

Phylogenetic model comparison (by) selection & averaging

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What does a model look like

startpage

phylogenetic models

go

≡

Web Images Videos Advanced



The search results page displays a variety of phylogenetic-related content:

- Classification models:**
 - Cladistics - sprout or branch
 - Studies traits to understand phylogeny
 - Cladogram - phylogeny of a species based on shared traits
- Phylogeny:** Ch. 7 & 8
- 17.2 The Six Kingdoms**
- UK 1B2:** Phylogenetic trees and cladograms are graphical representations (models) of evolutionary history that can be tested.
- Evolution and Sequence Variation:** Generating new models for detecting phylogenetic signals of selection and dispersal effects.
- Parts of a phylogenetic tree:** A diagram showing the components of a phylogenetic tree, including nodes, branches, leaves, and root.
- Modern phylogenetic comparative methods and their application in evolutionary biology:** A book cover for "Modern Phylogenetic Comparative Methods and Their Application in Evolutionary Biology" by Michael J. Alfrey III and Mark L. Pagel.
- The Six Kingdoms of Organisms:**
 - Archabacteria
 - Eubacteria
 - Protoctists
 - Fungi
 - Plants
 - Animals

Model = tree prior + site model + clock model + *priors* + *hyper priors*

Model Comparison: Which one is better?

Model Selection: Which one to pick?

Model Averaging: What if you don't want to choose?

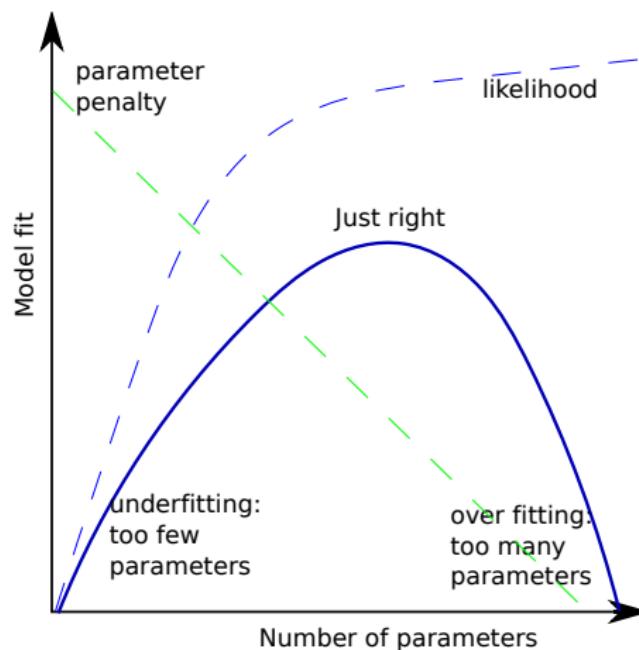
Model selection

Measures of fit:

- Super naive: compare posteriors
 - ▶ but priors are not normalised, cannot be compared
 - ▶ **Never do this!**
- Super naive: compare likelihoods
 - ▶ but overparameterisation/overfitting cannot be detected
 - ▶ **Never do this!**

Model selection: select model with best "fit"

Desirable model fit property 1: likelihood - parameter penalty



Desirable model fit property 2: replicability/low variance

Desirable model fit property 3: easy & cheap to calculate
(this list is not exhaustive)

Bayesian model selection: marginal likelihood

Posterior:

$$p(\theta|D, M) = \frac{\underbrace{p(\theta|M)}_{\text{prior}} \underbrace{p(D|M, \theta)}_{\text{likelihood}}}{\underbrace{P(D_M)}_{\text{marginal likelihood}}}$$

Marginal likelihood:

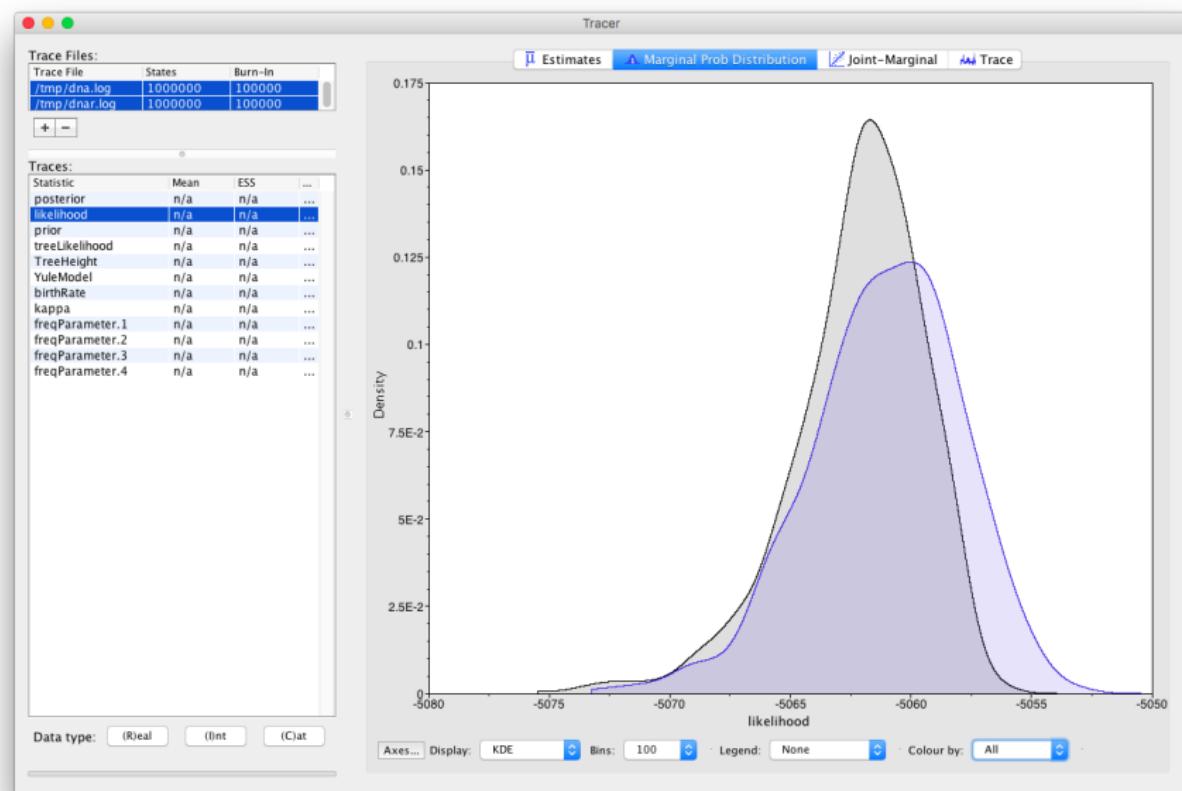
$$p(D|M) = \int_{\theta \in \Theta} p(\theta|M)p(D|M, \theta)d\theta$$

integrate/marginalise out θ

Bayes factor:

$$\frac{p(D|M_1)}{p(D|M_2)}$$

Model selection: marginal likelihood in Tracer



Model selection: marginal likelihood

Naive: Harmonic mean estimator (HME) of marginal likelihood

$$HME = \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{P(D|\theta_i)} \right)^{-1}$$

where $\theta_1, \dots, \theta_n$ a sample from the posterior

- Only requires a sample from the posterior
- Conveniently & quickly calculated in Tracer
- High variance estimator \Rightarrow unreliable
- A post on Dr. Radford Neal's blog <http://radfordneal.wordpress.com/2008/08/17/the-harmonic-mean-of-the-likelihood-worst-monte-carlo-method-ever>

“The total unsuitability of the harmonic mean estimator should have been apparent within an hour of its discovery.”

- **Never do this!**

Model selection: pseudo-marginal likelihood

- Conditional Predictive Ordinates (CPO) = leave one out cross validation
- Per site CPO:

$$\widehat{CPO}_i = \left(\frac{1}{m} \sum_{k=1}^m \frac{1}{p(x_i | \theta_k)} \right)^{-1}$$

where y_i the data for site i , θ_k the parameter at posterior sample k

Log pseudomarginal likelihood (LPML): $\sum_{i=1}^n \log \widehat{CPO}_i$

- Closely related to HME, but does not have infinite variance
- Convenient to calculate

Lewis et al, Sys Bio, 2014

AICM model selection

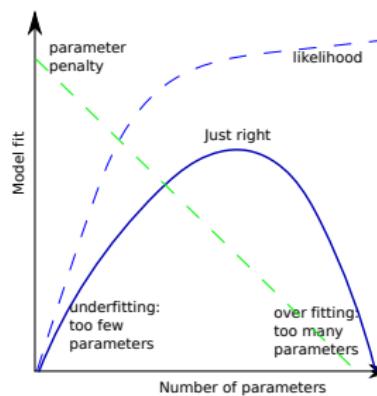
Akaike Information Criterion (AIC) by MCMC (AICM)

AIC:

$$2k - 2 \log P(D|\theta)$$

k = effective number of parameters

$P(D|\theta)$ = likelihood



- Estimate k from fitting gamma distribution to MCMC sample of likelihood
- Smaller AICM is better (unlike marginal likelihood)
- Conveniently calculated in Tracer (or by model-selection package)

Path sampling/Stepping stone theory

- Marginal likelihood:

$$p(D|M) = \int_{\theta} p(\theta|M)p(D|M, \theta)d\theta$$

hard to estimate directly.

- Define *power posterior* for some tractable reference distribution $\pi(\theta)$

$$P_{\beta}(\theta|D, M) = \frac{[p(D|\theta, M)p(\theta, M)]^{\beta}\pi(\theta)^{1-\beta}}{c_{\beta}}$$

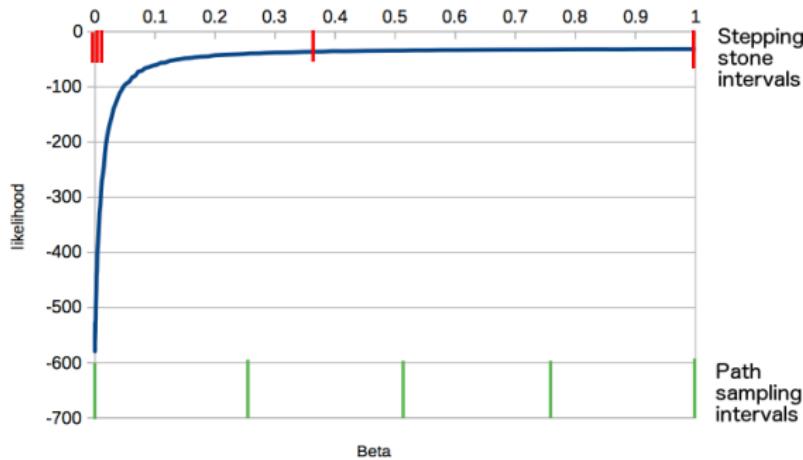
$P_1(\theta|D, M)$ is the posterior, c_1 the marginal likelihood.

$P_0(\theta|D, M)$ is the reference distribution, $c_0 = 1$

- $$\frac{c_{\beta k}}{c_{\beta k-1}} \approx \frac{1}{n} \sum_{i=1}^n p(D|M, \theta_{k-1, i})^{\beta_k - \beta_{k-1}}$$
- $$P(D|M) = \frac{c_1}{c_0} = \frac{c_1}{c_{0.3}} \frac{c_{0.3}}{c_{0.1}} \frac{c_{0.1}}{c_{0.01}} \frac{c_{0.01}}{c_0} = \frac{c_1}{\cancel{c_{0.3}}} \cancel{\frac{c_{0.3}}{c_{0.1}}} \cancel{\frac{c_{0.1}}{c_{0.01}}} \frac{c_{0.01}}{c_0}$$

Model selection: *Stepping stone vs path sampling*

Both use prior as reference distribution $\pi(\theta)$



Stepping stone uses different intervals (set of β values) from path sampling, but otherwise the same

Generalised Stepping Stone

Use 'working distribution' for $\pi(\theta)$ based on posterior sample

- For parameters, use empirical distribution based on kernel estimators
- For trees, we need a distribution on topology and branch lengths
- Promises lower variance estimates
- Currently tedious to set up, since working distribution needs to be specified

Holder et al, Bayesian phylogenetics, 2014, Beale et al, Sys Bio, 2016

Pairwise Stepping Stone

Use posterior of M_2 for $\pi(\theta)$.

- Calculates Bayes factor between M_1 and M_2 directly
- + requires fewer steps for accurate estimate
- - does not result in Bayes factors directly

Baele et al, BMC Bioinformatics, 2013

Model selection

Measures of fit:

- Naive: Harmonic mean estimator (HME) of marginal likelihood
 - ▶ High variance estimator \Rightarrow unreliable
 - ▶ Never do this!
- AICM: Akaike information criterion M?
 - ▶ Computational convenient
 - ▶ High variance estimator \Rightarrow unreliable (but better than HME)
 - ▶ only use when stepping stone is not feasible
- Pseudo marginal likelihood
 - ▶ Computational convenient
 - ▶ High variance estimator \Rightarrow unreliable (but better than HME)
 - ▶ only use when stepping stone is not feasible
- Path sampling/Stepping stone:
 - ▶ most stable marginal likelihood estimation we got (so far)
 - ▶ computationally expensive
 - ▶ use this if you can

Path sampling/Stepping stone in practice

Number of steps:

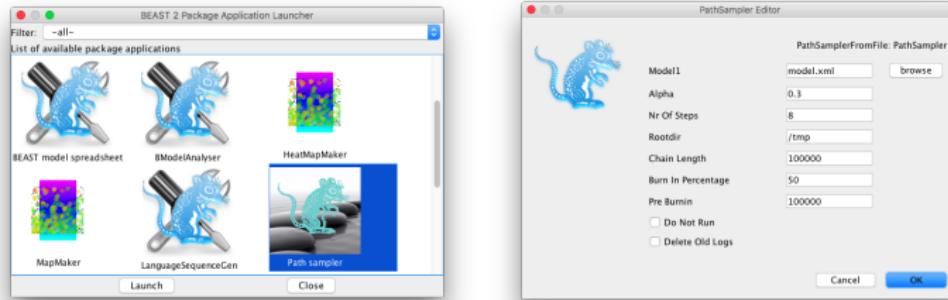
- Start with small nr of steps, say 16 and estimate ML
- increase nr of steps, estimate ML
- continue till ML estimate does not decrease any more

Chain length per step/ESS:

- total chain length at least as long as for posterior
- not all ESSs have to be 200 (errors cancel out)
- run different runs to get impression of variance of estimate
- use logcombiner to combine logs, for final estimate

Path sampling/Stepping stone in practice

Set up through XML or GUI



Set up through CLI:

- to list BEAST apps:
`/path/to/appstore -list`
- To show PathSampler options:
`/path/to/appstore -PathSampler -help`
- To set up PathSampler analysis:
`/path/to/appstore PathSampler -nrOfSteps 64 -rootdir dir/withs/steps -burnInPercentage 50 -model beast.xml`

Creates subdirectory structure, one for each step containing all log files.

Path sampling/Stepping stone in practice

To set up on a HPC cluster

- Set up locally, using 'doNotRun' flag = true
- Move steps to cluster, and run steps in parallel there
- Estimate ML using PathSampleAnalyser

```
/path/to/appstore PathSampleAnalyser -nrOfSteps 64 -rootdir  
dir/withs/steps -burnInPercentage 50
```

Path sampling/Stepping stone in practice

Trouble shooting

- ESS too small for a step: resume runs for that step
- Infinite likelihoods caused by numeric instability: improper priors – use proper priors instead
- -Infinite likelihoods: priors too wide – narrow priors
- Inspect log files in step directory to see which parameter escapes, so which prior to adjust

Summary model selection

- Use Stepping stone if you can
- Use AICM (LPML?) otherwise
- Use common sense to decide between the two

Model averaging

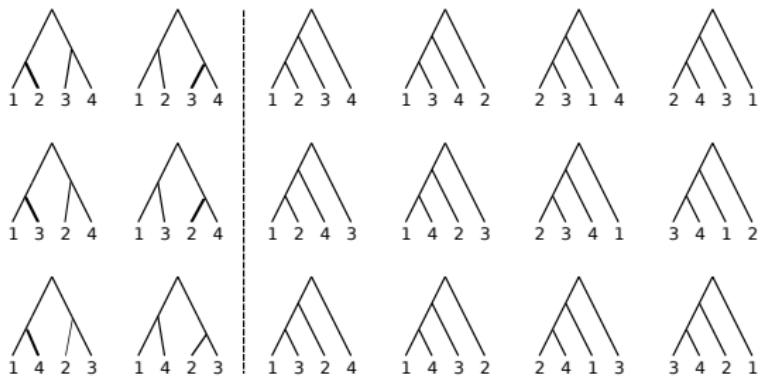
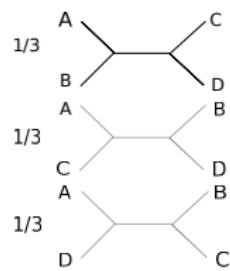
- Already been doing that this week: each tree topology is a model
- Posterior:

$$p(\theta|D) = \sum_k \overbrace{P(M_k)}^{\text{model prior}} \underbrace{p(\theta|M_k)p(D|M_k, \theta)}_{\text{posterior}}$$

- Models can be substitution models, clock models, tree topologies, etc.
- Accounts for model uncertainty
- Requires specifying another prior $P(M_k)$

Model averaging

Already been doing that this week: each tree topology is a model



18 ranked rooted trees – 1/3 probability of being balanced

Model averaging: stochastic variable selection

Use indicator variable to select model

- Example: ancestral state reconstruction using mask matrix I and rate matrix R

$$I = \begin{pmatrix} - & i_{12} & i_{13} & i_{14} \\ i_{21} & - & i_{23} & i_{24} \\ i_{31} & i_{32} & - & i_{34} \\ i_{41} & i_{42} & i_{43} & - \end{pmatrix} \quad R = \begin{pmatrix} - & r_{12} & r_{13} & r_{14} \\ r_{21} & - & r_{23} & r_{24} \\ r_{31} & r_{32} & - & r_{34} \\ r_{41} & r_{42} & r_{43} & - \end{pmatrix}$$

- Use r_{ij} if i_{ij} is true, but use rate 0 if i_{ij} is false
- Sample I and all rates in R throughout MCMC run.
- Use strong prior on number of $i_{ij} = \text{true}$ to reduce number of non-zero rates

Lemey et al, PLoS Comput Biol, 2009

Stochastic variable selection:

- Simple to implement
- Potentially inefficient in sampling unused parameters

Model averaging: reversible jump

The probability of acceptance of a (possibly trans-dimensional) proposal is

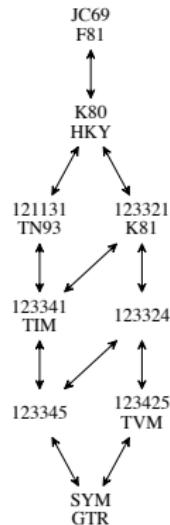
$$\min\{1, \text{posterior ratio} \times \text{proposal ratio} \times \text{Jacobian}\}$$

- **posterior ratio** is the posterior of the proposed state S' divided by that of the current state S ,
- **proposal ratio** the probability of moving from S to S' divided by the probability of moving back from S' to S
- **Jacobian** is the determinant of the matrix of partial derivatives of the parameters in the proposed state with respect to that of the current state

Green, Biometrika, 1995

Reversible jump:

- Hard to implement correctly
- Efficient sampling



Reversible-jump Based (RB) substitution model for nucleotides

$$R = \begin{vmatrix} - & \alpha & \beta & \gamma \\ \alpha & - & \delta & \epsilon \\ \beta & \delta & - & \omega \\ \gamma & \epsilon & \omega & - \end{vmatrix}$$

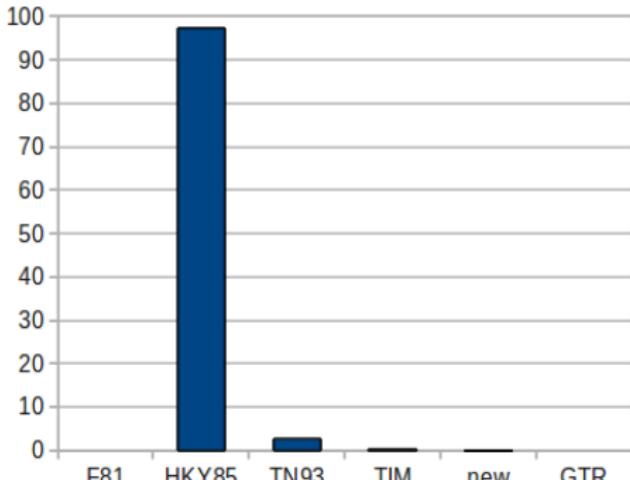
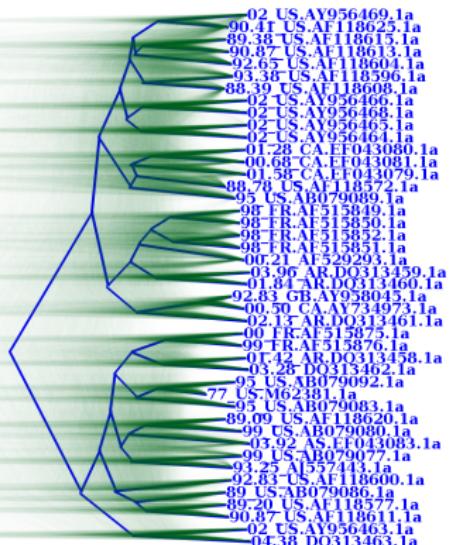
frequencies π
 $Q = \pi R$

transition prob.
 $P(t) = e^{Qt}$

	α	β	γ	δ	ϵ	ω	# dimensions
F81 (JC69)	1	1	1	1	1	1	0
HKY85 (K80)	a	1	a	a	1	a	1
TN93	a	b	a	a	1	a	2
TIM	a	b	c	c	1	a	3
new	a	b	c	d	1	a	4
GTR (SYM)	a	b	c	d	1	e	5

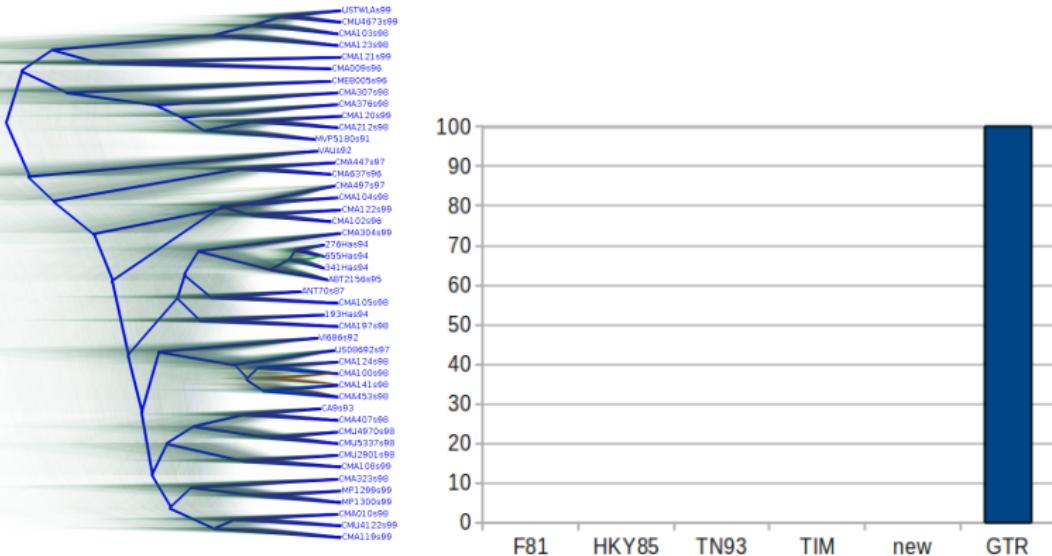
Increase dimension by drawing a new parameter value from $\Gamma(0.2, 5)$

Hepatitis C: HKY massively preferred



44 taxa, 576 sites, Bayesian skyline, 0 gamma, 0 prop invariant

HIV: only GTR will do



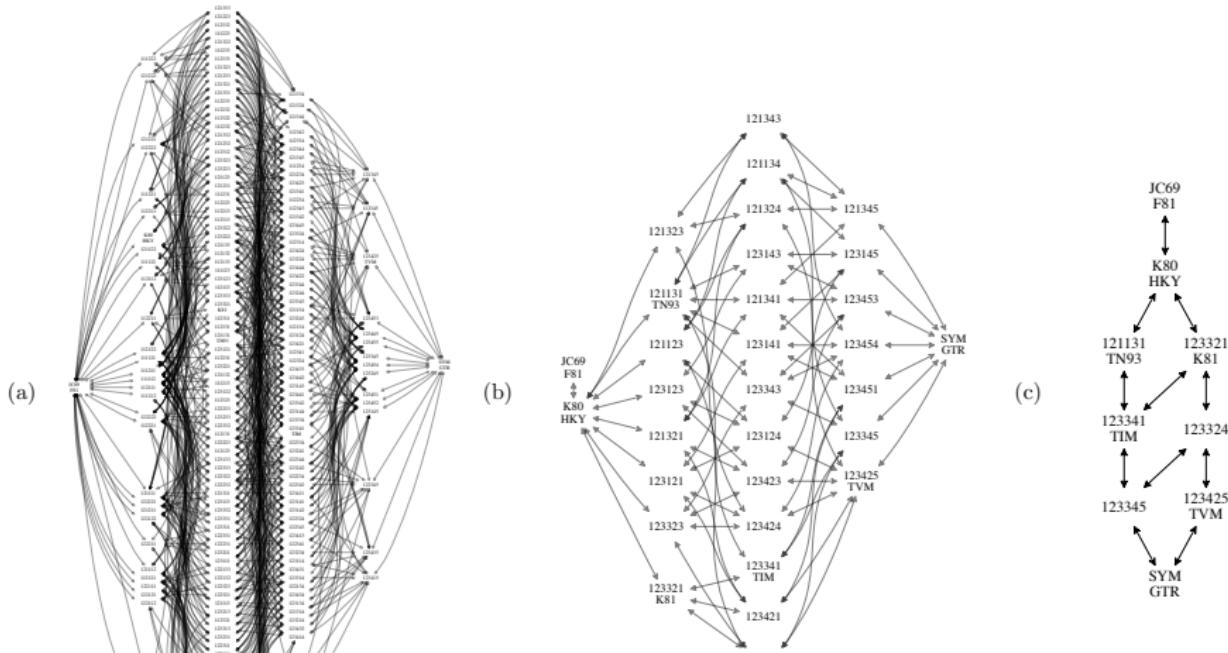
Same results without and with partitioning sites at codon positions {1,2},{3} or {1},{2},{3}

46 taxa, 2382 sites, Coalescent (exp), 0 Γ , 0 PI. MP, FPV, animal dna, primates.

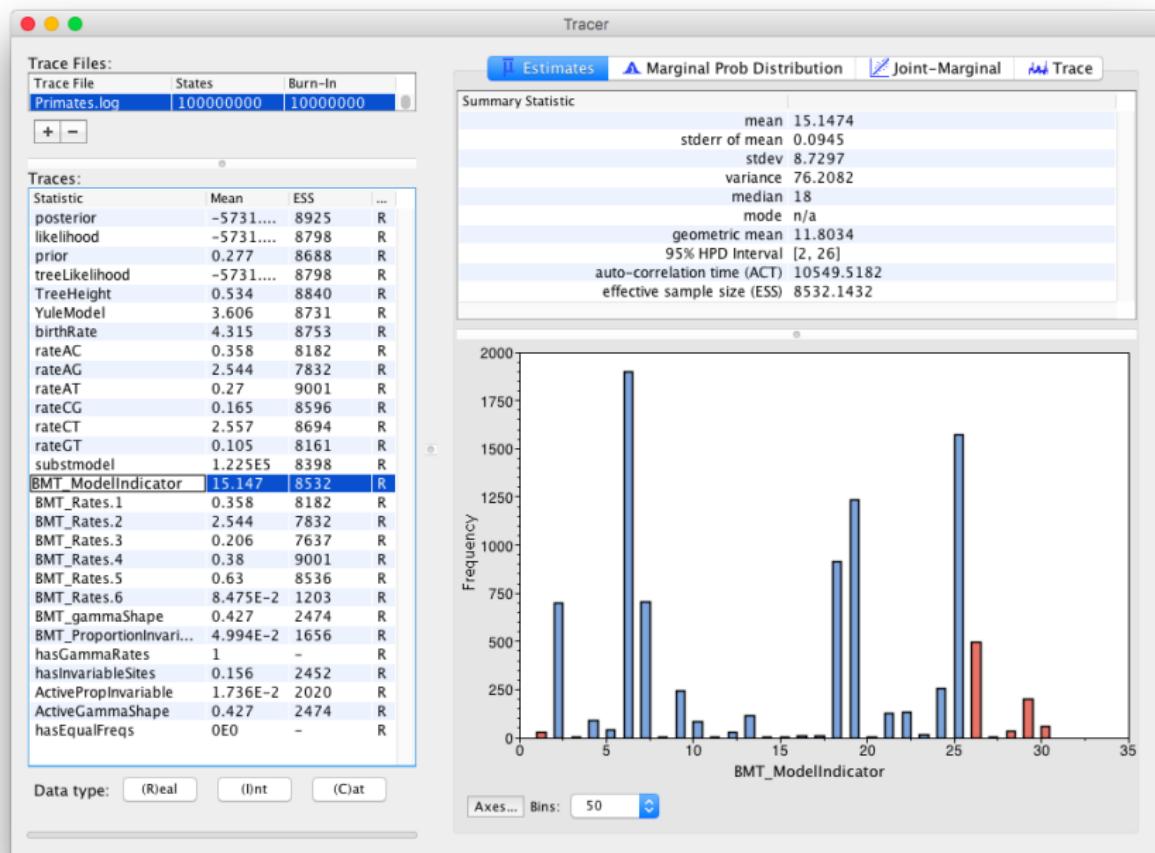
Model averaging: bModelTest

Bouckaert & Drummond, BMC Evo Bio, 6 Feb 2017

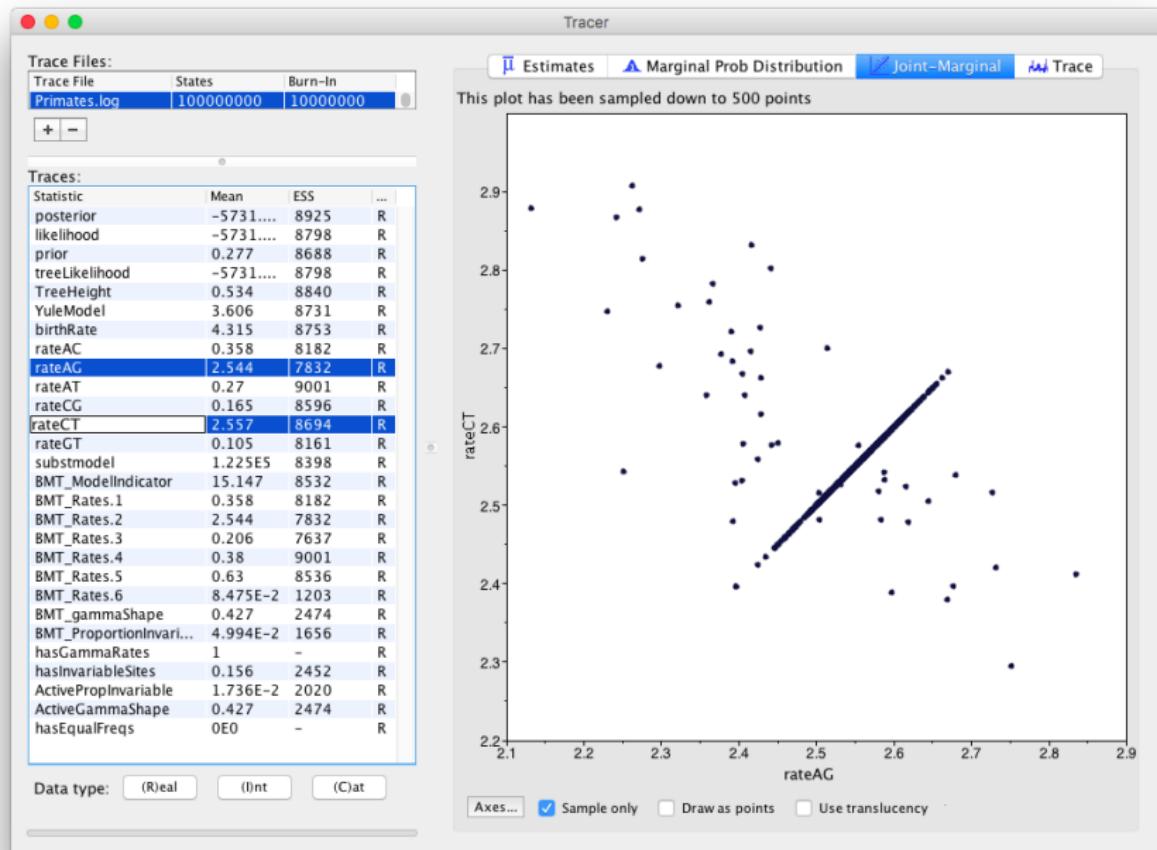
- Averages over substitution models
 - Estimated/fixed frequencies
 - With/without gamma rate heterogeneity
 - With/without gamma proportion invariable sites



Model averaging: bModelTest



Model averaging: bModelTest

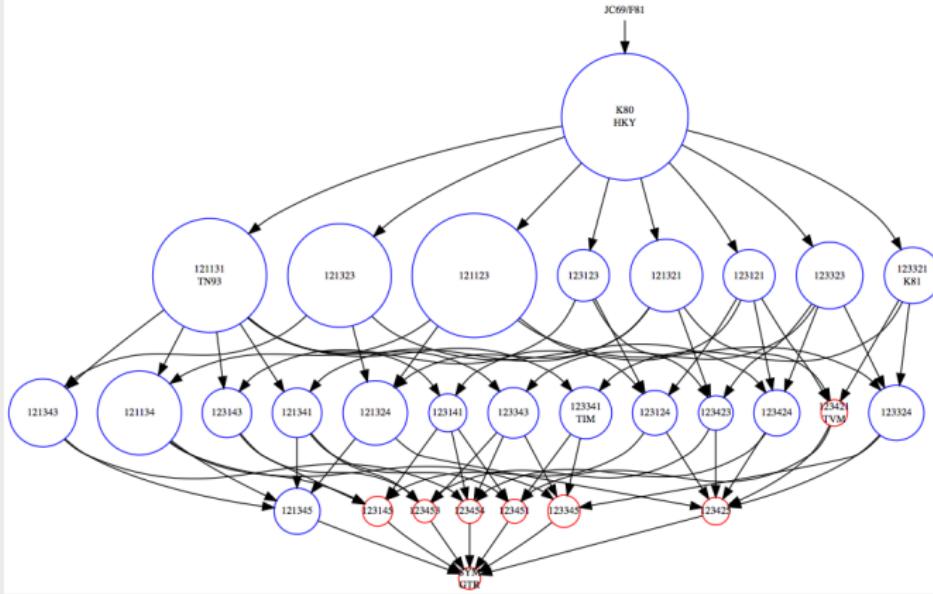


Model averaging: bModelTest

File: Primates.log item: substmodel

Models with blue circles are inside 95%HPD, red outside, and without circles have 0.00% support.

posterior support	cumulative support	model
13.77%	13.77%	121121
13.21%	26.99%	121123
11.16%	38.15%	121131
9.27%	47.42%	121323
6.05%	53.47%	121134
4.44%	57.91%	121321
3.94%	61.85%	121343
3.78%	65.63%	123323
3.50%	69.13%	121324
2.72%	71.85%	123321
2.61%	74.46%	123324
2.33%	76.79%	123121
2.28%	79.07%	123123
2.28%	81.34%	123341
2.17%	83.51%	123343
2.05%	85.56%	121341
2.05%	87.52%	123143
1.83%	89.45%	123424
1.78%	91.23%	121345
1.72%	92.95%	123124
1.22%	94.17%	123141
1.05%	95.22%	123423
0.89%	96.11%	123345



Model averaging: bModelTest model priors

Posterior:

$$p(\theta|D) = \sum_k P(M_k) p(\theta|M_k) p(D|M_k, \theta)$$

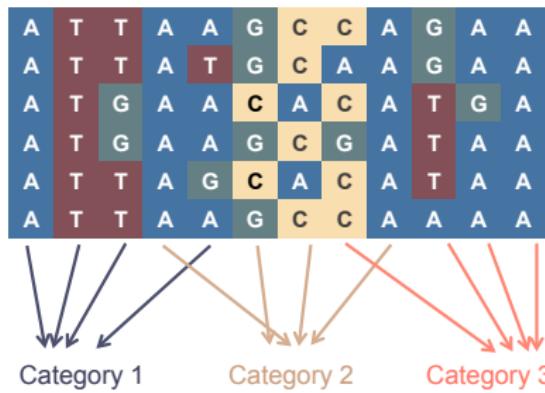
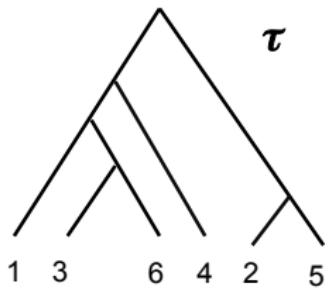
$P(M_k)$ model prior:

- uniform over substitution models in model set
 - ▶ For 31 model set: $P(JC) = P(HKY) = P(TN) = P(GTR) = \frac{1}{31}$
- uniform over number of parameters in substitution models
 - ▶ For 31 model set: $P(JC) = P(HKY) = P(GTR) = \frac{1}{6}$ but
 $P(TN) = \frac{1}{6} \cdot \frac{1}{8} = \frac{1}{48}$

Bayesian inference

- Posterior distributions of parameters of interest are simulated by an algorithm called Markov chain Monte Carlo (MCMC)

Phylogenetic tree



Substitution model parameters

 ϕ_1^*

Model

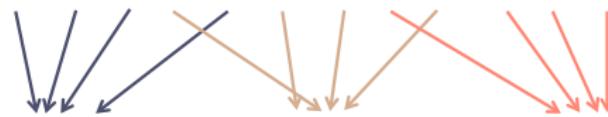
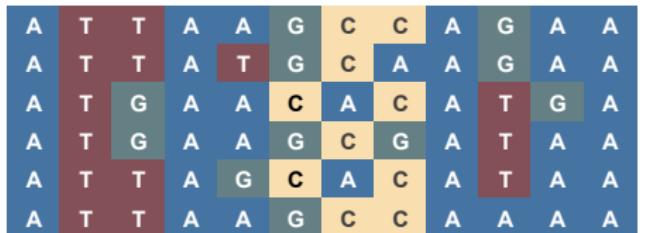
 M_1 ϕ_1^* M_2 ϕ_1^* M_3

Rate

 r_1 r_2 r_3 ϕ r Population history or speciation hyperparameters θ

Subst BMA

Site rates and substitution patterns share a common Dirichlet Process prior (DPM1)



Category 1

Category 2

Category 3

Substitution
parameters

ϕ_1^*

ϕ_1^*

ϕ_1^*

Model

M_1

M_2

M_3

Rate

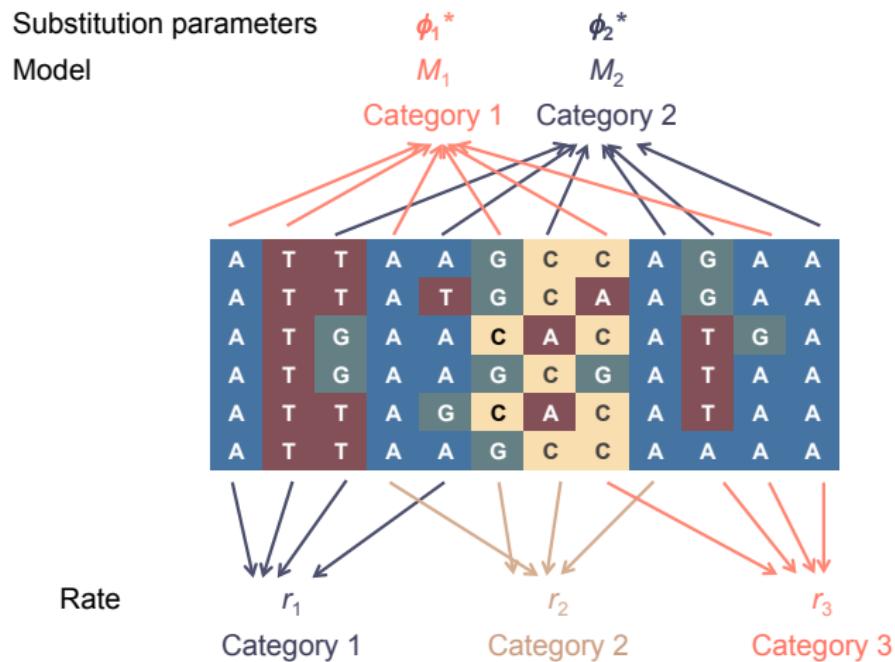
r_1

r_2

r_3

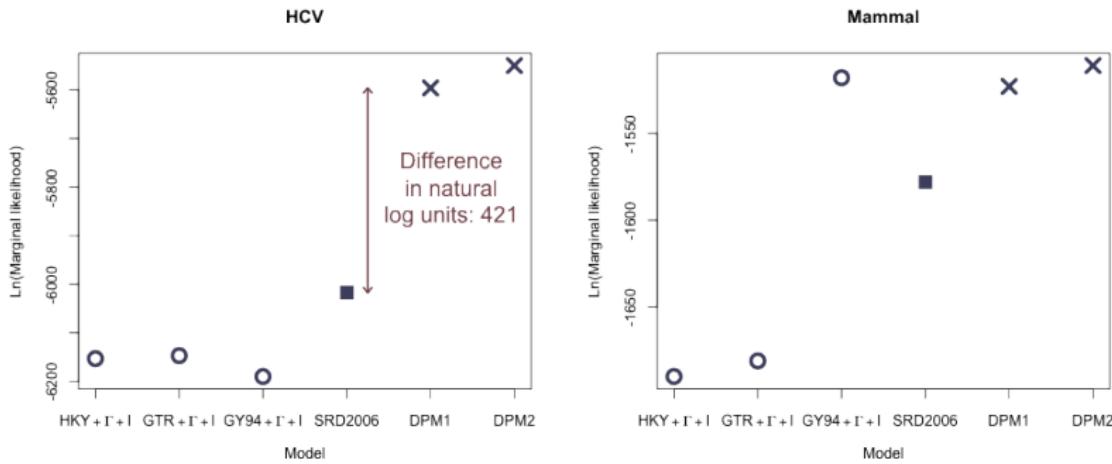
Subst BMA

Site rates and substitution patterns have independent Dirichlet Process priors (DPM2)



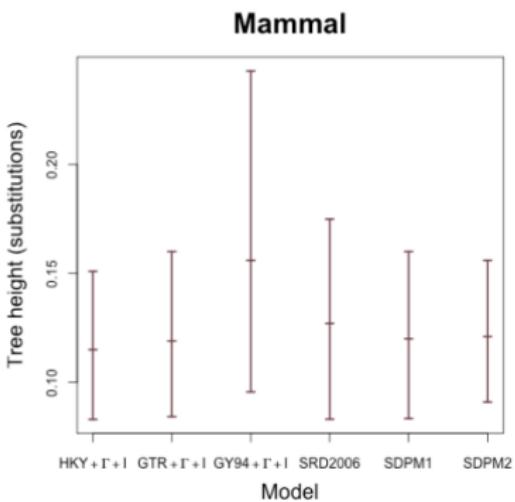
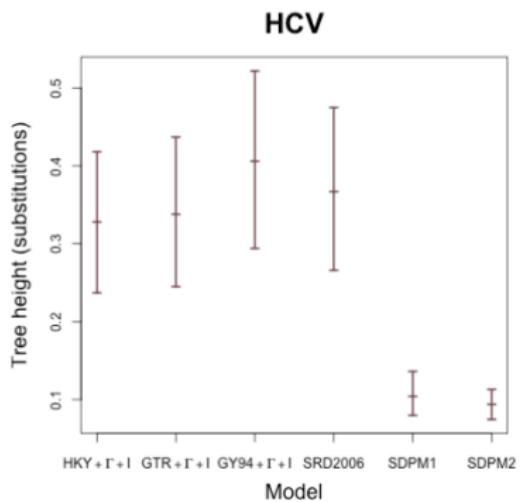
Marginal Likelihoods

- Use marginal likelihood as a measure of how well the model explains the data.

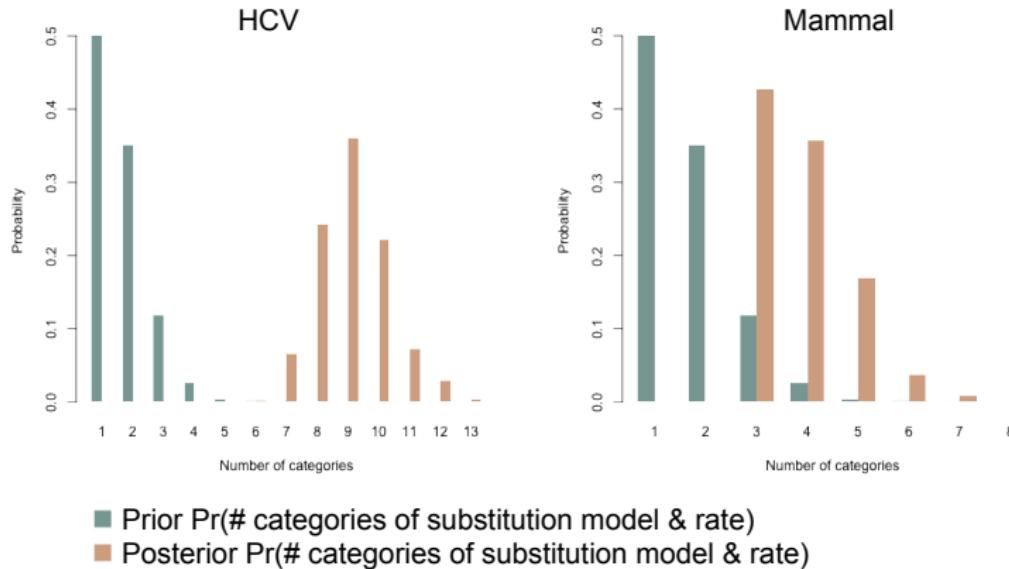


- Substitution pattern assumed homogeneous across sites
- Alignment partition for substitution pattern defined prior to the analysis
- ✗ Alignment partition for substitution pattern estimated

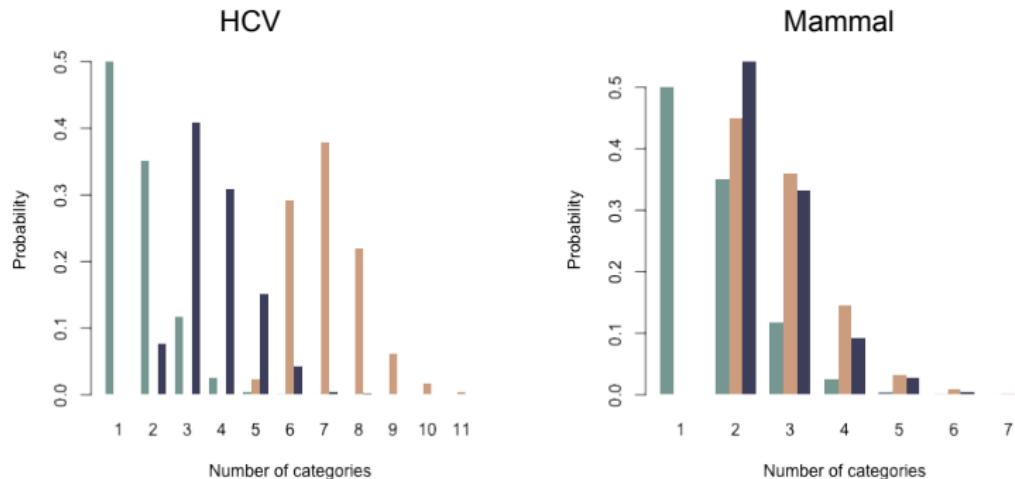
Subst BMA



Number of categories for substitution patterns and rates across sites (DPM1)



Number of categories for substitution patterns and rates across sites (DPM2)



- Prior $\text{Pr}(\# \text{ substitution model/rate categories})$
- Posterior $\text{Pr}(\# \text{ substitution model category})$
- Posterior $\text{Pr}(\# \text{ rate category})$

RBS vs bModelTest vs Subst BMA

	RBS	bModelTest	Subst BMA
Subst models	6	11/31/202	4
Average over Gamma	no	yes	yes
Average over Prop Invariant	no	yes	no
Average over Sites	no	no	yes
Average over Frequencies	no	yes	somewhat
Works with tip dates	yes	yes	yes
Works without tip dates	yes	yes	not yet

Model comparison/Bayesian hypothesis testing

- Through model selection:
 - ▶ compare Bayes factors based on ML estimates
- Through model averaging: post-hoc analysis
 - ▶ compare Bayes factors based on empirical estimates from prior and posterior samples

Bayes factor:

$$\frac{p(D|M_1)}{p(D|M_2)} \text{ estimated by } \frac{\frac{\text{empirical posterior}(M_1)}{\text{empirical prior}(M_1)}}{\frac{\text{empirical posterior}(M_2)}{\text{empirical prior}(M_2)}}$$

Obtain sample from prior for M_1 and M_2 .

Obtain sample from posterior for M_1 and M_2 .

Bayes Factors

BF range	$\ln(BF)$ range			$\log_{10}(BF)$ range			Interpretation
1 – 3	0	–	1.1	0	–	0.5	hardly worth mentioning
3 – 20	1.1	–	3	0.5	–	1.3	positive support
20 – 150	3	–	5	1.3	–	2.2	strong support
> 150	>	5		>	2.2		overwhelming support

Kass & Raftery, JASA, 1995

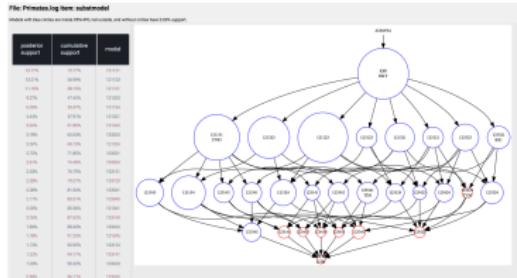
Model comparison of topologies

- Clade support for two alternative clades: M_1 : taxon X belongs with clade A M_2 : X belongs with B
- From sample from prior: $P(M_1) = 0.3$ $P(M_2) = 0.4$
- From sample from posterior: $P(D|M_1) = 0.6$ $P(D|M_2) = 0.1$
- Bayes factor

$$\frac{p(D|M_1)}{p(D|M_2)} = \frac{\frac{posterior(M_1)}{prior(M_1)}}{\frac{posterior(M_2)}{prior(M_2)}} = \frac{\frac{0.6}{0.3}}{\frac{0.1}{0.4}} = 8$$

- Positive support for M_1 : X belongs with clade A

Model comparison of substitution models



- bModelTest: M_1 : HKY vs M_2 : GTR
 - From sample from prior: $P(M_1) = \frac{1}{31}$ $P(M_2) = \frac{1}{31}$
 - From sample from posterior: $P(D|M_1) = 0.1377$ $P(D|M_2) = 0.006$
 - Bayes factor

$$\frac{p(D|M_1)}{p(D|M_2)} = \frac{\frac{posterior(M_1)}{prior(M_1)}}{\frac{posterior(M_2)}{prior(M_2)}} = \frac{0.1377/\frac{1}{31}}{0.006/\frac{1}{31}} = 22.95$$

- Strong support for M_1 : HKY

Model comparison of root age

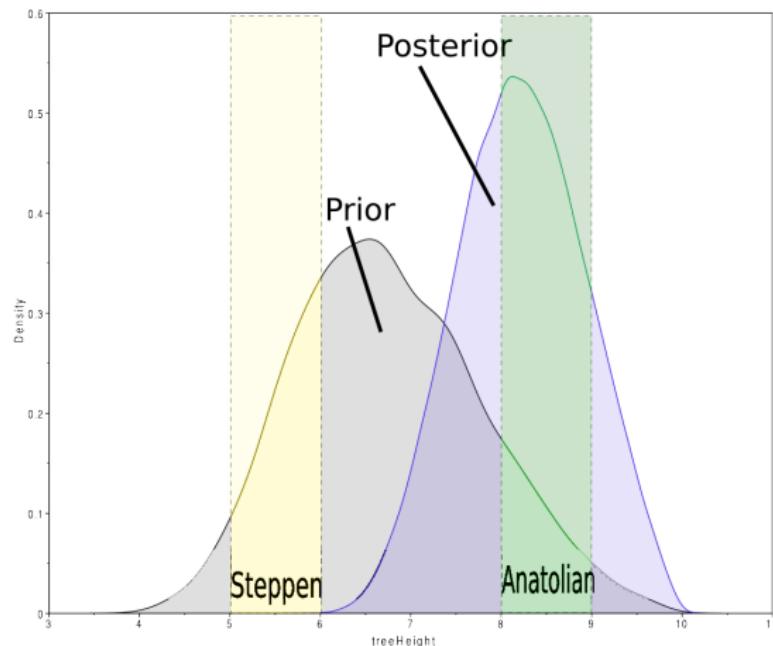
Origin of Indo-European: Two competing theories



Steppen 5000 – 6000BP, Anatolian 8000 – 9000BP

Model comparison of root age

Origin of Indo-European: Two competing theories



Root height Prior = 6.8 [4.9, 8.8] Posterior 8.2 [6.9, 9.6]
Bayes Factor $\gg 100$ in favour of Anatolian hypothesis

Model comparison of root location

Root location: Pama Nyungang M_1 M_2 M_3 M_4

Hypotheses3priorX.pdf	Hypotheses3X.pdf

Bayes Factors:

	M_1	M_2	M_3	M_4
M_1	—	6.22	76.66	486.34
M_2	0.16	—	12.33	78.23
M_3	0.01	0.08	—	6.34
M_4	0.00	0.01	0.16	—

Summary model comparison, selection & averaging

Questions?