# Model Fitting and Ancestral Character State Reconstruction

**Aim**: Test if a simulated character evolves under symmetric or asymmetric Markov model of character evolution using AIC. Reconstruct its ancestral states.

```
library(ape)
```

#### Calculating Likelihood on tree

See lecture 6 for Felsentein's pruning algorithm.

The general steps of the algorithm are as follows:

- 1. Initialize Q matrix and  $\pi$  (initial vector)
- 2. Recode data at tips as probabilities
- 3. Calculate conditional likelihoods  $L_c$  at each node by traversing the tree from tips to roots. For two branches left and right  $(b_l \text{ and } b_r)$  and their corresponding tip probabilities  $(T_l, T_r, \text{ both column vectors})$ , the conditional likelihood is  $L_c = e^{Qb_l}T_l * e^{Qb_r}T_r$ . Since R does not have inbuilt functionality for column vectors,  $T_l, T_r$  can be treated as row vectors through the following conversion  $L_c = T_l(e^{Qb_l})^{\mathbf{T}} * T_r(e^{Qb_r})^{\mathbf{T}}$ , where  $^{\mathbf{T}}$  is a matrix transpose
- 4. Upon reaching root, the tree likelihood is  $L = sum(L_c\pi)$

```
# install packages exmp if you do not have it library (expm)
```

#### 1. Initializing Q and pi

[,1] [,2]

##

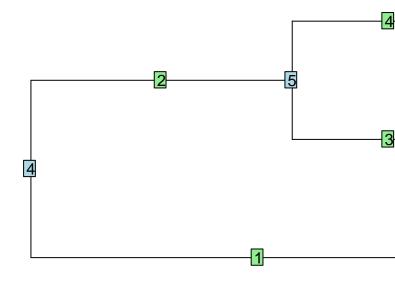
```
## Loading required package: Matrix
##
## Attaching package: 'expm'
## The following object is masked from 'package:Matrix':
##
##
## The following object is masked from 'package:ape':
##
##
       balance
Q <- matrix(
  c(
    -0.1, 0.1,
    0.1, -0.1
    ), 2,2, byrow = T)
pi=c(0.5, 0.5)
```

```
## [1,] -0.1 0.1
## [2,] 0.1 -0.1
рi
## [1] 0.5 0.5
# read in tree
tr <- read.tree(file='3_taxon.tree')</pre>
# Let's imagine that our taxa at tips (t1, t2, t3) have the following character states (we use a binary
data \leftarrow c(1,0,1)
names(data) <- c('t1', 't2', 't3')
data
2. Recoding data at tips as probabilities
## t1 t2 t3
## 1 0 1
We rate their tip probability vectors as matrix
data.probs <- matrix(c(</pre>
  0,1,
  1,0,
```

```
1,0,
0,1
   ), 3,2,byrow=T
)
rownames(data.probs) <- c('t1', 't2', 't3')
data.probs
## [,1] [,2]</pre>
```

```
## t1 0 1
## t2 1 0
## t3 0 1
```

```
# Let's plot a tree to see its structure that is encoded on the objects tr$edge and tr$edge.length
plot(tr)
nodelabels()
edgelabels()
tiplabels()
```



### 3. Calculating conditional likelihoods

Lr

```
First we calculate Lc for node 5 with tips t3 and t2
# get ids of two branches node5 -> t3 and node5 -> t2 in tr$edge object (they are 3 and 2)
t3t2.ids=which(tr$edge[,1]==5)
# get branch lengths for those branches
br_l_r=tr$edge.length[t3t2.ids]
# calculate conditional likelihood using matrix exponential expm(), and matrix multiplication %*%
 L5 = \text{data.probs[3,] } \%\% \text{ } t(\exp(Q*br_l_r[1])) * (\text{data.probs[2,]}\%\%t(\exp(Q*br_l_r[2]))) 
L5
##
               [,1]
                           [,2]
## [1,] 0.03916016 0.03916016
Now we calculate root likelihood (node4)
# get ids of two branches node4 -> t1 and node4 -> node5
n5t1.ids=which(tr$edge[,1]==4)
# get branch lengths for those branches
br_l_r=tr$edge.length[n5t1.ids]
br_l_r
## [1] 1.0000000 0.5740947
# calculate conditional likelihood at root using matrix exponential expm(), and matrix multiplication %
```

 $Lr = (\text{data.probs}[1,] \% * \% t (\text{expm}(Q * \text{br}_l_r[1]))) * (L5 \% * \% t (\text{expm}(Q * \text{br}_l_r[2])))$ 

```
## [,1] [,2]
## [1,] 0.003549267 0.0356109
```

```
L=sum(Lr*pi)
# likelihood and Log likelihood of the tree
L
```

## 4. Calculating tree likelihood

## [1] 0.01958008

log(L)

## [1] -3.933242