

# Q- the Matrix

## Introduction to Markov Chains

Modeling discrete traits



NSF-DEB 2323170



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SSB Breakthrough Meeting 2026.

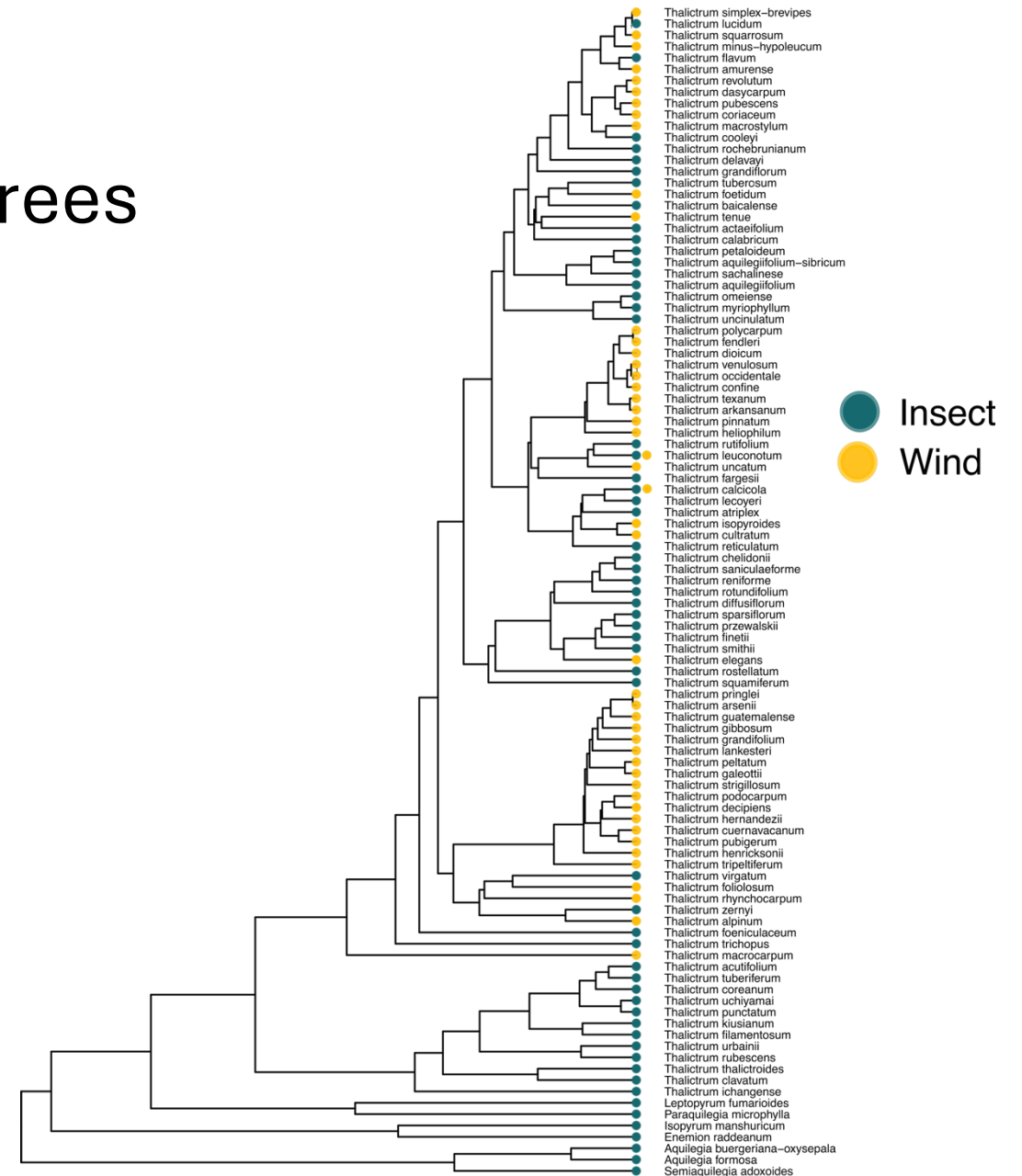
# Download slides and files

<https://roszenil.github.io/mytutorials>



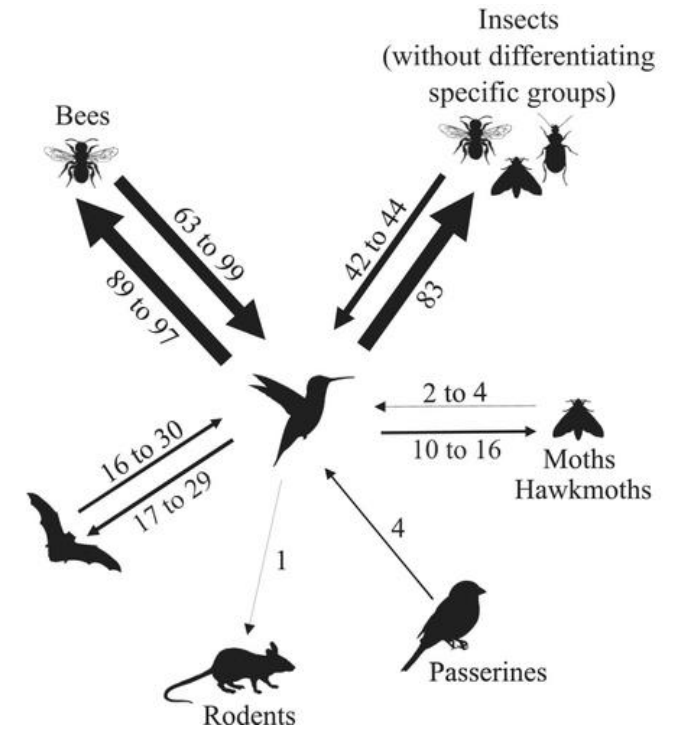
# Discrete traits and phylogenetic trees

- We assume we “know the phylogenetic tree”
- We are interested in the number of times a state evolved (and how quickly)

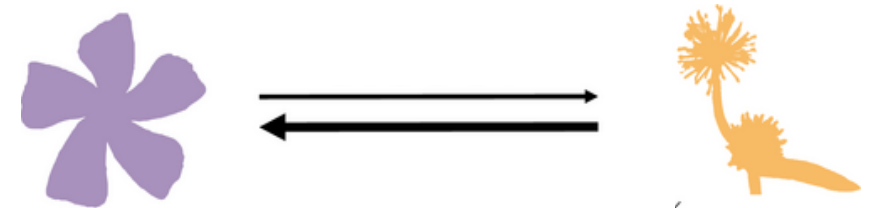


# Pollination

- Plants depend on pollination to start the breeding process
- Pollen can be transferred from plant to plant by insects, wind, vertebrates, or even water
- There are multiple types of pollination, and frequently within a flowering plant/genus or family we can find different strategies for pollination.
- Often flower shape tells us something about the type of pollination we can expect.



Barreto et al. 2024

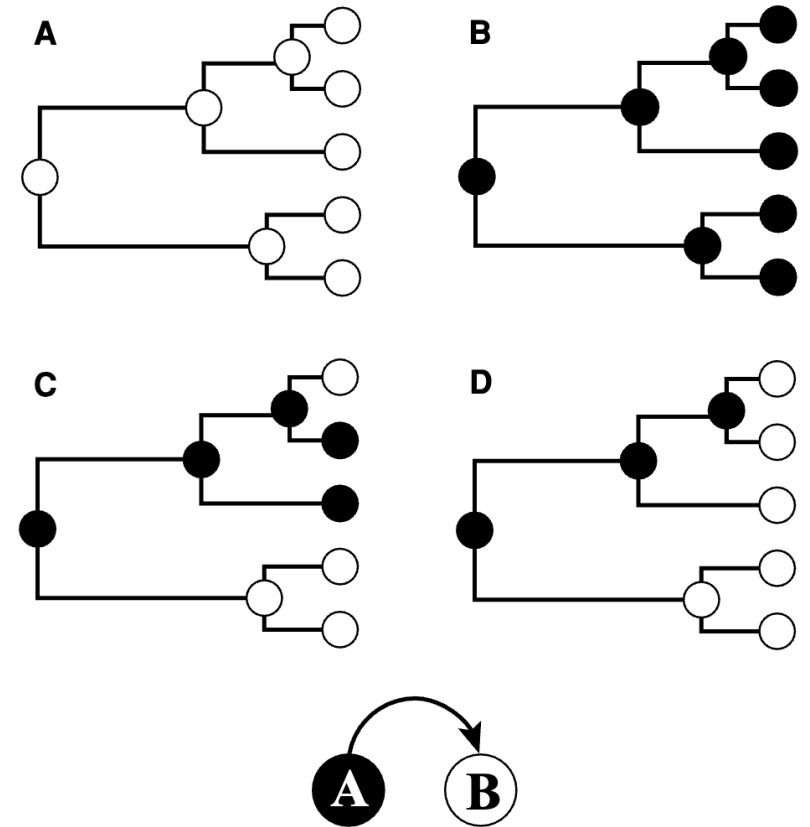


How do we estimate the number of transitions and the tempo?

# Biologically what are we testing?

- Dollo's law of irreversibility: An organism never returns exactly to a former state, even if it finds itself placed in conditions of existence identical to those which it has previously lived (Louis Dollo (1893))

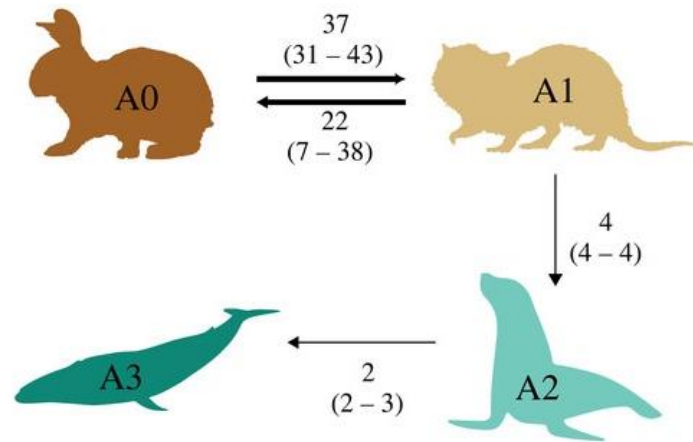
Goldberg and Igić. 2008



# Biologically what are we testing?

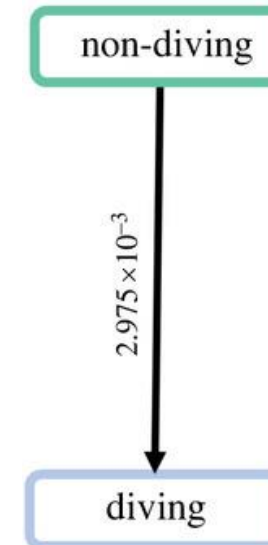
Dollo's law of irreversibility: An organism never returns exactly to a former state, even if it finds itself placed in conditions of existence identical to those which it has previously lived (Louis Dollo (1893)

(b)

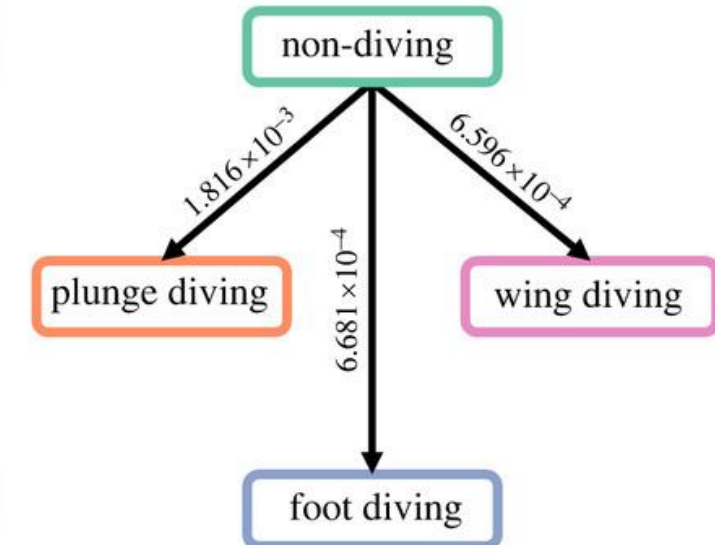


Secondary adaptation to aquatic environments (Farina and Silvestro, 2023)

(a)

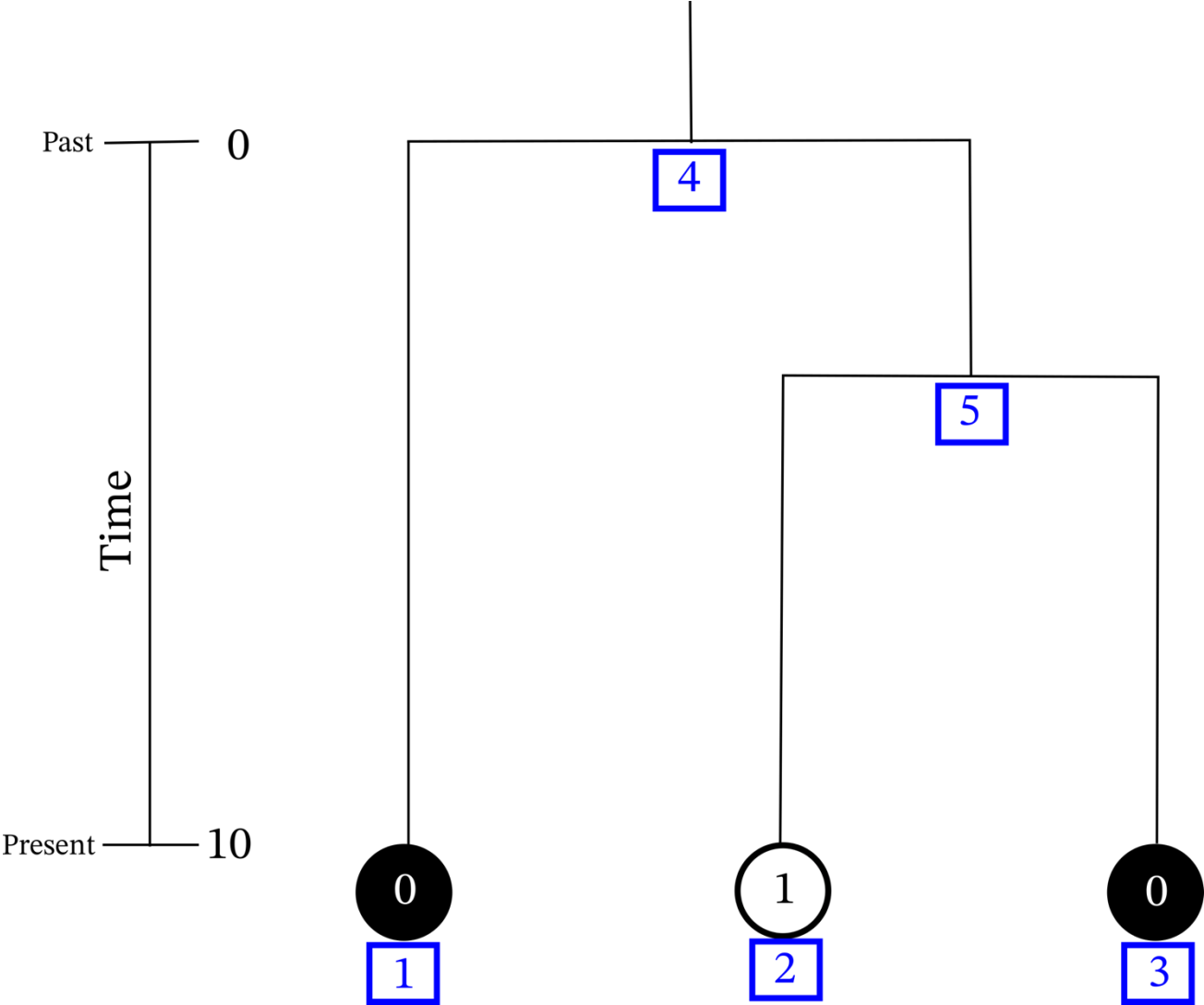


(b)



Waterbirds diving  
Tyler and Younger, 2022

# Enumerating nodes in the phylogenetic tree



# Random variable definition



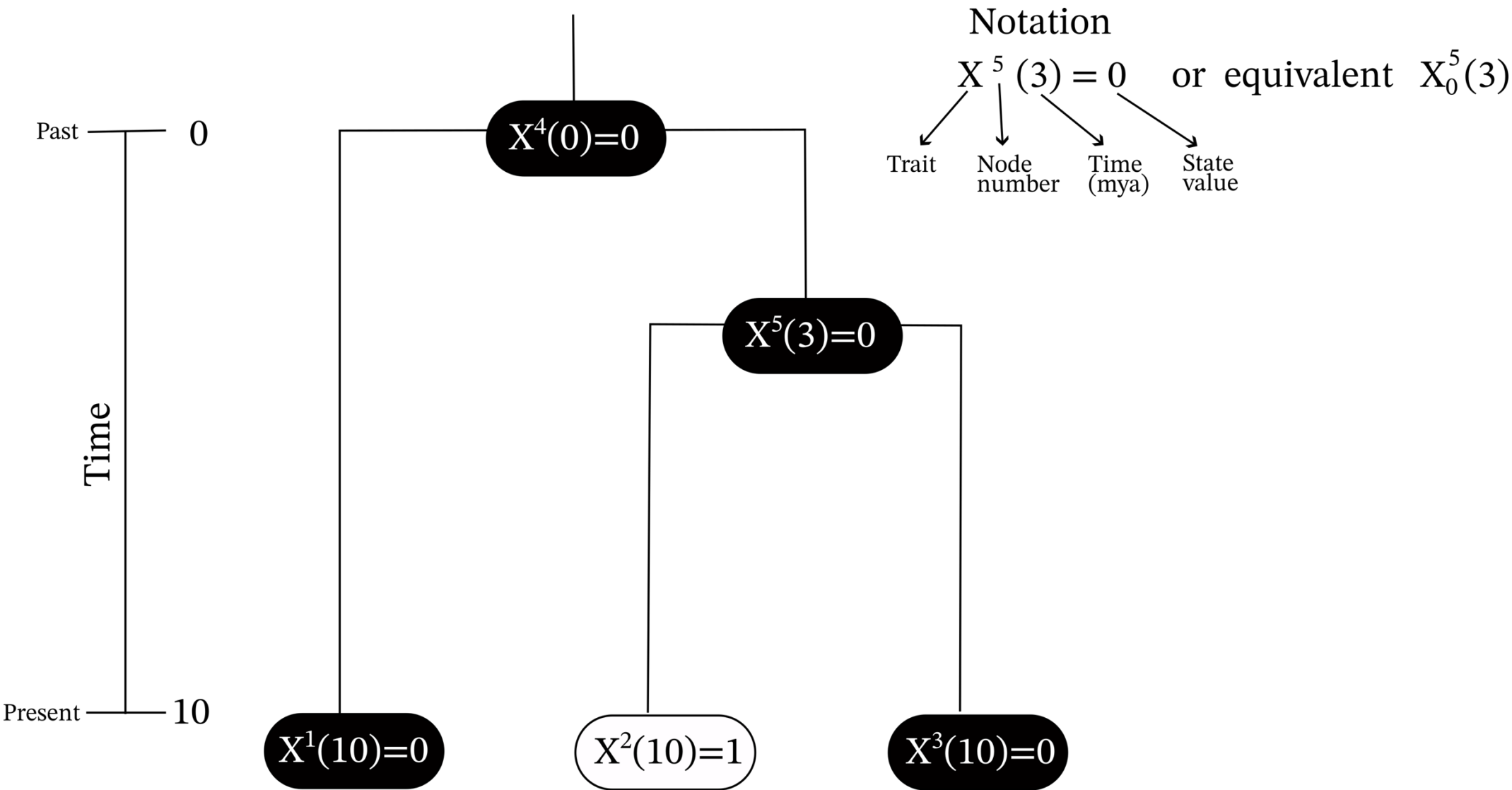
# Continuous-Time Markov Chains (CTMC)

$$\{X(t), t \geq 0\}$$

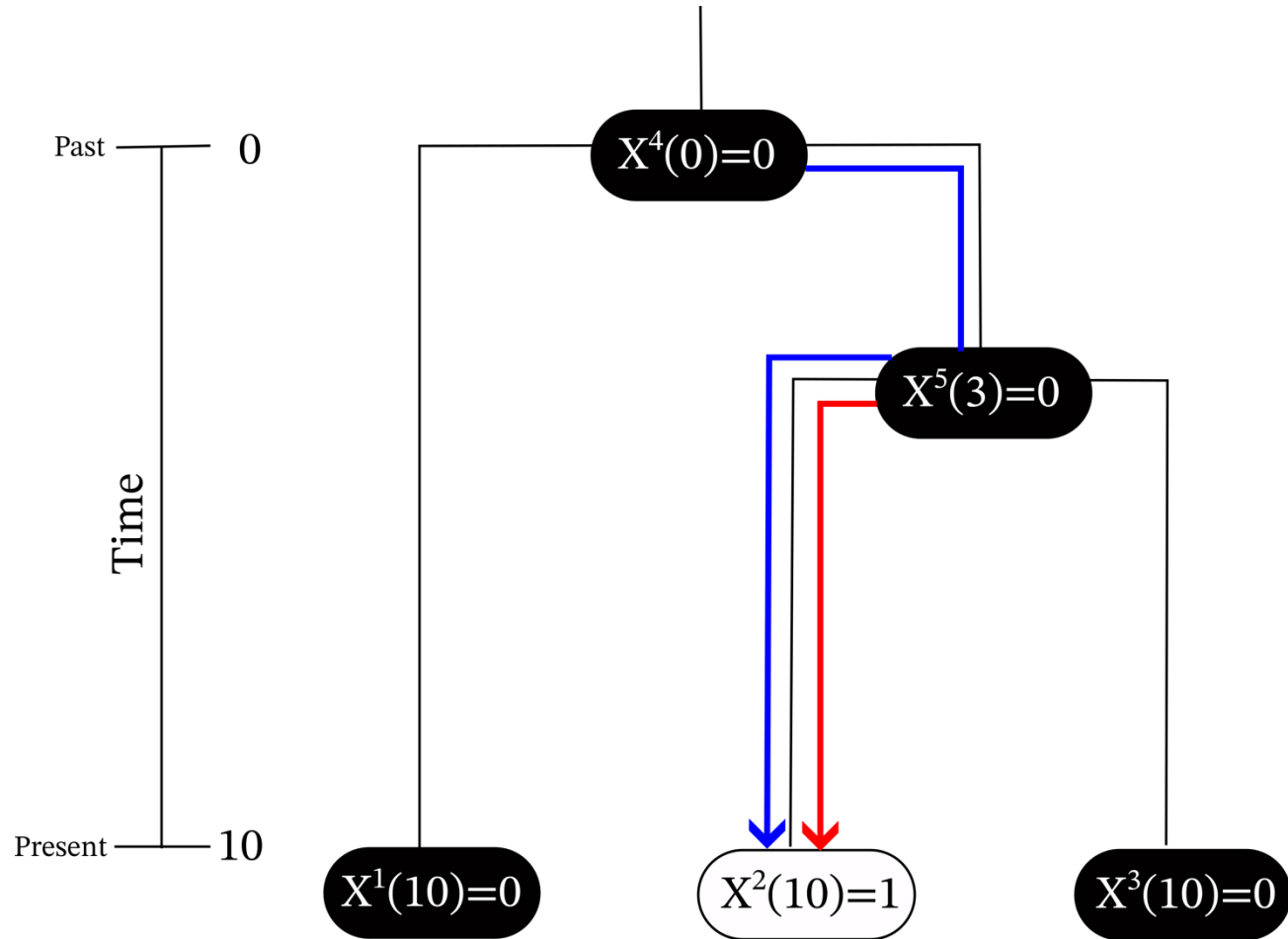
Stochastic models that follow change in time with an associated **probability**

$X(t)$  = phenotype (trait) value at time  $t$

$X(t)$  = Insect (0), Wind (1)



# The Markovian in Markovian chains



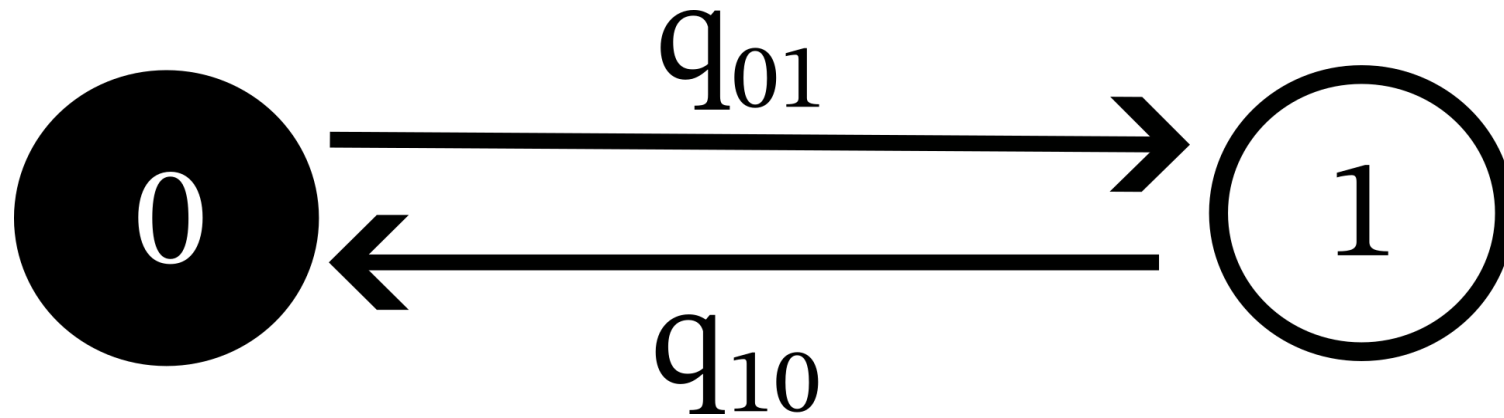
# Conditional probabilities

$$P(X^2(10)=1 | X^5(3)=0) = p_{01}(10-3) = p_{01}(7)$$

# Transition probabilities- The P matrix

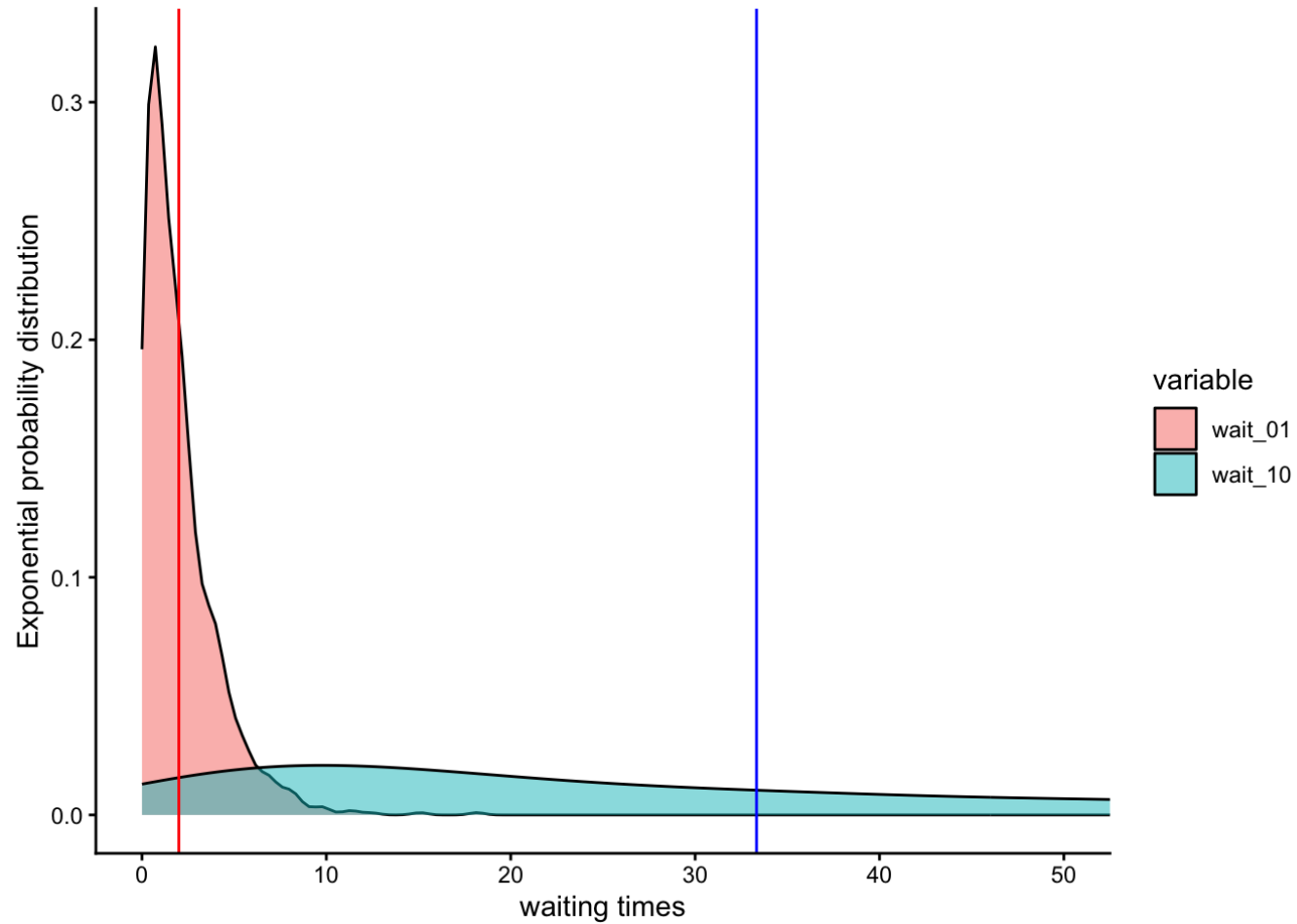
$$P(t) = \begin{pmatrix} p_{00}(t) & p_{01}(t) \\ p_{10}(t) & p_{11}(t) \end{pmatrix}$$

# Transition rates define CTMC

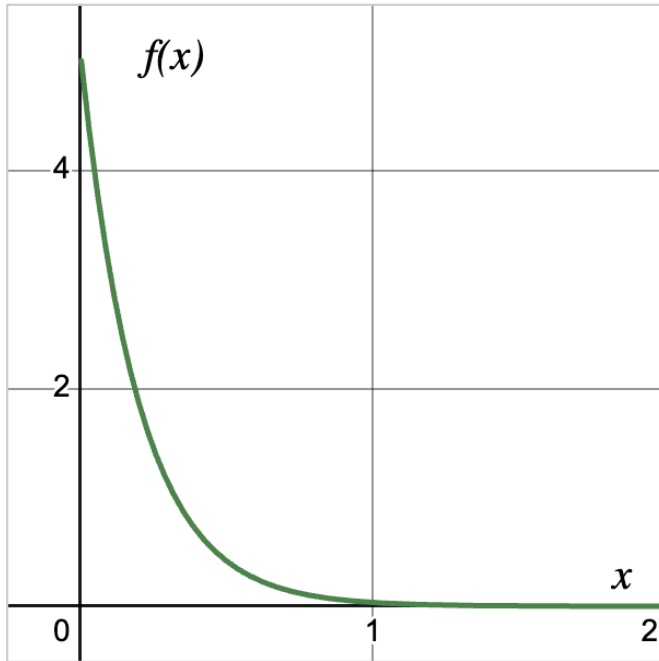


$$\lim_{h \rightarrow 0} P(X(t+h) = j | X(t) = i) = \lim_{h \rightarrow 0} p_{ij}(h) = q_{ij}$$

$1/(\text{transition rates}) = \text{average waiting time}$



# Exponential is a Gamma distribution

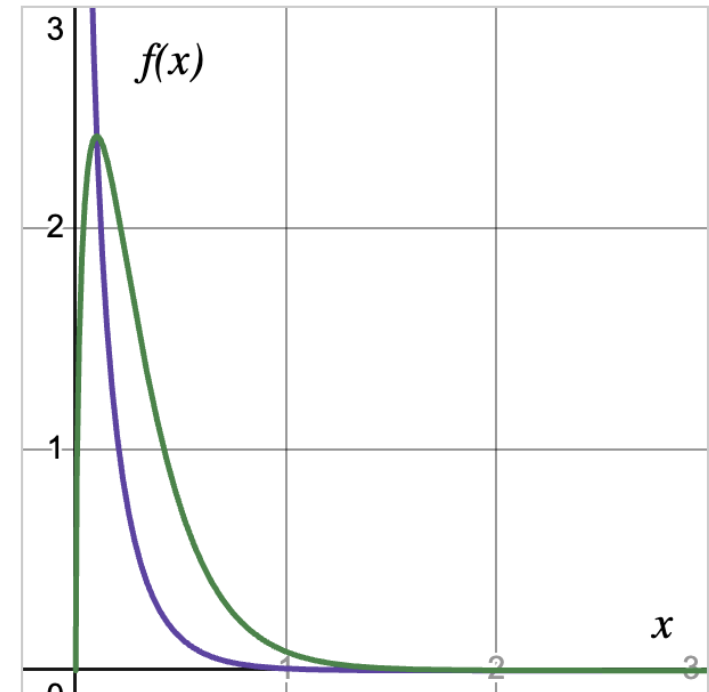


**exponential distribution** with parameter  $\lambda > 0$ , write  $X \sim \text{exponential}(\lambda)$ ,

$$f(x) = \begin{cases} \lambda e^{-\lambda x}, & \text{for } x \geq 0, \\ 0, & \text{otherwise.} \end{cases}$$

**gamma distribution** with parameters  $\alpha, \lambda > 0$ , write  $X \sim \text{gamma}(\alpha, \lambda)$

$$f(x) = \begin{cases} \frac{\lambda^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\lambda x}, & \text{for } x \geq 0, \\ 0 & \text{otherwise,} \end{cases}$$





# The Q to the Matrix

$$Q = \begin{pmatrix} -q_{01} & q_{01} \\ q_{10} & -q_{10} \end{pmatrix}$$

# P-matrix and the Q-matrix

$$P(t) = \frac{1}{q_{01} + q_{10}} \begin{pmatrix} q_{10} + q_{01}e^{-(q_{01}+q_{10})t} & q_{01} - q_{01}e^{-(q_{01}+q_{10})t} \\ q_{10} - q_{10}e^{-(q_{01}+q_{10})t} & q_{01} + q_{10}e^{-(q_{01}+q_{10})t} \end{pmatrix}$$

$$P(t) = e^{Qt}$$

# Rev to the Bayes

# Introduction to RevBayes

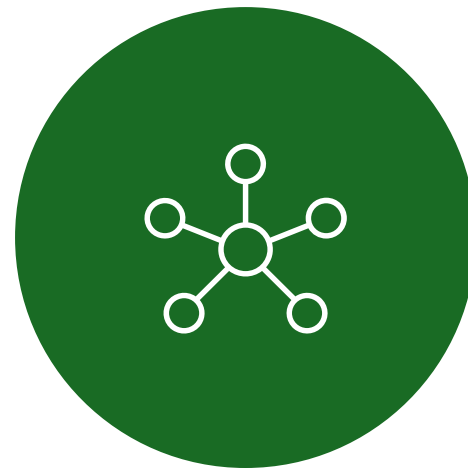
Very brief Bayesian Statistics through probabilistic modeling

Rosana Zenil-Ferguson  
Assistant Professor. University of Kentucky  
SSB Breakthrough Meeting 2026.

# Rev to the Bayes



BASICS OF BAYESIAN  
STATISTICS



DRAWING PROBABILISTIC  
MODELS

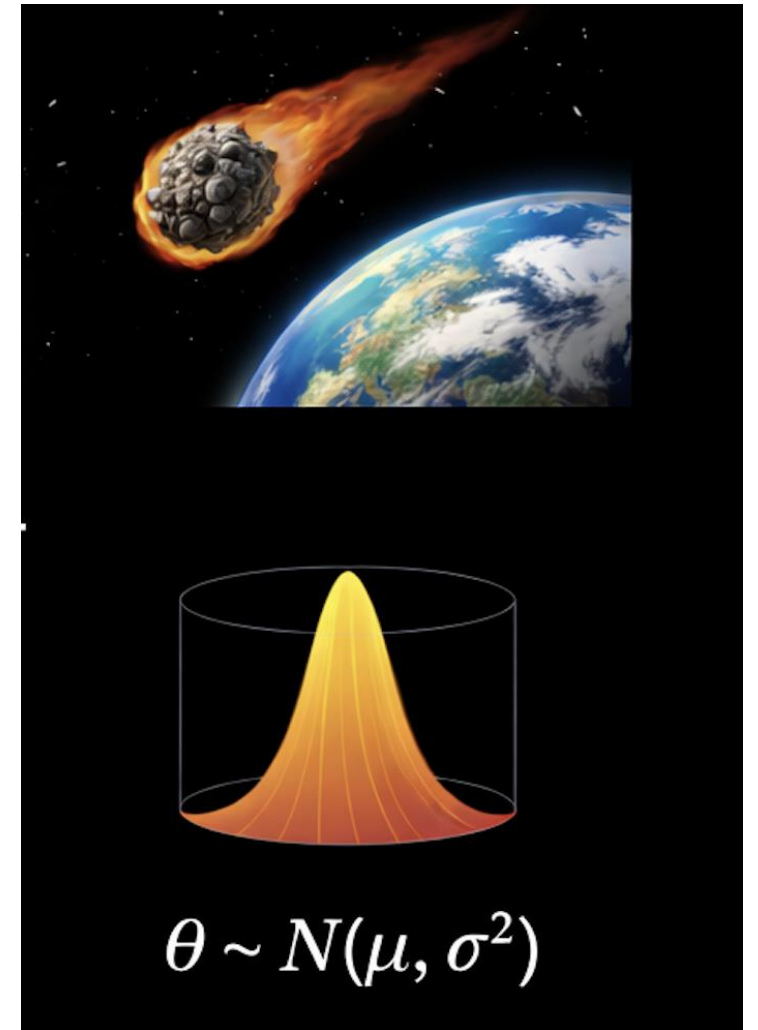
# Bayesian Inference: Two important concepts

1. Probabilities in Bayesian statistics are based on **previous knowledge or beliefs about uncertainty**.

E.g. What is the probability that an asteroid hit the Earth today?

2. Every **parameter** that we want to infer is **unknown and uncertain**.

Parameters are random variables with probability distributions





## Cumberland Falls State Park, KY



*Thalictrum*  
*multiple changes between*  
*insect and wind pollination*

Verónica di Stilio  
University of Washington



*Thalictrum pubescences*



*Thalictrum thalictroides*



# Pollination modes

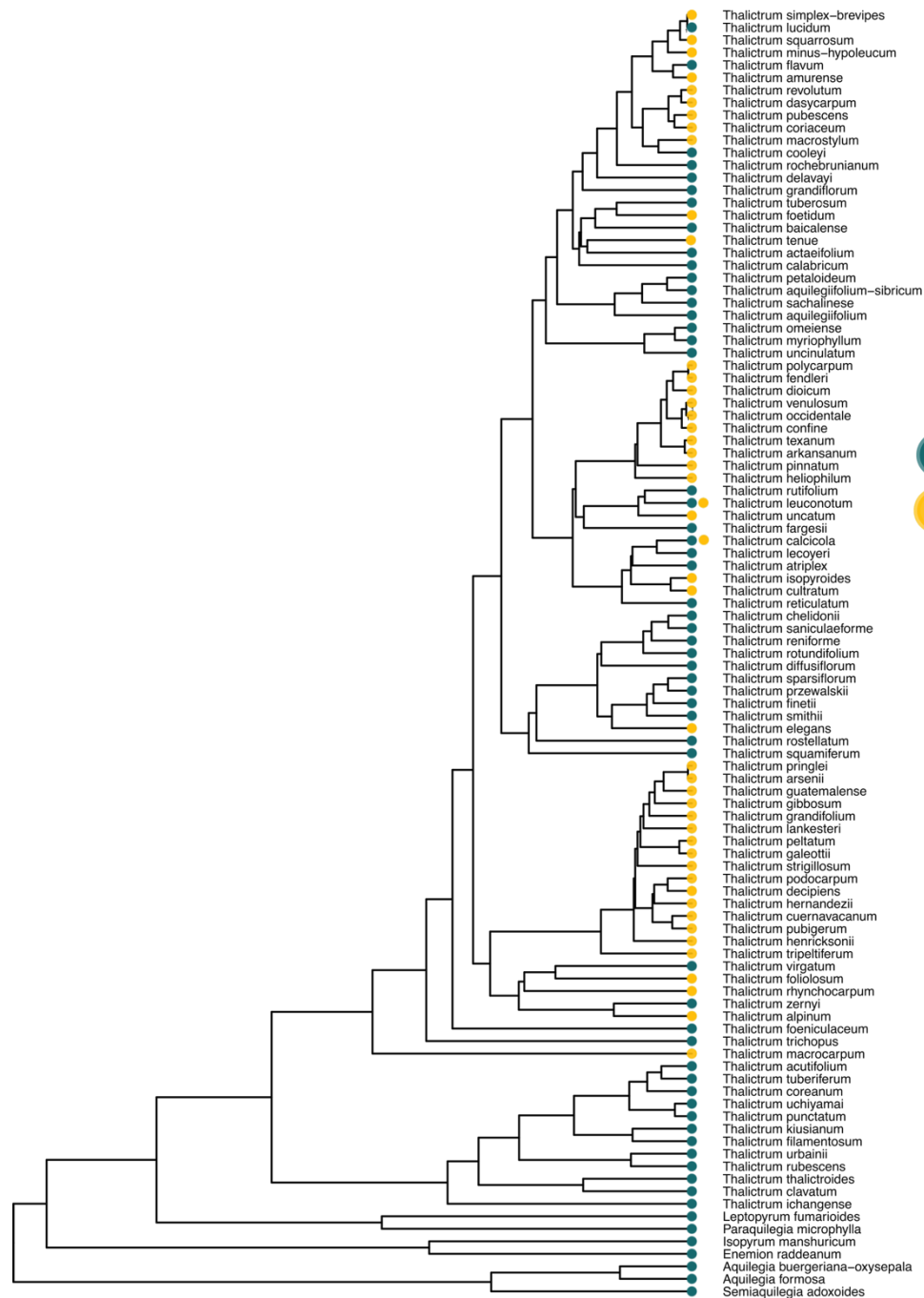
Insect= 0



many pollination  
mode changes

Wind =1





- Always plot your data!
- Check for nestedness of trait!
- Transitions are the effective sample size for these analyses

You cannot applied discrete models if you are in the "Felsenstein worst case scenario"



Maddison and Fitzjohn, 2014

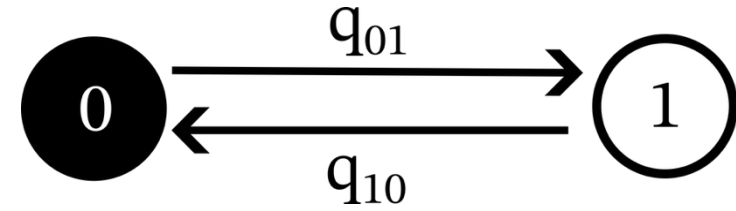


Uyeda, Zenil-Ferguson, and Pennell, 2018



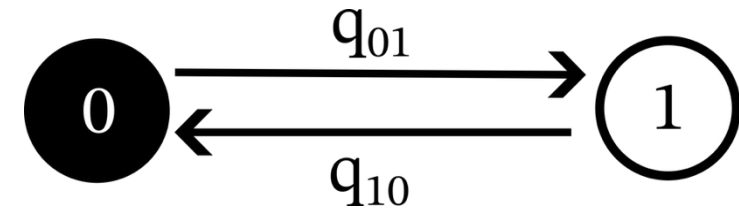
# Unknown and uncertain parameters in our Mkn models

## 1. Transition rates

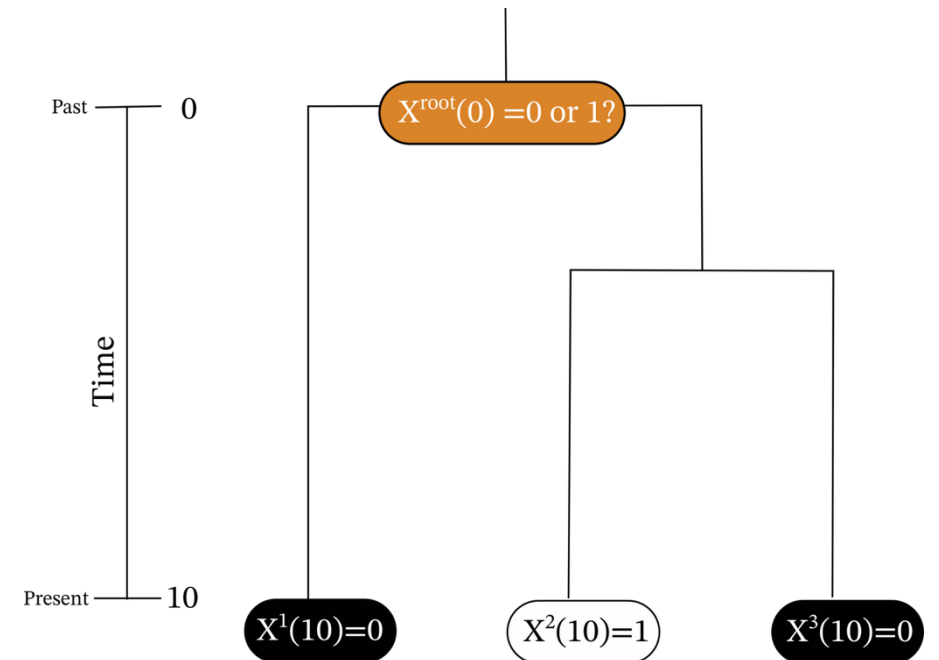


# Unknown and uncertain parameters in our Mkn models

1. Transition rates



2. Frequencies of states in the root



# Graphical probabilistic models in RevBayes and their computer notation



a) Constant node

`<-` constant variable



b) Stochastic node

`~` stochastic variable



c) Deterministic node

`:=` deterministic variable



d) Clamped node  
(observed)

`node.clamp(data)` observed value of stochastic variable

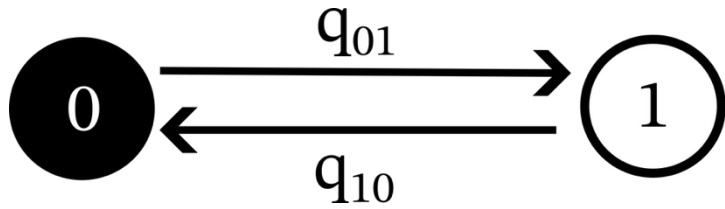


e) Plate

`for (i in 1:N) { ... }` plates (multiple connected nodes)

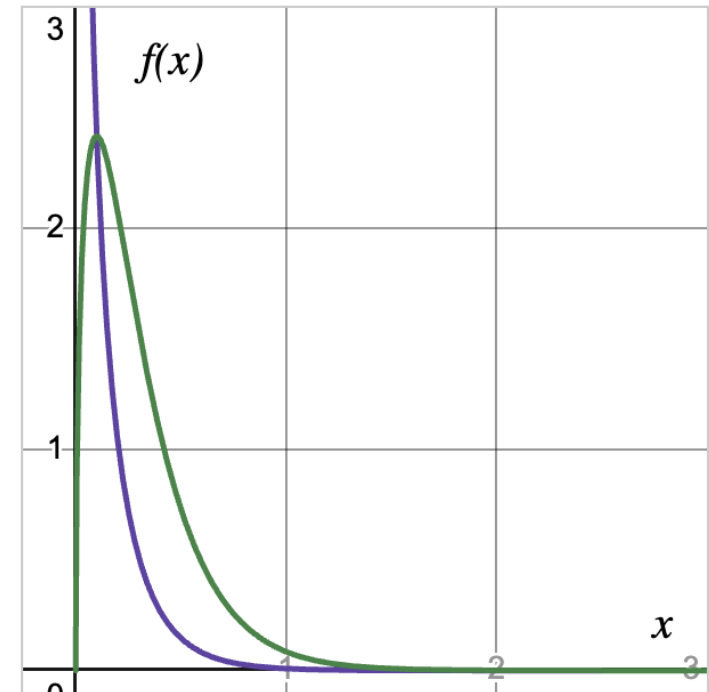
`=` for fixed operations (not part of graphical model)

# Transition rate prior distributions- Gamma

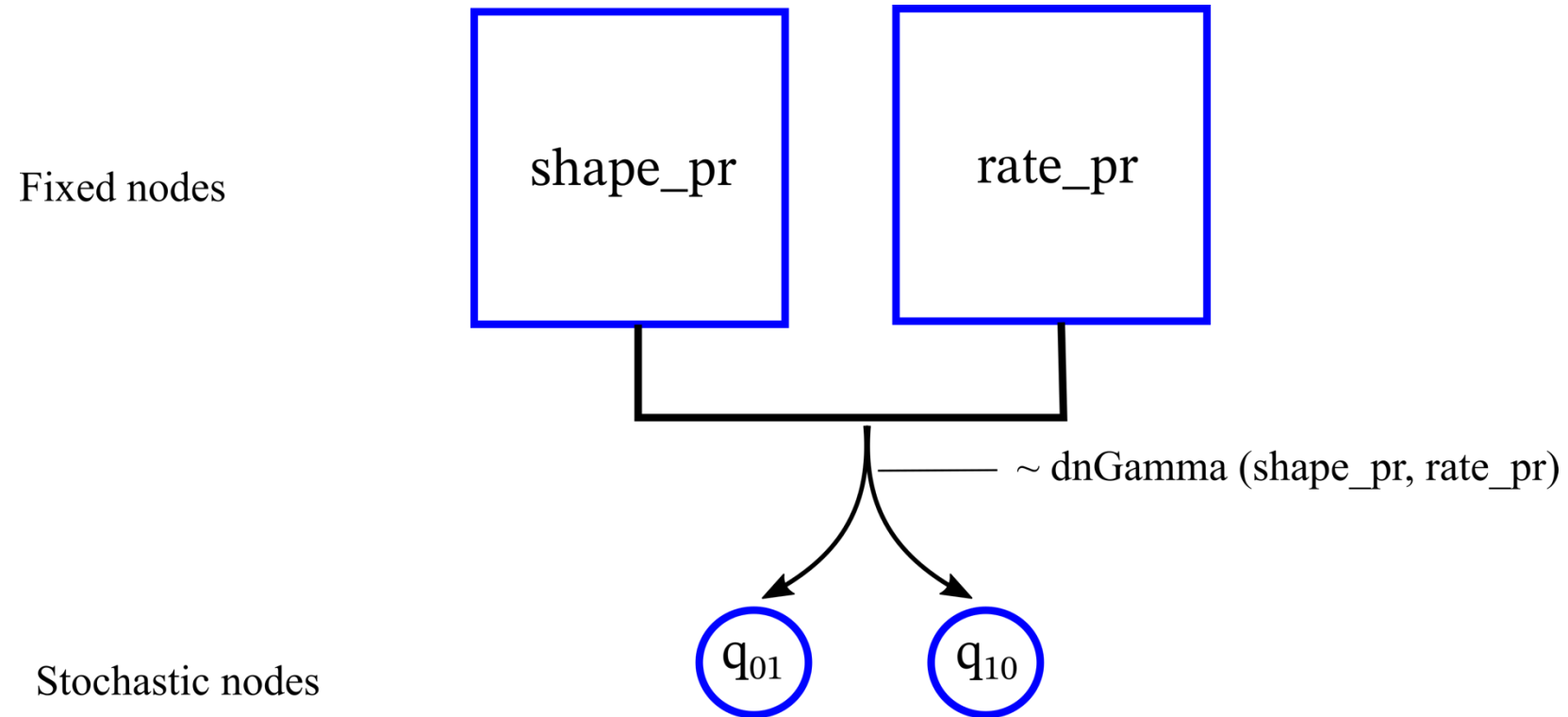


**gamma distribution** with parameters  $\alpha, \lambda > 0$ , write  $X \sim \text{gamma}(\alpha, \lambda)$

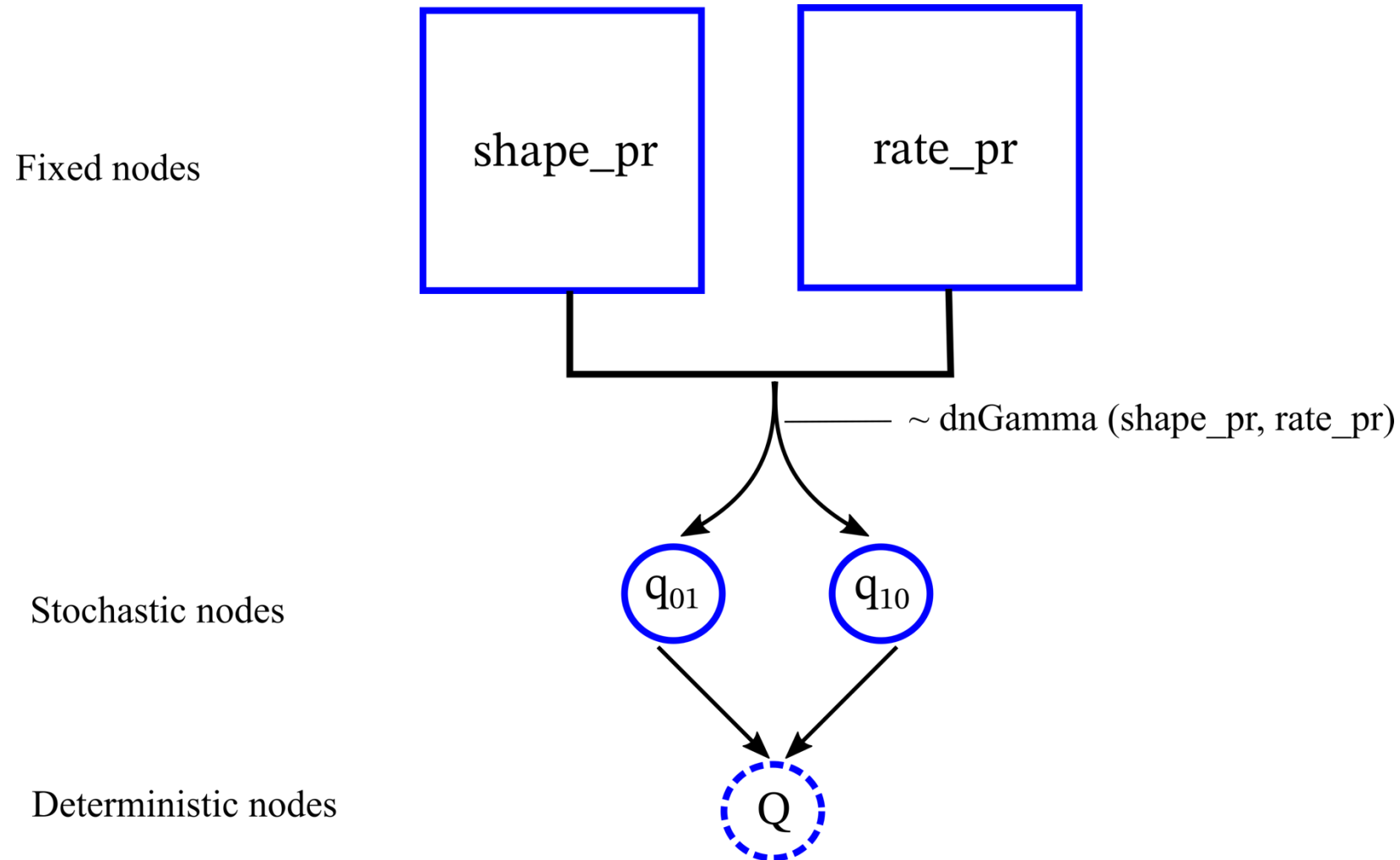
$$f(x) = \begin{cases} \frac{\lambda^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\lambda x}, & \text{for } x \geq 0, \\ 0 & \text{otherwise,} \end{cases}$$



# Transition rate prior distributions

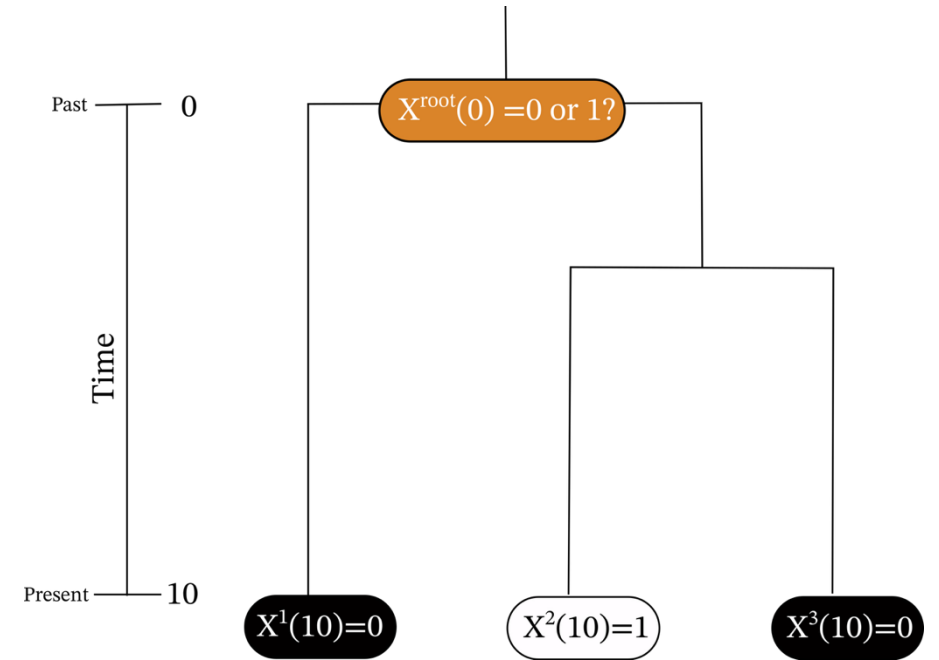
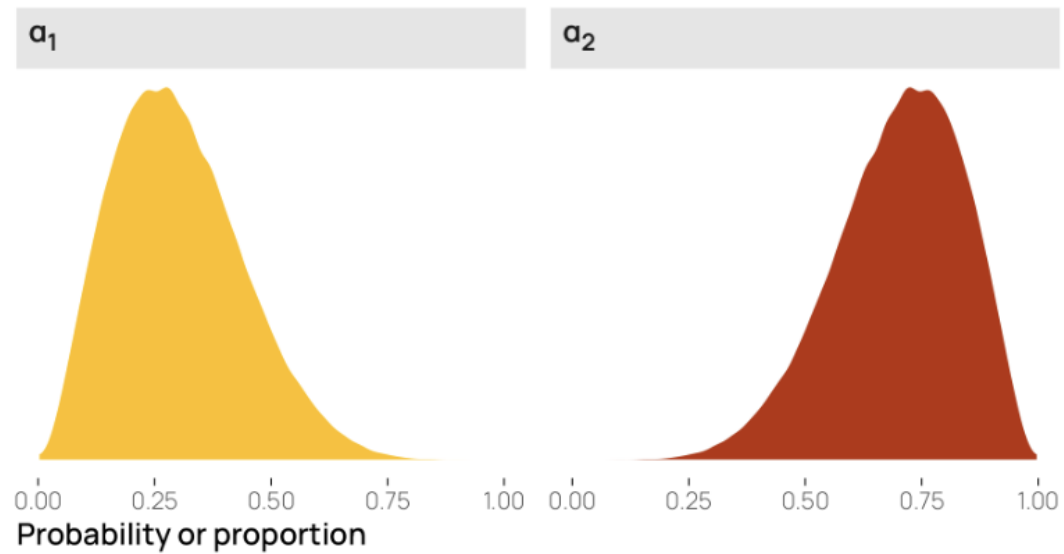


# Transition rate prior distributions

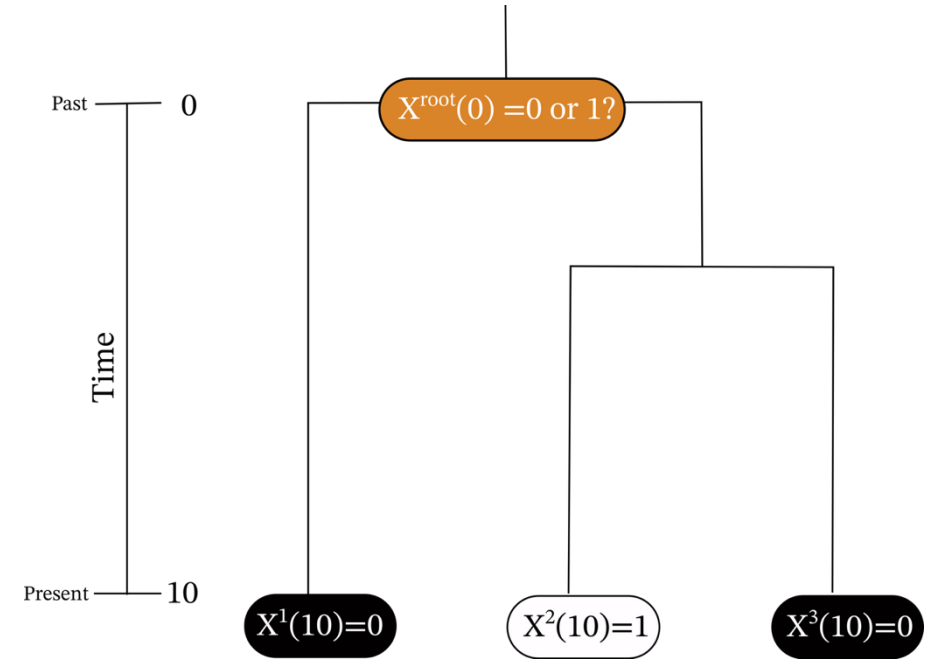
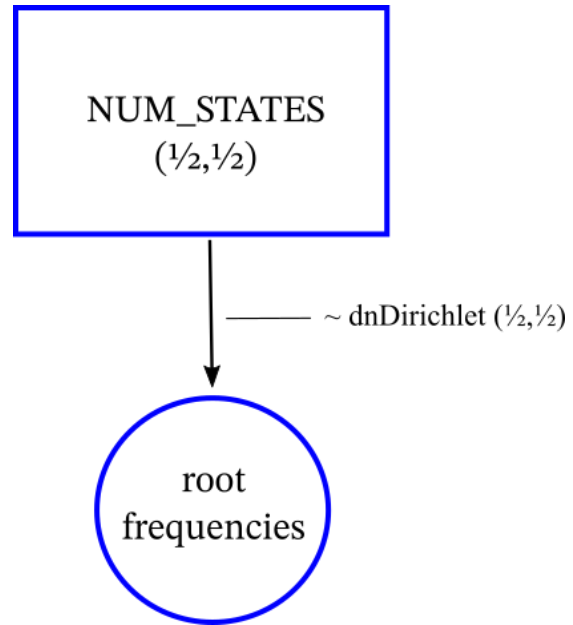


# Frequencies of the root

Dirichlet(3, 7)

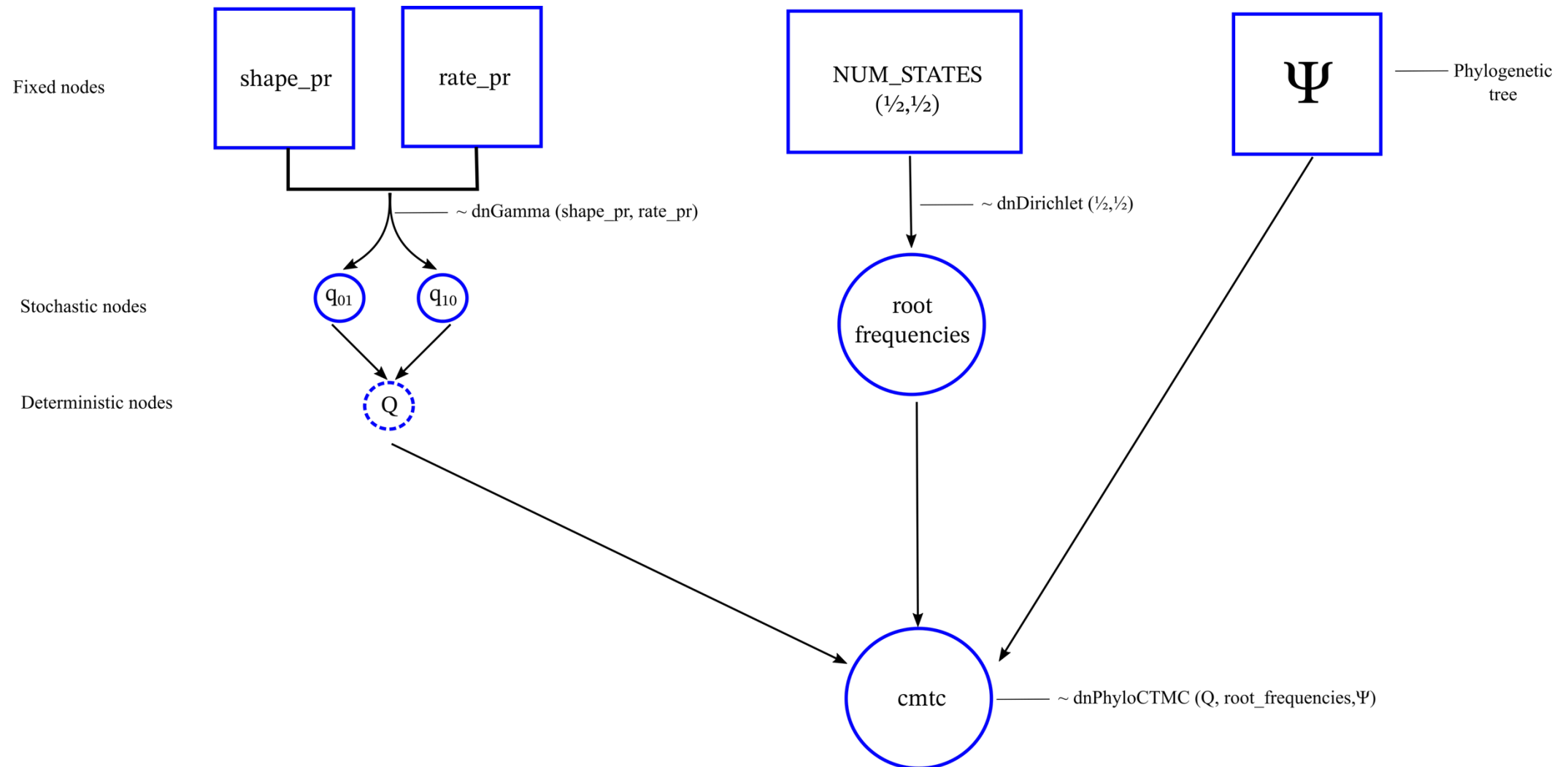


# Frequencies of the root

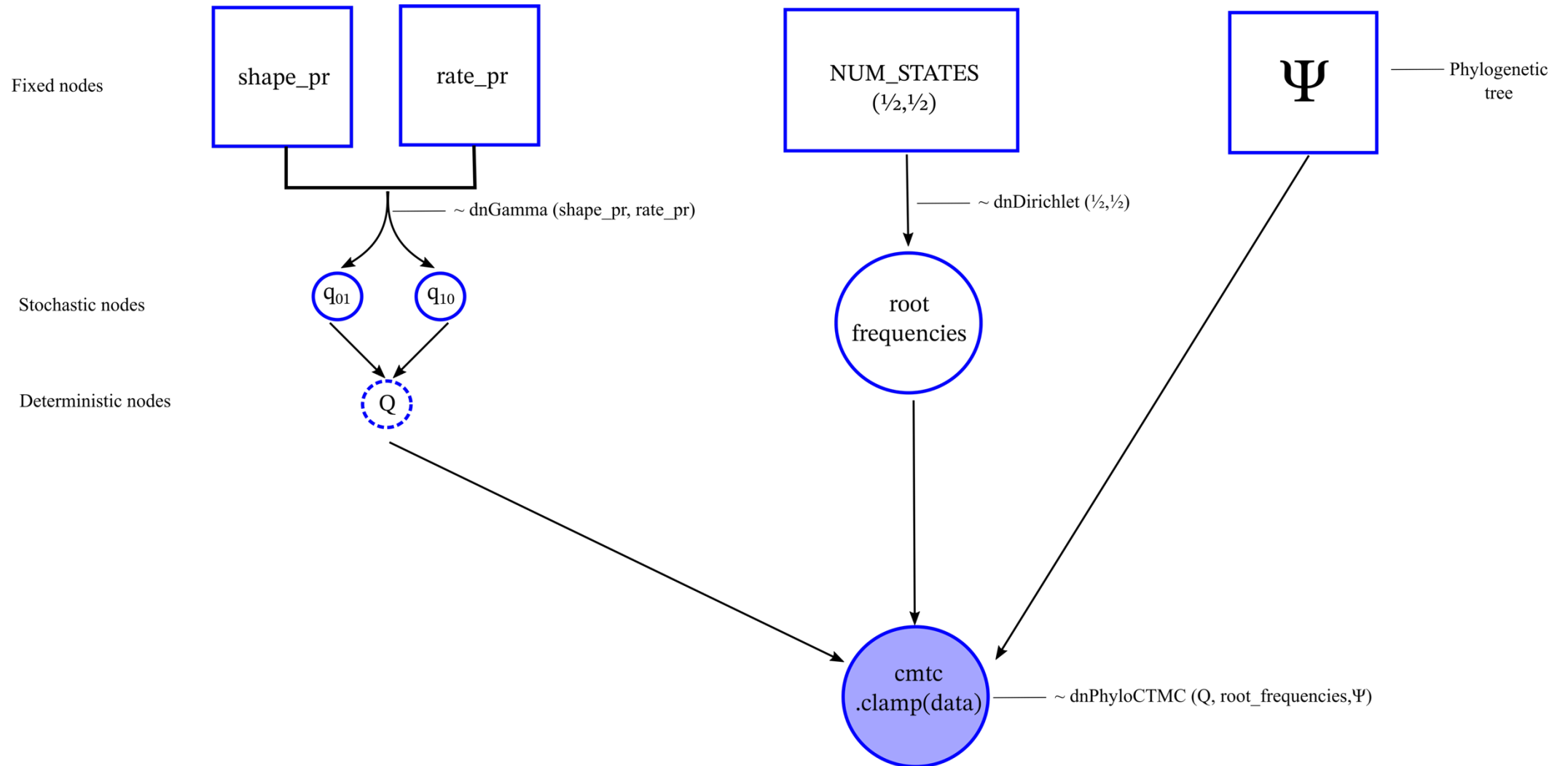




# Mk2- Continuous-Time Markov Chain with two states in RevBayes



# One more step- Add data (a.k.a. Clamping)



# What are moves?

---

`moves.append( )`

Reflect proposals for searching randomly values of the parameters for my graphical model.

A parameter value gets proposed its probability evaluated if it is very good with high chances it gets accepted. Otherwise is rejected and we keep the previous value.



Watch Dr. Paul Lewis  
Bayesian inference and MCMC  
Lecture

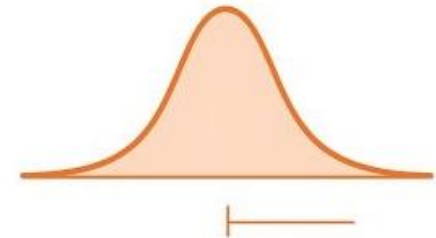
# What are monitors?

**monitors.append( )** Store the full inference.

In Bayesian Statistics, the object of inference is the **posterior distribution**. We care about **credible intervals** (95% probability).

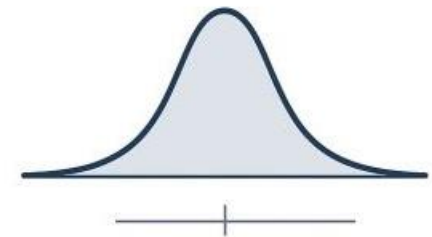
In likelihood inference (frequentist) often we care about **maximum likelihood estimates** and hopefully **confidence-likelihood intervals**.

**Credible Interval**  
(Bayesian)



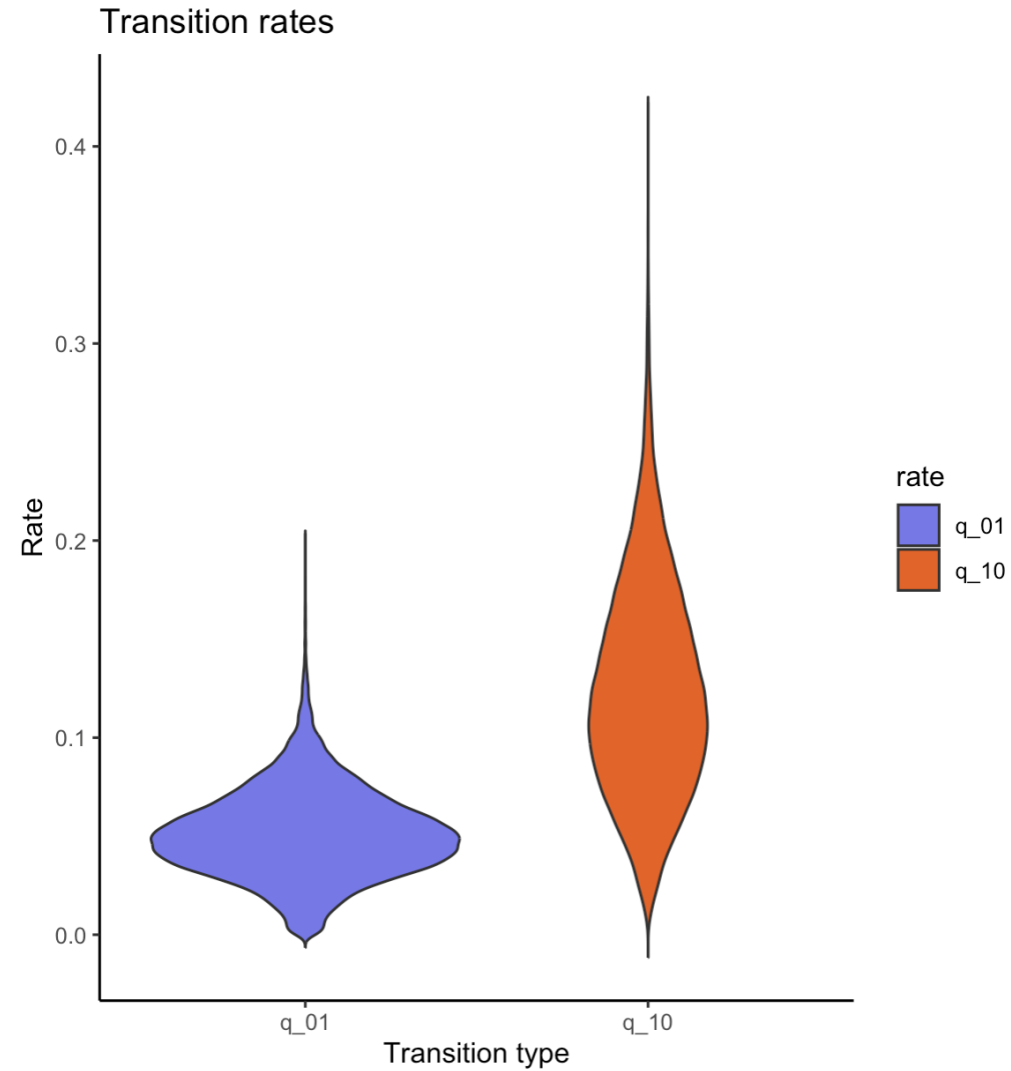
Given our data and prior,  
there's a 95% probability  
the true value lies here

**Confidence Interval**  
(Frequentist)



In 95 of 100 repeated  
experiments, the interval  
will contain the true value

# Posterior distribution: Transition rates

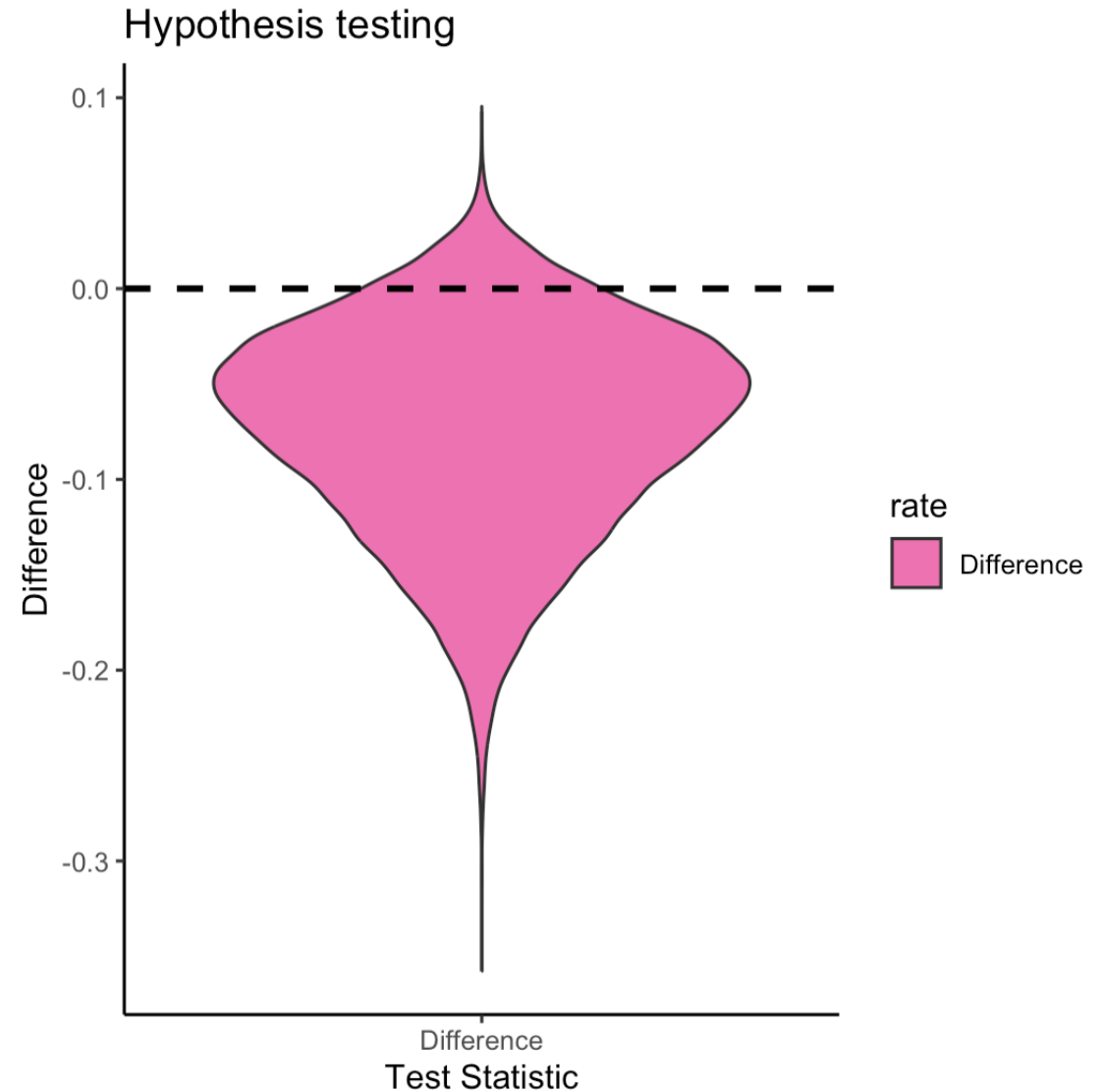


# Hypothesis testing- Bayesian framework

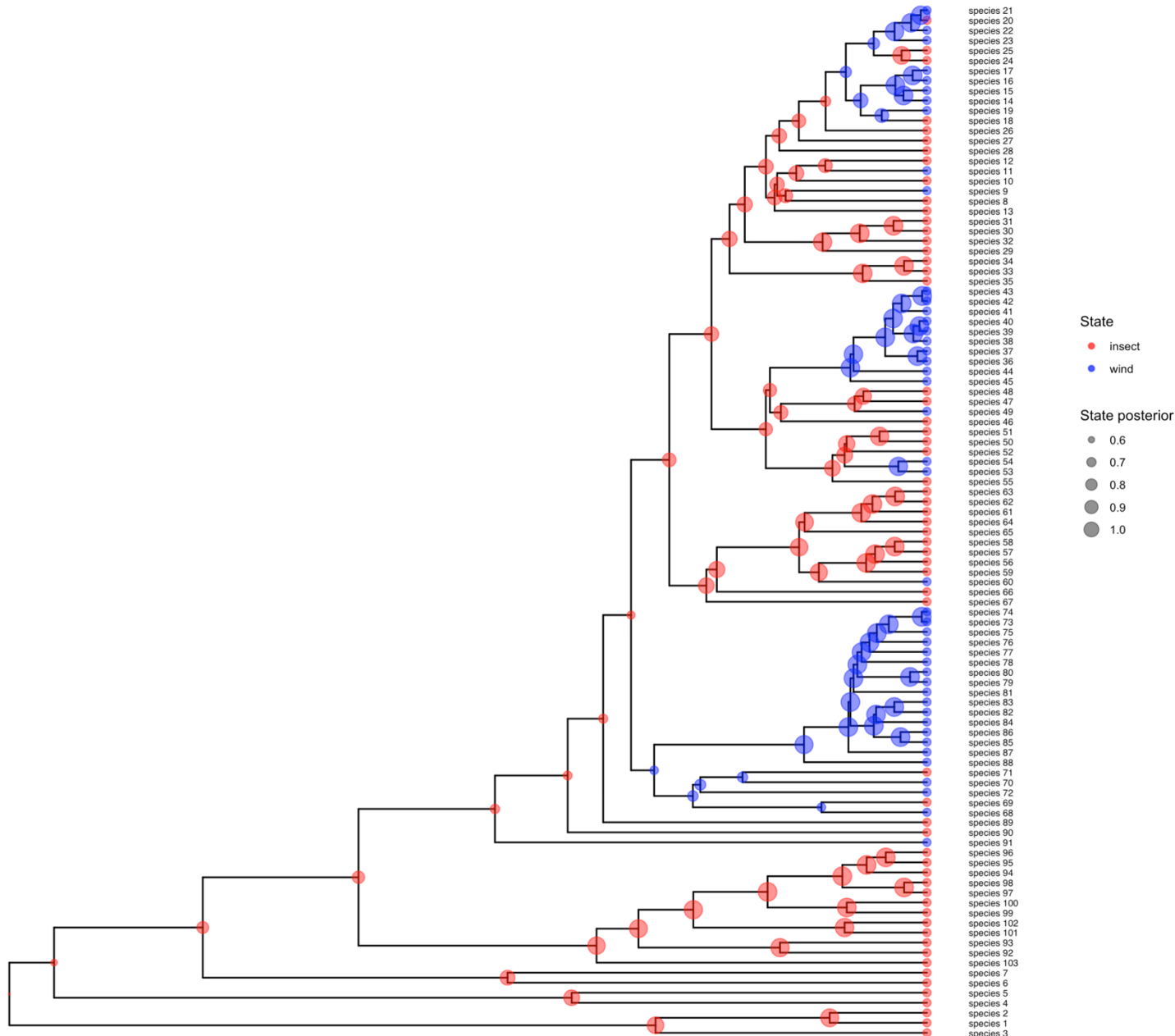
Null hypothesis  $H_0: q_{01} = q_{10}$

Test statistic  $D = q_{01} - q_{10}$

HPD (D)=



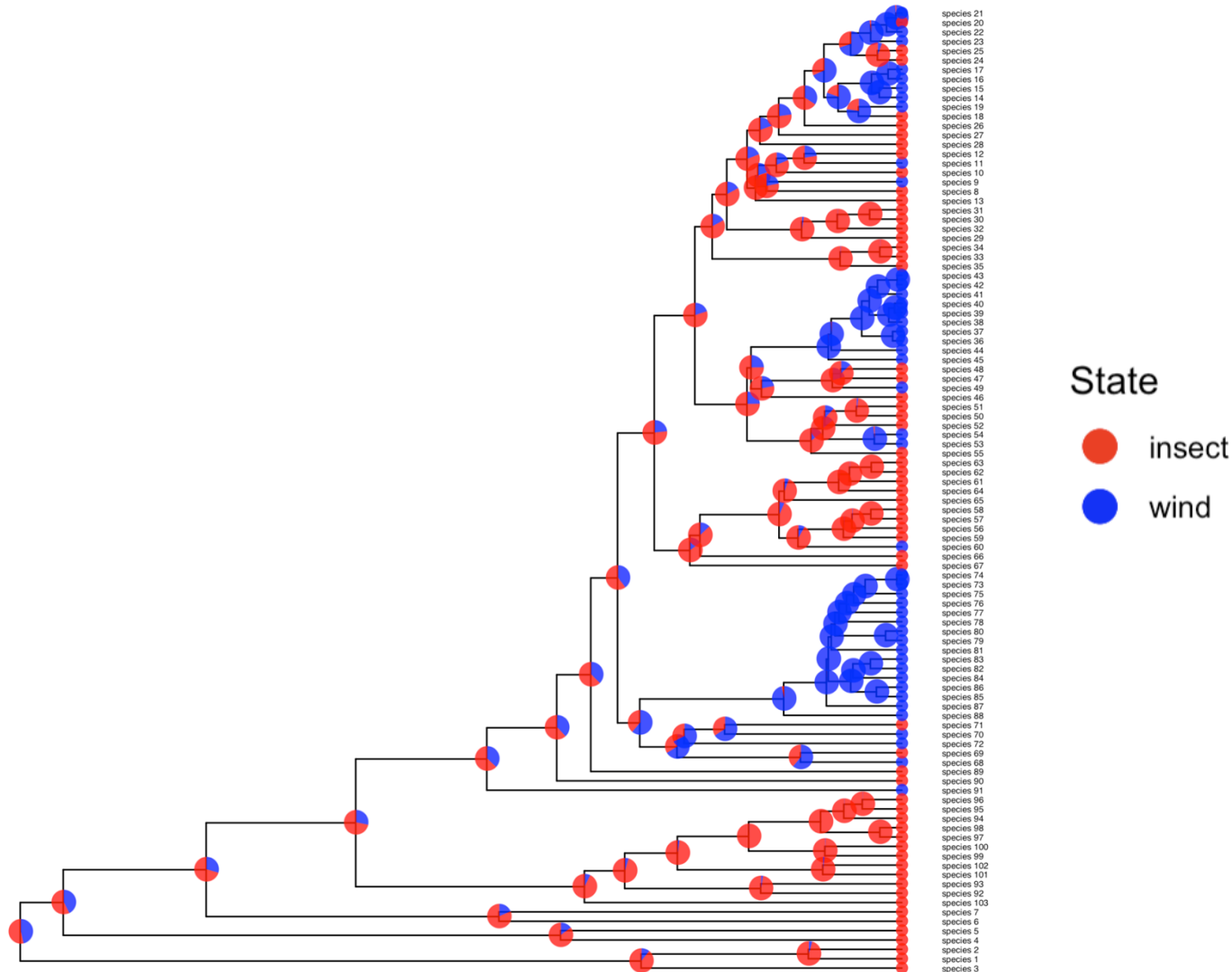
# Ancestral state reconstructions



- Bayesian: Posterior distribution at each node.
- Marginal: Focus on one node at a time summing (integrating) over the rest of the nodes and maximizing the probability of the given node
- Global: Find the combination of node values that maximizes the total probability

**Can you talk about the number of transitions with an ancestral reconstruction?**

# Ancestral state reconstruction (marginal)

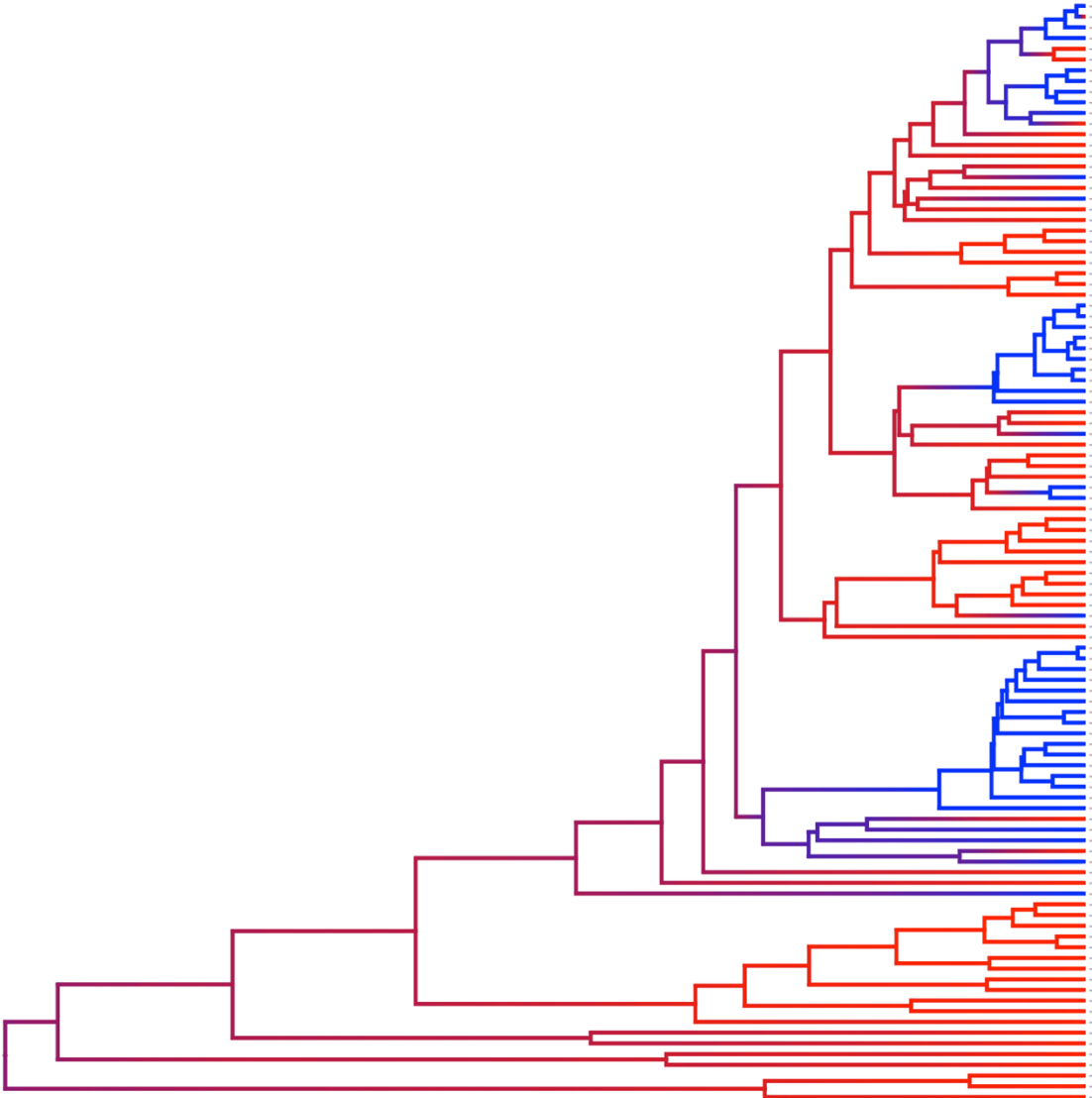


This is a posterior distribution pie

- **Warning:** Pies are often used by other non Bayesian software to do marginal ancestral state reconstructions. Those packages use the **marginal likelihood** function



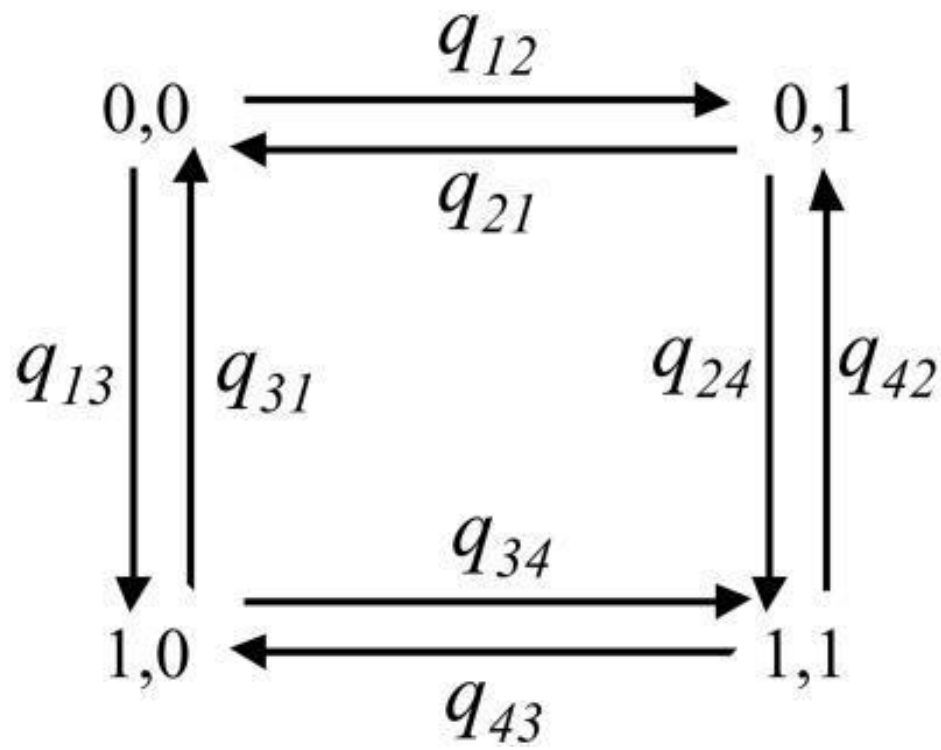
# Stochastic mapping



- Many simulations= stochastic maps
- Posterior distribution in small time slices along branches (summarized as the MAP in each of the chunks)
- \*Can be summarized with other statistics

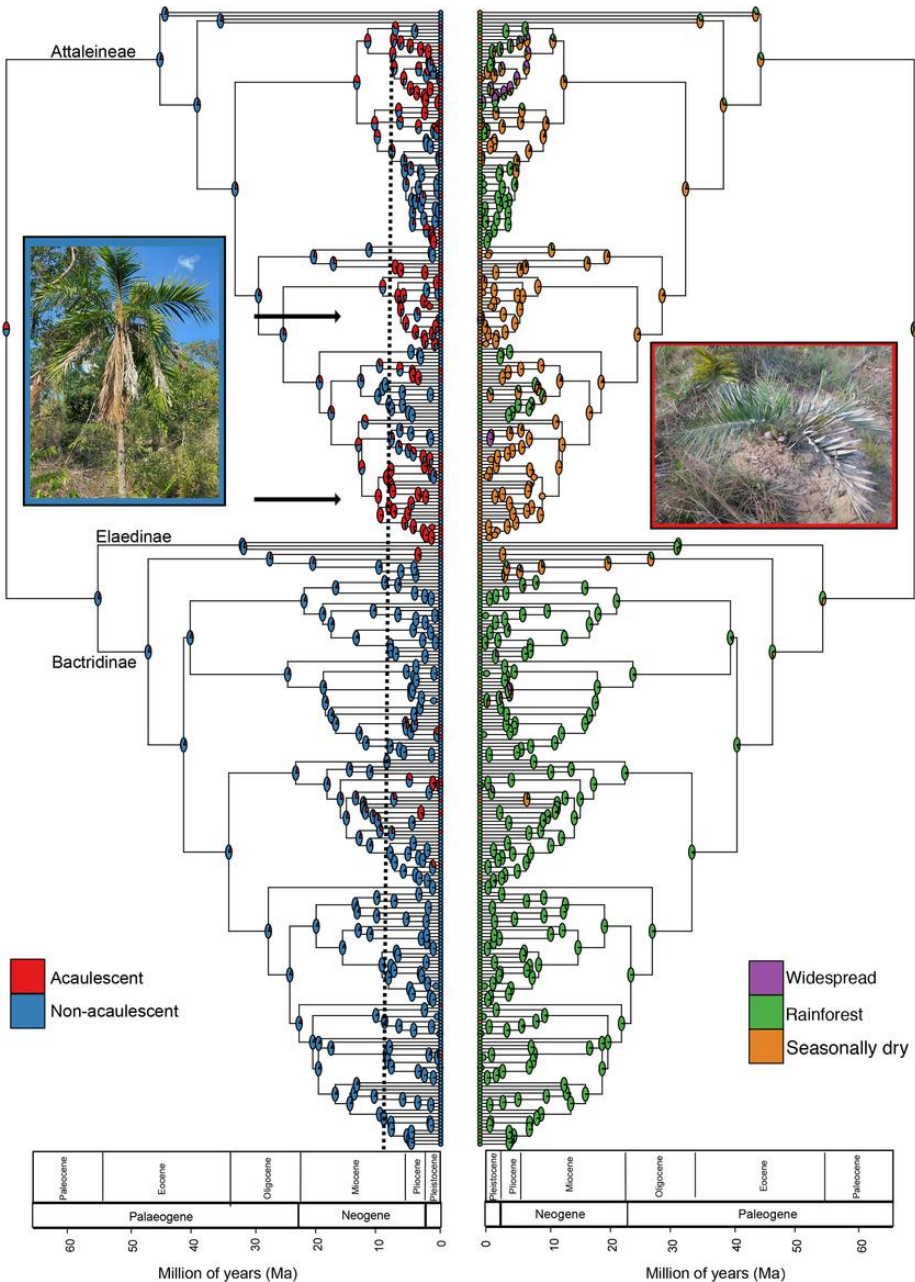
**Can you talk about the number of transitions with an stochastic map?**

The Q-matrix as the center of the universe  
(for discrete traits)



Pagel’s correlation test  
Pagel 1994

Acaulescence and dry environments  
Cassia Silva et al. Ecography. 2022

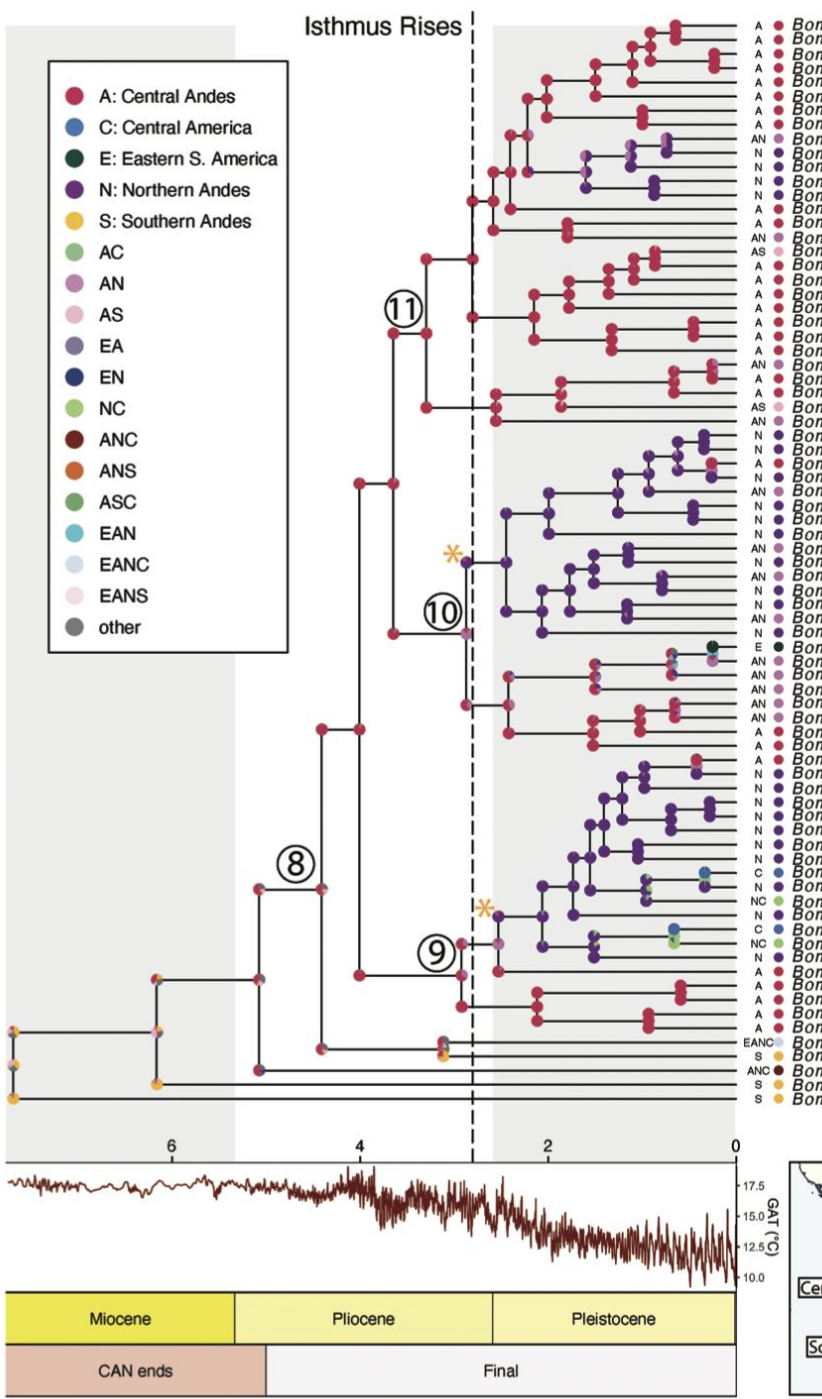


$Q =$

	$\emptyset$	$A$	$B$	$C$	$AB$	$AC$	$BC$	$ABC$
$\emptyset$	—	0	0	0	0	0	0	0
$A$	$e_A$	—	0	0	$d_{AB}$	$d_{AC}$	0	0
$B$	$e_B$	0	—	0	$d_{BA}$	0	$d_{BC}$	0
$C$	$e_C$	0	0	—	0	$d_{CA}$	$d_{CB}$	0
$AB$	0	$e_B$	$e_A$	0	—	0	0	$d_{AC} + d_{BC}$
$AC$	0	$e_C$	0	$e_A$	0	—	0	$d_{AB} + d_{CB}$
$BC$	0	0	$e_C$	$e_B$	0	0	—	$d_{BA} + d_{CA}$
$ABC$	0	0	0	0	$e_C$	$e_B$	$e_A$	—

Dispersal-Extinction Cladogenesis model  
(DEC)

Ree et al. 2005; Ree and Smith (2008)



$$Q_{ij} = \begin{cases} \gamma_a & j = i + 1, \\ \delta_a & j = i - 1, \\ \rho_a & j = 2i, \\ \eta_a & j = 1.5i, \\ 0 & \text{otherwise,} \end{cases}$$

ChromEvol (Mayrose et al. 2010)

BiChrom (Zenil-Ferguson et al. 2017)

