



## BAYESIAN MODELING WITH RJAGS

# The prior model

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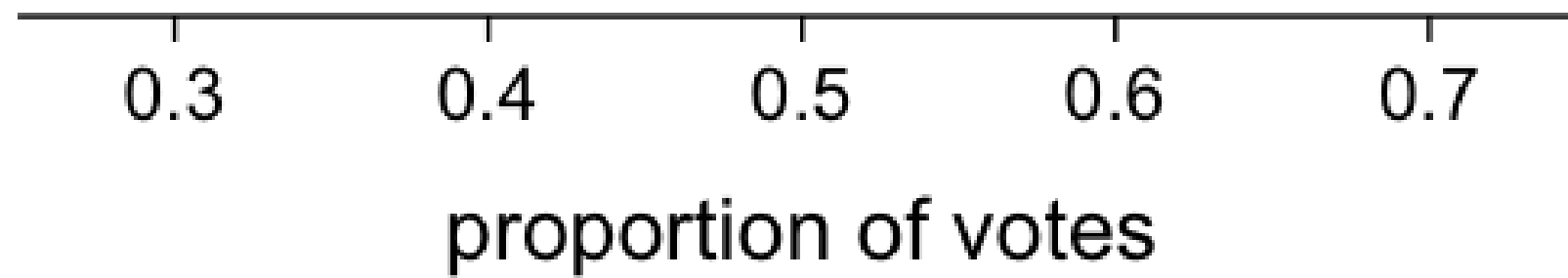


# Course Goals

- Explore foundational, generalizable Bayesian models (eg: Beta-Binomial, Normal-Normal, and Bayesian regression)
- **Define, compile, and simulate** Bayesian models using RJAGS
- Conduct Bayesian posterior inference using RJAGS output

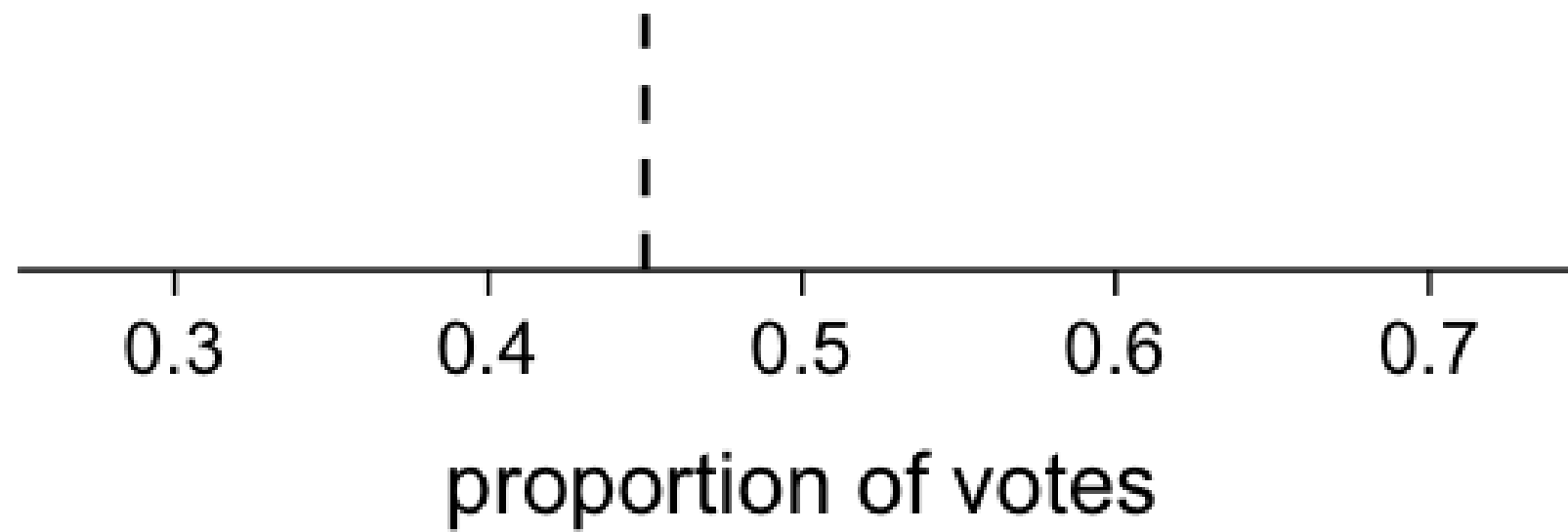


# Bayesian elections: The prior



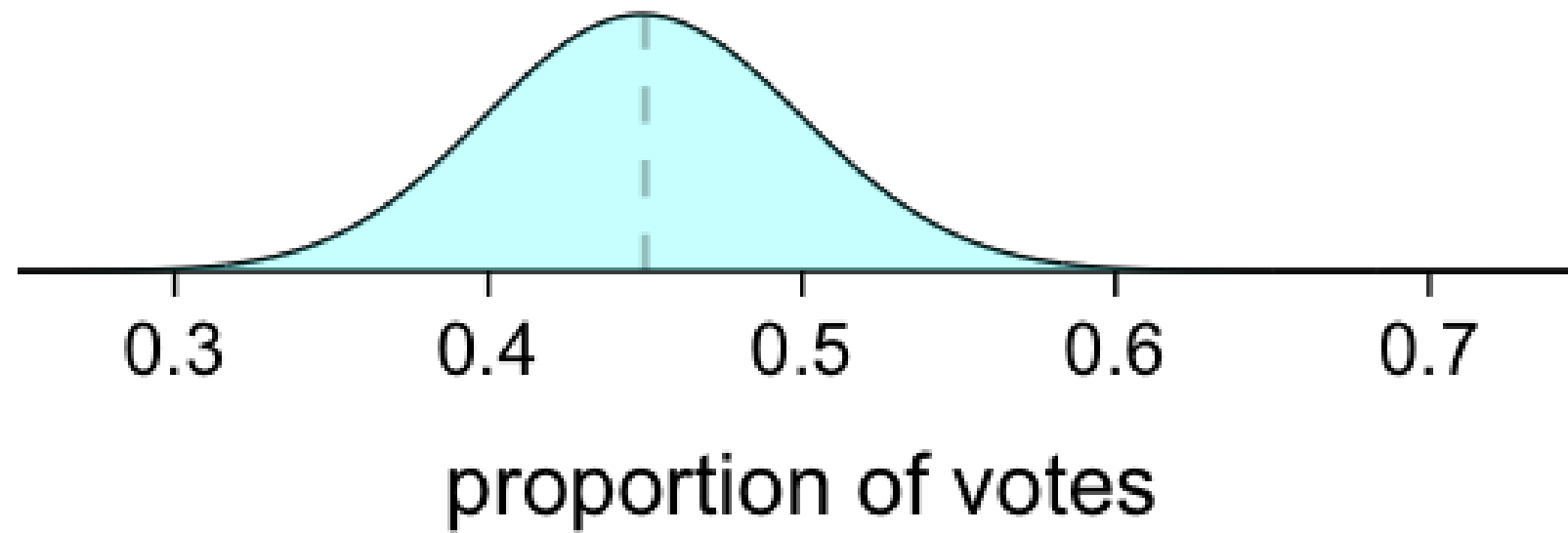


# Bayesian elections: The prior

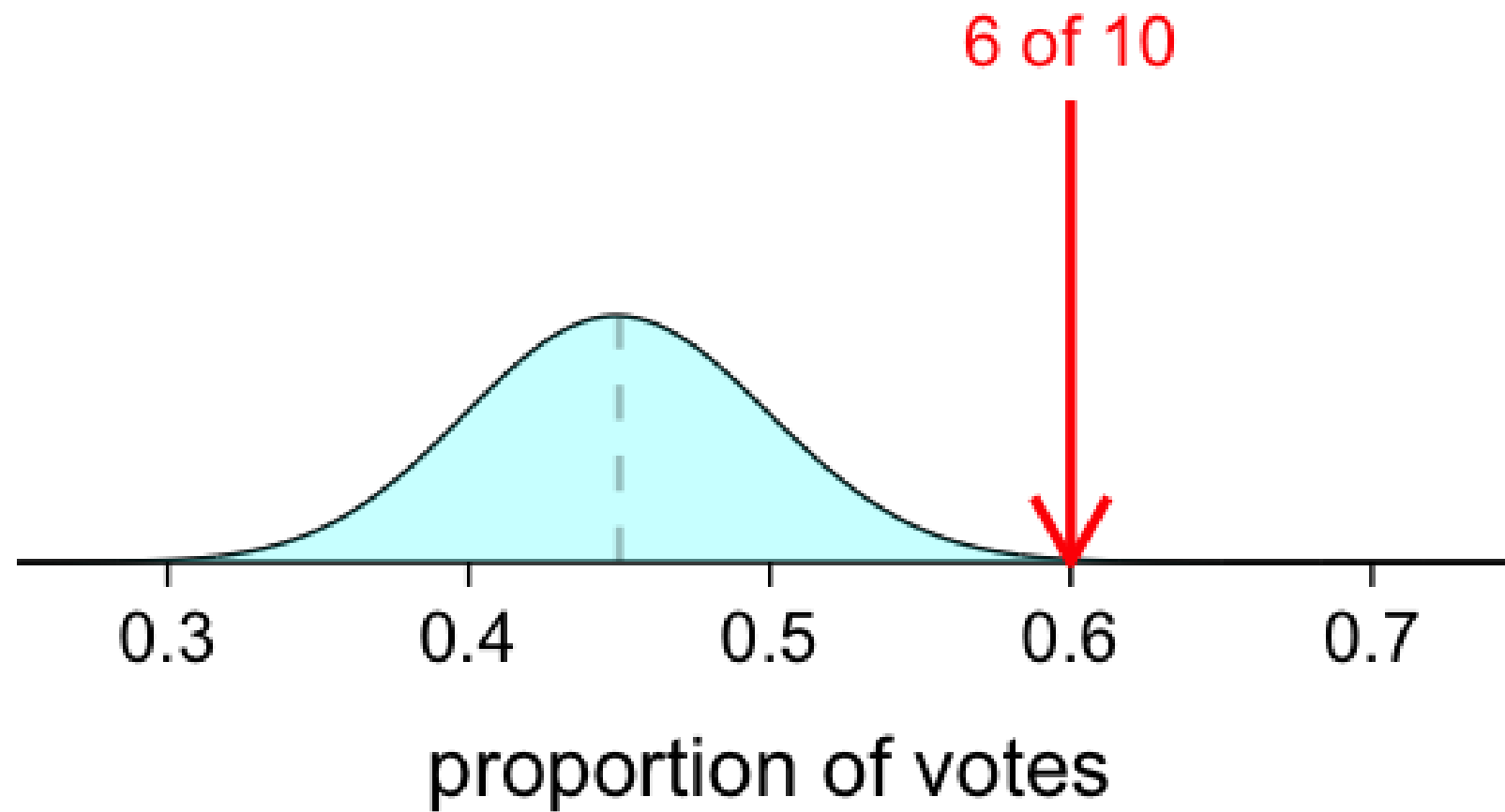




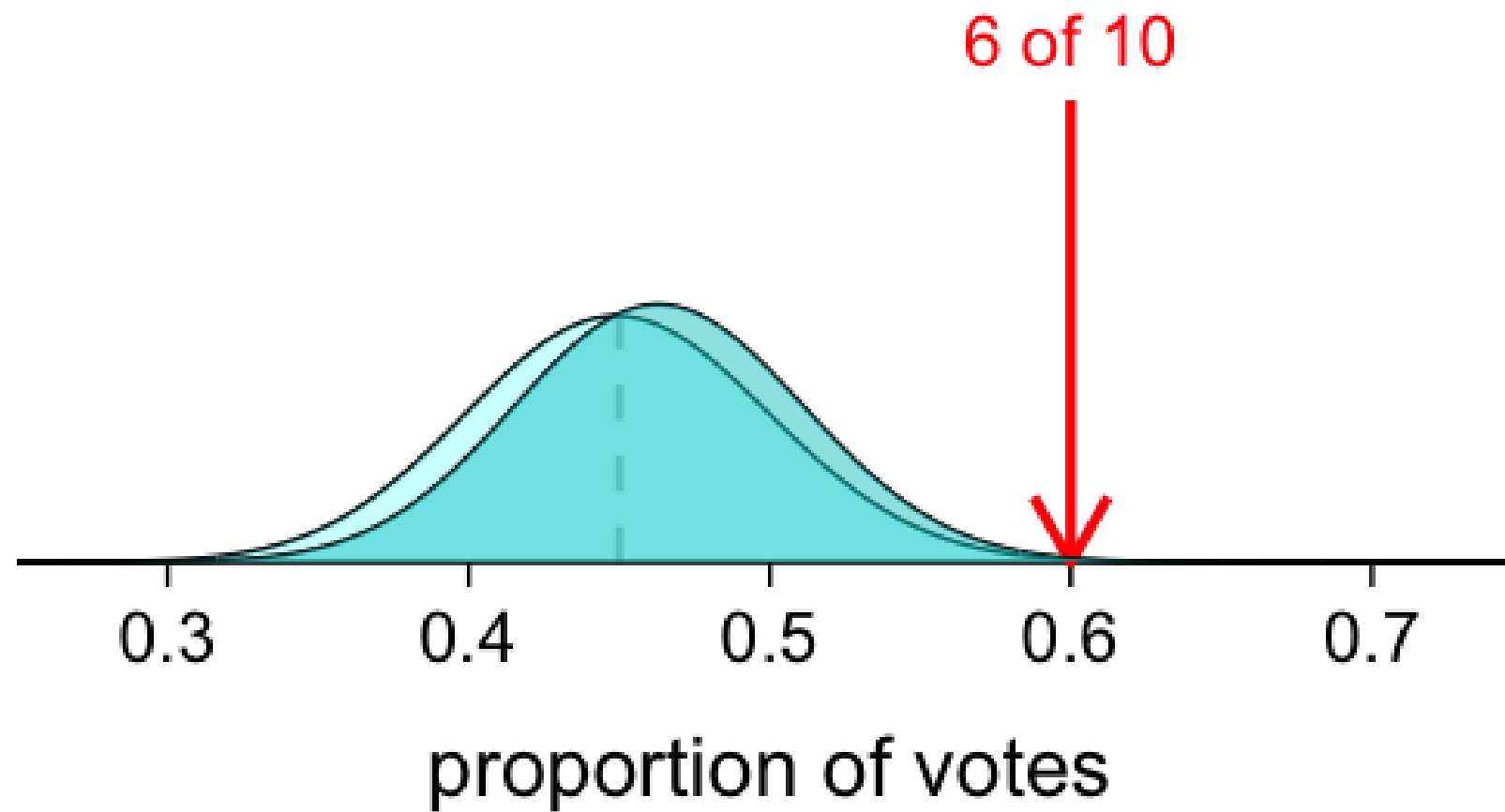
# Bayesian elections: The prior



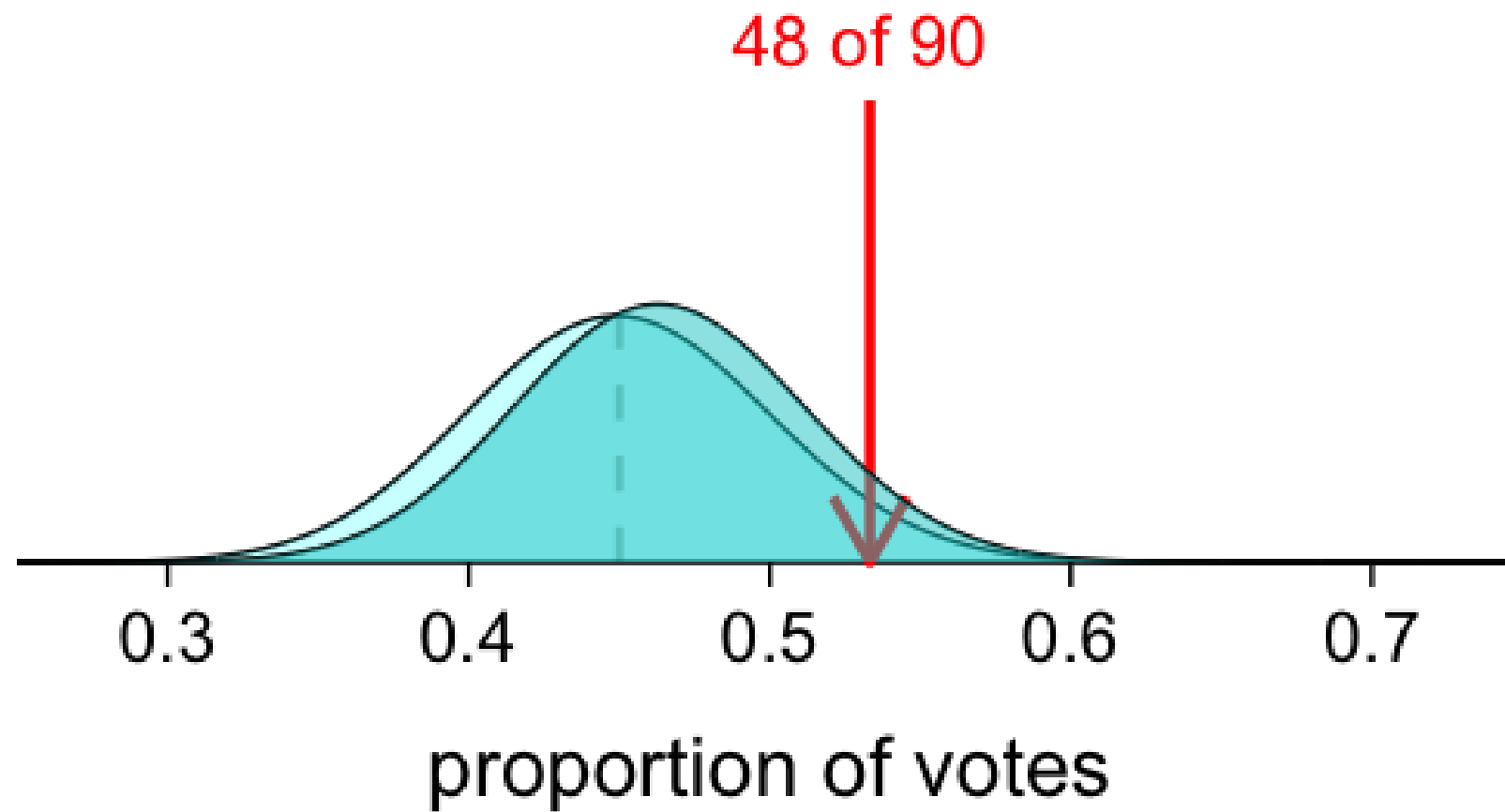
# Bayesian elections: The data



# Bayesian elections: The posterior

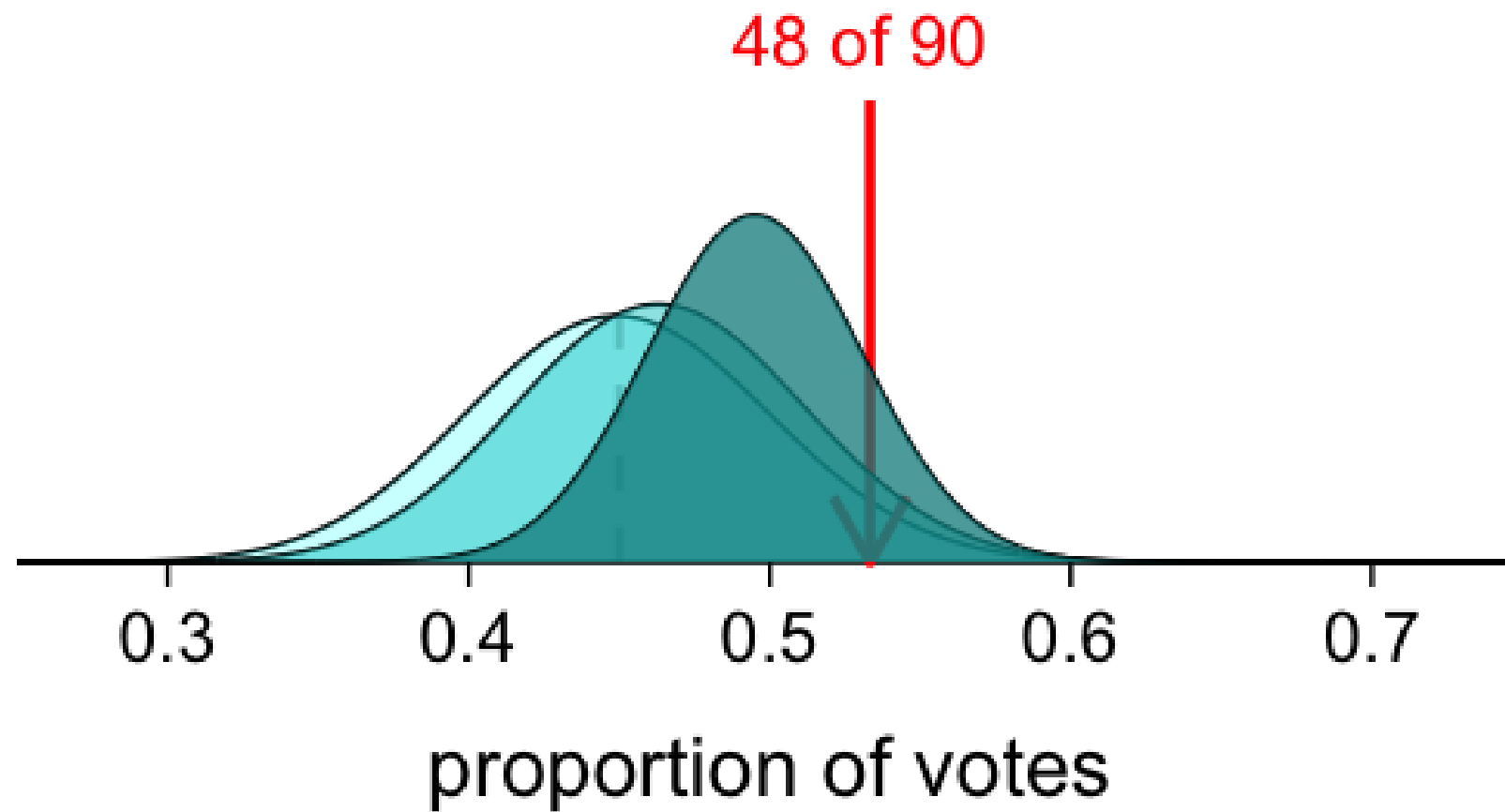


# Bayesian elections: New data



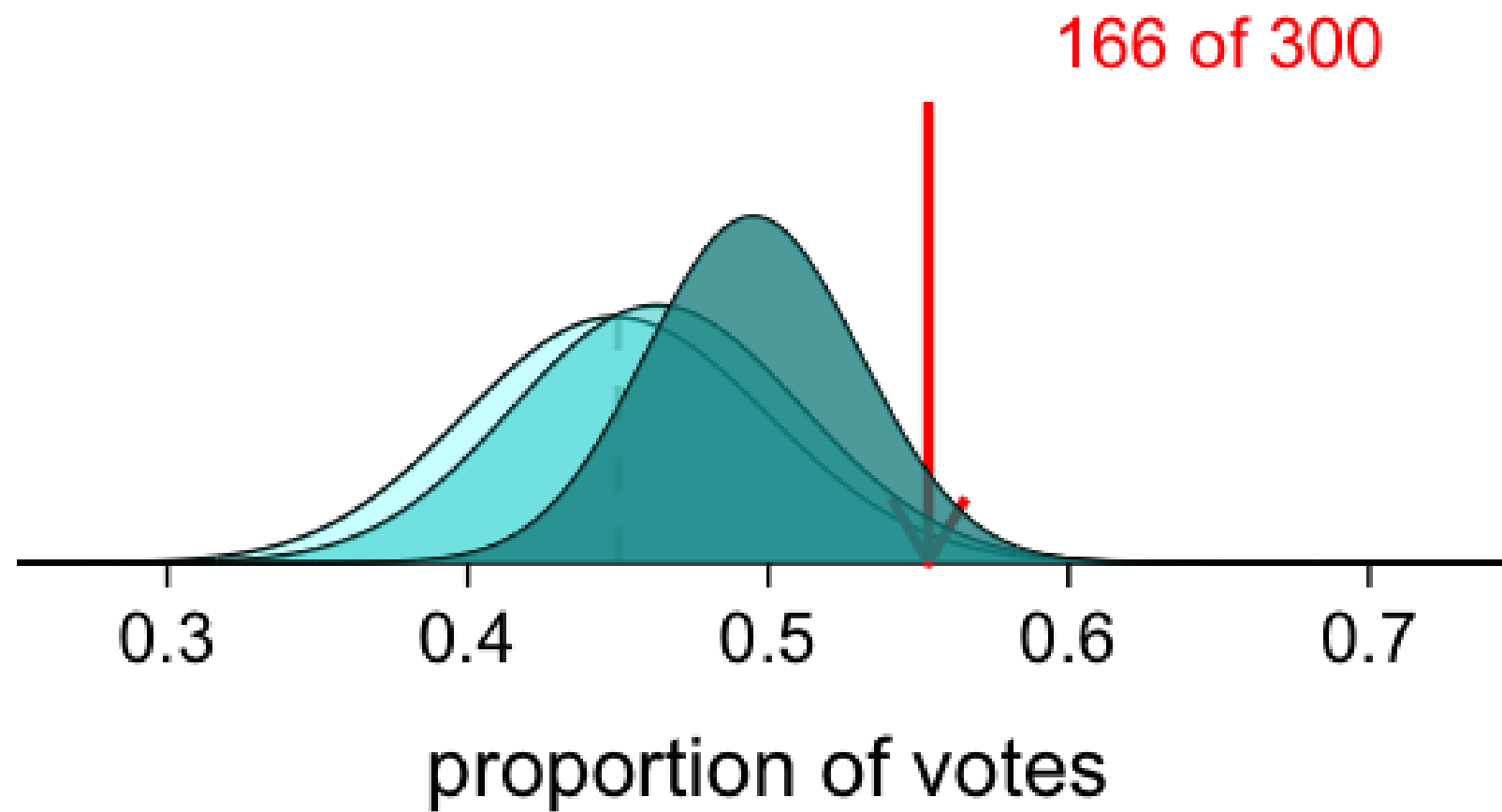


# Bayesian elections: New posterior

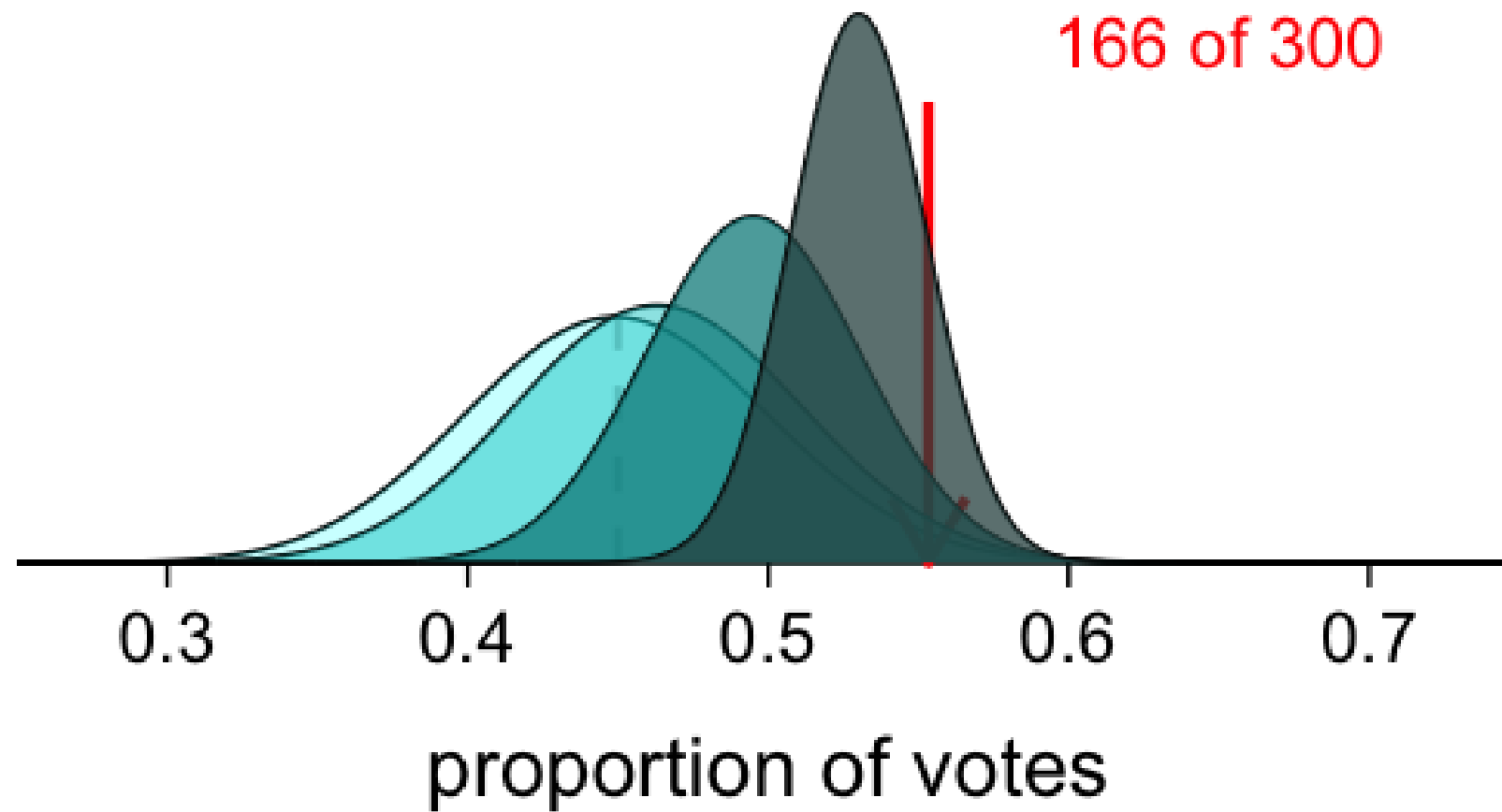




# Bayesian elections: Newer data



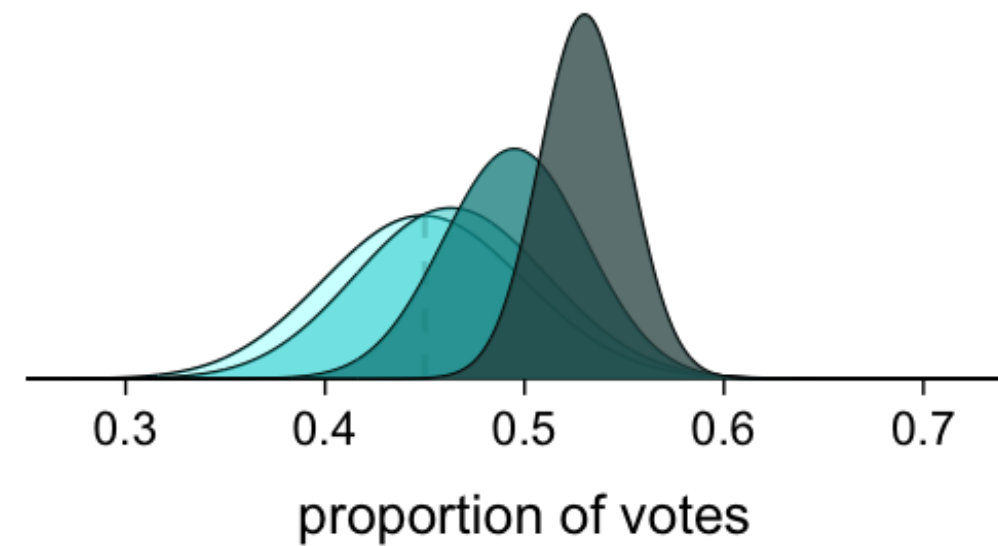
# Bayesian elections: Newer posterior



# Bayesian thinking

A Bayesian posterior model...

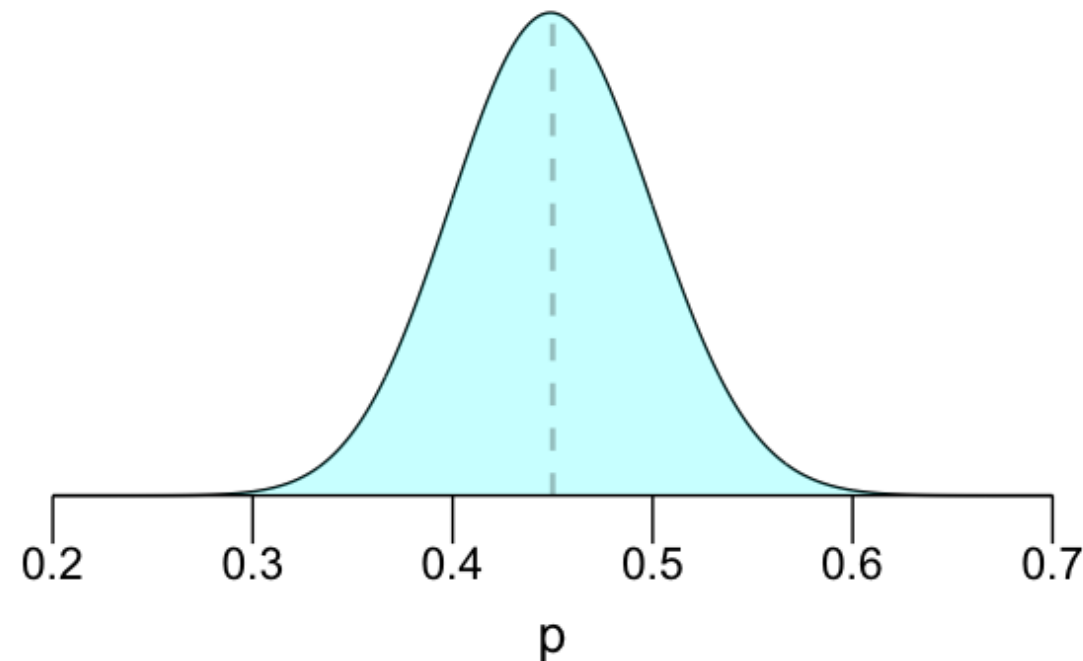
- combines insights from the prior model & observed data
- evolves as new data come in



# Building a prior model

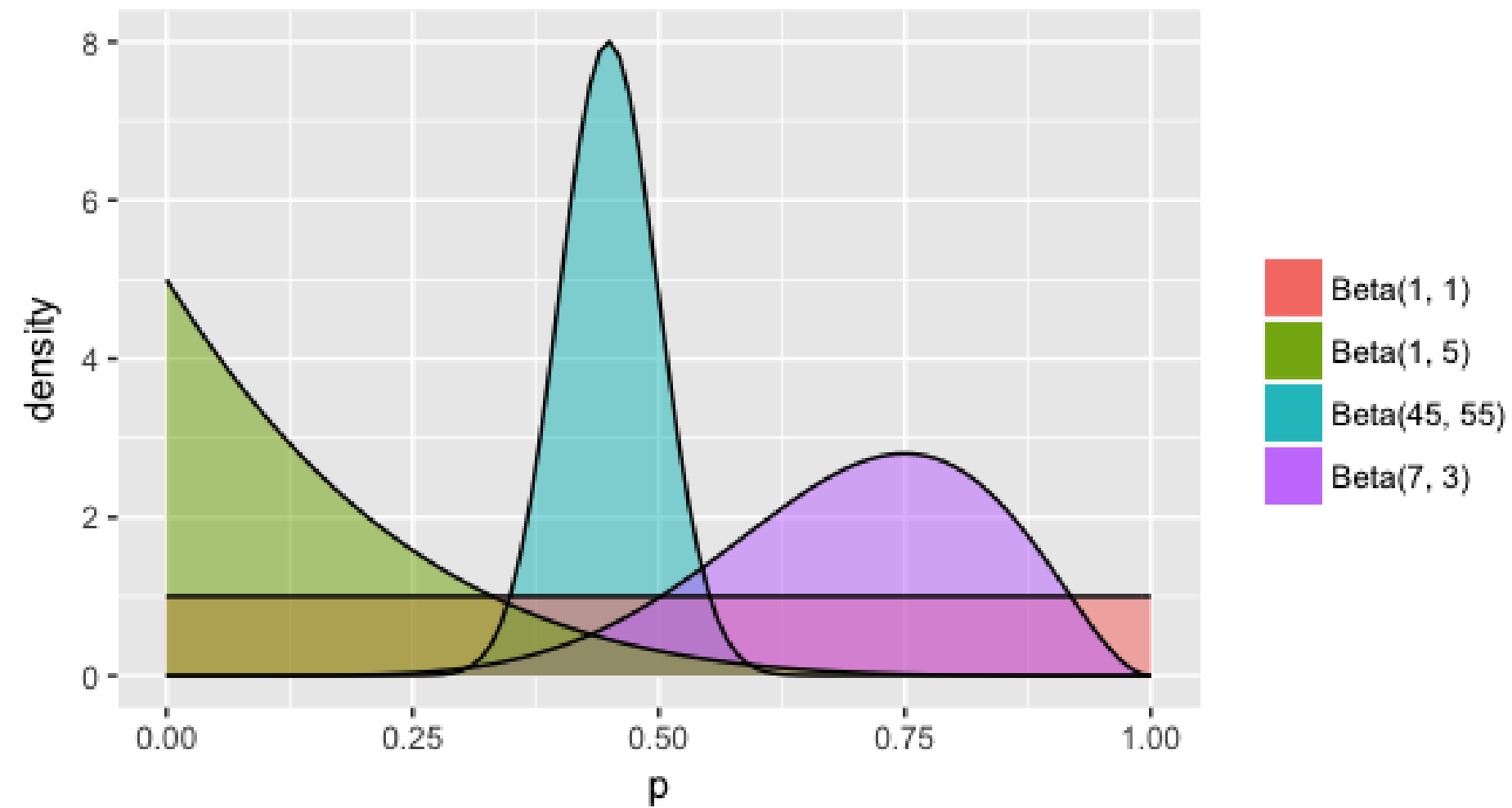
- $p$  = proportion that support you
- $p$  is between 0 and 1
- The prior model for  $p$  is a **Beta distribution** with **shape parameters** 45 and 55

$$p \sim \text{Beta}(45, 55)$$





# Tuning the prior





## BAYESIAN MODELING WITH RJAGS

**Let's practice!**



## BAYESIAN MODELING WITH RJAGS

# Data & the likelihood

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# Polling Data

- **parameter**

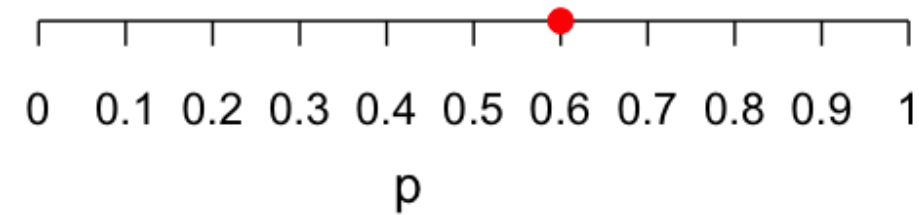
$p$  = proportion that support you

- **data**

$X = 6$  of  $n = 10$  polled voters plan to vote for you

- **insights**

You are more likely to have observed these data if  $p \approx 0.6$  than if  $p < 0.5$ .



# Modeling the dependence of $X$ on $p$

- **Poll assumptions:**

voters are independent

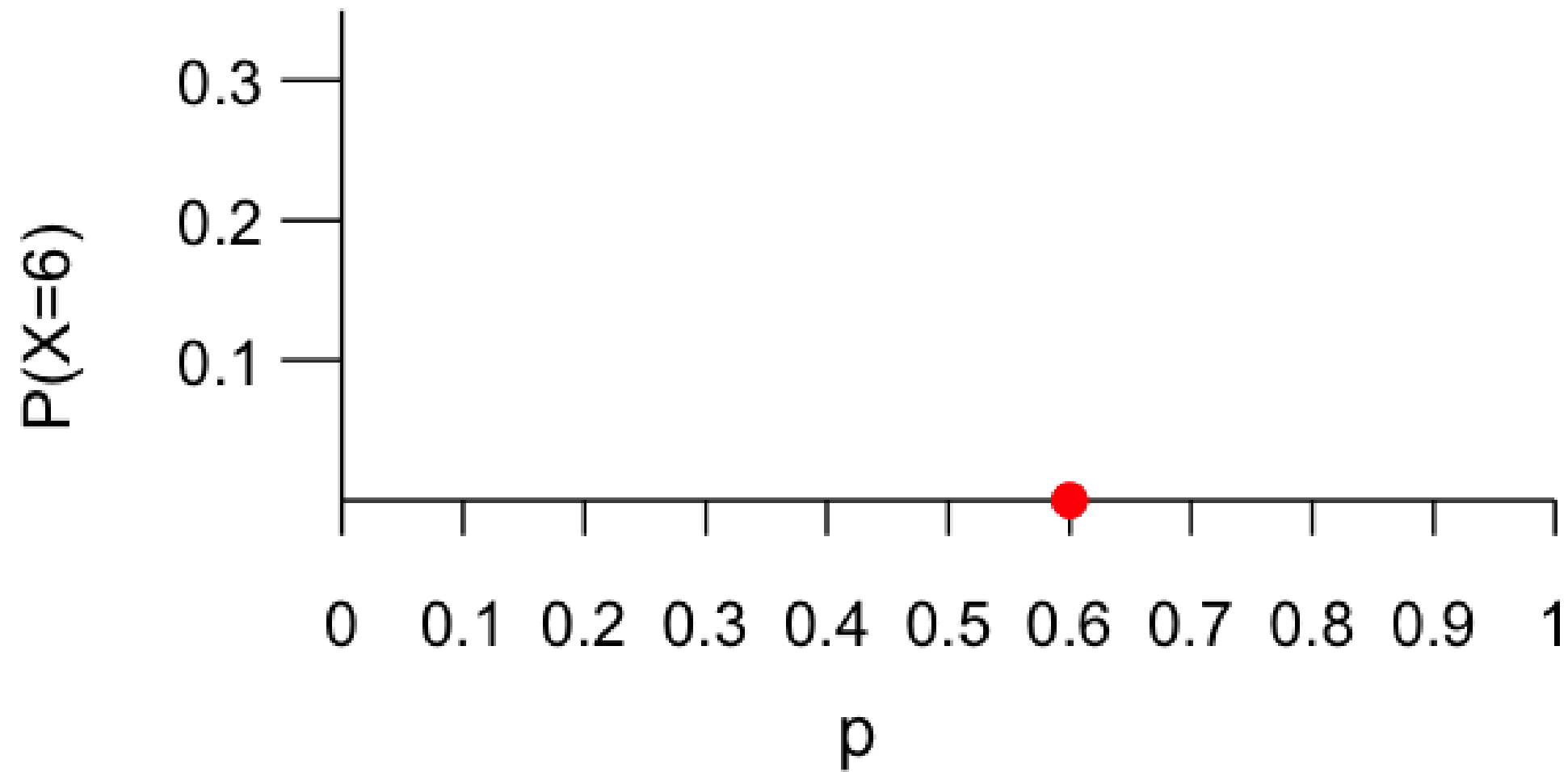
$p$  = probability that a voter supports you

- $X$  = number of  $n$  polled voters that support you  
(count of successes in  $n$  independent trials, each having probability of success  $p$ )

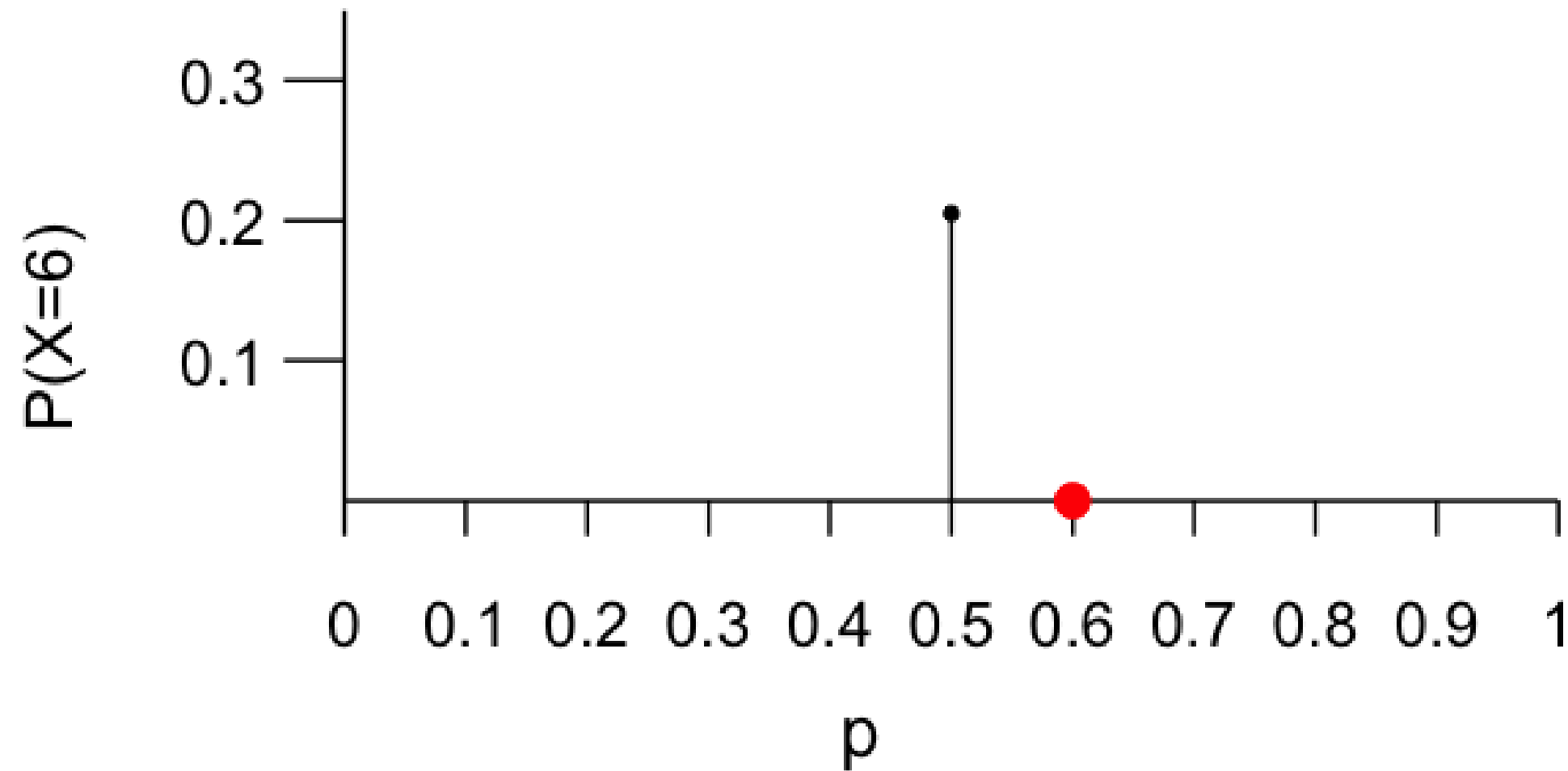
- **Conditional distribution of  $X$  given  $p$ :**

$$X \sim \text{Bin}(n, p)$$

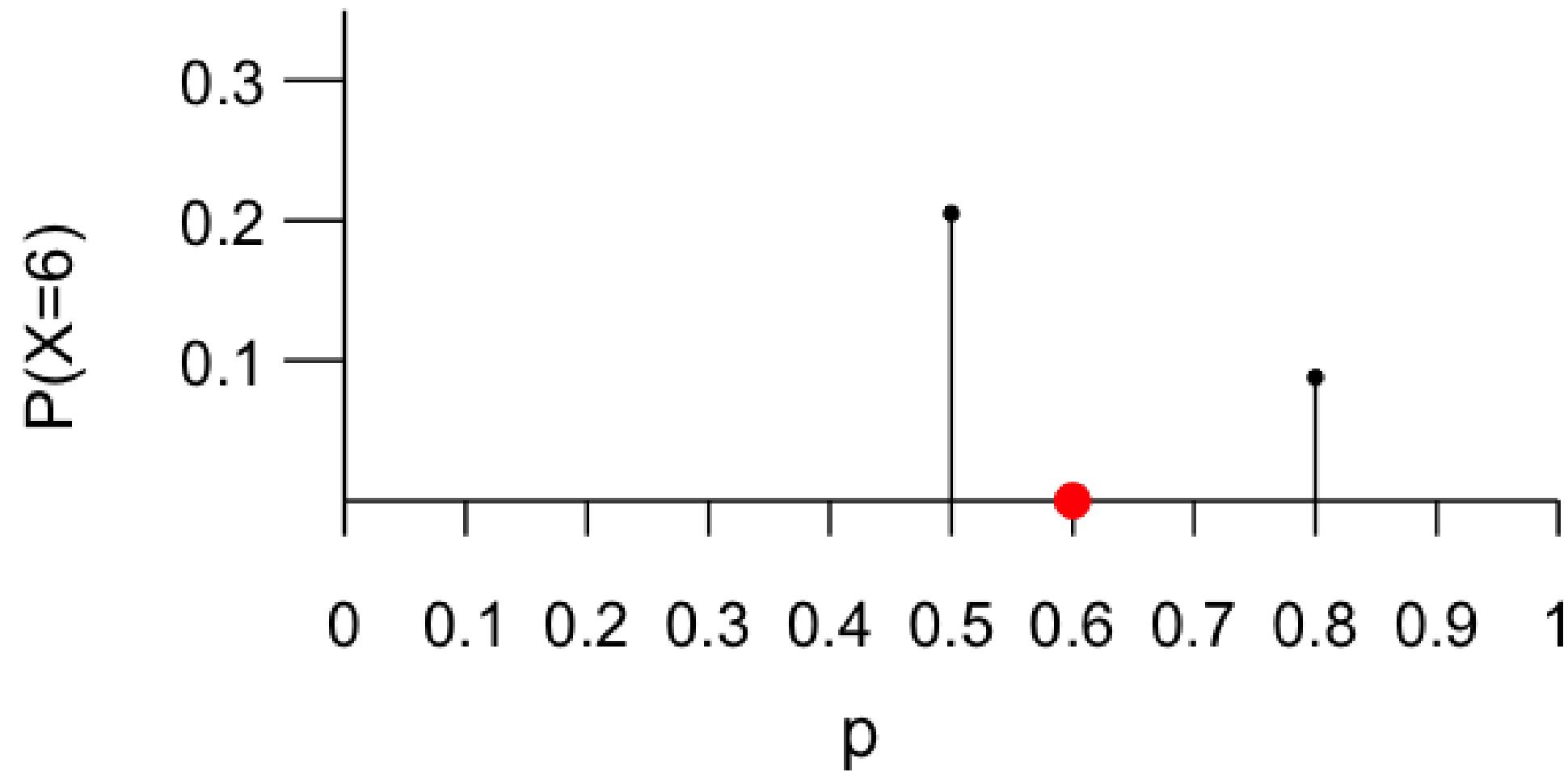
# Dependence of $X$ on $p$



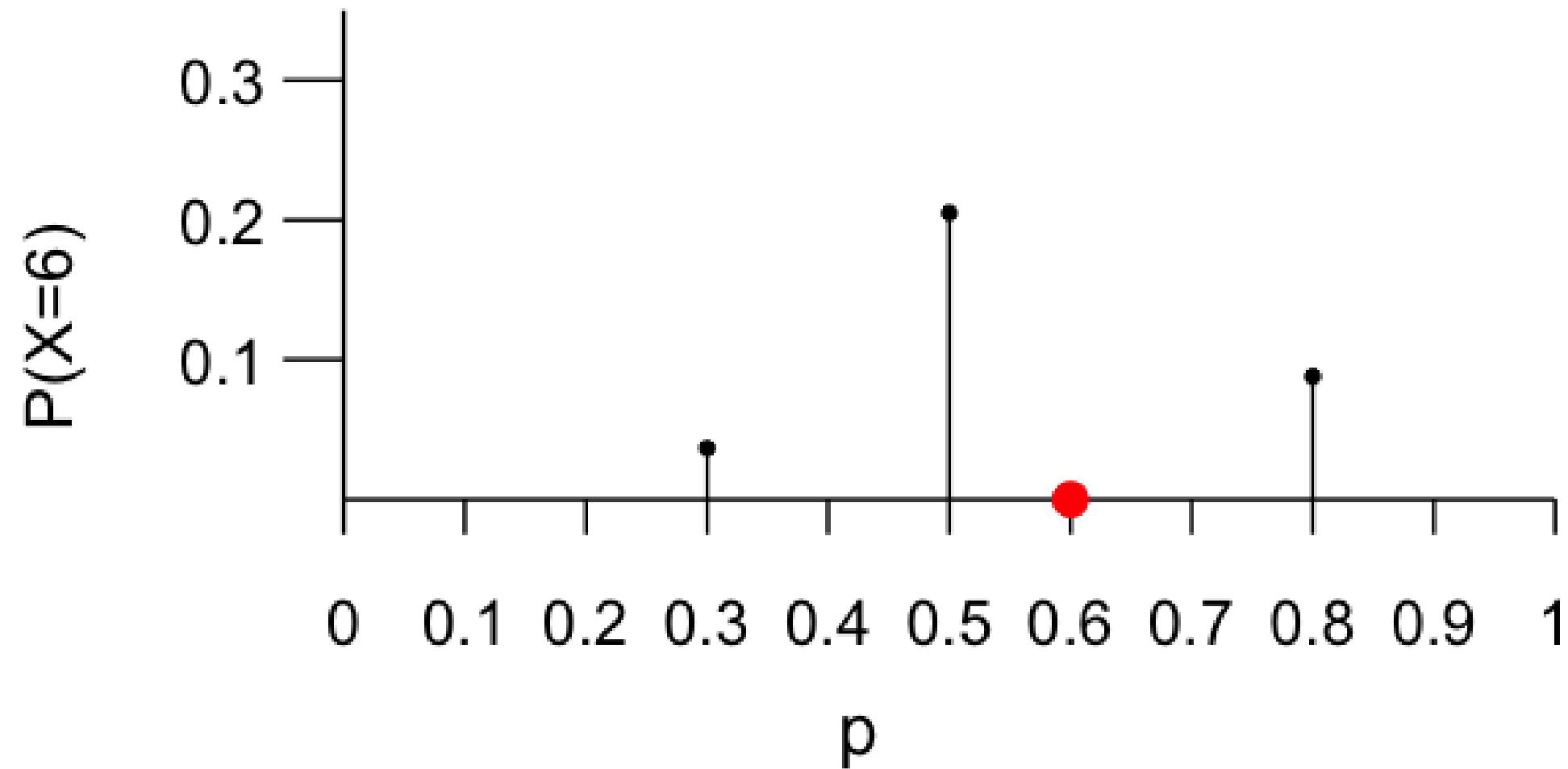
# Dependence of $X$ on $p$



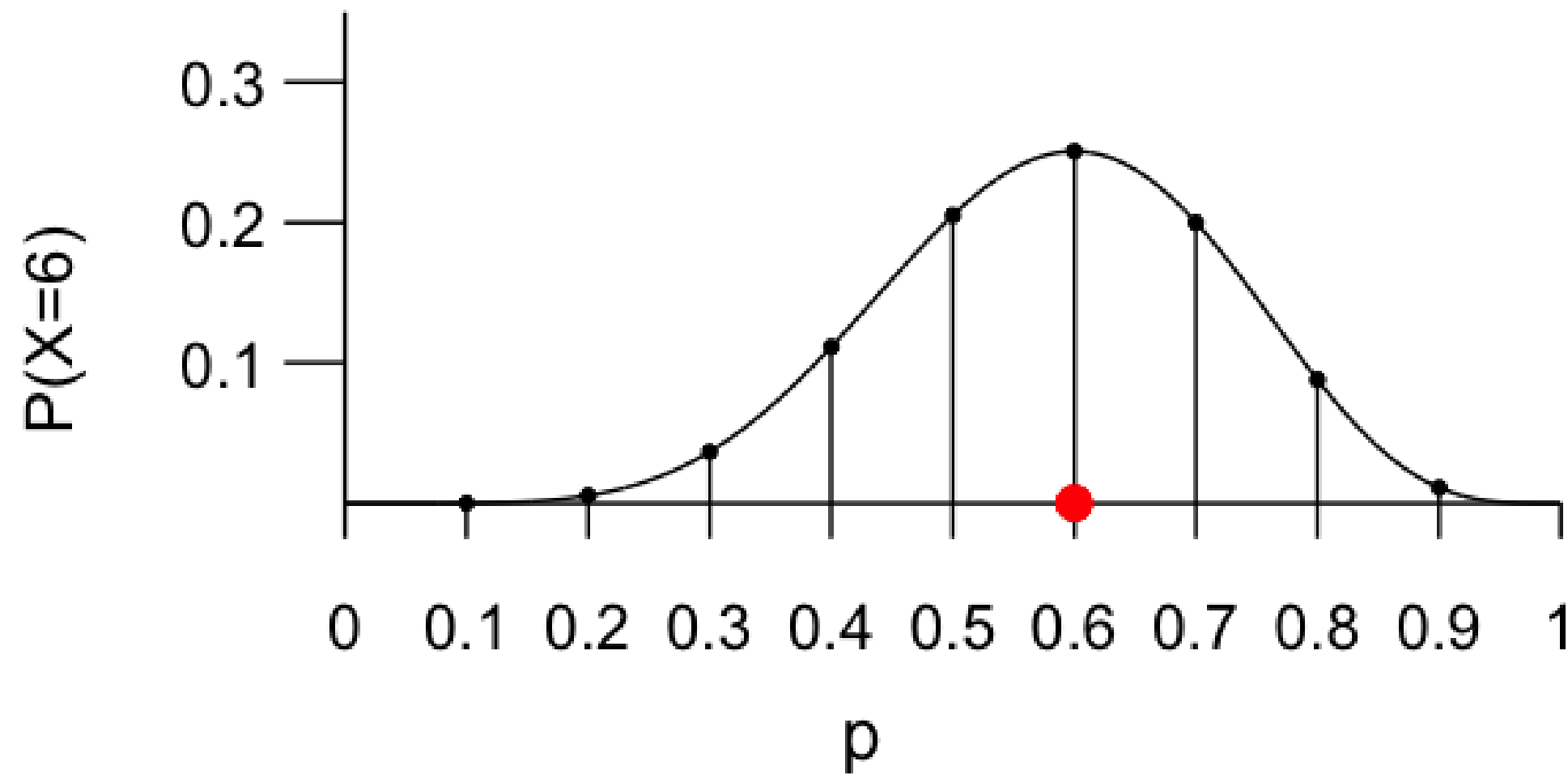
# Dependence of $X$ on $p$



# Dependence of $X$ on $p$



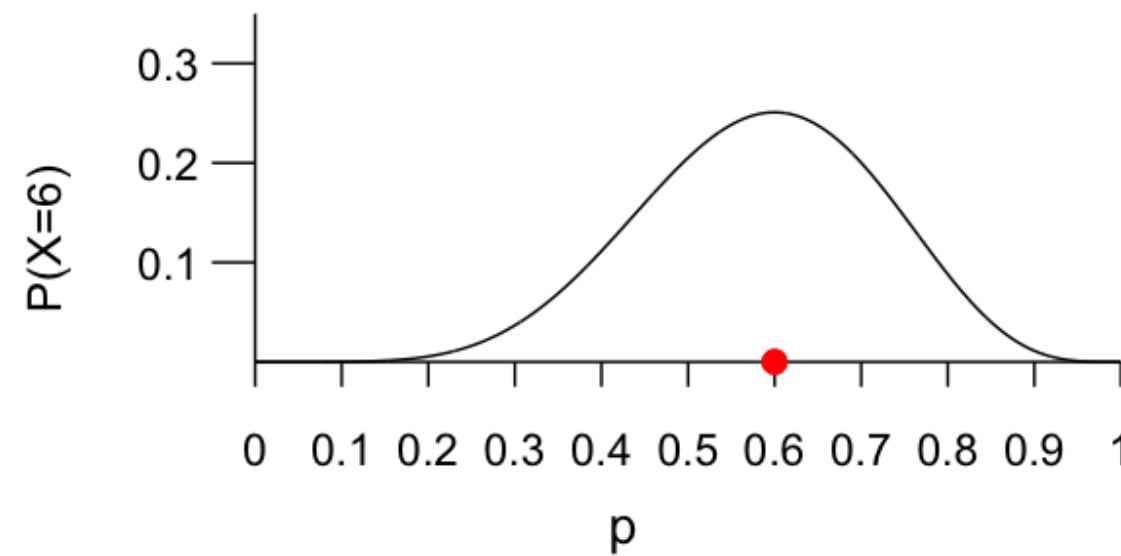
# What's the likelihood?



# Likelihood

The **likelihood function** summarizes the likelihood of observing polling data  $X$  under different values of the underlying support parameter  $p$ . It is a function of  $p$ .

- high likelihood  $\Rightarrow p$  is compatible with the data
- low likelihood  $\Rightarrow p$  is not compatible with the data







## BAYESIAN MODELING WITH RJAGS

**Let's practice!**



## BAYESIAN MODELING WITH RJAGS

# The posterior model

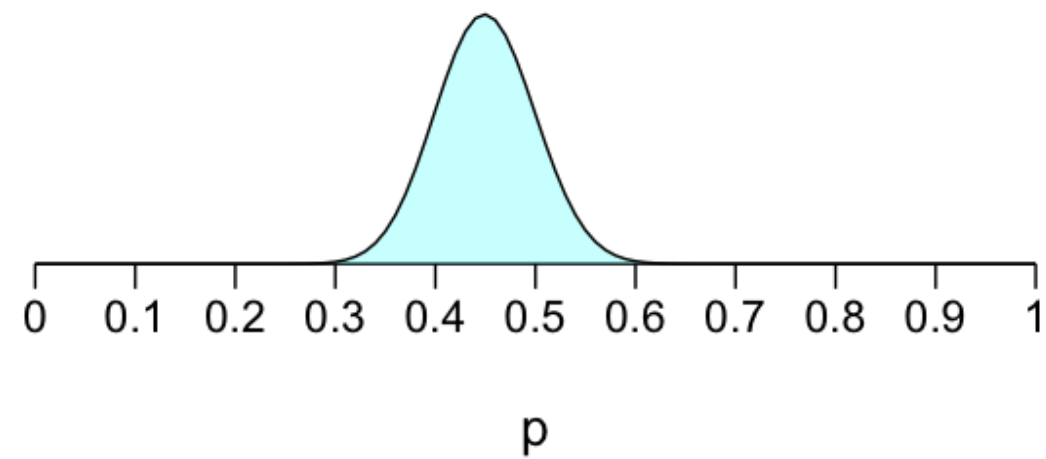
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# Bayesian election model

**prior:**  $p \sim \text{Beta}(45, 55)$

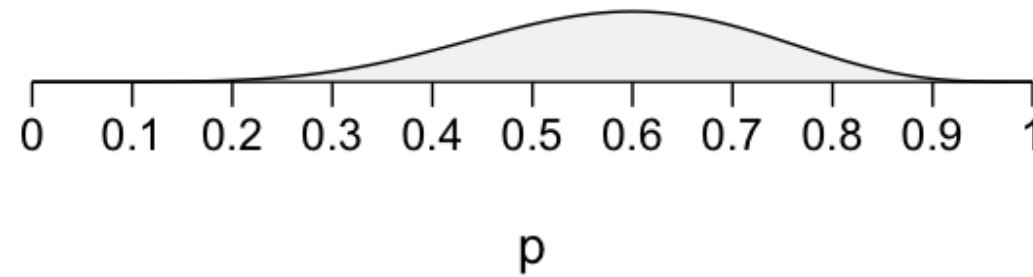




# Bayesian election model

**prior:**  $p \sim \text{Beta}(45, 55)$

**likelihood:**  $X \sim \text{Bin}(10, p)$

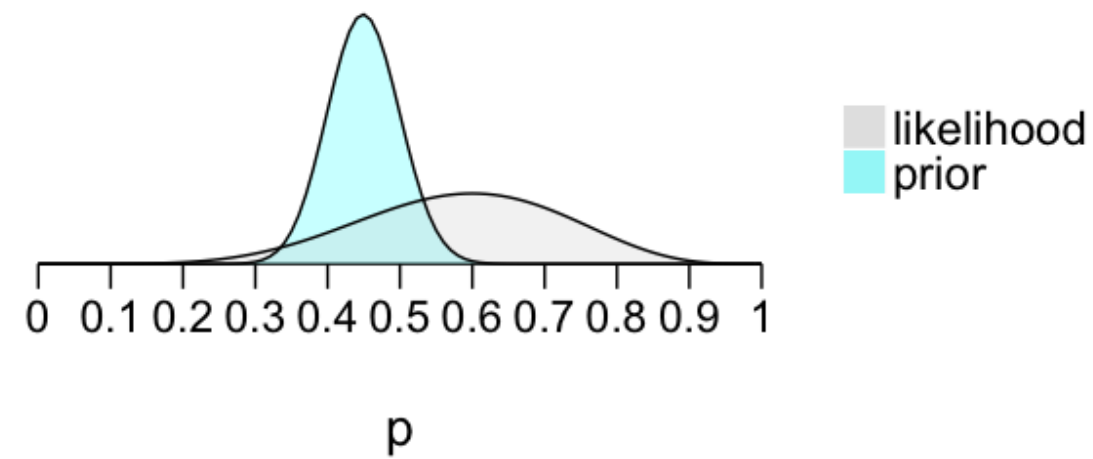




# Bayesian election model

**prior:**  $p \sim \text{Beta}(45, 55)$

**likelihood:**  $X \sim \text{Bin}(10, p)$





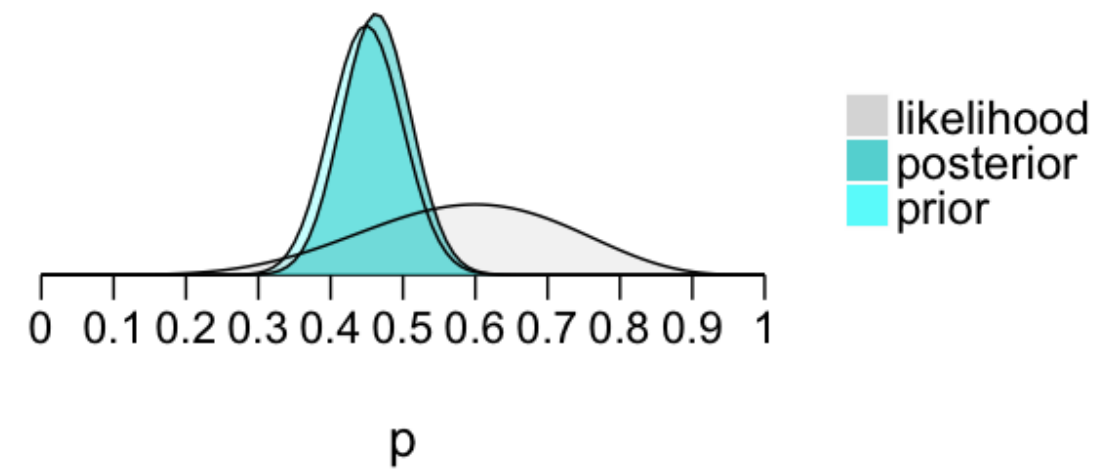
# Posterior model of p

**prior:**  $p \sim \text{Beta}(45, 55)$

**likelihood:**  $X \sim \text{Bin}(10, p)$

**Bayes' Rule:**

posterior  $\propto$  prior \* likelihood





# Getting Started with RJAGS

RJAGS combines the power of R with the JAGS (*Just Another Gibbs Sampler*) engine.  
To get started:

- Download the JAGS program outside R
- Within R, install the `rjags` package

# Bayesian Models in RJAGS: DEFINE

```
# DEFINE the model
vote_model <- "model{
  # Likelihood model for X
  X ~ dbin(p, n)

  # Prior model for p
  p ~ dbeta(a, b)
}"
```

- $X \sim \text{Bin}(n, p)$

- $p \sim \text{Beta}(a, b)$

- **Warning:**

the `rjags` function `dbin()` is different

than base `dbinom()`



# Bayesian Models in RJAGS: COMPILE

```
# DEFINE the model
vote_model <- "model{
  # Likelihood model for X
  X ~ dbin(p, n)

  # Prior model for p
  p ~ dbeta(a, b)
}"

# COMPILE the model
vote_jags_A <- jags.model(textConnection(vote_model),
  data = list(a = 45, b = 55, X = 6, n = 10),
  inits = list(.RNG.name = "base::Wichmann-Hill", .RNG.seed = 100))
```

# Bayesian Models in RJAGS: SIMULATE

```
# DEFINE the model
vote_model <- "model{
  # Likelihood model for X
  X ~ dbin(p, n)

  # Prior model for p
  p ~ dbeta(a, b)
}"

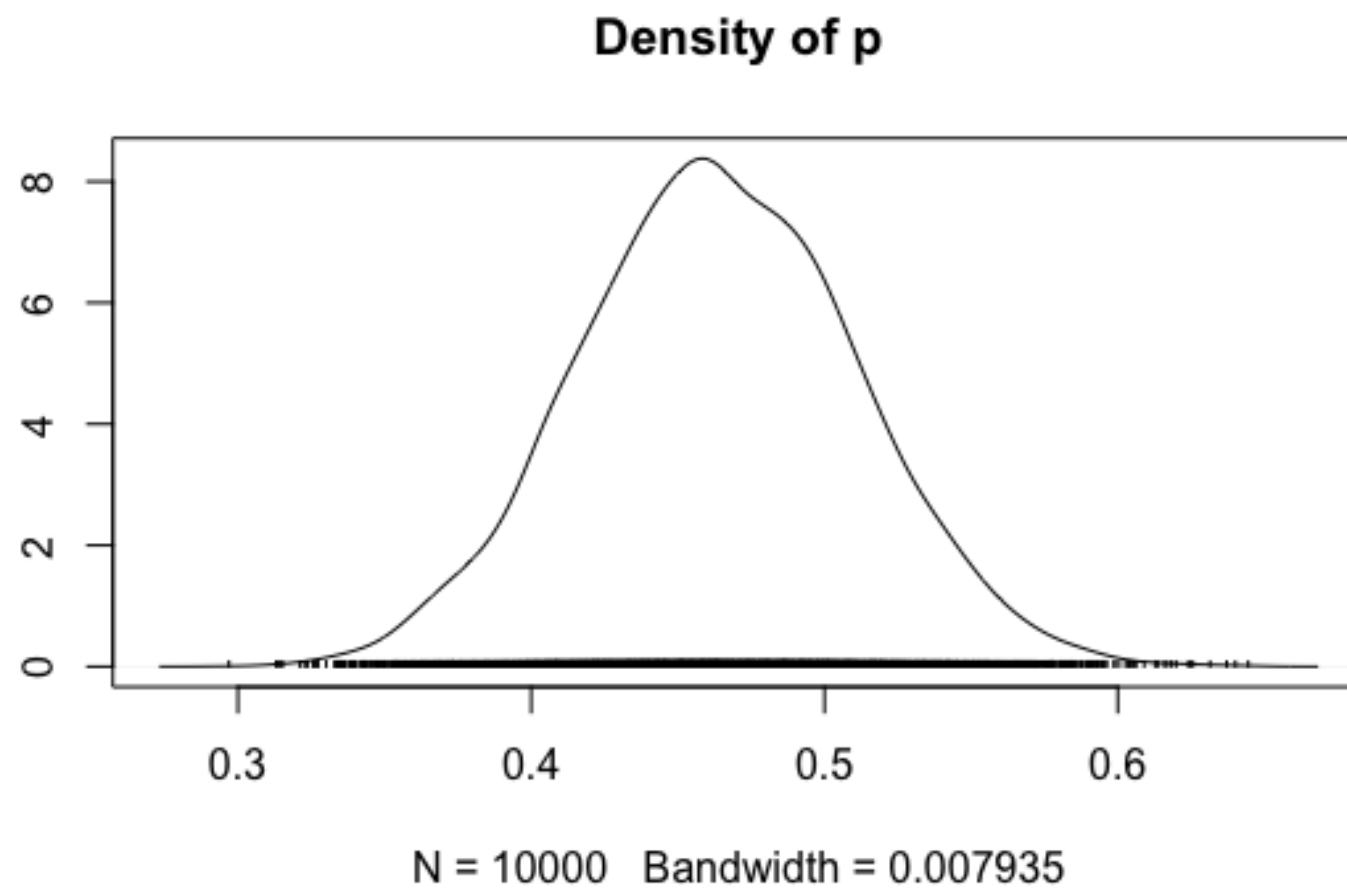
# COMPILE the model
vote_jags <- jags.model(textConnection(vote_model),
  data = list(a = 45, b = 55, X = 6, n = 10),
  inits = list(.RNG.name = "base::Wichmann-Hill", .RNG.seed = 100))

# SIMULATE the posterior
vote_sim <- coda.samples(model = vote_jags,
  variable.names = c("p"),
  n.iter = 10000)
```



# Bayesian Models in RJAGS: SIMULATE

```
# PLOT the simulated posterior  
plot(vote_sim, trace = FALSE)
```





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**Let's practice!**