
© 2001 United Feature Syndicate, Inc.

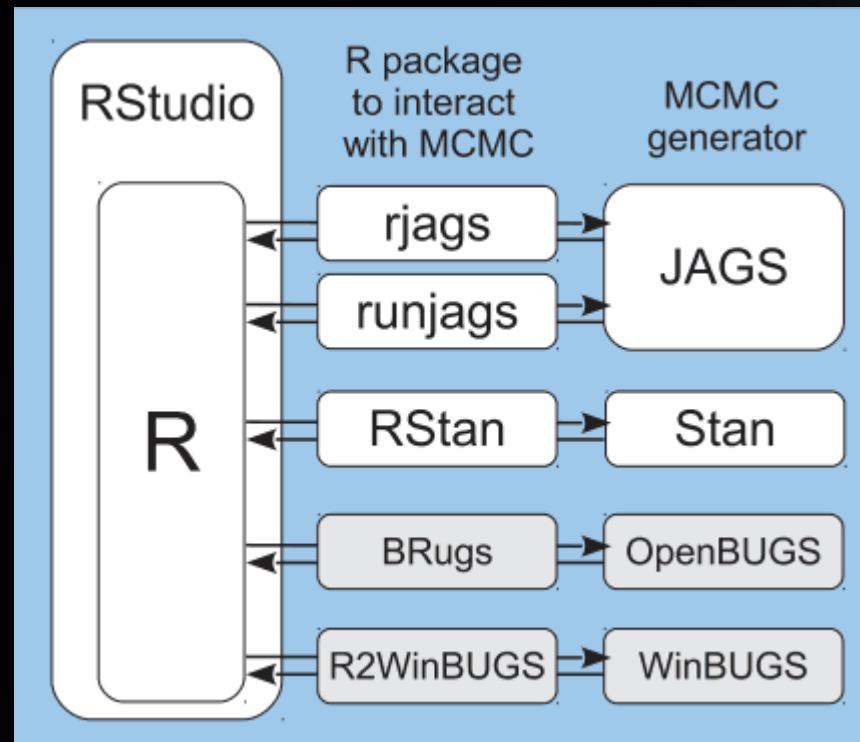
ARE  
YOU  
SURE  
THAT'S  
RANDOM?

THAT'S THE  
PROBLEM  
WITH RAN-  
DOMNESS:  
YOU CAN  
NEVER BE  
SURE.



```
int getRandomNumber()  
{  
    return 4; // chosen by fair dice roll.  
              // guaranteed to be random.  
}
```

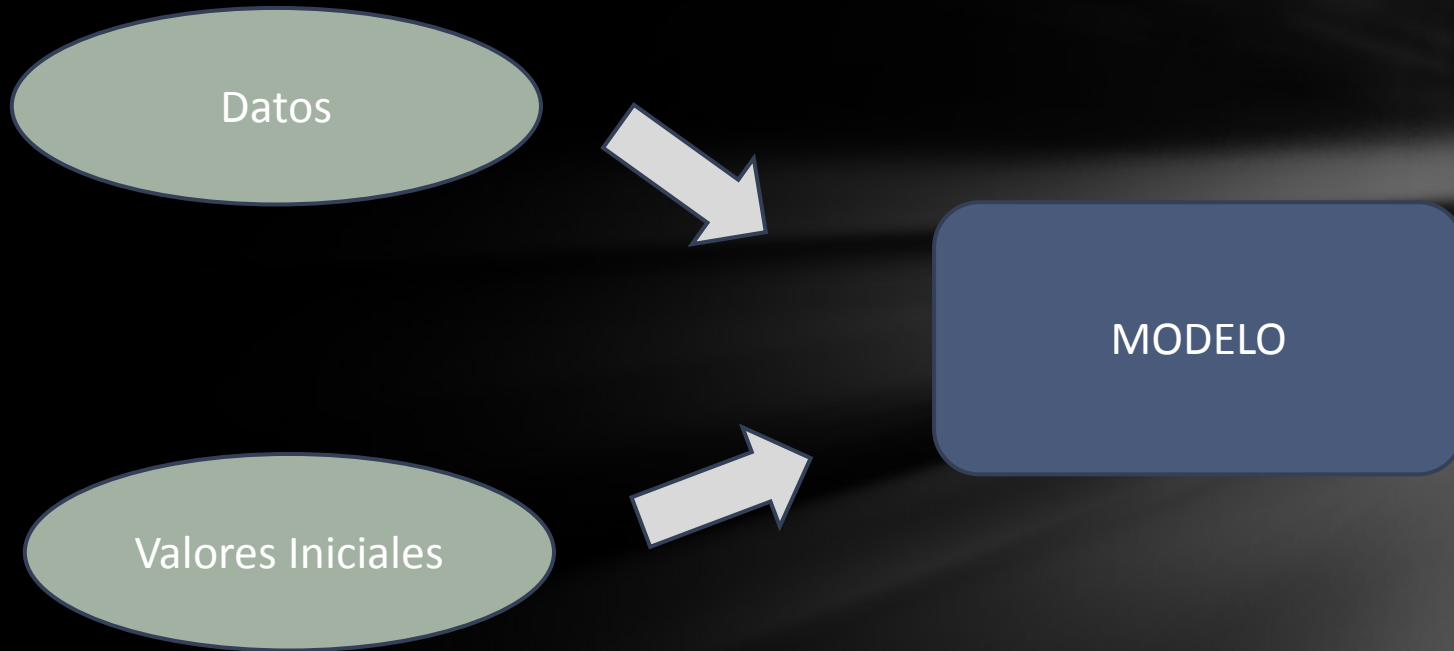




# BUGS - JAGS

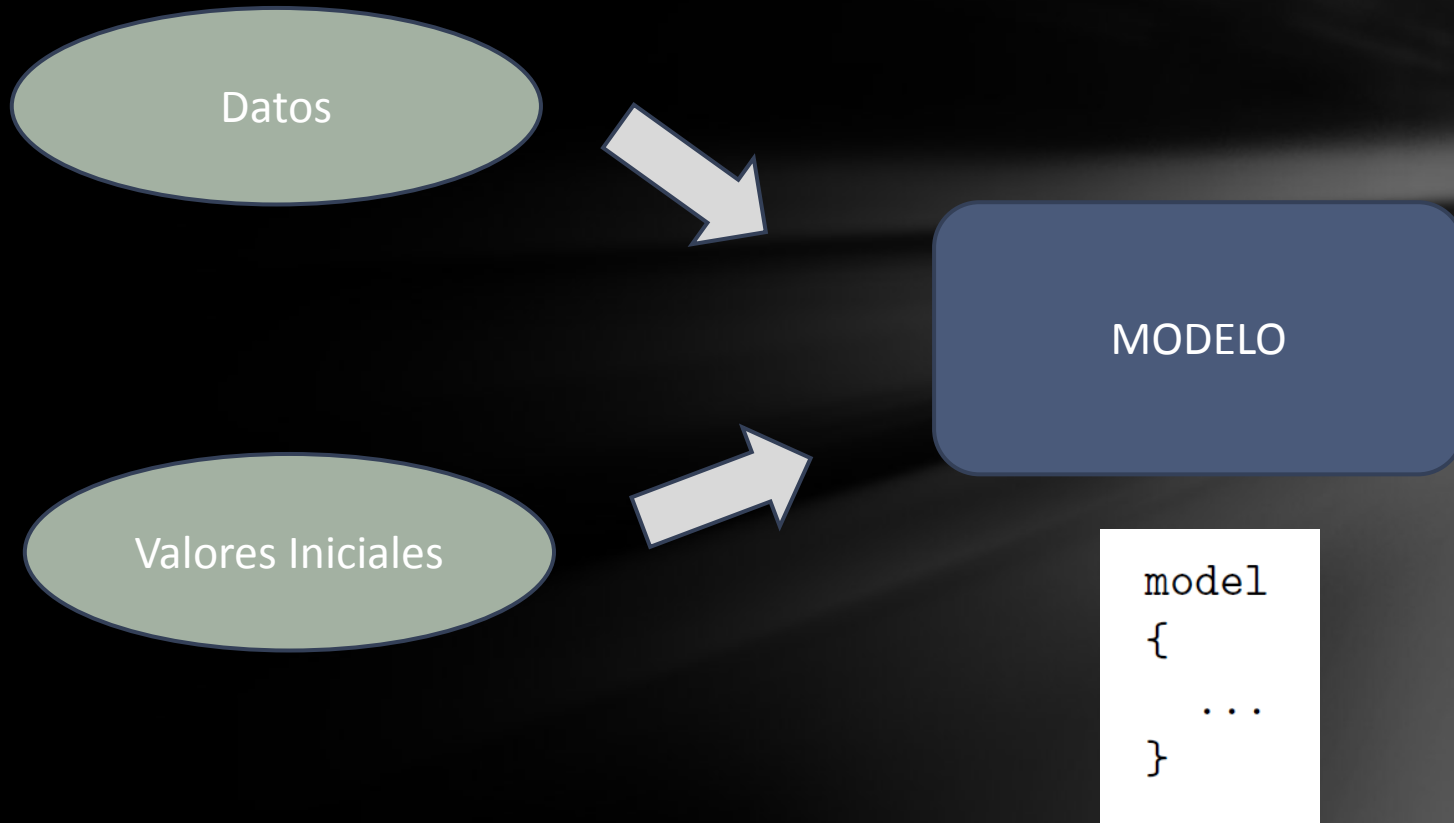
- BUGS → Bayesian inference Using Gibbs Sampling
- JAGS → Just Another Gibbs Sampler
- Stan → Stan (Ulam) → Hamiltonian Monte Carlo

# BUGS - JAGS





# BUGS - JAGS



# BUGS - JAGS

MODELO

```
alpha <- 1
```

Asignación determinística

```
model  
{  
  ...  
}
```

# BUGS - JAGS

MODELO

```
alpha <- 1
```

Asignación determinística

```
p ~ dbeta(1, 1)
```

Asignación estocástica

```
model  
{  
  ...  
}
```

# BUGS - JAGS

MODELO

```
alpha <- 1
```

Asignación determinística

```
p ~ dbeta(1, 1)
```

Asignación estocástica

```
model  
{  
  ...  
}
```

```
for (i in 1:N)  
{  
  x[i] ~ dbern(p)  
}
```

Bucles

# BUGS - JAGS

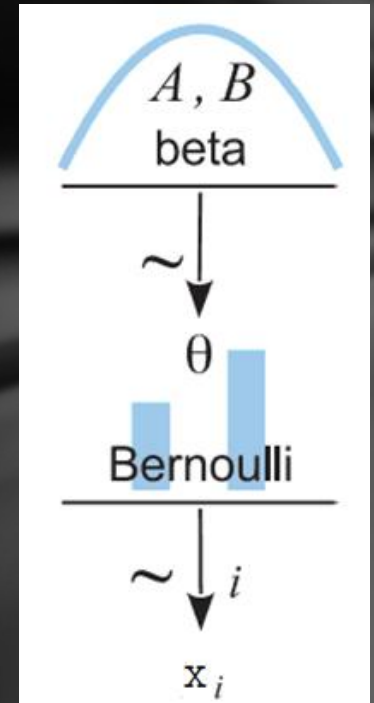
MODELO

```
model
{
  ...
}
```

```
model
{
  alpha <- 1
  beta <- 1

   $\theta \sim \text{dbeta}(\text{alpha}, \text{beta})$ 

  for (i in 1:N)
  {
     $x[i] \sim \text{dbern}(p)$ 
  }
}
```



¡BUGS es un lenguaje descriptivo!



# BUGS - JAGS

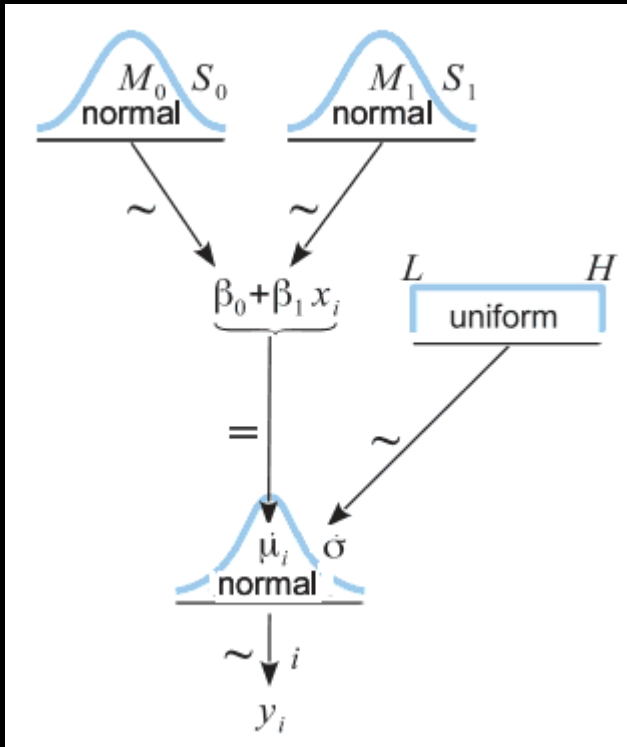
$$y_i = ax_i + b + \epsilon_i$$
$$\epsilon_i \sim \mathcal{N}(0, 1)$$

$$y_i \sim \mathcal{N}(ax_i + b, 1)$$



```
y[i] ~ dnorm(a * x[i] + b, 1)
```

# JAGS – Regresión Lineal

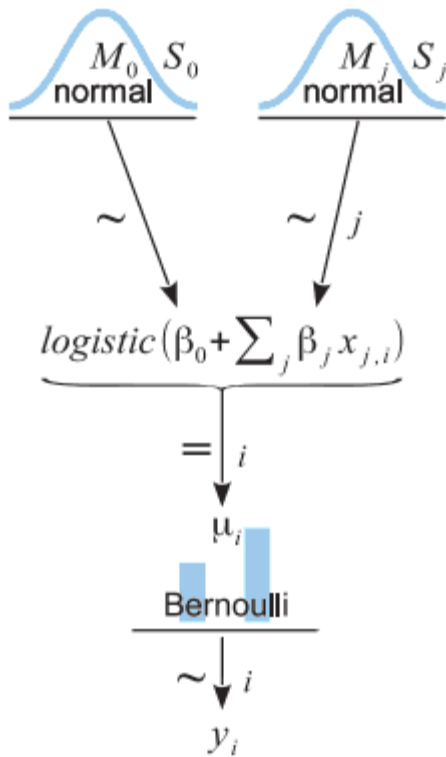


```
model
{
  a ~ dnorm(0, 0.0001)
  b ~ dnorm(0, 0.0001)

  tau <- pow(sigma, -2)
  sigma ~ dunif(0, 100)

  for (i in 1:N)
  {
    mu[i] <- a * x[i] + b
    y[i] ~ dnorm(mu[i], tau)
  }
}
```

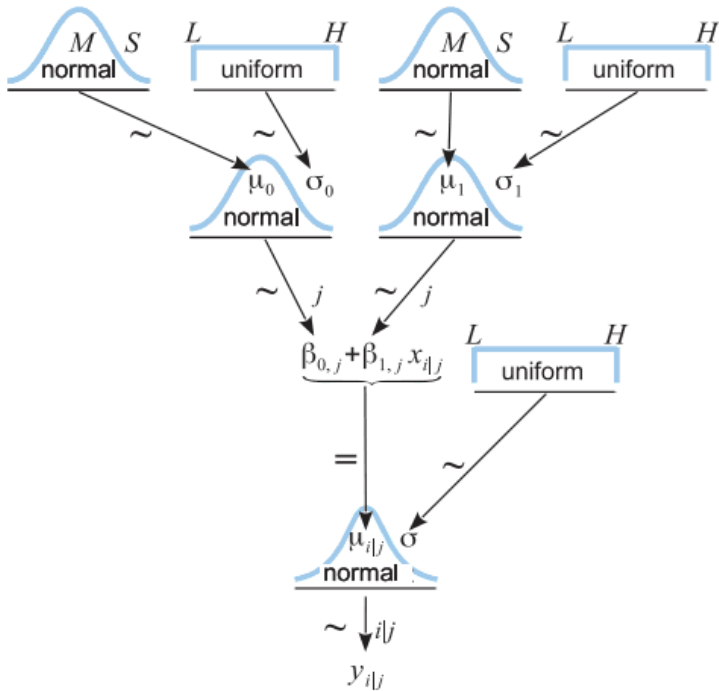
# JAGS – Regresión Logística



```
model
{
  a ~ dnorm(0, 0.0001)
  b ~ dnorm(0, 0.0001)

  for (i in 1:N)
  {
    y[i] ~ dbern(p[i])
    logit(p[i]) <- a * x[i] + b
  }
}
```

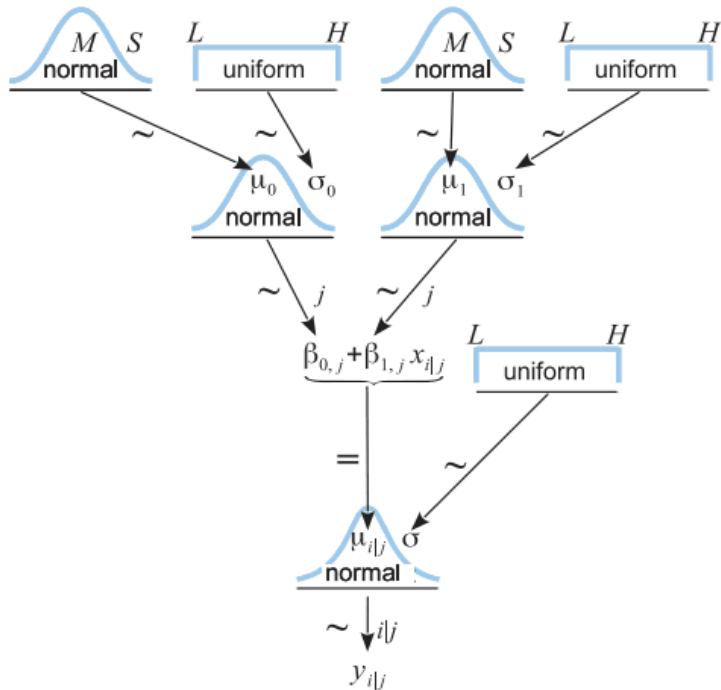
# JAGS – Regresión Lineal Jerárquica



```
model
{
  mu.a ~ dnorm(0, 0.0001)
  mu.b ~ dnorm(0, 0.0001)
  ...

  for (j in 1:K)
  {
    a[j] ~ dnorm(mu.a, tau.a)
    b[j] ~ dnorm(mu.b, tau.b)
  }
  for (i in 1:N)
  {
    mu[i] <- a[g[i]] * x[i] + b[g[i]]
    y[i] ~ dnorm(mu[i], tau)
  }
}
```

# JAGS – Regresión Lineal Jerárquica



```
model
{
  for (i in 1:N)
  {
    y[i] ~ dnorm(mu[i], tau)
    mu[i] <- a[g[i]] * x[i] + b[g[i]]
  }

  for (j in 1:K)
  {
    a[j] ~ dnorm(mu.a, tau.a)
    b[j] ~ dnorm(mu.b, tau.b)
  }

  mu.a ~ dnorm(0, 0.0001)
  mu.b ~ dnorm(0, 0.0001)

  tau <- pow(sigma, -2)
  sigma ~ dunif(0, 1000)

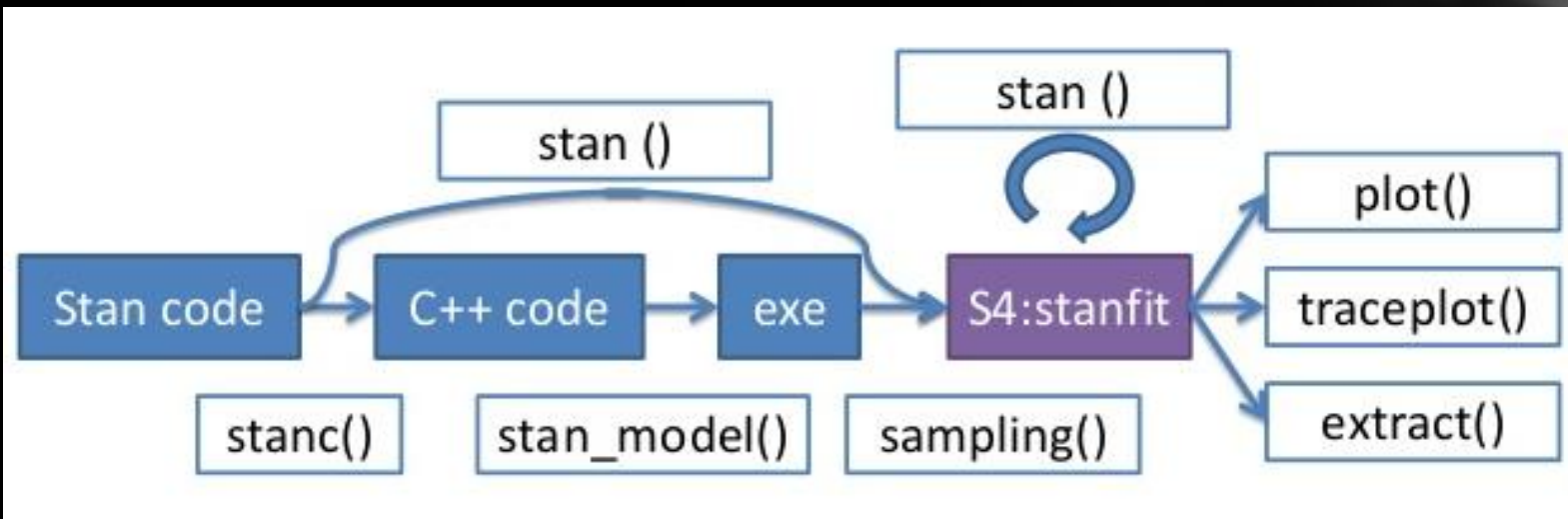
  tau.a <- pow(sigma.a, -2)
  tau.b <- pow(sigma.b, -2)
  sigma.a ~ dunif(0, 1000)
  sigma.b ~ dunif(0, 1000)
}
```



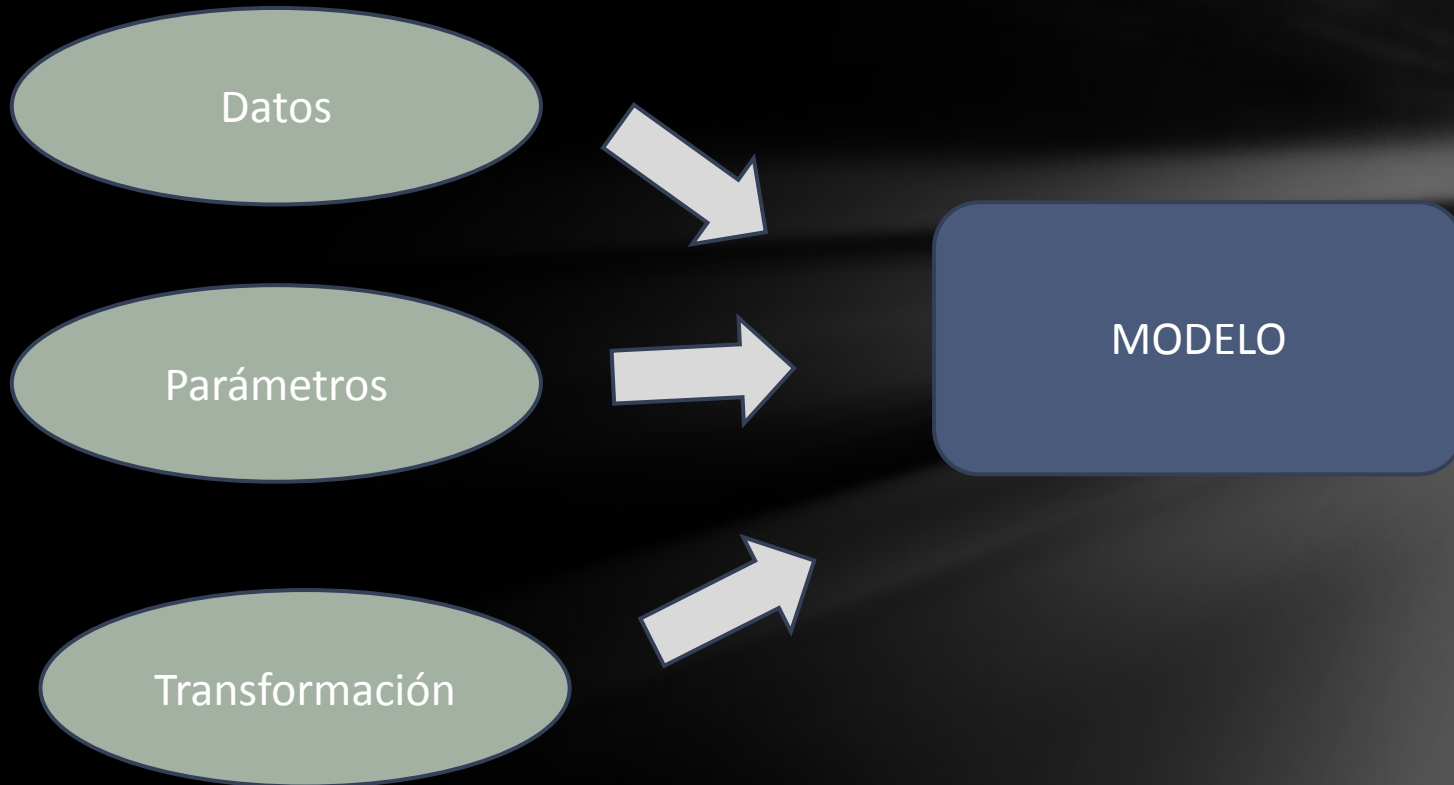
# Recopilación de funciones

Distribution	Density	Distribution	Quantile
Bernoulli	dbern	pbern	qbern
Beta	dbeta	pbeta	qbeta
Binomial	dbin	pbin	qbin
Chi-square	dchisqr	pchisqr	qchisqr
Double exponential	ddexp	pdexp	qdexp
Exponential	dexp	pexp	qexp
F	df	pf	qf
Gamma	dgamma	pgamma	qgamma
Generalized gamma	dgen.gamma	pgen.gamma	qgen.gamma
Noncentral hypergeometric	dhyper	phyper	qhyper
Logistic	dlogis	plogis	qlogis
Log-normal	dlnorm	plnorm	qlnorm
Negative binomial	dnegbin	pnegbin	qnegbin
Noncentral Chi-square	dchisqr	pchisqr	qchisqr
Normal	dnorm	pnorm	qnorm
Pareto	dpar	ppar	qpar
Poisson	dpois	ppois	qpois
Student t	dt	pt	qt
Weibull	dweib	pweib	qweib

# STAN

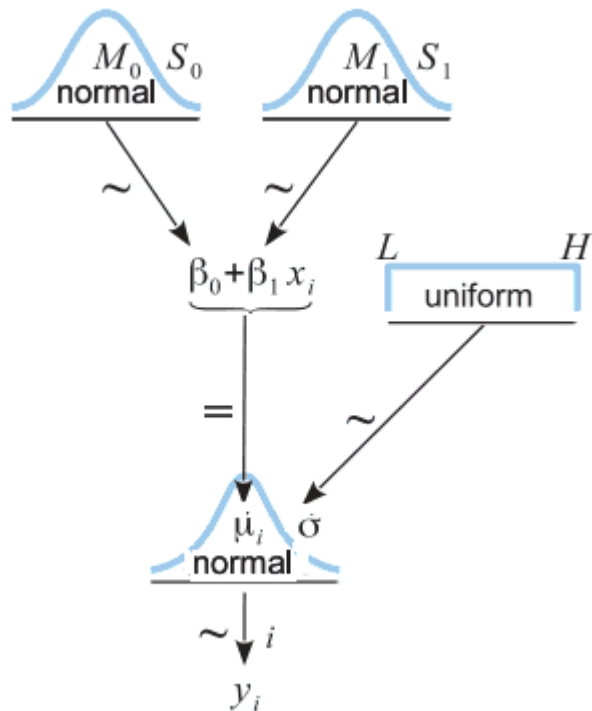


# STAN



¡Stan es un lenguaje imperativo!

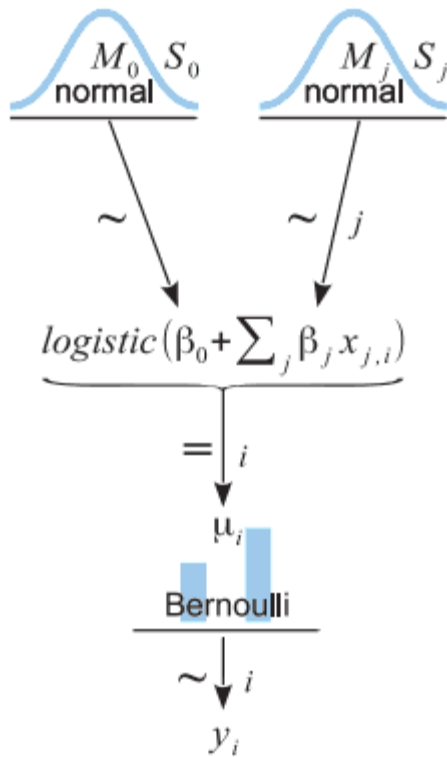
# STAN – Regresión Lineal



```
data {  
  int<lower=0> N;  
  vector[N] x;  
  vector[N] y;  
}  
parameters {  
  real alpha;  
  real beta;  
  real<lower=0> sigma;  
}  
model {  
  for (n in 1:N)  
    y[n] ~ normal(alpha + beta * x[n], sigma);  
}
```

```
model {  
  y ~ normal(alpha + beta * x, sigma);  
}
```

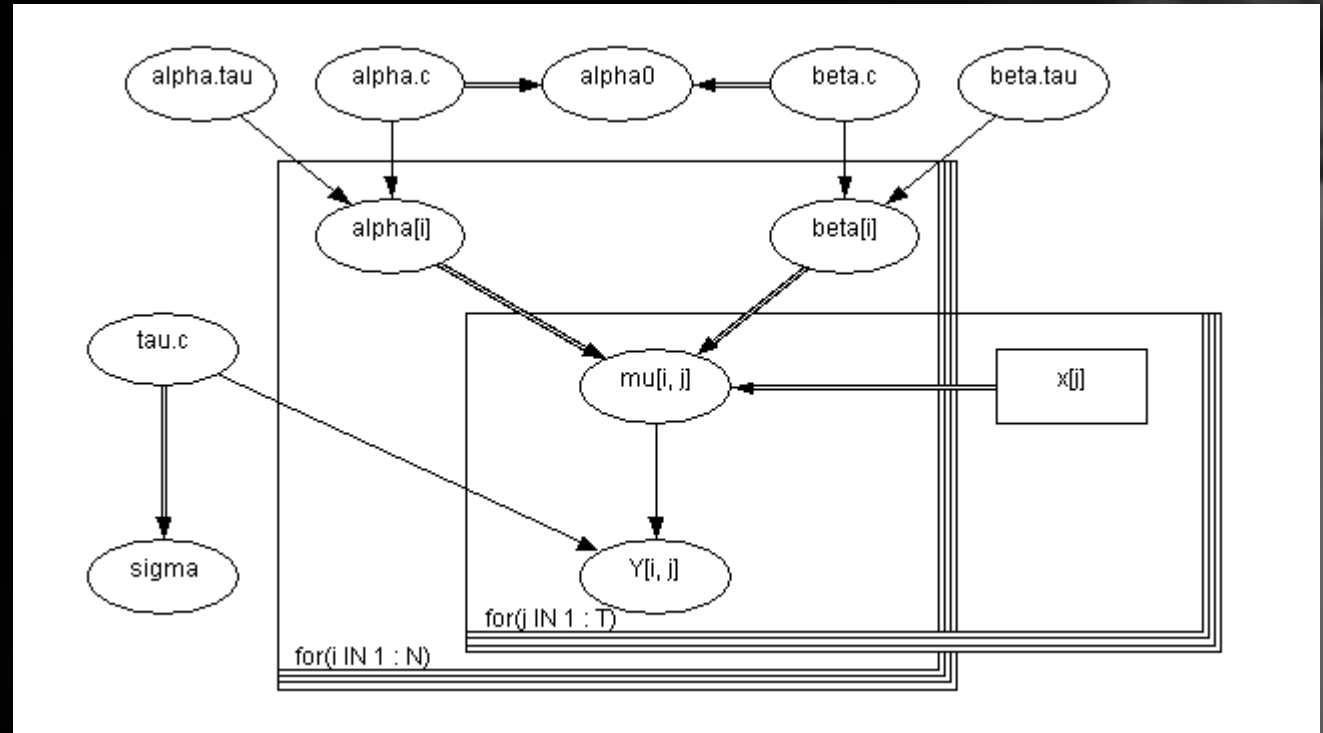
# STAN – Regresión Logística



```
data {  
  int<lower=0> N;  
  vector[N] x;  
  int<lower=0,upper=1> y[N];  
}  
parameters {  
  real alpha;  
  real beta;  
}  
model {  
  y ~ bernoulli_logit(alpha + beta * x);  
}
```

# Ratas – Regresión Lineal jerárquica

30 ratas son pesadas durante cinco semanas





## BUGS

```
model
{
  for(i in 1:N){
    for(j in 1:T){
      Y[i , j] ~ dnorm(mu[i , j],tau.c)
      mu[i , j] <- alpha[i] + beta[i] * (x[j] - xbar)
      culmative.Y[i , j] <- culmative(Y[i , j], Y[i , j])
      post.pv.Y[i , j] <- post.p.value(Y[i , j])
      prior.pv.Y[i , j] <- prior.p.value(Y[i , j])
      replicate.post.Y[i , j] <- replicate.post(Y[i , j])
      pv.post.Y[i , j] <- step(Y[i , j] - replicate.post.Y[i , j])
      replicate.prior.Y[i , j] <- replicate.prior(Y[i , j])
      pv.prior.Y[i , j] <- step(Y[i , j] - replicate.prior.Y[i , j])
    }
    alpha[i] ~ dnorm(alpha.c,alpha.tau)
    beta[i] ~ dnorm(beta.c,beta.tau)
  }
  tau.c ~ dgamma(0.001,0.001)
  sigma <- 1 / sqrt(tau.c)
  alpha.c ~ dnorm(0.0,1.0E-6)
  alpha.tau ~ dgamma(0.001,0.001)
  beta.c ~ dnorm(0.0,1.0E-6)
  beta.tau ~ dgamma(0.001,0.001)
  alpha0 <- alpha.c - xbar * beta.c
}
```

## STAN

```
data {
  int<lower=0> N;
  int<lower=0> T;
  real x[T];
  real y[N,T];
  real xbar;
}

parameters {
  real alpha[N];
  real beta[N];

  real mu_alpha;
  real mu_beta;

  real<lower=0> sigmasq_y;
  real<lower=0> sigmasq_alpha;
  real<lower=0> sigmasq_beta;
}

transformed parameters {
  real<lower=0> sigma_y;
  real<lower=0> sigma_alpha;
  real<lower=0> sigma_beta;

  sigma_y <- sqrt(sigmasq_y);
  sigma_alpha <- sqrt(sigmasq_alpha);
  sigma_beta <- sqrt(sigmasq_beta);
}

model {
  mu_alpha ~ normal(0, 100);
  mu_beta ~ normal(0, 100);
  sigmasq_y ~ inv_gamma(0.001, 0.001);
  sigmasq_alpha ~ inv_gamma(0.001, 0.001);
  sigmasq_beta ~ inv_gamma(0.001, 0.001);
  alpha ~ normal(mu_alpha, sigma_alpha); // vectorized
  beta ~ normal(mu_beta, sigma_beta); // vectorized
  for (n in 1:N)
    for (t in 1:T)
      y[n,t] ~ normal(alpha[n] + beta[n] * (x[t] - xbar), sigma_y);
}
```

# Conclusión

