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Estimating phylogenetic trees from genome-scale data

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Abstract

The heterogeneity of signals in the genomes of diverse organisms poses challenges for traditional phylogenetic analysis. Phylogenetic methods known as ‘species tree methods’ have been proposed to directly address one important source of gene tree heterogeneity, namely the incomplete lineage sorting that occurs when evolving lineages radiate rapidly, resulting in a diversity of gene trees from a single underlying species tree. Here we review theory and empirical examples that help clarify conflicts between species tree and concatenation methods, and misconceptions in the literature about the performance of species tree methods. Considering concatenation as a special case of the more general case provided by the multispecies coalescent model (MSC) helps explain differences in the behavior of the two methods on phylogenomic data sets. Recent work suggests that species tree methods are more robust than concatenation approaches to some of the classic challenges of phylogenetic analysis, including rapidly evolving sites in DNA sequences and long branch attraction. We show that approaches such as binning, designed to augment the signal in species tree analyses, can distort the distribution of gene trees and are inconsistent. Computationally efficient species tree methods incorporating biological realism are a key to phylogenetic analysis of whole genome data.

Keywords: bias-variance dilemma, transcriptome, isochore, anomaly zone, recombination.

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3 The emergence of phylogenomic data provides unprecedented opportunities to resolve
4 challenging phylogenies of species and, ultimately, the Tree of Life. In the last few years, a
5 number of phylogenetic and population genetic methods for analyzing the evolutionary history of
6 whole genomes have emerged¹⁻⁴. These new methods are gradually replacing methods that were
7 once the bulwarks of evolutionary genomics and molecular ecology in the PCR-era. For
8 example, recently the classic isolation-with migration model of phylogeography, originally
9 introduced by Hey, Nielsen and others⁵⁻⁷ and widely used in likelihood and Bayesian formats,
10 has been updated to accommodate whole genome data^{8,9}. Like most methods in
11 phylogeography, these methods model genomic data as a series of unlinked or partially linked
12 loci whose histories are influenced by the underlying demographic history of the species in
13 question. The coalescent provides a robust and general framework for many of these new
14 genome-scale models in phylogeography.

15
16 Like models in phylogeography, genome-scale methods in phylogenomics are
17 undergoing a transition, grappling with the heterogeneity of signals that frequently emerge from
18 genome-scale data^{10,11}. Recent research has revealed a surprising array of such heterogeneous
19 signals, including variation among loci in base composition, evolutionary rate, and, perhaps most
20 conspicuously, topological congruence¹²⁻¹⁶. Indeed, mirroring early insights into gene tree
21 heterogeneity discovered in the 1980s in the context of phylogeography, gene tree heterogeneity
22 in phylogenetics has emerged as a ubiquitous element, particularly as the number of loci in
23 phylogenetic studies has increased¹⁰. Yet, surprisingly, whereas phylogeography has dealt with
24 this heterogeneity by acknowledging and modeling stochasticity – indeed, statistical
25 phylogeography has not known any other means of modeling such variation – for decades such
26 models made few inroads into phylogenetics. Even as heterogeneity in gene trees was

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3 acknowledged as a significant issue in phylogenetics¹⁷, concatenation or supermatrix methods
4 provided the main paradigm in which phylogenetic models were developed to deal with diverse
5 signals found in multilocus data¹⁸. Perhaps more intriguing, then, is that, even as such so-called
6 ‘species tree’ or coalescent models have been developed in the context of phylogenetics, they are
7 being embraced by phylogeneticists cautiously, or in some cases openly questioned^{19,20}. Such
8 caution and questioning is no doubt healthy, but it also suggests that, for some researchers, the
9 heterogeneity observed in gene trees is either deemed unimportant or inconsequential for
10 phylogenetic analysis, or that the models developed thus far to deal with this heterogeneity are
11 unsatisfying, incomplete or flawed.

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Phylogenomic data have intensified debates over whether concatenation or coalescent methods in phylogenomics are more appropriate for analyzing multilocus sequence data^{10,19,21,22}. Although recent phylogenomic studies suggest that the majority of relationships yielded by concatenation and coalescent trees are consistent with each other, or differ from each other without high statistical support^{15,16,23,24}, recent examples of highly supported conflicting relationships favored by concatenation and coalescent methods have highlighted the details, weaknesses, and assumptions of both sets of methods^{15,25-30}. The significant differences in performance of concatenation and coalescent methods in estimating species trees flow directly from the distinct assumptions on which the two methods are based^{17,31,32}. Perhaps more importantly, it can be shown that under certain conditions the coalescent model reduces to the concatenation model²² (see below), which can help explain the frequent similarities between concatenation and coalescent trees in empirical data analyses. Finally, in comparing concatenation and coalescent methods, important questions have been raised regarding the performance of coalescent methods under genetic forces such as within-gene recombination and

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3 gene flow, or issues with data, such as sampling effort and strategies, missing data, misrooting of
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5 gene trees, binning (concatenating) of multiple loci or errors in gene tree estimation^{19,20,33-37}.

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8 Whereas population genetic effects such as gene flow and recombination rarely figured in
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10 discussions of phylogenetic models in the supermatrix era, recent discussions of these topics
11
12 appear to be a direct result of the advent of coalescent methods and mark a growing appreciation
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14 by phylogeneticists of the links between population genetics and phylogenetics^{38,39}. Overall, the
15
16 current debates offer a glimpse of a field in transition, grappling with new signals and
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18 heterogeneity brought on by phylogenomics.
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22 In this review we discuss a number of recent trends in the application of coalescent
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24 models to phylogenetic analysis, and address some recent criticisms of such models. At its
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26 simplest, the multispecies coalescent model builds on the neutral coalescent model for single,
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28 isolated populations, in which the genealogy of sampled alleles follows probability distributions
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30 governed by simple demographic models, such as the Wright–Fisher model^{40,41}. The
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32 multispecies coalescent model treats each branch in a species tree as a single, neutral
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34 coalescent population, and, going backwards in time, keeps track of the number of gene
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36 lineages entering extant or ancestral populations, and exiting those populations as they
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38 merge with other ancestral populations in the species tree (Figure 1). These gene lineages
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40 ultimately comprise gene trees, which in turn provide the signal for estimating the overarching
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42 species tree that is usually the primary interest (Figure 1). Most coalescent models in
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44 phylogenomics assume simple models of instantaneous speciation, in which no gene flow occurs
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46 after species begin to diverge. Moreover, these models assume complete neutrality, no
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48 recombination within loci and free recombination between loci, such that loci can be treated as
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50 independent neutral replicates conditional on the phylogenetic history of the lineages under study
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3 40,41. Several recent papers have shown that violations of these assumptions can have varying
4 effects on the outcome of phylogenetic analysis (Table 1), with some more severe than others.
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6 The main criticisms of coalescent methods in phylogenetics – articulated most forcefully in a
7 series of papers and comments by Gatesy and Springer^{19,20,25} – focus on features of
8 phylogenomic data sets that are perceived to violate the multispecies coalescent model (MSC).
9
10 Such concerns focus on several issues, including the potential for recombination within loci,
11 particularly for transcriptome data in which exons that might span megabases in the genome yet
12 are ‘concatenated’ together, either *in silico* or by the cell during the process of transcription; the
13 claim that different species tree methods yield conflicting results when applied to the same data
14 sets; the suggestion that most gene tree heterogeneity results from effects other than incomplete
15 lineage sorting (ILS); and confusion over the effects and implications of low-resolution gene
16 trees on species tree estimation. This last issue has also motivated the development of add-on
17 methods to species tree estimation, such as naïve and statistical binning^{42,43}, whose aim is to
18 augment phylogenetic signal when inferring species trees using coalescent methods.
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36 Here we discuss these various criticisms and concerns in an effort to clarify a host of
37 issues raised about coalescent models in phylogenetics. We also highlight recent empirical
38 studies that evaluate the signal in gene trees and explore their implications for the adoption or
39 rejection of species tree methods. We show that concatenation methods can be considered a
40 special case of the more general MSC. As such, the more specific concatenation model is
41 expected to yield results that are biased but with a smaller variance (e.g., higher bootstrap
42 support) for the estimates of model parameters than the more general MSC -- a perspective that
43 helps explain recent trends in observed phylogenomic data sets. We also suggest that naïve
44 binning – a proposal to augment the signal in multilocus data sets by concatenating genes at
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random into bins – will only work under highly restricted conditions, and that the lower performance of coalescent methods versus concatenation methods in those studies reflects an undue focus on point estimates and a restricted set of simulation conditions, an undervaluation of the variance of those estimates and the often inflated support of concatenation analyses. Overall we find that currently proposed species tree methods represent a promising start to the challenge of analyzing phylogenomic data and highlight conceptual and practical challenges for the future.

Concatenation versus Coalescent Models in Phylogenomics

The coalescent and concatenation models differ in their treatment of individual gene trees. In the coalescent model, which assumes free recombination among genes, the gene trees are treated as conditionally independent random variables $G = \{g_i, i = 1, \dots, k\}$ given the species tree S ⁴⁰, where k is the number of genes. However, independent gene trees may have the same topology, especially when the species tree has long internal branches in coalescent units^{44,45}. Under the coalescent model, the likelihood function of the species tree S given the multilocus sequence data $D = (d_1, d_2, \dots, d_k)$ is given by

$$L(S|D) = \int_G f(D|G, \lambda) \times \phi(G|S) dG. \quad (1)$$

In (1), $f(D|G, \lambda)$ is the probability density function of sequence data D given gene trees G and parameters λ in the substitution model, and $\phi(G|S)$ is the coalescent distribution function of gene trees G given the species tree S . The function $f(D|G, \lambda)$ is the traditional likelihood function used for building maximum likelihood gene trees. When gene trees G are identical with the species tree S (i.e., $g_1 = g_2 = \dots = g_k = S$), the coalescent probability function $\phi(G|S)$ is 1 for $G = S$ and 0 otherwise. Therefore, when all gene trees are identical with the species tree S , the likelihood function of the species tree S is reduced to

$$L(S|D) = f(D|S, \lambda). \quad (2)$$

As model parameters λ may or may not be linked across genes (i.e., partitions), $f(D|S, \lambda)$ in (2) is the likelihood function for the concatenation model with or without partitions. Equation (2) shows that the concatenation model with or without partitions is a special case of the coalescent model. This result has at least two important implications: (i) while concatenation methods may produce inconsistent estimates of species trees under the coalescent model³², coalescent methods can consistently produce the true species tree under the concatenation model, and (ii) the comparison between the coalescent and concatenation methods falls into the general bias-variance dilemma, i.e., the reduced model (concatenation) in general is biased and has smaller variance for the estimates of model parameters⁴⁶.

As a reduced model, concatenation has a smaller number of parameters, because all gene trees in the concatenation model are treated as the same variable. Thus, the estimates of parameters in the concatenation model tend to have a smaller variance. Since small variance corresponds to high bootstrap support or posterior probability, overestimation of bootstrap support by concatenation methods is a consequence of the fact that it is a reduced model. Moreover, ‘two-step’, gene-tree-based coalescent methods – those methods that estimate the species tree using separately estimated gene trees^{47,48} (Figure 1) – can in turn result in larger variance for their estimates of species trees, because these methods estimate gene trees and the species tree separately using summary statistics or a pseudo-likelihood function. This is the same as saying that gene-tree-based coalescent methods may sometimes result in bootstrap support that is lower than those coalescent methods using the full coalescent model, such as BEST³¹ and *BEAST⁴⁹. (Indeed, we have observed this empirically for the 30-locus data set from birds⁵⁰ analyzed by Liu and Pearl³¹, which yielded a posterior probability of 0.9 when

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3 analyzed by BEST but only ~54% bootstrap support when analyzed by the simpler model in
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5 STAR⁵¹). However, the problem of larger variance in gene-tree-based coalescent methods can be
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7 greatly alleviated by either improving the efficiency of these methods or by increasing the
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9 number of genes. Because phylogenomic data often contain hundreds of genes, species tree
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11 analyses using gene-tree-based coalescent methods have produced highly supported species trees
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13 for empirical phylogenomic data^{15,24,27,28,52}. In contrast, inconsistency of concatenation tends to
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15 become severe when there are a large number of genes³². Thus, the major concern of
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17 phylogenomic data analysis is not the high variance of gene-tree-based coalescent methods, but
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19 rather the inconsistency of concatenation methods due to model misspecification⁴⁸, especially in
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21 cases where phylogenomic inferences are based on highly supported relationships.
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27 In empirical phylogenomic data analyses, concatenation and coalescent methods often
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29 produce similar relationships for the majority of branches in the estimated trees. As discussed
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31 above, when the concatenation model applies, we do not expect to encounter highly supported
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33 relationships that conflict between concatenation and coalescent trees, because with the
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35 assumption of identical gene trees, the coalescent model is reduced to the concatenation model.
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37 Thus, highly supported but conflicting relationships in concatenation and coalescent trees, as has
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39 recently been observed in several phylogenomic data analyses^{15,28,53}, indicate either a high
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41 amount of ILS (due to short internal branches [in coalescent units] in the species tree) that
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43 mislead the concatenation method¹⁵, or that the major cause of gene tree variation is not ILS. In
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45 the latter case, neither concatenation nor coalescent models can adequately explain the
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47 distribution of heterogeneous gene trees.
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53 **Empirical examples of conflict between coalescent and concatenation methods**

54 *Coalescence versus concatenation in plant phylogenomics*

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3 To date, very few studies have utilized coalescent methods for inferring plant phylogenies^{34,54-56}.
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5 Of these studies, strongly conflicting relationships involving concatenation versus coalescent
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7 analyses have recently been demonstrated for key nodes in land plant phylogeny. (When we
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9 write “strongly” we typically mean supported by a bootstrap value of at least 75 – >90%,
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11 depending on context). Despite tremendous effort, relationships between the five main seed
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13 plant clades—angiosperms, conifers, cycads, *Ginkgo*, and gnetophytes—have remained uncertain.
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15 A first broad coalescent analysis of seed plants by Xi et al.²⁷ incorporated 305 nuclear genes and
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17 suggest an explanation for why concatenation methods may result in strong topological
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19 incongruence, manifested as phylogenetic ‘flip-flops’ between analyses involving different
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21 subsets of data. Unlike most previous analyses using concatenation, which have strongly placed
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23 cycads and *Ginkgo* as successive sisters to the remainder of extant gymnosperms, coalescent
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25 results instead strongly identified *Ginkgo* and cycads as monophyletic. Suspecting that the rate of
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27 nucleotide substitution might be influencing this difference, Xi et al.²⁷ binned sites into fast and
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29 slow evolving categories and reanalyzed these data. Coalescent analyses continued to support
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31 the monophyly of *Ginkgo* and cycads regardless of rate category, but concatenation did not.
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33 Instead, fast evolving sites strongly supported the more traditional placement of cycads and
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35 *Ginkgo* whereas slow evolving sites supported the placement inferred from coalescent methods.
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37 This finding raised the hypothesis that rate variation among sites may explain the striking
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39 topological differences observed in concatenated phylogenomic analyses, reflecting problems
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41 commonly encountered in, for example, cases of ‘long branch attraction’^{57,58}. Furthermore, more
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43 recent coalescent analyses using expanded taxon sampling and transcriptome data corroborated
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45 the monophyly of *Ginkgo* and cycads⁵⁵.
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3 In a second paper, Xi et al.²⁸ further explored this hypothesis by examining a slightly
4 larger phylogenomic dataset including 310 nuclear genes, mostly from flowering plants. Here,
5 phylogenetic relationships were congruent between concatenation and coalescent methods,
6 except for the placement of *Amborella*, which has long been heralded as the sister to all other
7 flowering plants^{59,60}. Here, coalescent analyses consistently and strongly support the less
8 traditional placement of *Amborella* as sister to water lilies across all nucleotide rate partitions.
9 By contrast, concatenation showed the same kind of strongly conflicting results that were
10 observed in earlier study involving the placement of *Ginkgo* and cycads: slow evolving sites
11 corroborated the results from coalescent analyses and fast evolving sites placed *Amborella* alone
12 as the first lineage of extant plants. An additional assessment of these fast evolving sites showed
13 particularly strong evidence of saturation, suggesting one explanation for these artifacts. In this
14 case, it appears that distributing saturated sites among many individual gene trees and analyzing
15 each separately as is done by commonly used coalescent methods may be more effective at
16 diluting the deleterious effects of such characters. By contrast, when analyzing all such sites
17 simultaneously within a single matrix as is done using concatenation, such deleterious effects
18 will be exacerbated. We should note that this question has been reevaluated more recently with
19 coalescent analyses using expanded taxon sampling and transcriptome data⁵⁵. This study
20 strongly supports the more traditional placement of *Amborella* alone. However, one of us (Z.X.)
21 has analyzed the nearly 400 transcripts common to both *Amborella* and water lilies using these
22 data. Here again, slow evolving nucleotide and amino acid sites strongly support the placement
23 of *Amborella* and water lilies as monophyletic (unpublished data).
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53 Xi et al. investigated this placement of *Amborella* further with simulations. The first of
54 these simulations used the *Amborella* dataset. Here, they randomly constrained each gene tree to
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3 be consistent with one of the alternative placements of *Amborella*. Branch lengths and
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5 substitution model parameters were then estimated on each constrained tree from the original
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7 data. Data sets were then simulated on these trees and the resulting simulated data were binned
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9 into fast and slow evolving sites. Coalescent analysis of these data reconstructed the constrained
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11 topologies as expected, regardless of rate category. Surprisingly, however, despite 60-80% of the
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13 gene trees constrained to the *Amborella* plus water lilies placement, concatenation of the fast
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15 evolving sites still resulted in the placement of *Amborella* and water lilies as successive sisters to
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17 all angiosperms. The fact that the concatenated data reconstructs the traditional *Amborella* alone
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19 topology, even when the fast evolving sites come from a tree in which *Amborella* and water lilies
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21 are sisters, shows that concatenation of fast evolving sites likely plays a strong role influencing
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23 the misleading placement of *Amborella*.
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29 Additional simulations²⁸ on species trees with both long and short branches suggested
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31 that when incomplete lineage sorting is high, concatenation methods perform very poorly,
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33 suggesting that concatenation may strongly be influenced by the shape of the species tree
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35 topology and its interaction with ILS. A related follow-up simulation study²⁹ suggests that when
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37 long external and short internal branches occur simultaneously with high ILS, concatenation
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39 methods can be misled, especially when two of these long branches are sister lineages. By
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41 contrast, species tree methods (in this case MP-EST⁴⁸ and STAR⁵¹) are more robust under these
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43 circumstances. This result is particularly relevant because many ancient radiations across the
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45 Tree of Life suggest this particular pattern of adjacent long and short branches. Because short
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47 internal branches in the species tree can increase the potential for ILS and gene tree discordance,
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49 these results indicate that coalescent methods are more likely to infer the correct species tree in
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3 cases of rapid, ancient radiations where short internal and long external branches are in close
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5 phylogenetic proximity.
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7 8 *Coalescence versus concatenation in mammal phylogenomics* 9

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11 Despite recent progress in classifying eutherian mammals into four superorders –
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13 Afrotheria, Xenarthra, Laurasiatheria and Euarchontoglires -- several key relationships within
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15 eutherian mammals remain controversial, including the root of Eutheria, and the interordinal
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17 relationships within Euarchontoglires, Laurasiatheria and Afrotheria^{61,62}. To date, however, the
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19 reconstruction of mammalian phylogeny has relied mostly on concatenation methods, which as
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21 we indicate above may suffer from systematic bias due to the unrealistic assumption of gene tree
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23 homogeneity across loci. To empirically address the effect of gene tree heterogeneity on
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25 estimating deeply diverging phylogenies, Song et al.⁶³ took the approach of subsampling loci and
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27 taxa so as to investigate the robustness of concatenation and coalescent methods to different
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29 analyses of the same taxa. Using a data set of 447 nuclear genes for 35 mammalian taxa, Song et
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31 al. demonstrated that concatenation indeed behaves inconsistently across data sets, as evidenced
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33 by the conflicting and strongly supported relationships from different subsamples of loci. In
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35 contrast, coalescent methods were able to estimate a consistent phylogeny for eutherian
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37 mammals from the same subsets of data, and demonstrated clear positive relationship between
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39 nodal support values and the number of loci. In this regard, the study on mammals was
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41 consistent with predictions of a recent simulation study that showed a correlation between
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43 number of loci and species tree support for nodes exhibiting high rates of ILS³⁵.
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51 Several studies⁶⁴, including the mammal study¹⁵, have revealed the sometimes striking
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53 contrast between support values for trees analyzed by concatenation versus coalescent methods,
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55 with the latter often yielding much lower values even when the tree is largely similar. It is often
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3 the case that a tree that appears well-resolved by concatenation methods is found to be poorly
4 resolved using coalescent methods. So which set of support values better reflects reality? Such
5 results likely reflects the tendency for concatenation methods, especially Bayesian concatenation
6 methods, to overestimate credibility values in phylogenetic trees^{65,66}. They may also partly
7 reflect the tendency of gene-tree-based coalescent methods to yield lower confidence levels than
8 full Bayesian coalescent methods when the number of gene trees is small (see above).

9
10 Differences in the method of bootstrapping may also contribute to these discrepancies; the
11 multilocus bootstrap⁶⁷ is generally believed to more accurately capture support in large data sets
12 than the simple bootstrap²⁰. In the study by Song et al.¹⁵, the 26 genes that resolved a sample of
13 mammalian taxa using concatenation resulted in a poorly resolved tree when analyzed by MP-
14 EST. They suggested that, in a coalescent framework, approximately 400 genes would be
15 required to resolve the sample of taxa in the particular tree for mammals. In this case, missing
16 data may also play a role, since coalescent methods appear to be more sensitive to missing data
17 than concatenation methods⁶⁴. However, one study⁶⁸ suggested that species tree methods were
18 “remarkably resilient to the effects missing data”. In our view, what sensitivity to missing data
19 displayed by species tree methods reflects the true impact of missing data on phylogenetic
20 analysis -- an impact that is obscured by analyses employing concatenation. There are now
21 many examples of well resolved phylogenies employing concatenation on highly incomplete
22 data sets^{55,69,70}. We believe these examples illustrate the power of concatenation to obscure the
23 true support for trees by the collected data (see also⁷¹).

50 **Maximizing signal in species tree analysis**

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52 Species tree analysis has moved past the stage of uncritical adoption to evaluation of sampling
53 strategies and methods for maximizing phylogenetic signal^{33,38,72-75}. Much of our understanding
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3 of the behavior of species tree reconstruction comes from simulation studies, although analyses
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5 of empirical data have also yielded important insights. An important rule of thumb that has
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7 emerged from both simulation and empirical studies is that species trees are only as good as the
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9 gene trees on which they are built^{14,38,64,72,76,77}. This maxim applies both to ‘two-step’ species
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11 tree methods, in which gene trees are used as input data, as well as to ‘single step’ approaches,
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13 such as Bayesian methods, in which gene and species trees are estimated simultaneously. For
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15 example, several empirical studies on organisms as varied as turtles, mammals, fish and
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17 flowering plants, have shown that species tree estimation can be misled by biased gene tree
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19 estimation due to long-branch attraction and base compositional heterogeneity among lineages, a
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21 manifestation of substitution model non-stationarity^{12,14,28}. Even so, recent work suggests that
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23 species tree methods, even those in which gene trees are estimated first and separately from the
24
25 species tree, may be less susceptible to classic challenges in phylogenetic analysis, such as long
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27 branch attraction (Table1)²⁹. This lowered susceptibility of species tree methods may be due to
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29 the fact that a typical gene tree is based on at most a few thousand base pairs, which may be
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31 small enough such that departures from stationarity may be less visible in the underlying data
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33 sets. While it is valid to criticize the ensemble of constituent approaches that comprise gene tree
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35 and species tree analysis, including gene tree and species tree reconstruction, it is unwarranted to
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37 criticize species tree methods per se, especially when it is the reconstruction of gene trees that is
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39 responsible for misestimation²⁰. Thus a number of authors have suggested improving and
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41 maximizing signal in gene tree estimation as a means of improving species tree estimation as a
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43 whole. Such improvements in signal take a variety of forms, including binning of subsets of
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45 genes, using longer or more informative genomic regions for each locus^{2,15,30,77}, minimizing
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47 base compositional heterogeneity among lineages, and even choosing genes with specific trends
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3 in base composition, for example those genes trending towards AT richness in mammals⁷⁸. In
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5 this section we evaluate a variety of suggestions for signal enhancement in species tree analysis.
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8 *Naïve and statistical binning*

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10 The naïve binning technique was proposed to improve the support of coalescent estimates of
11 species trees by reducing the estimation error of gene trees⁴³. This technique concatenates DNA
12 sequences across randomly selected genes, regardless of whether the selected genes share the
13 same history. The binned sequences are treated as a “super gene”, and used to estimate “super
14 gene trees”. As the binned sequences are longer than the original data, the resulted gene trees are
15 often well supported⁴³. However, as shown in Kubatko and Degnan³², binning sequences from
16 genes with distinct histories can mislead maximum likelihood (ML) concatenation methods,
17 which consistently produce the wrong estimate of the species tree under broad conditions. This
18 inconsistency problem may also occur for the “super genes” in the binning technique. Indeed,
19 although the paper title implied that binning yielded a general improvement for phylogenomic
20 data (“Naive binning improves phylogenomic analyses”), in the paper the authors were more
21 equivocal (“This paper should not be interpreted as recommending the use of naïve binning, but
22 instead as an indication of the potential for binning techniques to improve species tree
23 estimation”; p. 2284). From first principles we know that, for the case of 4-taxon aous species
24 tree (see Figure 3f in Kubatko and Degnan³²) when the bin size (BS) is large, all of the
25 concatenated genes (i.e., super genes) will have the same ML tree, a tree that is incongruent with
26 the species tree. These biased super gene trees can significantly mislead the MP-EST estimate of
27 the species tree. Even when the bin size is small (10-15 genes), binning sequences can increase
28 the probability of estimating gene trees that disagree with the species tree. When this probability
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3 is greater than a threshold, it will mislead the MP-EST and other methods to consistently produce
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5 the wrong estimate of the species tree.
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8 To demonstrate these phenomena, we simulated gene trees from a 5-taxon species tree
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10 (labeled species A–E, Figure 2a) under the coalescent model using the function *sim.coaltree.sp*
11
12 in the R package Phybase⁷⁹. Because the MP-EST method assumes that gene trees are rooted
13
14 trees, species E is used as the outgroup for rooting the estimated gene trees. To reduce the
15
16 rooting error, we intentionally set a small population size $\theta = 0.01$ and a long internal branch
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18 (length = 0.08) between the ingroup species (A–D) and the outgroup species E. Under these
19
20 conditions, the ingroup species (A–D) almost always form a monophyletic group in the simulated
21
22 gene trees. In addition, the population size parameter θ is set to 0.1 for other ancestral
23
24 populations in the species tree. This species tree is in the anomaly zone, because the internal
25
26 branches for species A, B, C, and D are very short ($0.005/0.1 = 0.05$ in coalescent unit), and the
27
28 most probable gene tree (PT) does not match the species tree⁸⁰. Although species trees in the
29
30 anomaly zone might be considered unrealistic⁸¹, recent empirical examples seem to suggest
31
32 otherwise⁵³. DNA sequences of length 1000 bp were generated from the simulated gene trees
33
34 using SeqGen⁸² with the Jukes-Cantor (JC69) model⁸³. The simulated DNA sequences were
35
36 binned at random to form super genes. The bin size was set to 10, 20, 30, 40, and 50 genes,
37
38 respectively. A ML super gene tree was estimated for each bin by PhyML⁸⁴. The estimated super
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40 gene trees were then used to estimate species trees using the MP-EST method. Each simulation
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42 was repeated 100 times.
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50 When the bin size is one (i.e., no binning was performed), the probabilities of the
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52 estimated gene trees are similar to the true probabilities of gene trees generated from the species
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54 tree (Figure 2b). However, the probability of the most probable gene tree (PT) significantly
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3 increases as the bin size increases (Figure 2b). When the bin size is 30, almost half of the
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5 estimated super gene trees are PT, which is incongruent with the species tree (Figure 2b). It is
6
7 clear from this exercise that binning sequences from genes with distinct histories can bias the
8
9 distribution of the estimated gene trees, with a high probability of producing the tree that is
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11 incongruent with the species tree.
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15 Without binning (BS = 1), the MP-EST method can consistently estimate the correct
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17 species tree as the number of genes increases (Figure 3a). The proportion of trials yielding the
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19 correct species tree appears to increase as the number of genes increases, and reach 1.0 when the
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21 number of genes is 1000. When the bin size is five, the probabilities of estimating the correct
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23 species tree are greater than those without binning. This result indicates that when the bin size is
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25 five, binning can improve the performance of MP-EST in estimating species trees. However,
26
27 when the bin size is greater than or equal to 10, the probability of estimating the correct species
28
29 tree is in general less than the probability without binning (Figure 3b). Moreover, the probability
30
31 of estimating the correct species tree appears to decrease as the number of bins (i.e., the number
32
33 of super genes) increases (Figure 3b). For bin sizes of 30, 40, and 50, the probability of yielding
34
35 the correct species tree decreases to zero when the number of bins reaches 80 (Figure 3b).
36
37 Meanwhile, when the bin size is greater than 10, the MP-EST tree based on the binned genes
38
39 appears to consistently estimate the wrong tree as the number of bins increases (Figure 3c).
40
41 Interestingly, for the simulation parameters studied here, for a bin size of 10, the probability of
42
43 the correct tree stabilizes around 0.6, while the probability of an incorrect tree stabilizes around
44
45 0.4. Although this result suggests that when the bin size is less than 10, the binning technique
46
47 can be beneficial for improving the performance of the MP-EST method in estimating species
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49 tree, additional simulation results suggest that this may not always be the case (not shown).
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3 Further research on naïve binning is needed. We can certainly state that when the bin size is
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5 greater than 10, binning sequences across genes with distinct histories can significantly bias the
6
7 distribution of estimated gene trees, and result in inconsistent estimates of species trees.
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11 Ideally, the loci should be concatenated if no or only a few recombination events
12
13 occurred between those loci. A model based on biology would suggest that binning should be
14
15 based on loci that are closely linked in genomes, such as often occurs in transcriptomes, because
16
17 the chance of recombination is positively related to the physical distance between two loci.
18
19 Recently, Mirarab et al⁴² proposed a statistical binning technique which attempts to bin loci with
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21 the same gene tree. In this approach, loci are binned when there are no strongly supported
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23 topological conflicts among the estimated gene trees of those loci, for example when the gene
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25 trees do not conflict on branches with $> 75\%$ bootstrap support. However, the statistical
26
27 properties of statistical binning are not yet fully explored. As discussed in the previous section,
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29 the assumption of free recombination between genes and no recombination within genes plays a
30
31 key role in the coalescent model. Loci are treated as conditionally independent, due to the
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33 assumption of free recombination between genes. Two loci may have the same gene tree even
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35 though they are conditionally independent. This may occur, for example, when the species tree
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37 has long internal branches (in coalescent units). When the genes have the same history, binning
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39 their sequences can improve gene tree estimation, but it also reduces the sample size of
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41 independent genes. Thus, from first principles we can state that binning sequences from genes
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43 with the same history may not necessarily improve species tree estimation. In addition, two trees
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45 with no strongly supported conflicts do not necessarily indicate that they are topologically
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47 identical with each other. As we discussed for the naïve binning, combining loci with different
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49 histories may seriously bias the distribution of the estimated gene trees, which in turn will
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3 mislead species tree estimation. In conclusion, further studies are needed to evaluate the
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5 performance of statistical binning.
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8 *Information content of genes for species tree reconstruction*

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10 Despite the recent arrival of genome-scale Bayesian phylogenetic methods for concatenation⁸⁵,
11
12 the Bayesian or approximate Bayesian coalescent model cannot presently be applied to
13
14 phylogenomic data due to excessive computational burden^{31,49,86}. Alternative gene-tree
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16 approaches, including MP-EST⁴⁸, GLASS⁸⁷, Maximum Tree⁴⁸, STAR⁵¹, STEM⁸⁸, STELLS⁸⁹,
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18 ASTRAL⁹⁰ and STEAC⁵¹, build species trees from estimated gene trees. These approaches have
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20 computational advantages that allow them to be used for phylogenomic data analyses⁷⁶ and novel
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22 molecular markers such as ultraconserved elements^{2,23}. Additionally, recent species tree
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24 methods utilizing information from SNPs^{91,92} and haplotypes⁹³ may be scalable to large data
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26 sets. However, the tree estimates given by gene-tree-based approaches often suffer the problem
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28 of big variance (i.e., low bootstrap support). As these approaches employ bootstrap techniques to
29
30 account for errors in estimating gene trees, large estimation error for gene trees can greatly lower
31
32 the bootstrap support of the species trees estimated by those approaches (Huang et al 2010).
33
34 Moreover, these approaches estimate species trees based only on the topologies of gene trees,
35
36 ignoring the branch length information, which further reduces the efficiency of those approaches.
37
38 The simulation study by Huang et al (2010) suggests that high amount of gene tree estimation
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40 error may be the major cause of low bootstrap support in estimates of species trees using STEM
41
42 (Table 1). It has been suggested by empirical studies that using highly supported gene trees
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44 (average bootstrap support value > 0.5) can improve bootstrap support of species trees estimated
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46 by gene-tree-based approaches^{15,21}, and adding poorly supported gene trees (i.e., weak genes)
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3 does not contribute more information regarding the phylogeny of species. We evaluated this
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5 hypothesis through a simple simulation analysis.
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8 To evaluate the effect of weak genes on the performance of gene-tree-based approaches
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10 in estimating species trees, DNA sequences were simulated from the true species tree
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12 (((A:0.002, B:0.02):0.002, (C:0.002, D:0.002):0.002):0.002, E:0.006):0.01, F:0.016) with $\theta =$
13
14 0.008. The population size parameter θ is constant across branches of the species tree.
15
16 Specifically, gene trees were generated from the species tree under the MSC, again using
17
18 Phybase⁷⁹. DNA sequences were generated from the simulated gene trees under the JC69 model
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20 using SeqGen⁸² with the Jukes-Cantor model⁸³. We generated 1000 base pairs for ‘strong’ genes,
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22 and 100 base pairs for ‘weak’ genes. The average bootstrap support values of strong genes range
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24 primarily from 70% (first quantile) to 91.75% (3rd quantile) with median = 81.83% (Figure 4a),
25
26 whereas the average bootstrap support values for 100 base pair genes are mostly < 50% (Figure
27
28 4a). Thus we selected 100 base pair genes with bootstrap values < 50% as weak genes. Species
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30 trees were reconstructed from 10, 20, up to 90 (in increments of 10) estimated gene trees for
31
32 strong genes using MP-EST. Each simulation was repeated 100 times. The proportion of trials
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34 estimating the true species tree was 0.33 for 30 strong genes, and it increased to 1 when the
35
36 number of strong genes was 40 (Figure 4b). However, when adding weak genes to the set of 30
37
38 strong genes, the proportion of estimating the true species tree increased slowly to 0.63 and then
39
40 decreased to 0.50 (Figure 4b). This result suggests that adding weak genes may not contribute
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42 more information to an otherwise strong data set when estimating species trees. When adding
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44 weak genes, the distribution of estimated gene trees becomes flat, and the coalescent signal
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46 contained in the estimated gene trees is significantly reduced. Thus adding weak genes may
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3 actually reduce the performance of species tree estimation methods, negating the old adage that
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5 “more data is always better”.
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8 *Transcriptomes, base composition, and location-aware concatenation*

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10 Transcriptomes have formed an important type of data lending itself to species tree estimation.
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12 Because of their ease of alignment and characterization, transcriptomes will continue to be an
13
14 important data type for many kinds of phylogenetic analysis. However, because transcriptomes
15
16 consist solely of coding regions, they are potential targets of natural selection⁹⁴. Indeed,
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18 genome-wide phylogenetic comparisons in primates have shown that the rate of ILS in coding
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20 regions is lower than that in non-coding regions⁹⁴. This higher incidence of reciprocal
21
22 monophyly and lower incidence of ILS in coding regions is likely driven by recurrent bouts of
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24 positive selection on coding regions, with surrounding noncoding regions adhering to patterns
25
26 more consistent with neutrality. Whether or not this type of departure from the neutral
27
28 coalescent will be problematic for species tree analysis is unclear, because by lowering the rate
29
30 of deep coalescence, natural selection could help eliminate some of the discordance that is
31
32 known to decrease phylogenetic signal in species tree analysis^{47,95}. However, recent genome-
33
34 wide analyses of avian phylogeny suggest substantial convergence in protein coding regions,
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36 resulting in species trees that are clearly incongruent with noncoding genomic partitions¹⁶.
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44 Transcriptomes are also characterized by strong base compositional biases, and it is well
45
46 known that the third positions of nuclear genes can evolve rapidly and become misleading over
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48 long time scales. Departures from base compositional stationarity in phylogenomic data sets
49
50 have long been known to cause serious problems for phylogenetic analysis, potentially linking
51
52 together lineages that are unrelated but share similar base compositions^{16,96-98}. Variation in base
53
54 composition among taxa is known for both transcriptome data and for whole-genome data.
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3 Additionally, it is well known that different subgenomes can possess different base
4 compositions; for example, coding regions are generally more GC-rich than noncoding regions.
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6 Examination of variation in base composition among lineages and genes as well as saturation
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8 patterns in different data partitions has shed some light on optimal choice of marker for species
9
10 tree analyses. For example, Chiari et al.¹⁴ showed that species tree analysis of turtle relationships
11
12 changed dramatically depending on whether amino acid sequence or nucleotide sequence data
13
14 were used to build gene trees, with amino acid data sets providing more congruent results.
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16
17 Betancur-R et al.¹² showed convincingly that substantial apparent gene tree heterogeneity in fish
18
19 data sets arises from mis-estimation of gene trees most likely due to base compositional
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21 heterogeneity among lineages. They found that choosing sets of genes with base compositional
22
23 homogeneity among lineages substantially reduced the apparent evidence for gene tree
24
25 heterogeneity and ILS. While we view this result as significant, we suggest that it does not
26
27 invalidate the use of species tree methods or necessarily support supermatrix approaches,
28
29 because species tree methods do not require gene tree heterogeneity to work well. A final
30
31 example in which base composition plays a role in species tree reconstruction was provided by
32
33 Romiguier et al.⁷⁸, who found that the gene trees in mammals based on GC-rich coding regions
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35 were more heterogeneous than those with an AT-bias. Moreover, the species tree suggested by
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37 AT-rich data sets favored the Afrotheria hypothesis, with Afrotheria as the first branch within
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39 placental mammals, whereas those based on the more heterogeneous GC-rich data sets favored
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41 the Atlantogenata rooting, in which Xenartha and Afrotheria are sister groups. These authors
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43 suggested that the way forward was not so much to account for ILS using novel phylogenetic
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45 methods as to reduce its incidence by using particular sets of markers. Again, while we do not
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47 dispute the observation of lower gene tree heterogeneity in AT-rich markers, this does not mean
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3 that supermatrix approaches are necessarily favored. So long as different genes are conditionally
4 independent from one another due to recombination, we suggest that species tree analysis will
5 still accumulate phylogenomic signal very differently, and we hypothesize more accurately, than
6 will concatenation approaches. Species tree approaches are not invalidated by the absence of
7 ILS; rather they represent a fundamental recognition of the importance of stochasticity from gene
8 to gene that is unaccounted for by concatenation methods, even when ILS is low or absent.
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17 An important issue in the ongoing discussion of concatenation versus coalescent methods
18 is whether the location-aware concatenation of exons in transcriptome data is reasonable or
19 whether it violates the MSC²⁵. Location-aware concatenation occurs when adjacent exons or
20 genomic regions are concatenated to one another. This type of concatenation has biological
21 realism in so far as adjacent regions of the genome are known to be correlated in their historical
22 ancestry, with stretches of chromosomes yielding information suggesting similarity in gene trees
23 as one moves along the chromosome. On the one hand, transcriptome data has been shown in
24 multiple studies to yield phylogenetic trees produced by MSC models that are either congruent
25 with previous results or provide novel hypotheses that are plausible (e.g., turtles, plants). On the
26 other hand, transcriptome data is indeed ‘concatenated’ by cells when converting pre-mRNAs
27 into the mature mRNAs that are often used in phylogenomic studies. A key difference between
28 the location-aware concatenation performed by cells and the naïve binning recommended by
29 Bayzid and Warnow⁴³ is that, in location-aware concatenation, exons that are adjacent to one
30 another in the genome are concatenated, whereas binning approaches are agnostic as to the
31 location of binned genes in the genome. Still, exons that are concatenated by cells can still occur
32 at varying distances from one another in the genome, and may experience levels of
33 recombination in their history that rivals those experienced by loci located at a distance in the
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3 genome. However, as Lanier and Knowles³⁹ point out, recombination will only be a challenge
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5 on extremely short internal branches of the species tree; recombination occurring on long
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7 branches will involve sequences closely related within species and will provide discordant signal
8
9 primarily when taking place in common ancestral species. The empirical effects of varying
10
11 genomic distance on the variety of observed gene trees need to be studied in more detail. Using
12
13 a variety of statistical methods, several studies, particularly in primates and rodents, have found a
14
15 patchwork of gene tree signals in chunks when moving along a chromosome⁹⁹⁻¹⁰¹. Methods for
16
17 delimiting genomic segments that display consistency of phylogenetic signal are emerging, and
18
19 these may prove extremely useful for delimiting loci for species tree analysis and minimizing the
20
21 negative effects of recombination. In general, however, when faced with insufficient signal in a
22
23 species tree analysis, we advocate increasing the size of phylogenomic data sets², rather than
24
25 pseudoconcatenation or naïve binning as a means of augmenting signal. Despite the plethora of
26
27 large-scale phylogenomic studies, empiricists have not yet exhausted phylogenetic information,
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29 and until then, data collection, rather than binning uninformed by genomic context, should be the
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31 method of choice for data augmentation.
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41 *Computational trade-offs in species tree analysis*

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43 In addition to concerns about marker choice and the statistical properties of species tree
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45 estimation methods, another major concern is computational cost. When phylogenomic data
46
47 include thousands of genes, the total length of the concatenated sequences will begin to explode,
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49 resulting in an extremely high computation burden when using concatenation methods. For such
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51 data sets, it is practically impossible to perform bootstrap concatenation analyses (with just 100
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53 replicates), or model selection analysis for choosing the best substitution model for the data. For
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3 some cases, it is even challenging to perform a single maximum likelihood analysis for the
4 concatenated sequences. Recent analyses of genome-scale data have been unable to complete
5 computation for concatenated data sets, and phylogenetic inferences are often made in the
6 absence of analyses that have reached convergence or have searched tree space substantively
7 (e.g.,^{16,102}). Recent advances in computer architecture of phylogenetic analyses may help
8 alleviate the challenges of analyzing genome-scale supermatrices¹⁰³. On the other hand,
9 Bayesian coalescent models^{31,49} have the same computational issues as concatenated analyses
10 when the sequence data involve hundreds of genes. Simpler coalescent methods such as MP-
11 EST, STAR, and STEAC rely on estimated gene trees to infer species trees, and their
12 computational costs are manageable, even for thousands of genes and species. Of course, as a
13 price for computational efficiency, gene-tree-based methods suffer low statistical efficiency, in
14 the sense that they often require more loci to produce a highly resolved tree. In practice, it is
15 extremely difficult to estimate the sample size for phylogenetic methods such that they can
16 achieve reasonable bootstrap support for their estimates of the species trees. Clearly the
17 landscape of phylogenetic methods for genome-scale data, whether for supermatrices or unlinked
18 loci, is rapidly changing.

Conclusion

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Phylogenetic analysis of genome-scale data inevitably invites the use of methods that
acknowledge the stochasticity of gene histories, and the MSC provides a robust framework for
incorporating the information in this stochasticity. Yet newer methods for analyzing genome-
scale data, relying on supertrees¹⁰⁴ or alignment graphs¹⁰⁵, will likely yield further insights. The
justification for species tree methods lies not in the ubiquity of gene tree heterogeneity in

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3 empirical data sets, although this heterogeneity has certainly spurred the advent of such methods.
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5 Rather, the justification lies in their acknowledgement of fundamental genetic processes inherent
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7 in all organisms, including recombination along the chromosome, which renders gene histories
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9 independent of one another, conditional on the phylogeny, and genetic drift, which generates
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11 stochasticity in gene tree topologies and branch lengths. Thus, even when all gene trees are
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13 topologically similar, species tree methods will yield results differing from concatenation
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15 methods, if not in phylogenetic topology then often in phylogenetic support, because species tree
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17 methods better model the accumulation of signal that is accrued with increasingly large data sets.
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19 Different methods of species tree inference incorporate different amounts of detail of the
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21 multispecies coalescent process, and there is a trade-off between model accuracy and
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23 computational burden. For now, ‘two-stage’ species tree methods, in which estimated gene trees
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25 are used as input data, are useful in so far as they can analyze large-scale genome-wide data sets
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27 with ease (Figure 1). But more complex and computationally efficient models are sorely
28
29 needed¹¹. Although concatenation and species tree approaches often yield similar estimates of
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31 phylogeny, an increasing number of examples of strong conflict between concatenation and
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33 coalescent analyses shows that the conditions for conflict among methods occur in empirical
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35 data. Additionally, concatenation methods appear more sensitive to classic phylogenetic
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37 challenges such as long-branch attraction and rate variation among lineages than are gene-by-
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39 gene species tree analyses. Some of the differences in behavior between concatenation and
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41 species tree methods can be understood as manifestations of the classic bias-variance problem in
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43 statistics, because concatenation is a special case of the more general model used by species tree
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45 methods, and therefore can exhibit low variance (such as high tree support) despite being more
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47 biased than species tree approaches. Further studies aimed at understanding the connections
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3 between concatenation and species tree methods and the types of data that maximize signal under
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5 the multispecies coalescent model will allow phylogenetics to take full advantage of the flood of
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7 data in the genomics era.
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Figure legends

Figure 1: Schematic of the concatenation and coalescent paradigms in phylogenetics. At the top is depicted a multilocus data set consisting of five species (A – E) and four genes (1 – 4). On the left is indicated the classic supermatrix approach, in which all genes are concatenated to produce a single ‘supergene’ which is then subjected to phylogenetic analysis by classical or updated traditional algorithms such as RAxML¹⁰⁹, ExaBayes¹⁰³ or MrBayes¹¹⁰. Although the resulting tree at lower left is in truth a gene tree, it is often called a species tree or phylogeny because it is the result of analysis of a complete data set. In the center is depicted a class of species tree (coalescent) methods in which both gene trees and species trees are estimated concurrently according to multilocus sequence data, priors and a multispecies coalescent likelihood model. Examples of algorithms estimating species trees in this way include *BEAST⁴⁹ and BEST¹¹¹. On the right is depicted ‘two-step’ species tree methods, in which gene trees are first estimated using the classical concatenation paradigm, and then used as input data to estimate a species tree using algorithms such as MP-EST⁴⁸, STAR⁵¹, STEM⁸⁸, NJst¹¹², STELLS⁸⁹, or ASTRAL⁹⁰. The methods depicted typically used sets of loci each consisting of linked DNA sites². Yet other species tree methods such as SNAPP⁹¹ use unlinked SNPs rather than linked sites, and require different statistical models.

Figure 2. Inconsistency of the binning technique. a) the species tree used for simulating gene trees. In this species tree, (((A:0.01, B:0.01):0.005, C:0.015):0.005, D:0.02):0.08, E:0.1), species E is used as the outgroup. To reduce the rooting error, we set a small population size $\theta = 0.01$ and a long internal branch (length = 0.08) between ingroup species A, B, C, and D and the outgroup species E. The population size parameter $\theta = 0.1$ for other ancestral populations in the

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3 species tree. b) The probabilities of two estimated gene trees for binned genes. We consider only
4 two trees, the matching tree (MT) and the most probable tree (PT). The bars at 0 represent the
5 true (coalescent) probabilities of MT and PT generated from the species tree under the coalescent
6 model.
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15 Figure 3. The probability of estimating the wrong and correct species trees without binning. A)
16 In these simulation parameters, bin sizes of 0 (no binning) or 5 converge on the correct tree. B)
17 For bin size (BS) 10, the probability of estimating the correct tree is stable around 0.6 as the
18 number of bins increases. C) In contrast, the probabilities of estimating the wrong species tree
19 for BS = 20, 30, 40, 50 increase to 1 as the number of bins increases.
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29 Figure 4. The effect of non-informative genes on the performance of gene-tree-based approaches
30 in estimating species trees. DNA sequence data were simulated from the true species tree. The
31 sequences of 1000 base pairs were generated for strong genes, while 100 base pairs were
32 generated for weak genes. a) the species tree used in the simulation. b) the boxplot of the
33 average bootstrap values for weak and strong genes. c) the effect of different numbers of strong
34 and weak genes on the performance of MP-EST in estimating species trees. See text for further
35 explanation.
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Table 1. Studies evaluating the robustness of species tree phylogenetic methods to various genetic forces and sampling schemes.

Topic (Reference number)	Conclusions/comments*
General violation of multispecies coalescent model (106)	Claims the majority of multilocus sequence datasets are a poor fit to the multispecies coalescent model, although much of the violation stems from fit of substitution model or unknown sources on a minority of genes.
Gene flow (74,107)	<ul style="list-style-type: none"> • The coalescent method is robust to low levels of gene flow • Concatenation performs poorly relative to the coalescent methods in the presence of gene flow. • Gene flow can lead to overestimation of population sizes and underestimation of species divergence times in species trees.
Sampling/mutation (33,75,95)	<ul style="list-style-type: none"> • Increased sampling of individuals per species can significantly improve the estimation of shallow species trees. • Sampling more individuals does not significantly improve accuracy in estimating deep species trees. Adding more loci can improve the estimation of deep relationships. • Mutational variance is a major source of error in estimates of species trees.
Recombination (39,108)	<ul style="list-style-type: none"> • Recombination has minor effect on species tree estimation except on extremely short species trees. • The negative effects of recombination can be easily overcome by increased sampling of alleles
Missing data (19,64,68)	<ul style="list-style-type: none"> • Missing data can decrease the support of species tree estimates • Missing data can significantly affect the accuracy of species tree estimation • Species tree methods are “remarkably resilient” to missing data⁶⁸
Taxon sampling (15)	Compared to concatenation, coalescent methods are more robust to poor taxa sampling
Long-branch attraction (29)	Species tree methods more resilient to the effects of long-branch attraction than concatenation methods
Random rooting of gene trees (36,37)	Misrooting of gene trees can mimic the coalescent process
Other (81)	Anomalous gene trees are unlikely to pose a significant danger to empirical phylogenetic study in part because species trees in the anomaly zone are likely to be rare.

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3 *Conclusions of different papers are presented as simplified bullets. In some cases
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5 conclusions of different papers may conflict, likely do to differences in simulation
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7 parameters and assumptions. Comments on papers are the opinion of the authors.
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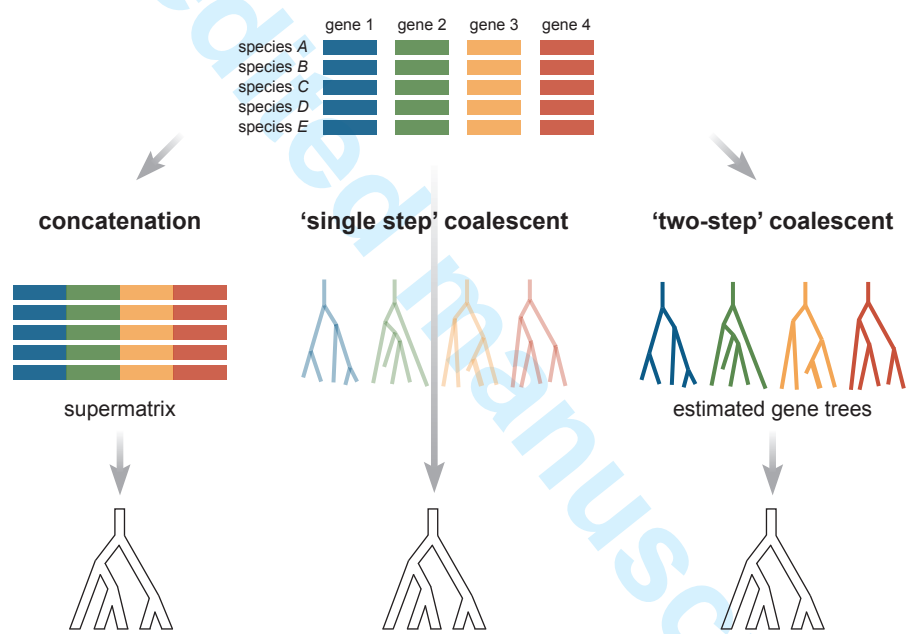


Fig. 1

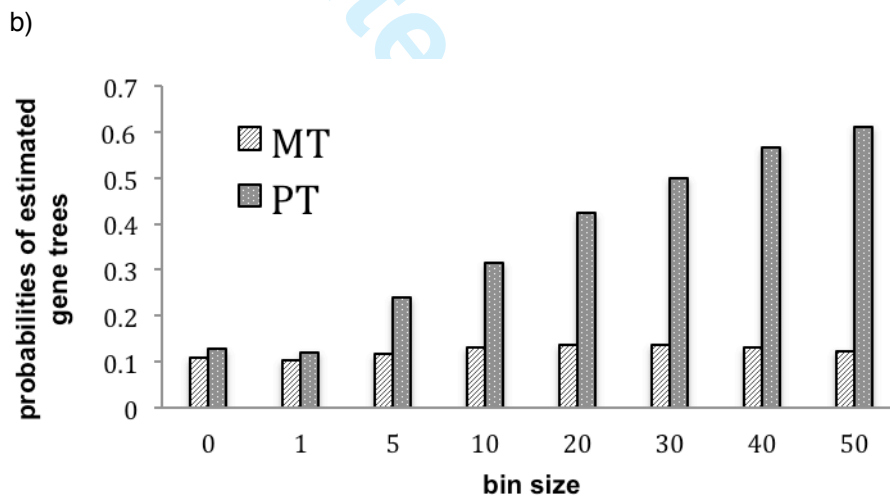
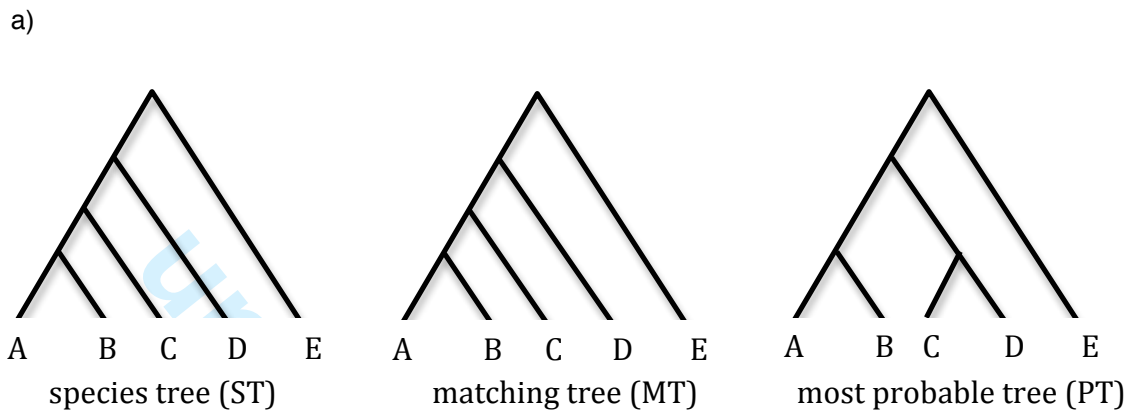


Figure 2

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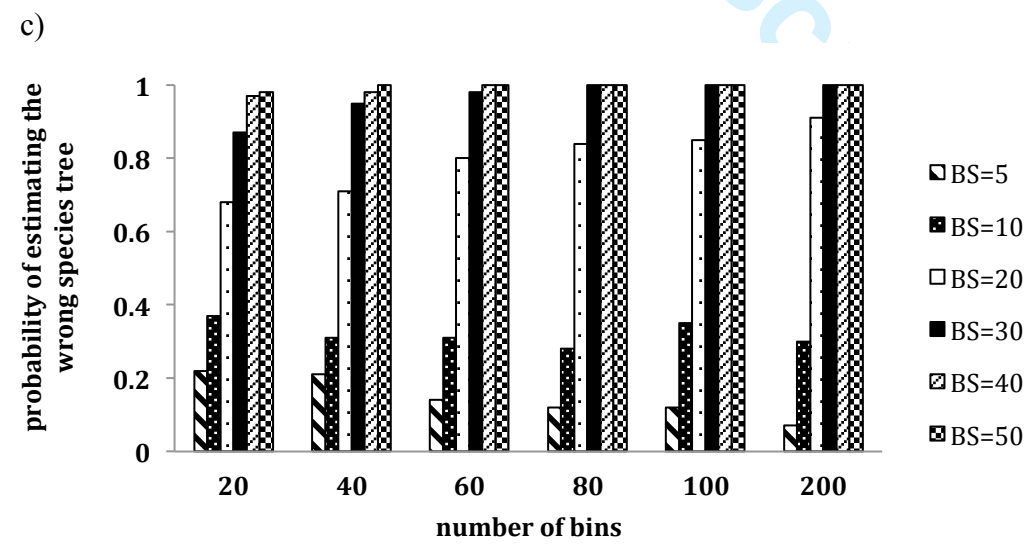
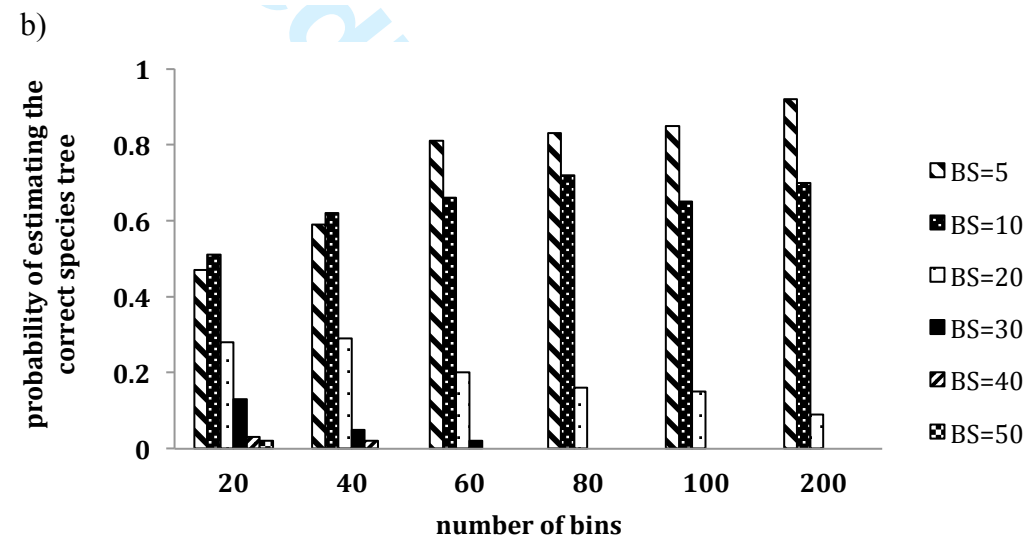
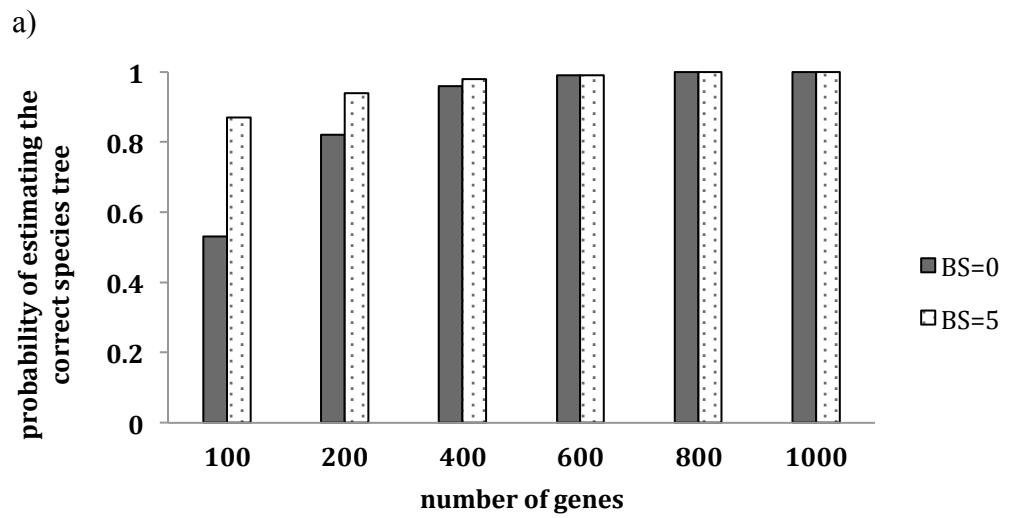
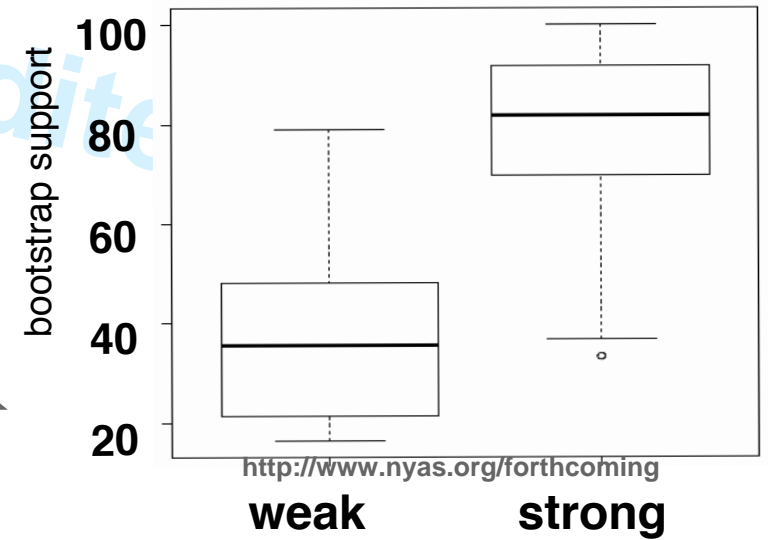


Fig. 3

a)



b) Annals of the New York Academy of Sciences



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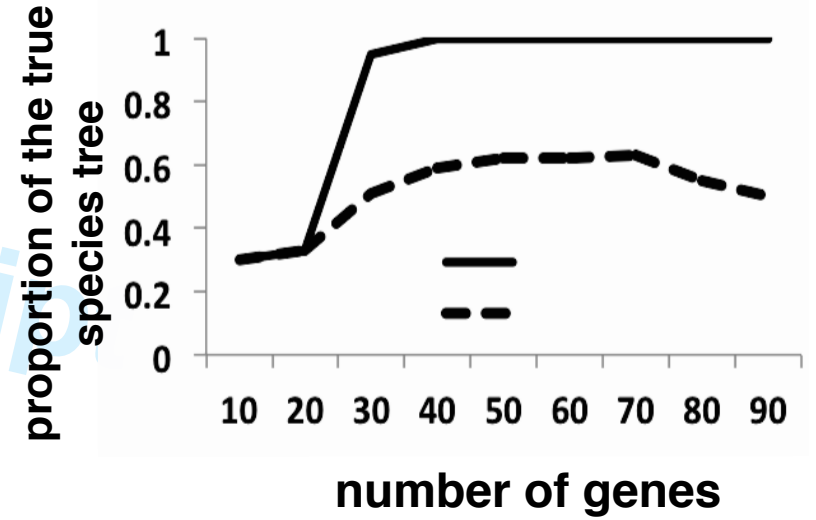


Fig. 4