

# Phylogenetics

## Introduction to Bayesian inference

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Discuss the Paul Lewis lecture series

Exercise: tree building using Bayesian inference in RevBayes

## Public holidays

Thursday 26.05 and Thursday 16.06 are public holidays.

Can we reschedule next week's class for Friday 27.05  
16:00?

Can we reschedule the class on 16.06 to Tuesday 14.05  
16:00?

# Part 1 - Trees and likelihood

Note that the answers provided are just *my* interpretation of these concepts and your (correct) answers may vary!

## Trees and likelihood

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→ conditional probability - the probability of an event, depending on the value of some other event.

→ likelihood - the probability of observing something, given a set of parameter values and assumptions.

*2. Why do we calculate likelihoods on a log scale?*



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→ because likelihoods can get incredibly small - see for yourself using R!

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use the [Transition probability tool](#) to explore this further

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→ the probability of change increases with time.

## Felsenstein's pruning algorithm

4a. *What do we need this for?*

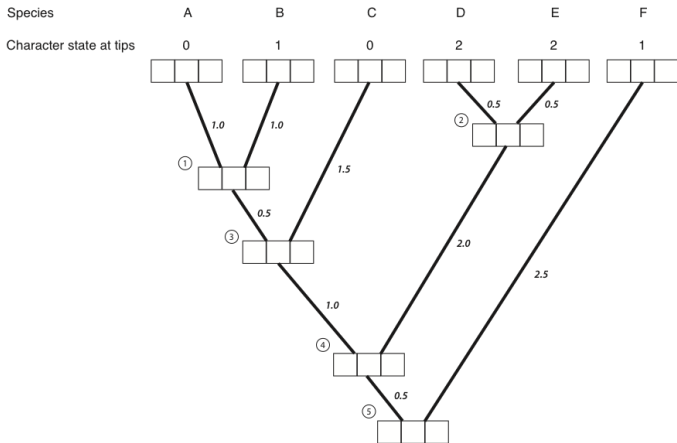
## Felsenstein's pruning algorithm

### *4a. What do we need this for?*

→ to calculate the likelihood of a tree (given an alignment and a substitution model, taking into account all possible ancestral states at every node).

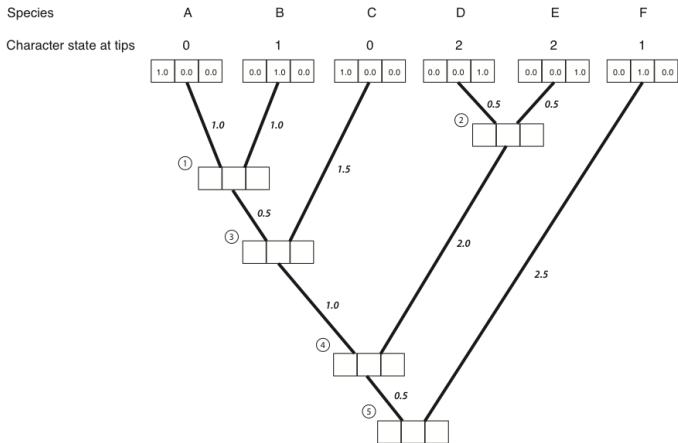
# Trees and likelihood

4b. Can you describe the gist of Felsenstein's pruning algorithm?



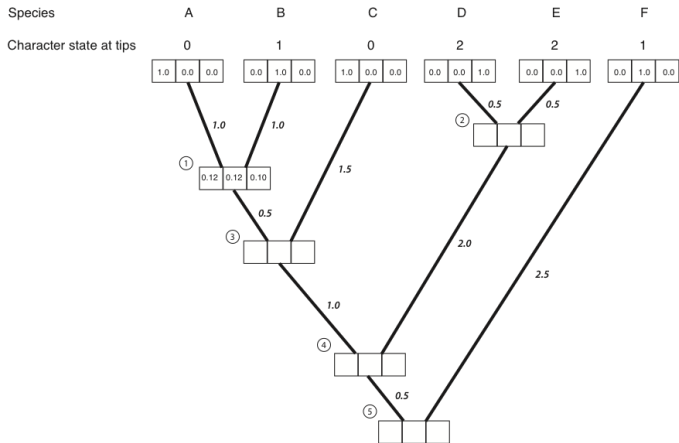
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# Trees and likelihood

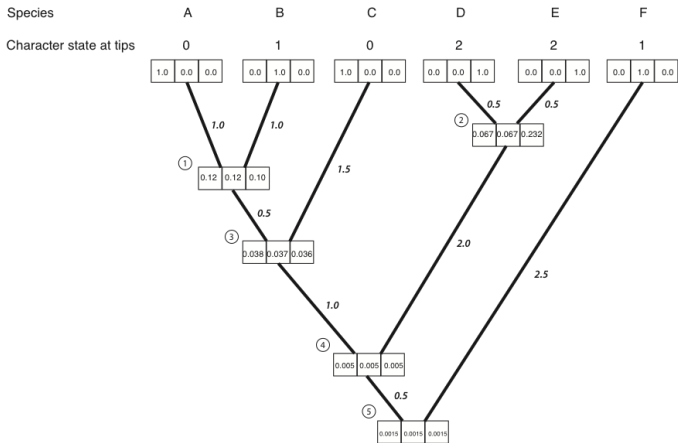
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# Trees and likelihood

4b. Can you describe the gist of Felsenstein's pruning algorithm?



**Part 2 - trees, likelihood and  
rate heterogeneity  
(substitution models)**

## Substitution models

1. *What are the assumptions of the following substitution models? Consider the rate of change between character states and the state frequencies.*

JC →

HKY →

GTR →

## Substitution models

1. *What are the assumptions of the following substitution models?* Consider the rate of change between character states and the state frequencies.

JC → equal frequencies, equal rates

HKY → unequal frequencies, unequal rates between transversions and transitions

GTR → unequal frequencies, unequal rates

## Substitution models

*Can you briefly describe the following three approaches that account for rate variation among characters?*

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### *2b. Invariant sites model*

## Substitution models

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### *2a. Site specific rates*

→ assign sites to separate partitions and allow each partition to have its own set of parameters.

### *2b. Invariant sites model*

→ assign a subset of sites to a “constant” (i.e. non-variable) category.



## *2c. Discrete Gamma model*

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→ calculate the likelihood assuming there are discrete (e.g. 4) rate categories. Variation in rate categories is represented by a gamma distribution and the distribution parameters are calculated from the data.

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→ the Q matrix is the instantaneous rate matrix, i.e. the instantaneous rates of change between 2 character states.

→ the P matrix is the transition probability matrix, i.e. the probabilities of change between 2 character states after relative time  $t$ , which is represented by the branch lengths.

# Part 3a - Introduction to Bayesian statistics

# Introduction to Bayesian statistics

*1. In your own words can you describe each component of Bayes' rule? Which parts are difficult to understand?*

# Bayes' theorem

$P(\text{parameters} \mid \text{data}, \text{model}) =$

$$\frac{P(\text{data} \mid \text{parameters}, \text{model}) P(\text{parameters} \mid \text{model})}{P(\text{data} \mid \text{model})}$$



# Bayes' theorem

$$P(\text{parameters} \mid \text{data}, \text{model}) =$$

posterior

likelihood

priors

$$\frac{P(\text{data} \mid \text{parameters}, \text{model}) P(\text{parameters} \mid \text{model})}{P(\text{data} \mid \text{model})}$$

marginal probability of the data

# Bayes' theorem

$P(\text{data} \mid \text{parameters, model})$  ← the model used to calculate the **likelihood**.

$P(\text{parameters} \mid \text{model})$  ← this represents our **prior knowledge** of the model parameters.

$P(\text{parameters} \mid \text{data, model})$  ← the **posterior** reflects our combined knowledge based on the likelihood and the priors.

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$P(\text{parameters} \mid \text{data}, \text{model})$  ← the **posterior** reflects our combined knowledge based on the likelihood and the priors.

$P(\text{data} \mid \text{model})$  ← the probability of the data integrated over all possible parameter values. Can be thought of as a normalising constant (i.e., ensuring the posterior sums to one).

# Posterior $\propto$ Likelihood $\times$ Priors

The posterior probability is proportional to the numerator, i.e. the likelihood times the prior.

# Introduction to Bayesian statistics

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→ continuous variables can take on any real number value within a range (e.g. length, body mass).

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→ continuous variables can take on any real number value within a range (e.g. length, body mass).

## And between probabilities and probability densities?

→ a probability assumes a singular value (e.g.  $P = 0.5$ ).

→ a probability density – a range of values represented by a distribution.



*3. What is the difference between vague vs. informative priors?*

### *3. What is the difference between vague vs. informative priors?*

→ a vague prior is used for parameters where we have little clue what the true value is, e.g. it could be anything between 0 and infinity.

→ an informative prior is used for parameters where we have some good existing knowledge about what the parameter value could be, e.g. maybe we already know the rate of evolution among a well studied group, so we could use a prior distribution with a mean equal to the known value and add a small variance.

*4. What is the aim of MCMC in Bayesian inference?*

## 4. *What is the aim of MCMC in Bayesian inference?*

→ the aim to approximate the posterior distribution.

The posterior distribution is hard to calculate analytically (i.e. exactly), so we use MCMC to traverse the parameter space and at each step calculate the likelihood  $\times$  the prior, spending time in different regions of the parameter in proportion to the posterior probability - that is, we spend most time in areas with the highest posterior probability.

# Part 3b - Introduction to Bayesian statistics part 2

*1. How are steps chosen in an MCMC analysis?*

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→ these depend on the type of parameter and landscape of the parameters space.

*2. Give an example of a parameter you would estimate under each of the following prior distributions and try to state why?*

Gamma distribution

Lognormal distribution

Beta distribution

Dirichlet distribution



*3. Why do we sometimes need to calculate the marginal likelihood?*

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→ this is required for model testing within a Bayesian framework.

4. *What is the difference between a hierarchical model and a non-hierarchical model?*

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→ in a hierarchical model different components of the model are nested, e.g. different models can be joined together to model different processes that apply to the data.

# Exercise 4