

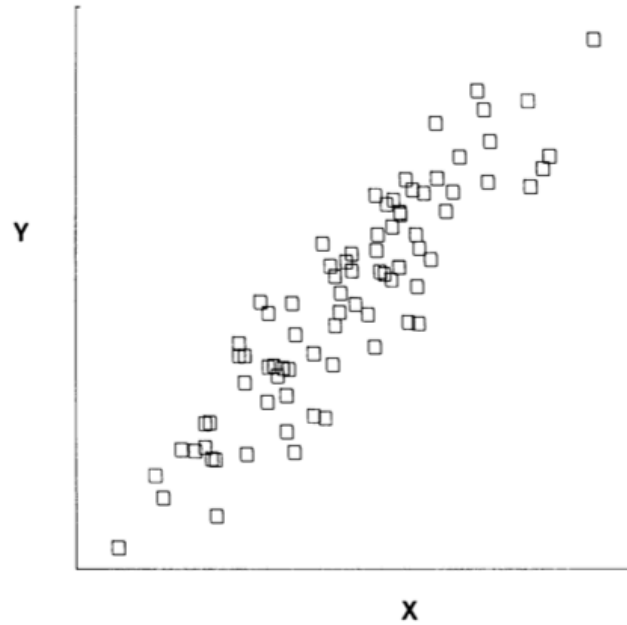
# A Brief Introduction to Phylogenetic Diffusion Models

The background of the slide features a light blue, semi-transparent image of a forest of evergreen trees, likely spruce or fir, arranged in a line across the top half of the frame.

Bodega Bay  
Applied Phylogenetics Workshop  
May 25 – June 2, 2019

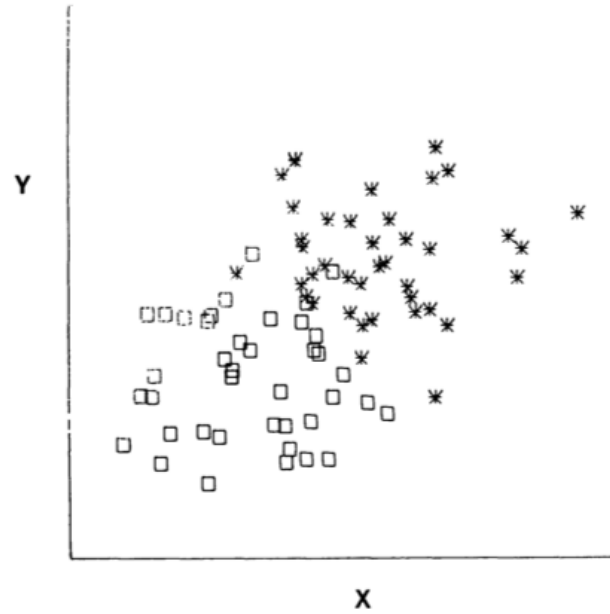
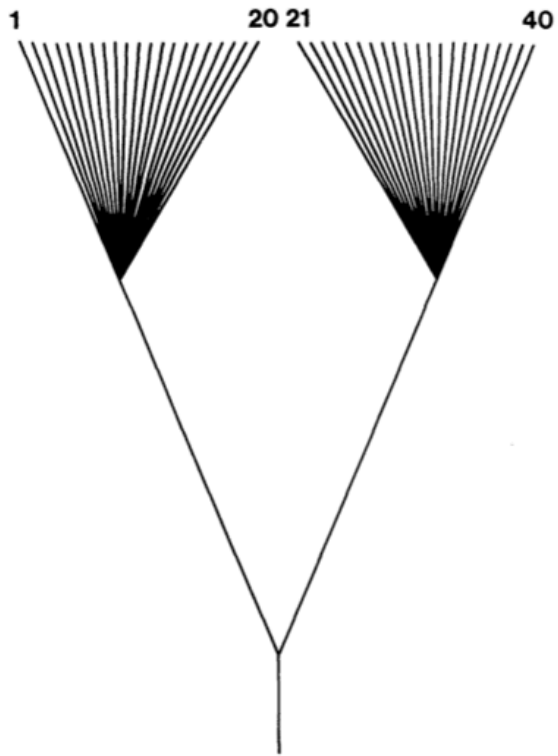
Are traits  $X$  and  $Y$  evolutionary correlated?

Pattern:  $X$  and  $Y$  look correlated!

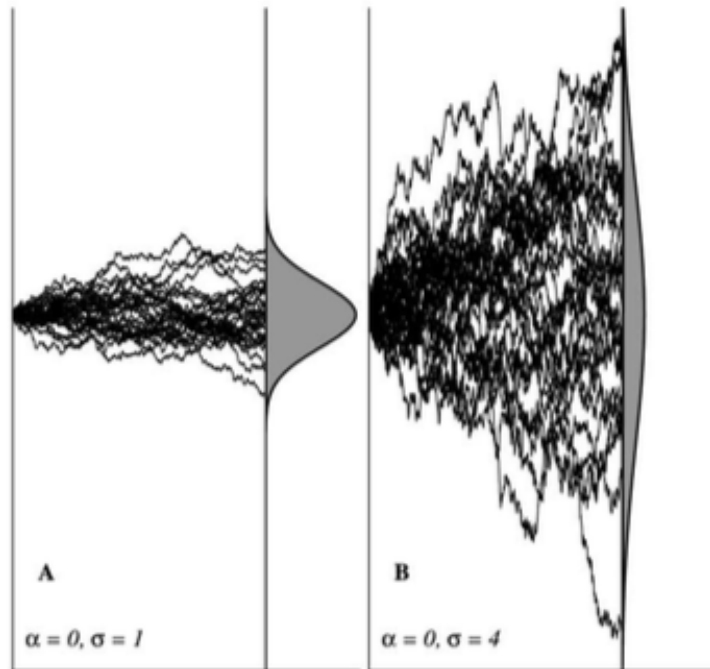


Are traits  $X$  and  $Y$  evolutionary correlated?

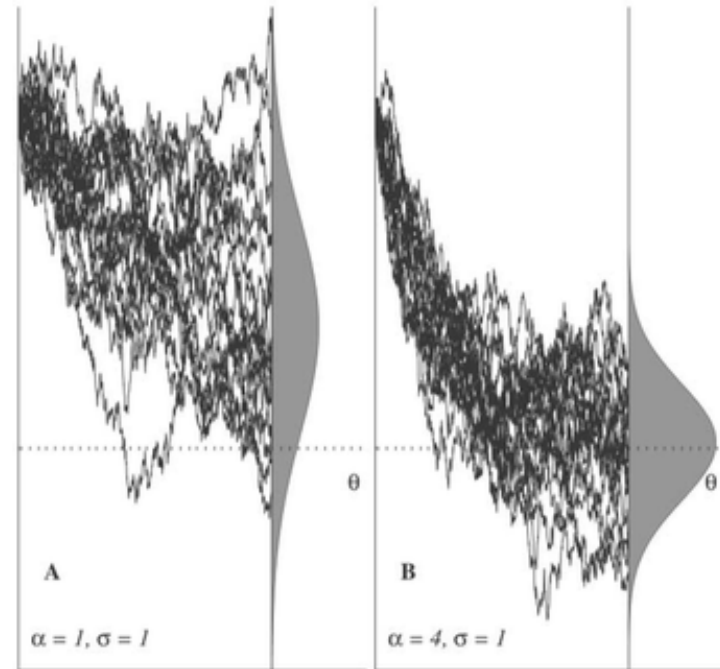
Process:  $X$  and  $Y$  evolved on a phylogeny!



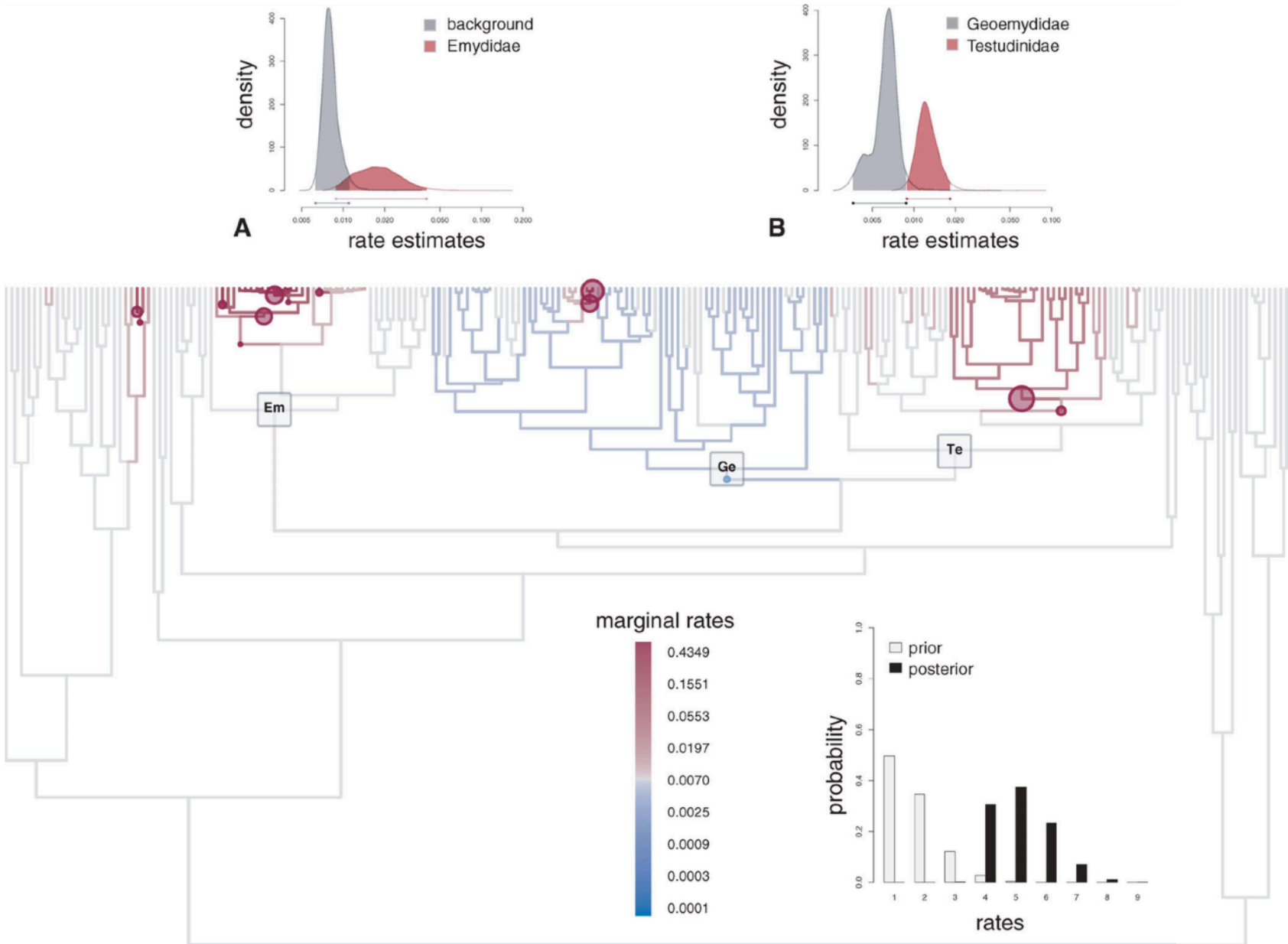
How is  $X$  evolving?



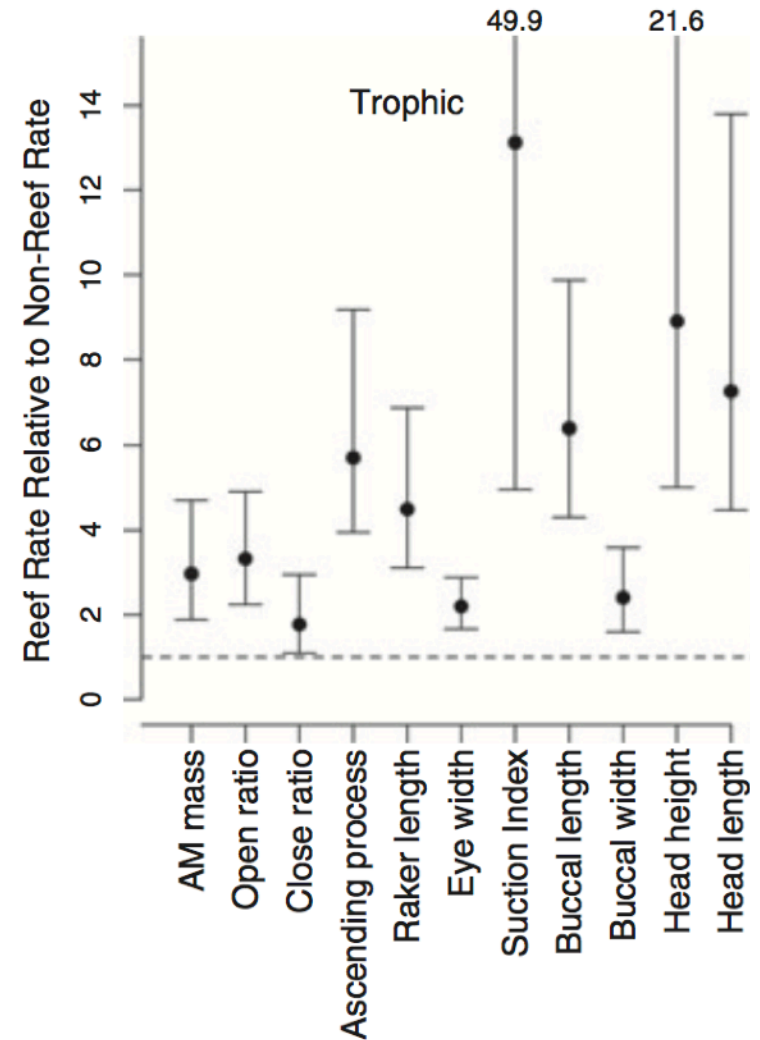
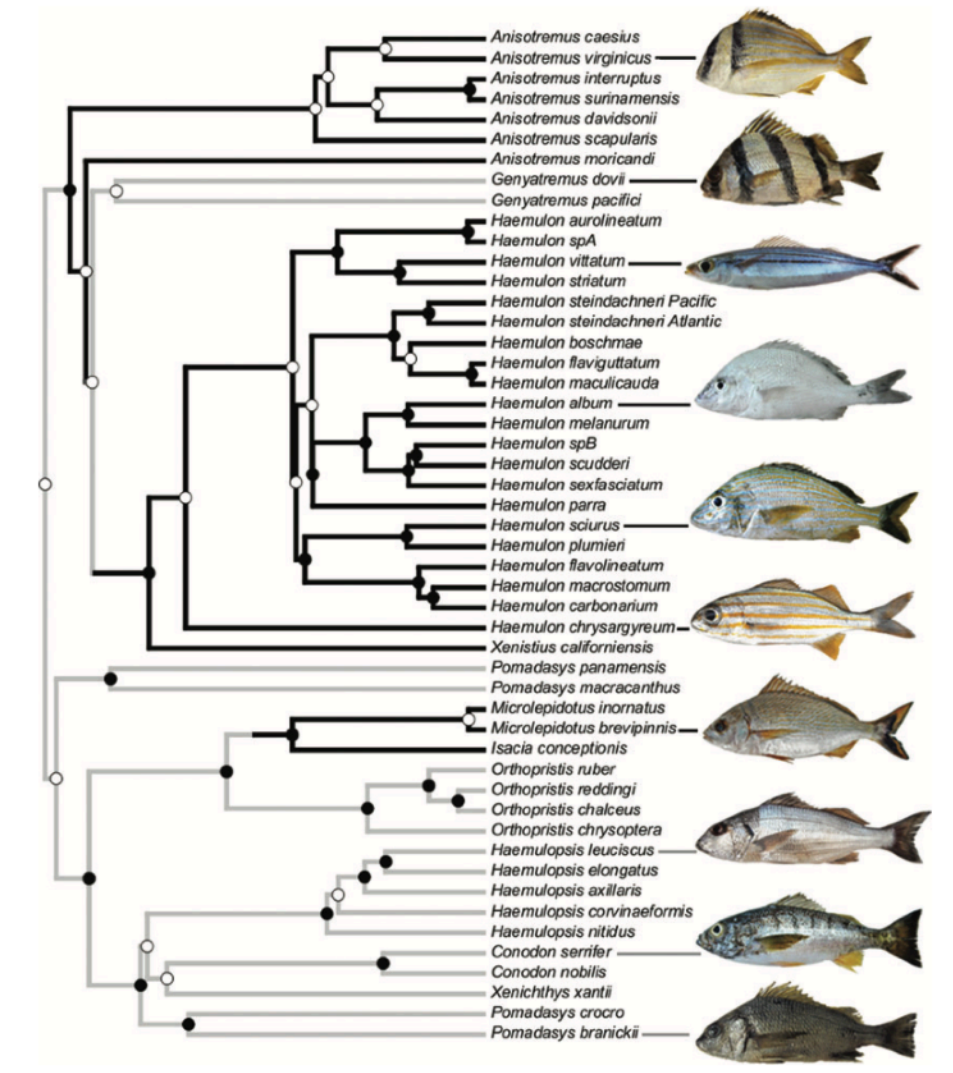
**VS.**



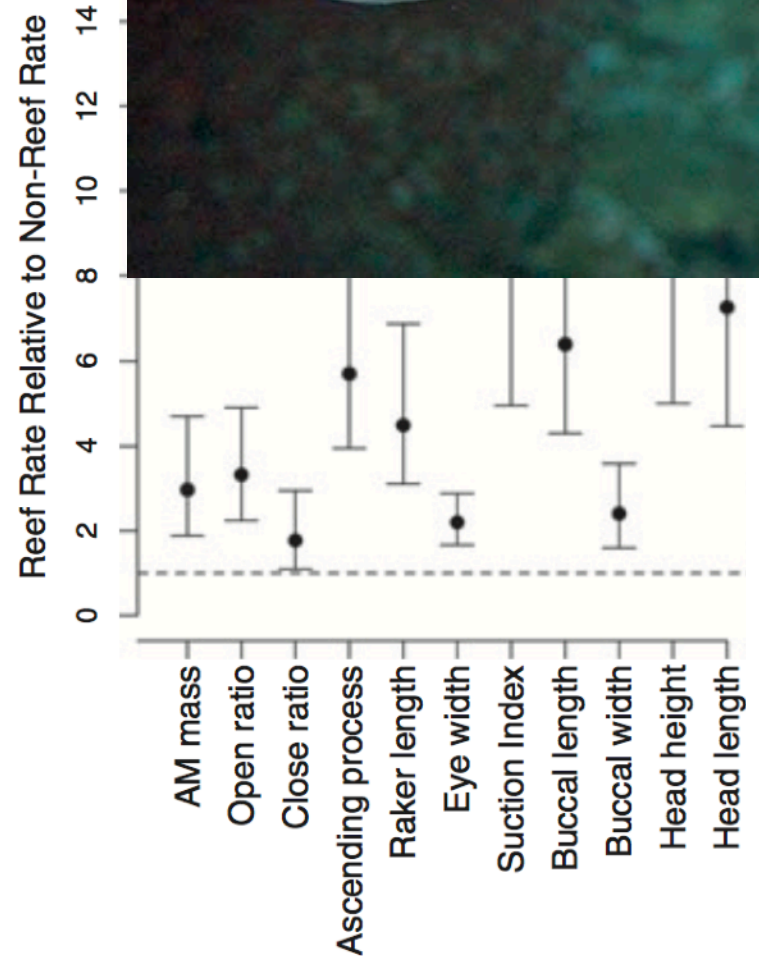
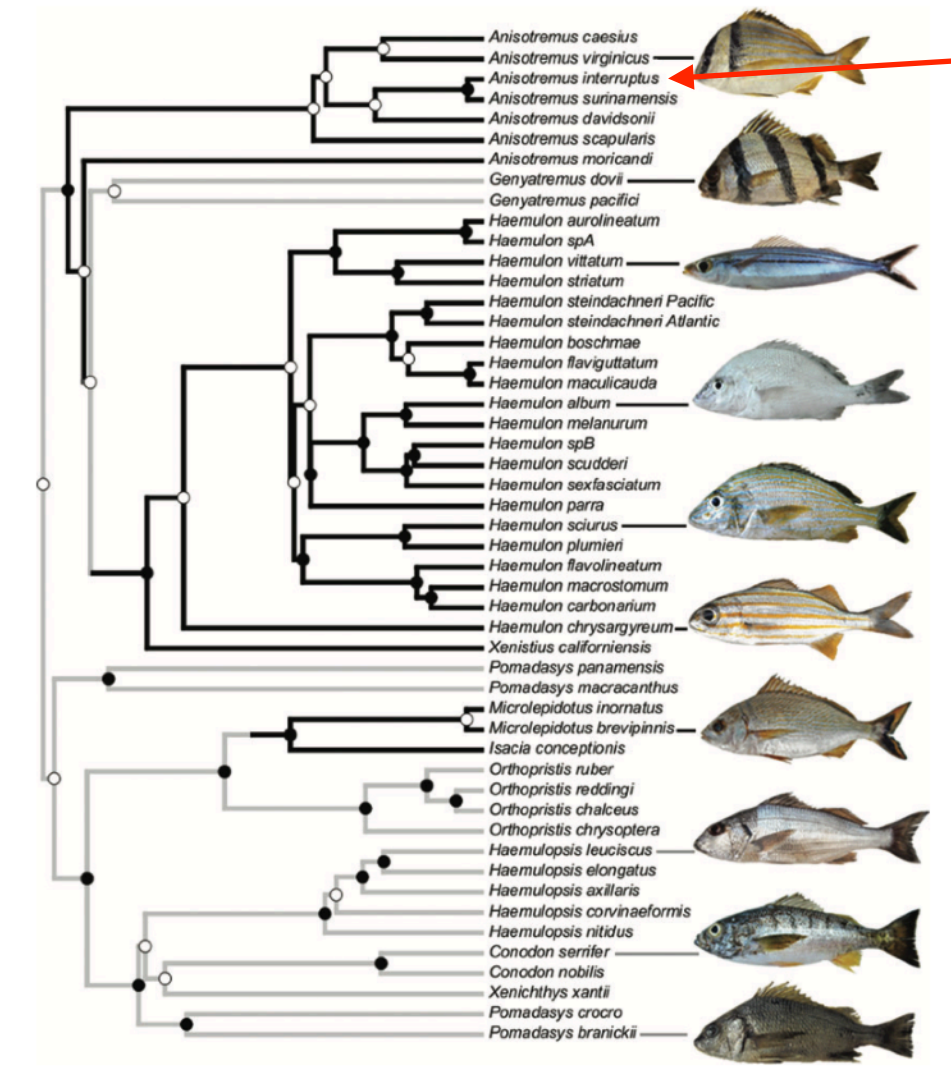
# Do rates of evolution vary?



# Do rates of continuous-trait evolution depend on a discrete variable?



# Do rates of continuous-trait evolution depend on a discrete variable?



# Outline



## I. Calculating likelihoods for continuous traits

A generic framework for calculating probabilities

## II. A simple model of continuous-character evolution

Brownian motion model

Multivariate Brownian motion model

## III. Exotic models of continuous-character evolution

Ornstein-Uhlenbeck model

Lévy models

State-dependent models



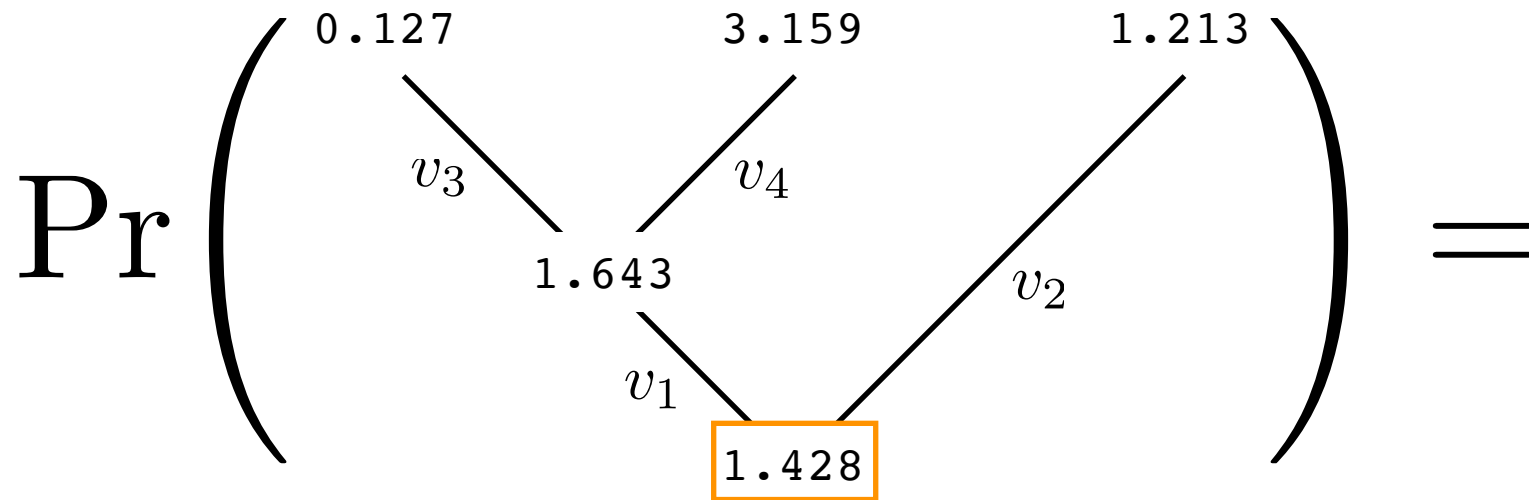
# Likelihoods for Continuous Characters

Species	Character data			
Species I	0.127	1.212	3.882	...
Species II	3.159	2.857	2.460	...
Species III	1.213	3.552	2.811	...

# Likelihoods for Continuous Characters

$$\text{Pr} \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & \swarrow v_3 & \searrow v_4 \\ & 1.643 & \\ & \swarrow v_1 & \searrow v_2 \\ & & 1.428 \end{array} \right) =$$

# Likelihoods for Continuous Characters



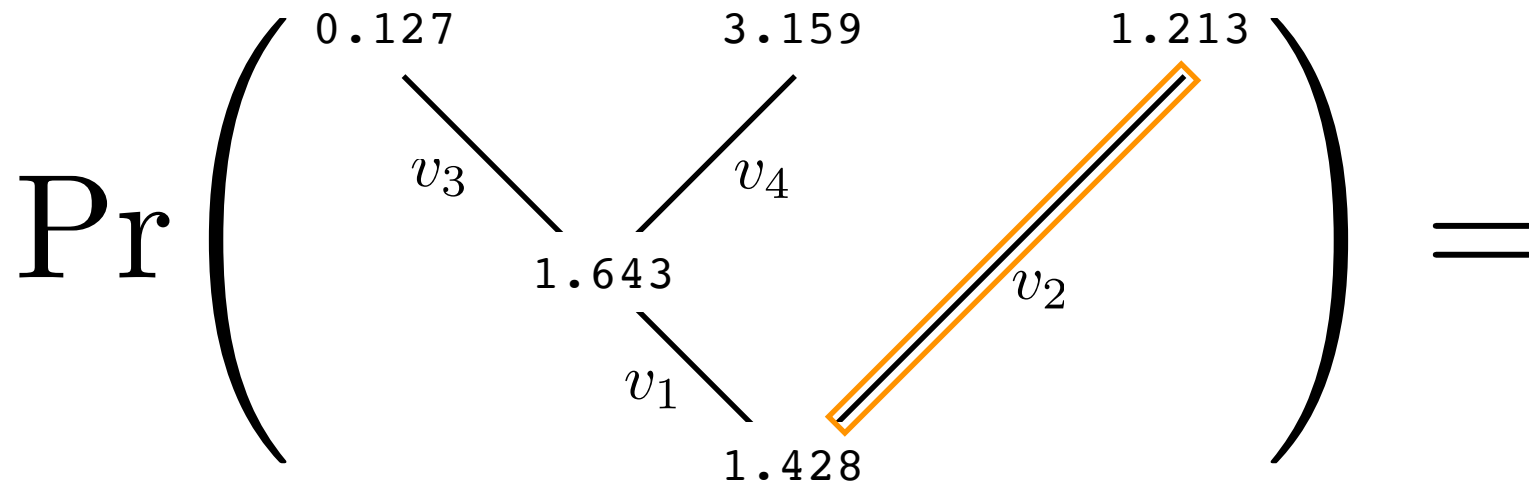
$p(1.428)$

# Likelihoods for Continuous Characters

$$\Pr \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & v_3 & v_4 \\ & 1.643 & v_2 \\ & v_1 & \\ & 1.428 & \end{array} \right) =$$

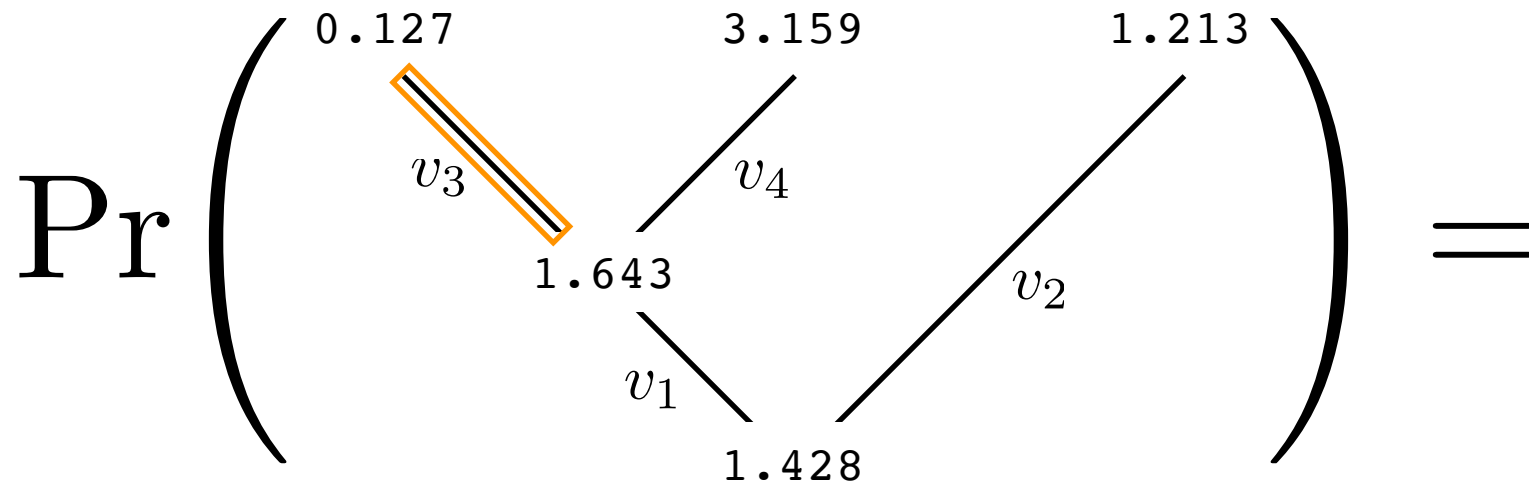
$$p(1.428) \times p(1.428 \rightarrow 1.643 \mid v_1)$$

# Likelihoods for Continuous Characters



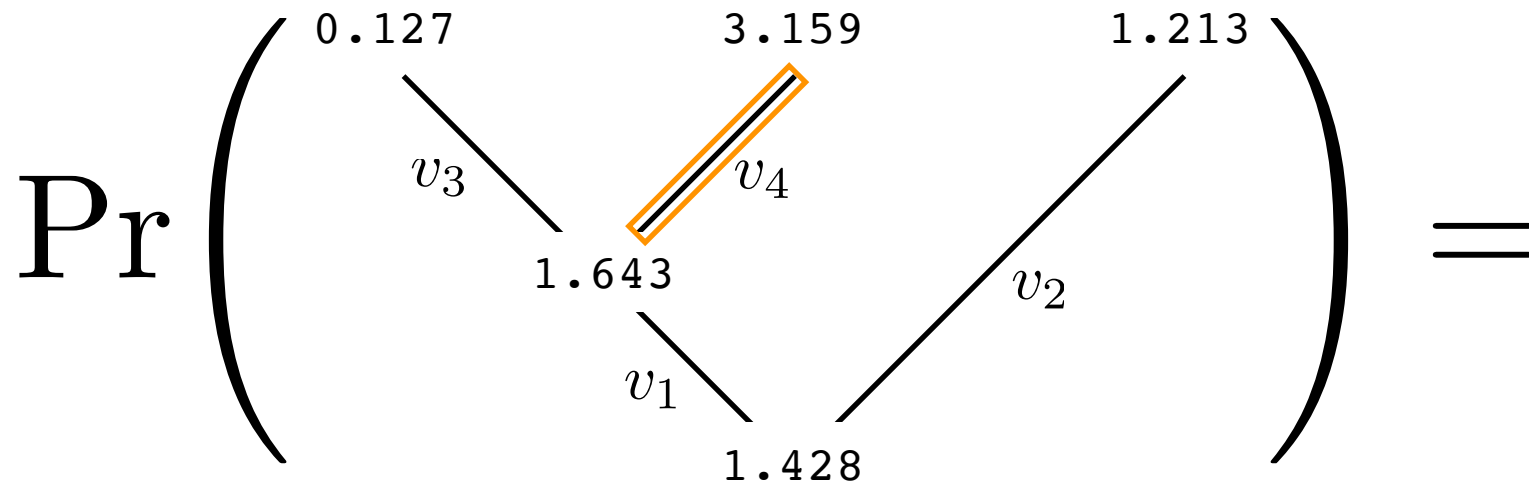
$$p(1.428) \times p(1.428 \rightarrow 1.643 \mid v_1) \times p(1.428 \rightarrow 1.213 \mid v_2)$$

# Likelihoods for Continuous Characters



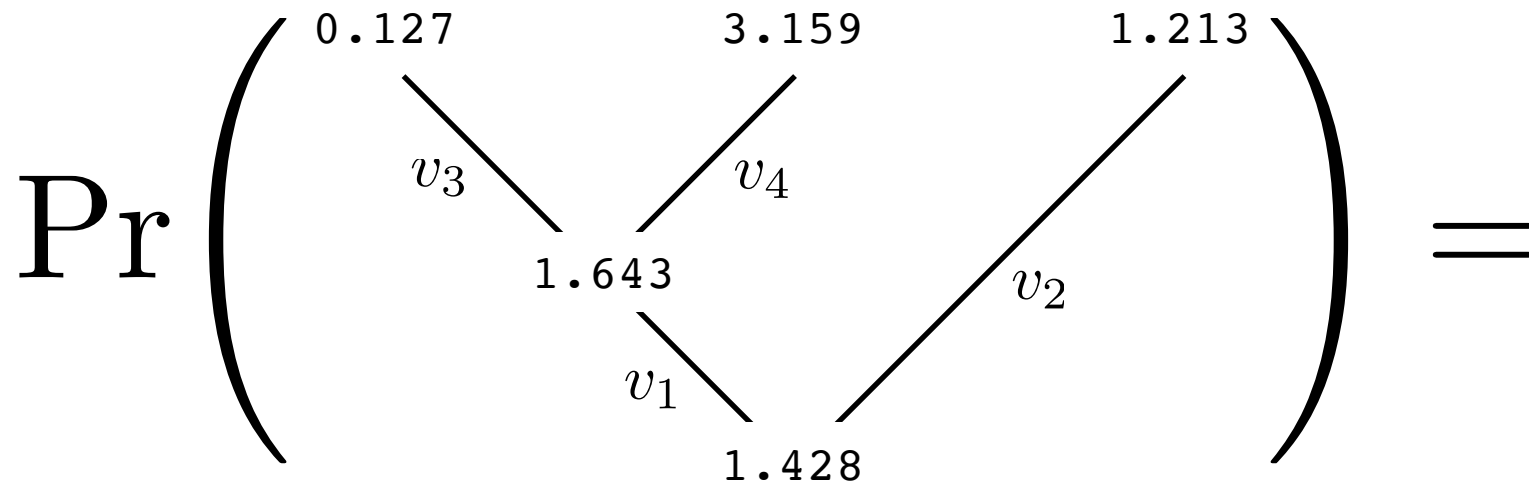
$$p(1.428) \times p(1.428 \rightarrow 1.643 \mid v_1) \times p(1.428 \rightarrow 1.213 \mid v_2) \times p(1.643 \rightarrow 0.127 \mid v_3)$$

# Likelihoods for Continuous Characters



$$p(1.428) \times p(1.428 \rightarrow 1.643 \mid v_1) \times p(1.428 \rightarrow 1.213 \mid v_2) \times \\ p(1.643 \rightarrow 0.127 \mid v_3) \times p(1.643 \rightarrow 3.159 \mid v_4)$$

# Likelihoods for Continuous Characters



$$p(1.428) \times p(1.428 \rightarrow 1.643 \mid v_1) \times p(1.428 \rightarrow 1.213 \mid v_2) \times p(1.643 \rightarrow 0.127 \mid v_3) \times p(1.643 \rightarrow 3.159 \mid v_4)$$

$p(x)$  Prior probabilities (root probabilities)

$p(x_i \rightarrow x_j \mid v)$  Transition probabilities



# Likelihoods for Continuous Characters

$$\text{Pr} \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & \swarrow v_3 & \searrow v_4 \\ & 1.643 & \\ & \swarrow v_1 & \searrow v_2 \\ & & 1.428 \end{array} \right) +$$

# Likelihoods for Continuous Characters

$$\text{Pr} \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & \diagdown \quad \diagup & \\ & 1.612 & \\ & \diagup \quad \diagdown & \\ & 1.428 & \end{array} \right) +$$

# Likelihoods for Continuous Characters

$$\text{Pr} \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & \diagdown \quad \diagup & \\ & 1.612 & \\ & \diagup \quad \diagdown & \\ & 1.317 & \end{array} \right) +$$

# Likelihoods for Continuous Characters

$$\text{Pr} \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & \diagdown \quad \diagup & \\ & 1.577 & \\ & \diagup \quad \diagdown & \\ & 1.317 & \end{array} \right) +$$

# Likelihoods for Continuous Characters

$$\text{Pr} \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & \diagdown & / \\ & 1.577 & \\ & / & \diagdown \\ & 1.411 & \end{array} \right) +$$

# Likelihoods for Continuous Characters

$$\text{Pr} \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & \diagdown \quad \diagup & \\ & 1.984 & \\ & \diagup \quad \diagdown & \\ & 1.411 & \end{array} \right) +$$

# Likelihoods for Continuous Characters

$$\text{Pr} \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & \diagdown \quad \diagup & \\ & 1.984 & \\ & \diagup \quad \diagdown & \\ & 1.754 & \end{array} \right) +$$

# Likelihoods for Continuous Characters

$$\text{Pr} \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & \diagdown \quad \diagup & \\ & 1.567 & \\ & \diagup \quad \diagdown & \\ & 1.754 & \end{array} \right) +$$



# Likelihoods for Continuous Characters

$$\text{Pr} \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & \diagdown & \diagup \\ & 1.567 & \\ & \diagup & \diagdown \\ & 1.223 & \end{array} \right) +$$

# Likelihoods for Continuous Characters

$$\text{Pr} \left( \begin{array}{ccc} 0.127 & 3.159 & 1.213 \\ & \diagdown & \diagup \\ & 1.567 & \\ & \diagup & \diagdown \\ & 1.223 & \end{array} \right) + \dots$$

# Likelihoods for Continuous Characters

Calculating transition probabilities and integrating over all ancestral states is the primary challenge of computing likelihoods for continuous characters.

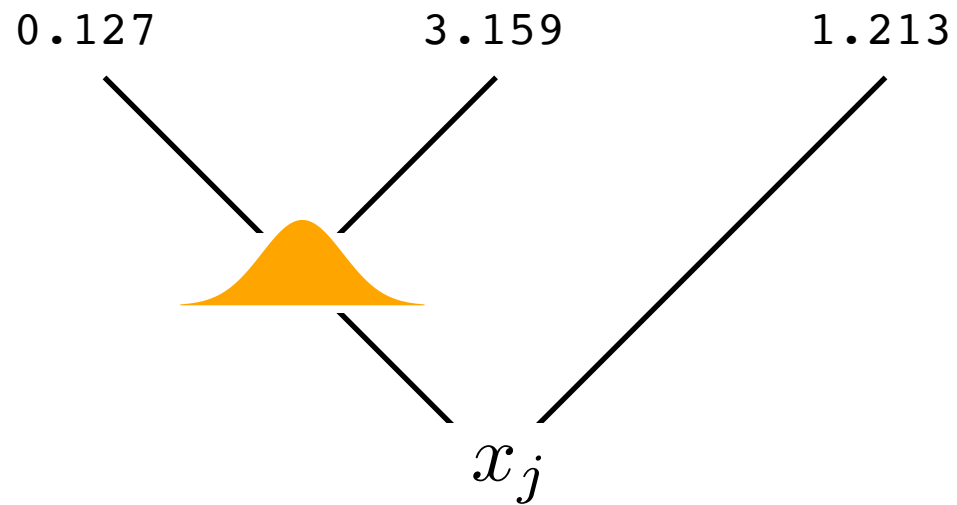
For some models (e.g., Brownian motion and OU), we can use a pruning algorithm (Felsenstein 1985) to efficiently calculate the likelihood.

# Likelihoods for Continuous Characters

Felsenstein's Other Pruning Algorithm

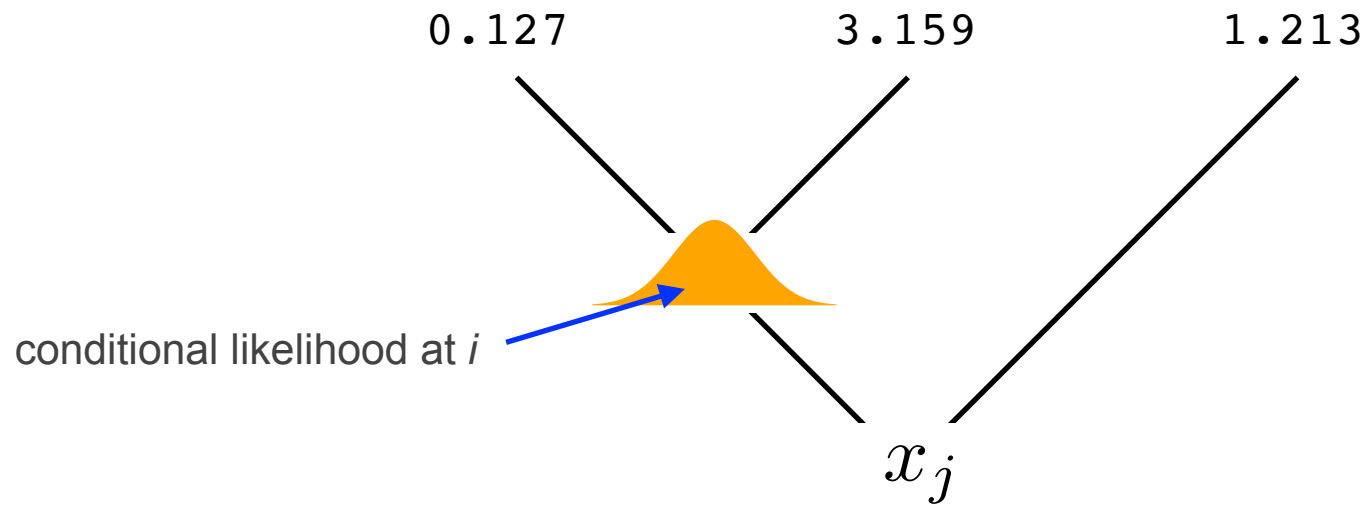
# Likelihoods for Continuous Characters

## Felsenstein's Other Pruning Algorithm



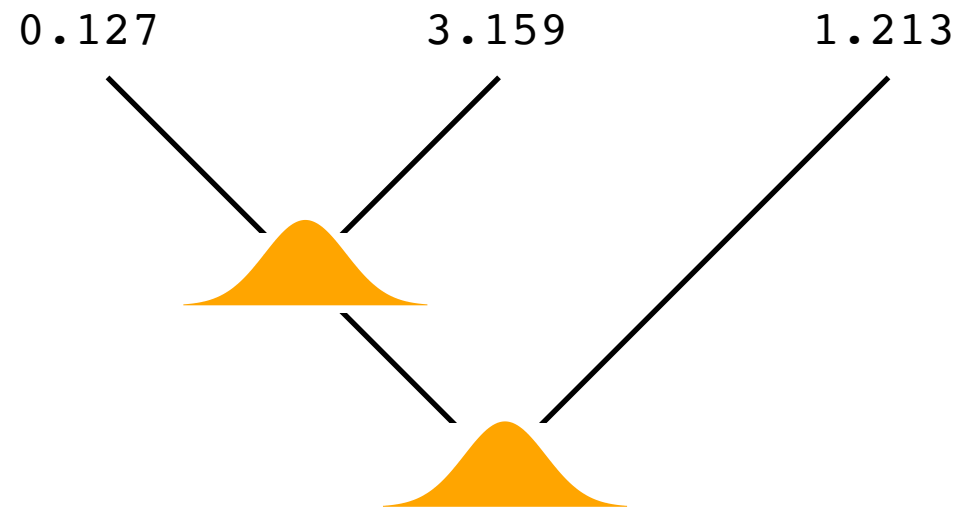
# Likelihoods for Continuous Characters

## Felsenstein's Other Pruning Algorithm



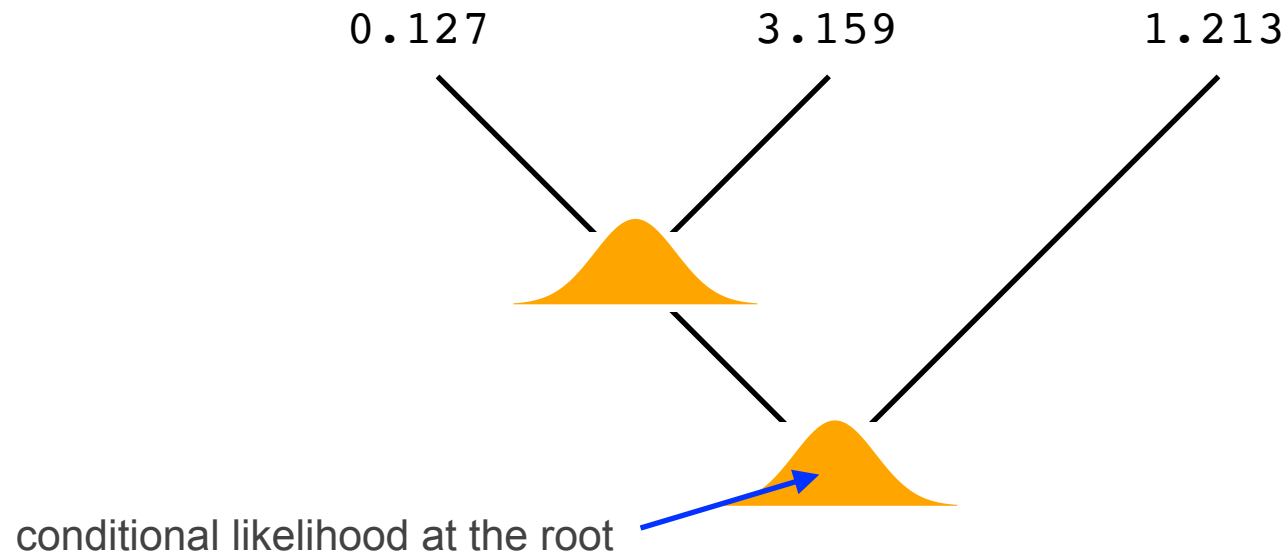
# Likelihoods for Continuous Characters

## Felsenstein's Other Pruning Algorithm



# Likelihoods for Continuous Characters

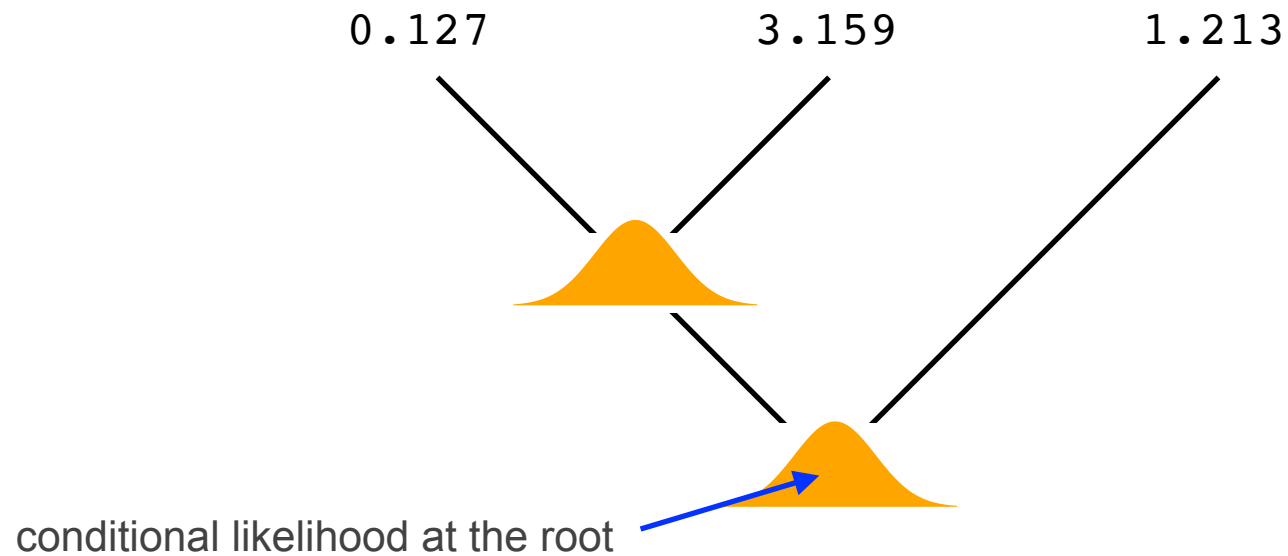
## Felsenstein's Other Pruning Algorithm





# Likelihoods for Continuous Characters

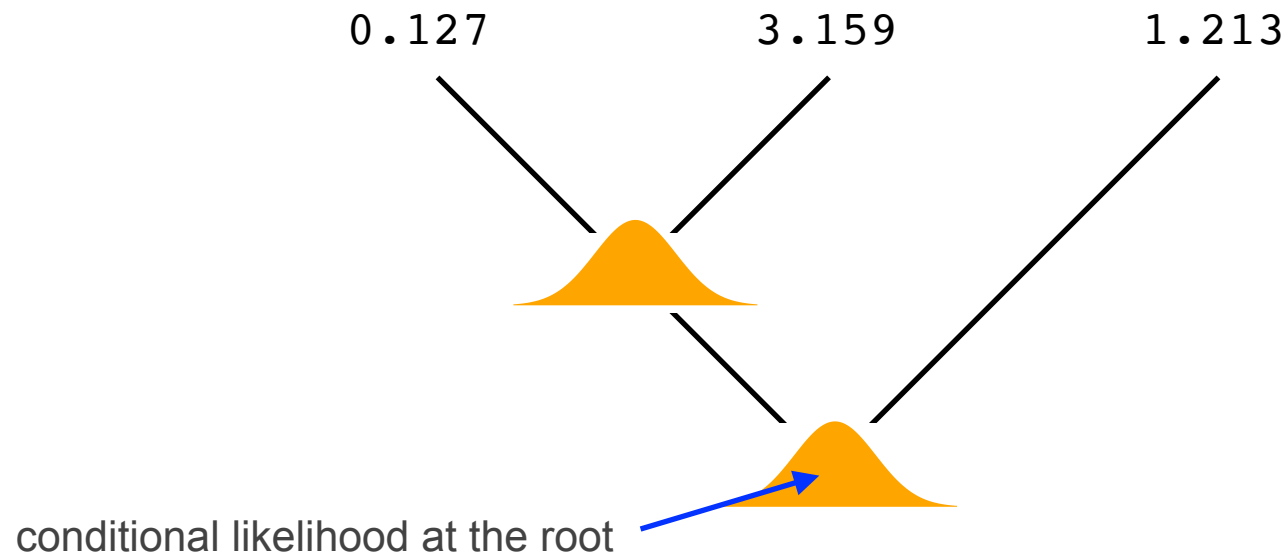
## Felsenstein's Other Pruning Algorithm



$$\mathbf{P}(\text{TTGT}) = \pi_{\text{A}} \mathcal{L}_{\text{A}}^{(\text{root})} + \pi_{\text{C}} \mathcal{L}_{\text{C}}^{(\text{root})} + \pi_{\text{G}} \mathcal{L}_{\text{G}}^{(\text{root})} + \pi_{\text{T}} \mathcal{L}_{\text{T}}^{(\text{root})}$$

# Likelihoods for Continuous Characters

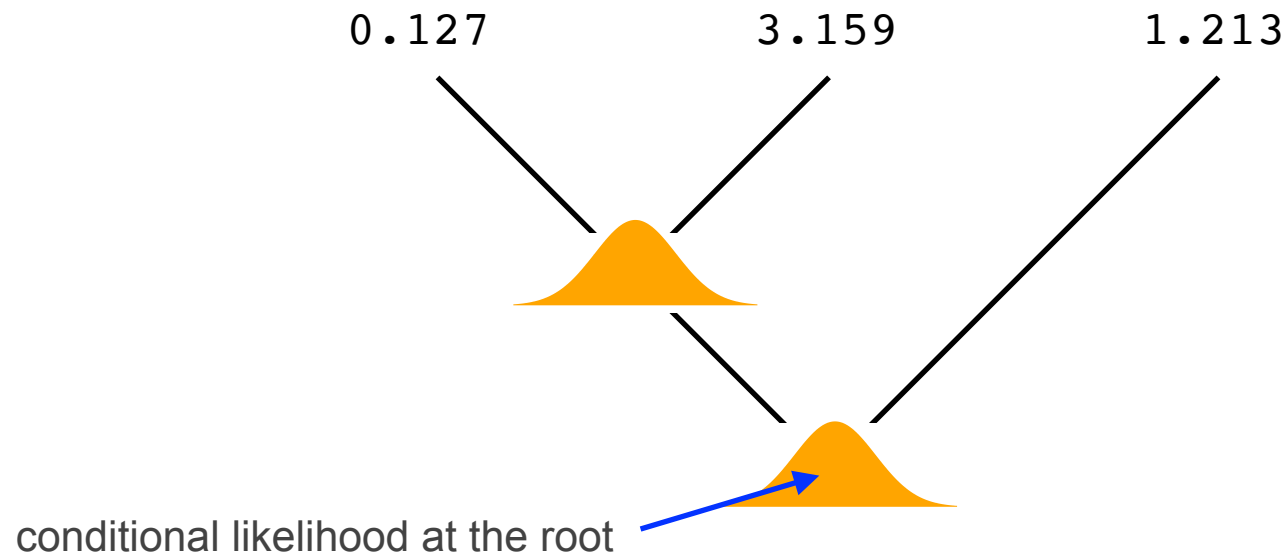
## Felsenstein's Other Pruning Algorithm



$$\mathbf{P}(\text{TTGT}) = \sum_{i \in \text{A,C,G,T}} \pi_i \mathcal{L}_i^{(\text{root})}$$

# Likelihoods for Continuous Characters

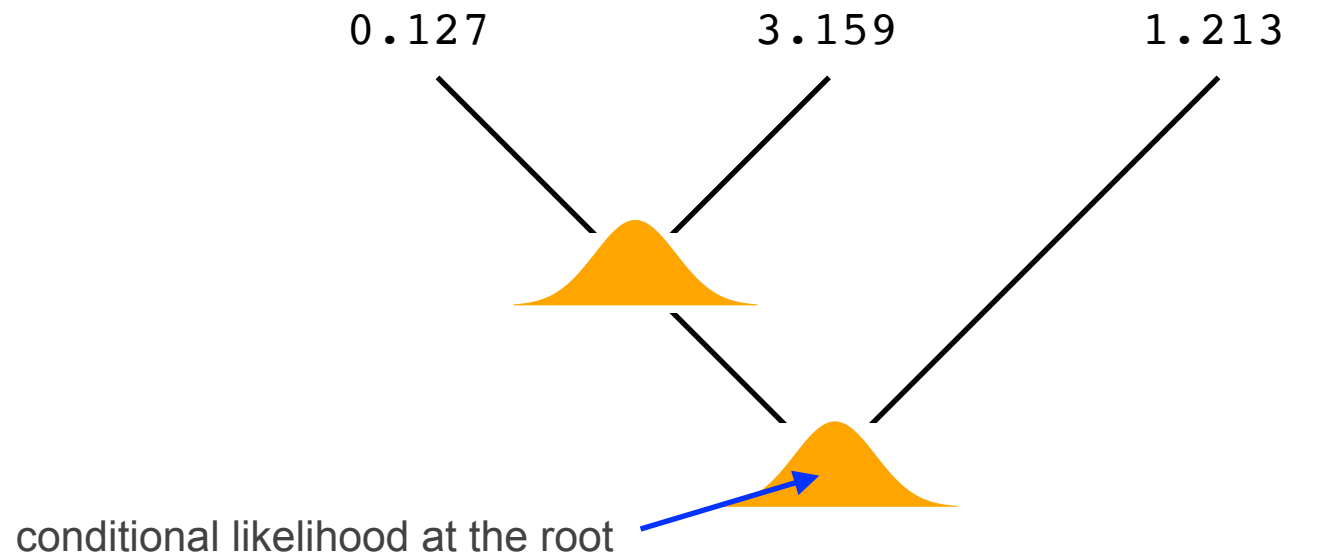
## Felsenstein's Other Pruning Algorithm



$$\mathbf{P}(\text{TTGT}) = \sum_{i \in \text{A,C,G,T}} \boxed{\pi_i} \mathcal{L}_i^{(\text{root})} \quad \text{prior probability}$$

# Likelihoods for Continuous Characters

## Felsenstein's Other Pruning Algorithm

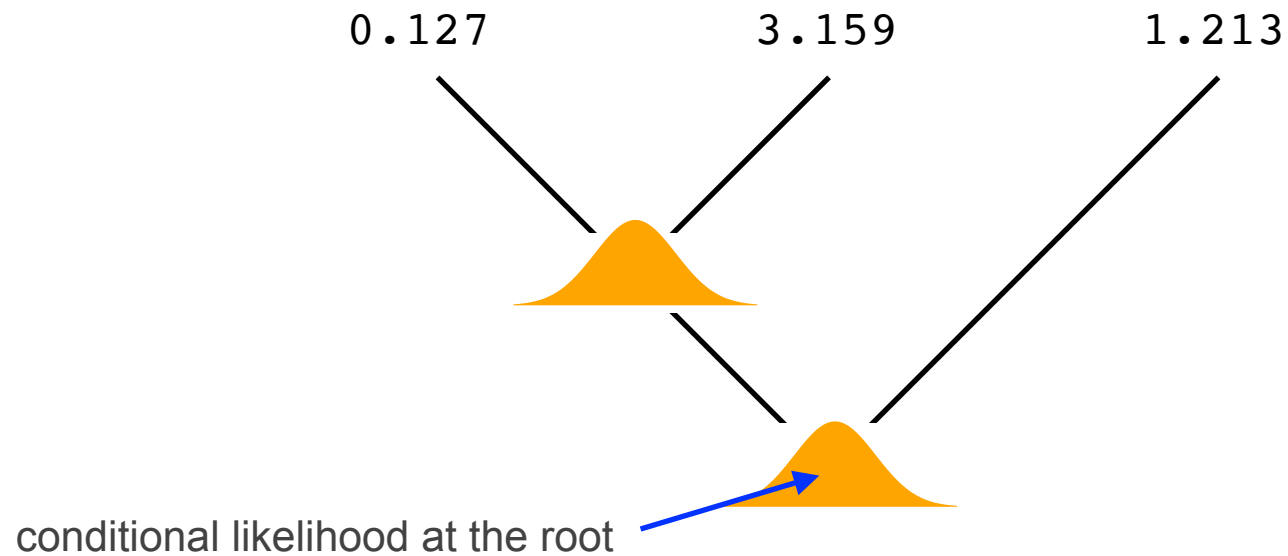


$$\mathbf{P}(\text{TTGT}) = \sum_{i \in \text{A,C,G,T}} \pi_i \mathcal{L}_i^{(\text{root})}$$

conditional likelihood

# Likelihoods for Continuous Characters

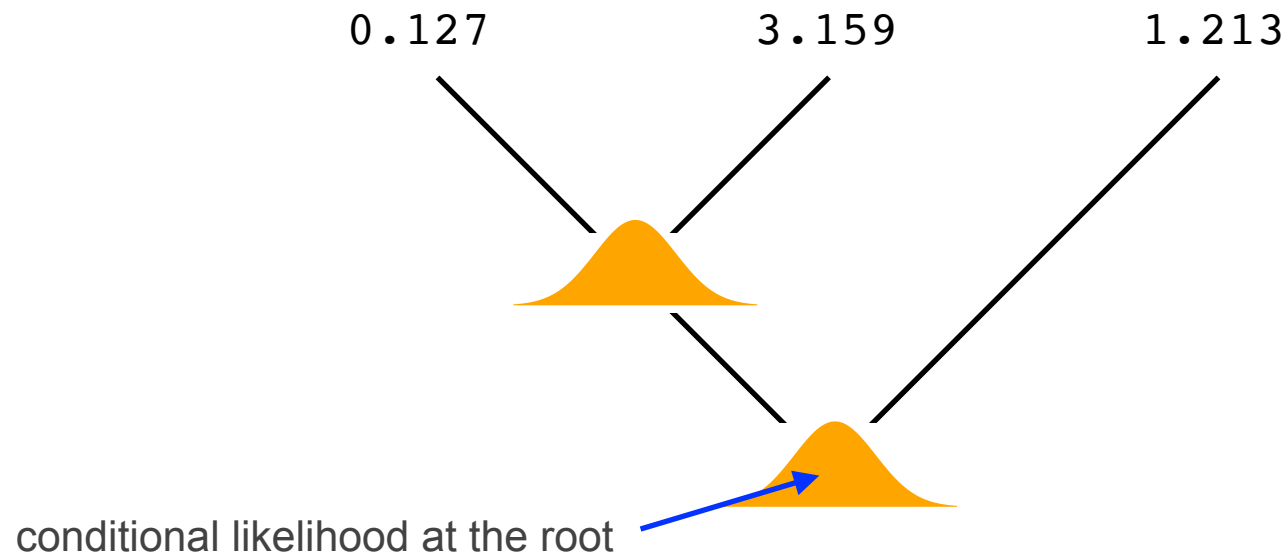
## Felsenstein's Other Pruning Algorithm



$$P(0.127, 3.159, 1.213) = \int p(x_i) \mathcal{L}_i^{(\text{root})} dx_i$$

# Likelihoods for Continuous Characters

## Felsenstein's Other Pruning Algorithm

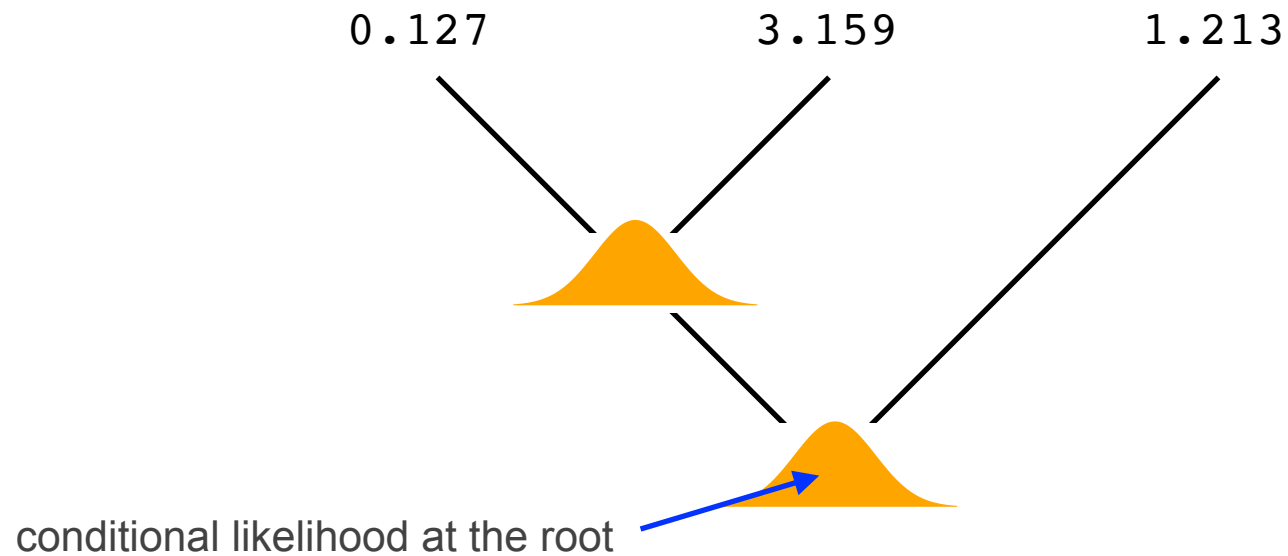


$$P(0.127, 3.159, 1.213) = \int \boxed{p(x_i)} \mathcal{L}_i^{(\text{root})} dx_i$$

prior probability

# Likelihoods for Continuous Characters

## Felsenstein's Other Pruning Algorithm



$$P(0.127, 3.159, 1.213) = \int p(x_i) \mathcal{L}_i^{(\text{root})} dx_i$$

conditional likelihood

# Outline

## I. Calculating likelihoods for continuous traits

A generic framework for calculating probabilities

## II. A simple model of continuous-character evolution

Brownian motion model

Multivariate Brownian motion model



# A Simple Model of Continuous-Character Evolution

## Brownian motion

Brownian motion was first used to describe the motion of microscopic particles moving in fluid.

Felsenstein proposed Brownian motion as a simple model of continuous-character evolution.

# A Simple Model of Continuous-Character Evolution

## Brownian motion

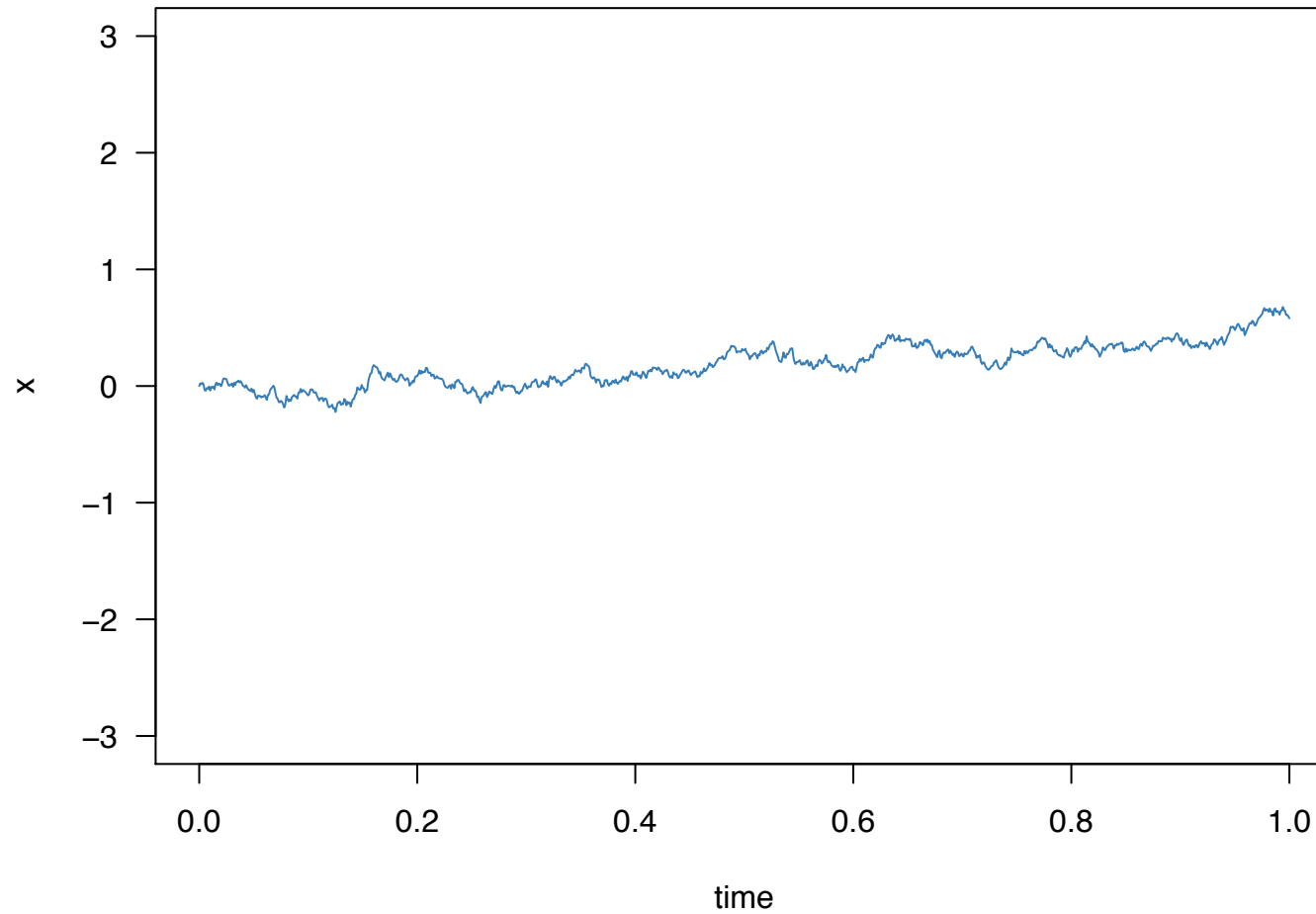
Brownian motion is defined by a single parameter,  $\sigma^2$ , which represents the *rate* of evolution.

The expected amount of character change is zero, but the opportunity for evolution is proportional to the rate of evolution and time.

# A Simple Model of Continuous-Character Evolution

## Brownian motion

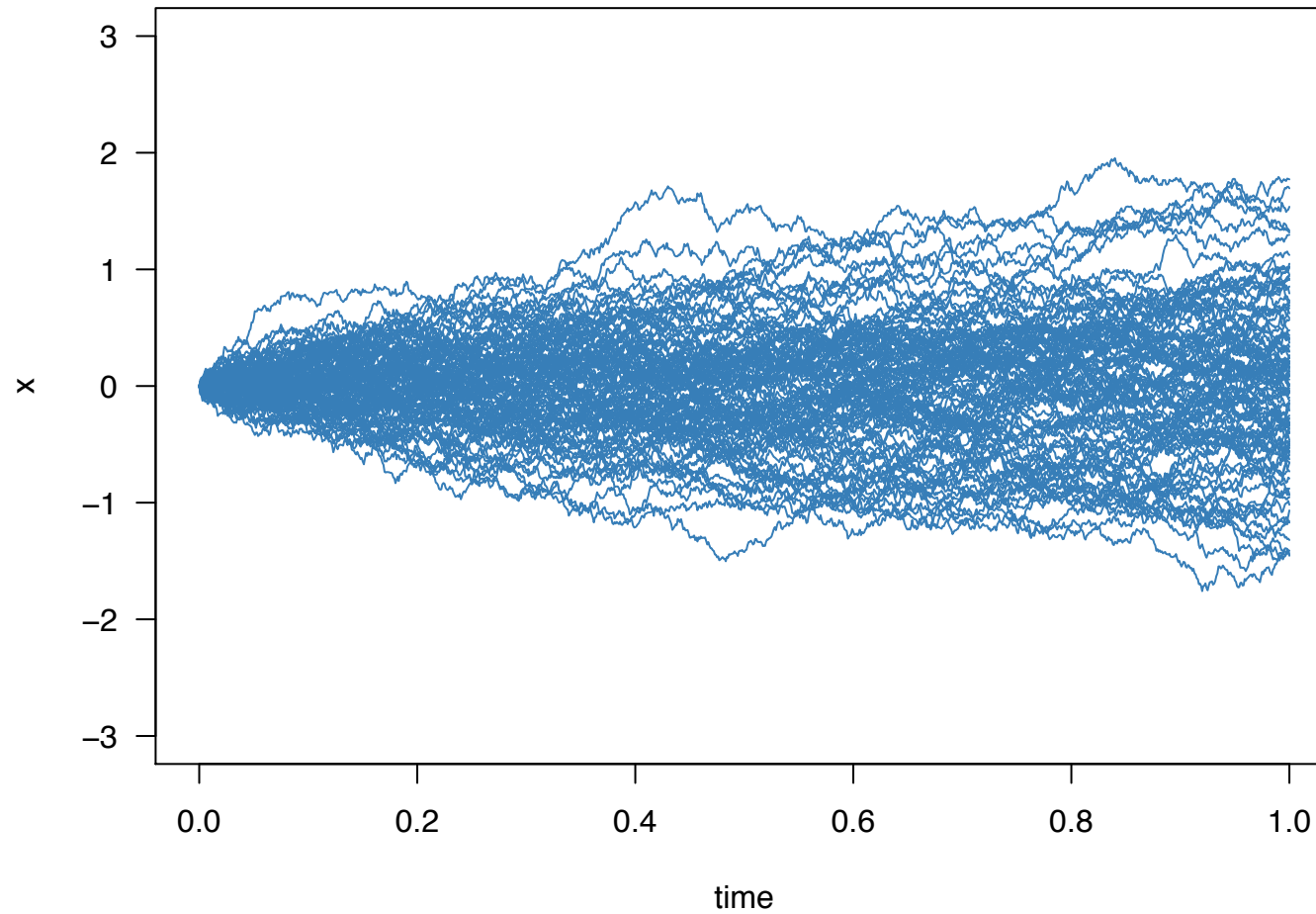
A single sample path under Brownian motion



# A Simple Model of Continuous-Character Evolution

## Brownian motion

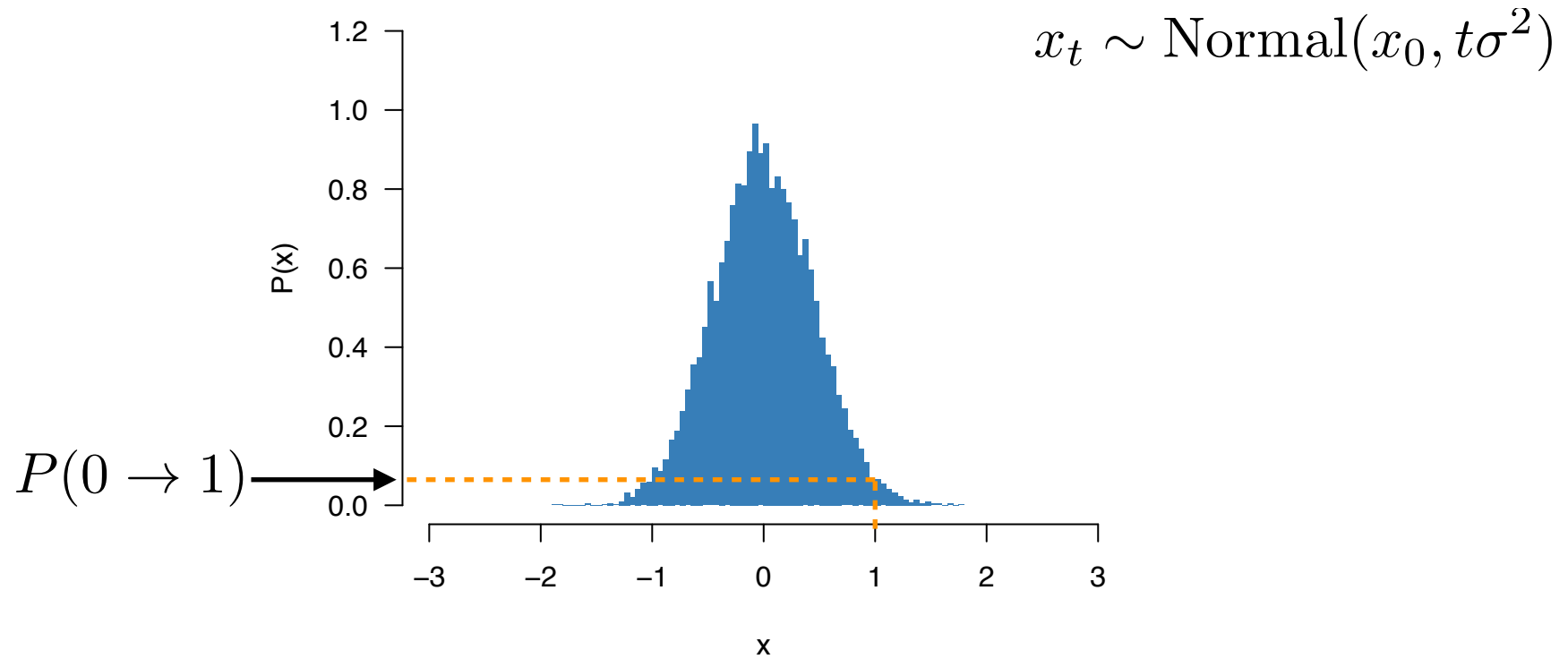
Many sample paths under Brownian motion



# A Simple Model of Continuous-Character Evolution

## Brownian motion

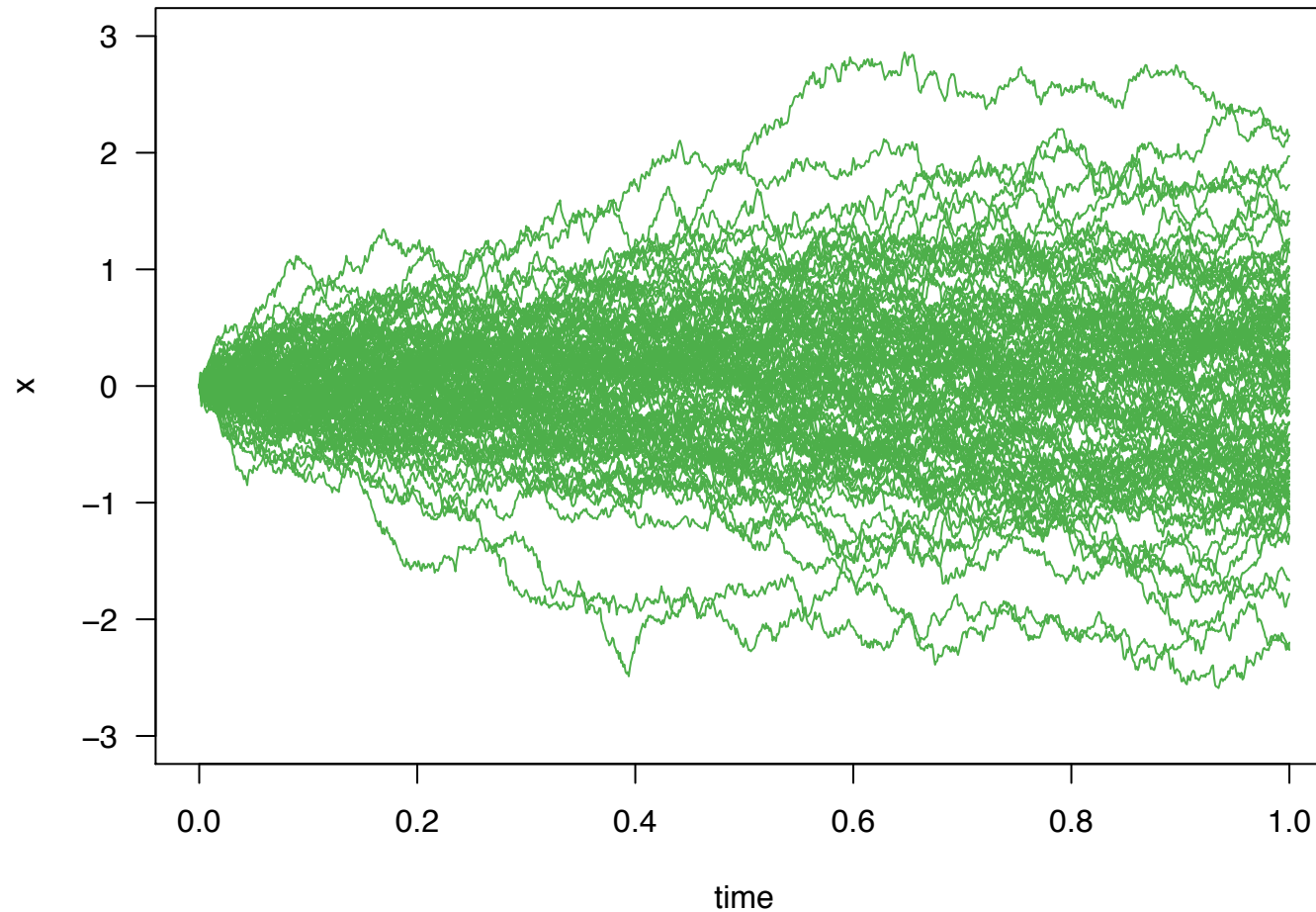
The transition probability under Brownian motion



# A Simple Model of Continuous-Character Evolution

Brownian motion

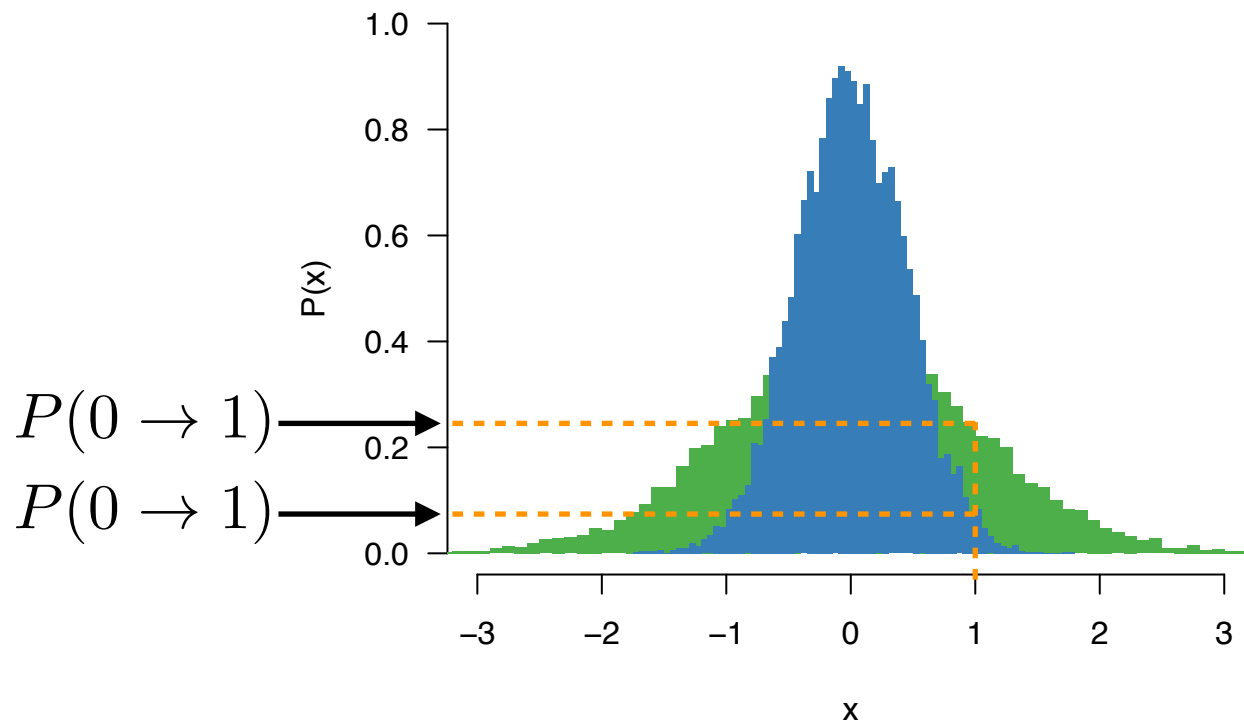
What if we turn up the rate parameter?



# A Simple Model of Continuous-Character Evolution

## Brownian motion

When the rate is higher, the process is more likely to evolve more.



# A Simple Model of Continuous-Character Evolution

## Brownian motion

We can use these transition probabilities to calculate the likelihood of a single character.

If we have multiple characters, we can make the same assumption that we did for molecular data: that the characters are independent.

$$P(X \mid \sigma^2) = \prod_i P(X_i \mid \sigma^2)$$



# A Simple Model of Continuous-Character Evolution

## Brownian motion

We can use the likelihood function to estimate the rate parameter!

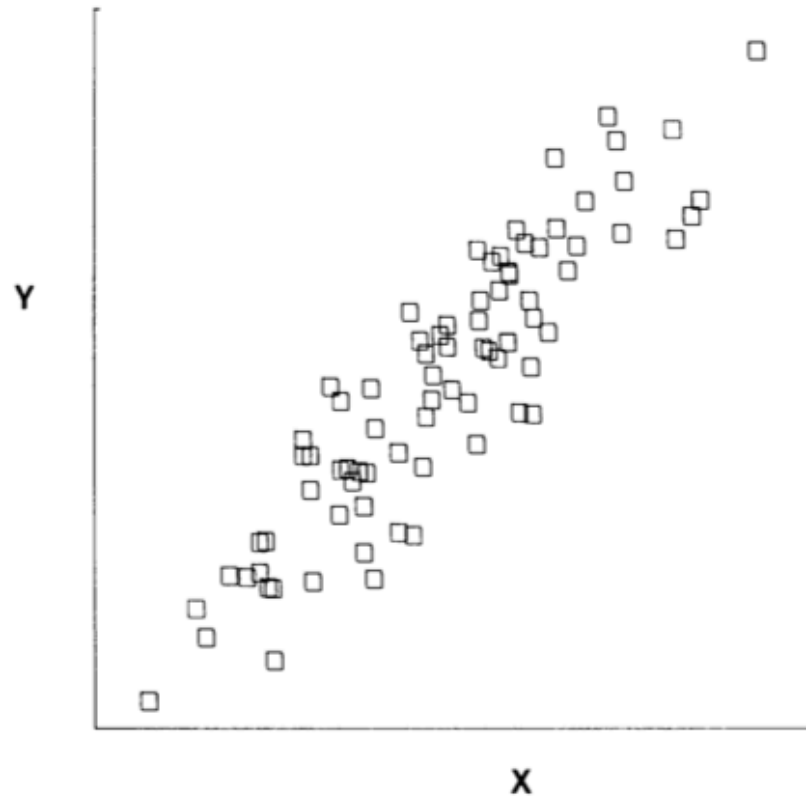
What if we don't want to assume that the characters are independent?

$$P(\sigma^2 | X) \propto P(X | \sigma^2)P(\sigma^2)$$

posterior

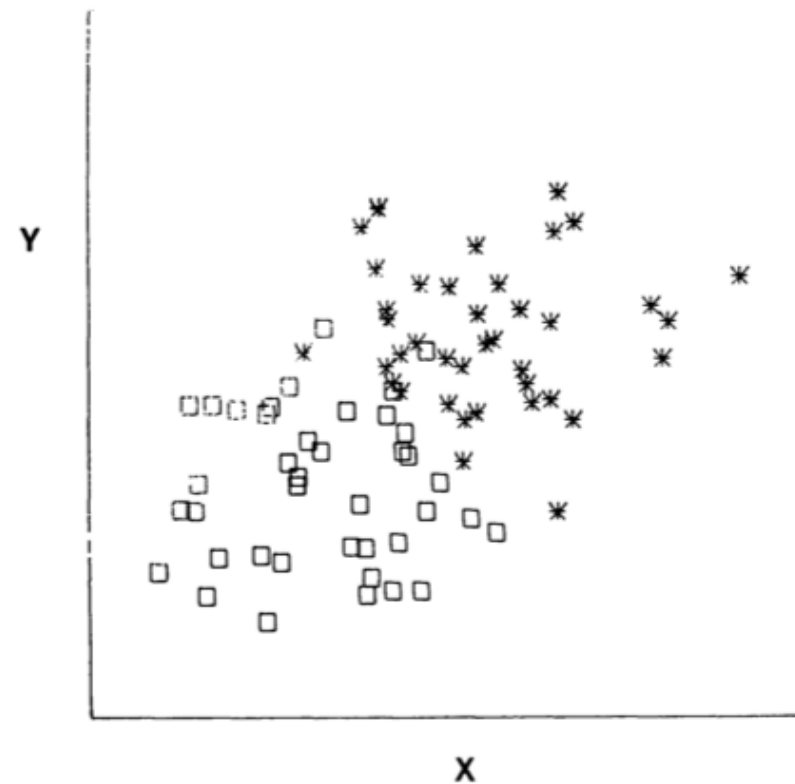
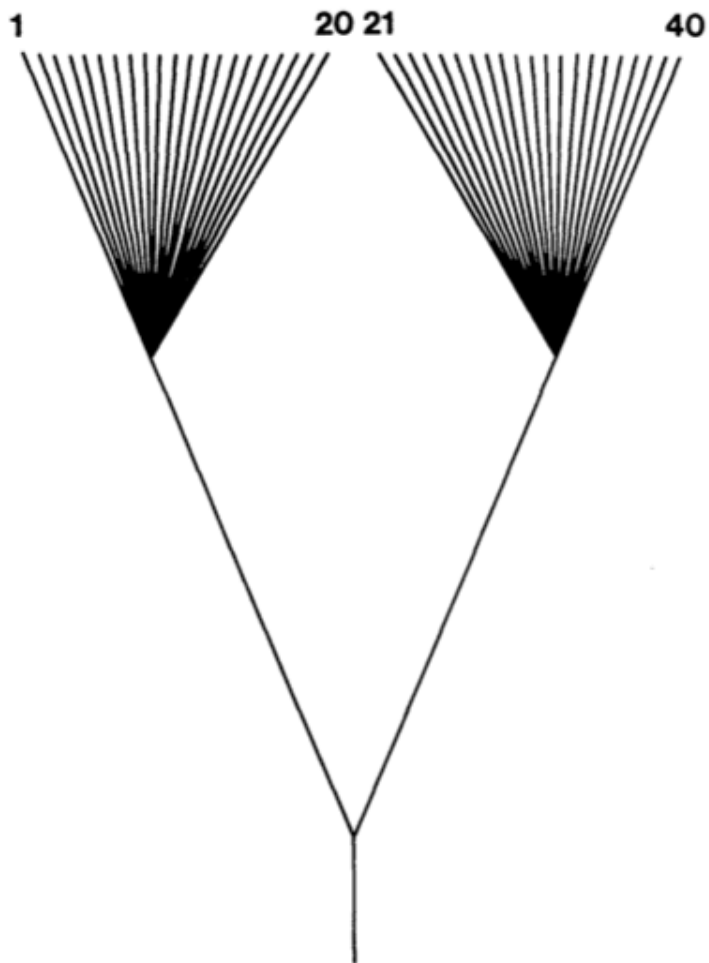
# A Simple Model of Continuous-Character Evolution

Are characters  $X$  and  $Y$  evolutionarily correlated?



# A Simple Model of Continuous-Character Evolution

Are characters  $X$  and  $Y$  evolutionarily correlated?



# A Simple Model of Continuous-Character Evolution

## Multivariate Brownian motion

Multivariate Brownian motion is the multivariate generalization of Brownian motion (when there are multiple continuous traits).

Rather than a single diffusion rate, there is one rate for each of  $c$  traits, as well as a correlation parameter for each pair of traits.

$$\sigma^2 = \sigma_1^2, \sigma_2^2, \dots, \sigma_c^2$$

evolutionary rates for each character

$$R = \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1c} \\ \rho_{12} & 1 & \cdots & \rho_{2c} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1c} & \rho_{2c} & \cdots & 1 \end{pmatrix}$$

evolutionary correlations between each pair of characters

# A Simple Model of Continuous-Character Evolution

## Multivariate Brownian motion

Multivariate Brownian motion is the multivariate generalization of Brownian motion (when there are multiple continuous traits).

Rather than a single diffusion rate, there is one rate for each of  $c$  traits, as well as a correlation parameter for each pair of traits.

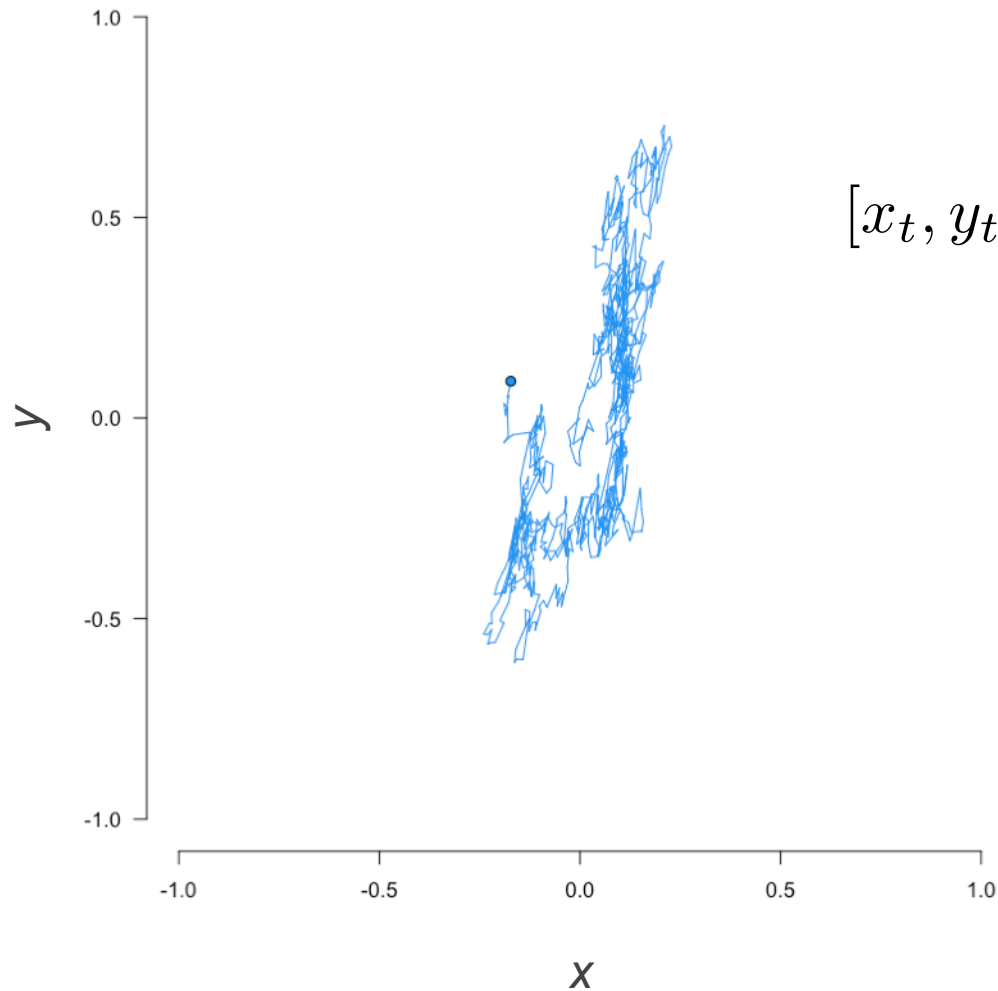
$$\Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho_{12} & \cdots & \sigma_1\sigma_c\rho_{1c} \\ \sigma_1\sigma_2\rho_{12} & \sigma_2^2 & \cdots & \sigma_2\sigma_c\rho_{2c} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_1\sigma_c\rho_{1c} & \sigma_2\sigma_c\rho_{2c} & \cdots & \sigma_c^2 \end{pmatrix}$$

evolutionary variance-covariance matrix

# A Simple Model of Continuous-Character Evolution

## Multivariate Brownian motion

The transition probability density is a multivariate normal density.



$$[x_t, y_t] \sim \text{MVN}([x_0, y_0], t\Sigma)$$

# A Simple Model of Continuous-Character Evolution

## Multivariate Brownian motion

We estimate the variance-covariance matrix using the likelihood function (and appropriately chosen priors).

$$\underbrace{P(\Sigma | X) \propto P(X | \Sigma)P(\Sigma)}$$

multivariate normal posterior

# Outline

## I. Calculating likelihoods for continuous traits

A generic framework for calculating probabilities

## II. A simple model of continuous-character evolution

Brownian motion model

Multivariate Brownian motion model

## III. Exotic models of continuous-character evolution

Ornstein-Uhlenbeck model

Lévy models

State-dependent models



# Exotic Diffusion Models

## Ornstein-Uhlenbeck (OU) model

The Ornstein-Uhlenbeck process describes diffusion toward (and around) an optimal value.

It is commonly used to model stabilizing selection.

There are three parameters:

$\sigma^2$  — rate of evolution

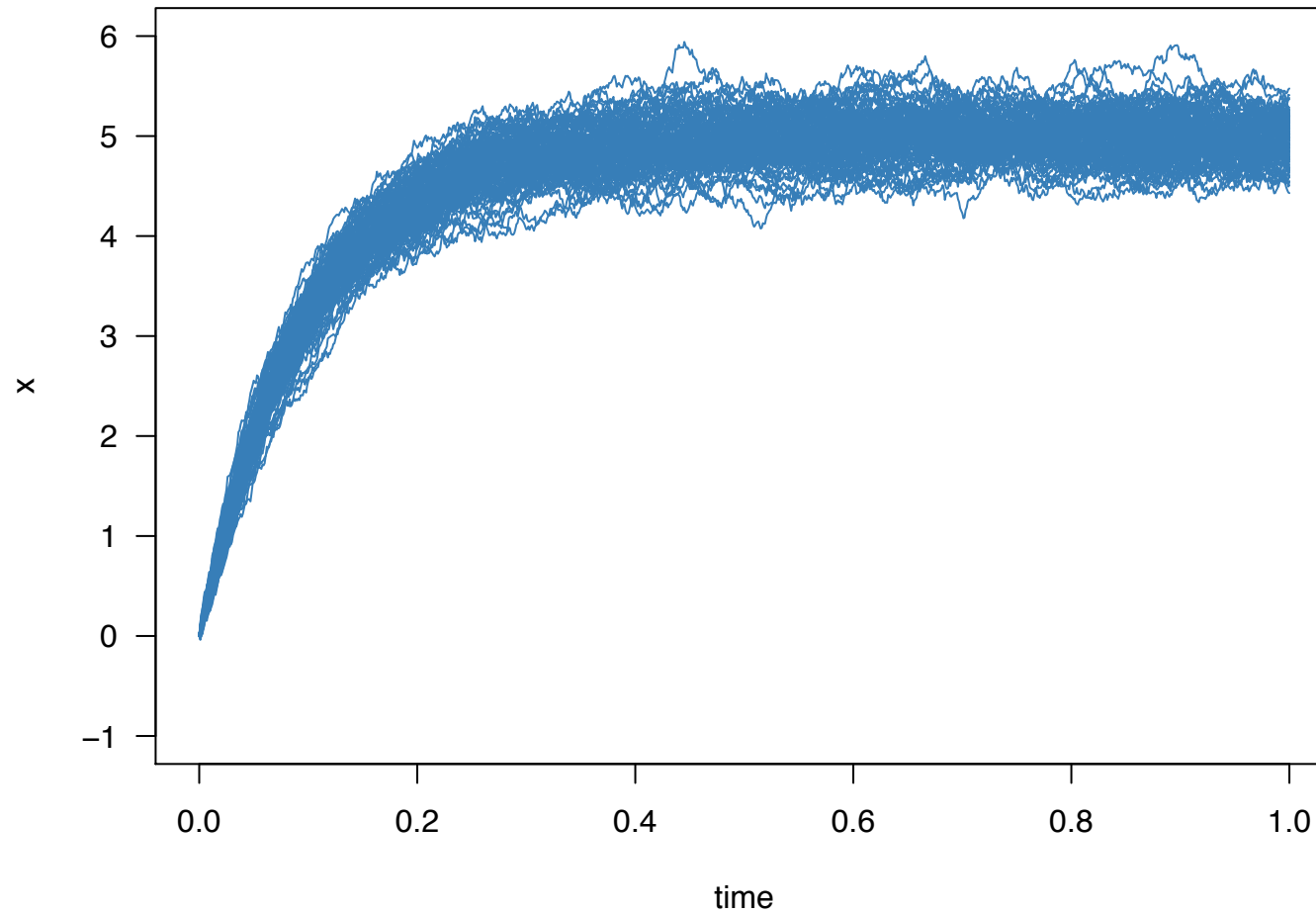
$\theta$  — optimal value

$\alpha$  — strength of selection

# Exotic Diffusion Models

## Ornstein-Uhlenbeck (OU) model

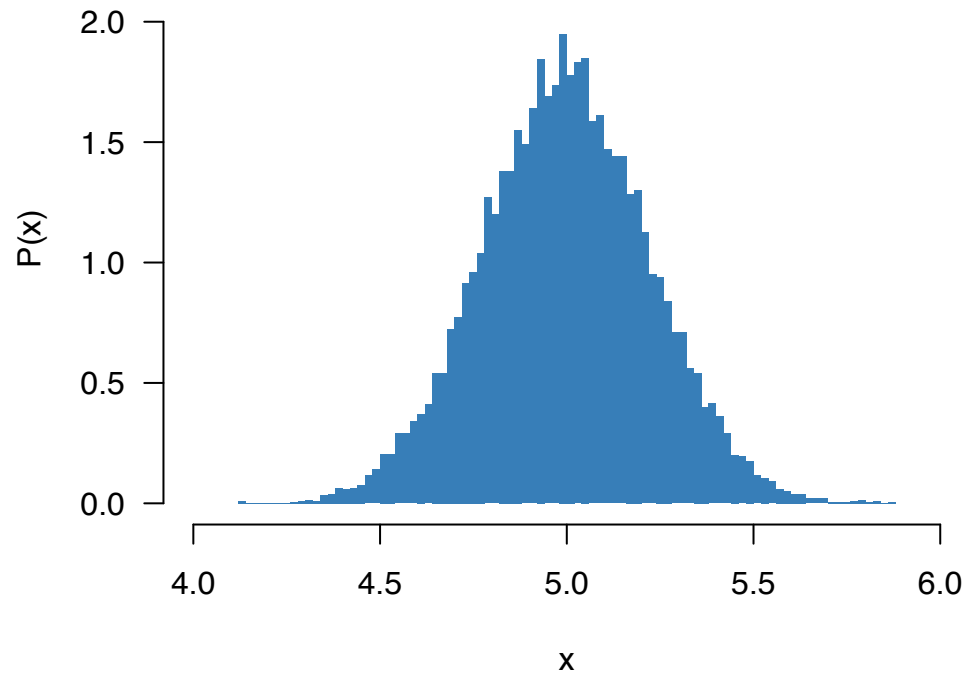
Many sample paths under OU



# Exotic Diffusion Models

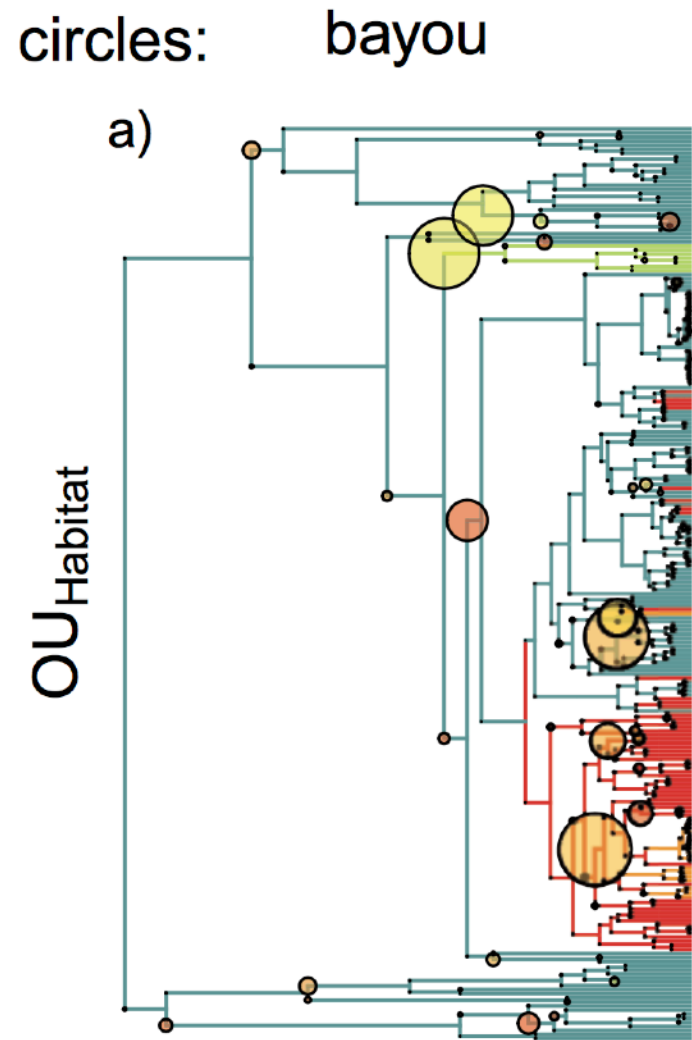
## Ornstein-Uhlenbeck (OU) model

The transition probability under the OU process is a known normal probability density (with complicated parameters!)



# Exotic Diffusion Models

Ornstein-Uhlenbeck (OU) model



# Exotic Diffusion Models

## Lévy process models

The Lévy processes are a family of models that allow for both continuous diffusion (as with the Brownian motion model) and sudden changes in the state of the character.

The Jump-Normal model is a Lévy process that models jumps using a Poisson process. At each jump event, the character changes by a normal random variable.

$\sigma^2$  — rate of evolution

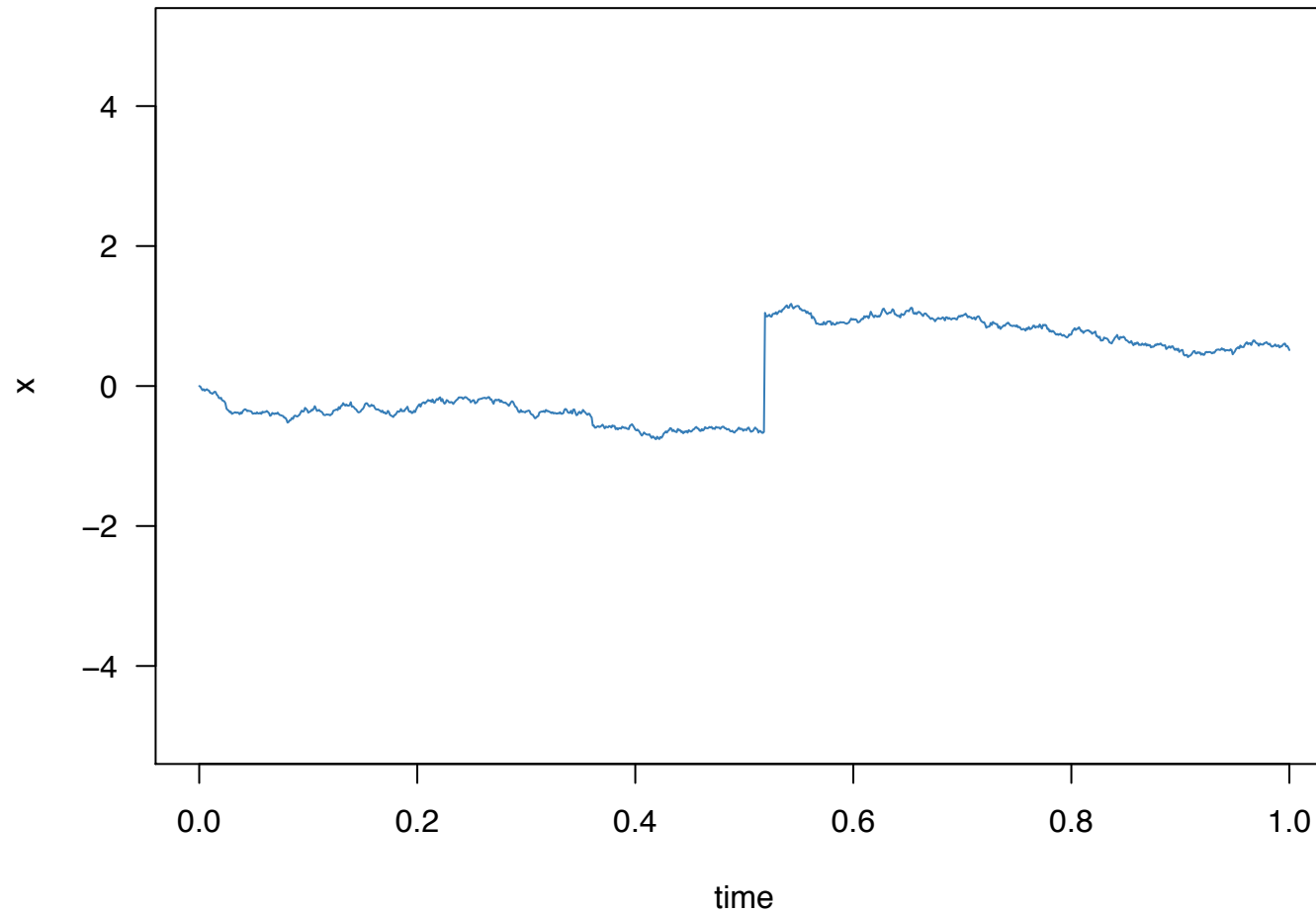
$\lambda$  — rate of jumps

$\delta$  — size of jumps

# Exotic Diffusion Models

## Jump-Normal (JN) model

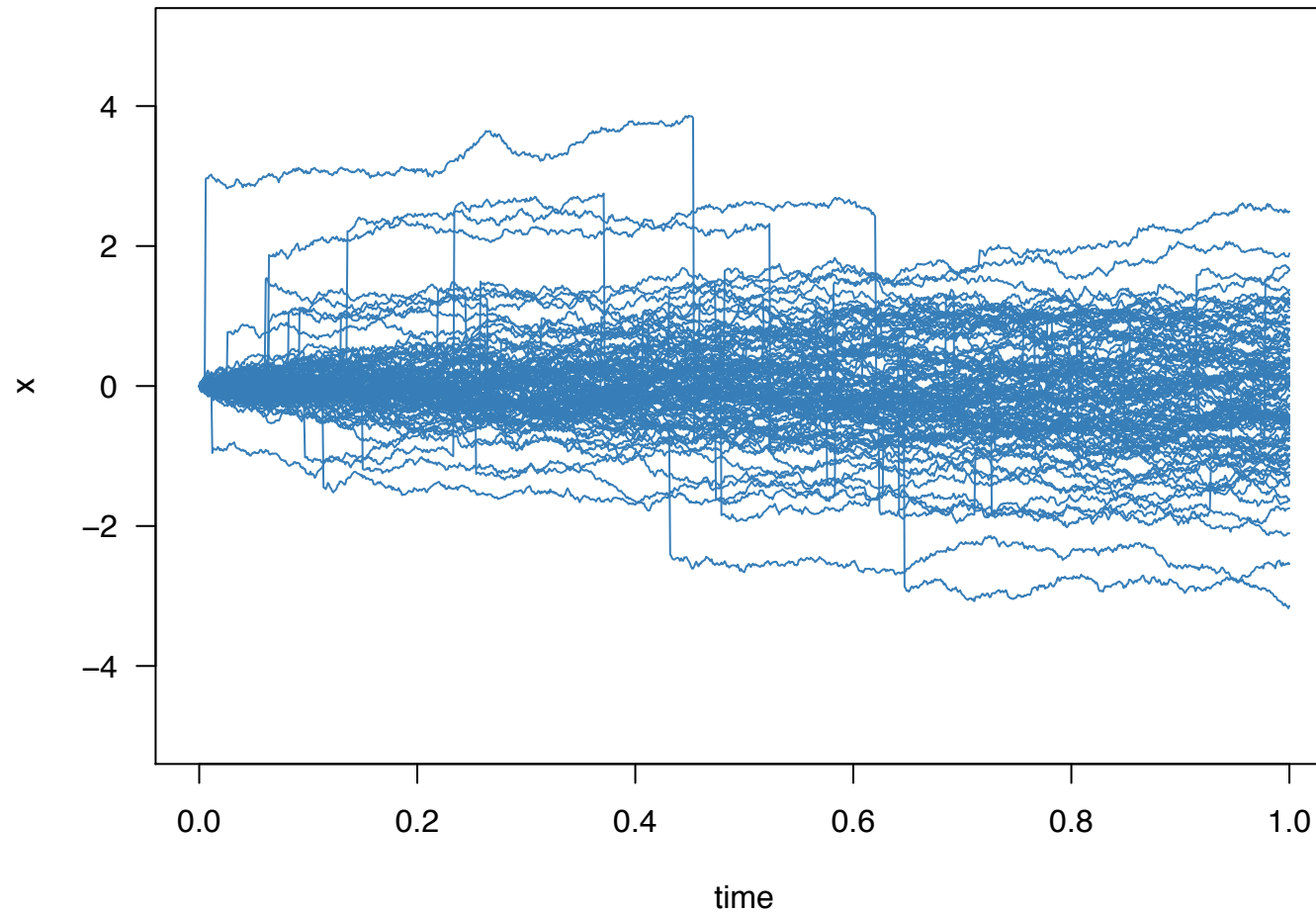
A single sample path under JN



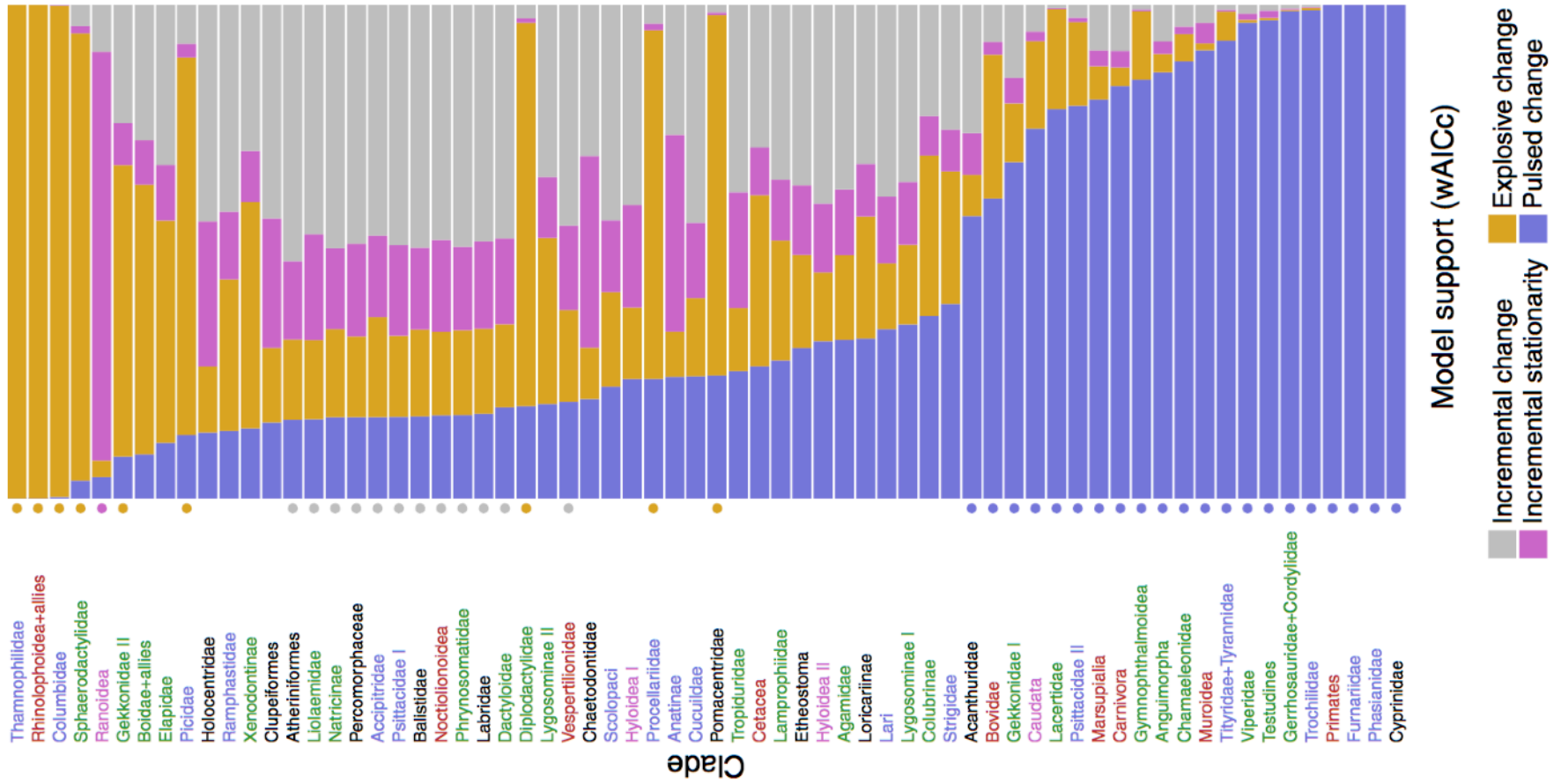
# Exotic Diffusion Models

## Jump-Normal (JN) model

Many sample paths under JN



# Exotic Diffusion Models





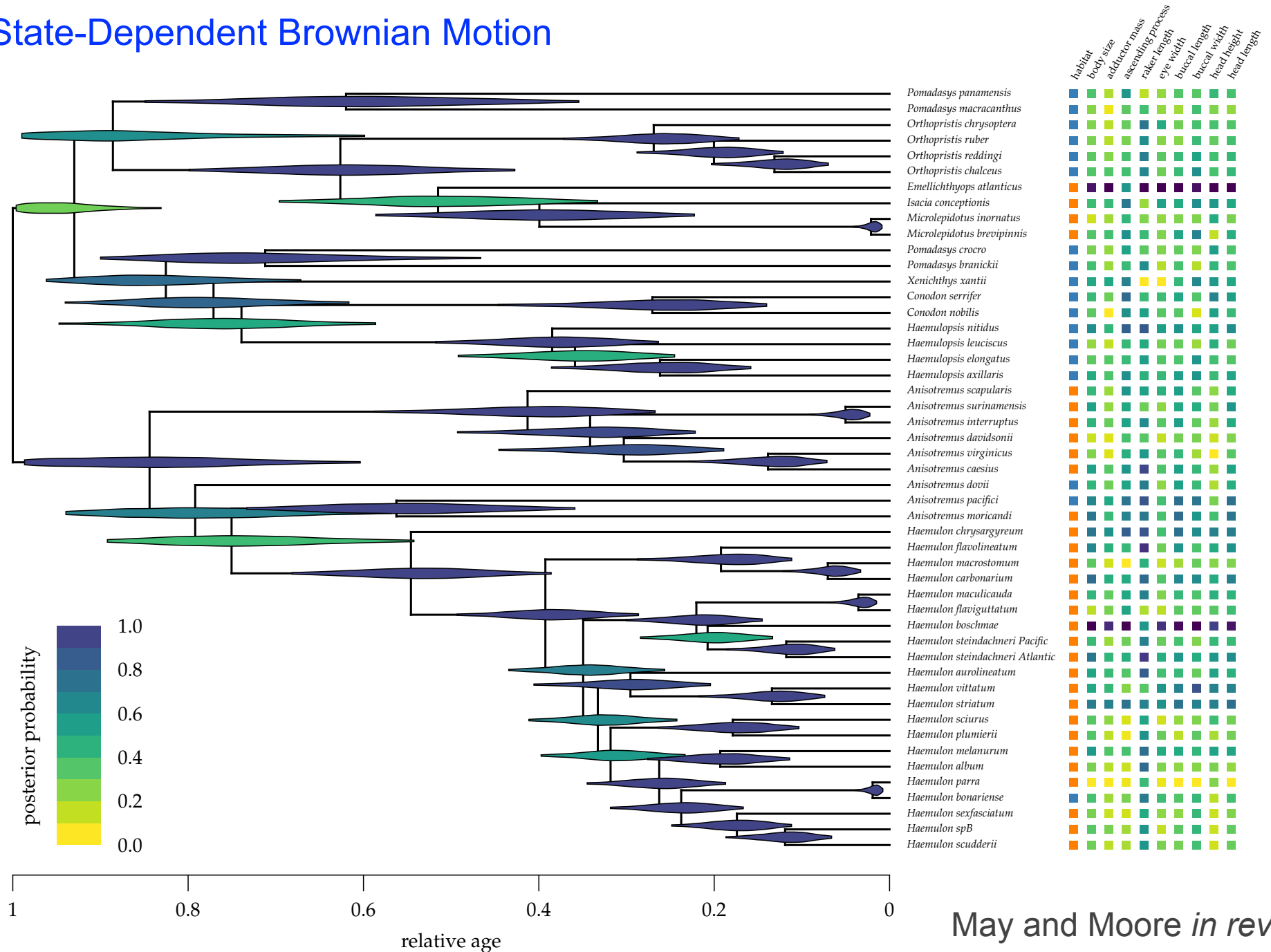
# Exotic Diffusion Models

## State-Dependent Brownian Motion

Sometimes we expect (or hypothesize) that rates of continuous-character evolution depend on the state of a discrete character.

# Exotic Diffusion Models

## State-Dependent Brownian Motion



# Exotic Diffusion Models

## State-Dependent Brownian Motion

$$X \in \{0, 1\}$$

Binary discrete character

$$q_{01}, q_{10}$$

Rates of change between discrete characters

$$Y \in \mathbb{R}$$

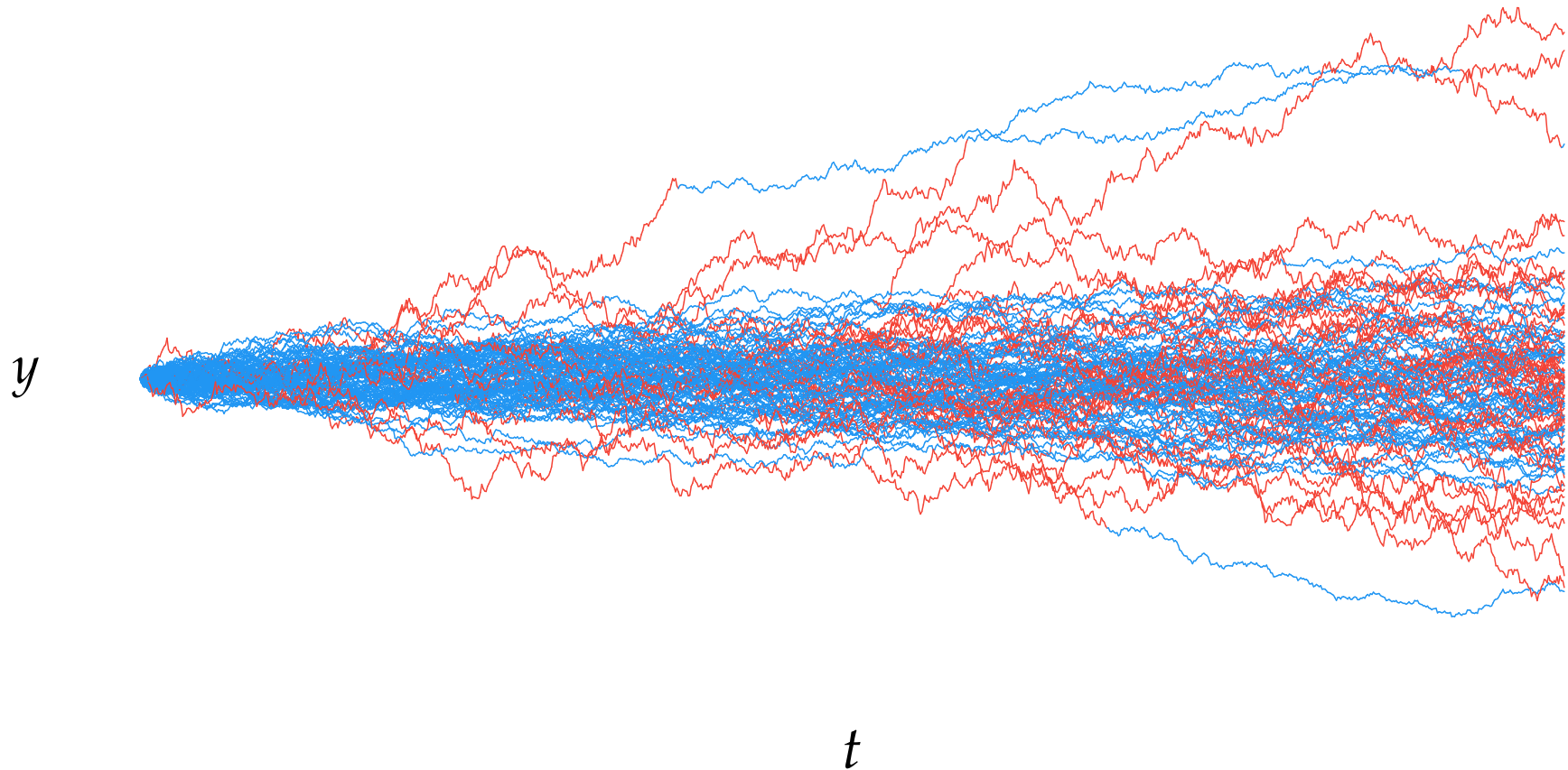
Continuous character

$$\sigma_0^2, \sigma_1^2$$

Rates of change for continuous character  
(depending on the state of the discrete  
character) under Brownian motion

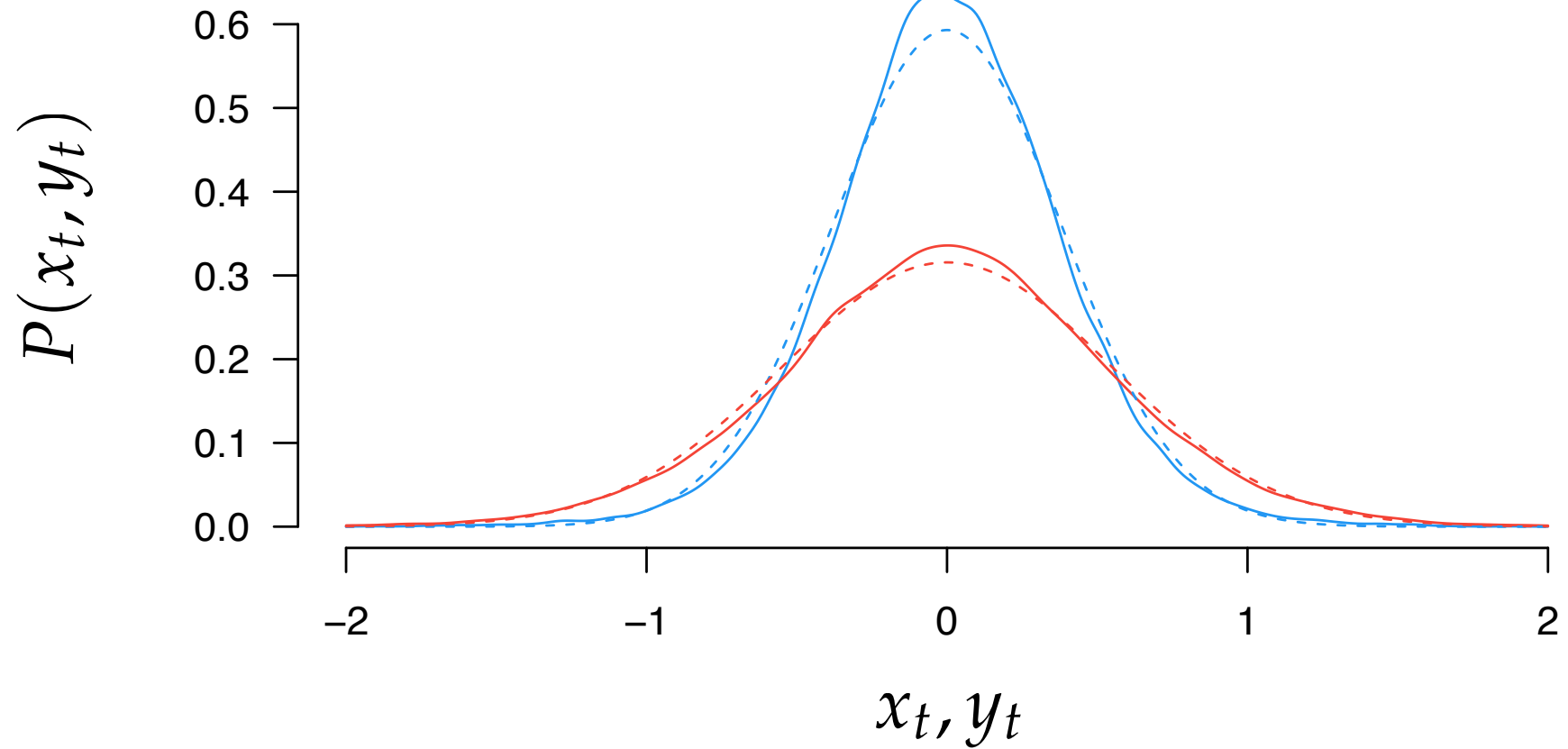
# Exotic Diffusion Models

## State-Dependent Brownian Motion



# Exotic Diffusion Models

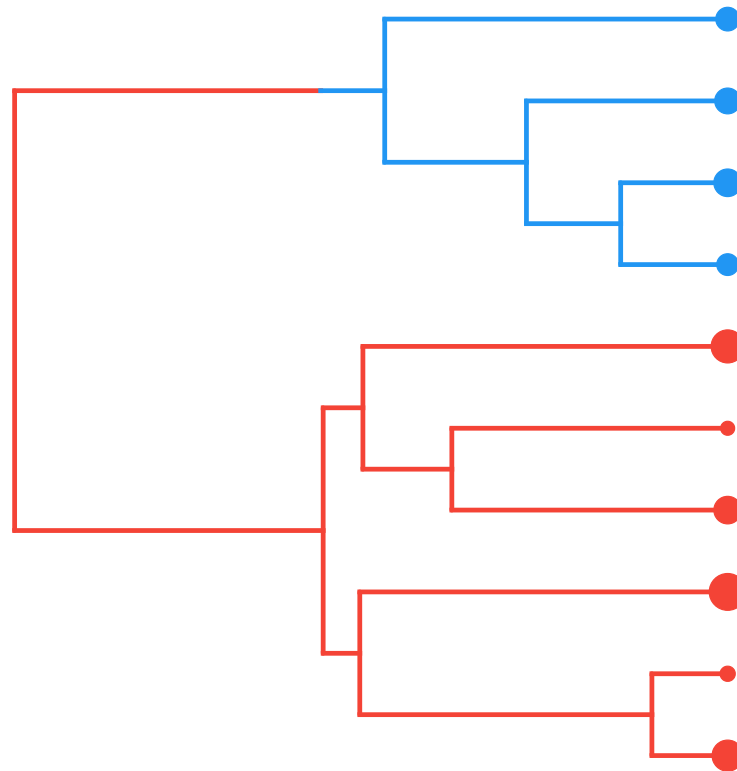
## State-Dependent Brownian Motion



# Exotic Diffusion Models

## State-Dependent Brownian Motion

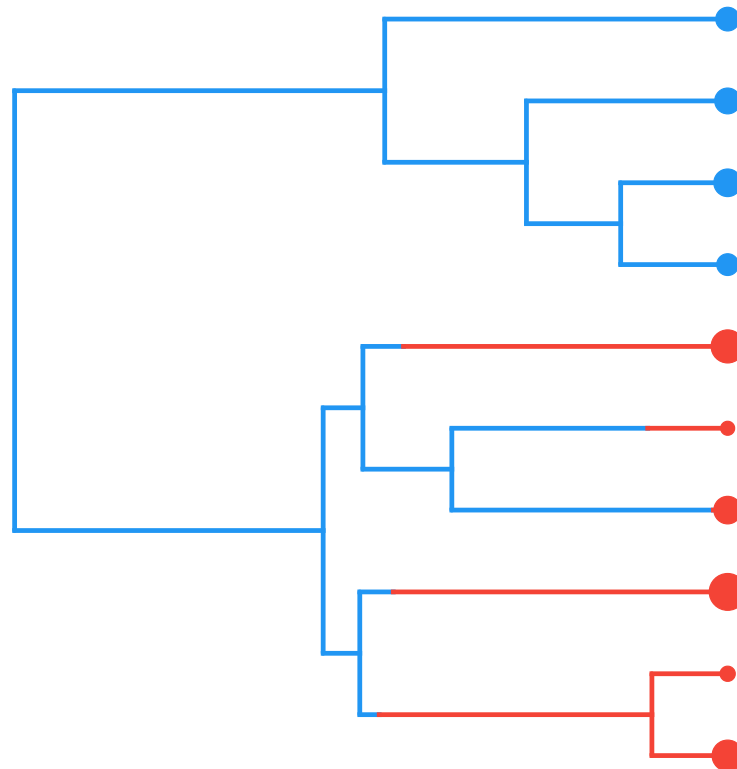
We can calculate the likelihood conditional on the complete history of the discrete character.



# Exotic Diffusion Models

## State-Dependent Brownian Motion

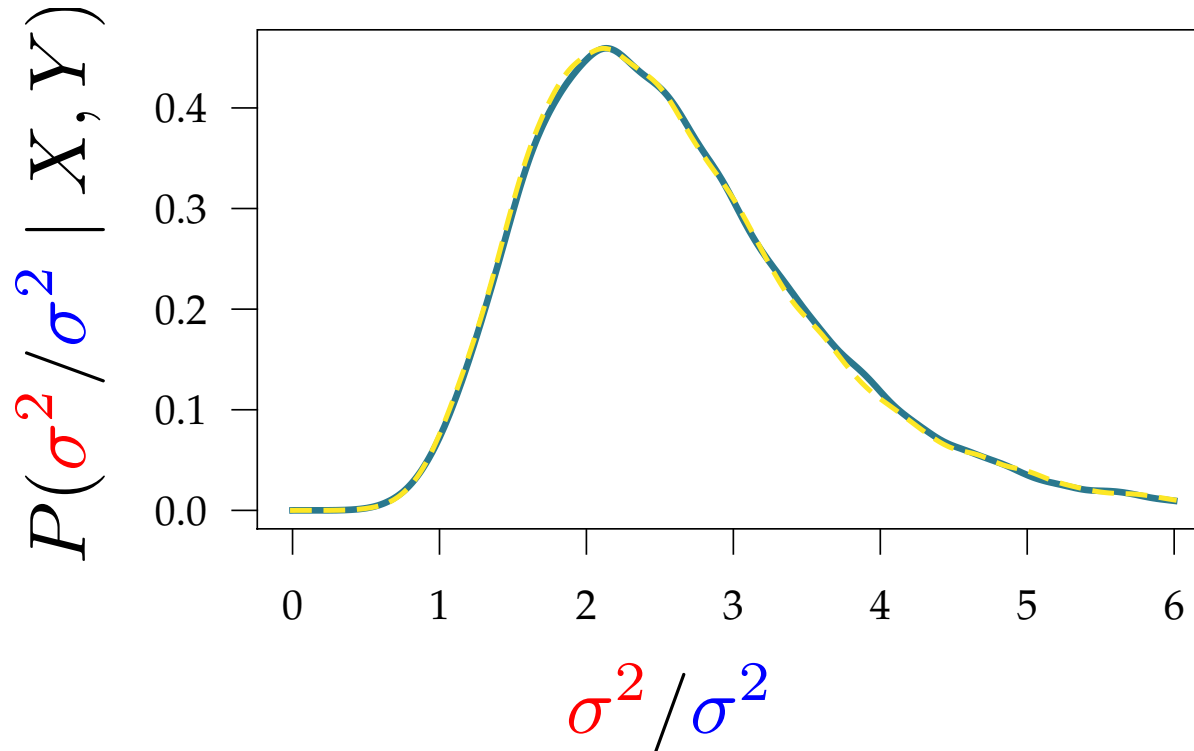
We integrate over all possible histories of the discrete character using a Bayesian technique called data augmentation.



# Exotic Diffusion Models

## State-Dependent Brownian Motion

We estimate the posterior distribution of the state-specific rate parameters.





# Outline

## I. Calculating likelihoods for continuous traits

A generic framework for calculating probabilities

## II. A simple model of continuous-character evolution

Brownian motion model

Multivariate Brownian motion model

## III. Exotic models of continuous-character evolution

Ornstein-Uhlenbeck model

Lévy models

State-dependent models