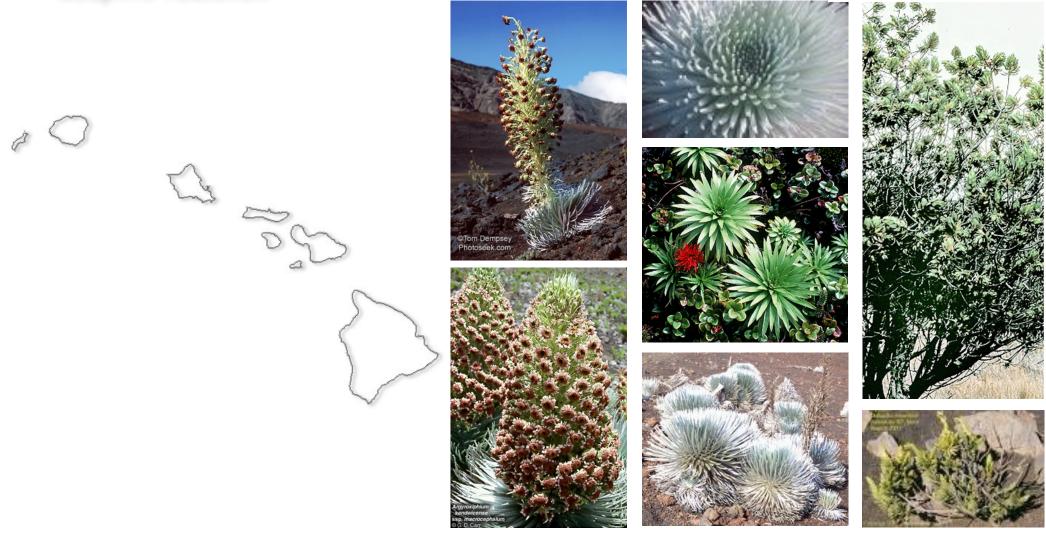
Phylogenetic Approaches for Exploring Differential Rates of Diversification*

*lineage diversification = (speciation – extinction)
aka *real* diversification!

Brian R. Moore & Mike R. May
Department of Evolution & Ecology
UC, Davis
2014 Bodega Workshop

Differential Rates of Diversification

adaptive radiation

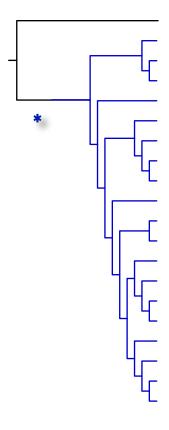


Hawaiian silverswords

Differential Rates of Diversification

adaptive radiation

key innovations





nectar spurs in columbines

Differential Rates of Diversification

adaptive radiation

key innovations

rapid cladogenesis



cichlids

Outline & Organization

- I. Brief overview of general approach to the study of lineage diversification
- II. Brief overview of popular methods for studying lineage diversification

 A beginners guide to the types of methods available
- III. How to apply popular methods for studying lineage diversification
 Using R packages to address various questions about diversification rates

Outline & Organization

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Me

III. How to apply popular methods for studying lineage diversification
Using R packages to address various questions about diversification rates

Mike

Statistical Phylogenetic Approaches for the Study of Diversification Rates

- I. Pose a substantive question
- II. Develop a stochastic model with parameters that, if known, would answer the question
- III. Collect observations that are informative about model parameters

Statistical Phylogenetic Approaches for the Study of Diversification Rates



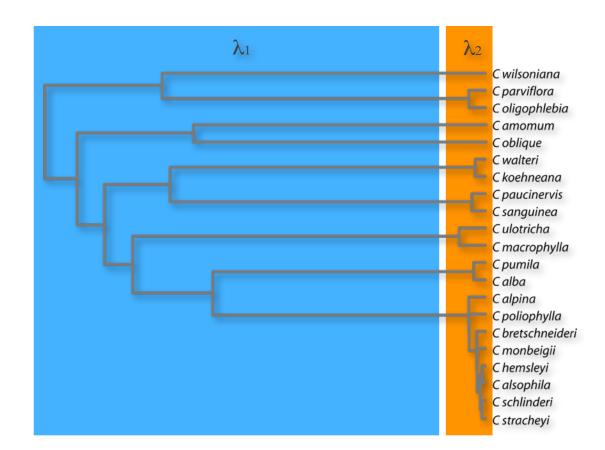
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- IV. Estimate the model parameters using some method conditioned on the data at hand

1. Estimating parameters of the stochastic branching-process model

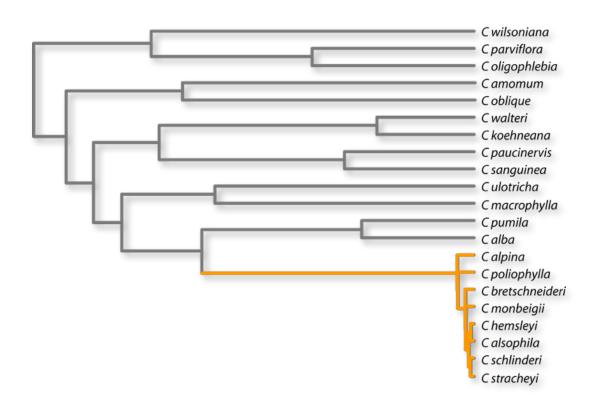
What are the absolute/relative rates of the branching process?

- speciation rate, λ
- $^{\bullet}$ extinction rate, μ
- diversification rate, $\partial = (\lambda \mu)$
- relative extinction rate, $\varepsilon = (\mu / \lambda)$

- 1. Estimating parameters of the stochastic branching-process model
- 2. Identifying significant diversification rate shifts through time Have tree-wide rates of diversification changed through time?

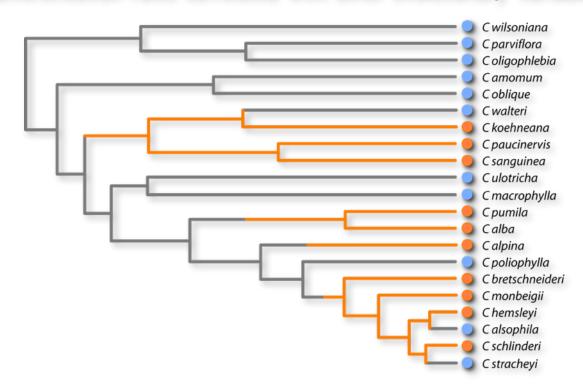


- 1. Estimating parameters of the stochastic branching-process model
- 2. Identifying significant diversification rate shifts through time
- 3. Locating significant diversification rate shifts along branches Along which branches have significant rate shifts occurred?

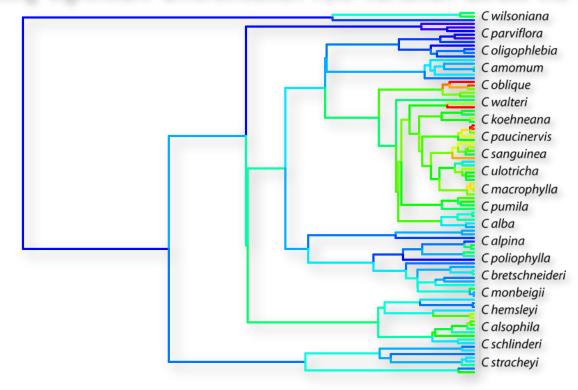


- 1. Estimating parameters of the stochastic branching-process model
- 2. Identifying significant diversification rate shifts through time
- 3. Locating significant diversification rate shifts along branches
- 4. Evaluating correlates of differential diversification rates

 Are diversification rates correlated with other evolutionary variables?



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Statistical Phylogenetic Approaches for the Study of Diversification Rates

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Stochastic-Branching Process Models

"All models are wrong, but some are useful" Box (1976)

Common Stochastic-Branching Process (SBP) Models

Generalized Birth-Death (GBD: Kendall, 1948)

• $\lambda(t)$ and $\mu(t)$, $\lambda > \mu$

Constant Birth-Death (CBD: Kendall, 1948)

• λ and μ , $\lambda > \mu$

Sampled Birth-Death (SBD: Gernhardt, 2008)

• λ , μ , ρ , $\lambda > \mu$

Generalized Pure Birth (GPB: Harris, 1964)

• $\lambda(t)$, $\mu = 0$

Constant Pure Birth (CPB: Yule, 1924)

• λ , $\mu = 0$

Stochastic-Branching Process Models

"All models are wrong, but some are useful" Box (1976)

General properties of SBP Markov models

Assume $\lambda(t)$ and/or $\mu(t)$ are:

- constant across all lineages at and instant
- independent across lineages at and instant
- events occur instantaneously

Assume ρ is:

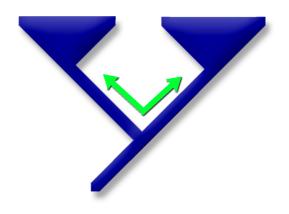
uniform/random with respect to phylogeny

Statistical Phylogenetic Approaches for the Study of Diversification Rates

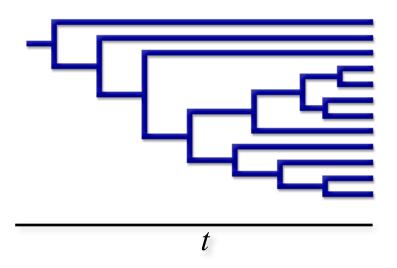
- I. Pose a substantive question
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What Are the Basic Phylogenetic Data for Studying Diversification Rates?

Topological Information



Temporal Information



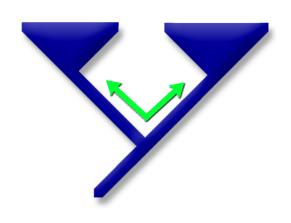
Distribution of species diversity across the tree

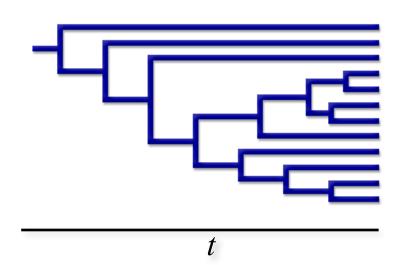
Distribution of speciation events through time

What Are the Basic Phylogenetic Data for Studying Diversification Rates?

Topological Information







The primary phylogenetic 'observations'—both the topological distribution of species diversity and the temporal distribution of waiting times—arise via stochastic processes

These 'observations' are estimates from data (and therefore associated with uncertainty)

Statistical Phylogenetic Approaches for the Study of Diversification Rates

- I. Pose a substantive question
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Statistical Inference Under Stochastic-Branching Process Models

SBP models are employed in two qualitatively different ways

- Null-modeling approaches calculate a summary statistic from the phylogenetic 'observations', which is then compared to a statistical distribution generated under an appropriate stochastic-branching process model
- Model-fitting approaches estimate parameters of the SBP models from the phylogenetic 'observations'; i.e., the topological distribution of species diversity and the temporal distribution of waiting times

Statistical Inference Under Stochastic-Branching Process Models

Inference under SBP models may adopt different statistical approaches

- <u>Maximum Likelihood Estimation</u> methods involve numerical optimization algorithms to identify the joint parameter estimates that collectively maximize the likelihood of the phylogenetic 'observations' under the SBP model
- Quasi-Bayesian Inference methods involve averaging ML estimates over a marginal posterior probability density of the phylogenetic 'observations'
- <u>Empirical Bayesian Inference</u> methods involve numerical algorithms to approximate the joint posterior probability density of the SBP model parameters given point (maximum-likelihood) estimates of the phylogenetic 'observations'
- <u>Sequential-Bayesian Inference</u> methods involve Bayesian inference of the SBP model parameters averaged over a previously estimated marginal posterior probability density of the phylogenetic 'observations'
- Hierarchical-Bayesian Inference methods involve joint (simultaneous) estimation of the SBP and other phylogenetic model parameters

Why Pursue These Questions in a Bayesian Statistical Framework?

Recent developments have largely been developed in Quasi-Bayesian ML framework

The study of diversification entails several sources of uncertainty

- phylogeny/topology
- branch lengths/durations
- rate parameters
- event histories

Bayesian framework provides a means for accommodating uncertainty

Outline & Organization



- I. Brief overview of general approach to statistical study of lineage diversification
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 - II. Develop a stochastic model with parameters that can answer the question
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 - IV. Estimate the model parameters using some method conditioned on the data
- II. Brief overview of popular methods for studying lineage diversification

 A beginners guide to the types of methods available

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II. Brief overview of popular methods for studying lineage diversification

A beginners guide to the types of methods available

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Lineage-Thru-Time Plots

(e.g., Nee et al., 1992, 1994a,b)

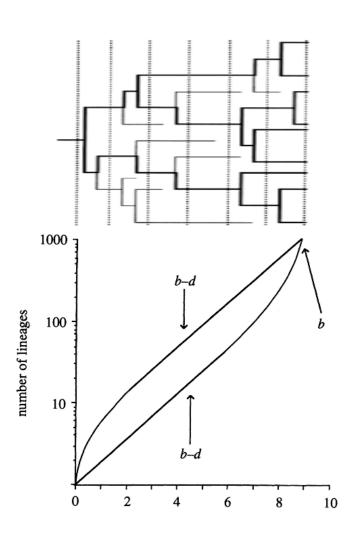
Semi-logarithmic accumulation of lineages

Primarily descriptive, characterized by:

- Push of the Past
- slope = diversification rate, $\partial = (\lambda \mu)$

If extinction rate, $\mu = 0$, also characterized by:

- Pull of the Present
- increased offset slope
- asymptotic behavior under random sub sampling



ML Estimation from Lineage-Thru-Time Plots

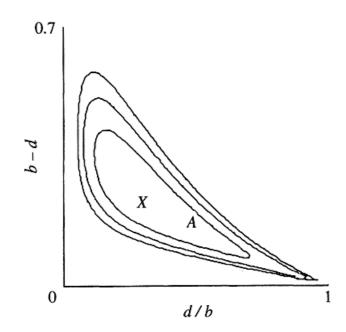
(e.g., Nee, 2001, Magallon & Sanderson, 2001)

Maximum likelihood is used to estimate composite rate parameters:

- diversification rate, $r = (\lambda \mu)$
- relative extinction rate, $\varepsilon = (\mu/\lambda)$

It is not possible to estimate individual rate parameters (e.g., Kubo & Iwasa, 1995; Paradis, 2004)

Comparing absolute diversification rates across clades of different ages is largely invalid if $\mu > 0$ (e.g., Kubo & Iwasa)



Reliable (valid) parameter estimation REQUIRES

- accommodating variance in divergence-time estimates
- no bias in divergence time estimates
- large phylogenies
- · complete or phylogenetically unbiased species sampling
- demonstration that diversification has been constant
 - across lineages
 - through time

Practical Demonstration 1

Extinction rates can be estimated from molecular phylogenies

SEAN NEE, EDWARD C. HOLMES, ROBERT M. MAY AND PAUL H. HARVEY

A.F.R.C. Unit of Ecology and Behaviour, Department of Zoology, University of Oxford, South Parks Road, Oxford OX1 3PS, U.K.

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Evolution, 49(4), 1995, pp. 694-704

INFERRING THE RATES OF BRANCHING AND EXTINCTION FROM MOLECULAR PHYLOGENIES

Takuya Kubo and Yoh Iwasa

Department of Biology, Faculty of Science, Kyushu University, Fukuoka 812-81, Japan
E-mail: tkuboscb@mbox.nc.kyushu-u.ac.jp; yiwasscb@mbox.nc.kyushu-u.ac.jp

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INFERRING THE RATES CERRANGIUMS AND EXTINCTION EDOM

MOLE

Taki
Department of Biology, Faculty
E-mail: tkubosch@mbox.nc

Figure 3 clearly illustrates that, in general, different pairs of branching rates and extinction rates can give exactly the same pattern of ancestral phylogeny, expressed in terms of the number of ancestral lineages over various times. We have shown the equivalence relationship between the case with a time-dependent branching rate and a constant extinction rate and the second case with a constant branching rate and a time-dependent extinction rate. Generating the same ancestral phylogeny does not mean that these two processes are equivalent in evolution, because temporal change in the actual number of taxa, denoted by S(t), may greatly differ between these processes. This shows a clear limitation of the method of inferring past events from detailed knowledge, such as of molecular phylogenies, of the extant species only.

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Locating Shifts in Diversification Rate Through Time

Gamma Statistic (APE)

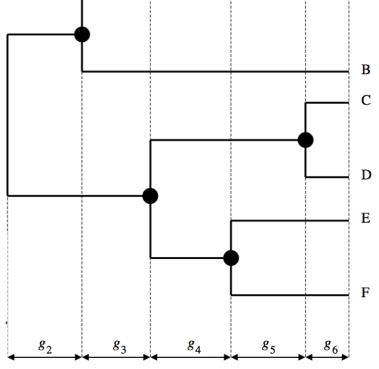
Under a Yule process, waiting times between speciation events are i.i.d. exponentially distributed random variables

If the process is constant, the sum of the waiting times will be a gamma distributed random variable

- the shape of the gamma is the speciation rate
- the scale of the gamma is (2N-2)

The gamma statistic exploits the Yule process, where the waiting times are maximally concentrated near the root

$$\gamma = \frac{\left(\frac{1}{n-2} \sum_{i=2}^{n-1} \left(\sum_{k=2}^{i} k g_k\right)\right) - \left(\frac{T}{2}\right)}{T \sqrt{\frac{1}{12(n-2)}}}, \ T = \left(\sum_{j=2}^{n} j g_j\right)$$



Any tree with a greater concentration of waiting times near the root must be rate variable (with decreasing rate)

Locating Shifts in Diversification Rate Through Time

Gamma Statistic (APE)

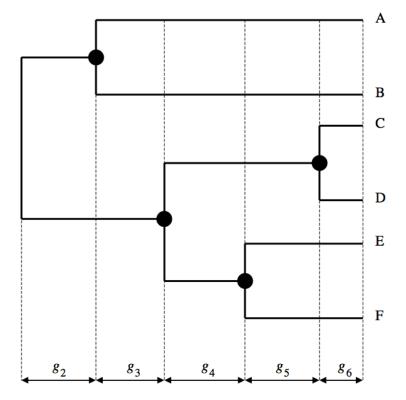
Incomplete species sampling can also create the illusion of temporally decreasing diversification rate

Accordingly, Monte Carlo simulation is required to generate a null distribution of the γ -statistic for incomplete trees

- assumes random species sampling
- departures from random sampling inflate FPR

Can detect diversification rate decreases, but not increases

Does not estimate parameters of the process: λ , μ , or the location of the temporal rate shift



Locating Shifts in Diversification Rate Through Time

Birth-Death Likelihood Method (LASER)

Concept

Fits various stochastic-branching process models to (parts of) the tree Selects among diversification models using AIC

Data

Vector of waiting times, x

Models

constant Yule

$$\bullet$$
 $(\lambda, \mu = 0)$

$$\bullet(\lambda,\mu=0,\lambda>\mu)$$

Yule-shift

$$\bullet(\lambda_1, \lambda_2, \mu = 0, t_s)$$

constant birth-death variable birth-death

•
$$(\lambda_1, \lambda_2 > 0; \mu_1, \mu_2 \ge 0; \epsilon_1 = \epsilon_2)$$

Birth-Death Likelihood Method (LASER)

Likelihood function

$$\mathcal{L}(\mathbf{x}|\epsilon, r) = \prod_{n=2}^{N-1} nr \exp[-nr(x_n - x_{n+1})] \times \frac{\{1 - \epsilon \exp[-r(x_{n+1})]\}^{n-1}}{\{1 - \epsilon \exp[-r(x_n)]\}^n}$$

Where
$$r = \lambda - \mu$$
; $\epsilon = \lambda/\mu$

Birth-Death Likelihood Method (LASER)

Model selection

Diversification models are compared using the AIC model selection criterion:

$$AIC = 2p - 2\log\mathcal{L}$$
 number of parameters maximum likelihood

The fit of the data to the best rate variable and rate constant models is calculated:

$$\Delta AIC_{RC} = AIC_{RC} - AIC_{RV}$$

The significance of the Δ AIC test statistic is assessed by Monte Carlo simulation under the null (Yule) stochastic-branching process model

Practical Demonstration 2

Methodological Concerns

Effects of branch-length estimation biases

 substitution-rate profile may lead to systematic estimation bias of deeper/shallower nodes (e.g., Revell et al., 2005)

Departure from random species sampling

 more realistic taxon sampling may produce spurious decrease in rate (e.g., Cusimano & Renner, 2010)

Effects of among-lineage rate variation

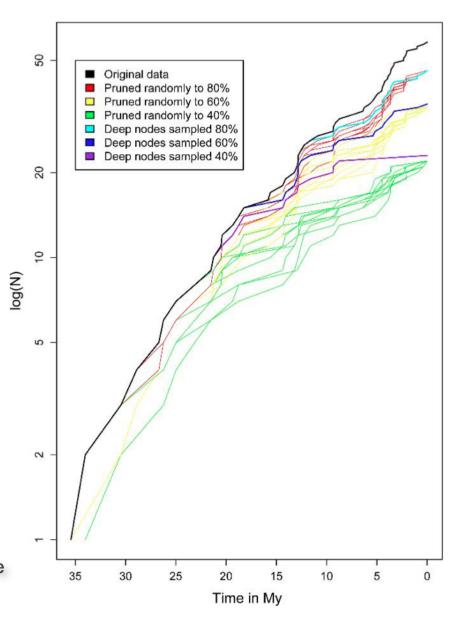
 violation of stochastically constant rates across lineages may produce spurious rate decreases

Effects of model-selection bigs

 reliance on AIC may lead to inflated rejection of simpler rate constant models

Effects of phylogenetic uncertainty

 reliance on point estimates of phylogeny and divergence times may render inferences unreliable



(Unsolicited) Methodological Advice



TreePar (Stadler, 2011)

Maximum-likelihood estimation of temporal shifts in diversification rate



TESS (Hohna, 2013)

Bayesian inference of temporal shifts in diversification rate

Five Fundamental Questions in the Study of Diversification Rates

- I. Estimating parameters of the branching process
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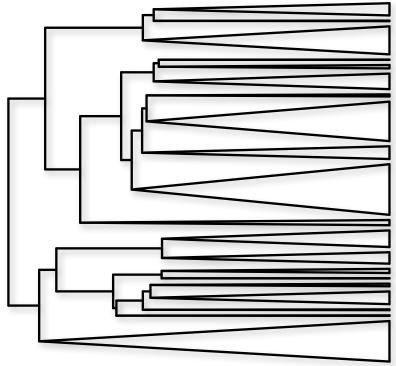
MEDUSA: Sequential AIC Model Fitting

Concept

Fits increasingly complex birth-death models to (parts of) the tree Selects among diversification models using stepwise AIC

Data

A dated phylogenetic tree T, with s terminal lineages Terminal lineage i represents n_i species.



MEDUSA: Sequential AIC Model Fitting

Likelihood function

Under constant diversification rates, the probability of observing a branch of length au that began at time t, conditional on the survival of its descendants is:

$$P(\tau \mid t, \lambda, \mu) = \frac{r \exp(-r\tau)}{1 - \epsilon \exp(-rt)}$$

and the probability of observing a subclade of stem age t with n descendants (conditional on n>0) is:

$$P(n \mid t, \lambda, \mu) = (1 - u) \times (u)^{n-1},$$
$$u = \frac{\exp(rt) - 1}{\exp(rt) - \epsilon}$$

MEDUSA: Sequential AIC Model Fitting

Likelihood function

To calculate the likelihood of the whole tree, we calculate the likelihood for each branch and each terminal unresolved subclade combine them as their product:

$$P(T, \boldsymbol{n} \mid \lambda, \mu) = \left(\prod_{\text{branches}} P(\tau_i \mid t_i, \lambda, \mu)\right) \times \left(\prod_{\text{triangles}} P(n_i \mid t_i, \lambda, \mu)\right)$$

MEDUSA: Sequential AIC Model Fitting

Likelihood function

Purportedly, this is valid even when diversification rates vary over branches and/or terminal unresolved subclades:

$$P(T, \boldsymbol{n} \mid \boldsymbol{\lambda}, \boldsymbol{\mu}) = \left(\prod_{\text{branches}} P(\tau_i \mid t_i, \lambda_i, \mu_i)\right) \times \left(\prod_{\text{triangles}} P(n_i \mid t_i, \lambda_i, \mu_i)\right)$$

MEDUSA: Sequential AIC Model Fitting

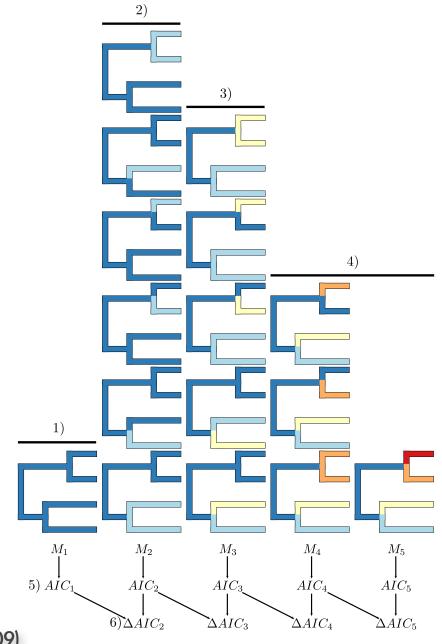
Model selection

Diversification models are compared using the AIC model selection criterion:

$$AIC = 2p - 2\log\mathcal{L}$$
 number of parameters maximum likelihood

The critical ΔAIC for choosing among models is arbitrary

MEDUSA: Sequential AIC Model Fitting
Algorithm

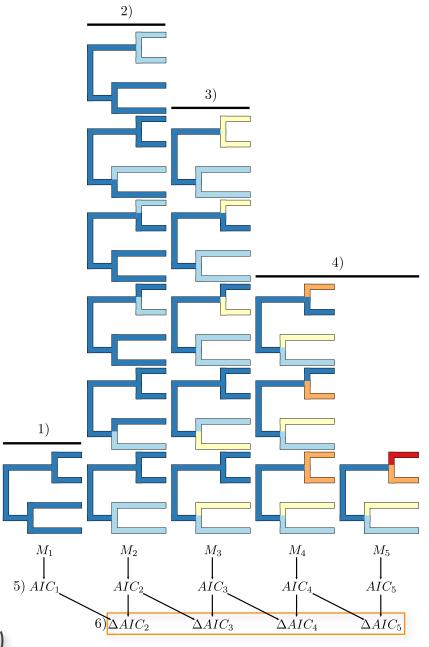


(Alfaro et al., 2009)

MEDUSA: Sequential AIC Model Fitting

Algorithm

- 1) Fit a one-rate model to the data.
- 2) Fit "every" two-rate model to the data.
- 3) Fit "every" three-rate model that contains the best two-rate model.
- 4) Keep fitting increasingly complex models.
- 5) Compute the AIC score for the best model in each level of model complexity.
- 6) Starting with the one-rate model, accept the next-most-complex model if the improvement in model fit is "good enough."



(Alfaro et al., 2009)

Practical Demonstration 3

Five Fundamental Questions in the Study of Diversification Rates

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Two fundamentally different types of questions:

Is there a general correlation between trait state and diversification rate? e.g., Are nectar spurs correlated with increase rates of diversification?

Is there a correlation between a specific event and and diversification rate?
e.g., Was a particular origin of nectar spurs in columbines correlated with increase rates of diversification?

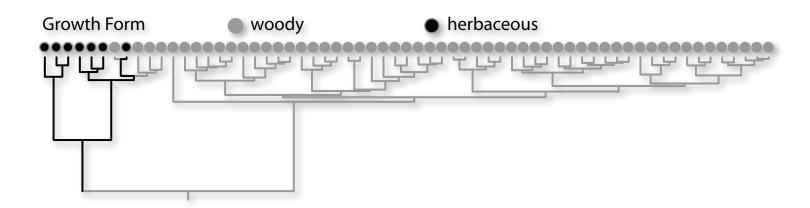
Recent advances for evaluating diversification-rate correlates

*SSE model; DiversiTree (Maddison et al., 2007; Fitzjohn et al., 2009; Fitzjohn, 2010...)

CVPPD; tRate (Moore & Donoghue, 2009)

Binary-State Speciation Extinction (BiSSE) Model

Motivation: Imagine that we see a preponderance of species with a given state

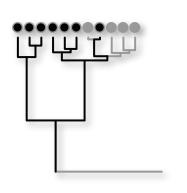


Explanations include:

increased woody speciation rate λ_{ullet} decreased woody extinction rate μ_{ullet} decreased herb speciation rate λ_{ullet} increased herb extinction rate μ_{ullet} biassed exchangeability rate q_{ullet}

Binary-State Speciation Extinction (BiSSE) Model

Solution: Specify a model that includes the parameters to tease these scenarios apart



 λ_0 speciation rate for state 0

 λ_1 speciation rate for state 1

 μ_0 extinction rate for state 0

 μ_1 extinction rate for state 1

 q_{01} rate of change to state 1

 q_{10} rate of change to state 0

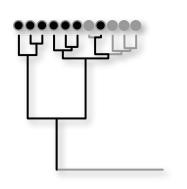
Solve numerically with PDEs:

$$D_{N0}(t + \delta t) = (1 - \mu_0 \delta t)[(1 - q_{01} \delta t)(1 - \lambda_0 \delta t)D_{N0}(t) + (q_{01} \delta t)(1 - \lambda_0 \delta t)D_{N1}(t) + (1 - q_{01} \delta t)(\lambda_0 \delta t)E_0(t)D_{N0}(t) + (1 - q_{01} \delta t)(\lambda_0 \delta t)E_0(t)D_{N0}(t) + (1 - q_{01} \delta t)(\lambda_0 \delta t)E_0(t)D_{N0}(t)] + (\mu_0 \delta t)0$$

$$D_{N1}(t+\delta t) = (1-\mu_1\delta t)[(1-q_{10}\delta t)(1-\lambda_1\delta t)D_{N1}(t) + (q_{10}\delta t)(1-\lambda_1\delta t)D_{N0}(t) + (1-q_{10}\delta t)(\lambda_1\delta t)E_1(t)D_{N1}(t) + (1-q_{10}\delta t)(\lambda_1\delta t)E_1(t)D_{N1}(t) + (1-q_{10}\delta t)(\lambda_1\delta t)E_1(t)D_{N1}(t)] + (\mu_1\delta t)0$$

Binary-State Speciation Extinction (BiSSE) Model

Solution: Specify a model that includes the parameters to tease these scenarios apart



 λ_0 speciation rate for state 0

 λ_1 speciation rate for state 1

 μ_0 extinction rate for state 0

 μ_1 extinction rate for state 1

 q_{01} rate of change to state 1

 q_{10} rate of change to state 0

Solve numerically with PDEs:

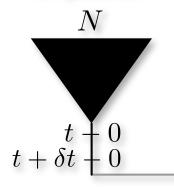
$$E_0(t + \delta t) = \mu_0 \delta t + (1 - \mu_0 \delta t)(1 - q_{01} \delta t)(1 - \lambda_0 \delta t)E_0(t) + (1 - \mu_0 \delta t)$$
$$(q_{01} \delta t)(1 - \lambda_0 \delta t)E_1(t) + (1 - \mu_0 \delta t)(1 - q_{01} \delta t)(\lambda_0 \delta t)E_0(t)^2$$

$$E_1(t + \delta t) = \mu_1 \delta t + (1 - \mu_1 \delta t)(1 - q_{10} \delta t)(1 - \lambda_1 \delta t)E_1(t) + (1 - \mu_1 \delta t)$$
$$(q_{10} \delta t)(1 - \lambda_1 \delta t)E_0(t) + (1 - \mu_1 \delta t)(1 - q_{10} \delta t)(\lambda_1 \delta t)E_1(t)^2$$

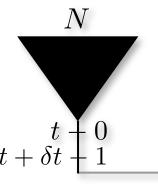
 $+(\mu_0\delta t)0$

Binary-State Speciation Extinction (BiSSE) Model

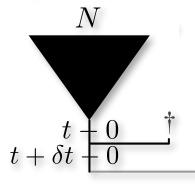
no state change, no speciation



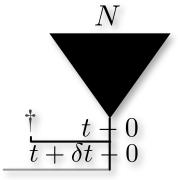
state change, no speciation



no state change, speciation & extinction



no state change, speciation & extinction



PDEs for branch probabilities:

nch probabilities:
$$D_{N0}(t+\delta t) = (1-\mu_0\delta t)$$
 $[(1-q_{01}\delta t)(1-\lambda_0\delta t)D_{N0}(t) + (q_{01}\delta t)(1-\lambda_0\delta t)D_{N1}(t) + (1-q_{01}\delta t)(\lambda_0\delta t)E_0(t)D_{N0}(t) + (1-q_{01}\delta t)(\lambda_0\delta t)E_0(t)D_{N0}(t)]$

no extinction in the interval no state change, no speciation state change, no speciation no state change, speciation & extinction no state change, speciation & extinction if extinct, zero probability of being observed

Binary-State Speciation Extinction (BiSSE) Model

extinction in interval

no state change, no speciation, extinction since t

state change, no speciation, extinction since t no state change, speciation, extinction of both since t

$$\begin{array}{cccc}
t & \overline{} & 0 \\
t + \delta t & \overline{\dagger} & 0
\end{array}$$

$$\begin{array}{cccc}
t & 0 \\
t + \delta t & 0
\end{array}$$

$$\begin{array}{cccc}
t & 1 \\
t + \delta t & 0
\end{array}$$

$$t + 1 \\ t + \delta t + 0$$

PDEs for branch probabilities:

$$E_0(t+\delta t) =$$

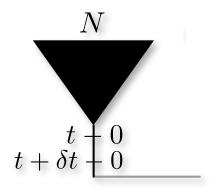
$$\mu_0 \delta t$$

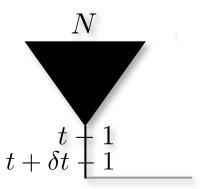
$$+(1 - \mu_0 \delta t)(1 - q_{01} \delta t)(1 - \lambda_0 \delta t)E_0(t) +(1 - \mu_0 \delta t)(q_{01} \delta t)(1 - \lambda_0 \delta t)E_1(t) +(1 - \mu_0 \delta t)(1 - q_{01} \delta t)(\lambda_0 \delta t)E_0(t)^2$$

extinction in the interval no state change, no speciation state change, no speciation no state change, speciation

Binary-State Speciation Extinction (BiSSE) Model

We start at the tips of the tree and move root-ward in small increments...





If N is a tip species with state 1:

$$D_{N0}(t_0) = 0$$

$$D_{N1}(t_0) = 1$$

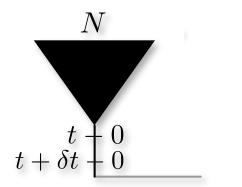
If N is a tip species with state 0:

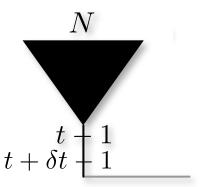
$$D_{N0}(t_0) = 1$$

$$D_{N1}(t_0) = 0$$

Binary-State Speciation Extinction (BiSSE) Model

solving coupled differential equations to obtain conditional branch probabilities...





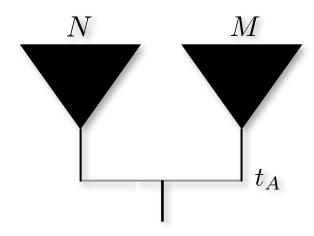
We take the derivative of the PDEs to shrink δt :

$$\frac{dD_{N0}}{dt} = -(\lambda_0 + \mu_0 + q_{01})D_{N0}(t) + q_{01}D_{N1}(t) + 2\lambda_0 E_0(t)D_{N0}(t)$$

$$\frac{dD_{N1}}{dt} = -(\lambda_1 + \mu_1 + q_{10})D_{N1}(t) + q_{10}D_{N0}(t) + 2\lambda_1 E_1(t)D_1(t)$$

Binary-State Speciation Extinction (BiSSE) Model

and then combine branch probabilities at internal nodes...

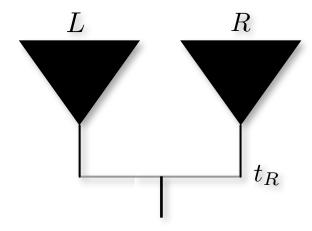


$$D_{A0}(t_A) = D_{N0}(t_A)D_{M0}(t_A)\lambda_0$$

$$D_{A1}(t_A) = D_{N1}(t_A)D_{M1}(t_A)\lambda_1$$

Binary-State Speciation Extinction (BiSSE) Model

and at the root scale the conditional probabilities by the stationary frequencies



$$D_0 = D_{R0}(t_R)\pi_0$$

$$D_1 = D_{R1}(t_R)\pi_1$$

How well can we do inference under the BiSSE model?

Davis et al. BMC Evolutionary Biology 2013, 13:38 http://www.biomedcentral.com/1471-2148/13/38



RESEARCH ARTICLE

Open Access

Exploring power and parameter estimation of the BiSSE method for analyzing species diversification

Matthew P Davis^{1*}, Peter E Midford² and Wayne Maddison³

How well can we do inference under the BiSSE model?

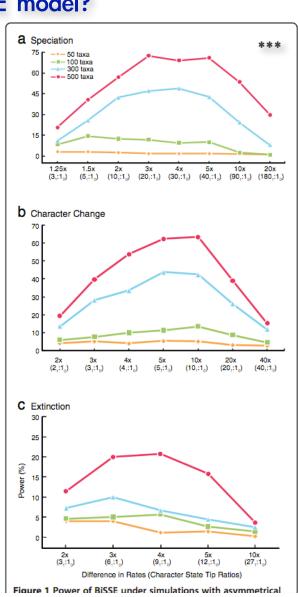
Set a:
$$\lambda_{ullet}
eq \lambda_{ullet}$$
 $\mu_{ullet} = \mu_{ullet}$ $q_{ullet} = q_{ullet}$

Set b:
$$\lambda_{ullet} = \lambda_{ullet}$$
 $\mu_{ullet} = \mu_{ullet}$ $q_{ullet} \neq q_{ullet}$

Set c:
$$\lambda_{ullet} = \lambda_{ullet}$$
 $\mu_{ullet} \neq \mu_{ullet}$ $q_{ullet} = q_{ullet}$

***Assuming no phylogenetic uncertainty

Davis et al. (BMC Biology, 2013)



a Speciation

How well can we do inference under the BiSSE model?

Conclusion

The power of the BiSSE likelihood method to test hypotheses of rate asymmetry is susceptible to both tree size and variation in parameter rates. Overall, power of the BiSSE method is low if the tree size is below 300 taxa, and investigators should take special care to investigate the power of their results if applying the BiSSE method to topologies with fewer than 300 tips. Power is increased when estimating fewer parameters, so utilizing a four parameter model to test hypotheses may be preferable if appropriate.

This study indicates that contrary to the hope expressed in Maddison [20], the problem of confounding effects can still occur while estimating process parameters simultaneously if there is low sample size and/or high tip ratio bias. Under scenar-

Practical Demonstration 4

And now for some complicated models...meet the *SSE family!

BiSSE (Binary-State Speciation Extinction): Maddison et al. (Syst Biol, 2007)

Two states, 6 parameters

MuSSE (Multi-State Speciation Extinction): Fitzjohn et al. (Syst Biol, 2009)

• $(2^N-2)+2N$ parameters

QuaSSE (Quantitative-State Speciation Extinction): Fitzjohn (Syst Biol, 2010)

lots and lots of parameters

GeoSSE (Geographic-State Speciation Extinction): Goldberg et al. (Syst Biol, 2011)

even more parameters!

BiSSEness (BiSSE-Node Enhanced State Shift): Magnuson-Ford & Otto (Am Nat, 2012)

two states, 10 parameters

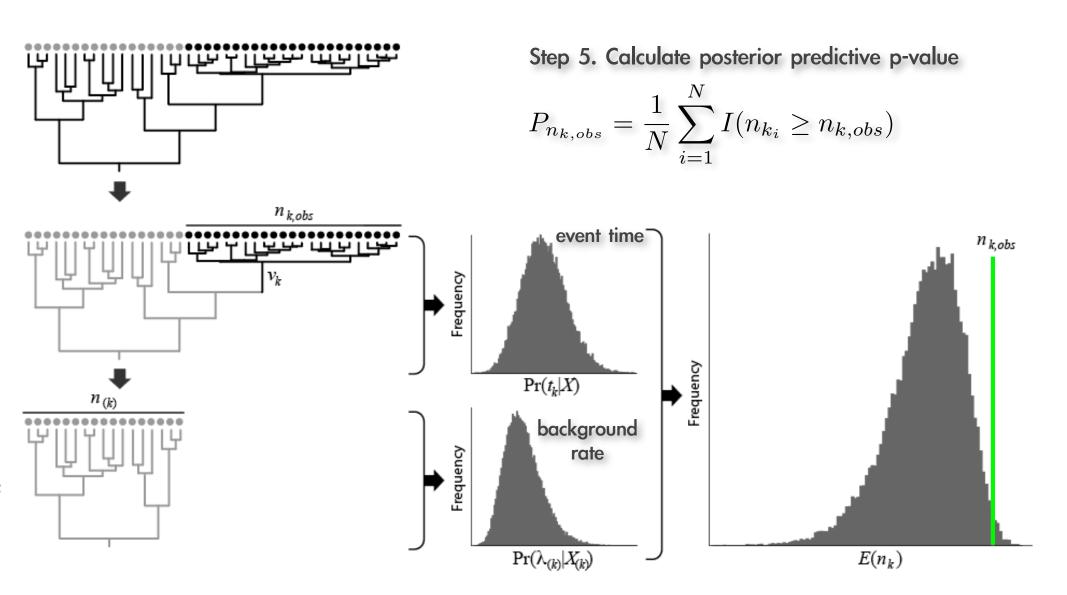
Recent advances for evaluating diversification-rate correlates

*SSE model; DiversiTree (Maddison et al., 2007; Fitzjohn et al., 2009; Fitzjohn, 2010...)

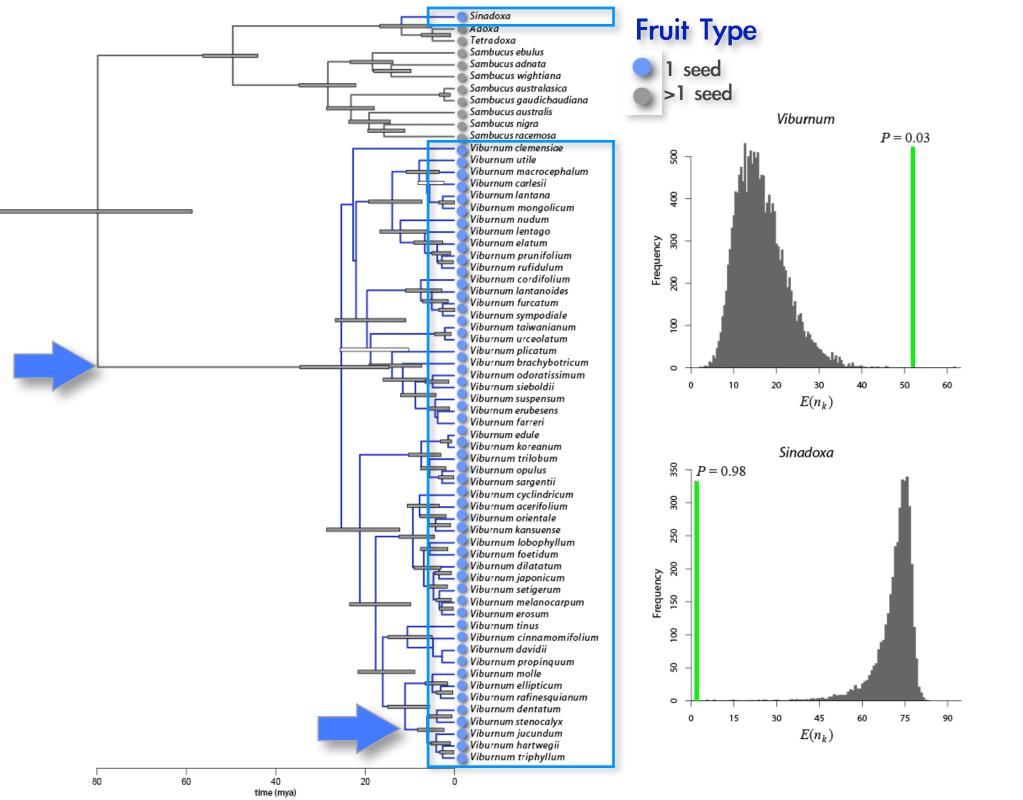


CVPPD; tRate (Moore & Donoghue, 2009)

Cross-Validation Predictive Densities



Moore & Donoghue (PNAS, 2009)



Summary: Some General Advice for Exploring Diversification Rates

- 1. Expectations under SBP models are diffuse to a degree that defies intuition this makes it difficult to detect departures from stochastic expectations
- 2. When using methods that entail SBP models for estimation it's critical to: carefully assess model fit/adequacy carefully assess our ability to reliably estimate under the assumed model
- 3. It's important to accommodate various sources of phylogenetic uncertainty inferences based on point estimates are unlikely to be reliable
- 4. The statistical behavior of many recent methods is poorly characterized power analyses may be useful for assessing the ability of methods to make the desired inferences from your data
- 5. Make an effort to understand—and assess—the (implicit) assumptions the assumptions are often cryptic, critical and frequently violated in real data

Five Fundamental Questions in the Study of Diversification Rates

- I. Estimating parameters of the branching process
- II. Identifying significant diversification rate shifts through time
- III. Locating significant diversification rate shifts along branches
- IV. Evaluating correlates of differential diversification rates
- V. Detecting significant diversification rate variation across the tree

Detecting Diversification Rate Variation Across Branches

Whole-Tree Model-Based Methods

(Chan & Moore, 2002; Moore, Chan & Donoghue, 2004)

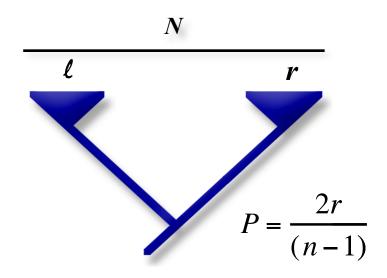
Topological approach

Combines individual ERM nodal probabilities over internal nodes as the product, $M \square$, sum, $M \Sigma$, which may be weighted by the sample size of each node, $M^* \square$, sum, $M^* \Sigma$

Significance estimated by Monte Carlo simulation of the null distribution of the test statistic under an ERM stochastic branching process

Power: HIGH

- + statistically robust (accommodates phylogenetic uncertainty, polytomies)
- + can accommodate incomplete taxon sampling
- + incorporates more of the tree
- does not identify anomalously large/small groups



$$\Pi^* = \frac{\sum_{i=1}^{n-1} \ln(n_i) \ln(P_i)}{\sum_{i=1}^{n-1} \ln(n_i)} \qquad \Sigma^* = \frac{\sum_{i=1}^{n-1} \ln(n_i) P_i}{\sum_{i=1}^{n-1} \ln(n_i)}$$