

1 The error in Bayesian phylogenetic reconstruction 2 when speciation co-occurs

3 Giovanni Laudanno¹, Richèl J.C. Bilderbeek¹, and Rampal S.
4 Etienne¹

5 ¹Groningen Institute for Evolutionary Life Sciences, University of
6 Groningen, Groningen, The Netherlands

7 November 27, 2018

8 **Abstract**

9
10 **Keywords:** computational biology, evolution, phylogenetics, Bayesian anal-
11 ysis, tree prior [RJCB: Have you already looked up for a target journal?]
12 [GL: Honestly I have literally no idea how to select a good journal
13 for this kind of article.] [RJCB: May I suggest we aim for Molecular
14 Phylogenetics and Evolution, the same journal as the raket paper?]

15 1 Introduction

- 16 • There are many contemporary tools that provide the possibility to infer a
17 phylogeny from genetic data (DNA, RNA, proteins). A popular Bayesian

18 phylogenetic tool is called BEAST (Drummond & Rambaut 2007) and its
19 cousin BEAST2 (Bouckaert *et al.* 2014).

- 20 • BEAST is very flexible, providing the user with the option to set up all
21 possible phylogenetic priors (e.g. site/clock/speciation model).
- 22 • However, currently available priors can be not suitable to analyze some
23 specific datasets. With this work we aim to test whether or not the im-
24 plementation of a new prior model is beneficial to study a specific kind of
25 diversification process.
- 26 • BEAST2 gives us the possibility to introduce new tree priors to infer
27 phylogenies based on different assumptions on how the speciation process
28 takes place.
- 29 • One of such speciation processes is the multiple birth hypothesis, a new
30 model (described below) and thus currently absent in BEAST.
- 31 • The Multiple birth hypothesis can be useful to explain a phenomenon
32 that has always puzzled evolutionary biologists: what are the drivers of
33 the diversification processes for those phylogenies that show an impressive
34 amount of speciation events in relatively short times? The (constant-rate)
35 birth-death (BD) model embodies the common assumption that only a
36 single speciation event can occur at any given time. The multiple-birth-
37 death (MBD) model relaxes this assumption, allowing events in which
38 large-scale environmental changes lead to a great number of species in
39 relatively short time intervals. Such a hypothesis may be a better fit to
40 describe the burst in systems like cichlid fish diversification in the African
41 Great Lakes: Malawi, Tanganyika and Victoria (Janzen *et al.* 2016, Janzen
42 *et al.* 2017).

- 43 • However, it may be that current BD tree priors are good enough at de-
44 tecting such events, with a (preferred) lower level of complexity. If this is
45 the case one should always be more keen to adopt the simplest model.
- 46 • Here we present our study with the aim of exploring when using a more
47 complex MBD tree prior is warranted.
- 48 • We hypothesize that the error made today, using BD tree priors, increases
49 with an increased number or stronger effect of multiple birth events. This
50 is straightforward: without multiple birth events or such event having no
51 effect, the MBD model falls back to a BD model. We expect larger errors
52 when we deviate more from the BD model's assumptions.
- 53 • Additionally, we hypothesize MBD having a stronger effect if the normal
54 speciation process is less pronounced. The more speciations are caused by
55 the BD process, there are relatively less multiple-birth events.
- 56 • We expect the effect of extinction rates to be neutral, as extinctions will
57 hit lineages created by both speciation processes equally.
- 58 • Summarized, we expect the error made be correlated to the number of
59 species created by the multiple-birth process over the total number of
60 species created:

$$< e > = f\left(\frac{n_{taxa}^{MBD}}{n_{taxa}^{BD} + n_{taxa}^{MBD}}\right) \quad (1)$$

61 Where $< e >$ denotes the expected error, f is a monotonously increas-
62 ing function of unknown shape, n_{taxa}^{MBD} is the number of taxa created in
63 multiple-birth events and n_{taxa}^{BD} is the number of taxa created by the stan-
64 dard BD speciation process.

65 2 Methods

66 2.1 Model

- 67 • Current phylogenetic tools assume that only a single speciation event can
68 occur at any given time. While this assumption is useful to construct
69 a wide variety of successful models (e.g Maddison *et al.* 2007, Valente
70 *et al.* 2015, Etienne *et al.* 2012, Etienne *et al.* 2014), they disallow for
71 environmental changes that trigger speciations in multiple clades at a same
72 point in time.
- 73 • The (constant-rate) birth-death (BD) model embodies the common as-
74 sumption that only a single speciation event can occur at any given time.
75 The multiple-birth-death (MBD) model relaxes this assumption, allowing
76 events in which large-scale environmental changes lead to a great num-
77 ber of species in relatively short time intervals. Such hypothesis can be
78 useful to describe, for example, systems like cichlid fish diversification in
79 the African Great Lakes: Malawi, Tanganyika and Victoria (Janzen *et al.*
80 2016, Janzen *et al.* 2017).
- 81 • In the MBD model, parameters λ and μ correspond, respectively, to the
82 common per-species speciation and extinction rates present also in the
83 standard BD model. Additionally, MBD relies on two additional param-
84 eters. Parameter ν is the rate at which an environmental change is trig-
85 gered. When such event is triggered, all species present in the phylogeny
86 at that moment have a probability q to speciate at that time, which is
87 independent on λ . Polytomies are not allowed in such process as each
88 species can speciate only once at the time.
- 89 • It is also possible to write down a likelihood function for such processes
90 as in Laudanno 2018.

91 2.2 Simulations

- 92 • To prove our hypothesis we simulate two twin datasets. All the simulations
93 are produced in continuous time, using the Doob-Gillespie algorithm.
 - 94 • We start simulating $N_S = 1000$ MBD trees. From each MBD tree, a
95 DNA sequence alignment is simulated. For each sequence alignment we
96 then perform a Bayesian analysis to recover a posterior distribution of
97 trees, each composed of N_P phylogenies. Such analysis is performed using
98 the 'pirouette' package (Bilderbeek 2018) to call the BEAST2 tool suite
99 from R. We let the Bayesian analysis assume a BD prior in both cases, to
100 investigate the extent of the error we make under this assumption.
 - 101 • For each tree generated under the MBD model we aim to generate a
102 "twin" tree under the BD model. With the word "twin" we denote a
103 tree generated starting from the respective MBD tree, in order to perform
104 a fair comparison with it. This operation has to be done, because we
105 want to compare two trees that are generated by different processes. To
106 do so we infer the parameters λ_{BD} and μ_{BD} from the MBD maximizing
107 the likelihood under a BD model. To perform this operation we use the
108 function "bd_ML" from the package "DDD" (Etienne *et al.* 2012).
 - 109 • We then exploit such parameters to generate a BD tree using the function
110 "tess.sim.taxa.age" from the package "TESS" (Hhna 2013). We simu-
111 late the tree in such a way the new tree has the same number of tips and
112 the same crown age as the MBD tree. We furthermore require that the
113 BD tree conserve the topology of the MBD tree.
- 114 We want the MBD and twin BD trees to contain the same amount of in-
115 formation, i.e. the same number of DNA mutations and the same number
116 of taxa at the present:

$$m_{MBD} = m_{BD} \quad (2)$$

117 The expected number of mutations m of a phylogeny with crown age $-T$
 118 (with $T > 0$) in fact is given by [RJCB: So one of use likes '-T', the
 119 other likes 'T'. How to resolve this?]

$$m = L \cdot \rho \cdot \int_0^T n(t) dt \quad (3)$$

120 where L is the number of DNA nucleotides, ρ is the per-site per-species
 121 mutation rate and $n(t)$ the number of species at each time.

122 The parameter we'll tune is ρ ... [RJCB: elaborate here :-)]

123 Since we cannot know $n_{BD}(t)$ before running simulations we need to re-
 124 place it with a proxy. For this reason we will use the average number of
 125 species in time according to the BD model. It's well known that this is
 126 equal to [GL: insert proper citation]

$$\langle n_{BD} \rangle (t) = n_0 \cdot e^{(\mu_{BD} - \lambda_{BD})t} \quad (4)$$

127 where $n_0 = n_{BD}(-T) = n_{MBD}(-T)$ is the initial number of species at
 128 the crown age. From 2, 3 and 4 follows:

$$m_{MBD} = L \cdot \rho \cdot \int_0^T \langle n_{BD} \rangle (t) dt = L \cdot \rho \cdot n_0 \cdot \left[\frac{e^{(\mu_{BD} - \lambda_{BD})T} - 1}{\mu_{BD} - \lambda_{BD}} \right] \quad (5)$$

129 If we set $\mu_{BD} = \mu_{MBD}$ and reverse this relation we can extrapolate the
 130 value of λ_{BD} to use to generate BD trees.

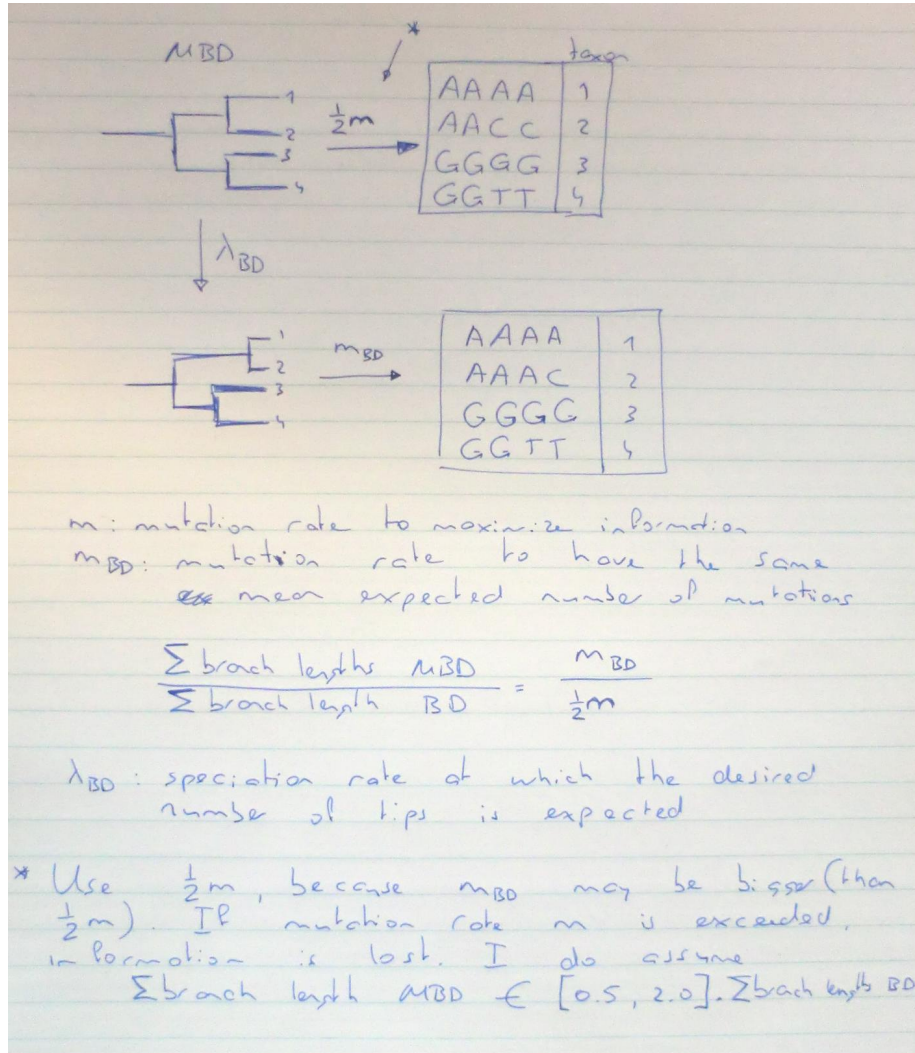


Figure 1: How to create twin trees and alignments. From a focal MBD tree, a twin tree is produced as such: (1) estimate the λ_{BD} to get the same expected number of tips, (2) simulate a BD tree with that amount of tips (discard trees with different number of tips), (3) estimate a mutation rate to get an alignment with the same expected number of mutations, (4) simulate alignments with that amount of mutations (discard those that don't, the picture shows an alignment that should be discarded)

- We explained how we set the parameters for each twin BD tree. Using this rules we generate a BD dataset. We repeat the analysis, producing alignments for each tree and subsequently using BEAST to produce a posterior for each of them.

2.3 Measuring the inference error

- So far we have simulated two datasets of trees under the two models: $\{T_i^{BD}\}_{i=1}^{N_S}$ and $\{T_i^{MBD}\}_{i=1}^{N_S}$. We used them to generate a dataset of alignments for each model: $\{X_i^{BD}\}_{i=1}^{N_S}$ and $\{X_i^{MBD}\}_{i=1}^{N_S}$. From each dataset we produced a posterior distribution from a BD prior: $P_i(\theta|X_i^{BD}, BD)$ and $P_i(\theta|X_i^{MBD}, BD)$. **[GL: 1) We might want to rename the models, e.g. BD = (0) and MBD = (1). These names with capital letters are too big and ugly;] [RJCB: I would strongly prefer MBD and BD, as I feel replacing the big ugly capital letters by short pretty numbers hurts readability even more]**
 - To compare the results for the two models we measure the inference error using the nLTT statistic between known/true tree and posterior/inferred trees (Janzen 2015). To obtain such statistics the procedure is the following:
 - From each tree $T_{i,j}^M$ (with $j = 1, \dots, N_S$) belonging to the posterior $P_i(\theta|X_i^M, BD)$ and relative to the model M , we extrapolate the lineage-through-time (LTT), in other words we measure the number of species as a function of time $n_{i,j}(t)$. To allow a comparison we normalize dividing by the maximum number of species of each tree, i.e. the number of tips at the present $N_{i,j}(t) = \frac{n_{i,j}(t)}{n_{i,j}^{max}}$. We then define the nLTT measure as
$$nLTT_{i,j} = \int_0^T |N_{i,j}(t) - N_{T_i}| dt$$

156 [GL: I am running out of letters :(] [RJCB: Haha! I suggest to
 157 use the same equation and symbols as equation 1 in the nLTT
 158 article of Janzen, Hoehna and Etienne, 2015:]

$$\Delta nLTT = \int_0^1 |nLTT_1(t) - nLTT_2t| dt$$

159 2.4 Model selection

160 3 Results

- 161 •
- 162 •

163 References

- 164 Bilderbeek, R.J. (2018) *pirouette: create a posterior from a phylogeny*.
- 165 Bouckaert, R., Heled, J., Kühnert, D., Vaughan, T., Wu, C.H., Xie, D., Suchard,
 166 M.A., Rambaut, A. & Drummond, A.J. (2014) Beast 2: a software platform
 167 for bayesian evolutionary analysis. *PLoS computational biology*, **10**, e1003537.
- 168 Drummond, A.J. & Rambaut, A. (2007) Beast: Bayesian evolutionary analysis
 169 by sampling trees. *BMC evolutionary biology*, **7**, 214.
- 170 Etienne, R.S., Haegeman, B., Stadler, T., Aze, T., Pearson, P.N., Purvis, A.
 171 & Phillimore, A.B. (2012) Diversity-dependence brings molecular phylogenies
 172 closer to agreement with the fossil record. *Proc R Soc Lond B: Biol Sci*, **279**,
 173 1300–1309.
- 174 Etienne, R.S., Morlon, H. & Lambert, A. (2014) Estimating the duration of
 175 speciation from phylogenies. *Evolution*, **68**, 2430–2440.

- 176 Hhna, S. (2013) Fast simulation of reconstructed phylogenies under global time-
177 dependent birth–death processes. *Bioinformatics*, **29**, 1367–1374.
- 178 Janzen, T. (2015) *nLTT: Calculate the NLTT Statistic*. R package version 1.1.
- 179 Janzen, T., Alzate, A., Muschick, M., Maan, M.E., van der Plas, F. & Etienne,
180 R.S. (2017) Community assembly in lake tanganyika cichlid fish: quantifying
181 the contributions of both niche-based and neutral processes. *Ecology and*
182 *Evolution*, **7**, 1057–1067.
- 183 Janzen, T., Alzate, A., Muschick, M., van der Plas, F. & Etienne, R.S. (2016)
184 Stochastic processes dominate community assembly in cichlid communities in
185 lake tanganyika.
- 186 Laudanno, G. (2018) *MBD: Multiple Birth Death Diversification*. R package
187 version 0.1.
- 188 Maddison, W.P., Midford, P.E. & Otto, S.P. (2007) Estimating a binary char-
189 acter’s effect on speciation and extinction. *Systematic Biology*, **56**, 701–710.
- 190 Valente, L.M., Phillimore, A.B. & Etienne, R.S. (2015) Equilibrium and non-
191 equilibrium dynamics simultaneously operate in the galápagos islands. *Ecol-*
192 *ogy Letters*, **18**, 844–852.