

Posterior inference

Joachim Vandekerckhove

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- ▶ The posterior distribution gives a lot of information
- ▶ Ideally, we could just show a graph of it and leave the interpretation to the reader
 - ▶ But often the posterior will have many dimensions
 - ▶ And also that seems lazy
- ▶ We need a way to describe the posterior distribution
 - ▶ Mean? SD? Skew? Kurtosis? Mass at or around a certain value? $p(.8 \leq P_R \leq .9 | \#R, \#W)$?

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Here, with the discrete domain of P_R :

$$\begin{aligned} p(.8 \leq P_R \leq .9 | \#R, \#W) = \\ p(P_R = .80 | \#R, \#W) \\ + p(P_R = .85 | \#R, \#W) \\ + p(P_R = .90 | \#R, \#W) \end{aligned}$$

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 - ▶ Beta distribution, say $\alpha = \beta = 2$

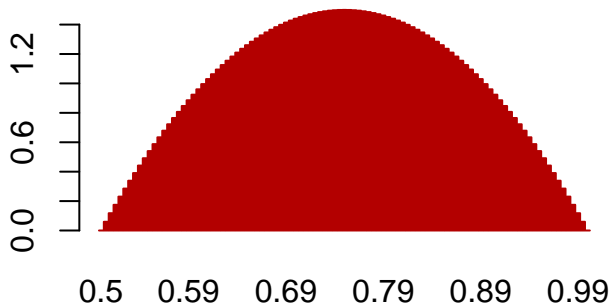
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wine



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 - ▶ Likelihood is the same: $p(\#R, \#W|P_R) = CP_R^{\#R}(1-P_R)^{\#W}$

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 - ▶ $p(x) = Kx^{\alpha-1}(1-x)^{\beta-1} = B(x|\alpha, \beta)$
 - ▶ Beta distribution, say $\alpha = \beta = 2$
 - ▶ Likelihood is the same: $p(\#R, \#W|P_R) = CP_R^{\#R}(1-P_R)^{\#W}$
 - ▶ So the posterior must be:
$$p(P_R|\#R, \#W) \propto \left(\frac{P_R+1}{2}\right)^{\alpha-1} \left(1 - \frac{P_R+1}{2}\right)^{\beta-1}$$

Functional programming

Sometimes it is useful in R to turn a function into a variable to change it quickly

You can make a function “on the fly” inside a function or script file like this:

```
funcname <- function(n, x) { rep(x, n) }
```

So that prior and likelihood can be written like:

```
prior <- function(p) { dbeta(2 * (p-.5), 2, 2) }  
likelihood <- function(p) { dbinom(5, 6, p) }
```

Functional programming

Prior and likelihood:

```
prior <- function(p) { dbeta(2 * (p-.5), 2, 2) }  
likelihood <- function(p) { dbinom(5, 6, p) }
```

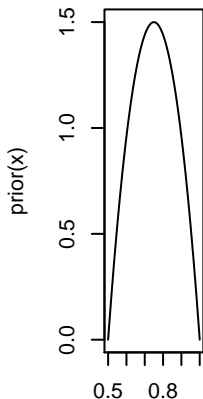
Given those, building the posterior is trivial:

```
post.usc <- function(p) { prior(p) * likelihood(p) }
```

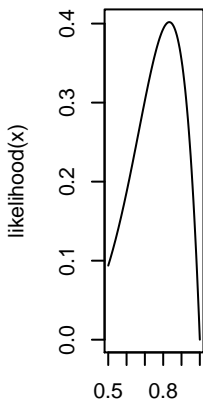
Exercise: implement this, plot the three functions

Functional programming

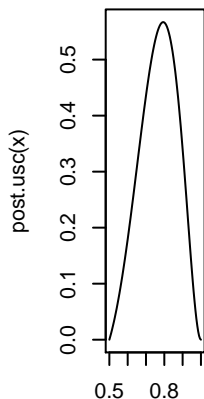
```
par(mfrow=c(1,3))  
curve(prior, 0.5, 1)  
curve(likelihood, 0.5, 1)  
curve(post.usc, 0.5, 1)
```



x



x



x

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- ▶ How do we determine the mean of an arbitrary, somewhat complicated function?
- ▶ As it turns out, drawing random samples from a distribution is an efficient way to do that
 - ▶ Methods for doing this are called Monte Carlo methods

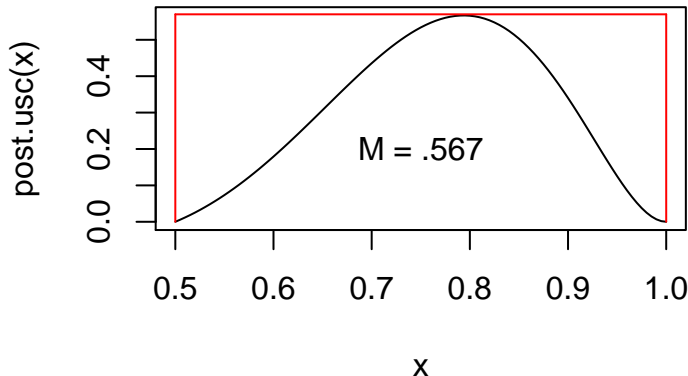
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- ▶ These graphs don't tell us the mean of the posterior (or any other useful statistic)
- ▶ How do we determine the mean of an arbitrary, somewhat complicated function?
- ▶ As it turns out, drawing random samples from a distribution is an efficient way to do that
 - ▶ Methods for doing this are called Monte Carlo methods
 - ▶ Math win: Monte Carlo methods don't need those hard-to-compute K and C scaling constants

Posterior sampling

One Monte Carlo method is the rejection sampler:

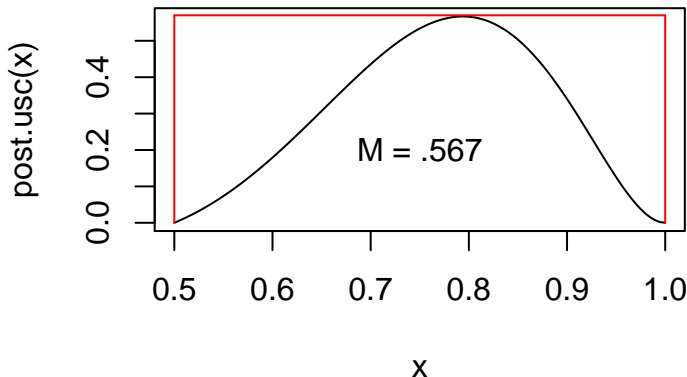
- 1) Draw a sample from some basic distribution $S(x|...)$



Posterior sampling

One Monte Carlo method is the rejection sampler:

- 1) Draw a sample from some basic distribution $S(x|...)$
- 2) Reject the sample with probability $q = \frac{f_x}{M \times S(x)}$, where M is chosen so that this is always ≤ 1 (but ideally sometimes close to 1)



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- 3. Repeat many times to get a few thousand samples

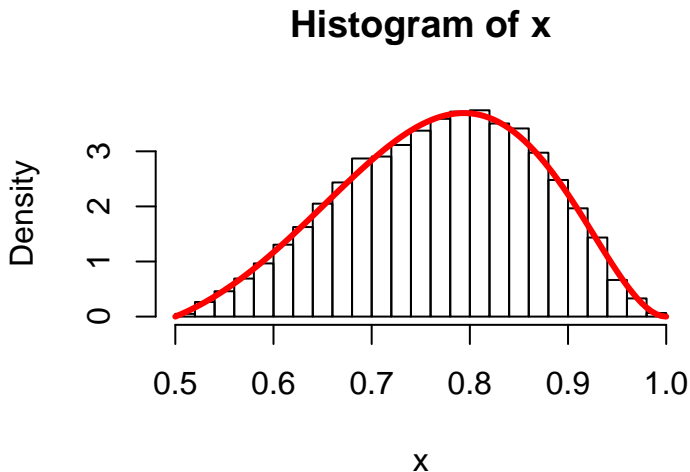
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- 3. Repeat many times to get a few thousand samples
- 4. Make a histogram and compare the shapes of the distribution

Posterior sampling

```
N <- 10000
x <- vector(,N)
c <- 1
M <- .567
while(c <= N) {
  x[c] <- runif(1, 0.5, 1)
  u <- runif(1, 0, M)
  if (u < post.usc(x[c])) c <- c + 1;
}
hist(x, breaks=25,freq=FALSE)
K <- integrate(post.usc, 0.5, 1)$value
lines(domain, post.usc(domain)/K, lwd=3, col='red')
```

Posterior sampling



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 - ▶ Now we can compute the mean of that sample: 0.7699174
 - ▶ ... or the proportion of samples that are $> .85$: 0.2314
 - ▶ ... or indeed any quality we fancy

Generative model representation

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- ▶ Basic unit of a Bayesian model is a distribution function
- ▶ The posterior is defined through a *generative model representation*
 - ▶ ... which is basically a sequence of distributional assumptions
 - ▶ In Bayesian statistics, a “model” is just a special kind of distribution function over parameters and data (and so with possibly very many dimensions)

Generative model representation

Let's define a really trivial model \mathcal{M}_t in which we estimate the parameters μ and τ ($= 1/\sigma^2$) of a normal distribution, applied to some data points d_j :

$$\mathcal{M}_t : \begin{cases} \forall j \in (1, \dots, J) : d_j \sim N(\mu, \tau) \\ \mu \sim N(0, 0.1) \\ \tau \sim \Gamma(4, 0.01) \end{cases}$$

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$$\begin{aligned} p(d_1, \dots, d_J \mid \mathcal{M}_t) &= \left(\prod_{j=1}^J N(d_j \mid \mu, \tau) \right) \\ &\times N(\mu \mid 0, 0.1) \\ &\times \Gamma(\tau \mid 4, 0.01) \end{aligned}$$

JAGS code is (almost) perfect

$$\mathcal{M}_s : \begin{cases} \forall j \in (1, \dots, J) : d_j \sim N(\mu, \tau) \\ \mu \sim N(0, 0.1) \\ \tau \sim \Gamma(4, 0.01) \end{cases}$$

The program needs to know the specifics of the model:

```
model {  
  for (j in 1:J) {  
    d[j] ~ dnorm(mu, tau)  
  }  
  mu ~ dnorm(0,0.1)  
  tau ~ dgamma(4,0.01)  
}
```

A psychological model: Signal detection theory

$$\mathcal{M}_{sdt} : \begin{cases} \delta \sim N(1, 1) & \beta \sim N(0, 1) \\ \phi_h = \Phi(\delta/2 - \beta) & \phi_f = \Phi(-\delta/2 - \beta) \\ h \sim B(\phi_h, n_s) & f \sim B(\phi_f, n_n) \end{cases}$$

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```
model {  
  d ~ dnorm(1, 1)  
  b ~ dnorm(0, 1)  
  
  phih <- phi( d / 2 - b)  
  phif <- phi(-d / 2 - b)  
  
  h ~ dbin(phih, sigtrials)  
  f ~ dbin(phif, noistrials)  
}
```

Signal detection theory ~ implementation

```
library(rjags)

data <- list( h = 32 ,  sigtrials  = 39 ,
              f = 12 ,  noistrials = 60 )

modelString = "
  model {
    d ~ dnorm(1, 1)
    b ~ dnorm(0, 1)

    phih <- phi( d / 2 - b)
    phif <- phi(-d / 2 - b)

    h ~ dbin(phih, sigtrials)
    f ~ dbin(phif, noistrials)
  }
"
```

Signal detection theory ~ implementation

```
writelnLines( modelString , con = "sdt.txt" )

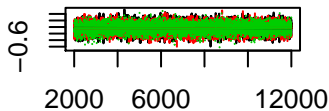
jagsModel = jags.model( file      = "sdt.txt" ,
                        data      =      data ,
                        n.chains  =      3 ,
                        n.adapt   =    1000 )

set.seed(0)
update( jagsModel , n.iter = 1000 ) # burn-in

samples = coda.samples( jagsModel ,
                        variable.names = c("d", "b") ,
                        n.iter         =    10000 )
```

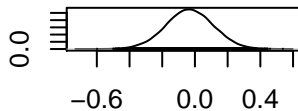
Signal detection theory ~ results

Trace of b



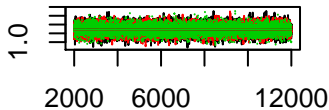
Iterations

Density of b



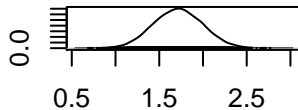
$N = 10000$ Bandwidth = 0.0195

Trace of d



Iterations

Density of d



$N = 10000$ Bandwidth = 0.0380

Signal detection theory ~ summary statistics

```
summary(samples)$statistics
```

	Mean	SD	Naive SE	Time-series SE
## b	-0.03266666	0.1457046	0.0008412261	0.001123618
## d	1.71660631	0.2819677	0.0016279415	0.002204741

```
summary(samples)$quantiles
```

	2.5%	25%	50%	75%	97.5%
## b	-0.3220917	-0.1297417	-0.03296358	0.06490917	0.2515783
## d	1.1728148	1.5231667	1.71565854	1.90753640	2.2731700

Signal detection theory ~ convergence

```
effectiveSize(samples)
```

```
##           b           d  
## 16833.72 16365.17
```

```
gelman.diag(samples)
```

```
## Potential scale reduction factors:
```

```
##
```

```
## Point est. Upper C.I.
```

```
## b           1           1
```

```
## d           1           1
```

```
##
```

```
## Multivariate psrf
```

```
##
```

```
## 1
```

Summary and conclusion

The outcome of a Bayesian analysis is a probability distribution over parameters of interest

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The outcome of a Bayesian analysis is a probability distribution over parameters of interest

To communicate results, we needed a method to summarize arbitrary distributions

Monte Carlo methods provide such a method

JAGS (and Stan) have a straightforward modeling language that lets users specify a model

They then draw samples from the posterior distributions, so we can calculate any summaries we like