

Final Assignment

Anna E. Hiller

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Divergence Time Estimation using *Diglossa* (Aves: Thraupidae) Informative Prior on the Root Age and Universal Molecular Clock

I chose to run a divergence time analysis to date a tree because I want to apply phylogenetic methods to phylogeographic analyses. One of the key components of phylogeography is understanding *when* speciation events occur (e.g., splits between taxa). Because there are often no fossils of recent taxa in birds, especially Passerines, molecular clock estimates are used instead. I choose a group I am interested in working on (the *Diglossa* tanagers). In the future I want to use this same approach to estimate phylogeographic divergence times and then compare to estimates of divergence times obtained via estimation of population genetic parameters.

Overview of Dating

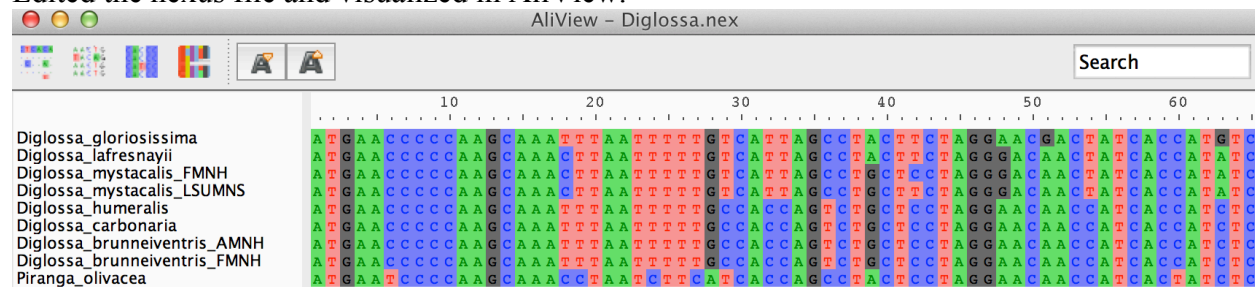
Given a phylogenetic tree with branch lengths (rate*time) and a calibration to constrain the node (either a fossil calibration, or a node from a previous phylogeny, can also use tips), you can estimate divergence times for other nodes (e.g., you can date speciation events).

Obtained Data

Downloaded ND2 mitochondrial gene sequences for 8 tips representing 6 species.

The screenshot shows the NCBI GenBank entry for the ND2 gene of *Diglossa brunneiventris* voucher FMNH 430118. The sequence is displayed in FASTA format, and the entry includes details about the gene, its location, and related information like PopSet and Protein.

Edited the nexus file and visualized in AliView.



Overview of Key Code

Types of functions in RevBayes

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.e., non-model) variable
<code>for(i in 1:N){...}</code>	plate

I used a GTP+G model of sequence evolution and the default settings for the model of constant-rate birth-death processes.

```
rho <- n_species/18
```

Rho represents $n_{\text{Taxa}} / \text{totalTaxa}$, the probability of sampling species at the present. For this dataset I changed the value to be 6 / 18, since there are 18 described *Diglossa* species. I am curious how altering this value effects the results though, because *Diglossa* is a highly polymorphic group with many subspecies that could potentially be elevated to species rank.

```
root_time ~ dnNormal(mean=10.1, sd=6.3, min=0.0, max=1000.0)
```

Root time is the informative prior used to condition the root age and inform our dating. I used the estimated date for the split between the *Diglossa lafresnayii* and *Diglossa carbonaria* species complexes as the prior, taken from:

Mauck III, W. M., & Burns, K. J. 2009. Phylogeny, biogeography, and recurrent evolution of divergent bill types in the nectar-stealing flowerpiercers (Thraupini: *Diglossa* and *Diglossopsis*). *Biological Journal of the Linnean Society*. 98:14-28.

I then back-calculated (see code) the standard deviation based on the number of tips and 95% confidence interval given in the paper.

```
#add a deterministic variable for the age of
#Diglossa carbonaria superspecies~
clade_carbonaria = clade("Diglossa_carbonaria", "Diglossa_humeralis", "Diglossa_brunneiventris_AMNH", "Diglossa_
age_carbonaria := tmrca(psi, clade_carbonaria)~
~
#Diglossa lafresnayii superspecies~
clade_lafresnayii = clade("Diglossa_lafresnayii", "Diglossa_gloriosissima")~
age_lafresnayii := tmrca(psi, clade_lafresnayii)~
```

Also, I added in deterministic variables for certain ages I was interested in.

This analysis used a global molecular clock rate, which assumes a constant rate of substitution across the tree (vs. a relaxed molecular clock which allows for rate variation across lineages). Because the analysis was based on an informative prior, the clock rate is estimated from the data.

I then created a model of sequence evolution, and attach the sequence data to the tip nodes using the .clamp function (used for observed data).

Executed the Analysis

I set up monitors (mni), which record the states of the Markov Chain, created the MCMC object, and ran the analysis. Note that I used 2 replicate runs and two chains (1 cold, 1 heated) to make sure I got good estimates.

Burnin

```
> mymcmc = mcmcmc(mymodel, monitors, moves, nruns = 2, nchains = 2)
> mymcmc.burnin(generations=10000,tuningInterval=250)
```

```
Running burn-in phase of Monte Carlo sampler for 10000 iterations.
This simulation runs 2 independent replicates.
The MCMCMC simulator runs 1 cold chain and 1 heated chains.
The simulator uses 13 different moves in a random move schedule with 44 moves per iteration
```

Progress:

```
0-----25-----50-----75-----100
```

```
*****
```

MCMC

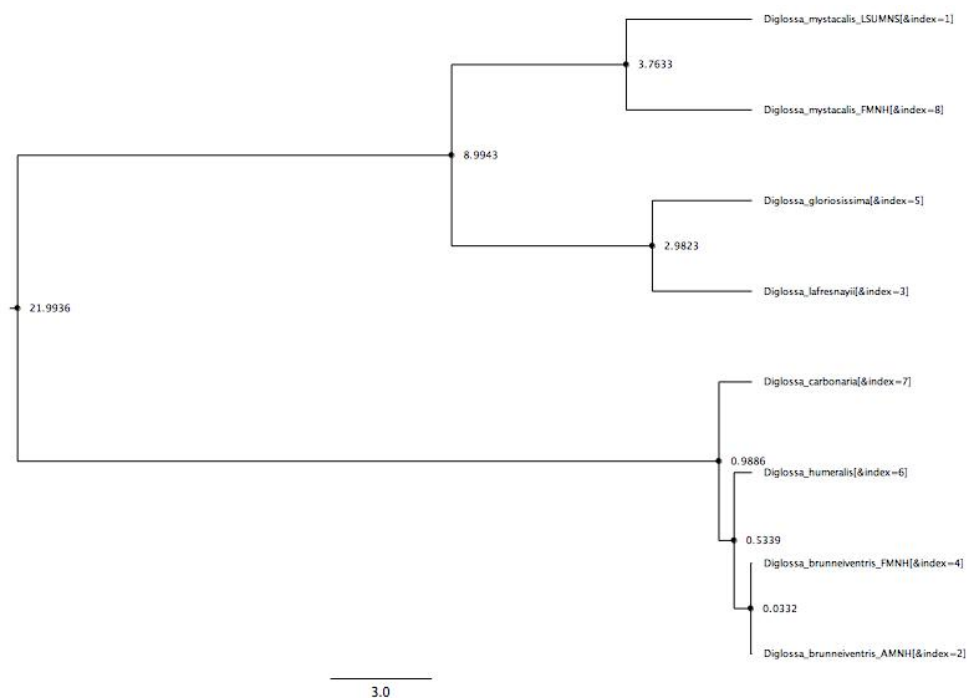
```
> mymcmc.run(generations=30000)
```

```
Running MCMC simulation
This simulation runs 2 independent replicates.
The MCMCMC simulator runs 1 cold chain and 1 heated chains.
The simulator uses 13 different moves in a random move schedule with 44 moves per iteration
```

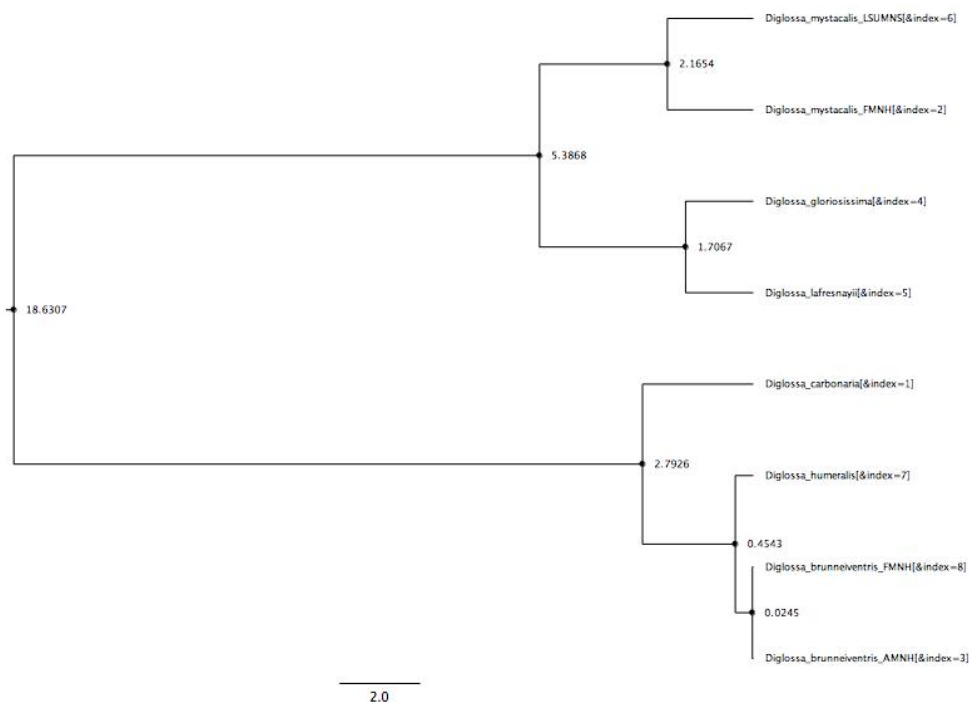
Iter	Posterior	Likelihood	Prior	age_lafres..	clockRate	root_time	elapsed	ETA
0	-2292.1	-2257.86	-34.2383	12.2561	0.000736485	96.1155	00:00:00	--:--:--
1000	-2285.32	-2253.87	-31.4507	10.9045	0.000900883	89.4981	00:00:07	--:--:--
2000	-2296.31	-2260.6	-35.7118	11.6477	0.000975027	79.3053	00:00:15	00:03:30
3000	-2289.56	-2255.15	-34.408	10.7652	0.000878235	90.3067	00:00:22	00:03:18
4000	-2285.22	-2253.31	-31.9082	9.07479	0.00090157	90.5803	00:00:29	00:03:08
5000	-2287.99	-2255.13	-32.862	10.7802	0.000944904	85.4912	00:00:36	00:03:00
6000	-2290.26	-2257.37	-32.8902	10.6718	0.000822529	93.5729	00:00:43	00:02:52
7000	-2285.57	-2252.56	-33.0111	12.7611	0.000766938	88.8018	00:00:50	00:02:44
8000	-2295.94	-2263.57	-32.3795	13.7241	0.000817348	91.5022	00:00:58	00:02:39
9000	-2292.31	-2255.95	-36.36	11.4262	0.000754574	103.607	00:01:05	00:02:31
10000	-2290.68	-2255.8	-34.8891	13.2636	0.000780142	89.6835	00:01:12	00:02:24
11000	-2289.99	-2257.93	-32.0568	7.35357	0.000865846	92.3037	00:01:20	00:02:18
12000	-2292.48	-2257.46	-35.0192	9.57762	0.000782738	101.631	00:01:27	00:02:10
13000	-2290.21	-2256.59	-33.6207	11.727	0.000993018	75.5213	00:01:34	00:02:02
14000	-2286.77	-2253.12	-33.646	12.4926	0.000890559	87.2029	00:01:41	00:01:55
15000	-2294.73	-2262.53	-32.193	9.55978	0.00100815	88.813	00:01:48	00:01:48
16000	-2286.26	-2253.63	-32.6342	11.0599	0.000895169	93.0417	00:01:56	00:01:41
17000	-2287.15	-2254.31	-32.8389	8.06368	0.000897044	87.8188	00:02:03	00:01:34
18000	-2288.29	-2254.52	-33.7705	17.7318	0.000738153	101.399	00:02:10	00:01:26
19000	-2287.69	-2255.46	-32.2374	8.67076	0.000917996	89.0355	00:02:17	00:01:19

Outputs

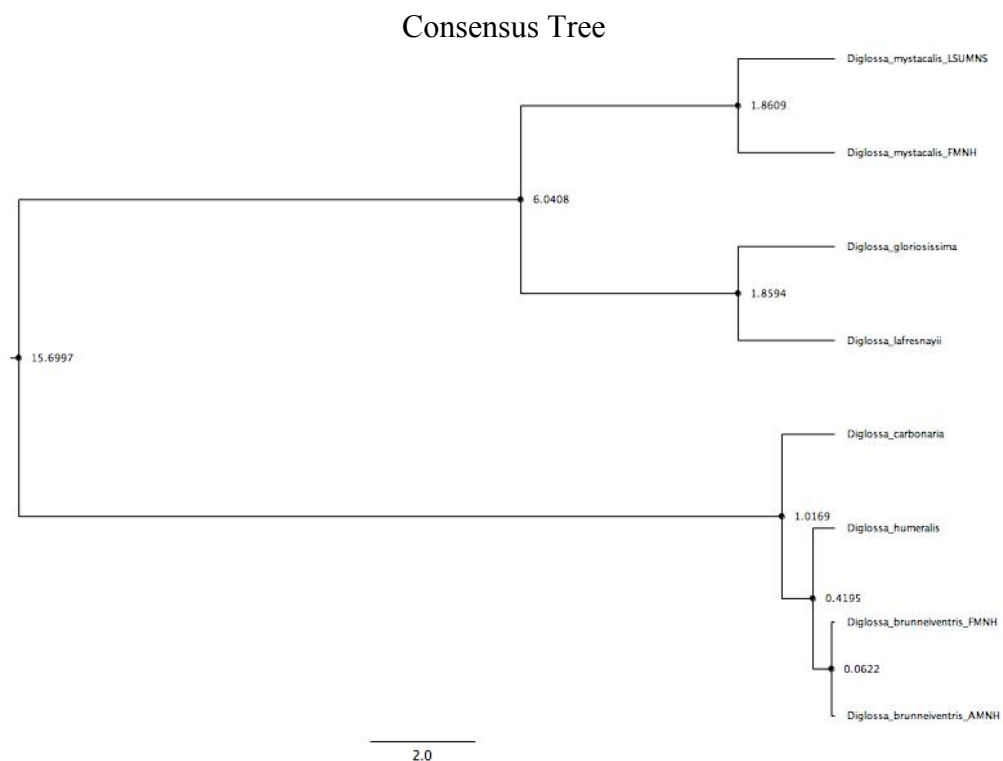
Tree from Run 1



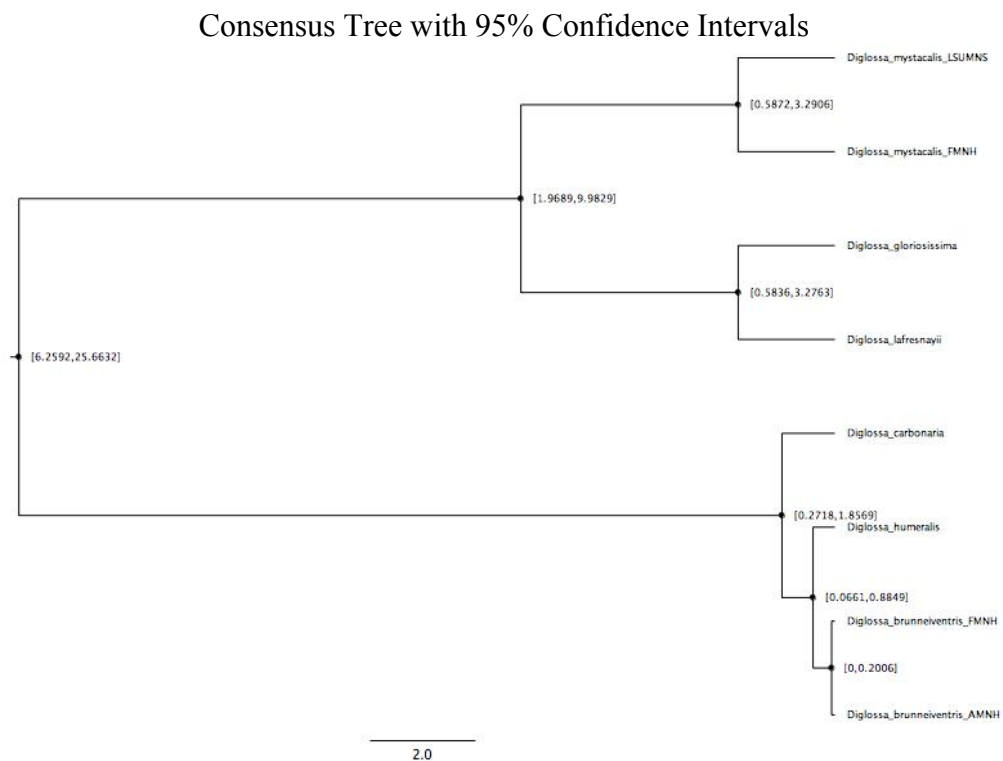
Tree from Run 2



* The topologies and dates look similar across runs. Both recover the short branches in the *D. carbonaria* complex (consistent with published literature).

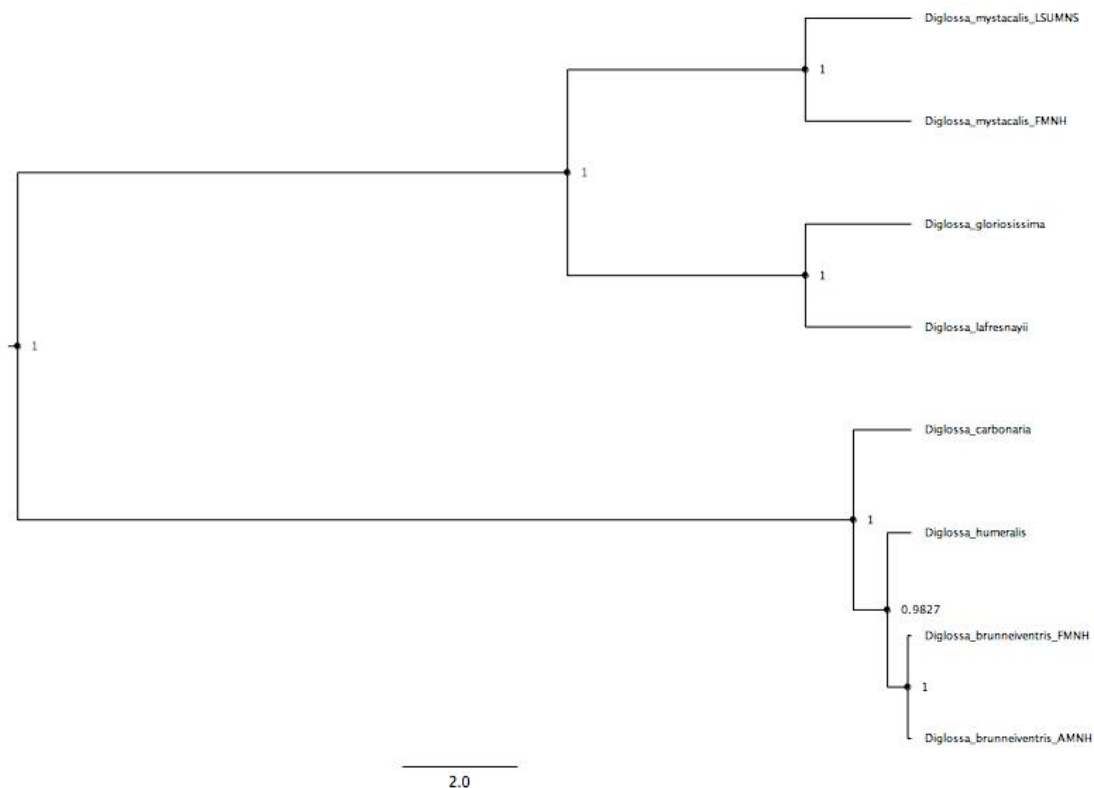


* This tree has a single consensus date on each node.



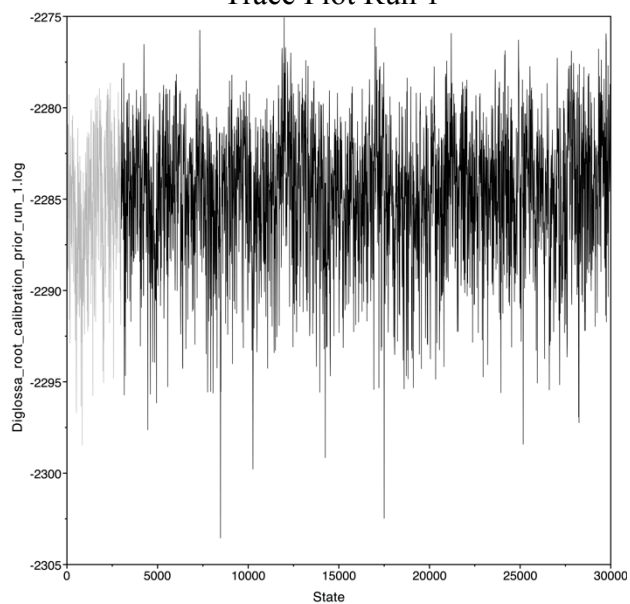
* This tree has the 95% confidence interval for the date on each node, taking uncertainty into account.

Consensus Tree with Posterior Probabilities

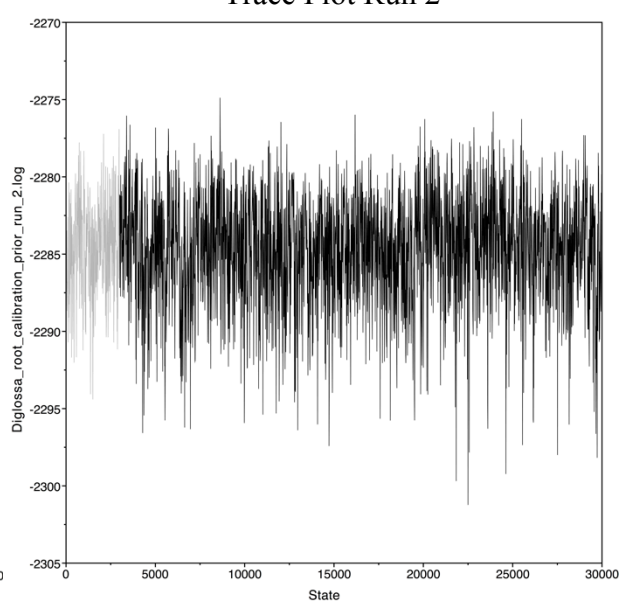


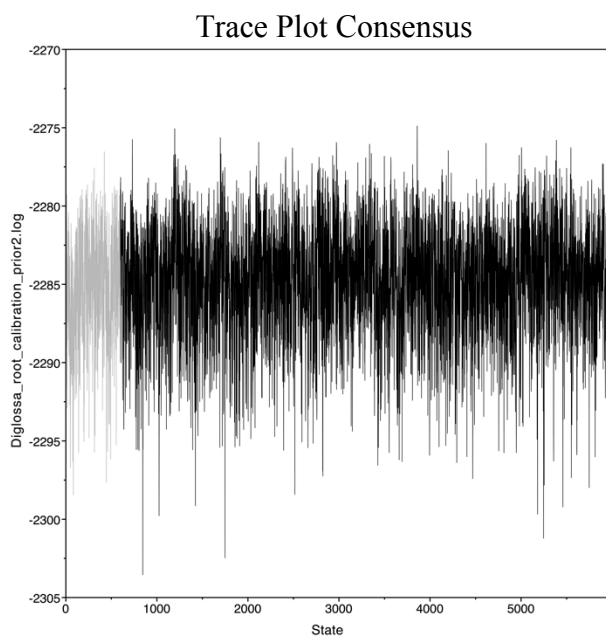
* Posterior Probabilities are close to 1, which corresponds to a high probability that the tree is correct assuming the models are accurate.

Trace Plot Run 1

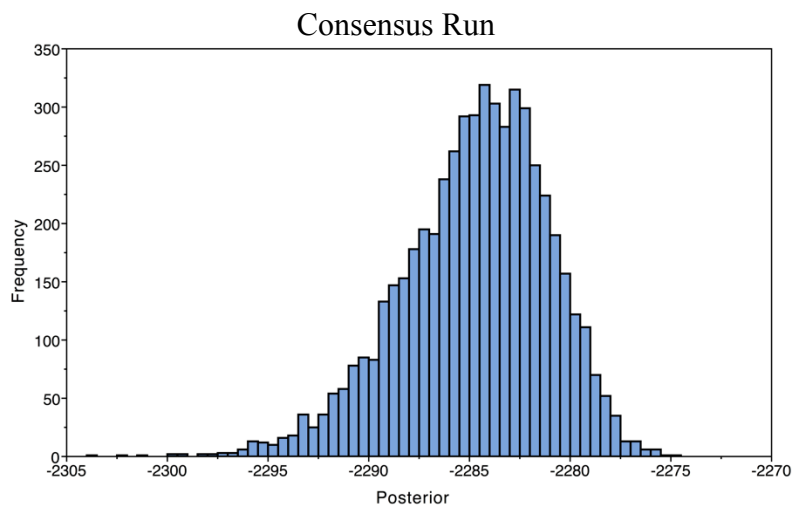
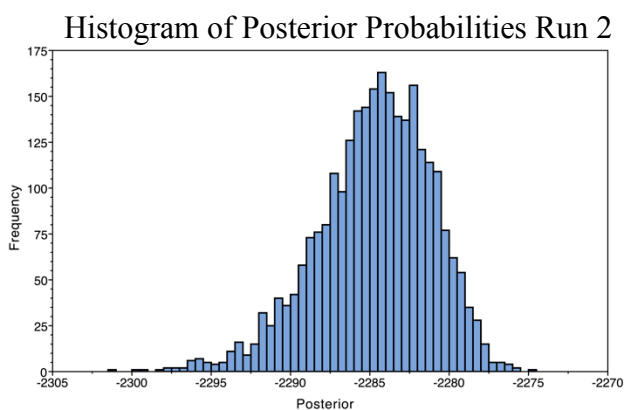
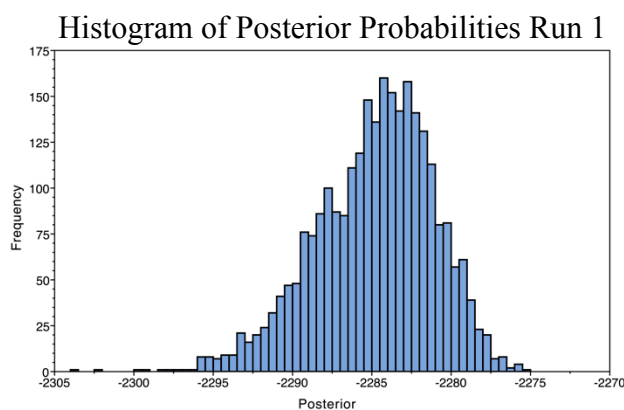


Trace Plot Run 2

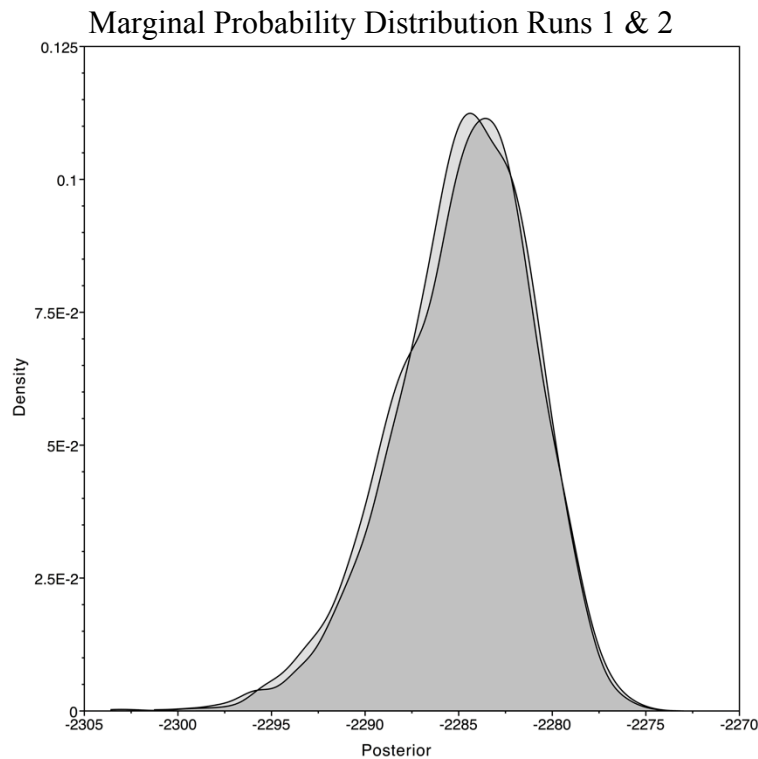




* All three trace plots are very “fuzzy” and linear, so the analysis had good mixing.



* Histograms look similar across runs.



* Probability Distributions are similar across runs, curves overlay.

Effective Sample Size (ESS) Values:

Run 1 = 306.6

Run 2 = 452.1

Consensus = 684.8

* All are above 200 so analysis had good mixing.

Glossary

Molecular Clock: a method of using the mutation rate of nucleotide sequences (DNA) or amino acids (proteins) to estimate the time since divergence. Evidence suggests that there is a linear relationship, molecular differences between species pairs are proportional to the time since they diverged. First described by:

Zuckerkandl, E. and Pauling, L.B. (1962). "Molecular disease, evolution, and genetic heterogeneity". In Kasha, M. and Pullman, B (editors). Horizons in Biochemistry. Academic Press, New York. pp. 189–225.

Model of Sequence Evolution: Markov models of substitution, are matrices of the probability that one amino acid will 'transition' into another (e.g., A → T). Many are described, Jukes Cantor (1969) model uses fixed values (frequencies and mutation rates) and is the simplest. GTR (Generalized Time-Reversible) uses equilibrium base frequencies (π) and transition rate parameters (r) and is one of the most complex, but also flexible.

Birth-Death Processes: a continuous-time Markov process where states transitions are birth (increase states by 1) or death (decrease states by 1).

Prior: from “prior beliefs”, parameters based on existing knowledge set *before* data are input.

Posterior: from Bayes’ theorem, the prior probability of a tree $P(A)$ combined with the likelihood of the data $P(B)$ produce a posterior probability distribution on trees $P(A|B)$. The posterior probability of a tree will indicate the probability of the tree being correct given the data observed and specified models.

Heated Chain: during MCMC sampling, the ‘heated’ chain traverses a space where the peaks and valleys have been flattened out making them easier to cross. After each iteration the cold chain traverses (unflattened peaks) then accepts or rejects a move based on the space sampled by the heated chain. Genna’s Mother and baby robot analogy!

Burn-in: trees generated early in the analysis are discarded. Common method of evaluating nodal support in a Bayesian phylogenetic analysis, by calculating the percentage of trees in the posterior distribution (post-burn-in) that contain the node observed in the ‘actual’ tree.

Markov Chain Monte Carlo: a method or class of algorithm for sampling from a probability distribution by constructing a Markov chain that has the desired distribution as its equilibrium. The state of the chain after a number of steps is then used as a sample of the desired distribution. It is a way of approximating a distribution.

Effective Sample Size (ESS): the number of effectively independent draws from the posterior distribution that the Markov chain is equivalent to. If ESS is small then the distribution is poor, meaning there is a large standard deviation and bad mixing. $ESS < 100$ is bad, < 200 is poor, but > 100 is excessive computational time (ref: BEAST documentation)

* In full disclaimer I got many of these definitions from Wikipedia, and then edited to make more phylogenetics specific. This is more for my future use than anything.