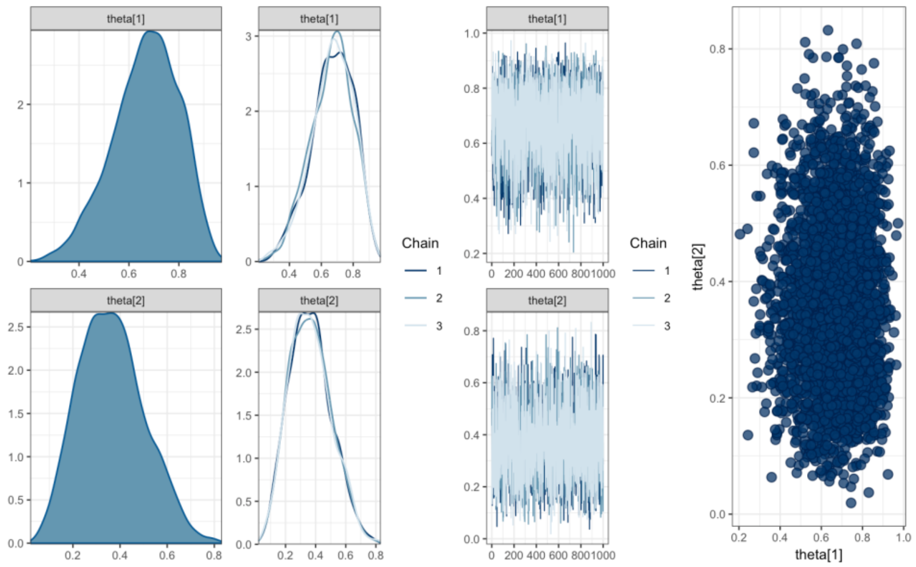
2. Priors: estimating band-recovery and harvest probability



JAGS

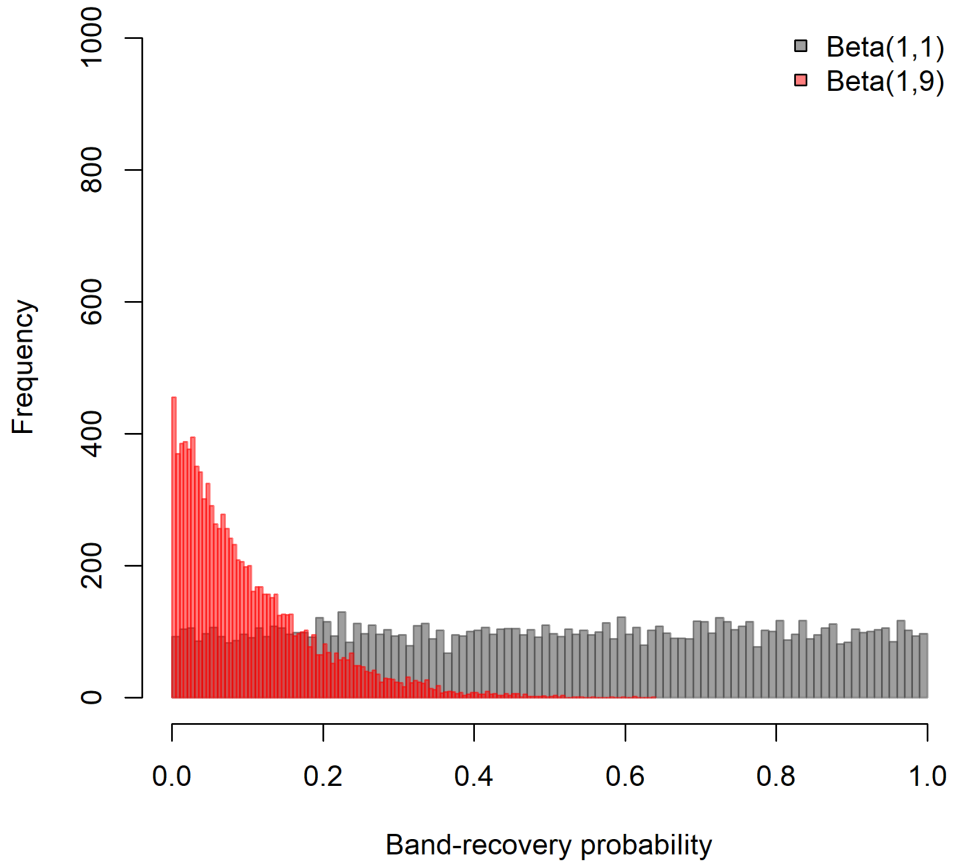
Just Another Gibbs Sampler

Stan

NIMBLE

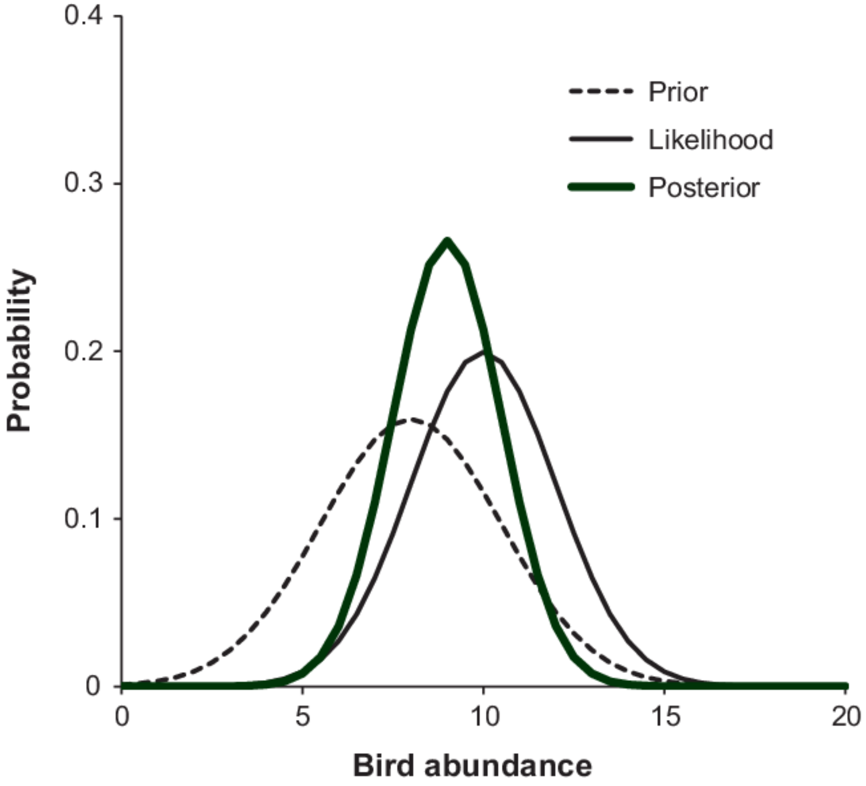
What is a prior?

- Your prior belief in the distribution of a parameter.



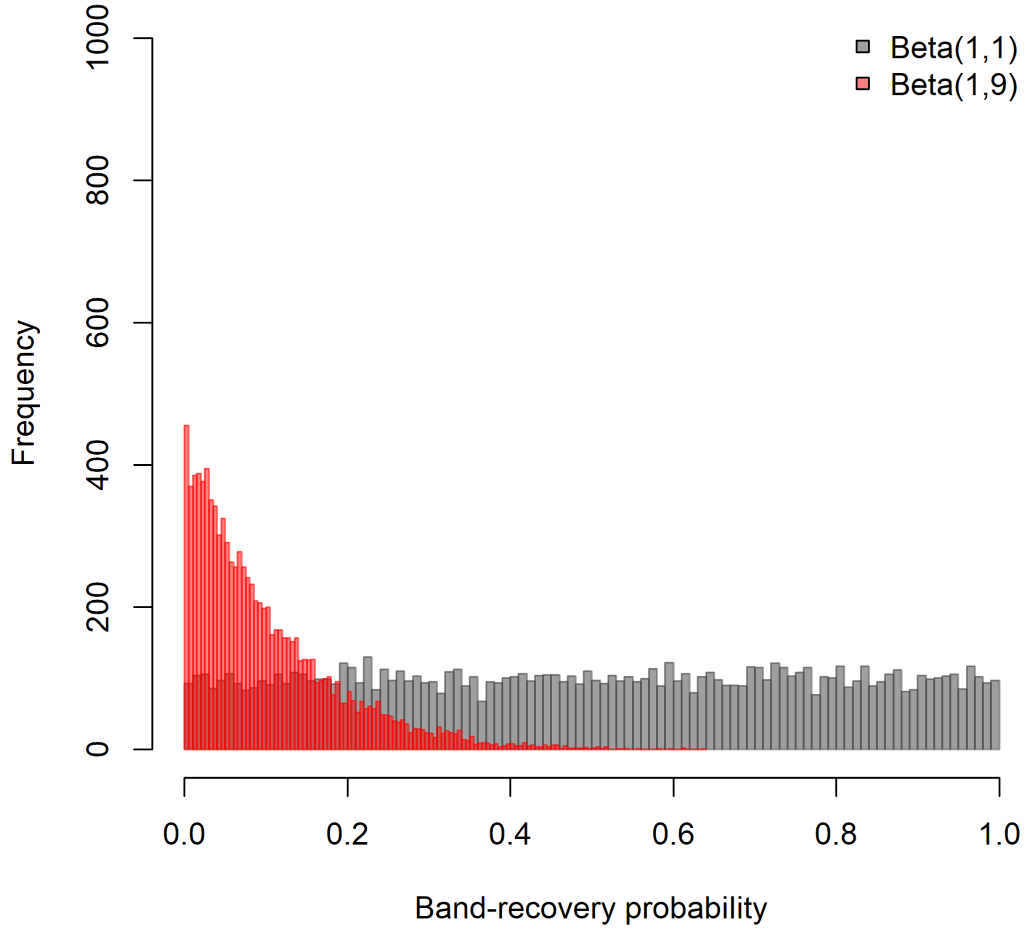
What is a posterior?

- The distribution of a parameter <u>given your prior belief and the data.</u>



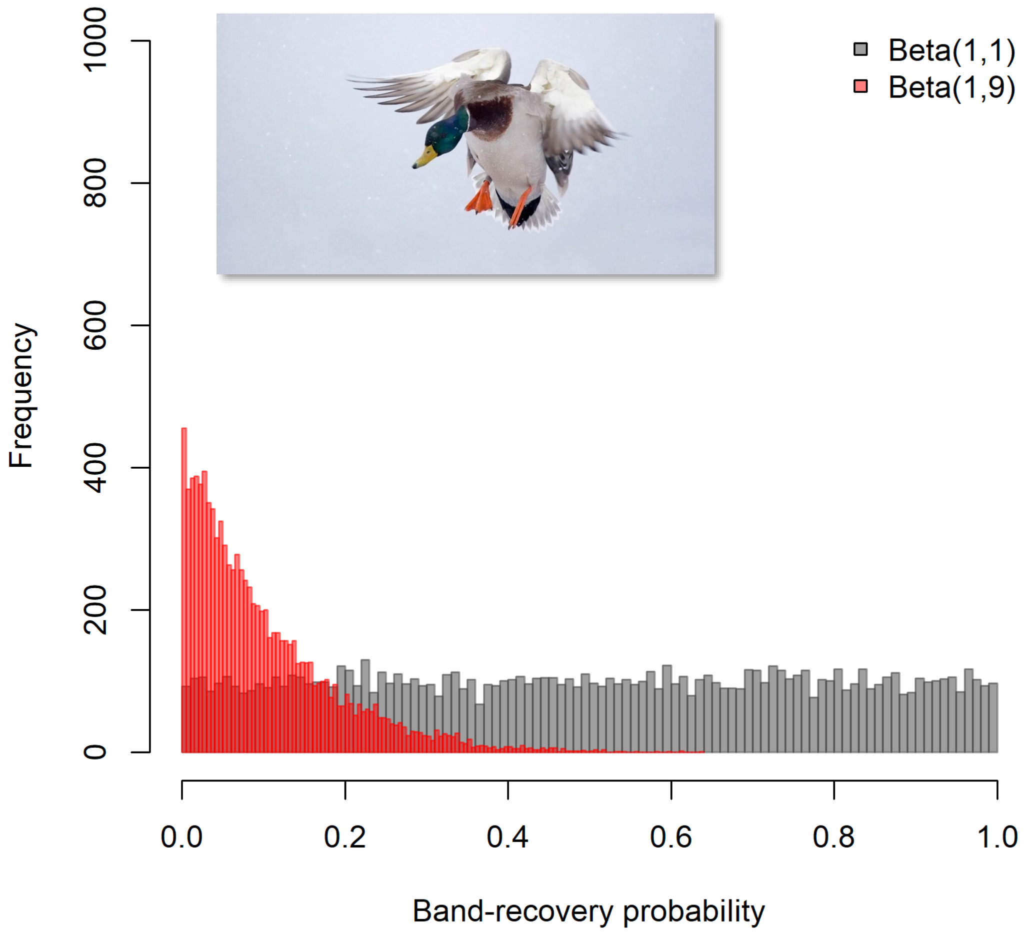
A huge 'non-Bayesian' fear is that priors drive inference

‘Uninformative*’ priors

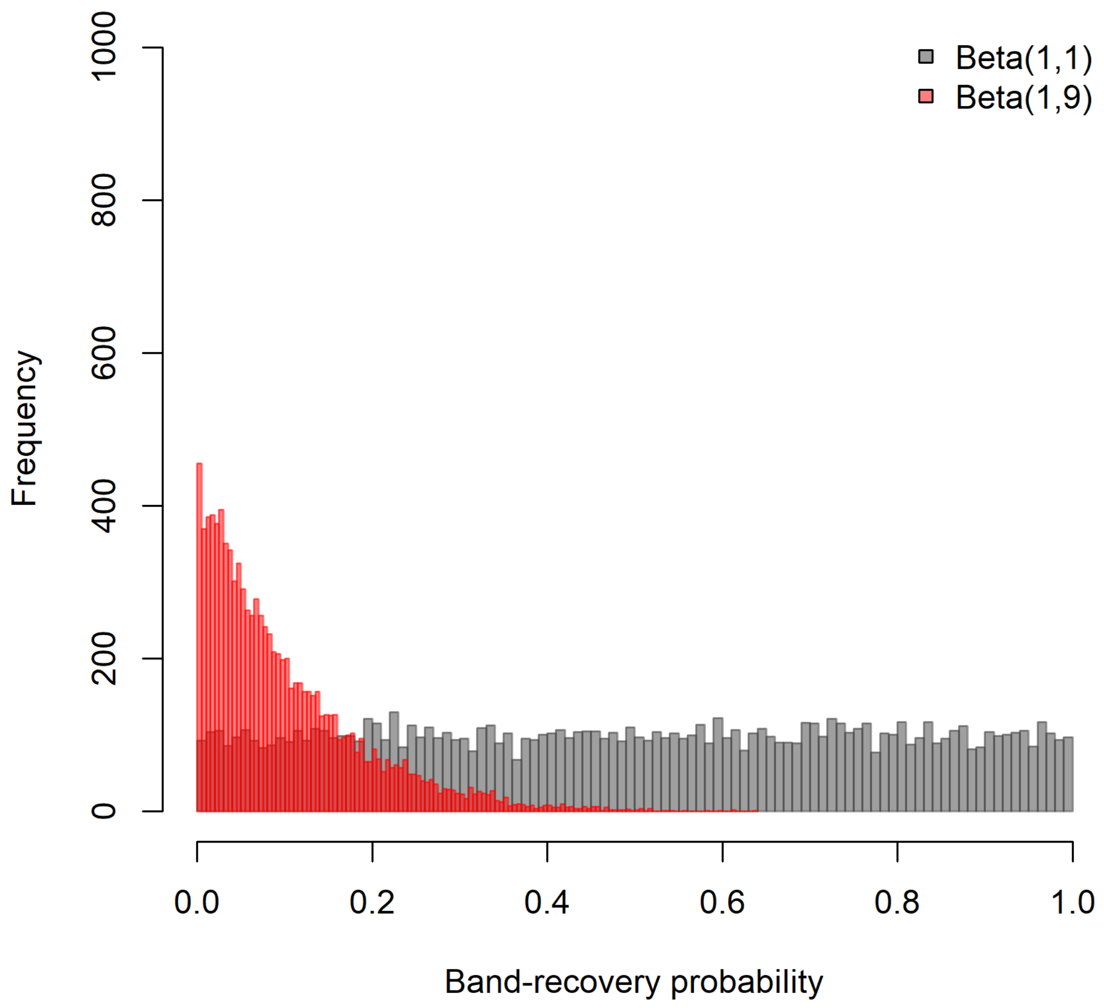


***Priors are never ‘uninformative.’**

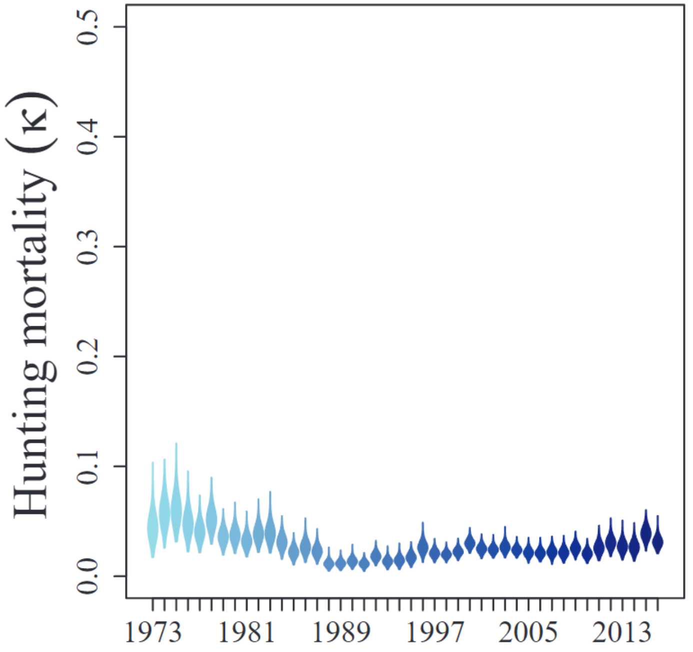
Sometimes priors are too ‘uninformed’



‘Biologically informative’ or ‘reasonably vague’ priors



What is the band-recovery probability for adult female blue-winged teal?



An example: how tall is a man you’ve never met before?

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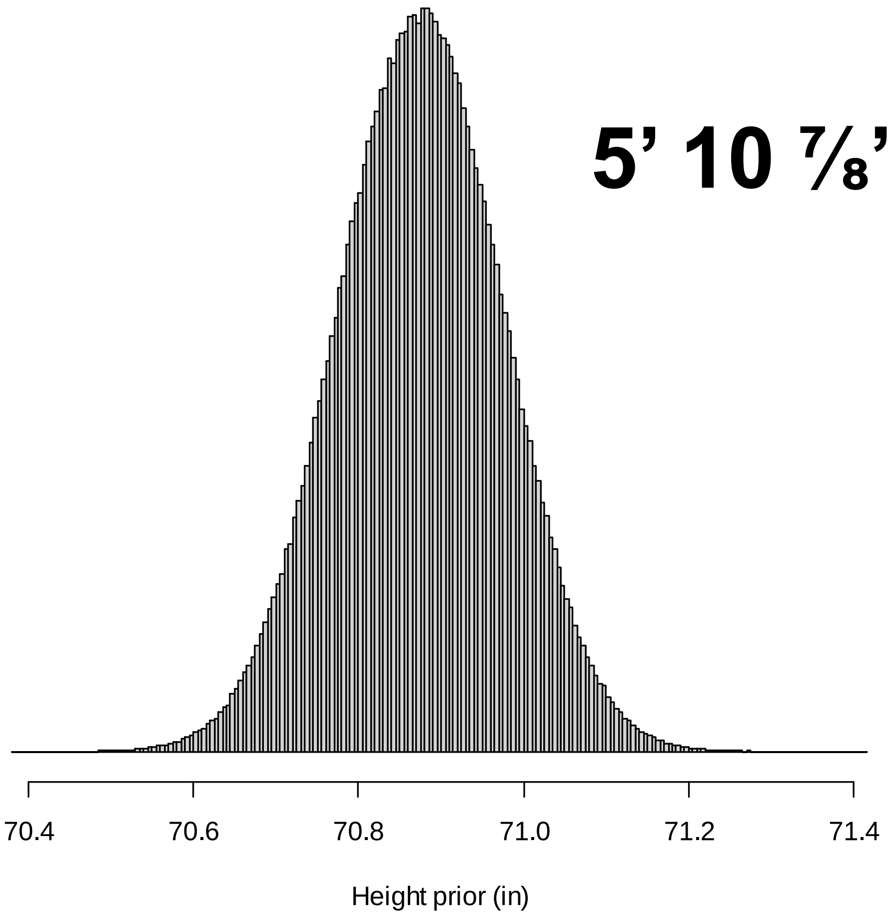


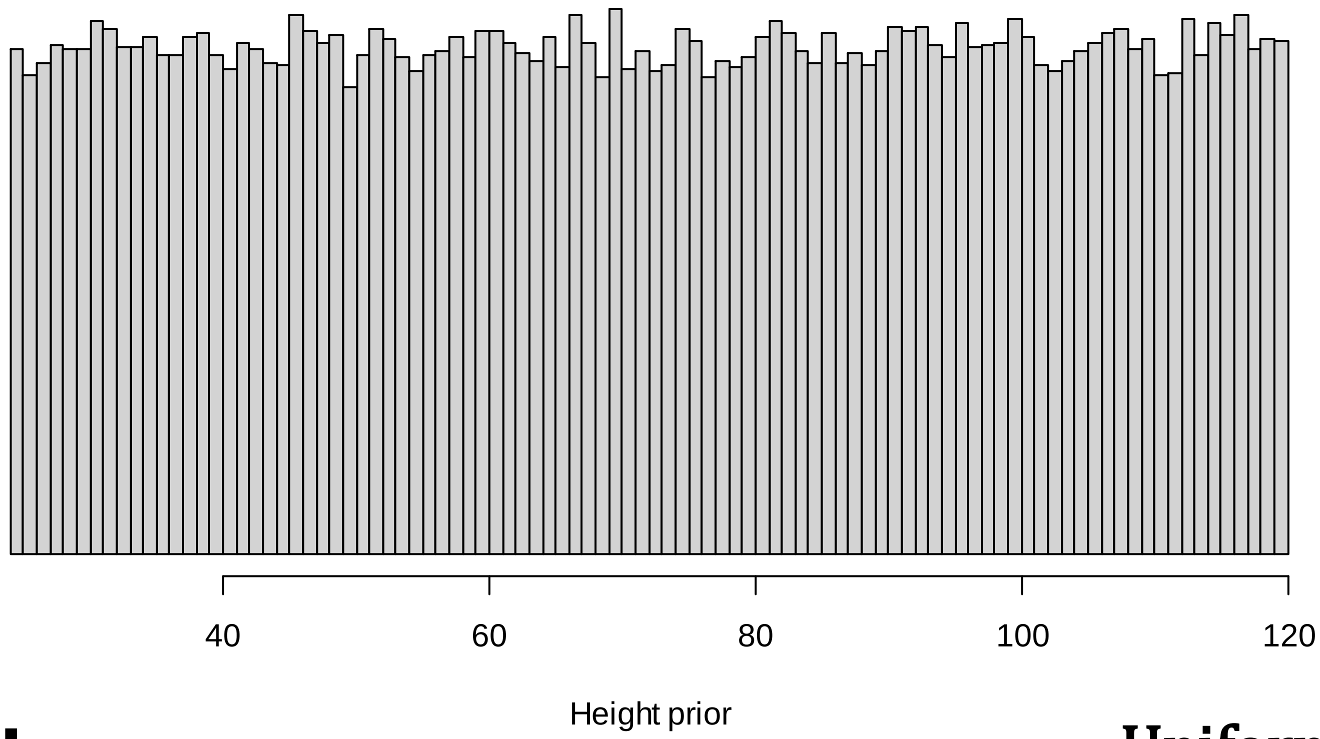
5' 10 ⅞" ± ⅓"

'Overly informative'

$\text{Normal}(\mu = 70.875, \sigma = 0.1)$

An example: how tall is a man you've never met before?

Equally likely that they're between 2' and 10' tall

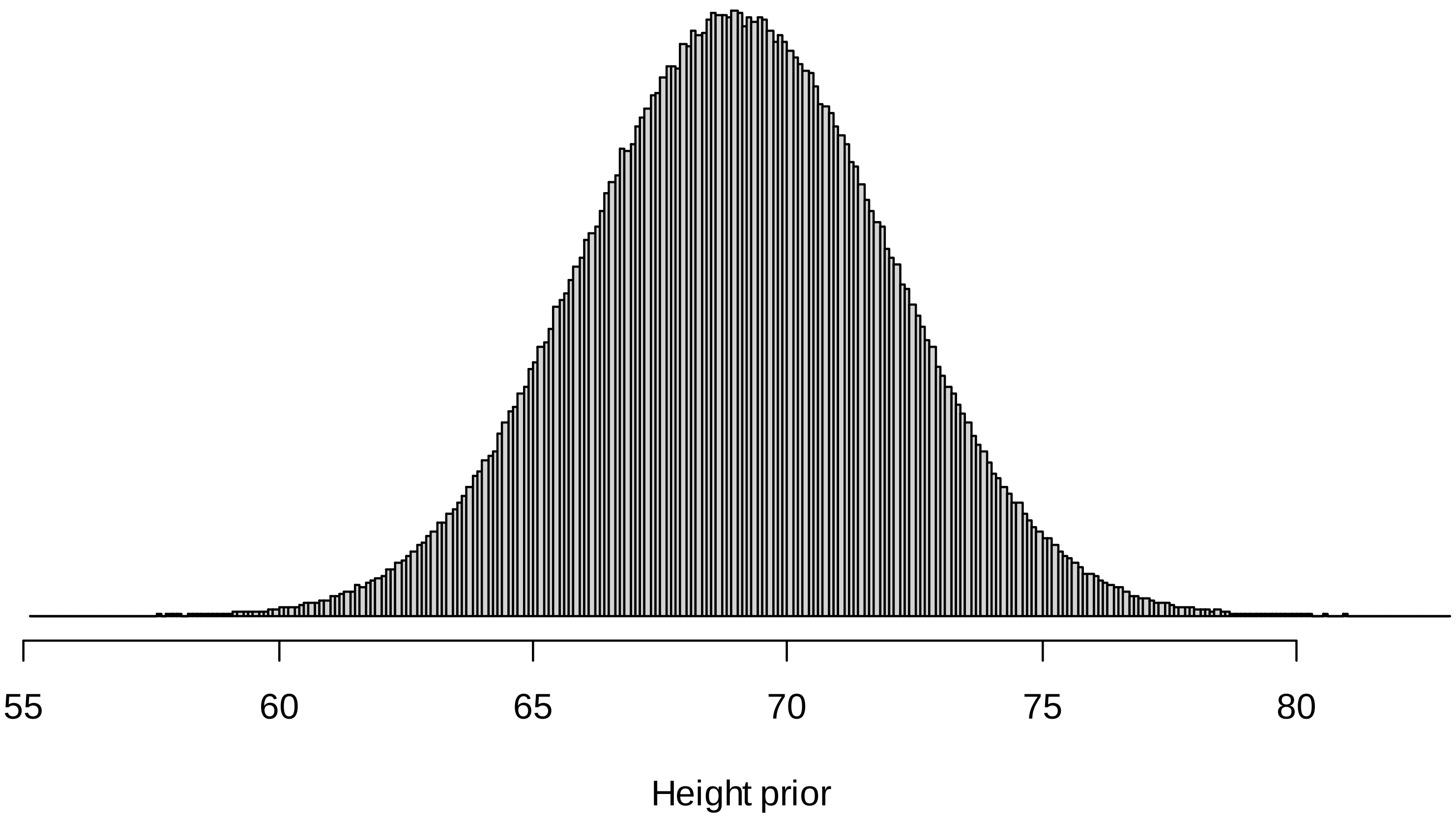


'Uninformative'

$\text{Uniform}(24, 120)$

An example: how tall is a man you've never met before?

5' 10" ± 12"



'Biologically informative!'

$\mathrm{Normal}(\mu = 70, \sigma = 3)$

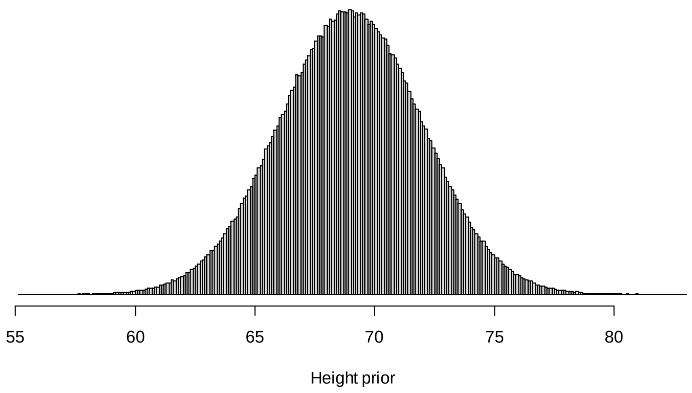
An example: how tall is a man you’ve never met before?

‘Please stop talking to me.’

Also an acceptable answer.

‘Biological informative’ or ‘reasonably vague’ priors

5’ 10 ⅞” ± ⅓”



2’-10’

The beta distribution

Number of 'successes'

Beta(1,1)

Number of 'failures'

$$\mathrm{Beta}(\alpha, \beta)$$

$$\mu = \frac{\alpha}{\beta}$$

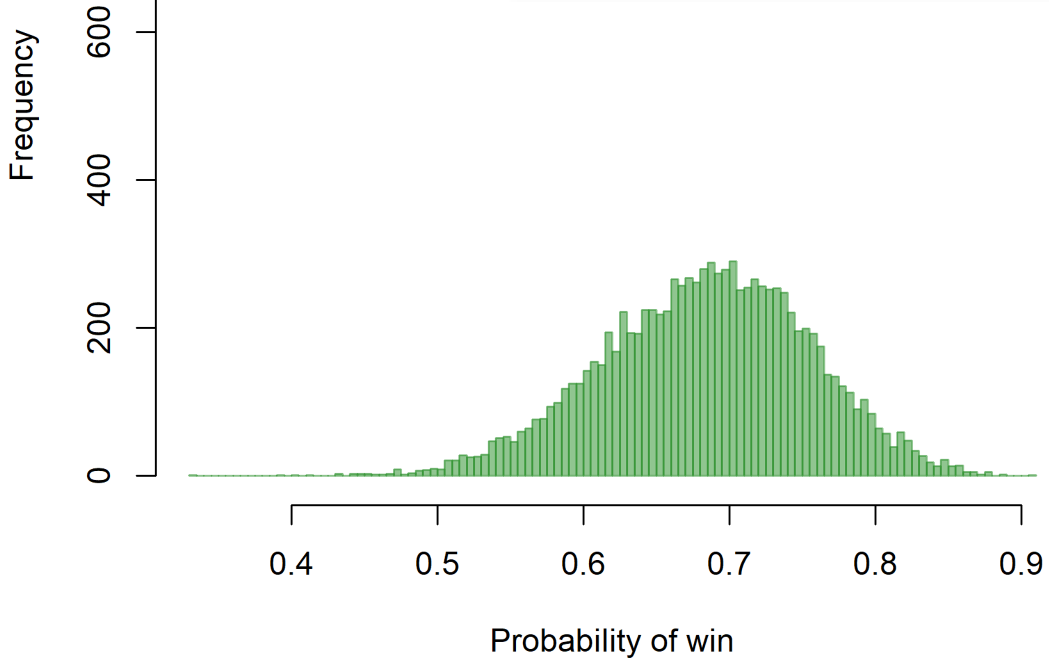
$$\sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

The beta distribution: sports

Number of wins

Beta(28,13)

Number of losses



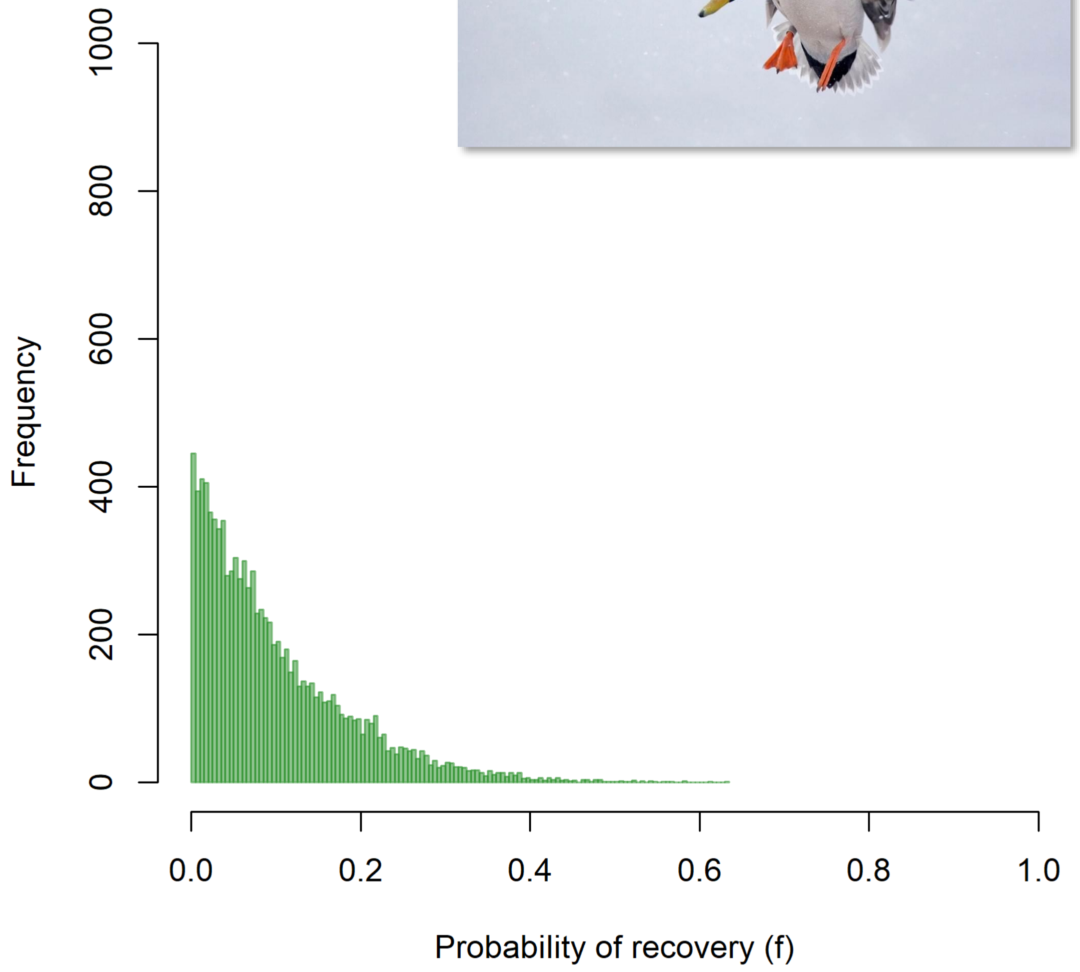
***hockey isn’t a great example because they also have ties…**

The beta distribution: ducks

Number of recoveries

Beta(1,9)

Number of not recoveries

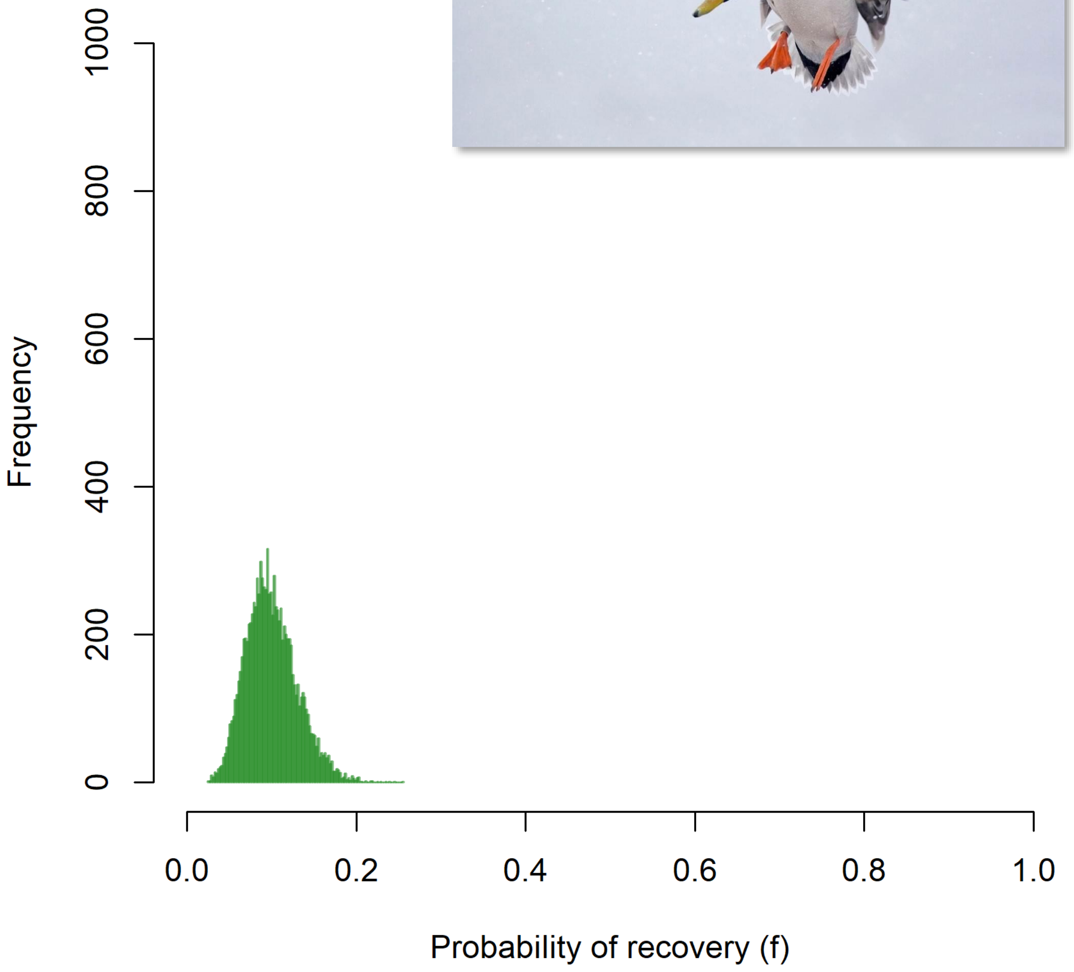


The beta distribution: ducks

Number of recoveries

Beta(10,90)

Number of not recoveries

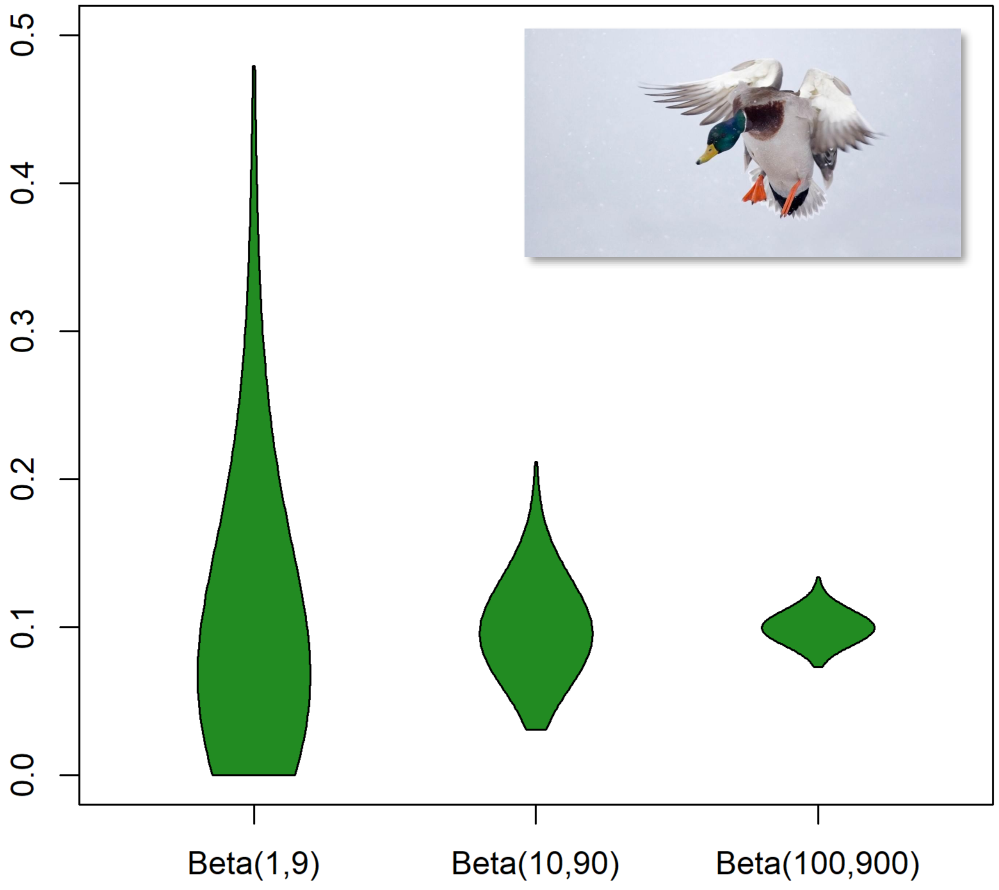


The beta distribution: ducks

Number of recoveries

Beta(α,β)

Number of not recoveries

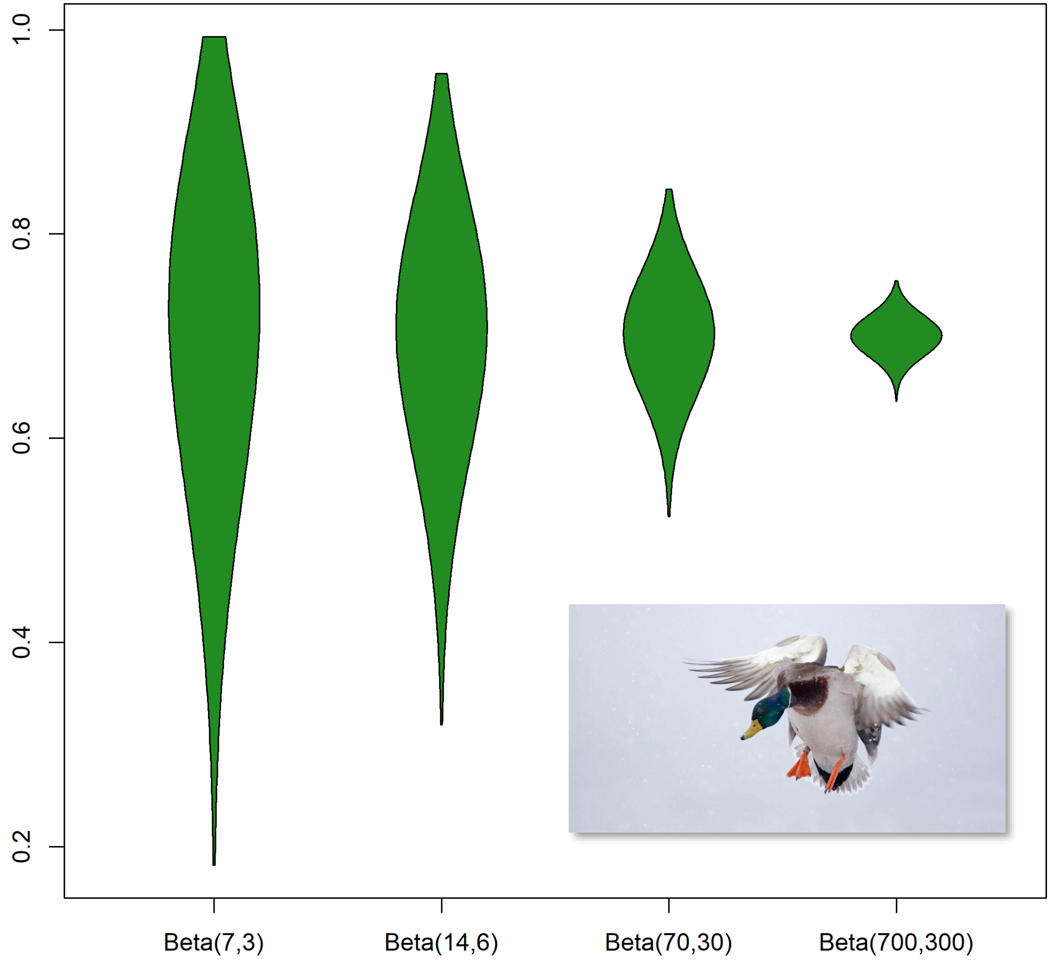


The beta distribution: ducks

Number of survivors

Beta(α,β)

Number of mortalities



Our first Bayesian analysis

Prior: **Beta(α, β)**

Likelihood: **Beta(Successes, Failures)**

Posterior: **Beta(α + Successes, β + Failures)**

Combining priors and data: ducks

Let's remember our first example (1000 releases, 100 recoveries)

Prior: Beta(α, β)

Likelihood: **Beta(100, 900)**

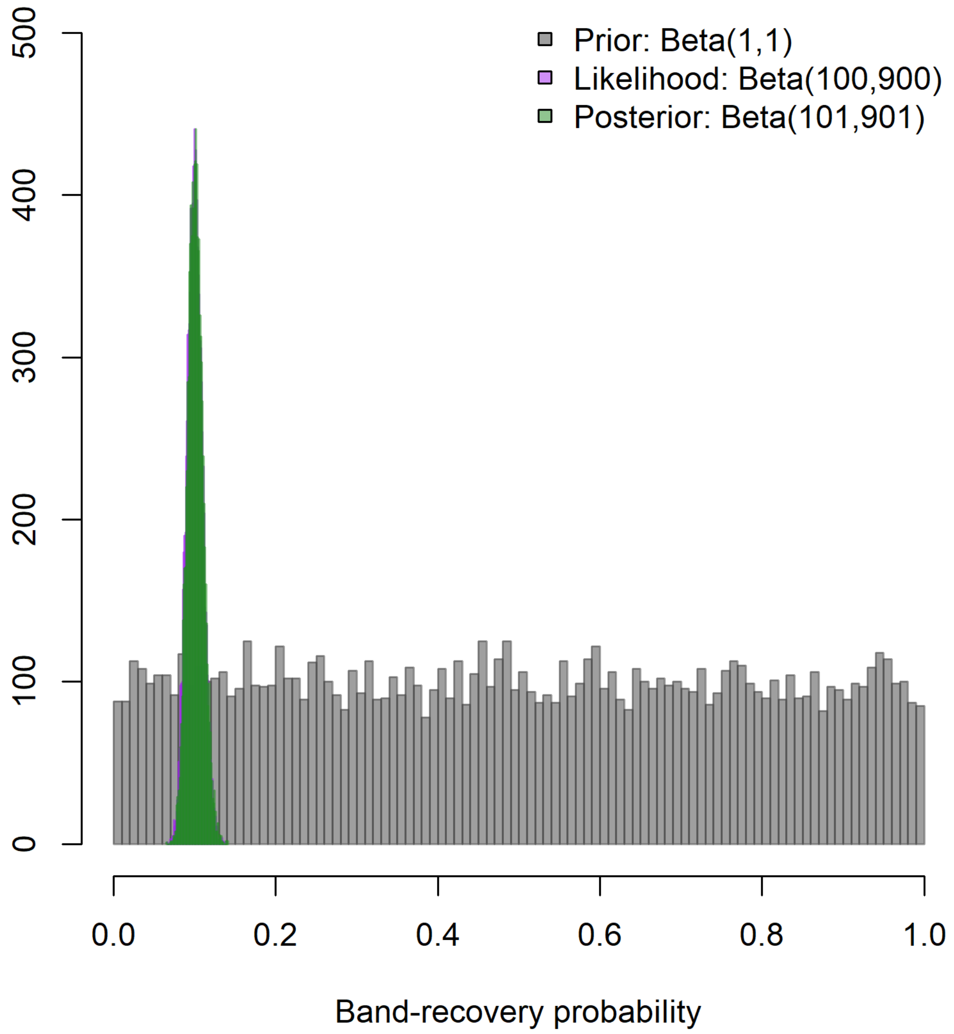
Posterior: Beta(α + Successes, β + Failures)

Let’s remember our first example (1000 releases, 100 recoveries)

Prior: **Beta(1, 1)**

Likelihood: **Beta(100, 900)**

Posterior: **Beta(α + Successes, β + Failures)**

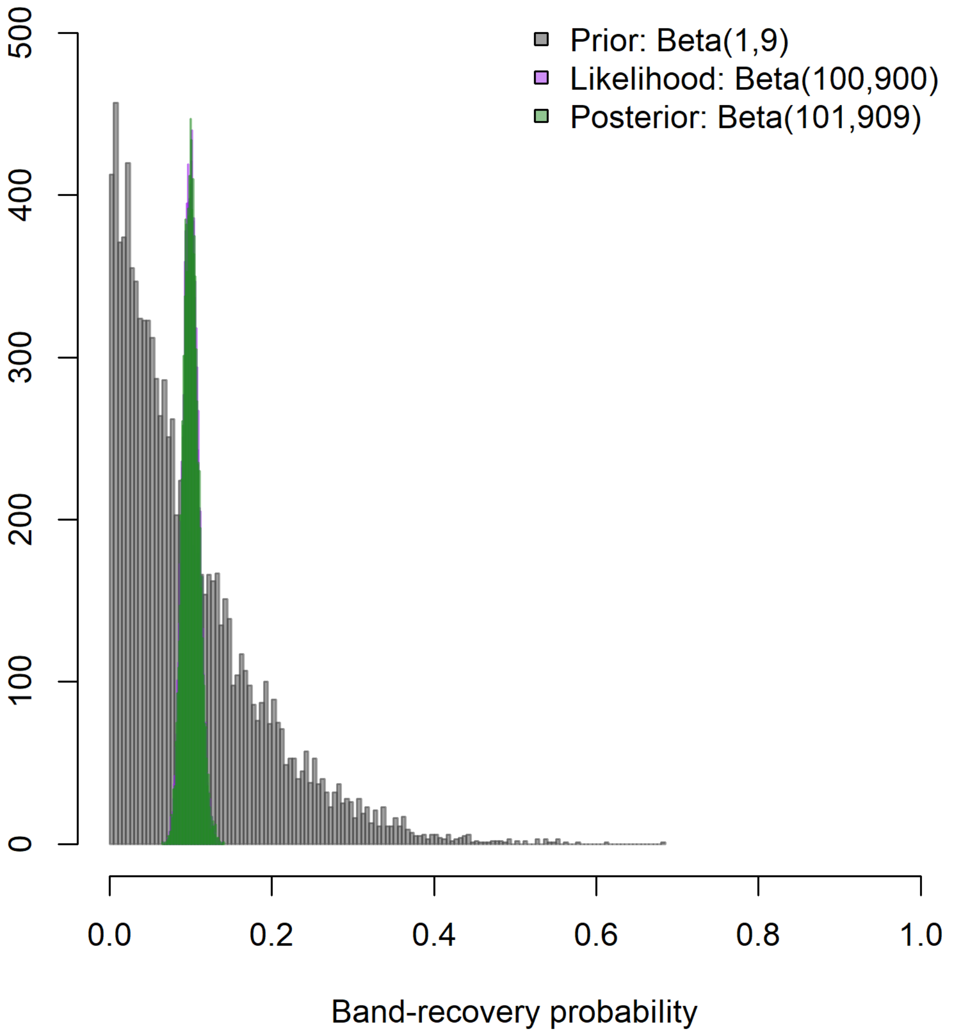


Let’s remember our first example (1000 releases, 100 recoveries)

Prior: **Beta(1, 9)**

Likelihood: **Beta(100, 900)**

Posterior: **Beta(α + Successes, β + Failures)**

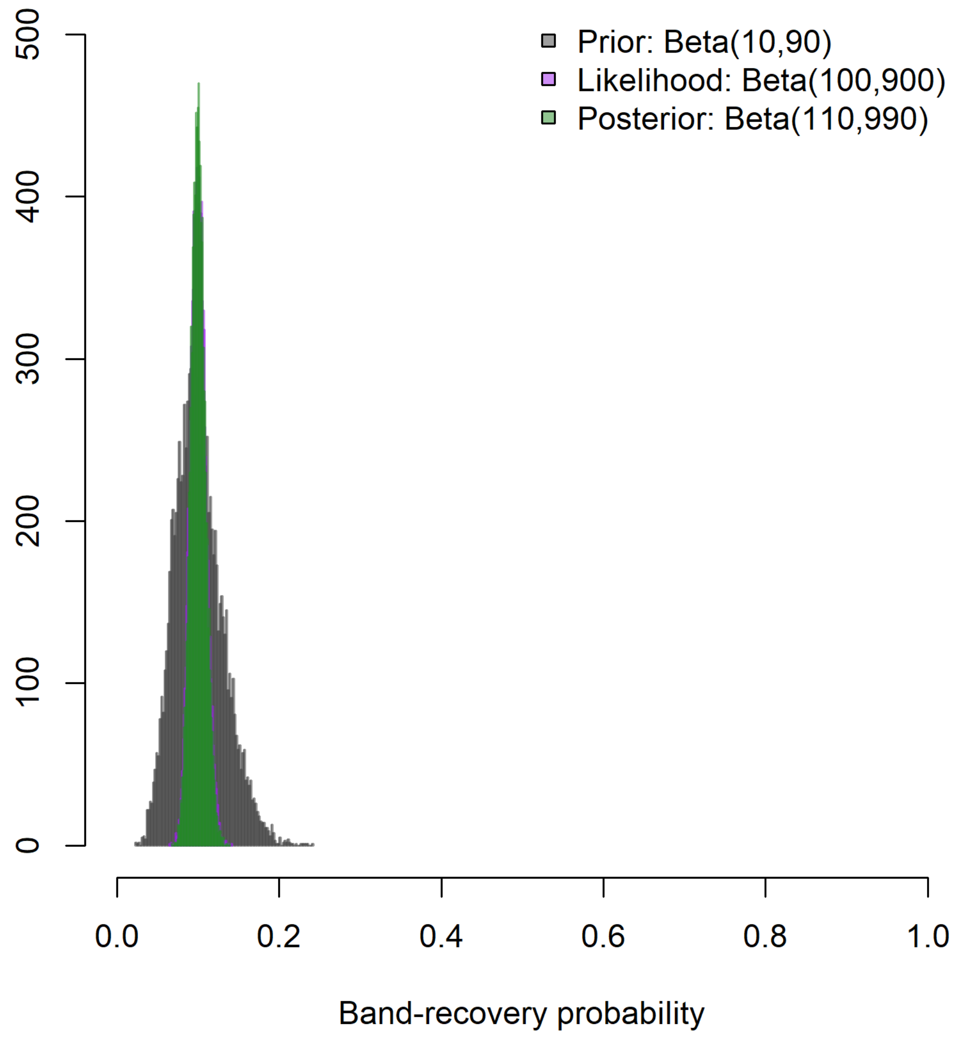


Let’s remember our first example (1000 releases, 100 recoveries)

Prior: **Beta(10, 90)**

Likelihood: **Beta(100, 900)**

Posterior: **Beta(α + Successes, β + Failures)**

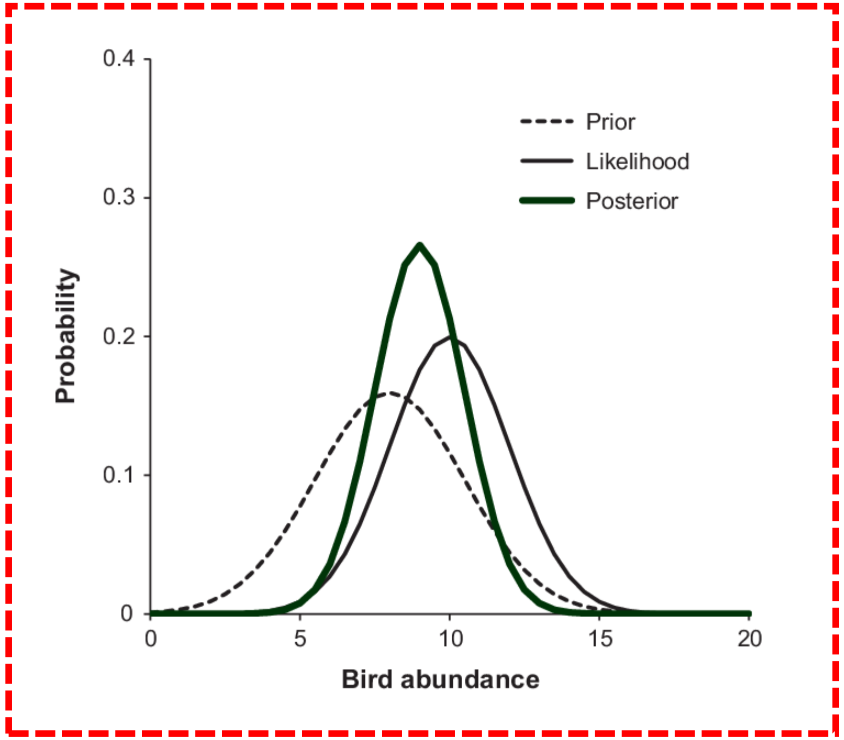


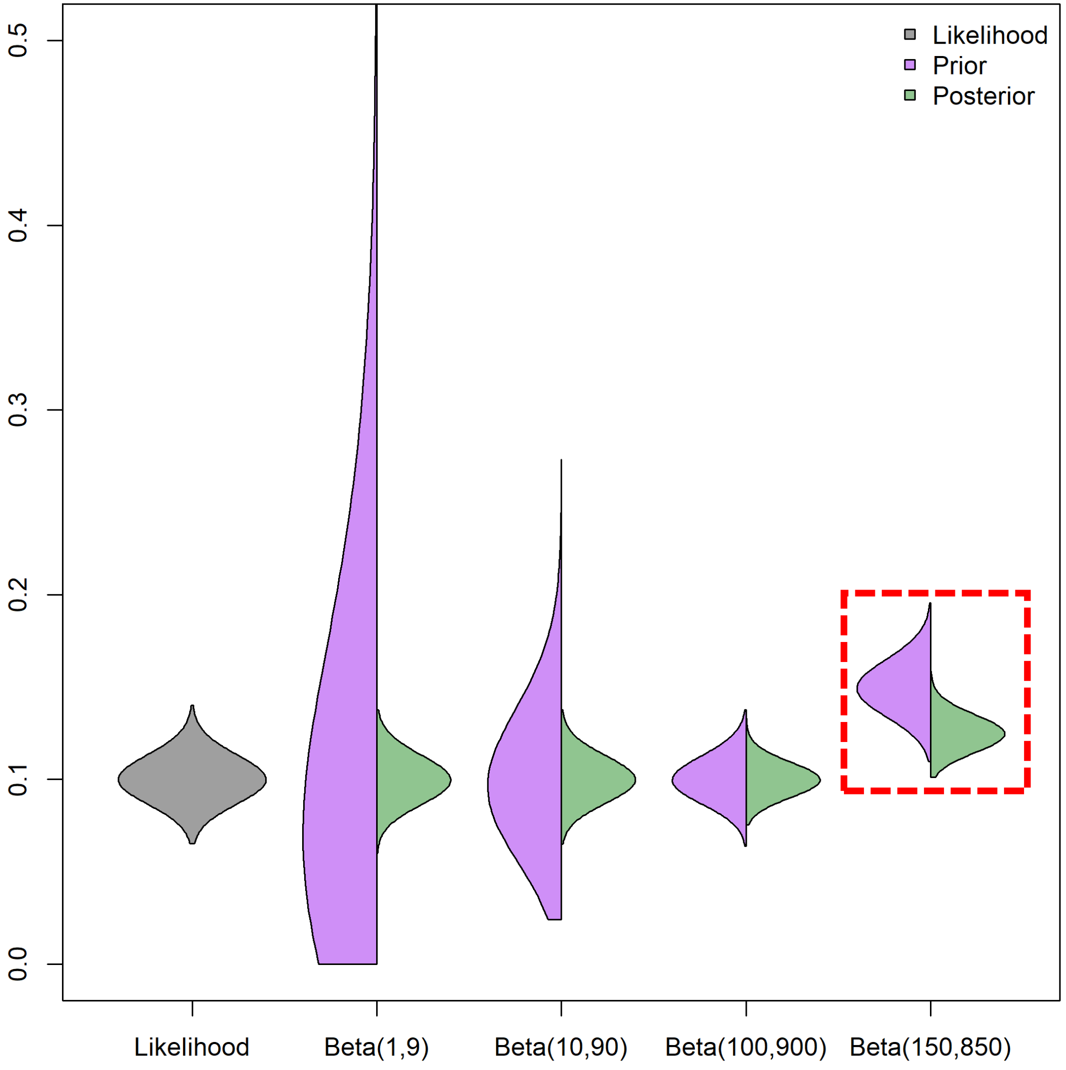
Let's remember our first example (1000 releases, 100 recoveries)

Prior: **Beta(α, β)**

Likelihood: **Beta(100, 900)**

Posterior: **Beta(α + Successes, β + Failures)**





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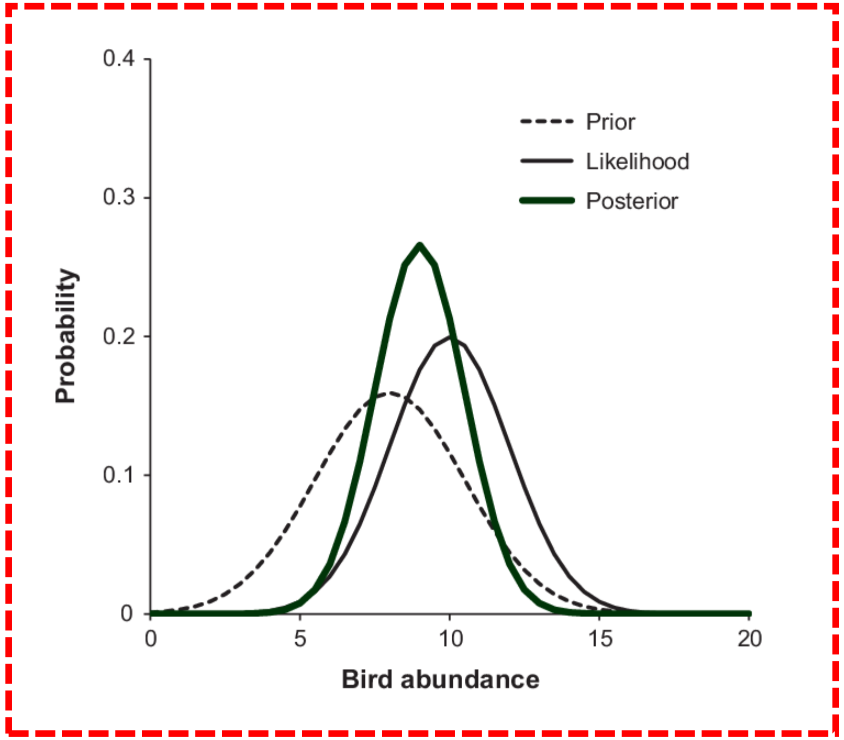
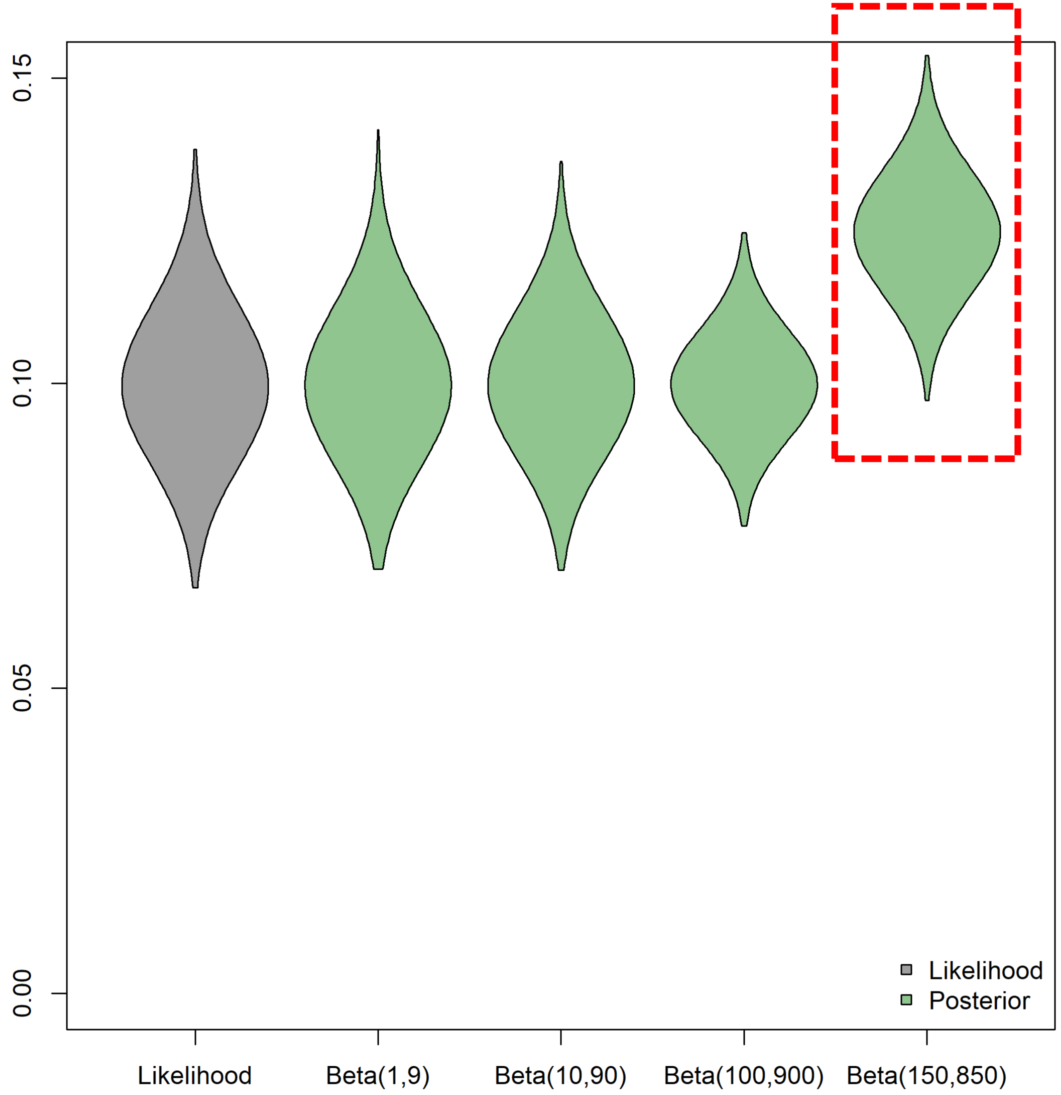
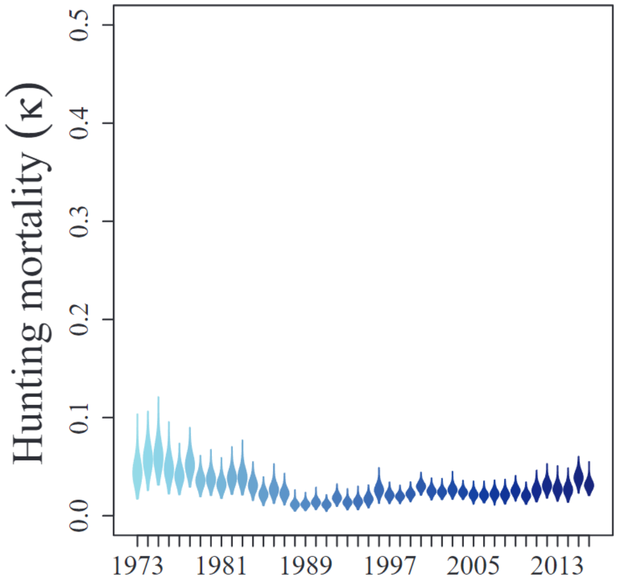




There’s a subjective ‘sweet spot’

- Don’t go too far:
- e.g., Survival is 0.723458 with a SE of 0.00001*

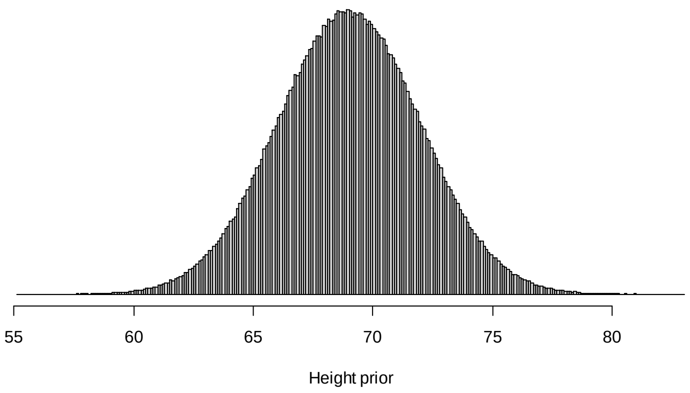
- Don’t pretend it could be any number:
- e.g., dispersal to the moon, hunting mortality is equally likely to be 0 or 1!**

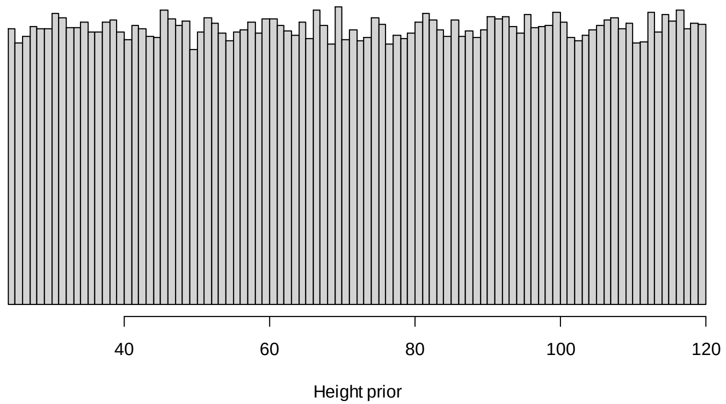


*A huge ‘non-Bayesian’ fear is that priors drive inference
**A ‘hardcore Bayesian’ fear is that we often use priors that are overly vague

‘Biologically informative’ or ‘reasonably vague’ priors

5’ 10 ⅞” ± ⅓”





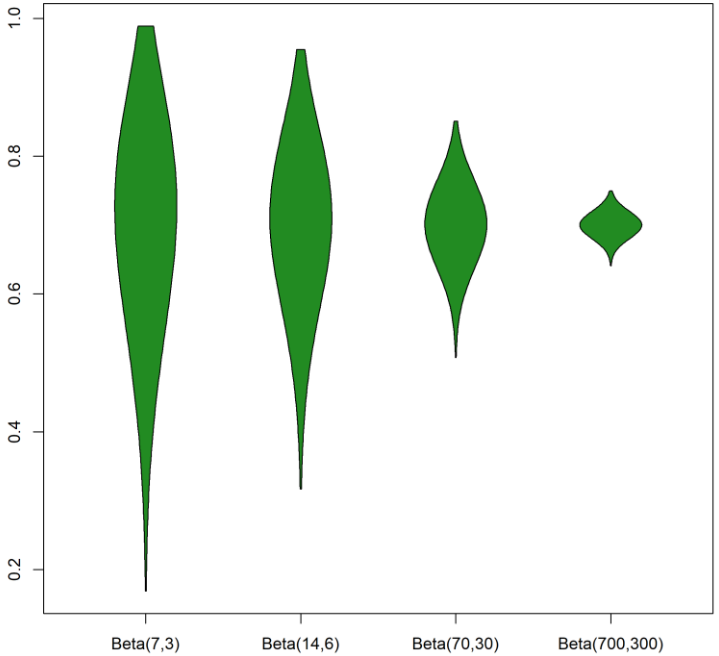
There's a subjective 'sweet spot'

- Finding 'it' takes some time and careful thinking

- Spend time familiarizing yourself with distributions

- Make histograms!

```
> s1 <- rbeta(10000, 7, 3)
> s2 <- rbeta(10000, 14, 6)
> s3 <- rbeta(10000, 70, 30)
> s4 <- rbeta(10000, 700, 300)
>
> png("E:/O_Final/Duck_Symposium_9/band_recovery_workshop/figures/prior6.png",
+     height = 8, width = 8, units = 'in', res = 300)
> vioplot(s1, s2, s3, s4, names = c('Beta(7,3)','Beta(14,6)','Beta(70,30)','Beta(700,300)'),
+         drawRect = F, col = 'forestgreen', wex = 0.5)
> dev.off()
```



Our first example (script 0)!

Model

$$r \sim \mathrm{binomial}(nR, f)$$

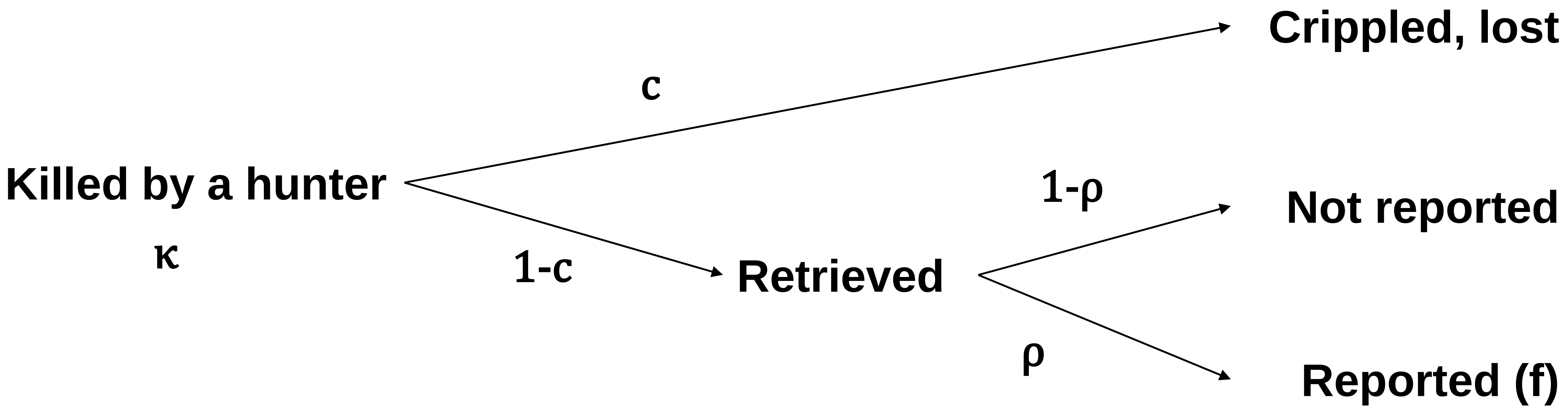
Prior

$$r \sim \mathrm{beta}(1,1)$$

Simulating direct recoveries

Script 0

From band-recovery probability to κ and harvest (script 1)



***Killed but crippled (lost):** $\kappa * c$
***Killed, recovered, but not reported:** $\kappa * (1\text{-}c) * (1\text{-}\rho)$
***Killed, recovered, and reported:** $\underline{\kappa * (1\text{-}c) * \rho = f}$

***Brownie et al. uses c as a ‘retrieval probability,’ but here we treat it as ‘crippling loss probability’**

From band-recovery probability to κ and harvest (script 1)

Model

$$r \sim \text{binomial}(nR, f)$$

$$f = \kappa \times (1 - c) \times \rho$$

Prior

$$\kappa \sim \text{beta}(1,1)$$

$$\rho \sim \text{beta}(100,100)$$

$$c \sim \text{beta}(20,80)$$

Script 1