1	Phylogenomic approaches to detecting and characterizing introgression
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9 Abstract

Phylogenomics has revealed the remarkable frequency with which introgression occurs across the tree of life. These discoveries have been enabled by the rapid growth of methods designed to detect and characterize introgression from whole-genome sequencing data. A large class of phylogenomic methods makes use of data from one sample per species to infer introgression based on expectations from the multispecies coalescent. These methods range from simple tests, such as the *D*-statistic, to model-based approaches for inferring phylogenetic networks. Here, we provide a detailed overview of the various signals that different modes of introgression are expected leave in the genome, and how current methods are designed to detect them. We discuss the strengths and pitfalls of these approaches and identify areas for future development, using a small simulation study to highlight the different signals of introgression and the power of each method to detect them. We conclude with a discussion of how to visualize and interpret the results of introgression analyses.

Introduction 42

- 43 The potential for hybridization and subsequent backcrossing between lineages-also known as
- introgression-has long been understood (Heiser 1949, Heiser 1973, Rieseberg and Wendel 44
- 1993, Dowling and Secor 1997). However, until genome sequencing became widely available to 45
- biologists, it was difficult to quantify patterns of introgression effectively and reliably. As a 46
- result, introgression's role in evolution was under-appreciated, especially in animal systems. In 47
- part precipitated by the discovery of introgression between archaic human populations (Green et 48
- al. 2010, Huerta-Sanchez et al. 2014), the past decade has seen an explosive increase in the rate 49
- 50 of discovery of reticulate evolution across the tree of life (Mallet et al. 2016, Taylor and Larson
- 2019). Although great efforts have been made in recent years to synthesize the biological 51
- implications of these discoveries (Hedrick 2013, Ellstrand et al. 2013, Harrison and Larson 2014, 52
- 53 Racimo et al. 2015, Ottenburghs et al. 2017, Suarez-Gonzalez et al. 2018), comparatively little
- synthesis has been provided on the accompanying growth in methods used to detect and 54
- characterize introgression. 55
- The information that can be gleaned from genomic data about introgression depends on both the 56
- number of sampled species and the number of sampled individuals. Methods with only two 57
- species or populations depend on sampling multiple individuals within at least one of them. 58
- Patterns of nucleotide variation among individuals and across loci can then be used to make 59
- inferences about introgression (e.g. Wakeley and Hey 1997, Nielsen and Wakeley 2001, Joly et 60
- 61 al. 2009, Lohse and Frantz 2014, Rosenzweig et al. 2016, Schrider et al. 2018). Because less
- information is available about phylogenetic relationships, these methods often rely on the 62
- assumption that all sequenced loci are evolving neutrally or that all loci have the same rate of 63 nucleotide substitution (or both). For these reasons such methods are more prone to model
- 64
- 65 violations, such as the heterogeneous effects of background selection across loci (Roux et al.
- 2016). Despite these limitations, population-genetic methods are one of the few approaches that 66
- can infer gene flow between pairs of sister taxa (see Hahn 2018 for more details). 67
- When there is data for a rooted triplet of species—or an unrooted quartet—it becomes possible to 68
- construct more powerful tests for introgression using genome-scale datasets. Importantly, this 69
- 70 can be done using only a single sample per species and without assumptions about neutrality.
- 71 The robustness to non-neutral processes occurs because much of the genealogical signal of
- introgression is not mimicked by selection (Przeworski et al. 1999, Williamson and Orive 2002, 72
- Vanderpool et al. 2020). This class of "phylogenomic" methods is largely based on one sample 73
- 74 per species, but also includes methods based on multiple samples. One-sample methods include
- the D statistic (also known as the ABBA-BABA test; Green et al. 2010, Durand et al. 2011), its 75
- numerous analogs and extensions (see below), methods based on pairwise sequence divergence 76
- such as the D_3 statistic (Hahn and Hibbins 2019), and phylogenetic network approaches such as 77
- those implemented in PhyloNet (Than et al. 2008, Wen et al. 2018), SNaQ (Solís-Lemus and Ané 78 2016), and *SpeciesNetwork* (Zhang et al. 2018). When multiple individuals are sampled from 79
- very closely related species or populations, additional power may be gained by measuring the 80

- 81 deviation from covariances in allele frequency expected under strictly treelike evolution (Reich
- et al. 2009, Patterson et al. 2012, Pickrell and Pritchard 2012, Peter 2016).
- 83 In this review, we focus on phylogenomic methods for studying introgression, most of which are
- 84 based on the multispecies coalescent model. We provide a detailed overview of the signals that
- various introgression scenarios are expected to leave in the genome, and the methods that are
- 86 designed to detect these signals. We discuss common misuses and misinterpretations of these
- 87 methods, as well as providing recommendations for best-use practices. Finally, we present
- results from a small simulation study conducted across different introgression scenarios to
- 89 highlight the advantages and limitations of currently available methods. Based on these results,
- 90 we identify areas for future theoretical and methodological advancement.

91 Biological processes that generate gene tree heterogeneity

- 92 We begin our discussion of phylogenomic methods with the simplest possible sampling scheme:
- 93 genomic data from a single sampled haploid individual from each of three focal species and an
- outgroup. By "genomic data" we mean data sampled from many loci across the genome, with the
- standard assumption of no intra-locus recombination and free inter-locus recombination. This
- 96 data structure will hereafter be referred to as a quartet or rooted triplet. For three ingroup species,
- 97 *P1*, *P2*, and *P3*, and an outgroup species, *O*, there are three possible tree topologies describing
- 98 how they can be related: (((P1,P2),P3),O), (((P2,P3),P1),O), or (((P1,P3),P2),O) (Figure 1). In
- addition to a single phylogeny describing the evolutionary history of the quartet, trees can be
- 100 constructed for each individual locus. The frequencies of each topology across loci are referred
- to as gene tree frequencies, even when they do not come from protein-coding genes. This
- heterogeneity in both the topology and branch lengths of gene trees is caused by two different
- biological processes: incomplete lineage sorting and introgression. Below we describe the
 expected effects of both processes in order to understand how tests for introgression work.

105 Incomplete lineage sorting as a null hypothesis for tests of introgression

- 106 The phenomenon of incomplete lineage sorting (ILS), in which two or more lineages fail to
- 107 coalesce with each other before reaching an ancestral population (looking backwards in time),
- 108 can result in individual gene trees that are discordant with the species history (Figure 1).
- 109 Phylogenomic methods must account for this phenomenon to make accurate inferences about
- 110 introgression. Discordant gene trees occur because, when ILS occurs, it becomes possible for the
- order of coalescent events to differ from the order of splits in the species phylogeny (Figure 1,
- top right panel). Gene tree discordance due to ILS is very common in modern phylogenomic
- datasets (e.g. Pollard et al. 2006, Fontaine et al. 2015, Pease et al. 2016, Novikova et al. 2016,
- 114 Copetti et al. 2017, Wu et al. 2018a; Edelman et al. 2019) and can arise within phylogenies that
- 115 contain no introgression events. Because both ILS and introgression can generate many of the
- same genealogical patterns, it is essential to incorporate ILS into the null hypothesis of tests for
- 117 introgression.

118 Fortunately, the parameters mostly likely to influence the probability of ILS—time between

- speciation events and ancestral population size—are well understood from the multispecies
- 120 coalescent (MSC) model (Hudson 1983, Tajima 1983, Pamilo and Nei 1988). For a rooted

- triplet, the probability that the two sister lineages (e.g. *P1* and *P2* in Figure 1) coalesce in their
- 122 most recent common ancestral population is given by the formula $1 e^{-\tau}$, where τ is the length
- 123 of this internal branch in units of 2N generations (sometimes referred to as "coalescent units").
- 124 Conversely, the probability of ILS (i.e. that they do not coalesce) is $e^{-\tau}$. If ILS occurs, all three
- lineages (P1, P2, and P3) enter their joint ancestral population. Within this population the
- coalescent events happen at random, such that lineages leading to each pair of species have a 1/3
 chance of coalescing first. This means that the two discordant gene tree topologies are expected
- to be equal in frequency (Figure 1, top right), with probabilities of $1/3 e^{-\tau}$ each. In addition, the
- 129 concordant tree topology can be produced either by lineage sorting with probability $1 e^{-\tau}$ or
- incomplete lineage sorting with probability $1/3 e^{-\tau}$ (Figure 1, top left). This guarantees that the
- 131 concordant tree topology will always be at least as frequent as the two discordant trees (Figure 1,
- top row). These expectations under ILS form the null hypothesis for tests of introgression basedon gene tree frequencies.
- 134 In addition to gene tree frequencies, ILS affects expected coalescence times, and therefore
- sequence divergence, between pairs of species. In any population, the expected times to
- 136 coalescence depends on how many lineages are present (Kingman 1982, Hudson 1983, Tajima
- 137 1983). If three lineages are present, the first coalescence is expected to occur 2/3 N generations
- 138 in the past. After this first coalescence—or if only two lineages were present to begin with—the
- 139 next coalescence is expected a further 2N generations in the past. These expectations are equally
- 140 applicable to current populations as to ancestral populations, but coalescence cannot occur until
- 141 the lineages under consideration are in a common population. Therefore, expected coalescence
- 142 times between species always have the time of speciation included as a constant, no matter how
- 143 far back lineage-splitting occurred (Gillespie and Langley 1979).
- 144 For example, the time to coalescence between species P1 and P2 in Figure 1 is expected to be 2N
- 145 generations prior to their speciation event. If this coalescent event happens in their most recent
- 146 common ancestral population (i.e. lineage sorting), then the next coalescent event occurs
- between the resulting single lineage and the lineage leading to *P3* in the common ancestral
 population of all three species (Figure 1, bottom row). This event is again 2N generations prior to
- population of all three species (Figure 1, bottom row). This event is again 2N generations prior to the speciation event between P3 and the common ancestor of P1+P2. If ILS occurs, then the first
- 145 the spectation event between 75 and the common ancestor of 77772. If it is becaus, then the ins 150 coalescence (regardless of which lineages are involved) occurs 2/3 N generations prior to this
- same speciation event, and the second coalescence 2N generations before this. Note that, if we
- condition on lineage sorting having occurred, the expected coalescence times become slightly
- more complicated (see Mendes and Hahn 2018, Hibbins and Hahn 2019 for exact expectations)
- 154 The two pairs of non-sister lineages in a rooted triplet (*P1* and *P3* or *P2* and *P3* in Figure 1) can
- 155 coalesce at one of two times, depending on whether they are the first or second pair to coalesce
- in a gene tree (there can only be a discordant topology if they are the first to coalesce). Owing to
- the symmetry of gene tree topology shapes and frequencies, these times are equivalent across
- loci, leading to the null expectation under ILS that genome-wide divergence between both pairs
- of non-sister taxa should be equal (Figure 1, bottom row). Finally, each of these coalescence
- times is expected to follow a unimodal exponential distribution under ILS alone (Hudson 1983,
- 161 Tajima 1983).

The effects of introgression on gene trees 162

Introgression between two lineages occurs when an initial hybridization event is followed by 163 back-crossing into one or both of the parental lineages. Hybridization itself-the creation of a 164 hybrid individual—is generally not sufficient to be called introgression, though polyploid or 165 homoploid hybrid species will be identified by many of the same tests described here (e.g. Meng 166 and Kubatko 2009; Blischak et al. 2018; Folk et al. 2018). Similarly, horizontal gene transfer 167 will also generate discordant gene trees, but introgression is generally distinguished from this 168 169 process by the requirement that there be mating between the hybridizing lineages in order to be considered introgression. In addition, the mating requirement means that the hybridizing species 170 are closely related enough such that the tree topologies produced by introgression will likely be 171 172 the same as those produced by ILS. Horizontal gene transfer, on the other hand, can produce highly discordant topologies that can only be produced by the interspecific exchange of genetic 173

- material (e.g. Knowles et al. 2018). 174
- 175 There are a large number of different introgression scenarios, each with a different effect on the
- underlying gene trees. While there are well-developed mathematical tools that describe the 176
- 177 effects of introgression on gene tree topologies (e.g. the multispecies network coalescent;
- reviewed in Degnan 2018, Elworth et al. 2019), we generally do not need the predictions from 178
- these models to test for the presence of introgression (with some exceptions discussed below). 179
- Instead, because our tests are often simply looking for a rejection of the ILS-only model, a 180
- general understanding of the key outcomes of introgression will be sufficient. Figure 2 181
- summarizes the scenarios involving introgression that are most commonly encountered. 182
- 183 As a first key distinction, introgression can occur either between sister lineages (events 1 and 2
- in Figure 2A) or non-sister lineages (events 3, 4, and 5 in Figure 2A). As a general rule, 184
- introgression between sister lineages should increase the proportion of concordant gene trees 185
- relative to the case of ILS alone. To see why this is, consider introgression event 1 in Figure 2: 186
- gene flow after speciation between P1 and P2 effectively increases τ , the length of the internal 187
- branch separating these two lineages from their common ancestor with P3. Loci with an 188
- 189 introgressed history therefore have a reduced probability of ILS because of the increased time for
- them to coalesce. While there are some exceptions to this rule—all of which involve 190
- introgression between sister lineages on an internal branch of the species tree (i.e. event 2 in 191
- Figure 2; Solis-Lemus et al. 2016, Long and Kubatko 2018, Jiao and Yang 2020)—in no cases 192
- should gene flow between sister lineages result in one discordant topology becoming more 193
- common than the other discordant topology. 194
- Because an increase in concordant topologies can also be generated under an ILS-only model 195
- with a longer internal branch in the species tree, gene tree frequencies alone cannot tell us 196
- 197 whether introgression has occurred between sister lineages. Note, however, that loci with a
- history of introgression can have a different distribution of branch lengths in this scenario than 198
- expected under ILS alone: the coalescence times are more recent than expected under ILS for 199
- either event 1 or 2 (Figure 2B). Our ability to determine whether the distribution of branch 200
- lengths is due to a history of introgression partly depends on whether gene flow is continuously 201
- occurring after speciation or occurs as a single pulse of hybridization and backcrossing at a 202

- 203 period considerably after speciation: pulses of introgression following secondary contact
- between species will almost always be easier to detect (see section on "*Detecting introgression*
- *using coalescence times*"). Using only a single sample from each species, we also cannot
- determine the direction of gene flow between sister lineages; this is why we have drawn events 1
- and 2 as bidirectional introgression. In order to make this determination between sister species
- 208 we must use population genetic methods (e.g. Schrider et al. 2018).

209 When introgression occurs between non-sister lineages (events 3, 4, and 5 in Figure 2A) then one 210 discordant tree topology can become more common than the other. The resulting asymmetry in discordant tree topologies is one of the clearest signals of introgression. In both events 3 and 4 211 we expect loci that have introgressed to be more likely to have a gene tree topology placing P2 212 and P3 sister to one another: ((P2,P3),P1) (Figure 2C). While not all loci following this 213 introgression history will have this discordant topology, the extended period of shared history 214 between P2 and P3 makes it more likely for these lineages to coalesce. In general, the strength of 215 the asymmetry in discordant topologies will depend on the net rate, timing, and direction of 216 introgression (Durand et al. 2011; Martin et al. 2015; Zheng and Janke 2018), as well as the 217 absence of introgression between the other non-sister pair (in which case the other discordant 218

- topology would also go up in frequency). Although the same discordant topology will be
- produced in excess by events 3 and 4 (Figure 2C), note that the resulting branch lengths will
- differ on average between the two. This difference makes it possible to determine the main
- direction of introgression between non-sister taxa (see below). Although we have drawn gene
- flow as unidirectional to highlight the fact that this distinction can be made, bidirectional gene
- flow between these lineages is equally biologically plausible.

225 Finally, event 5 depicts an introgression event involving an unsampled ("ghost") lineage. For many of the signals of introgression discussed here, the sampled lineages included in a study 226 may not be the ones that actually hybridized. Whether species go unsampled because they are 227 extinct or simply unavailable, non-sister ghost lineages that act as donors in introgression events 228 will often generate detectable patterns of gene flow. These patterns can result in misleading 229 inferences about the lineages involved in gene flow and the direction of gene flow, and should 230 therefore always be kept in mind; we include introgression from ghost lineages in our simulation 231 study below to demonstrate some of these effects. Ghost lineages that are either the recipients of 232 gene flow or are sister to sampled taxa are much less likely to leave any signal of introgression. 233 For similar reasons, the sister lineages shown in Figure 2 do not need to be one another's most 234 235 closely related species in nature; what is important is whether they are sister (or non-sister)

among sampled species.

237 Detecting introgression using gene tree frequencies

238 The D statistic

- 239 Perhaps the most widely used method for inferring introgression is the *D* statistic, or—perhaps
- because there are already so many *D*'s in use—what is commonly referred to as the ABBA-
- 241 BABA test. This test was originally formulated to test for evidence of gene flow between

- Neanderthals and archaic humans (Green et al. 2010, Durand et al. 2011), and is based on the
- 243 effect of introgression between non-sister taxa on gene tree frequencies.
- 244 The statistic counts the occurrence of two configurations of shared derived alleles across three
- species and an outgroup. Assuming the species tree (((P1,P2),P3)O), and denoting the ancestral
- allele as "A" and the derived allele as "B," there are two phylogenetically informative patterns of
- 247 discordant sites. The pattern "ABBA" represents sites where *P2* and *P3* share a derived allele,
- while *P1* and the outgroup have the ancestral allele. The pattern "BABA" represents sites where
- 249 *P1* and *P3* share a derived allele, to the exclusion of *P2* and the outgroup (Figure 3). For clarity,
- note that sites supporting the species topology would have the pattern BBAA; however, these are
- not used in this statistic.
- 252 The *D* statistic assumes an infinite sites model, meaning that the two discordant site patterns can
- only arise via single mutations on the internal branches of discordant gene trees (Figure 3, blue
- dots/branches). Under this assumption, the frequencies of ABBA and BABA site patterns are
- expected to reflect the frequencies of underlying gene trees. If the number of ABBA and BABA
- sites differ significantly, then an asymmetry in gene tree topologies is inferred, with
- introgression occurring between the species sharing the derived state more frequently. Figure 3
- depicts the scenario when the site pattern ABBA is more common, implying introgression
- 259 between *P2* and *P3*.
- To make it comparable across studies, the value of the *D* statistic is typically reported after normalization using the sum of ABBA and BABA pattern counts, giving the following formula:

$$D = \frac{ABBA - BABA}{ABBA + BABA}$$

where ABBA and BABA represent the number of sites of each type. This statistic has an expected value of D = 0 if there is no gene flow. When used as a whole-genome test of

introgression between non-sister taxa, the *D*-statistic is robust under many different scenarios

- 266 (Zheng and Janke 2018, Kong and Kubatko 2021), but can be affected by certain forms of
- ancestral population structure (Slatkin and Pollack 2008, Durand et al. 2011, Lohse and Frantz
- 268 2014) (see section entitled "Distinguishing introgression from ancestral population structure"
- 269 for more discussion of this issue).
- 270 Despite the widespread popularity and relative robustness of *D*, there are several important
- considerations and limitations to its use, some of which are often overlooked. The first of these
- concerns how to properly test the null hypothesis that D = 0. The expected site pattern counts of
- the *D*-statistic can easily be calculated, so it may be tempting to use a parametric test for
- differences. However, such tests assume that individual observations represent independent
 samples: this assumption is violated because closely spaced sites often share the same underlyin
- samples: this assumption is violated because closely spaced sites often share the same underlying
 local genealogy, making them non-independent. The pseudoreplication that results from treating
- all sites independently leads to inaccurate *p*-values. The solution to this issue is to use a block-
- bootstrap (or block-jackknife) approach to estimate the sample variance and then to calculate the
- p-value (Green et al. 2010). This approach correctly accounts for correlations within blocks of
- adjacent sites.

Although formulated as a single genome-wide test, there are cases where the *D*-statistic has been 281 282 applied to look for introgression in smaller genomic windows (e.g. Kronforst et al. 2013, Zhang 283 et al. 2016, Wu et al. 2018b, Grau-Bové et al. 2020). However, the genome-wide expectation under ILS alone that D = 0 does not hold true for smaller genomic windows. Since a single non-284 recombining locus contains a single genealogy by definition, it is only capable of generating one 285 phylogenetically informative biallelic site pattern (again assuming an infinite sites mutation 286 model). The consequence is that the value of D at a single locus can only be +1, 0, or -1,287 depending on the local genealogy (i.e. only ABBA, BBAA, or BABA). Therefore, even in ILS-288 only scenarios, there will be regions of the genome with extreme values of D, either positive or 289 negative. This situation is more likely to occur in regions of low recombination, as in these 290 regions even large genomic windows may only contain a small number of independent 291 genealogies. Highlighting this problem, Martin et al. (2015) found that the variance of D is 292 293 inflated in regions of low recombination, resulting in an excess of false positives if tests were to be performed on a per-window basis. Similar caution is warranted when applying D to 294 inversions, as the entire inversion can act as a single locus (cf. Fuller et al. 2018). For these 295 296 reasons, while it may be informative to plot the value of the D statistic along chromosomes, tests using D should be applied only to whole genomes, or at least to genomic regions that are 297 sufficiently large to guarantee sampling a large number of underlying genealogies. 298

Finally, the *D*-statistic does not provide any information about introgression other than its

300 presence or absence. While its value does increase with the rate of introgression, it is not a good 301 estimator of this quantity, tending to greatly overestimate the true value (Martin et al. 2015,

Hamlin et al. 2020). In addition, the sign of *D* is sometimes interpreted as providing information

303 on the direction of introgression, though it can only identify which taxa are involved, and not the

- donor and recipient populations. For example, a significant *D* statistic implying introgression
- between P2 and P3 could involve the $P3 \rightarrow P2$ direction, the $P2 \rightarrow P3$ direction, or some
- 306 combination of the two. Overall, the *D* statistic is a very reliable genome-wide test for
- introgression, but alternative methods are needed to infer more details about any detected
- 308 introgression events.

309 Inferring the rate and direction of introgression using derived allele counts

310 Many researchers are interested not only in the presence or absence of introgression, but in

311 quantifying its magnitude. Methods for inferring introgression can often be used to estimate its

312 "rate," which can generally be taken to mean one of two things. In the context of phylogenomic

- approaches and phylogenetic networks, the rate refers to the proportion of the genome that
- originates from a history of introgression. This is also sometimes referred to as the "inheritance
- probability" or "admixture proportion." Alternatively, in the isolation-with-migration (IM)
- framework, the rate refers to the movement of migrant individuals over continuous time
- 317 (Wakeley and Hey 1998, Nielsen and Wakeley 2001). In this and following sections, we will
- take the "rate" to have the former definition.
- 319 The degree of asymmetry in discordant gene tree topologies contains information about the
- 320 proportion of introgressed loci across the genome. However, simply using the D statistic does not
- provide an unbiased estimation of the rate (Martin et al. 2015, Hamlin et al. 2020). A recently

proposed extension of D called D_p makes one simple addition that improves the estimate of the 322 323 proportion of introgressed loci. The statistic adds the counts of BBAA sites to the denominator to form:

324

$$D_p = |\frac{ABBA - BABA}{BBAA + ABBA + BABA}$$

Taking the degree of asymmetry as a fraction of the total number of phylogenetically informative 326 biallelic sites brings D_p conceptually closer to estimating a genome-wide introgression 327 proportion. The statistic tends to slightly underestimate the true rate of introgression-and its 328 accuracy is affected by the direction of introgression—but it scales linearly with the rate of 329 introgression and has better precision for lower true amounts of introgression (Hamlin et al. 330 2020). 331

In an alternative approach, the observed value of an introgression test statistic is compared to the 332

value that would be expected under a scenario where the entire genome was introgressed. The 333 F_4 -ratio or α statistic (Green et al. 2010, Patterson et al. 2012, Peter 2016) makes this comparison 334

by taking the ratio of two F_4 statistics (a genome-wide test for introgression based on allele 335

frequencies). The α statistic requires data from five samples and assumes an admixed population

336 with two parent populations. HyDe (Blischak et al. 2018, Kubatko and Chifman 2019) estimates

337 the rate in a similar way under a hybrid speciation scenario using linear combinations of derived 338

site patterns. The assumptions of these methods are somewhat restrictive and are likely not 339

340 reflective of the majority of introgression in nature (Schumer et al. 2014). However, HyDe gives

highly accurate estimates of the rate of introgression when its assumptions about hybridization 341

are met, and still provides reasonable estimates for the rate when these assumptions are violated 342

(Kong and Kubatko 2021). 343

The f_d statistic of Martin et al. (2015) also takes the ratio of two *D*-statistics. However, by 344

making the assumption that allele frequencies would be completely homogenized in a complete 345

introgression scenario, f_d can be applied to quartets rather than requiring an additional sample. 346 Like D_p , f_d is sensitive to the direction of introgression because it estimates the proportion of the

347 genome that came from the donor population during introgression. The f_d statistic somewhat 348

overcomes this issue by assuming that the population with the higher derived allele frequency is 349

the donor at each site. Nonetheless, f_d tends to underestimate the proportion of introgressed loci 350

when P2 is the donor population. 351

Unless additional assumptions are made, there is not enough information contained in the 352

frequency of gene tree topologies (i.e. site pattern counts) alone to estimate the direction of 353

introgression in a quartet or rooted triplet. However, if a sample is obtained from a fifth species 354

(Eaton and Ree 2013, Pease and Hahn 2015) or if polymorphism data is available for the quartet 355

(Martin and Amos 2020), then it is possible to infer the direction of introgression. The 356

357 "partitioned D-statistics" of Eaton and Ree (2013) were the first attempt to infer the direction of

introgression in a five-taxon phylogeny. Unfortunately, redundant site pattern counts make the 358

results of this directionality test uninterpretable. The D_{FOIL} method of Pease and Hahn (2015) 359

resolves this problem by setting up a system of four D statistics, explicitly testing each of the 16 360

- possible introgression events and directions. *D*_{FOIL} assumes that the 5-taxon phylogeny is
- 362 symmetric, with two pairs of sister species. In this particular configuration of species it becomes
- 363 possible to polarize introgression events because the direction of introgression affects
- relationships between the donor and both the recipient species and its sister taxon. Unfortunately,
- D_{FOIL} does not work if the species tree is an asymmetric, or "caterpillar," tree.
- Martin and Amos (2020) showed that information about the rate, direction, and timing of
- introgression in a quartet becomes available using site patterns if multiple individuals are
- 368 sampled per lineage. Their approach, called the "D frequency spectrum" or $D_{\rm FS}$ for short,
- 369 estimates the *D* statistic in each bin of the joint derived allele frequency spectrum constructed for
- the two sister taxa in a quartet. The shape of the D_{FS} is expected to be affected by the direction of introgression. If one of the sister taxa is the recipient, then the spectrum is left-skewed, as the
- 372 signal of introgression will be enriched among low-frequency alleles. In contrast, if a sister
- 373 lineage is the donor and the non-sister lineage is the recipient, the spectrum is expected to be flat,
- because the frequency spectrum of the non-sister lineage is not used to construct the $D_{\rm FS}$. The
- degree of left-skewness is affected by the timing of introgression, while the rate of introgression
- affects the magnitude of the *D*-statistic across bins. The shape of the D_{FS} is also affected by
- 377 demographic history and changes under more complex introgression scenarios, so it will
- typically be necessary to perform simulations to explicitly test different introgression scenarios
- 379 with this approach (Martin and Amos 2020).

380 Inferring introgression events from reconstructed gene trees

381 While methods based on site patterns and allele frequencies can be powerful, there are also fundamental limitations to the kinds of data they can be applied to. First, as mentioned earlier, a 382 key assumption of the D statistic is an infinite sites model of mutation. When applied to closely 383 related, extant species, this assumption is likely to hold. However, with increasing divergence it 384 becomes more likely that ABBA and BABA site patterns can accumulate due to convergent 385 substitutions. For this reason, site patterns are generally not a reliable way to test for 386 introgression between more distantly related extant species, or along branches deeper in a species 387 388 tree. Second, as the number of sampled species increases, the number of possible trees and quartets increases super-exponentially (Felsenstein 2004). This makes it impractical to apply 389 quartet-based methods to trees with many taxa. 390

A solution to these problems is to estimate gene tree topologies directly, as many different 391 methods can be used to accurately infer the topology at a locus. Once gene trees have been 392 393 reconstructed from a large number of loci, the counts of discordant topologies can be used in much the same way as ABBA and BABA sites are in the D test. In fact, Huson et al. (2005) 394 proposed such a test, using a statistic they called Δ . Significance in genome-scale datasets can be 395 evaluated by bootstrap-sampling the estimated gene trees (Vanderpool et al. 2020) or by 396 assuming a χ^2 distribution (Suvorov et al. 2021), with $\Delta = 0$ again representing the null 397 hypothesis under ILS alone. While Δ has greater potential to be affected by sources of technical 398 error such as systematic bias in gene tree inference—and may have limited power to detect very 399 ancient introgression—it has the advantage of being more robust to the infinite-sites assumption 400 401 and allows for testing of introgression along deep, internal branches of a phylogeny. Therefore, Δ 402 represents a straightforward way to test for introgression using a small number of additional403 assumptions.

- Estimated gene trees can also be used as input to phylogenetic network methods. These methods
- 405 construct a likelihood or pseudolikelihood function that is explicitly derived from a phylogenetic
- 406 network model, for which parameters can then be estimated using either maximum-likelihood or
- 407 Bayesian approaches. Phylogenetic network methods can handle several different data types
- (which will be discussed in subsequent sections), but some of them can make inferences usingonly gene tree topologies as input. *PhyloNet* (Than et al. 2008, Wen et al. 2018) infers networks
- directly from gene tree topologies using either maximum likelihood or maximum pseudo-
- 411 likelihood. Similarly, *SNaO* (Solis-Lemus & Ane 2016) estimates a network with reticulation
- 412 edges via maximum pseudo-likelihood using quartet concordance factors (Baum 2007)—
- essentially just the counts of the three possible unrooted tree topologies. The principles outlined
- in previous sections apply equally well to these methods, showing how phylogenetic network
- 415 approaches can detect, polarize, and estimate the rate of introgression events in a tree with a
- 416 minimum of five taxa. Additionally, they can be applied to species trees with many more than
- five taxa, making use of all available information available. We will discuss phylogenetic
- network methods in more detail later, in the section entitled "Application and interpretation of
- 419 *methods for inferring introgression*".

420 **Detecting introgression using coalescence times**

- 421 While much can be learned about introgression from the frequency of gene tree topologies alone,
- 422 including additional information about the distribution of coalescence times can lead to much
- richer inferences. Some advantages of including coalescence times include more flexibility in
- 424 inferring introgression between non-sister species, detection of introgression between sister taxa,
- and distinguishing introgression from ancestral population structure. In the following sections we
- 426 expand on the expected effects of introgression on coalescence times and branch lengths,
- 427 followed by a description of how this information is used in concert with gene tree frequencies to
- 428 make inferences about introgression.

429 Detecting introgression using signals of pairwise divergence

- 430 Just as was the case for gene tree topologies, it is possible to make inferences about introgression
- 431 by studying violations of expected patterns of pairwise coalescence times under an ILS-only
- model. As previously mentioned, one of these expected patterns is a symmetry in coalescence
- times between the two pairs of non-sister taxa in a quartet (Figure 1, bottom). If one pair of non-
- 434 sister taxa has more recent coalescence times on average than the other, post-speciation
- 435 introgression between that pair is a likely explanation. Coalescence times can be approximated
- 436 using simple measures of pairwise sequence divergence, assuming an infinite sites model (or at
- 437 least that genetic distance is proportional to coalescence time). Therefore, one of the simplest
- 438 ways to test for introgression is to test for an asymmetry in pairwise sequence divergence. This
- 439 logic has been informally applied to test for introgression (Brandvain et al. 2014) and has
- 440 recently been formalized in several test statistics including D_3 (Hahn and Hibbins 2019) and the

- branch-length test (Suvorov et al 2021). D_3 is straightforward, and has the following definition
- 442 (changed from the original to be consistent with the notation used here):

443
$$D_3 = \frac{d_{P2P3} - d_{P1P3}}{d_{P2P3} + d_{P1P3}}$$

Where *d* denotes the genetic distance between the specified populations. This statistic takes the same general form as the *D*-statistic, where the relevant difference in the numerator is normalized by the sum of the two values in the denominator. Like the *D*-statistic, significance of D_3 can be evaluated using a block-bootstrap. A major advantage of D_3 over site-pattern based tests is that it does not require data from an outgroup—it only needs one sample from three ingroup species. As with D, D_3 can only detect introgression between non-sister lineages.

450 Characterizing introgression using reconstructed gene trees with branch lengths

451 Using pairwise divergences between only non-sister taxa ignores information about the full

distribution of coalescence times within different gene tree topologies. More information is

contained within these branch lengths, allowing for estimation of the timing and direction of

introgression in a quartet. Because introgressing taxa can coalesce via either introgression

455 (Figure 4A, blue) or speciation (Figure 4A, red) depending on the history at a locus, a bimodal

456 distribution arises when coalescence times are measured across loci (Figure 4A). This

distribution is not expected under ILS alone, and can therefore be used to test for introgression.

458 In addition, the more recent peak provides information about the timing of introgression, while

the frequency of gene trees under this peak compared to the older peak provides information on

the rate of introgression.

461 This approach to characterizing introgression is implemented in the software *QuIBL*

462 (Quantifying Introgression via Branch Lengths) (Edelman et al. 2019). *QuIBL* takes gene trees

with inferred branch lengths as input, using maximum-likelihood to infer whether one

distribution (ILS-only) or two distributions (ILS + introgression) is a better fit. If two

distributions is a better fit, then introgression between non-sister species is inferred. QuIBL may

also be able to infer the timing and rate of introgression using information contained within thesedistributions.

468 The direction of introgression uniquely affects the coalescence times of the non-sister pair of

species uninvolved in introgression (Figure 2C, Figure 4B). For example, the direction of

470 introgression between P2 and P3 has predictable effects on the coalescence time between P1 and

471 *P3*. When introgression occurs from *P3* into *P2* (Figure 4B, left), *P2* traces its ancestry through

the *P3* lineage at introgressed loci (note that while the direction of introgression is typically

described forward in time, the coalescent process occurs backwards in time). Because of this,

divergence between *P1* and *P3* is unchanged by introgression in this direction. By contrast, when

475 introgression is from P2 into P3 (Figure 4B, right), P3 traces its ancestry through the P2 lineage

476 at introgressed loci. This allows *P3* to coalesce with *P1* earlier than it normally would, which

477 decreases the divergence between *P1* and *P3*.

- These genealogical processes lead to general predictions that can be used to infer the primary
- direction of introgression between taxa. Gene trees that are concordant with the species tree can
- 480 be used as a baseline for the expected amount of *P1-P3* divergence; although these trees can
- arise from ILS at introgressed loci, the effect of the direction will not be manifest since they are
- 482 concordant. By comparing this baseline divergence to the amount of *P1-P3* divergence in gene
- trees consistent with a history of introgression, the direction of introgression can be inferred.
- 484 Lower *P1-P3* divergence in the latter class of trees provides evidence for $P2 \rightarrow P3$ introgression,
- but does not necessarily rule out the other direction (i.e. there could simply be less gene flow in
- the other direction). Alternatively, if P1-P3 divergence is the same in both topologies, then
- 487 introgression is primarily $P3 \rightarrow P2$. This logic to polarizing introgression is used by the D_2
- statistic (Hibbins and Hahn 2019) and the *DIP* method (Forsythe et al. 2020).
- 489 Finally, *PhyloNet* (Than et al. 2008, Wen et al. 2018) is able to infer phylogenetic networks with
- 490 reticulation edges (i.e. discrete introgression events) from gene trees with branch lengths using
- 491 maximum likelihood. Based on the previously discussed patterns, this method should be capable
- 492 of accurately estimating the presence, timing, direction, and rate of introgression by making use
- 493 of all available information on the distribution of coalescence times. It can also estimate multiple
- independent events on the same species tree, and on trees with more than five taxa. As we
- discuss in a following section, it is also capable of detecting the signals of introgression between
- 496 sister species.

497 Distinguishing introgression from ancestral population structure

- 498 In addition to being generated by introgression, asymmetric gene tree topology frequencies can
- arise from certain kinds of ancestral population structure (Slatkin and Pollack 2008, Durand et al.
 2011, Lohse and Frantz 2014). The scenario that generates asymmetries imagines that the
- 500 2011, Lonse and Franz 2014). The scenario that generates asymmetries imagines that the 501 population ancestral to all three species is split into at least two subpopulations, such that the
- ancestors of P3 are more closely related to either the ancestors of P1 or P2 (but not both)
- 502 (Supplementary Figure 1A). Because the gene tree topologies in this ancestral species will be
- see skewed toward relationships joining *P3* and one of the sister lineages, this scenario can lead to a
- significant asymmetry in gene tree topologies even in the absence of post-speciation
- 506 introgression (Durand et al. 2011). This will also result in a slight asymmetry of genome-wide
- 507 pairwise divergence times, since the more common discordant tree will contribute more to the
- average value. All of this means that ancestral structure can result in false positives when testing
- 509 for introgression using simple patterns of asymmetry.
- 510 Fortunately, while these two scenarios are indistinguishable using only gene tree topologies
- alone, they are distinguishable when using the distribution of branch lengths. Under ancestral
- 512 population structure, divergence between the sister taxa in whichever discordant gene tree
- becomes more frequent will be higher than it would be under introgression. Lohse and Frantz
- 514 (2014) incorporated the expected branch length differences in these two models into a
- 515 maximum-likelihood framework, which was then used to confirm the signal of human-
- 516 Neanderthal introgression that was originally uncovered by the *D*-statistic. Additionally,
- ancestral population structure is not expected to result in a bimodal distribution of coalescence

- times. This means that methods capable of detecting two peaks of coalescence, such as *QuIBL*
- and *PhyloNet*, should also be robust to the effects of population structure.

520 Detecting introgression between sister species

- 521 Introgression between sister species is very difficult to detect using a single sample from each
- 522 species. The classic asymmetry patterns described in previous sections do not apply in this
- 523 scenario, either for gene tree topologies or coalescence times. While introgression between sister
- species should lead to an increased variance in coalescence times compared to an ILS-only
- 525 model, this signal is easily confounded by other processes such as non-equilibrium demography
- or linked selection (Cruickshank and Hahn 2014; Roux et al. 2016; Sethuraman et al. 2019).
- 527 These limitations have typically been addressed by combining two alternative sources of
- information: 1) polymorphism data for the two introgressing species, and 2) local reductions in
- 529 between-species divergence relative to a genome-wide baseline.
- 530 Most available methods for inferring introgression between sister taxa are not phylogenomic in
- 531 multiple senses: they typically require polymorphism data, they often identify locally
- introgressed regions rather than genome-wide signals, and they do not explicitly test against an
- 533 ILS-only case. Genome scans using summary statistics such as F_{ST} (Wright 1949) and d_{xy} (Nei
- and Li 1979) are common, though relative measures of divergence such as F_{ST} are confounded
- by natural selection when used for this task (Charlesworth 1998, Noor and Bennett 2009,
- Nachman and Payseur 2012, Cruickshank and Hahn 2014). There are multiple statistics based on
- 537 minimum pairwise distances between multiple haplotypes in two species that avoid problems
- caused by selection (Joly et al. 2009, Geneva et al. 2015, Rosenzweig et al. 2016), and new
- machine learning methods combine multiple summary statistics into a single comparative
- 540 framework that is powerful and robust (e.g. Schrider et al. 2018). However, these methods also
- usually require coalescent simulation under known demographic history to evaluate patterns of
- 542 introgression, and this information is not always available.
- 543 None of the aforementioned limitations mean that genome-wide tests with one sample per
- species are not possible. Introgression between sister taxa—at least when it occurs in relatively
- 545 discrete pulses—should result in the same multimodal distribution of coalescence times
- 546 described above for non-sister taxa. This may be the most promising avenue for a genome-wide
- 547 test of sister introgression when only one sample per species is available, since coalescence times
- 548 for two species should follow an exponential distribution under ILS alone. Nevertheless, no
- 549 methods have been developed to date that explicitly test for this pattern (*QuIBL* can only infer it
- 550 for non-sister taxa). However, PhyloNet appears to be capable of reliably inferring introgression
- 551 (including estimating the timing and rate) between sister taxa using gene trees with branch
- lengths using this signal (Wen and Nakhleh 2018), at least when nested within a tree containing
- more taxa. Despite this, the direction of introgression between sister taxa may not be inferable
- from only one sample per species.
- 555 Finally, while introgression between extant sister species is not detectable using gene tree
- 556 frequencies, this may not necessarily be the case for introgression between ancestral sister
- 557 lineages. Several studies have now shown that when introgression occurs between *P3* and the

- ancestor of *P1* and *P2* (event 2 in Figure 2), it becomes possible under specific conditions for
- both discordant gene tree topologies to become more common than the species tree topology,
- while remaining at equal frequencies (Solís-Lemus et al. 2016, Long and Kubatko 2018, Jiao and
- 561 Yang 2020). It should be possible in principle to infer introgression using this pattern, but it
- requires sufficiently high rates of introgression to result in the anomalous trees, in addition to
- 563 independent knowledge of the species tree topology.

564 Application and interpretation of methods for inferring introgression

565 *Evaluating the power to detect and characterize introgression*

- To illuminate many of the patterns and approaches discussed in this review, we conducted a
- small simulation study using *ms* (Hudson 2002) and *Seq-Gen* (Rambaut and Grassly 1997). We
- used the five introgression scenarios shown in Figure 2, as well as one scenario with only ILS
- and several additional scenarios involving ghost introgression (Supplementary Figure 2). For
- each set of conditions, we performed 100 replicate simulations each consisting of 3000 gene
- trees with branch lengths. We simulated 1kb per locus using *Seq-Gen* with $\theta = 0.005$ per 2N
- 572 generations. We evaluated the performance of three different test statistics designed to capture
- slightly different information about introgression: D, D_3 , and Δ . In addition, we applied the
- 574 InferNetwork_ML method (Yu et al. 2014) in *PhyloNet*, which infers a phylogenetic network
- using maximum-likelihood. For the three test statistics, we evaluated significance by bootstrap-
- 576 resampling the gene trees in each dataset to estimate the sampling variance. The *z*-score obtained 577 from bootstrap-resampling was used to estimate a two-tailed *p*-value. The method we use in
- *PhyloNet* evaluates the fit of a phylogenetic network internally (Yu et al. 2012) using a
- 579 combination of the model selection measures AIC (Akaike 1974), AICc (Burnham and Anderson
- 580 2002), and BIC (Schwarz 1978). For our purposes, a positive result was taken as any result
- 581 where *PhyloNet* selected a network over a strictly bifurcating tree. See Supplementary Table 1
- 582 for the simulation parameters used for each condition.
- 583 The power of each method to detect introgression under each scenario is shown in Figure 6. All
- four methods yielded low false positive rates in the presence of high ILS but no introgression,
- confirming that they are effective tests against an ILS-only null hypothesis. For non-sister taxa,
- 586 *PhyloNet* was always capable of identifying introgression, while the power of the other methods
- 587 was strongly affected by the direction of introgression. A reduction of power for $P1 \rightarrow P3$
- introgression is consistent with the effect of direction on gene tree branch lengths described
- above, but the magnitude of the reduction is somewhat surprising: there is almost three times as
- 590 much power to detect $P3 \rightarrow P1$ introgression. Of the four methods, only *PhyloNet* appears
- capable of reliably inferring introgression between sister lineages, again consistent with
- 592 expectations.
- 593 The D and Δ statistics, as well as *PhyloNet*, did not give significant results when introgression
- occurred between P1 and an unsampled ingroup lineage. The D_3 statistic, interestingly, does
- appear to be sensitive to this scenario, at least when the ghost population is the donor. This
- suggests that patterns of pairwise divergence may be especially useful for detecting introgression
- with unsampled populations. When introgression occurs between *P1* and an outgroup ghost

- 598 lineage, there is no effect when the ghost is the recipient, while all four methods are strongly
- affected when the ghost is the donor. These observations are consistent with expectations for
- 600 ghost populations, highlighting the importance of careful interpretation of the potential taxa
- 601 involved in a positive result. In this case, all methods appear to suggest introgression between P2
- and P3, even though neither of these lineages was involved in the introgression. This occurs
- because introgression from outside the rooted triple draws PI to the outside as well, leaving P3
- 604 more closely related to P2.
- In addition to testing for the presence of introgression, we evaluated the ability of *PhyloNet* to
- 606 infer the direction of introgression, and of several methods to infer the rate of introgression. We
- evaluated the ability of *PhyloNet* to correctly identify the taxa involved, the donor and recipient
 lineages, and the rate of introgression. For the two conditions involving introgression between
- non-sister taxa, we additionally estimated the rate of introgression using the D_p statistic and an
- analogous version of the Δ statistic where the count of the concordant tree topology was added to
- 611 the denominator; we refer to this statistic as Δ_p .
- 612 We found that *PhyloNet* was highly accurate at identifying the taxa and direction for $P1 \rightarrow P3$
- 613 introgression (Supplementary Figure 3). However, somewhat surprisingly, it often failed to
- 614 identify the taxa involved when introgression was $P3 \rightarrow P1$ (although it always correctly
- 615 identified that introgression had occurred somewhere). While it is more difficult to detect
- 616 introgression in the $P1 \rightarrow P3$ direction, once it is detected it appears that the additional signal in
- 617 gene tree branch lengths makes it easier for *PhyloNet* to infer the direction. For sister lineages,
- 618 *PhyloNet* always correctly identified the taxa, but cannot accurately infer the direction. However,
- 619 *PhyloNet* must always specify the direction of introgression (see below for more explanation),
- and its behavior differs between scenarios. For introgression between extant sister species, the
- direction of introgression appears to be assigned randomly, while for ancestral sister species
 introgression is always inferred to be in one direction. For the rate of introgression, *PhyloNet*
- appears to slightly overestimate the true rate under all scenarios in which it correctly identified
- introgression (Supplementary Figure 4). By contrast, D_p and Δ_p tend to slightly underestimate the
- rate of introgression between non-sister taxa (Supplementary Figure 4).

626 *Inferring the number of introgression events*

627 A major challenge that remains in the inference of introgression is how to assess the fit of 628 different numbers of introgression events inferred on the same tree. The mostly widely used 629 methods are formulated to test for the presence of introgression versus no introgression, but provide no rigorous way to evaluate the number of distinct introgression events. One approach is 630 to perform many quartet-based tests, and then to infer the most parsimonious set of introgression 631 events by collapsing sets of positive tests that share the same ancestral populations (Pease et al. 632 2016, Suvorov et al. 2021). However, this approach is highly conservative, as it can collapse 633 cases where there truly are multiple instances of post-speciation introgression within a clade. 634 Additionally, it requires large datasets and the piecing together of many quartets, which makes it 635 impractical in many cases. Nonetheless, it can be used to generate a conservative estimate for the 636

637 minimum number of introgression events.

- Even with likelihood methods, estimating the number of introgression events is not a solved
- 639 problem. One issue is that adding additional parameters to the likelihood model always improves
- 640 the likelihood score. This makes it necessary to penalize model complexity when comparing
- 641 estimated likelihoods. Unfortunately, the information measures that are classically used to
- 642 perform model selection, such as AIC and BIC, do not adequately scale with the increased
- 643 complexity of adding a new reticulation to a phylogenetic network. This is because adding a new
 644 reticulation does not just add a new model parameter—it adds a whole new space of possible
- 645 networks, with different taxa involved in introgression, at different times and in different
- 646 directions (Blair and Ané 2020). AIC and BIC penalize the increased complexity of model
- parameters, but not the increased complexity of models within a set of parameters. The problem
- 648 is greater for methods based on pseudo-likelihood such as *SNaQ*, because these information
- 649 measures are not intended for pseudo-likelihood estimates. Bayesian approaches such as those
- 650 implemented in *PhyloNet* (Wen and Nakhleh 2018) and *SpeciesNetwork* can incorporate
- appropriate penalties for model complexity, but unfortunately scale poorly to larger datasets and
- larger numbers of reticulations (Elworth et al. 2019).
- 653 While no methods currently exist that can both explicitly penalize model complexity and scale to
- large datasets, there are several alternate approaches available for assessing the fit of
- 655 phylogenetic networks. One simple, empirical approach is to use a slope heuristic where
- networks are inferred across different numbers of reticulations, and the best network is taken as
- the least complex one after which the likelihood score appears to stop improving. This is the
- method recommended for use with *SNaQ* (Solís-Lemus and Ané 2016). *PhyloNet* has methods
- that can evaluate the fit of a network using k-fold cross-validation or parametric bootstrapping
- 660 (Yu et al. 2014), which can both address this problem. Finally, a promising approach from Cai
- and Ané (2020) involves using the multispecies network coalescent to calculate the quartet
- 662 concordance factors expected from an estimated network. A goodness-of-fit function is then used
 663 to evaluate the fit of these expected concordance factors to those observed in the data. This is
- to evaluate the fit of these expected concordance factors to those observed in the data. This is similar to the method implemented in *admixturegraph* (Leppälä et al. 2017) for use with D
- 665 statistics (see next section).
 - 666 Visualizing and interpreting phylogenetic networks
 - 667 When visualizing inferred phylogenetic networks, reticulations represent the histories of loci that 668 have introgressed. Visually, the relative placement, orientation, and length of these reticulations 669 imply specific information about the timing and direction of introgression, as well as the identity 670 of the species involved. However, not all phylogenetic networks are constructed from the same 671 underlying models, and therefore they may not always convey the same information (Huson and 672 December 2005) the same information (Huson and
 - Bryant, 2005). As a result, choices for network visualization that are primarily stylistic can
 - 673 unintentionally imply specific introgression processes. In this section we discuss these different
 - 674 visualizations and how to interpret them.
 - 675 One important distinction when visualizing networks is the contrast between introgression that
 - occurs among extant lineages and introgression that results in the formation of a new lineage.
 - 677 Supplementary Figure 5A depicts the former scenario, which corresponds to the introgression
 - 678 scenarios considered in this paper thus far. In such cases, a single horizontal reticulation is

typically used to connect the two taxa involved. Such visualizations do not naturally convey any 679 680 information about the direction of introgression. By contrast, methods that assume the formation 681 of an admixed population (e.g., Bertorelle and Excoffier 1998, Wang 2003) or hybrid species (e.g., Meng and Kubatko 2009) often use the visualization shown in Supplementary Figure 5B, 682 where reticulations connect each parent lineage to the newly formed lineage. This representation 683 implies a directionality of introgression: from the two parent lineages into the newly formed 684 lineage. In both cases, a horizontal reticulation edge is used to denote the instantaneous exchange 685 of alleles between the involved lineages. Supplementary Figure 5C shows an example using non-686 horizontal branches, which may imply a period of branching off and independent evolution from 687 the parent species before the hybrid lineage is formed (e.g., Patterson et al 2012, Yu et al. 2014, 688 Zhang et al. 2018). Alternatively, this could represent "standard" introgression involving a now-689 extinct species, in which case the extinct lineage was the donor in the introgression scenario. In 690 691 all three cases, the placement of the reticulation edge conveys information about the timing of introgression and/or lineage formation. 692

693 The key take-away from this last representation is that non-horizontal reticulation edges often imply directionality, with the introgressed alleles travelling toward the tips. Unfortunately, many 694 automated methods for visualizing species networks do not allow strictly horizontal edges-695 instead, all reticulations must have a bifurcating "parent" node that occurs closer to the root than 696 the "daughter" node, which has two incoming lineages. This was the behavior observed in 697 *PhyloNet* in the previous section. To highlight how different network visualizations can 698 potentially be (mis-)interpreted, with particular emphasis on the direction of introgression, we 699 plotted the same inferred networks using four popular tools (Figure 5): Dendroscope (Huson and 700 Scornavacca 2012), IcyTree (Vaughan 2017), PhyloPlots, which is part of the Julia package 701 PhyloNetworks (Solis-Lemus et al. 2017), and admixturegraph (Leppälä et al. 2017). The 702 703 networks were inferred using *PhyloNet* on simulated gene trees from the two non-sister introgression scenarios (i.e. both $P1 \rightarrow P3$ and $P3 \rightarrow P1$) discussed in the previous section. For 704 admixturegraph, we simply plotted the outcome of applying the D-statistic to the data under both 705 706 scenarios.

In *Dendroscope*'s visualizations (Figure 5A, 5B), the position of the hybrid node (the node with

two parents) is made clear, but it is not clear which parent corresponds to a history of

introgression vs. the species tree history, since both are represented using a curved blue line (and

therefore both resemble reticulation edges). As a result, the direction of introgression confounds

- accurate representation of the underlying introgression scenario. For the $P3 \rightarrow P1$ direction
- 712 (Figure 5A), the visualization strongly implies that *P1* is a hybrid species that formed from
- hybridization between *P2* and *P3*. While this representation accurately conveys the fact that *P1*
- is the recipient of introgressed alleles, it unfortunately suggests that P2 was involved in
- hybridization when it was not. The $P1 \rightarrow P3$ visualization (Figure 5B) is easier to interpret,
- because one of the blue edges cannot possibly represent an introgression history. Additionally,
- the curvature of the blue edges suggests a non-horizontal reticulation, which may imply a period
- of independent evolution. However, in this case it is purely stylistic as the network does not
- contain any branch lengths. Finally, it is important to note that all the visualizations we discuss
- do not take branch lengths into account, so the placement of the reticulation edges within

- branches of the species tree are arbitrary and do not convey information about the timing of
- introgression. *IcyTree* and *PhyloPlots* are capable of plotting networks with branch lengths, in
- which case the timing of introgression within lineages can be displayed. Since our primary
- concern is with the direction of introgression, we have not shown these visualizations.

IcyTree uses a different style of visualization (Figure 5C, D). A dashed line represents the 725 reticulation edge, which branches off from the donor population and enters the recipient 726 population. This allows the introgression and species tree histories to be more visually distinct, 727 728 while still depicting the direction of introgression. However, it implies that a lineage branched off from the donor and underwent a period of independent evolution before entering the 729 recipient, which did not happen in either case. As the network is plotted without branch lengths, 730 731 the point at which the reticulation leaves the donor branch is arbitrary. *PhyloPlots* (Figure 5E, F) visually distinguishes the reticulation edge (light blue) from the species tree history (black) while 732 explicitly labelling the hybrid node. The reticulation edge is not horizontal, erroneously implying 733 some period of independent evolution, though it does effectively convey the direction of 734 introgression. The distinct coloration of each history, in combination with labelling of the hybrid 735 node, means that the direction of introgression can be easily visualized. Finally, admixturegraph 736 (Figure 5G, 5H) plots the network solely from the results of a series of D tests. This means that 737 no inference of directionality is possible. As with Dendroscope, this method plots phylogenetic 738 networks as admixture graphs, which have the same issues with implied directionality and hybrid 739 speciation. In our case, this results in P1 being the implied recipient of introgression regardless 740 741 of the true direction.

- 742 The message we hope to convey from this discussion is that it is very difficult to simultaneously
- visualize the direction of introgression and to preserve the underlying model of hybridization.
- This is especially challenging for cases when network visualization needs to be automated,
- because the standard computational representation of phylogenetic networks, the Extended
- Newick format (Cardona et al. 2008), requires labeling of parent and daughter nodes, and
- 747 therefore implies directionality any time a hybrid node is inferred. "Tube tree" representations
- 148 like the ones we use for figures in this paper (e.g. Figure 4) can be effective for individual cases,
- but to our knowledge no automated approaches exist as of yet that can accurately convey all the
- 750 necessary information. In general, care should be taken not to over-interpret phylogenetic
- 751 network visualizations.

752 **Conclusions**

- 753 In conclusion, several methodological and technical challenges remain in the inference of
- introgression, including: more accurate estimation of the rate, timing, and direction of
- introgression; detection of introgression between sister taxa; spurious results generated by
- unsampled lineages; inference of the number of introgression events in a clade; and accurate
- automated visualization of phylogenetic networks. Despite these challenges, currently available
- approaches have remarkable power to detect and characterize introgression under a wide variety
- of conditions, especially when used in a complementary fashion. Overall, these methods will
- continue to reveal the nature and influence of introgression throughout the natural world.

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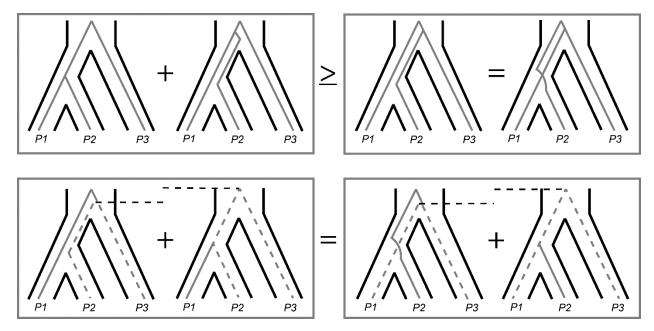




Figure 1: Expected gene tree topologies and coalescence times under ILS only. For a rooted triplet, four topologies are possible (top row): two concordant with the species tree, which can result either from lineage sorting or ILS (top left), and two that are discordant with the species tree and arise from ILS only (top right). The two concordant trees must be at least as frequent as the two discordant trees, which are equally frequent to each other. For non-sister pairs of taxa-either P2-P3 (bottom left) or P1-P3 (bottom right)—coalescence is expected to occur at one of two times, depending on whether they coalesce first or second in a gene tree (grey dotted lines). These expected times are symmetrical across gene trees, and so pairwise divergences between the non-sister lineages are expected to be equal when averaged across loci.

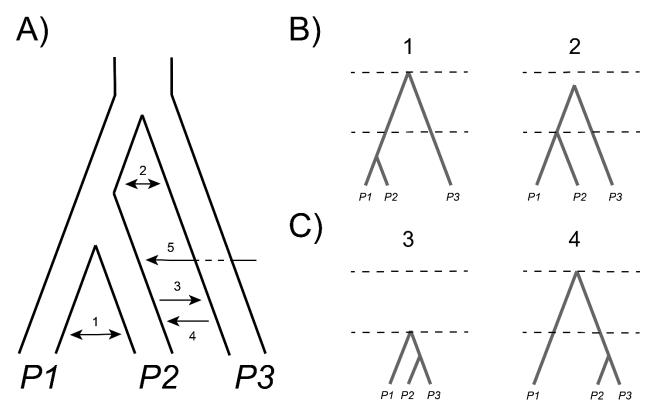
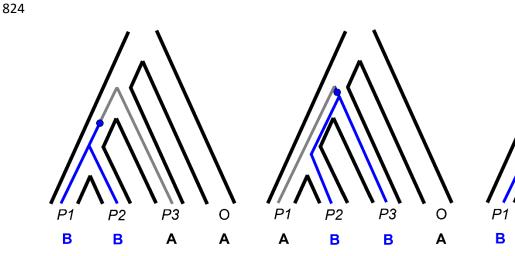
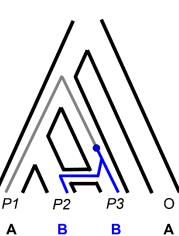


Figure 2: An overview of detectable introgression scenarios for a rooted triplet, and their effects 803 on gene tree frequencies and branch lengths. A. The species tree relating three lineages. 804 Introgression can occur between extant (1) or ancestral (2) sister lineages, or between non-sister 805 taxa, with P3 as either the recipient (3) or the donor (4). One of the sampled taxa may also be the 806 recipient of introgression from an unsampled taxon (5). B. Gene trees for introgression between 807 sister lineages. Introgression between sister taxa reduces divergence between the involved taxa 808 but does not generate discordant gene trees (events 1 and 2). In both trees the expected time to 809 coalescence for pairs of lineages in the absence of introgression is denoted with dashed 810 horizontal lines. C. Gene trees for introgression between non-sister lineages. When P3 is the 811 recipient of introgression (event 3), discordant gene trees are generated uniting P2 and P3. In 812 addition, divergence is reduced between both P2 and P3 and between P1 and P3. When P3 is the 813 donor of introgression (event 4) discordant gene trees are again generated uniting P2 and P3. In 814 this case divergence is reduced only between P2 and P3, while divergence is increased between 815 Pl and P2. In both trees the expected time to coalescence for pairs of lineages in the absence of 816 introgression is denoted with dashed horizontal lines. No example gene tree is shown for 817 introgression from a ghost lineage outside the triplet (event 5). The expectation is that these 818 events will generate topologies with P2 pulled outside the clade, sister to the two unintrogressed 819 820 lineages. 821

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Α

P2

Α

Р3

В

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Figure 3: Biallelic site patterns are informative of underlying gene tree topologies. With the

827 exception of low levels of homoplasy, such patterns can only arise from mutations (blue) on

828 internal branches of the local genealogy. The occurrence of the incongruent site patterns

*ABBA" (top middle) and "BABA" (top right) are therefore expected to reflect the frequency of
discordant gene tree topologies. With introgression between a specific non-sister species pair,

discordant gene tree topologies. With introgression between a specific non-sister species pair,
one incongruent pattern (bottom) can increase in frequency over the other due to the underlying

832 asymmetry in gene tree frequencies.

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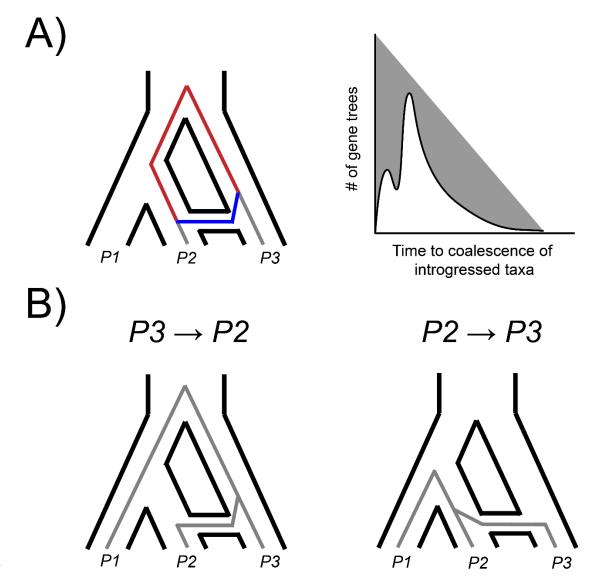




Figure 4: Coalescence times provide information on the timing, direction, and presence of 838 introgression. A) Post-speciation introgression between P2 and P3 allows them to coalesce more 839 quickly at introgressed loci (blue). This reduces their whole-genome divergence relative to P1 840 and P3, an asymmetry that can be used to test for introgression. Since coalescence can now occur 841 at one of two times, after introgression (blue) or after speciation (red), it also results in a bimodal 842 distribution of coalescence times across loci (right figure). The more recent peak of this 843 distribution can be used to estimate the timing of introgression. B) The direction of introgression 844 between P2 and P3 affects the time to coalesce of P1 and P3 at introgressed loci. $P2 \rightarrow P3$ 845 introgression allows P1 and P3 to coalesce more quickly (right), reducing their divergence at 846 introgressed loci. 847

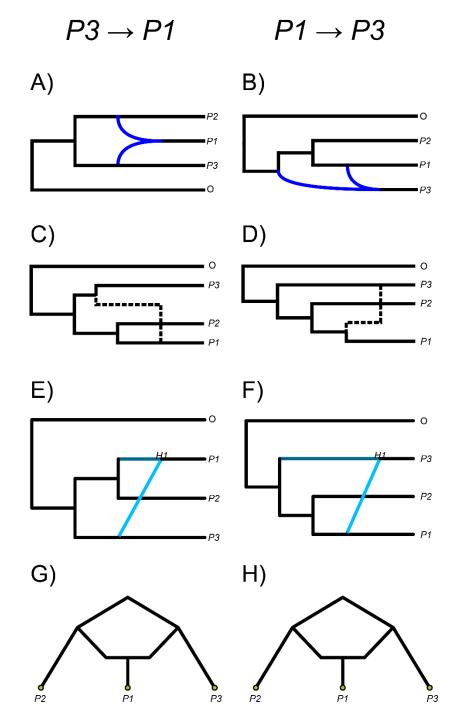
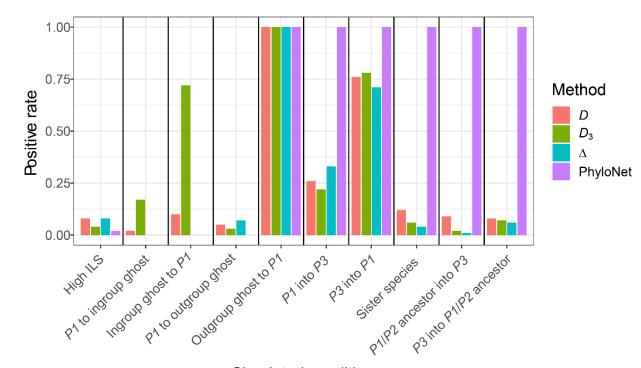




Figure 5: Different visualizations of the same underlying phylogenetic networks. The left column comes from a network representing $P3 \rightarrow P1$ introgression, while the right column comes from a network representing $P1 \rightarrow P3$ introgression. The rows, from top to bottom, show

- visualizations from *Dendroscope* (A, B), *IcyTree* (C, D), *PhyloPlots* (E, F), and *admixturegraph*
- 854 (G, H), respectively.
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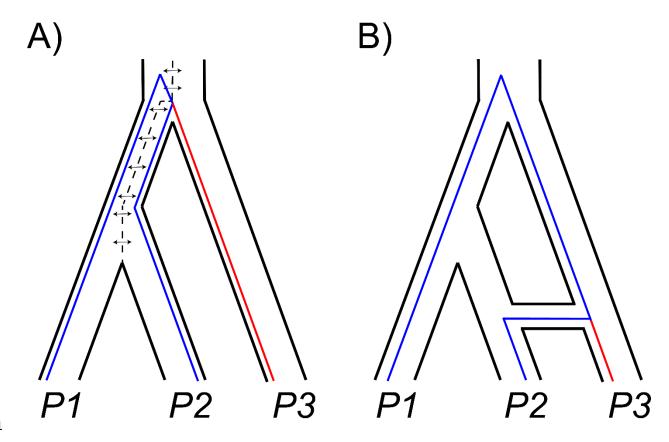


Simulated condition

Figure 6: Power (y-axis) of four different methods (color legend) to infer the presence of

introgression across ten different simulation conditions (x-axis). Power is measured as the

proportion of tests that are significant; for the "High ILS" condition it therefore represents thefalse positive rate.



Supplementary Figure 1: Distinguishing ancestral population structure (A) from introgression (B). Persistent structure in the ancestral population of a quartet, which may or may not continue

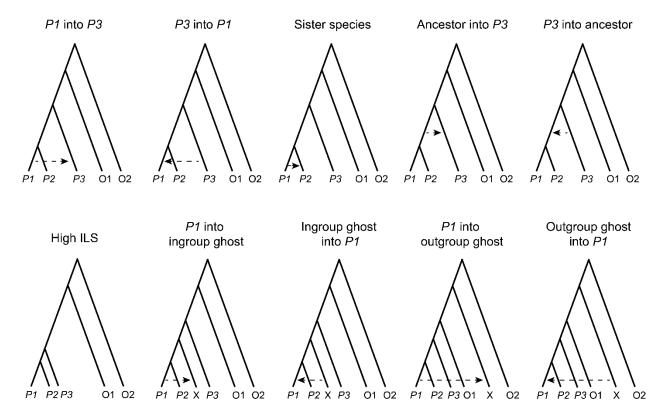
after the first speciation event, can result in the same asymmetries in gene tree topologies and

divergence times that are expected from introgression between non-sister taxa. These two

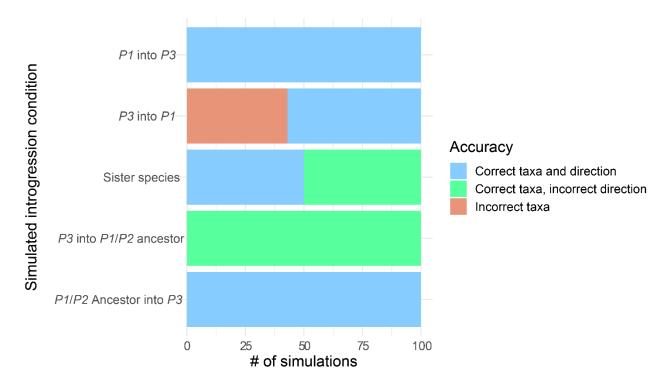
scenarios are distinguishable by studying the distribution of branch lengths, in particular the

length of the tip branch leading to P3 (red).

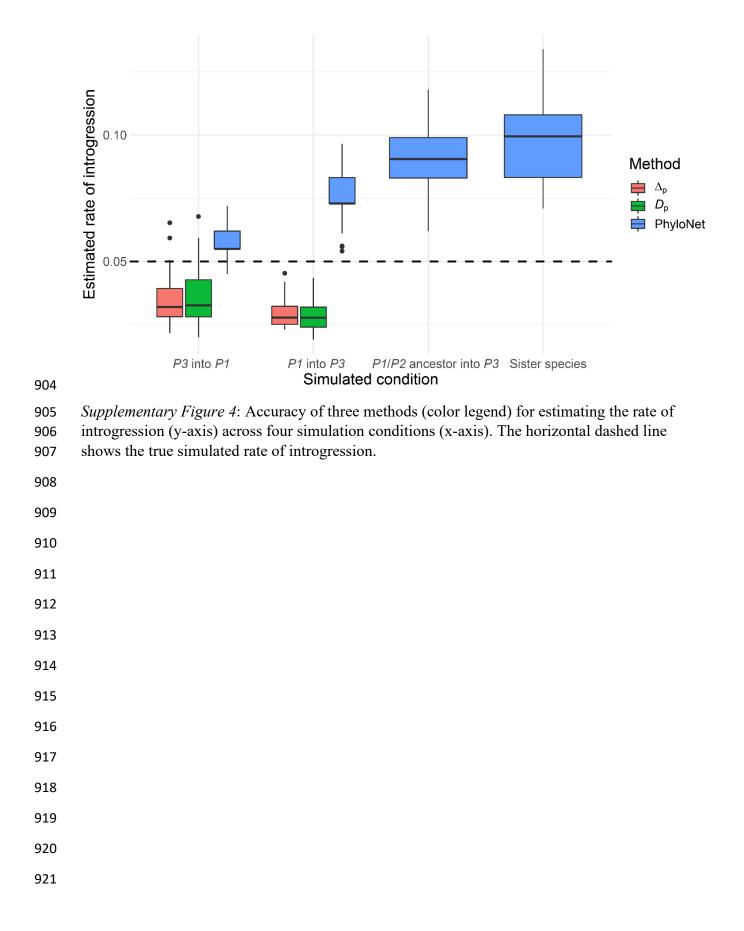


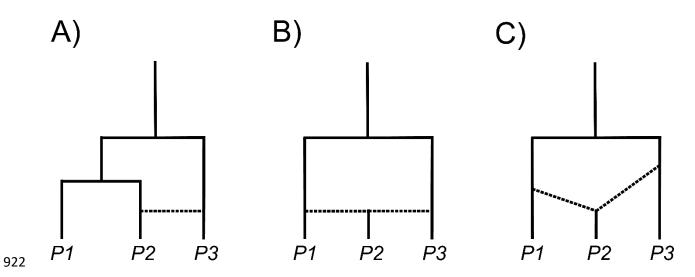


Supplementary Figure 2: A visual overview of the ten different conditions used in our simulation
study. Branch lengths are not to scale.



Supplementary Figure 3: The power of *PhyloNet* to identify the taxa involved and direction of 899 introgression across five simulation conditions.





Supplementary Figure 5: Network representations of introgression between extant lineages (A)
vs. introgression that results in the formation of a new lineage (B, C).

Condition	P1/P2_split	P1P2/P3_split	P1P2P3/O1_split	O1/O2_split	intro_timing	intro_rate	ghostpop_split	theta
P1 into P3	0.6	1.2	8	20	0.3	0.05	N/A	0.005
P3 into P1	0.6	1.2	8	20	0.3	0.05	N/A	0.005
Sister species	0.6	1.2	8	20	0.3	0.05	N/A	0.005
Ancestor into P3	0.6	1.2	8	20	0.9	0.05	N/A	0.005
P3 into ancestor	0.6	1.2	8	20	0.9	0.05	N/A	0.005
High ILS	0.6	0.62	8	20	N/A	0.05	N/A	0.005
P1 into ingroup ghost	0.6	8	20	30	0.3	0.05	1.2	0.005
Ingroup ghost into P1	0.6	8	20	30	0.3	0.05	1.2	0.005
P1 into outgroup ghost	0.6	1.2	8	30	0.3	0.05	20	0.005
Outgroup ghost into P1	0.6	1.2	8	30	0.3	0.05	20	0.005

944 Supplementary Table 1: Parameters used for introgression simulation conditions in ms. Split

- 945 times and theta are in units of 2N generations.

References

968 969	Akaike, H. (1974). A new look at the statistical model identification. <i>IEEE Transactions on Automatic Control</i> 19(6), 716-723. doi:10.1109/TAC.1974.1100705
970	
971 972	Baum, D. A. (2007). Concordance trees, concordance factors, and the exploration of reticulate genealogy. <i>Taxon</i> 56(12), 417-426. doi:10.1002/tax.562013
973	
974	Bertorelle, G., & Excoffier, L. (1998). Inferring admixture proportions from molecular data.
975 976	Molecular Biology and Evolution, 15(10), 1298-1311. doi:10.1093/oxfordjournals.molbev.a025858
976 977	doi.10.1095/0x1010journais.inoidev.a025858
978	Blischak, P. D., Chifman, J., Wolfe, A. D., & Kubatko, L. S. (2018). HyDe: a Python package
979 980	for genome-scale hybridization detection. <i>Systematic Biology</i> , 67(5), 821-829. doi:10.1093/sysbio/syy023
981	
982 983 984	Brandvain, Y., Kenney, A. M., Flagel, L., Coop, G., & Sweigart, A. L. (2014). Speciation and introgression between <i>Mimulus nasutus</i> and <i>Mimulus guttatus</i> . <i>PLoS Genetics</i> , 10(6), e1004410. doi:10.1371/journal.pgen.1004410
985	
986	Burnham, K. P., & Anderson, D. R. (2002). Model selection and multimodel inference: a
987 988	practical information-theoretic approach (2 ed.). New York: Springer-Verlag.
989 990 991	Cai, R., & Ané, C. (2020). Assessing the fit of the multi-species network coalescent to multi- locus data. <i>Bioinformatics</i> , btaa863. doi:10.1093/bioinformatics/btaa863
992 993	Cardona, G., Rossello, F., & Valiente, G. (2008). Extended Newick: it is time for a standard representation of phylogenetic networks. <i>BMC Bioinformatics</i> , 9, 532. doi:10.1186/1471-
994 005	2105-9-532
995 006	Charlesworth, B. (1998). Measures of divergence between populations and the effect of forces
996 997 998	that reduce variability. <i>Molecular Biology and Evolution</i> , 15(5), 538-543. doi:10.1093/oxfordjournals.molbev.a025953
999 999	doi.10.1095/0x101djournais.in010ev.a025955
1000	Copetti, D., Burquez, A., Bustamante, E., Charboneau, J. L. M., Childs, K. L., et al. (2017).
1001	Extensive gene tree discordance and hemiplasy shaped the genomes of North American
1002	columnar cacti. Proceedings of the National Academy of Science of the United States of
1003	<i>America</i> , 114(45), 12003-12008. doi:10.1073/pnas.1706367114
1004	
1005	Cruickshank, T. E., & Hahn, M. W. (2014). Reanalysis suggests that genomic islands of
1006 1007	speciation are due to reduced diversity, not reduced gene flow. <i>Molecular Ecology</i> , 23(13), 3133-3157. doi:10.1111/mec.12796
1008	
1009 1010	Degnan, J. H. (2018). Modeling hybridization under the network multispecies coalescent. Systematic Biology, 67(5), 786-799. doi:10.1093/sysbio/syy040
1011 1012	Dowling, T.E., Secor, C. L. (1997). The role of hybridization and introgression in the

diversification of animals. Annual Review of Ecology, Evolution, and Systematics, 28, 1013 1014 593-619. doi:10.1146/annurev.ecolsys.28.1.593 1015 1016 Durand, E. Y., Patterson, N., Reich, D., & Slatkin, M. (2011). Testing for ancient admixture between closely related populations. *Molecular Biology and Evolution*, 28(8), 2239-2252. 1017 doi:10.1093/molbev/msr048 1018 1019 1020 Eaton, D. A., & Ree, R. H. (2013). Inferring phylogeny and introgression using RADseq data: an example from flowering plants (Pedicularis: Orobanchaceae). Systematic Biology, 62(5), 1021 1022 689-706. doi:10.1093/sysbio/syt032 1023 Edelman, N. B., Frandsen, P. B., Miyagi, M., Clavijo, B., Davey, J., et al. (2019). Genomic 1024 architecture and introgression shape a butterfly radiation. Science, 366(6465), 594-599. 1025 doi:10.1126/science.aaw2090 1026 1027 Ellstrand N.C., M. P., Rong J., Bartsch D., Ghosh A., de Jong T.J., et al. (2013). Introgression of 1028 1029 crop alleles into wild or weedy populations. Annual Review of Ecology, Evolution, and Systematics, 44, 325-345. doi:doi.org/10.1146/annurev-ecolsys-110512-135840 1030 1031 1032 Elworth, R. A. L., Ogilvie, H. A., Zhu, J., & Nakhleh, L. (2019). Advances in computational methods for phylogenetic networks in the presence of hybridization. In T. Warnow (Ed.), 1033 Bioinformatics and Phylogenetics (Vol. 29, pp. 317-360). Cham: Springer. 1034 1035 Felsenstein, J. (2004). Inferring phylogenies. Sunderland, MA: Sinauer Associates. 1036 1037 1038 Folk, R. A., Soltis, P. S., Soltis, D. E., & Guralnick, R. (2018). New prospects in the detection and comparative analysis of hybridization in the tree of life. American Journal of Botany, 1039 1040 105(3), 364-375. doi:10.1002/ajb2.1018 1041 Fontaine, M. C., Pease, J. B., Steele, A., Waterhouse, R. M., Neafsey, D. E et al. (2015). 1042 Extensive introgression in a malaria vector species complex revealed by phylogenomics. 1043 1044 Science, 347(6217), 1258524. doi:10.1126/science.1258524 1045 Forsythe, E. S., Nelson, A. D. L., & Beilstein, M. A. (2020). Biased gene retention in the face of 1046 introgression obscures species relationships. Genome Biology and Evolution, 12(9), 1047 1646-1663. doi:10.1093/gbe/evaa149 1048 1049 Forsythe, E. S., Sloan, D. B., & Beilstein, M. A. (2020). Divergence-based introgression 1050 1051 polarization. Genome Biology and Evolution, 12(4), 463-478. doi:10.1093/gbe/evaa053 1052 1053 Fuller, Z. L., Leonard, C. J., Young, R. E., Schaeffer, S. W., & Phadnis, N. (2018). Ancestral 1054 polymorphisms explain the role of chromosomal inversions in speciation. PLoS Genetics, 14(7), e1007526. doi:10.1371/journal.pgen.1007526 1055 1056 1057 Geneva, A. J., Muirhead, C. A., Kingan, S. B., & Garrigan, D. (2015). A new method to scan genomes for introgression in a secondary contact model. PLoS One, 10(4), e0118621. 1058

1059	doi:10.1371/journal.pone.0118621
1060	
1061	Gillespie, J. H., & Langley, C. H. (1979). Are evolutionary rates really variable? Journal of
1062	Molecular Evolution, 13(1), 27-34. doi:10.1007/BF01732751
1063	
1064	Grau-Bové, X., Tomlinson, S., O'Reilly, A. O., Harding, N. J., Miles, A., et al. (2020). Evolution
1065	of the insecticide target <i>Rdl</i> in African <i>Anopheles</i> is driven by interspecific and
1066	interkaryotypic introgression. Molecular Biology and Evolution, 37(10), 2900-2917.
1067	doi:10.1093/molbev/msaa128
1068	
1069	Green, R. E., Krause, J., Briggs, A. W., Maricic, T., Stenzel, U., et al. (2010). A draft sequence
1070	of the Neandertal genome. <i>Science</i> , 328(5979), 710-722. doi:10.1126/science.1188021
1070	of the recondential genome. Science, 526(5777), 710 722. doi:10.1120/science.1100021
1071	Hahn, M. W. (2018). Molecular population genetics Sunderland, MA: Oxford University Press.
1072	mann, W. (2010). Molecular population genetics bunderland, WA. Oxford Oniversity (1655.
1073	Hahn, M. W., & Hibbins, M. S. (2019). A three-sample test for introgression. <i>Molecular Biology</i>
	and Evolution, 36(12), 2878-2882. doi:10.1093/molbev/msz178
1075 1076	<i>una Evolution</i> , 50(12), 2878-2882. doi:10.1095/11010ev/1182178
	Hamlin I A D Hibbing M S. & Mayle I C (2020) Accessing high given frateworth
1077	Hamlin, J. A. P., Hibbins, M. S., & Moyle, L. C. (2020). Assessing biological factors affecting
1078	postspeciation introgression. Evolution Letters, 4(2), 137-154. doi:10.1002/evl3.159
1079	$\mathbf{H}_{\text{min}} = \mathbf{D} \cdot \mathbf{C} + 0 \cdot \mathbf{E} \cdot \mathbf{E} \cdot \mathbf{E} \cdot 1 = 1 $
1080	Harrison, R. G., & Larson, E. L. (2014). Hybridization, introgression, and the nature of species
1081	boundaries. Journal of Heredity, 105(1), 795-809. doi:10.1093/jhered/esu033
1082	
1083	He, C., Liang, D., & Zhang, P. (2020). Asymmetric distribution of gene trees can arise under
1084	purifying selection if differences in population size exist. Molecular Biology and
1085	Evolution, 37(3), 881-892. doi:10.1093/molbev/msz232
1086	
1087	Hedrick, P. W. (2013). Adaptive introgression in animals: examples and comparison to new
1088	mutation and standing variation as sources of adaptive variation. Molecular Ecology,
1089	22(18), 4606-4618. doi:10.1111/mec.12415
1090	
1091	Heiser, C. B. (1949). Natural hybridization with particular reference to introgression. Journal of
1092	<i>Heredity</i> , 15(10), 795-809.
1093	
1094	Heiser, C. B. (1973). Introgression reexamined. Botanical Review, 39(4), 347-366.
1095	
1096	Hibbins, M. S., & Hahn, M. W. (2019). The timing and direction of introgression under the
1097	multispecies network coalescent. Genetics, 211(3), 1059-1073.
1098	doi:10.1534/genetics.118.301831
1099	
1100	Hudson, R. R. (1983). Testing the constant-rate neutral allele model with protein sequence data.
1101	<i>Evolution</i> , 37(1), 203-217. doi:10.1111/j.1558-5646.1983.tb05528.x
1102	J
1103	Hudson, R. R. (2002). Generating samples under a Wright-Fisher neutral model of genetic
1104	variation. <i>Bioinformatics</i> , 18(2), 337-338. doi:10.1093/bioinformatics/18.2.337
•	

1105	
1106	Huerta-Sanchez, E., Jin, X., Asan, Bianba, Z., Peter, B. M., Vinckenbosch, N., et al. (2014).
1107	Altitude adaptation in Tibetans caused by introgression of Denisovan-like DNA. <i>Nature</i> ,
1108	512(7513), 194-197. doi:10.1038/nature13408
1109	
1110	Huson, D. H., & Bryant, D. (2006). Application of phylogenetic networks in evolutionary
1111	studies. <i>Molecular Biology and Evolution</i> , 23(2), 254-267. doi:10.1093/molbev/msj030
1111	studies. <i>Molecular biology and Evolution</i> , $25(2)$, $254-267$. doi:10.1095/100007/105050
1112	Huson, D. H., Klöpper, T., Lockhart, P. J., & Steel, M. A. (2005). Reconstruction of reticulate
	<i>networks from gene trees.</i> Paper presented at the The 9th Annual International
1114	
1115	Conference Research in Computational Molecular Biology, Berlin.
1116	$H_{\text{res}} = D H_{\text{res}} R C_{\text{res}} (2012) D_{\text{res}} A_{\text{res}} 2 \dots (1 + 1 + 1 + 1 + 1 + 1 + 1 + 1 + 1 + 1 $
1117	Huson, D. H., & Scornavacca, C. (2012). Dendroscope 3: an interactive tool for rooted
1118	phylogenetic trees and networks. <i>Systematic Biology</i> , 61(6), 1061-1067.
1119	doi:10.1093/sysbio/sys062
1120	
1121	Jiao, X., & Yang, Z. (2020). Defining species when there is gene flow. Systematic Biology,
1122	70(1), 108-119. doi:10.1093/sysbio/syaa052
1123	
1124	Joly, S., McLenachan, P. A., & Lockhart, P. J. (2009). A statistical approach for distinguishing
1125	hybridization and incomplete lineage sorting. The American Naturalist, 174(2), E54-70.
1126	doi:10.1086/600082
1127	
1128	Kingman, J. F. C. (1982). The coalescent. Stochastic Processes and their Applications, 13(3),
1129	235-248.
1130	
1131	Knowles, L. L., Huang, H., Sukumaran, J., & Smith, S. A. (2018). A matter of phylogenetic
1132	scale: distinguishing incomplete lineage sorting from lateral gene transfer as the cause of
1133	gene tree discord in recent versus deep diversification histories. American Journal of
1134	Botany, 105(3), 376-384. doi:10.1002/ajb2.1064
1135	
1136	Kong, S., & Kubatko, L. S. (2021). Comparative performance of popular methods for hybrid
1137	detection using genomic data. Systematic Biology, syaa092. doi:10.1093/sysbio/syaa092
1138	
1139	Kronforst, M. R., Hansen, M. E., Crawford, N. G., Gallant, J. R., Zhang, W., et al. (2013).
1140	Hybridization reveals the evolving genomic architecture of speciation. <i>Cell Reports</i> , 5(3),
1141	666-677. doi:10.1016/j.celrep.2013.09.042
1142	
1143	Kubatko, L. S., & Chifman, J. (2019). An invariants-based method for efficient identification of
1144	hybrid species from large-scale genomic data. <i>BMC Evolutionary Biology</i> , 19(1), 112.
1145	doi:10.1186/s12862-019-1439-7
1145	uvi.10.1100/312002-01/-1+3/-/
	Lannälä K. Nielson S. V. & Mailund T. (2017) administrationale on D. neekage for administration
1147 1149	Leppälä, K., Nielsen, S. V., & Mailund, T. (2017). admixturegraph: an R package for admixture
1148	graph manipulation and fitting. <i>Bioinformatics</i> , 33(11), 1738-1740.
1149	doi:10.1093/bioinformatics/btx048
1150	

1151 1152 1153	Lohse, K., & Frantz, L. A. (2014). Neandertal admixture in Eurasia confirmed by maximum- likelihood analysis of three genomes. <i>Genetics</i> , 196(4), 1241-1251. doi:10.1534/genetics.114.162396
1155	doi.10.1554/genetics.114.102570
1155	Long, C., & Kubatko, L. (2018). The effect of gene flow on coalescent-based species-tree
1156	inference. Systematic Biology, 67(5), 770-785. doi:10.1093/sysbio/syy020
1157 1158 1159	Mallet, J., Besansky, N., & Hahn, M. W. (2016). How reticulated are species? <i>Bioessays</i> , 38(2), 140-149. doi:10.1002/bies.201500149
1160	
1161	Martin, S. H., & Amos, W. (2020). Signatures of introgression across the allele frequency
1162 1163	spectrum. <i>Molecular Biology and Evolution</i> , 38(2), 716-726. doi:10.1093/molbev/msaa239
1164	
1165 1166 1167	Martin, S. H., Davey, J. W., & Jiggins, C. D. (2015). Evaluating the use of ABBA-BABA statistics to locate introgressed loci. <i>Molecular Biology and Evolution</i> , 32(1), 244-257. doi:10.1093/molbev/msu269
1168	
1169	Mendes, F. K., & Hahn, M. W. (2018). Why concatenation fails near the anomaly zone.
1170	Systematic Biology, 67(1), 158-169. doi:10.1093/sysbio/syx063
1171	
1172	Meng, C., & Kubatko, L. S. (2009). Detecting hybrid speciation in the presence of incomplete
1173	lineage sorting using gene tree incongruence: a model. Theoretical Population Biology,
1174	75(1), 35-45. doi:10.1016/j.tpb.2008.10.004
1175	
1176	Nachman, M. W., & Payseur, B. A. (2012). Recombination rate variation and speciation:
1177	theoretical predictions and empirical results from rabbits and mice. Philosophical
1178	Transactions of the Royal Society B: Biological Sciences, 367(1587), 409-421.
1179	doi:10.1098/rstb.2011.0249
1180	
1181	Nei, M., & Li, W. H. (1979). Mathematical model for studying genetic variation in terms of
1182	restriction endonucleases. Proceedings of the National Academy of Science of the United
1183	States of America, 76(10), 5269-5273. doi:10.1073/pnas.76.10.5269
1184	
1185	Nielsen, R., & Wakeley, J. (2001). Distinguishing migration from isolation: a Markov chain
1186	Monte Carlo approach. <i>Genetics</i> , 158(2), 885-896.
1180	Monte Carlo approach. Genetics, 156(2), 885-876.
	Near M. A. & Pennett S. M. (2000) Islands of speciation or mirages in the desort? Examining
1188	Noor, M. A., & Bennett, S. M. (2009). Islands of speciation or mirages in the desert? Examining
1189	the role of restricted recombination in maintaining species. <i>Heredity</i> 103(6), 439-444.
1190	doi:10.1038/hdy.2009.151
1191	
1192	Novikova, P. Y., Hohmann, N., Nizhynska, V., Tsuchimatsu, T., Ali, J., et al. (2016).
1193	Sequencing of the genus Arabidopsis identifies a complex history of nonbifurcating
1194	speciation and abundant trans-specific polymorphism. Nature Genetics, 48(9), 1077-
1195	1082. doi:10.1038/ng.3617
1196	

1197 1198	Ottenburghs J., K. R. H. S., van Hooft P., van Wieren S.E., Ydenberg R.C., Prins H.H.T. (2017). Avian introgression in the genomic era. <i>Avian Research</i> , 8. doi:10.1186/s40657-017-
1199 1200	0088-z
1201 1202 1203	Pamilo, P., & Nei, M. (1988). Relationships between gene trees and species trees. <i>Molecular Biology and Evolution</i> , 5(5), 568-583. doi:10.1093/oxfordjournals.molbev.a040517
1203 1204 1205 1206	Patterson, N., Moorjani, P., Luo, Y., Mallick, S., Rohland, N., <i>et al.</i> (2012). Ancient admixture in human history. <i>Genetics</i> , 192(3), 1065-1093. doi:10.1534/genetics.112.145037
1200 1207 1208 1209 1210	Pease, J. B., Haak, D. C., Hahn, M. W., & Moyle, L. C. (2016). Phylogenomics reveals three sources of adaptive variation during a rapid radiation. <i>PLoS Biology</i> , 14(2), e1002379. doi:10.1371/journal.pbio.1002379
1211 1212	Pease, J. B., & Hahn, M. W. (2015). Detection and polarization of introgression in a five-taxon phylogeny. <i>Systematic Biology</i> , 64(4), 651-662. doi:10.1093/sysbio/syv023
1213 1214 1215 1216	Peter, B. M. (2016). Admixture, population structure, and <i>F</i> -statistics. <i>Genetics</i> , 202(4), 1485-1501. doi:10.1534/genetics.115.183913
1210 1217 1218 1219 1220	Pickrell, J. K., & Pritchard, J. K. (2012). Inference of population splits and mixtures from genome-wide allele frequency data. <i>PLoS Genetics</i> , 8(11), e1002967. doi:10.1371/journal.pgen.1002967
1221 1222 1223	Pollard, D. A., Iyer, V. N., Moses, A. M., & Eisen, M. B. (2006). Widespread discordance of gene trees with species tree in Drosophila: evidence for incomplete lineage sorting. <i>PLoS Genetics</i> , 2(10), e173. doi:10.1371/journal.pgen.0020173
1224 1225 1226 1227 1228	Przeworski, M., Charlesworth, B., & Wall, J. D. (1999). Genealogies and weak purifying selection. <i>Molecular Biology and Evolution</i> , 16(2), 246-252. doi:10.1093/oxfordjournals.molbev.a026106
1228 1229 1230 1231 1232	Racimo, F., Sankararaman, S., Nielsen, R., & Huerta-Sanchez, E. (2015). Evidence for archaic adaptive introgression in humans. <i>Nature Reviews Genetics</i> , 16(6), 359-371. doi:10.1038/nrg3936
1232 1233 1234 1235 1236	Rambaut, A., & Grassly, N. C. (1997). Seq-Gen: an application for the Monte Carlo simulation of DNA sequence evolution along phylogenetic trees. <i>Bioinformatics</i> , 13(3), 235-238. doi:10.1093/bioinformatics/13.3.235
1230 1237 1238 1239	Reich, D., Thangaraj, K., Patterson, N., Price, A. L., & Singh, L. (2009). Reconstructing Indian population history. <i>Nature</i> , 461(7263), 489-494. doi:10.1038/nature08365
1235 1240 1241 1242	Rieseberg L.H., Wendel. J. F. (1993). Introgression and its consequences in plants. In Hybrid Zones and the Evolutionary Process (pp. 70-109): Oxford University Press.

1243	Rosenzweig, B. K., Pease, J. B., Besansky, N. J., & Hahn, M. W. (2016). Powerful methods for
1244	detecting introgressed regions from population genomic data. <i>Molecular Ecology</i> , 25(11),
1245 1246	2387-2397. doi:10.1111/mec.13610
1240	Roux, C., Fraisse, C., Romiguier, J., Anciaux, Y., Galtier, N., & Bierne, N. (2016). Shedding
1248	light on the grey zone of speciation along a continuum of genomic divergence. <i>PLoS</i>
1249	<i>Biology</i> , 14(12), e2000234. doi:10.1371/journal.pbio.2000234
1250	<i>Diology</i> , 17(12), 02000251. doi:10.1571/journal.poi0.2000251
1251	Schrider, D. R., Ayroles, J., Matute, D. R., & Kern, A. D. (2018). Supervised machine learning
1252	reveals introgressed loci in the genomes of <i>Drosophila simulans</i> and <i>D. sechellia. PLoS</i>
1253	Genetics, 14(4), e1007341. doi:10.1371/journal.pgen.1007341
1254	
1255	Schumer, M., Rosenthal, G. G., & Andolfatto, P. (2014). How common is homoploid hybrid
1256	speciation? <i>Evolution</i> , 68(6), 1553-1560. doi:10.1111/evo.12399
1257	
1258	Schwarz, G. (1978). Estimating the dimension of a model. The Annals of Statistics, 6(2), 461-
1259	464.
1260	
1261	Sethuraman, A., Sousa, V., & Hey, J. (2019). Model-based assessments of differential
1262	introgression and linked natural selection during divergence and speciation. <i>BioRxiv</i> .
1263	doi:10.1101/786038
1264	
1265	Slatkin, M., & Pollack, J. L. (2008). Subdivision in an ancestral species creates asymmetry in
1266	gene trees. Molecular Biology and Evolution, 25(10), 2241-2246.
1267	doi:10.1093/molbev/msn172
1268	
1269	Solís-Lemus, C., & Ané, C. (2016). Inferring phylogenetic networks with maximum
1270	pseudolikelihood under incomplete lineage sorting. PLoS Genetics, 12(3), e1005896.
1271	doi:10.1371/journal.pgen.1005896
1272	
1273	Solís-Lemus, C., Bastide, P., & Ané, C. (2017). PhyloNetworks: A package for phylogenetic
1274	networks. Molecular Biology and Evolution, 34(12), 3292-3298.
1275	doi:10.1093/molbev/msx235
1276	
1277	Solís-Lemus, C., Yang, M., & Ané, C. (2016). Inconsistency of species tree methods under gene
1278	flow. Systematic Biology, 65(5), 843-851. doi:10.1093/sysbio/syw030
1279	
1280	Suarez-Gonzalez, A., Lexer, C., & Cronk, Q. C. B. (2018). Adaptive introgression: a plant
1281	perspective. <i>Biology Letters</i> , 14(3). doi:10.1098/rsbl.2017.0688
1282	
1283	Suvorov, A., Kim, B. Y., Wang, J., Armstrong, E. E., Peede, D., et al. (2021). Widespread
1284	introgression across a phylogeny of 155 Drosophila genomes. BioRxiv.
1285	doi:10.1101/2020.12.14.422758
1286	
1287	Tajima, F. (1983). Evolutionary relationship of DNA sequences in finite populations. <i>Genetics</i> ,
1288	105(2), 437-460.

1289	
1290	Taylor, S. A., & Larson, E. L. (2019). Insights from genomes into the evolutionary importance
1291	and prevalence of hybridization in nature. <i>Nature Ecology and Evolution</i> , 3(2), 170-177.
1292	doi:10.1038/s41559-018-0777-y
1293	
1294	Than, C., Ruths, D., & Nakhleh, L. (2008). PhyloNet: a software package for analyzing and
1295	reconstructing reticulate evolutionary relationships. <i>BMC Bioinformatics</i> , 9, 322.
1296	doi:10.1186/1471-2105-9-322
1297	doi.10.1100/14/1 2105 / 522
1297	Vanderpool, D., Minh, B. Q., Lanfear, R., Hughes, D., Murali, et al. (2020). Primate
1298	phylogenomics uncovers multiple rapid radiations and ancient interspecific introgression.
1300	PLoS Biology, 18(12), e3000954. doi:10.1317/journal.pbio.3000954
1301	Venshan T. C. (2017) IsriTuss and harmon based viewelingtion for about sometic trace and
1302	Vaughan, T. G. (2017). IcyTree: rapid browser-based visualization for phylogenetic trees and
1303	networks. Bioinformatics, 33(15), 2392-2394. doi:10.1093/bioinformatics/btx155
1304	
1305	Wakeley, J., & Hey, J. (1997). Estimating ancestral population parameters. <i>Genetics</i> , 145(3),
1306	847-855.
1307	
1308	Wakeley, J., & Hey, J. (1998). Testing speciation models with DNA sequence data. In R.
1309	DeSalle & B. Schierwater (Eds.), Molecular Approaches to Ecology and Evolution:
1310	Birkhäuser, Basel.
1311	
1312	Wang, J. (2003). Maximum-likelihood estimation of admixture proportions from genetic data.
1313	<i>Genetics</i> , 164(2), 747-765.
1314	
1315	Wen, D., & Nakhleh, L. (2018). Coestimating reticulate phylogenies and gene trees from
1316	multilocus sequence data. Systematic Biology, 67(3), 439-457. doi:10.1093/sysbio/syx085
1317	
1318	Wen, D., Yu, Y., Zhu, J., & Nakhleh, L. (2018). Inferring phylogenetic networks using
1319	PhyloNet. Systematic Biology, 67(4), 735-740. doi:10.1093/sysbio/syy015
1320	
1321	Williamson, S., & Orive, M. E. (2002). The genealogy of a sequence subject to purifying
1322	selection at multiple sites. Molecular Biology and Evolution, 19(8), 1376-1384.
1323	doi:10.1093/oxfordjournals.molbev.a004199
1324	
1325	Wright, S. (1931). Evolution in Mendelian Populations. Genetics, 16(2), 97-159.
1326	(1) (1)
1327	Wu, D. D., Ding, X. D., Wang, S., Wojcik, J. M., Zhang, et al. (2018a). Pervasive introgression
1327	facilitated domestication and adaptation in the <i>Bos</i> species complex. <i>Nature Ecology and</i>
	<i>Evolution</i> , 2(7), 1139-1145. doi:10.1038/s41559-018-0562-y
1329	<i>Lyoiullon, 2(7), 1157-1145.</i> doi:10.1050/841557-010-0502-y
1330	Wy M Kastrup I I Hahn M W & Mayle I C (2019h) Disposition the basis of social trait
1331	Wu, M., Kostyun, J. L., Hahn, M. W., & Moyle, L. C. (2018b). Dissecting the basis of novel trait
1332	evolution in a radiation with widespread phylogenetic discordance. <i>Molecular Ecology</i> , 27(16), 2201, 2216, doi:10.1111/mag.14780
1333	27(16), 3301-3316. doi:10.1111/mec.14780
1334	

1335	Yu, Y., Degnan, J. H., & Nakhleh, L. (2012). The probability of a gene tree topology within a
1336	phylogenetic network with applications to hybridization detection. PLoS Genetics, 8(4),
1337	e1002660. doi:10.1371/journal.pgen.1002660
1338	
1339	Yu, Y., Dong, J., Liu, K. J., & Nakhleh, L. (2014). Maximum likelihood inference of reticulate
1340	evolutionary histories. Proceedings of the National Academy of Science of the United
1341	States of America, 111(46), 16448-16453. doi:10.1073/pnas.1407950111
1342	
1343	Zhang, C., Ogilvie, H. A., Drummond, A. J., & Stadler, T. (2018). Bayesian inference of species
1344	networks from multilocus sequence data. Molecular Biology and Evolution, 35(2), 504-
1345	517. doi:10.1093/molbev/msx307
1346	
1347	Zhang, W., Dasmahapatra, K. K., Mallet, J., Moreira, G. R., & Kronforst, M. R. (2016).
1348	Genome-wide introgression among distantly related Heliconius butterfly species.
1349	Genome Biology, 17, 25. doi:10.1186/s13059-016-0889-0
1350	
1351	Zheng, Y., & Janke, A. (2018). Gene flow analysis method, the D-statistic, is robust in a wide
1352	parameter space. BMC Bioinformatics, 19(1), 10. doi:10.1186/s12859-017-2002-4
1353	