Outline	Basics	Models	Likelihoods	

# Efficient Likelihood Estimation for Growth Models

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Outline	Basics	Models	Likelihoods	
Outline				
Outime				

Reasons for considering probability models of phylogenetic trees and generate random trees with models :

- Understand speciation and extinction.
- Do predictions that models make about tree shape which can be used to test hypothesis concerning speciation.
- Testing models: how likely is it that model reconstructs a observed tree

Aim: infer how diversity has arisen.

How: fitting stochastic models to tree data.

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#### Databases of Phylogenetic Trees

#### TreeBASE

- 5212 trees
- leaves are species
- amount of leaves: 4...960
- monotomies and polytomies solved randomly

#### PANDIT

- 46428 trees
- leaves are proteins
- amount of leaves: 2...5121
- monotomies and polytomies solved randomly

Outline	Basics	Models	Likelihoods	
FRM mo	odel			

Null model of growing trees (simple continous-time branching process).

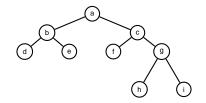
Assumption: Each branch has an equal probability of splitting.

**Initialize** t = 0: Generate root with target number of leaves *I*.

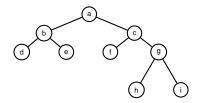
**Iterate** while  $\exists$  leaf *I* with label n > 1:

- Replace leaf *I* by a cherry.
- Assign new leaves with labels *i* and n-i.
- Probability that the left sister clade contains *i* taxa is independent of *n*

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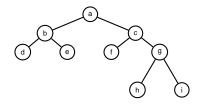


Outline	Models	Likelihoods	



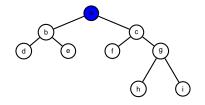
$$L_{\text{ERM}}(T) = \prod_{x \in I(T)} p_{\text{A}}(s(\text{left}(x))|s(x))$$

Outline	Basics	Models	Likelihoods	



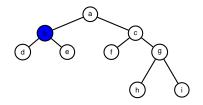
 $L_{ERM}(T) =$ 

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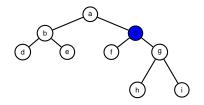
 $L_{ERM}(T) = p_a(2|5)$ 

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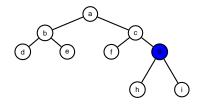
 $L_{\textit{ERM}}(T) = p_a(2|5) \cdot p_b(1|2) \cdot$ 

Outline	Basics	Models	Likelihoods	



 $L_{ERM}(T) = p_a(2|5) \cdot p_b(1|2) \cdot p_c(1|3) \cdot$ 

Outline	Basics	Models	Likelihoods	



 $L_{ERM}(T) = p_a(2|5) \cdot p_b(1|2) \cdot p_c(1|3) \cdot p_g(1|2)$ 

Outline	Basics	Models	Likelihoods	
Age mo	del			

**Idea:** The longer species *i* has not been involved in speciation, the less likely it is to do so now.

**Initialize:** Set time t = 0, generate root node.

Iterate:

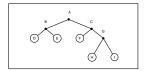
- Increment time t.
- From the set of leaves, choose leaf / with probability

$$p_i \propto (t-t_l)^{-1}$$

• Replace *I* by a cherry.

t = number of leaves = current time;  $t_l$  creation time of leaf l

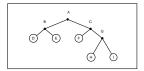
Outline	Models	Likelihoods	



# $\begin{array}{l} t=0\\ L_{t=0}=\left\{ A_{age=0}\right\} \end{array}$



Outline	Models	Likelihoods	

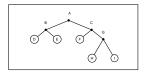


$$t = 1$$
  
old :  $L_{t=0} = \{A_{age=0}\}$   
new:  $L_{t=1} = \{B_{age=0}, C_{age=0}\}$ 

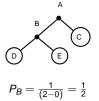


$$P_A = \frac{1}{(1-0)} = 1$$

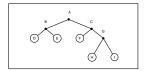
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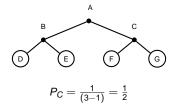
$$t = 2$$
  
old :  $L_{t=1} = \{B_{age=0}, C_{age=0}\}$   
new:  $L_{t=2} = \{C_{age=1}, D_{age=0}, E_{age=0}\}$ 



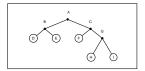
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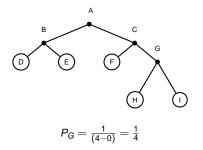
$$\begin{split} t &= 3 \\ \text{old} : \textit{L}_{t=2} = \{\textit{C}_{age=1},\textit{D}_{age=0},\textit{E}_{age=0}\} \\ \text{new: } \textit{L}_{t=3} = \{\textit{D}_{age=1},\textit{E}_{age=1},\textit{F}_{age=0},\textit{G}_{age=0}\} \end{split}$$



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$$t = 4 old : L_{t=3} = \{ D_{age=1}, E_{age=1}, F_{age=0}, G_{age=0} \} new: L_{t=4} = \{ D_{age=2}, E_{age=2}, H_{age=0}, I_{age=0} \}$$



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# Likelihood - Exact Calculation

#### For ERM model

$$L_{\text{ERM}}(T) = \prod_{x \in I(T)} p_{A}(s(\text{left}(x))|s(x))$$

- For AGE model
  - Calculate P<sub>AGE</sub>(T) exactly by adding up probabilities of all sequences of branchings for T

$$L_{\rm AGE}(T) = \sum_{s \in S_c(t)} p(s, T)$$

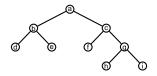
with

$$p(s,T) = \prod_{i=2}^{n-1} \frac{(s(i) - s(m(i))^{-1}}{\sum_{j \in B(s,s(i))} (s(i) - s(m(j))^{-1}}$$

and

$$B(s,t) = \{j \in I \setminus \{1\} \mid s(m(j)) < t < s(j)\} \cup \{j \in A \setminus I \mid s(m(j)) < t\}$$

Outline	Basics	Models	Likelihoods	



$$L_{\rm AGE}(T) = \sum_{s \in S_c(t)} p(s, T)$$

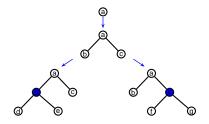
Outline	Models	Likelihoods	

0

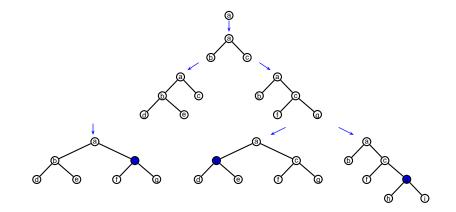
Outline	Basics	Models	Likelihoods	



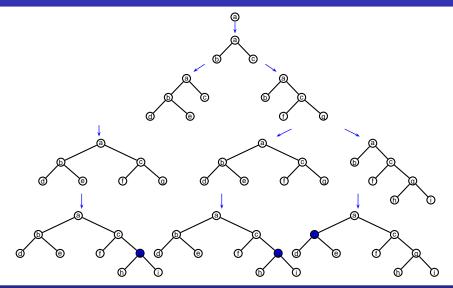
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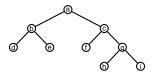
Outline	Models	Likelihoods	



Outline	Basics	Models	Likelihoods	



Outline	Models	Likelihoods	



$$L_{\text{AGE}}(T) = \sum_{s \in S_c(t)} p(s, T)$$

 $L_{AGE}(T) = p((b, c, g), T) + p((c, b, g), T) + p((c, g, b), T)$ 

Outline	Basics	Models	Likelihoods	

Naive ways of sampling:

Enough calculation capacity

Or

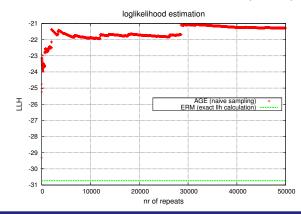
- B is set of all branching sequences leading to "target tree"
- $C \subseteq B$  is sample of *B* with |C| << |B|
- Each possible path has same probability

$$L = \frac{|B|}{|C|} * \sum_{\vartheta \in C} p(\vartheta)$$

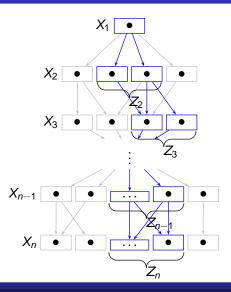
Outline	Basics	Models	Likelihoods	

What if |Z| is too large?

Naive Approach: Sample each trajectory with equal probability. Problem: # trajectories  $\uparrow$  and # samples  $\downarrow \mid$  small  $Z_n \rightsquigarrow L(\Theta \in Z_n) \downarrow$ 



Outline	Basics	Models	Likelihoods	



 $\Rightarrow$  *q*-dynamics restricted to  $Z_1, \ldots Z_n$ 

$$q_i(y|x) = \frac{p_i(y|x)}{s(x)},$$

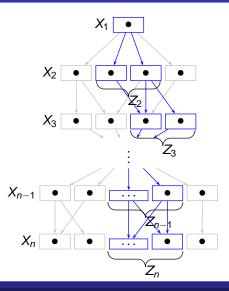
 $i \in \{1, \dots, n-1\}, x \in Z_i, y \in Z_{i+1}$ 

 $\Rightarrow$  normalization

$$s(x) = \sum_{y \in Z_i+1} p(y|x) .$$

$$S(\Theta) = \prod_{i=1}^{n-1} q_i(\Theta_{i+1}|\Theta_i)$$

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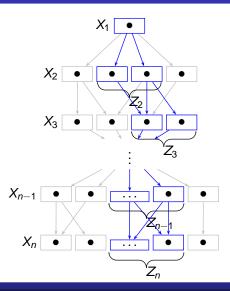
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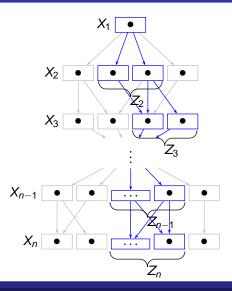
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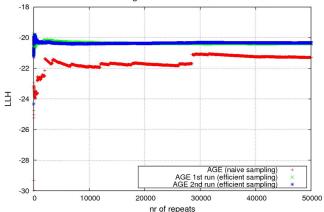
Assign "output" A for each trajectory  $\Theta \in Z$ 

$$A(\Theta) = \prod_{i=1}^{n-1} s(\Theta_i)$$
.

Expectation value of *A* over trajectories under *q*-dynamics = probability *L* that *p*-dynamics ends up in the target set  $Z_n$ .

$$\Rightarrow \langle A \rangle = L$$

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#### loglikelihood estimation

Outline	Basics	Models	Likelihoods	Summary
Summary				

- Sample loglikelihood of growth models using an importance sampling method.
- Applicable if for each  $i \in \{1, ..., n-1\}$  and all states  $x \in X_i$ 
  - it can be decided efficiently (fast) if  $x \in Z_i$  or not.
  - 2 the normalization s(x) can be computed efficiently.
- Requirements are fullfilled by the models of tree growth
   ⇒ Use the most probable branching sequences only.

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#### Thanks to Konstantin

and



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Expectation value of A over trajectories under q-dynamics = probability L that the p-dynamics ends up in the target set  $Z_n$ , as shown by the following sequence of term replacements.

$$\langle A \rangle = \sum_{\Theta \in Z} S(\Theta) A(\Theta)$$
 (1)

$$= \sum_{\Theta \in Z} \prod_{i=1}^{n-1} q_i(\Theta_{i+1} | \Theta_i) \prod_{j=1}^{n-1} s(\Theta_j)$$
(2)

$$= \sum_{\Theta \in \mathbb{Z}} \sum_{i=1}^{n-1} q_i(\Theta_{i+1} | \Theta_i) s(\Theta_i)$$
(3)

$$= \sum_{\Theta \in \mathcal{Z}} \prod_{i=1}^{n-1} p_i(\Theta_{i+1} | \Theta_i)$$
(4)

$$= \sum_{\Theta \in Z} R(\Theta)$$
 (5)

$$= \sum_{\Theta \in X} R(\Theta) \tag{6}$$

$$=$$
 L (7)