

Introduction to graphical models using RevBayes

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FAU

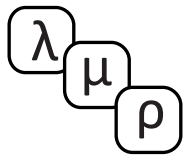
05.09. 2022



Friedrich-Alexander-Universität
Erlangen-Nürnberg

Phylogenetic inference — the old way

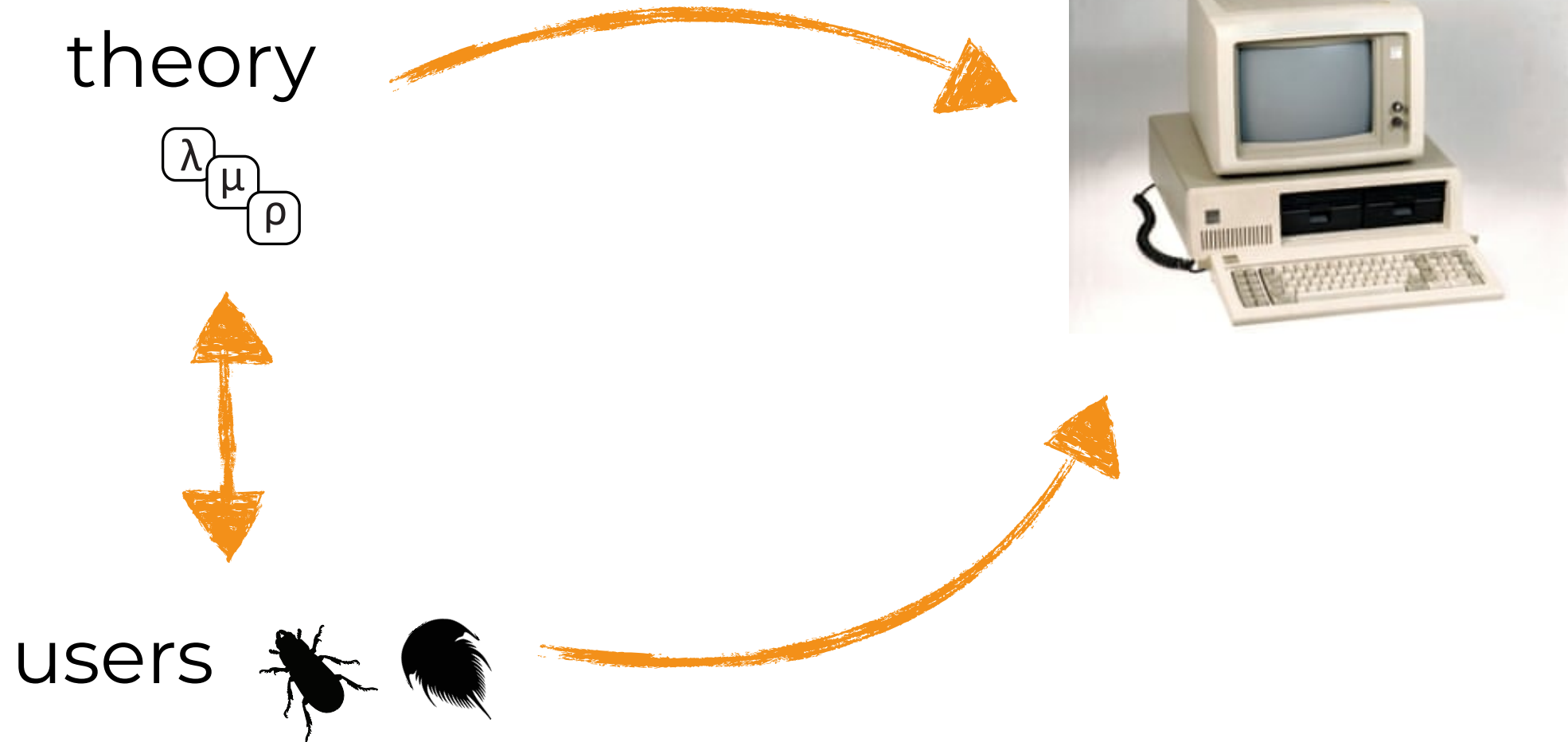
theory



users



Phylogenetic inference — a better way?



Aims for RevBayes

Flexible model specification

- Availability of (common) models
- Extendability

Easy to learn

- Well structured model specification
- Explicit models
- Documentation, examples and tutorials

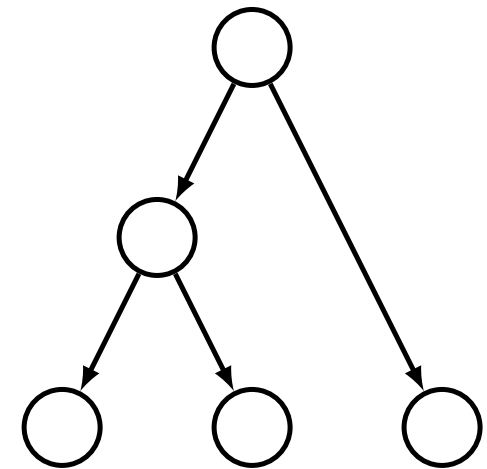
Computational efficiency

- Fast likelihood calculators
- Efficient (MCMC) algorithms

RevBayes uses a graphical model framework

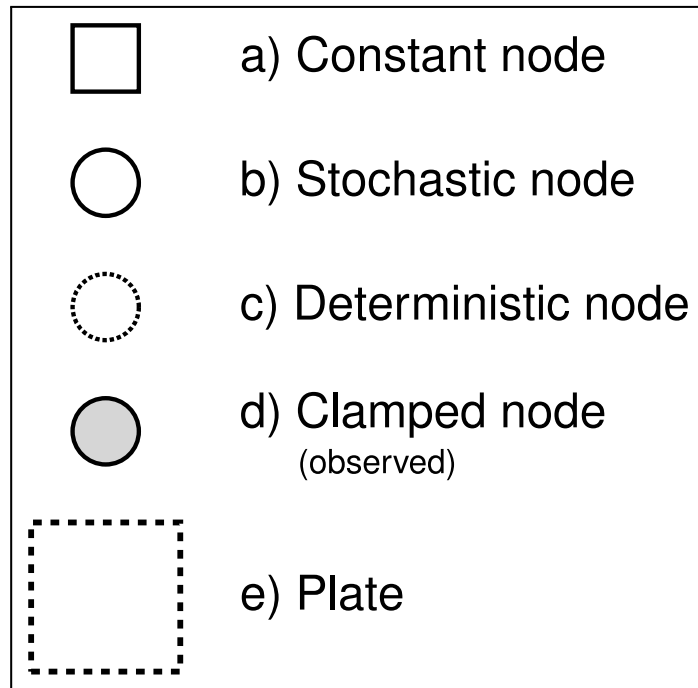
Graphical models provide tools for visually and computationally representing complex, parameter-rich probabilistic models.

We can depict the conditional dependence structure of various parameters and other random variables.



Höhna et al. 2014. Sys Bio

Graphical models — types of variables (nodes)



a) fixed-value variables

b) random variables that depend on other variables

c) variables determined by a specific function applied to another variable (transformations)

d) observed stochastic variables (data)

e) replication over a set of variables

Specifying graphical models using the Rev syntax

Table 1: Rev assignment operators, clamp function, and plate/loop syntax.

Operator	Variable
<code><-</code>	constant variable
<code>~</code>	stochastic variable
<code>:=</code>	deterministic variable
<code>node.clamp(data)</code>	clamped variable
<code>=</code>	inference (<i>i.e.</i> , non-model) variable
<code>for(i in 1:N){...}</code>	plate

a)

r

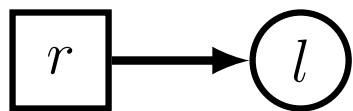
```
# constant node  
r <- 10
```


a)



```
# constant node  
r <- 10
```

b)



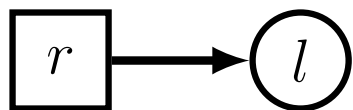
```
# stochastic node  
l ~ dnExp(r)
```

a)



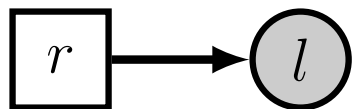
```
# constant node  
r <- 10
```

b)



```
# stochastic node  
l ~ dnExp(r)
```

c)



```
# stochastic node (observed)  
l.clamp(0.1)
```



```
# constant node  
r <- 10
```



```
# stochastic node  
l ~ dnExp(r)
```



```
# stochastic node (observed)  
l.clamp(0.1)
```



```
# deterministic node  
l := exp(r)
```



```
# constant node
r <- 10
```



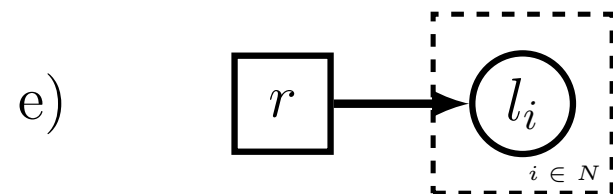
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```



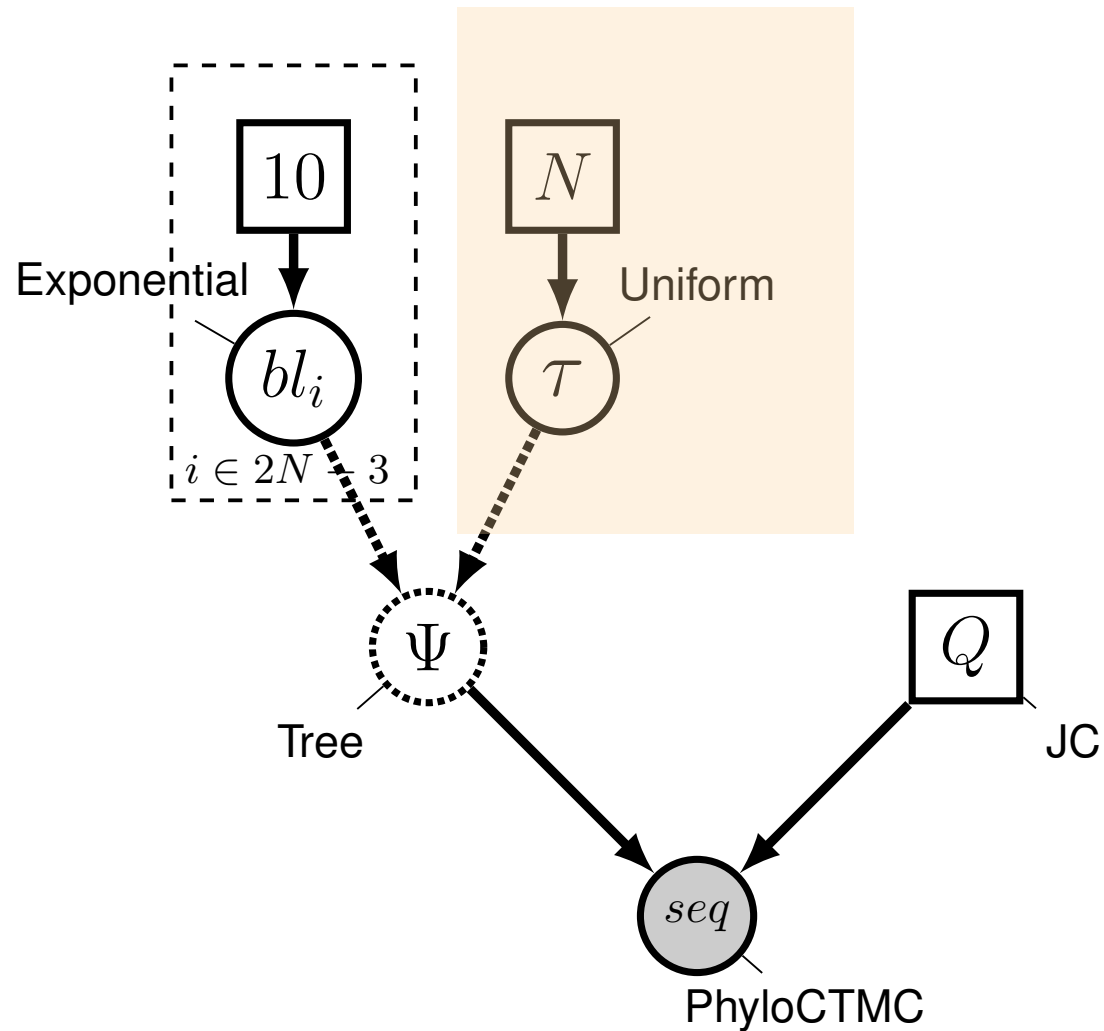
```
# stochastic node (observed)
l.clamp(0.1)
```



```
# deterministic node
l := exp(r)
```



```
# stochastic nodes (iid)
for (i in 1:N) {
  l[i] ~ dnExp(r)
}
```



```
# prior on the tree topology
topology ~ dnUniformTopology(taxa)
```

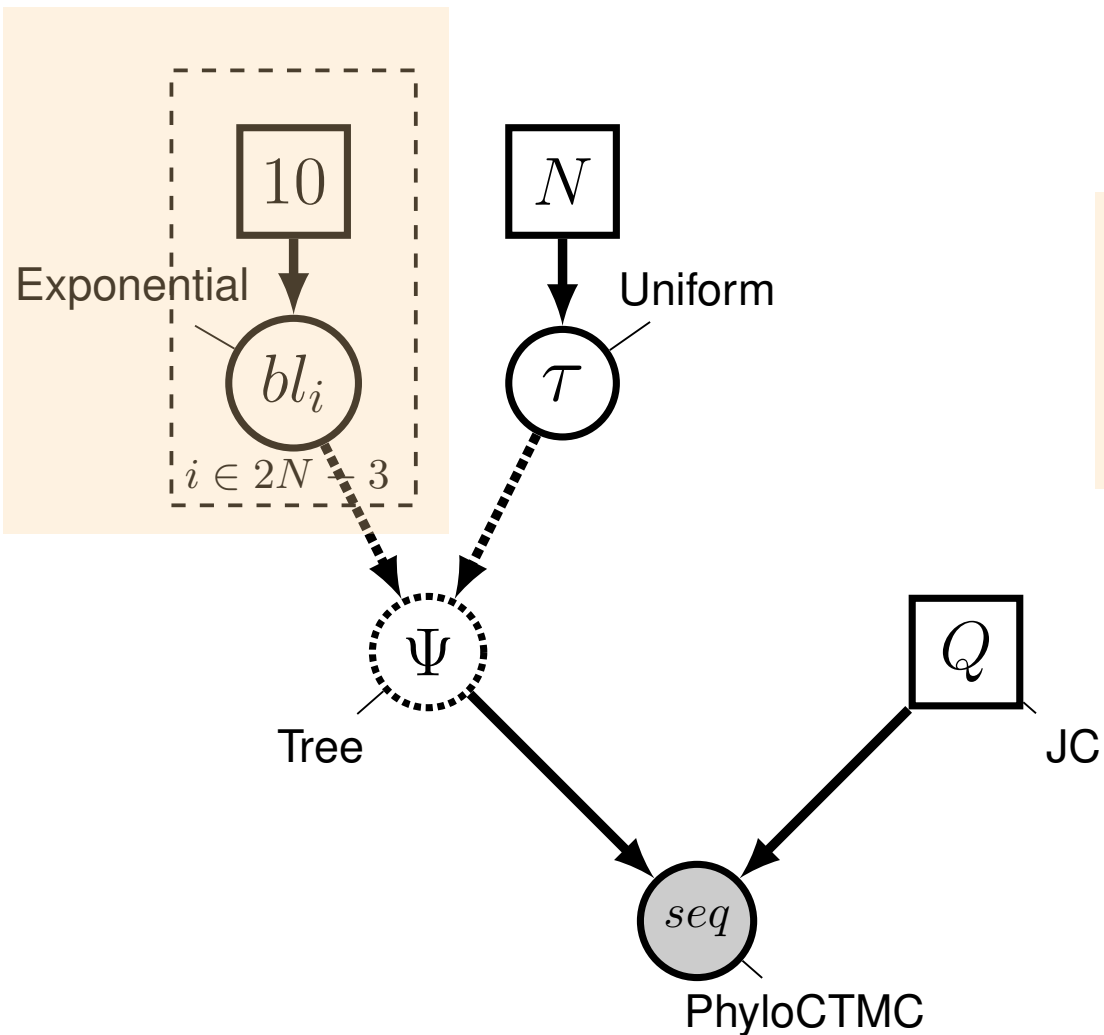
```
# prior on the branch lengths
for (i in 1:num_branches) {
  br_lens[i] ~ dnExponential(10)
  moves.append( mvScale(br_lens[i]) )
}
```

```
tree := treeAssembly(topology, br_lens)
```

```
TL := sum(br_lens)
```

```
# 4 state rate maxtrix (JC model)
Q <- fnJC(4)
```

```
# attach the model to your sequence data
seq ~ dnPhyloCTMC(tree = tree, Q = Q, type = "DNA")
seq.clamp(data)
```



```
# prior on the tree topology
topology ~ dnUniformTopology(taxa)
```

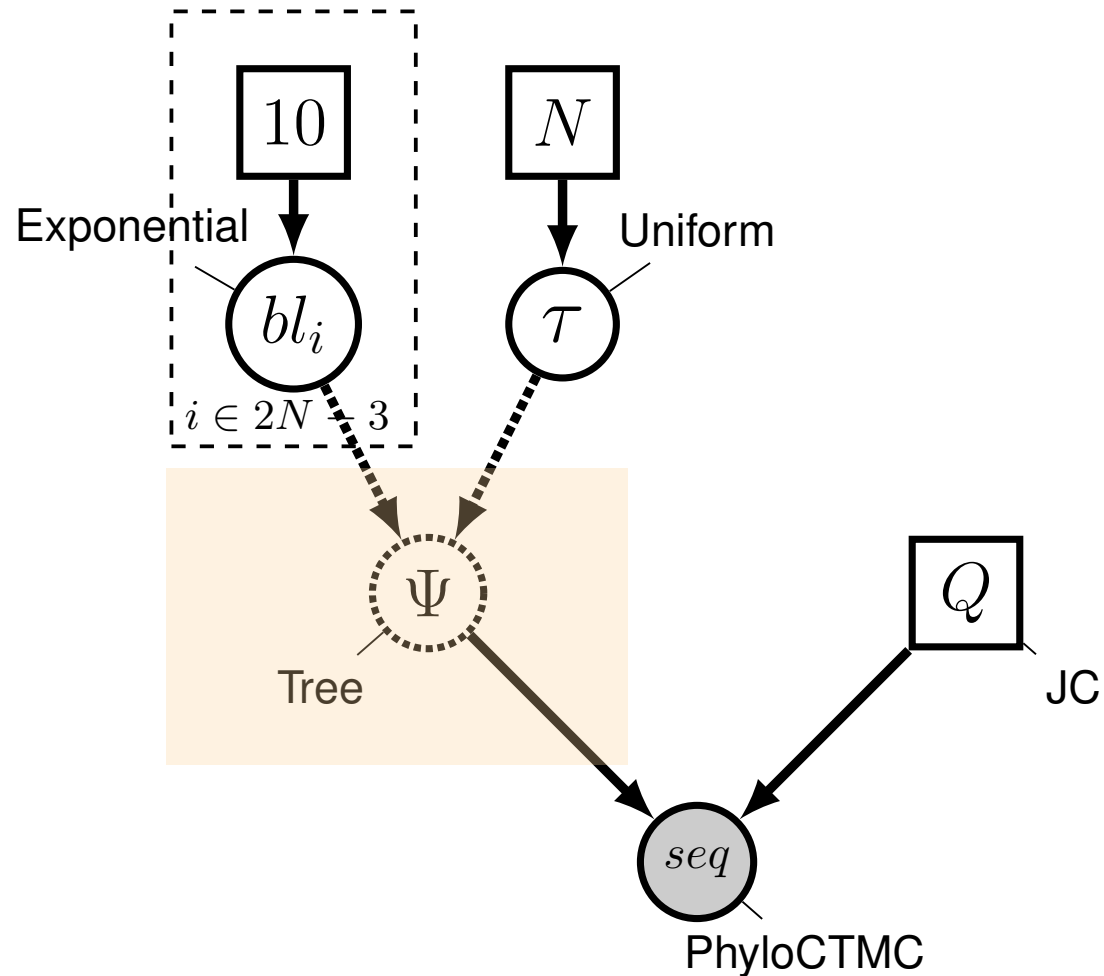
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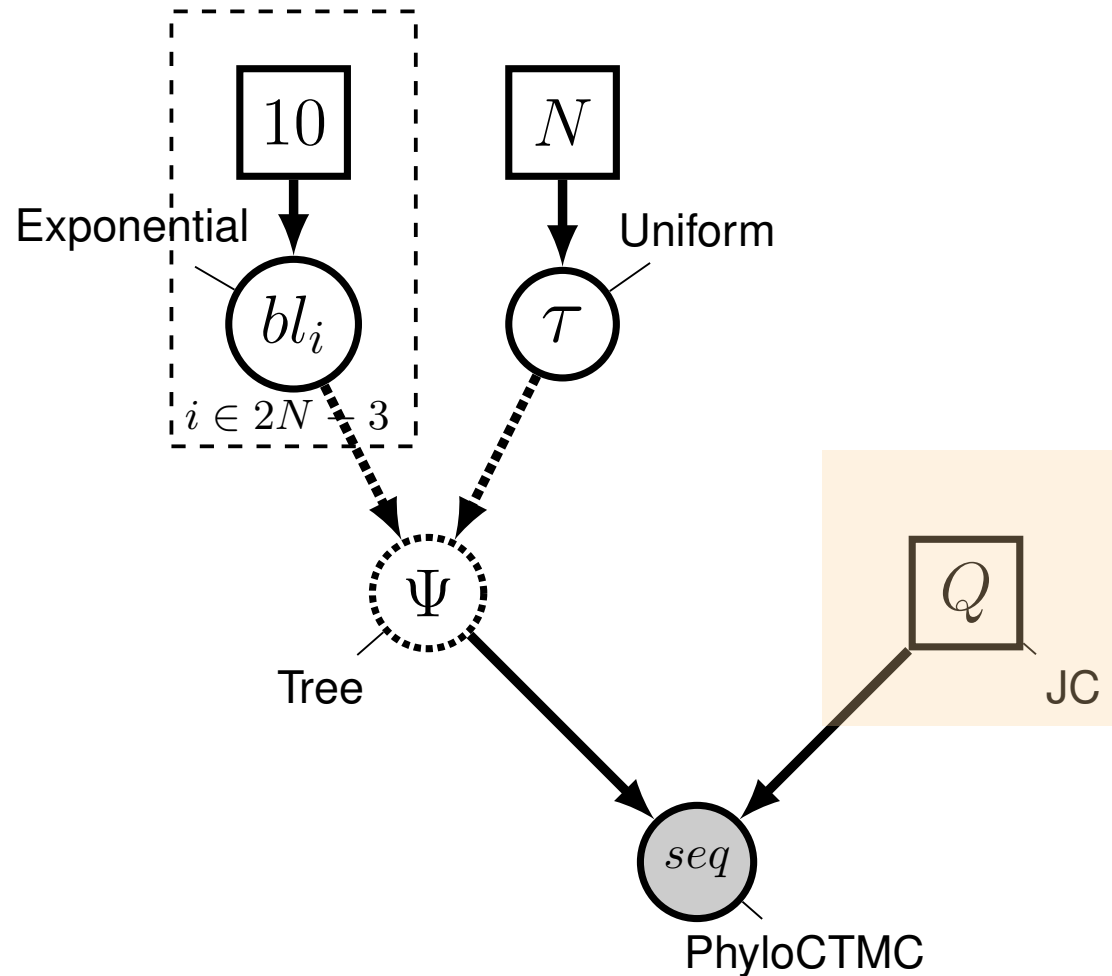
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```

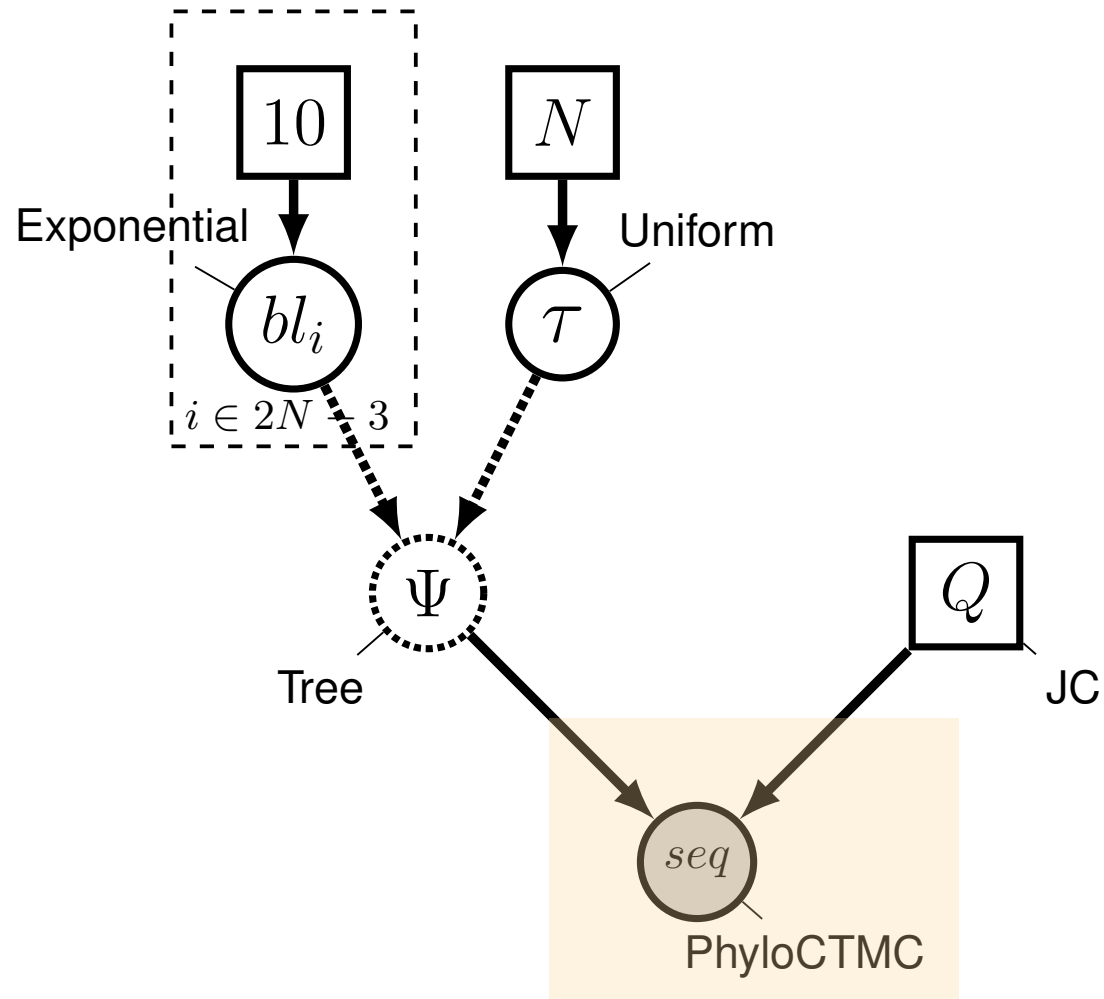
```
# prior on the branch lengths
for (i in 1:num_branches) {
  br_lens[i] ~ dnExponential(10)
  moves.append( mvScale(br_lens[i]) )
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# prior on the branch lengths
for (i in 1:num_branches) {
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*The Weeping Woman by
Picasso*

Bayesian inference is like a cubist painting, the more you stare at it the more it begins to make sense.

—Something Kat spotted in a textbook