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Phylogenetic tree building in the genomic age

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Abstract | Knowing phylogenetic relationships among species is fundamental for many studies in biology. An accurate phylogenetic tree underpins our understanding of the major transitions in evolution, such as the emergence of new body plans or metabolism, and is key to inferring the origin of new genes, detecting molecular adaptation, understanding morphological character evolution and reconstructing demographic changes in recently diverged species. Although data are ever more plentiful and powerful analysis methods are available, there remain many challenges to reliable tree building. Here, we discuss the major steps of phylogenetic analysis, including identification of orthologous genes or proteins, multiple sequence alignment, and choice of substitution models and inference methodologies. Understanding the different sources of errors and the strategies to mitigate them is essential for assembling an accurate tree of life.

Homologous
When features, including morphological characters and gene loci, are inherited from a common ancestor, for example, a gene in two species originating from a single ancestral gene.

Orthologous
Homologous sequences that have diverged due to speciation events.

Substitution models
Continuous time Markov Chain probabilistic models that describe changes between nucleotides or amino acids over evolutionary time.

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Knowledge of how living (and extinct) species are related to one another underpins much of evolutionary biology. Knowing the relationships between species is an important goal in its own right and underlies our system of phylogenetic classification. The tree of life is also the essential framework for studying the origins of novel phenotypes and the processes that underlie biological evolution[1,2]. Mapping heritable character states (phenotypic or genotypic) onto a tree is the basis of different evolutionary analyses: it allows us, for example, to make inferences about character homology and also to gain insights into character loss and convergent evolution. Homologous characters of two taxa were, by definition, present in their common ancestor, allowing us to infer the characteristics of these ancestors. More generally, character mapping allows us to follow the changing character states across a tree to reconstruct the historical path of evolution. Trees (and molecular data) also underpin methods for fitting a timescale to the evolutionary process and trees underlie the comparative method used to establish trends in the processes of evolution[2].

Reconstructing the relationships across all life, although prefigured in attempts at classification as long ago as Aristotle and Linnaeus, is an endeavour that began seriously in the 19th century with Darwinism. Whereas trees were initially based to a great extent on morphological characters, biological molecules — nucleic acids and proteins — provide a far more powerful and plentiful source of information for reconstructing trees[3]. Since the development of DNA sequencing and sequence data being first used for phylogenetics, our understanding of the tree of life has changed radically and major progress has been made towards Darwin's dream of "very fairly true genealogical trees of each great kingdom of nature"[4].

For almost two decades, molecular phylogenies depended on data from one or a few genes, typically generated using PCR amplification and Sanger sequencing[5,6]. The development of new sequencing technologies has resulted in large datasets containing numbers of genes that have increased by orders of magnitude[7]. The ease and low cost of genome and transcriptome sequencing have also meant that the number of taxa that can be considered is expanding massively, as manifest in recent proposals to sequence the genomes of all species on Earth[8]. The data for reconstructing the tree of life are increasingly available, but accurate tree reconstruction is not always straightforward.

In this Review, we describe the major steps in the phylogenetic pipeline (FIG. 1) involving hundreds or thousands of genes (the so-called phylogenomic approach). For every step, we outline the various methodological choices and several corresponding trade-offs between model sophistication and computational demands. We begin with the identification of orthologous genes (that is, genes whose relationships will reliably reflect species relationships) from sets of genome or transcriptome sequences. We then discuss how to align orthologues from different species to account for insertions and deletions, and strategies for trimming unreliably aligned regions. Finally, we discuss in detail the choice of inference methods and substitution models and consider potential errors as well as approaches to identify and avoid or mitigate them.

Generating databases of orthologous genes

The first years of molecular phylogenetics were dominated by studies using a small set of universal orthologous genes, including the small and large subunit ribosomal RNAs[9] and (for eukaryote phylogenies) the mitochondrial genome[10]. The widespread use of rRNAs stemmed from the ease of PCR amplification using universal primers (unlike protein coding genes, for which degenerate primers are required), the fact that orthology was clear amongst these universal genes and the existence of a large database of these sequences.

The advances in high-throughput sequencing technologies of recent years mean that gene sequence data are abundant in sequence databases and new data are cheaply and easily produced. The challenges for data collection we now face are to ensure the data are free from contaminants, to identify orthologous genes that will reflect species relationships and, ideally, to select those genes that are less prone to biases that may result in inaccurate trees[11].

Data compilation and preparation. Initial gene sequence data can be derived either from gene predictions based on genome sequences (even from draft-quality genomes) or from transcriptomes generated by sequencing libraries derived from mRNA[12] (FIG. 1a). An important part of this step is to identify and eliminate contamination (either by bacteria, commensals, parasites or gut contents, or by cross contamination post DNA extraction)[13,14] (FIG. 1b). We start the description of the phylogenomic pipeline assuming the availability of gene sequences from each of the organisms of interest. Our ultimate aim is to produce an accurate tree of species relationships (a species tree).

Orthology predictions. Two genes are homologous if they are inherited from an ancestral gene (FIG. 2). Orthology is a special type of homology in which genes in different species have diverged from each other due to speciation[15,16]. As a result, orthologous genes recapitulate the relationships among the species they derive from (FIG. 2b). Other forms of homology include paralogy, in which genes from two species are derived from gene duplications deeper in time than the common ancestor of the two species (FIG. 2c), and xenology, where a gene in one species derives from a distantly related species through horizontal gene transfer (HGT). Paralogy and xenology do not reflect the relationships among species (FIG. 2c). Therefore, determining orthologous genes is an essential step for reconstructing species phylogenies[16,17] (FIG. 1c). Gene duplications and losses in different lineages are common and may lead to paralogous relationships even among single-copy genes, posing a challenge to orthology identification.

Approaches for de novo identification of orthologues fall into two main categories (TABLE 1): tree based and graph based[18]. Tree-based orthology inference identifies orthologues by aligning homologous sequences and reconstructing a tree to find those that are most plausibly related by speciation rather than by duplication or HGT[19–21]. These methods are conceptually closest to the definition of orthology, but they are computationally expensive as they require both alignment and phylogenetic inference of entire gene families that often comprise hundreds of sequences. Deeper divergences pose a greater challenge to the inference of a gene tree as the phylogenetic signal erodes (that is, multiple mutations accumulate resulting in homoplasy) and the risk of systematic errors increases (discussed in more detail in the later sections)[22,23]. Gene family relationships may be further obscured if other processes causing gene-tree discordance are not accounted for such as incomplete lineage sorting, horizontal gene transfer, hybridization, introgression and non-allelic gene conversion[22,24]. Particular groups of organisms are characterized by the frequent occurrence of some of these processes, for example, HGT in bacteria and hybridization, genome duplication, and polyploidy in plants, which makes them more likely to suffer from orthology prediction errors.

Graph-based orthology inference methods[25–29] rely on the assumption that a gene in one species should be more similar to its orthologue than to any other gene in a second species and vice versa[30,31]. This concept of orthology gave rise to the most popular graph-based approach, the 'bidirectional best hits' method[31] and several subsequent alternatives[25,32,33]. All such methods are based on all-against-all pairwise sequence comparisons mostly performed using Basic Local Alignment Search Tool (BLAST) for defining sequence similarity[34]. Graph-based approaches are not immune to the problems described for tree-based methods, but they have the advantage of being computationally efficient and scaling well with large datasets[27].

Given the complexity of sequence and gene evolution, de novo orthology prediction is bound to be approximate. It is encouraging that phylogenomic studies based on these procedures yield consistent and accurate phylogenies. Orthology prediction errors can, however, be a source of incongruence in challenging phylogenetic problems[27]. An alternative to de novo prediction is to use a set of reference orthologues and to identify their co-orthologues in newly sequenced species. Several dedicated databases offer orthologous sequences suitable for this cause, some spanning all domains of life, for example, OrthoDB[29] and OMA[35] and others focused on specific groups of organisms such as plants (Plaza[36]) and mammals (OrthoMam[37]). Several pipelines are available for automating this procedure (for example, REF.[38]) and there are two advantages in following this strategy. First, it is computationally cheaper than de novo inference and, second, it may alleviate errors associated with incomplete gene sampling. This is particularly relevant when using transcriptomic data, which usually contain only a subset of the genes. The incompleteness of data combined with differential gene loss may increase misidentification of paralogues for orthologues in de novo prediction. Using reference orthologous groups based on good quality genome data minimizes this risk by ensuring the completeness of the gene repertoire for the group of interest[39].

Given that the identification of orthologues and the inference of a species phylogeny are intertwined, the hypothesis of orthology may also be tested at the same

Species tree
A phylogenetic tree for a set of species that underlies the gene trees at individual loci.

Paralogy
Homologous sequences that have diverged due to duplication events so that both copies have descended side by side during the history of an organism.

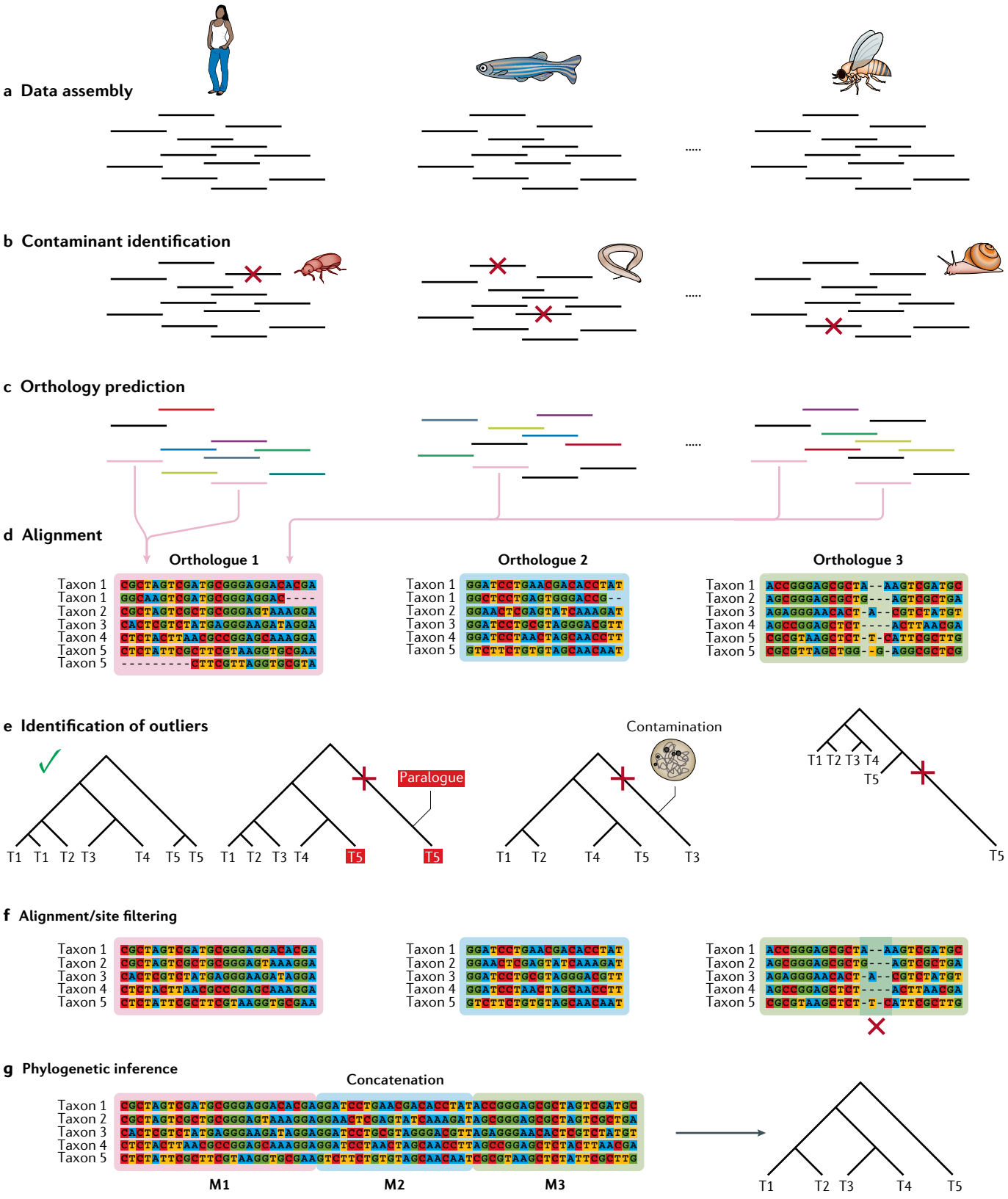
Xenology
Homologous sequences originating from horizontal gene transfer (also known as lateral gene transfer).

Alignment
Insertion of gaps in homologous sequences so that nucleotides or amino acids in the same column are homologous.

Gene tree
The phylogenetic or genealogical tree of sequences at a gene locus or genomic region.

Systematic errors
Errors due to incorrect model assumptions.

Incomplete lineage sorting
Discordance of gene trees from the species tree due to ancestral polymorphism.



time as the species phylogeny. In particular, multi-copy gene data can be used simultaneously to estimate the species and gene-family evolution[40,41]. Several methods have been described either in a full Bayesian framework[41] or in heuristic alternatives (for example, REFS[42–44]). Comparative assessment of the performance of these methods shows promising results[45].

A final consideration for orthology prediction is the genetic fragment that is used as the unit. It is typical to use genes (entire or partial) as a means of identifying

Fig. 1 | **Phylogenomic pipeline. a** | The starting material is a set of gene sequences (typically translated protein sequences) predicted from a genome sequence or derived from transcriptome sequencing. **b** | Contamination from commensals/symbionts, parasites, gut contents in animals, environmental sources or experimental errors, especially in multiplexed transcriptome sequencing, must be identified and removed. Contaminants can be identified and excluded based on the GC content of sequences, read coverage and taxonomy of sequence similarity matches. **c** | All-against-all comparisons (Basic Local Alignment Search Tool (BLAST) or similar) are used to identify sequences that are homologous between all species of interest. Clustering algorithms are used to identify putative orthologous genes whose relationships should reflect the species phylogeny. **d** | The sequences of putative orthologues are aligned to generate a multiple sequence alignment (MSA). **e** | The MSA can be analysed to produce an initial phylogenetic tree for the putative orthologues, which can be used to identify remaining paralogues, contaminants and other problematic sequences indicated by unusually long branches. **f** | The MSA is typically filtered to remove regions of unreliable alignment. **g** | The orthologues are concatenated to produce a supermatrix, which is analysed to infer the species phylogeny. Different models (or independently estimated substitution parameters under the same general model) may be used for different partitions of the MSA.

orthologous parts of a species' genome. However, most genes consist of multiple domains and, through time, their order and number may change. In this context, it has been suggested that domains may be more suitable units for orthology and consequently for phylogenetic inference[46,47].

Alignment and trimming

Sequence alignment. Due to insertions and deletions (indels), genes and proteins typically differ in length between species and, even in genes of identical length today, residues at the same location in a gene need not necessarily be homologous. Identifying homologous residues across genes entails aligning the genes, through the addition of gaps within the sequences[48] so that, in the final multiple sequence alignment, the residues in each column of the alignment should have descended from the same ancestral residue (FIG. 1d). Accurate alignment is fundamental in the inference of evolutionary relationships but, for genes in which indels have been frequent, it is a challenging task. When aligning protein-coding DNA sequences, the nucleotides naturally evolve as codon triplets rather than as single nucleotides. This property, as well as the fact that amino acid sequences change less rapidly than the corresponding nucleotides, means that initial alignment at the protein level rather than at the DNA level is usually appropriate. The codon triplets can then be aligned according to their corresponding amino acids[49–51].

Alignment methods can be classified into three main categories (TABLE 1). The most commonly used methods adopt the progressive approach, including Muscle[52], Clustal[53] and MAFFT[54]. These methods first make a rough estimate of how similar each pair of sequences is and use this information to produce an approximate guide tree of relationships between sequences. They then build up the alignment by first aligning the most similar pair of sequences and progressively adding more distantly related sequences, according to the guide tree, to this fixed alignment.

Second are the consistency-based methods, including T-Coffee[55], ProbCons[56] and some versions of MAFFT[54]. Initially, these methods estimate all pairwise alignments and, for each sequence pair, keep a record of alternative high-scoring solutions. Subsequently, they attempt to identify the overall alignment that maximizes the consistency among all pairs. Consistency-based methods are slower but more accurate overall than progressive methods[57].

Finally, the most computationally expensive are the statistical or evolution-based methods such as Bali-Phy[58] and StatAlign[59]. These assume an explicit evolutionary model of insertions and deletions[60] and jointly infer, in a Bayesian framework, both the alignment and the tree relating the sequences[58,59,61]. The statistical approach is the most methodologically sound; however, with large datasets, it may become computationally demanding. In such cases, using well performing heuristics, such as PRANK[62] and MAFFT, is a suitable compromise. For deeper divergences in particular, versions of MAFFT ('MAFFT E-INS-i' and 'MAFFT L-INS-i'), which accommodate the possibility of long internal or terminal gaps, respectively[54], may be practical alternatives[50,63].

Filtering aligned putative orthologues. Any orthology identification procedure may falsely identify contaminants, paralogues or xenologues as orthologues. Such errors may have an effect on the accuracy of phylogenetic inference, for example, by yielding longer branches, biased model parameters or even changes to tree topology. To minimize this source of error, phylogenomic projects typically follow methods that aim to identify outlier sequences, often employing BLAST-based sequence comparisons[34] to test the compatibility of closest neighbours with phylogenetic expectations[64,65] (FIG. 1e). A true insect orthologue, for example, is expected to show higher similarity to homologues from bilaterian phyla than to those from non-bilaterians and, if such an assumption is not met, the sequence can be removed from the dataset. These protocols can be efficient in data sanitizing, but they typically require some knowledge of the phylogenetic relationships of the taxa involved.

Several tools are available that either automate such BLAST-based procedures (for example, REFS[64,66]) or use alternative approaches for outlier detection (for example, Phylo-MCOA is based on multiple co-inertia analysis[67]). Tools aiming to identify and eliminate sequences with characteristics that may be associated with systematic error[66,68] or low phylogenetic information also exist[65]. Finally, to enrich orthologue groups that might have been produced by too-stringent orthology prediction (that is, leading to many false negatives), it is possible to use reference-based orthology prediction pipelines[38,64] under more relaxed criteria.

Alignment trimming. Alignment quality naturally decreases with increasing sequence divergence[69]. Because alignment errors may affect subsequent phylogenetic analyses[69,70], it is common to filter ambiguously aligned regions (FIG. 1f). Filtering can be based on ad hoc criteria regarding alignment quality such as gappyness and sequence similarity[71–73] or by retaining only the alignment positions that are robust to changes in alignment parameters[74]. Reports on the impact of alignment trimming on the quality of downstream phylogenetic analysis vary[75,76], and hence trimming should be used cautiously.

Topology
The branching pattern of a phylogenetic tree indicating relationships between taxa.

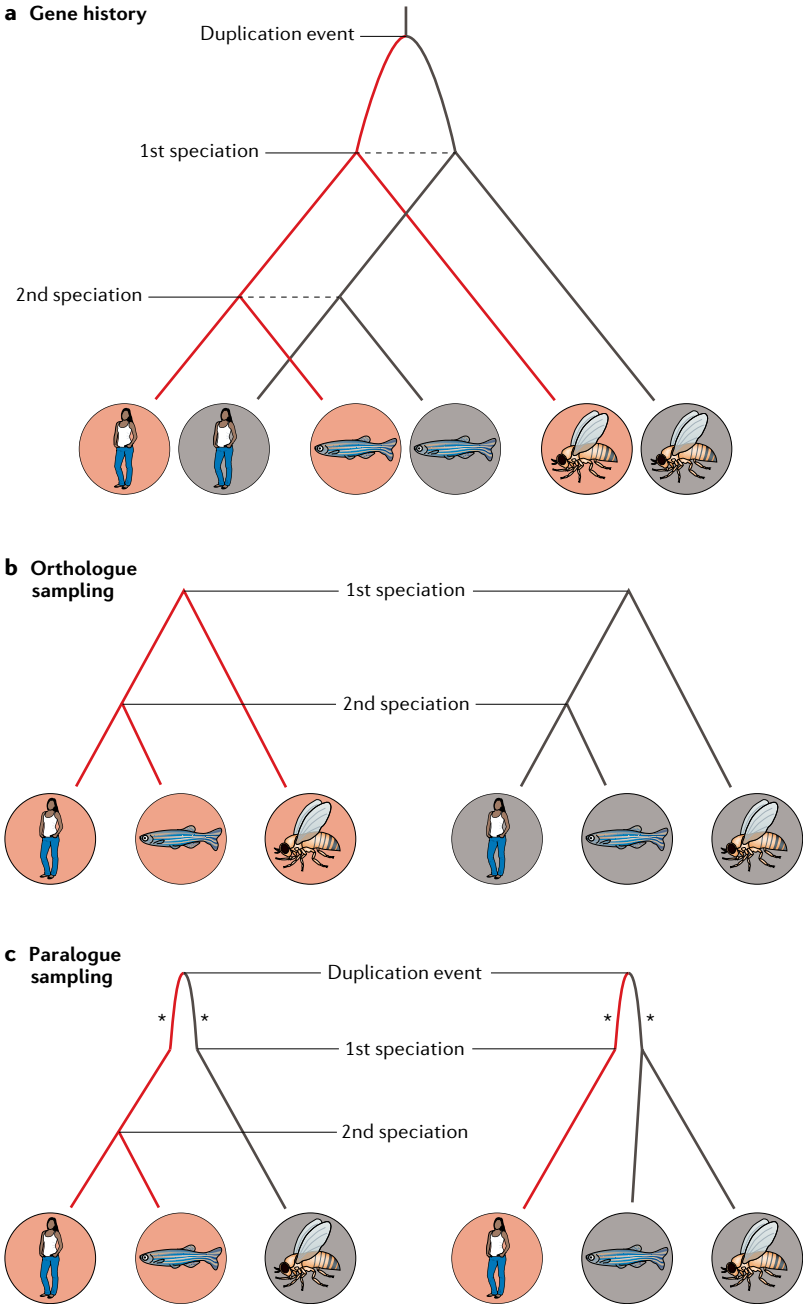


Fig. 2 | **Distinguishing orthologous and paralogous relationships between genes.** **a** | A gene has duplicated in a common ancestor of the species of interest. Two paralogous copies (red and grey) now evolve independently and each is inherited by descendant taxa following speciation events. **b** | Each of the duplicated genes (red or grey) have orthologous relationships amongst themselves such that reconstructing the relationships using just red or just grey orthologues will result in a tree that reflects the species relationships. **c** | Red and grey copies are related by duplication so that a tree based on a mixture of red and grey genes will not reflect the correct branch lengths of the species tree (left) and can also result in an incorrect species tree topology (right). The asterisks denote the part of the branch length that corresponds to the time between the duplication and the speciation events.

Phylogenetic inference methods

Classification of phylogenetic inference methods. Given a set of aligned and trimmed orthologous genes, there are two approaches to deriving a species tree. First, each of the gene alignments can be analysed independently to provide an estimate of the tree and the different trees can then be integrated to produce an estimate of the species tree. This is known as the super-tree approach. Second, the aligned genes can be concatenated into a supermatrix, which is analysed to produce a global estimate of the species tree. Although we discuss methods for the reconciliation of multiple gene trees in the context of genealogical heterogeneity across genes (below), the supermatrix method (FIG. 1g) is most commonly used and is the main focus of this Review.

Phylogeny reconstruction methods fall into two categories: distance based and character based. Distance methods involve calculating a genetic distance between every pair of species (based on comparison of their aligned sequences) and using the resulting distance matrix iteratively to construct a tree. The most popular distance method is the neighbour joining (NJ) algorithm[77]. Because NJ does not search (according to a certain criterion) for the optimal tree in the huge space of all possible trees, it is computationally very efficient. There are several implementations of the NJ method or variants[78] as well as versions capable of producing phylogenies of several thousands of samples[79,80]. However, distance methods tend to perform poorly for distantly related species because large distances are hard to estimate and distance methods exacerbate this problem by summing up the branch lengths on the path between species on the phylogeny when defining the pairwise distance.

Character-based phylogenetic inference methods. Character-based methods include maximum parsimony, maximum likelihood (ML) and Bayesian inference (BI)[81–83]. The maximum parsimony method calculates the minimum number of nucleotide or amino acid changes that are required to explain the data using each possible tree topology[84,85]. The tree topology with the smallest number of changes is known as the most parsimonious tree and is the estimate of the species phylogeny. For large datasets, exhaustive comparison of all possible trees is impossible (for 10 species there are 8.2×10^{21} possible rooted trees), and various heuristic tree searching approaches are typically used. Parsimony is attractive because of its mathematical simplicity and computational efficiency. Nevertheless, the method involves apparently unrealistic, implicit assumptions about the evolutionary process[86]. The lack of an explicitly stated model in the method makes it hard to incorporate well-known features of the process of sequence evolution such as different rates between character states (for example, different rates for transitions and transversions) and different rates among sites (for example, higher rates at the third codon position than at the first and second positions). Parsimony is known to be more prone than likelihood methods to systematic errors, including long-branch attraction (LBA)[87] (see below). The method is nevertheless useful for data types for which it is difficult to devise appropriate models of character evolution such as rare-event characters based on genome rearrangements or unique morphological characters.

In contrast to parsimony, both ML and BI methods are based on an explicitly stated model of sequence

Long-branch attraction (LBA). The phenomenon of inferring an incorrect tree in which taxa with long branches are grouped together.

Table 1 | **Features of different orthology prediction and sequence alignment programs**

Software	Method	Key features	Link	Ref.
Orthology prediction				
OMA standalone	Graph based	Infers OMA groups (that is, sets of genes for which all pairs are orthologous) and hierarchical orthologous groups; predicts gene function annotations, phylogenetic profiling (patterns of gene presence or absence across species); has been used to infer orthologous groups across the tree of life (https://omabrowser.org)	https://omabrowser.org/standalone/	27
OrthoDB pipeline	Graph based	Infers hierarchical orthologous groups; has been used to estimate orthologous groups across the tree of life (https://www.orthodb.org/) as well as near-universal single-copy orthologues (that is, BUSCO genes) for different clades (https://busco.ezlab.org/); the BUSCO genes completeness is used as a quality metric for genome and transcriptome samples	https://www.orthodb.org/?page=software	29
OrthoFinder	Graph based	Corrects a previously undetected bias related to BLAST hits and gene lengths; offers options for different BLAST algorithms, alignments, building gene and species trees and comparative genomic statistics; easy to add or subtract species	https://github.com/davidemms/OrthoFinder	26
OrthoMCL	Graph based	Uses BLAST and Markov clustering to group proteins of multiple species into groups of putative orthologues	https://orthomcl.org/orthomcl/	25
InParanoid/HieranoiDB	Graph based	Infers hierarchical orthologous groups for multiple genomes by combining pairwise orthology analysis by InParanoid and a guide tree	http://hieranoidb.sbc.su.se/	28
PhylomeDB	Tree based	Infers phylogenies of homologous genes using a two-step optimization (neighbour joining and maximum likelihood); each node of the phylogeny is identified as a duplication or speciation event based on the overlap of species	http://phylomedb.org/	20
Alignment inference				
Clustal	Progressive	Infers alignment of DNA or protein sequences and can take into account protein structural information; provides a graphical interface	http://www.clustal.org/	53
Muscle	Progressive	Infers alignment of DNA or protein sequences; similar to (but faster than) Clustal	http://www.drive5.com/muscle	52
ProbCons	Consistency	Infers alignment of amino acid sequences using a combination of probabilistic modelling and consistency-based techniques; provides alignment quality scores per site	http://probcons.stanford.edu/	56
MAFFT	Progressive and consistency	Infers alignment of DNA or protein sequences; implements several different algorithms for accommodating low sequence similarity as well as long internal and terminal branches	https://mafft.cbrc.jp/alignment/software/	54
PRANK	Evolution based	Infers alignment of DNA, codon or amino acids in a maximum likelihood framework; it is based on a guide tree (either provided by the user or inferred using neighbour joining) and it explicitly models insertions and deletions; it breaks ties randomly and therefore the result may differ across runs	https://code.google.com/archive/p/prank-msa/	62
Bali-Phy	Evolution based	Jointly estimates the alignment (DNA, codon or amino acid sequences) and the phylogeny in a Bayesian framework; assumes an explicit model for insertions and deletions; performs ancestral sequence reconstruction	http://www.bali-phy.org/	58
StatAlign	Evolution based	Jointly estimates the alignment (DNA or amino acid sequences) and the phylogeny in a Bayesian framework; assumes an explicit model for insertions and deletions; offers a graphical interface and can take into account protein structure information	https://statalign.github.io/	59

BLAST, Basic Local Alignment Search Tool; BUSCO, Benchmarking Universal Single-Copy Orthologues; OMA, Orthologous MAtrix.

Clades
A clade is a group of taxa on a tree that includes their most recent common ancestor and all its descendants, also known as a monophyletic group.

Stochastic errors
Errors due to the finite length of sequences in the alignment.

Homogeneous-process model
A model that assumes the same substitution rate or process across alignment sites, taxa and time.

evolution and on the likelihood function. Under a statistical model parametrized by unknown parameter θ, the likelihood $L(\theta)$ is the probability of the observed data viewed as a function of θ. Here, θ may include the parameters of the substitution model and the branch lengths on the tree. In phylogenetics, almost all models assume that different sites or columns in the alignment are independent; the likelihood is then the product of the probability of observing the data at the different sites. The likelihood contains all the information in the data concerning the unknown parameter under the model[88]. In other words, a parameter value that makes the observed data look highly likely to occur is expected to be closer to the truth than a parameter value that makes the data look nearly impossible. The ML estimate of the parameter is the parameter value that maximizes the likelihood. The ML method of tree estimation was introduced by Felsenstein[89] and has been implemented in programs such as PAML[90], PhyML[91], RAxML-NG[92], IQ-Tree[93] and FastTree[94] (TABLE 2). For each tree topology, the substitution parameters and branch lengths are optimized to maximize the likelihood and the tree topology that achieves the highest likelihood is the ML tree.

The Bayesian method also relies on an explicitly stated model and on the likelihood function. It differs from ML in that it uses statistical distributions to quantify uncertainties in the parameters. Before the data are observed, the prior distribution is used to describe our prior information concerning the species tree and model parameters. After the data have been collected and analysed, the posterior distribution does the same thing. The posterior is the prior multiplied by the likelihood, rescaled so that it becomes a proper distribution. The posterior thus captures all information relevant for the parameters from the data and is an update of the prior.

The Bayesian method was introduced into molecular phylogenetics in the 1990s[95–97] and has been implemented in programs such as MrBayes[98], RevBayes[99], BEAST1 (REF.[100]), BEAST2 (REF.[101]) and PhyloBayes[102,103] (TABLE 2). Computation in Bayesian phylogenetics is achieved using the Markov chain Monte Carlo (MCMC) algorithm, which is a computer simulation algorithm that generates a sample of the tree topologies and parameters from their posterior. In practical terms, the frequency with which the algorithm visits a given tree topology is an estimate of the posterior probability for that tree. The maximum posterior probability tree (or the MAP tree) is our best estimate of the true tree[95]. The 95% credible set of trees includes the most probable trees with a total posterior probability of ≥95%; the credible set has the interpretation that the set includes the true tree with a probability of 95%, given the data and model[95,104].

A serious drawback of likelihood-based methods, including both ML and BI, is their heavy computational demand since they may take many thousands of CPU hours to run; this is particularly true of MCMC algorithms. Formulation of the likelihood function requires explicit specification of model assumptions concerning sequence evolution; this was considered by some as a disadvantage (because all models are wrong). However, it means that the assumed model can be tested, its impact on the analysis can be assessed and the model can be improved by incorporating important features of the evolutionary process. Indeed, most modern developments in statistical phylogenetics have been achieved in the likelihood framework[83,105].

Confidence in clades using the bootstrap. The NJ tree, parsimony tree or ML tree may be considered a point estimate of the true phylogeny from the respective methods. It is desirable to attach a measure of confidence in the point estimate as the confidence interval on a conventional parameter does. The most commonly used method for this purpose is bootstrapping, introduced to phylogenetics by Felsenstein[106]. This generates a number of bootstrap pseudo-datasets (say, 100), of the same size as the original dataset formed by resampling, with replacement of alignment sites. The pseudo-datasets are then analysed in the same way as the original dataset. The bootstrap support for a tree is the frequency at which that tree is inferred among the pseudo-datasets. The bootstrap is often used to attach support values for clades (as opposed to the whole tree): the support for a clade is the frequency at which the clade is recovered following phylogenetic tree reconstruction based on the bootstrap datasets. Unlike the bootstrap in other applications of statistics, the phylogenetic bootstrap does not have well-accepted or straightforward interpretations[107].

The bootstrap is applied to assess confidence in estimated trees for the distance, parsimony and ML methods. For Bayesian methods, the posterior probabilities for trees and clades provide the natural measure of confidence so that the bootstrap is unnecessary.

In analyses of phylogenomic datasets, a common observation is that bootstrap and posterior support values are very high (near 100%) whether the relationships are correct or not. This is particularly obvious for Bayesian posterior probabilities[108]. In phylogenomic-scale datasets, random errors become unimportant, and such strong support for incorrect relationships typically derives from systematic errors.

We now review the most common and important sources of error in phylogenetic analysis of deep phylogenies. The reader may consult Felsenstein[81] and Yang[83] for more detailed discussions.

Accommodating phylogenetic errors

There are two main kinds of errors in phylogenetic inference. Stochastic errors (also known as random errors) are due to the dataset having a finite size (that is, a limited number of sites in the alignment), whereas systematic errors are due to the violation of the model assumptions in the method[11]. In general, systematic errors arise when phylogenies are inferred under a simple homogeneous-process model of sequence evolution (assuming homogeneous rates of evolution between character states, among sites or genes, and across taxa or time) when, in reality, the process is heterogeneous. The explosive accumulation of sequence data in recent years means that random errors in phylogenetic analysis have been greatly reduced, but systematic errors actually increase with longer alignments.

Table 2 | **Features of different tree reconstruction programs**

Software	Statistical approach	Input data				Profile mixture models	Parallel environment	Key features	Link	Refs
		Protein	DNA	Binary	Gene trees					
Phylogenetic inference										
RAxML-ng	Maximum likelihood	Yes	Yes	Yes	–	No	Yes	Phylogenetic inference on a single or partitioned matrix; specifically designed for large phylogenomic analyses	https://github.com/amkozlov/raxml-ng	92
PAML	Maximum likelihood	Yes	Yes	No	–	No	No	Tree comparisons, divergence times estimation, ancestral state reconstruction, sequence simulation, detection of positive selection, tree search only for small datasets	http://abacus.gene.ucl.ac.uk/software/paml.html	90
Phyml	Maximum likelihood	Yes	Yes	No	–	No	No	Phylogenetic inference on a single or partitioned matrix, ancestral state reconstruction, divergence times estimation (PhyTime), competition and dispersal phylogeography model (PhyloGeo), demographic inference (PhyREX)	http://www.atgc-montpellier.fr/phyml/	91
FastTree	Heuristic maximum likelihood	Yes	Yes	No	–	No	Yes	Specifically designed for efficiently estimating large phylogenies in terms of number of taxa (up to one million); restricted to a small number of substitution models	http://www.microbesonline.org/fasttree/	94
IQ-Tree	Maximum likelihood	Yes	Yes	Yes	–	Yes	Yes	Phylogenetic inference on a single or partitioned matrix; also implements partition and model selection, codon models, heterotachy models, approximation to empirical profile mixture models	http://www.iqtree.org/	93
MrBayes	Bayesian inference	Yes	Yes	Yes	–	No	Yes	Phylogenetic inference on a single or partitioned matrix, divergence times estimation; also implements ancestral state reconstruction, topology comparison and a covarion model	http://mrbayes.net	98
PhyloBayes	Bayesian inference	Yes	Yes	No	–	Yes	Yes	Phylogenetic inference on a single or partitioned matrix; also implements ancestral reconstruction, divergence times estimation, data recoding, posterior predictive analyses, cross validation for model comparison, and sequence simulations	http://www.atgc-montpellier.fr/phylobayes/	102,103
BEAST	Bayesian inference	Yes	Yes	Yes	–	No	Yes	Primarily designed for divergence times estimation, all inferences are performed on rooted, time-scaled phylogenies; additionally, it includes, phylogeography models and estimation of demographic parameters under several coalescent models	http://beast.community	100
BEAST2	Bayesian inference	Yes	Yes	Yes	–	No	Yes	Primarily designed for divergence times estimation, all inferences are performed on rooted, time-scaled phylogenies; it comprises several independently implemented plugins (for example, model selection, demographic parameter estimation, species delimitation and species network inference)	https://www.beast2.org/	101
P4	Bayesian inference/ maximum likelihood	Yes	Yes	No	–	No	Yes	Python package for phylogenetic analyses; implements site and taxa heterogeneous models; particularly useful for model comparison and sequence simulations; requires knowledge of Python	http://p4.nhm.ac.uk/	116

Table 2 (cont.) | **Features of different tree reconstruction programs**

Software	Statistical approach	Input data				Profile mixture models	Parallel environment	Key features	Link	Refs
		Protein	DNA	Binary	Gene trees					
Phylogenetic inference (cont.)										
RevBayes	Bayesian inference	Yes	Yes	Yes	–	Yes	Yes	Software package written in 'Rev' language; it is entirely based on probabilistic models and it provides the user with the flexibility to implement any combination of models, Markov chain Monte Carlo algorithms, sampling proposals or any other component of the phylogenetic inference in a Bayesian framework; requires knowledge of Rev	http://revbayes.com	99
Coalescent-based species-tree estimation										
BPP	Bayesian inference	No	Yes	No	–	No	Yes	Full likelihood method for species tree, species delimitation and coalescent model parameter estimation	https://github.com/bpp/bpp	174,175
*BEAST	Bayesian inference	Yes	Yes	–	–	No	Yes	Full likelihood method for species-tree and coalescent model parameter estimation	http://beast.community	173
*BEAST2	Bayesian inference	Yes	Yes	–	–	No	Yes	Full likelihood method for species-tree and coalescent model parameter estimation	https://www.beast2.org/	172
MP-EST	Maximum likelihood	–	–	–	Yes	No	No	Two-step species-tree estimation, that is, the species tree is estimated given pre-calculated and rooted gene trees	http://faculty.franklin.uga.edu/lliu/mp-est	171
Astral	Maximum likelihood	–	–	–	Yes	No	No	Two-step species-tree estimation, that is, the species tree is estimated given pre-calculated unrooted gene trees	https://github.com/smirarab/ASTRAL	170

Heterogeneity of rates across taxa and long-branch attraction. LBA is perhaps the best-known systematic error affecting phylogenetic reconstruction. At the root of LBA errors are unequal rates of evolution in different lineages; the resulting variance in the expected amount of change per lineage is represented by long branches (highly divergent sequences) and short branches (less divergent sequences) on a tree[87]. LBA manifests itself as the incorrect grouping of long but, in reality, distantly related branches on the tree (FIG. 3). Two unrelated long branches can experience occasional identical substitutions. Parsimony methods will reconstruct these convergences as a homologous shared character inherited from a common ancestor. Likelihood methods (ML and BI) are more robust to LBA errors than is parsimony, as they are branch-length aware and hence consider the increased possibility of convergence on two long branches. ML and BI can nevertheless suffer from LBA if the assumed substitution model is incorrect or too simplistic[109] such as wrongly assuming a homogeneous rate of change across sites.

LBA may be hard to identify in empirical datasets. Its symptoms include two or more rapidly evolving lineages grouping together or a long-branch taxon joining a distant outgroup. It is then important to assess the robustness of such relationships to changes of the substitution model.

Several ad hoc strategies have been suggested to alleviate potential LBA artefacts such as exclusion of problematic species with very high evolutionary rates[6], removal of genes or gene regions with very high rates (which also tend to have poor alignment quality), and the addition of species that serve to break up long branches on the tree[110–112]. More recently, measures of branch length heterogeneity have been used to identify genes that appeared less rate heterogeneous and which were therefore assumed to be less susceptible to LBA. In a similar spirit are methods for identifying and removing substantially longer branches from individual gene trees, thereby reducing rate heterogeneity[67,68,113].

Heterogeneity of nucleotide or amino acid compositions across taxa (compositional bias). Most phylogenetic inference models assume that the substitution process has been stationary throughout the history of the species under study and that all species therefore share the same frequencies of the 4 nucleotides or 20 amino acids. This assumption of compositional homogeneity is often violated in analyses of distantly related species; an obvious example is when distantly related taxa have independently evolved adenine/thymine-rich genomes. In such a case, assumption of the homogeneous model will tend to artefactually group species with similar base compositions[114].

The optimal approach to dealing with compositional bias is to relax the assumption of compositional homogeneity by allowing the character state frequency parameters to drift across the phylogeny[115–117]. Such models

Compositional homogeneity
Homogeneity in nucleotide or amino acid frequencies across lineages of a phylogeny.

involve a set of frequency parameters for every branch on the tree and result in a large number of parameters, with a high computational cost.

A more practical approach to circumventing this problem is to identify and remove from the analysis genes or taxa that show compositional bias[118]. There are several measures of compositional deviation that are available (for example, in the software packages p4 (REF.[116]), IQ-Tree[93] and PhyloBayes[102,103]). However, removing genes or taxa will not be possible if the most biased taxa are of central interest or if the majority of genes fails the homogeneity tests.

A final approach that has been proposed is to aggregate character states[119]. The 4 nucleotides can, for example, be recoded into purines (A and G) and pyrimidines (C and T), which removes any AT bias. Similarly, the 20 amino acids have been recoded into a reduced set, grouped according to their inter-exchangeability as represented in a substitution matrix[120]. The recoding naturally leads to information loss, which on its own may lead to topological changes. However, it can be informative to examine how the placement of compositionally divergent taxa changes when the data are recoded.

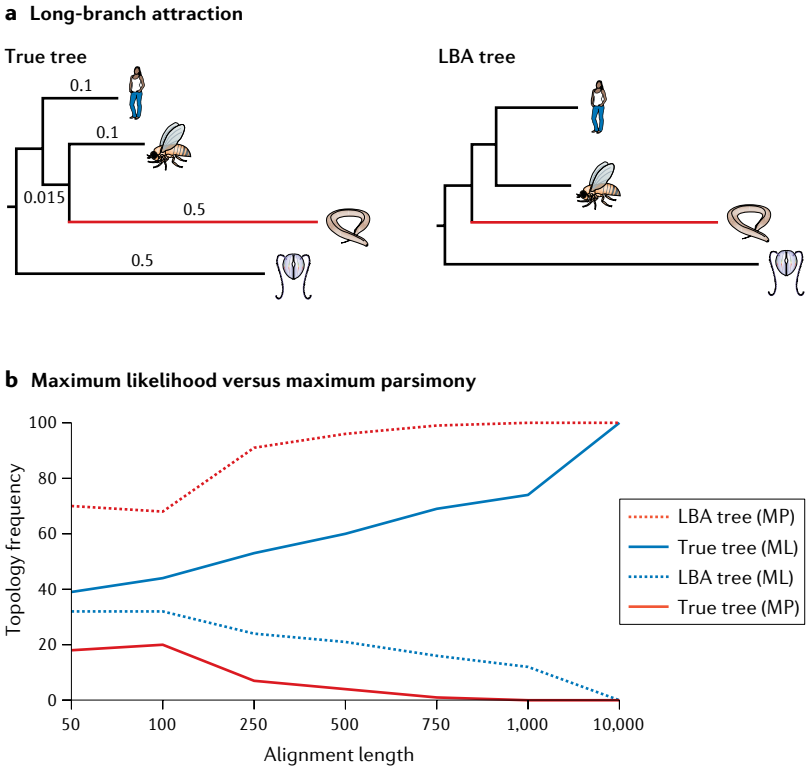


Fig. 3 | **Heterogeneous rates across lineages and long-branch attraction.** Heterogenous rates of substitution across lineages, if not accommodated by the model, may result in a long-branch attraction (LBA) artefact. **a** | The tree on the left is the true tree relating four species, in which substitution rates are heterogeneous among taxa, with long branches reflecting many changes along the lineages. The numbers on the branches denote the number of substitutions per site, and the given example is vulnerable to the LBA artefact. The tree on the right shows the effect of interpreting the occasional convergent changes arising in the long branches as shared characters indicating a close relationship between the long branches. This erroneous tree is inferred using maximum parsimony (MP), whereas branch length-aware likelihood methods such as maximum likelihood (ML) and Bayesian inference are less prone to this error. **b** | We used the true tree shown in part **a** to simulate 1,000 replicate datasets (sequence alignments) of increasing length (with 50–10,000 sites) under the Jukes–Cantor model. We analysed each replicate dataset using ML (blue) and MP (red) and recorded whether the correct (solid lines) or LBA tree (dotted lines) were recovered. For ML, small datasets show errors due to small sample size (stochastic errors), which decrease with larger samples. For MP, the systematic errors caused by LBA become larger with increasing sample size.

Heterogeneity of rates across sites. Different parts of the genome evolve at different rates. Collagens change more quickly than histones, introns change more quickly than exons, third positions in a codon change more quickly than the first and second positions, and some amino acids within a protein are under strong stabilizing selection while others are free to vary; ultimately, assuming a constant rate among sites of a gene is unrealistic. Assuming a single (average) rate results in a systematic underestimation of the likelihood of change at sites with higher rates[121]. As we have seen, underestimating the likelihood of change (and hence the probability of convergent evolution) tends to exacerbate LBA. To accommodate this among-site rate variation, Yang[121,122] proposed the modelling of rates of sites as a random variable following a gamma distribution (FIG. 4a). The resulting model is represented by a suffix '+Γ' or '+G' and can be combined with any nucleotide or amino acid substitution model (for example, 'JC69+Γ', 'GTR+Γ' or 'LG+Γ'). This strategy for accounting for rate heterogeneity among sites is implemented in all phylogenetic inference and model-selection tools. Alternative models to accommodate among-site rate variation include the free-rates model (which assumes a few discrete rate classes)[123,124] and the gamma-mixture model (which assumes a mixture of two gamma distributions)[125]. In addition to heterogeneities across sites in an alignment, substitution rate and processes can also vary over time, perhaps reflecting structural and functional changes in the proteins in different taxa[126]. As a consequence, the substitution rate and pattern at a given site may differ substantially among the lineages of a phylogeny (FIG. 5); this phenomenon is called 'heterotachy'[127,128] and current methods for dealing with it are only computationally feasible for tree searching on very small datasets or for comparisons of single trees for larger datasets[129].

Heterogeneity of substitution patterns across sites — partition and mixture models. Different rates for different types of substitutions are easily accommodated in the Markov models used in phylogenetics. For example, transitions and transversions can be assigned distinct rates, with two parameters used[130]. The general time reversible model assumes all nucleotides occur at different frequencies (that is, three free model parameters) and change to one another at different rates (that is, six exchangeability parameters).

For the 20 amino acids, the general time reversible model will involve 209 parameters (19 frequencies and 190 exchangeabilities). This model is parameter rich but can be fitted to moderately sized datasets[131]. However, it is computationally expensive to estimate so many parameters during tree searching. Instead, empirical amino acid models derived from the analysis of hundreds or thousands of protein sequences are more often used, including Dayhoff[132], JTT[133], WAG[134] and LG[135].

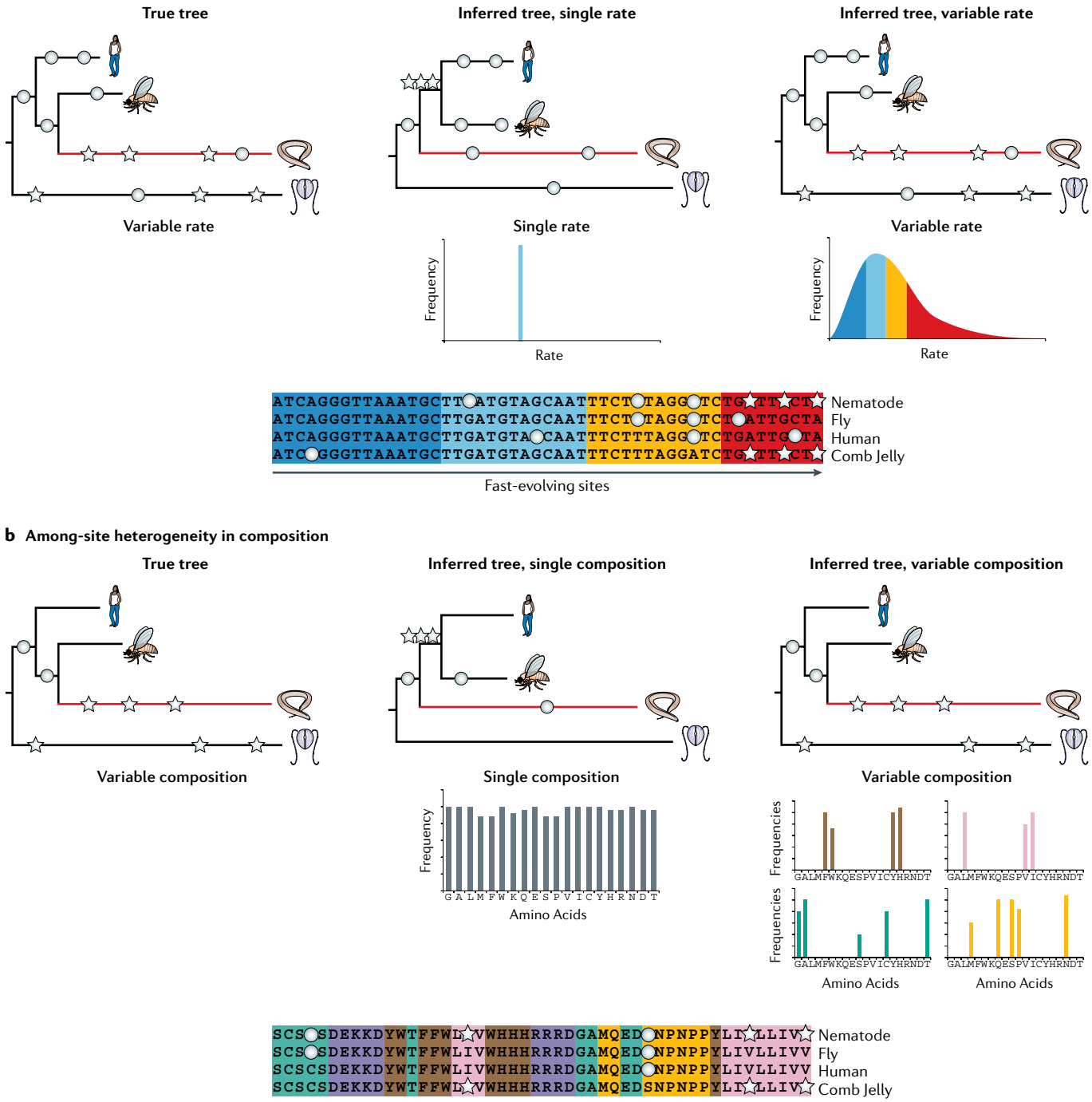


Fig. 4 | **Heterogeneous substitution rates and patterns across sites. a** | When different sites have different substitution rates (in different colours in the multiple sequence alignment at the bottom of the panel), more mutations (white circles) are accumulated at fast evolving sites, resulting in more homoplasy (convergent substitutions independently acquired by unrelated taxa, white stars). A model that assumes homogenous rates across sites (middle panel) will lead to underestimation of the amount of change at the fast-evolving sites and underestimation of the likelihood of convergence. Such systematic errors can lead to an erroneous long-branch attraction tree, whereas assuming the heterogeneous model incorporating variable rates across sites (right panel) recovers the true tree. **b** | When different sites in the protein prefer different amino acids (for example, two of the five different colours in the multiple sequence alignment and corresponding amino acid frequency bar charts denote hydrophobic or hydrophilic amino acids), rates of change within each composition category (for example, amongst hydrophobic amino acids) are higher than the average rate across the whole alignment. The homogeneous model ignoring among-site composition heterogeneity (middle panel) tends to underestimate the amount of change expected for sites with restricted compositions and to underestimate the likelihood of convergence, resulting in an erroneous long-branch attraction tree. The heterogeneous model incorporating among-site composition variation (right panel) recovers the true tree.

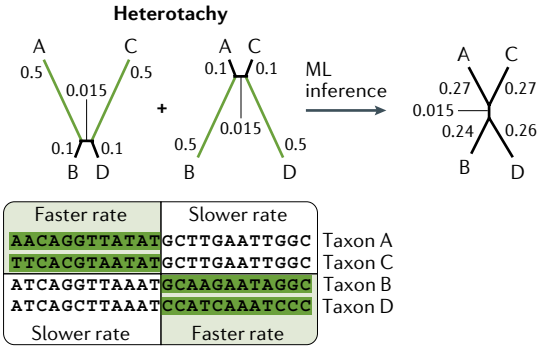


Fig. 5 | **Heterogeneities across time or lineages.** The first half of the sites in species A and C evolve faster than those in species B and D but the opposite is true for the second half. Such a heterogeneous substitution process is called 'heterotachy'[136]. The numbers on the two trees on the left denote the true branch lengths of the two heterotachous partitions. This particular case is vulnerable to errors in the tree inference if heterotachy is ignored. To show the effect, we simulated 5,000 sites for each of the partitions assuming the Jukes–Cantor model and inferred the phylogeny with IQ-Tree for the concatenated alignment (that is, 10,000 sites) with the Jukes–Cantor model, ignoring heterotachy. The black tree shown on the right was inferred, with A and C erroneously joined. ML, maximum likelihood.

Empirical models have also been calculated based on specific subsets of proteins (for example, viral[136], chloroplast[137] and mitochondrial[138]); different genes will fit different models best.

The common practice in a phylogenomic study has been to concatenate all genes into a super gene from which a single tree is inferred. Nevertheless, genes may differ in the rate and process of evolution. Such differences between genes may be accommodated by partition models that construct partitions with distinct parameters, such that sites in the same partition share evolutionary features and parameters whereas different partitions have distinct parameters[139]. Partition models provide a way of reducing errors from model misspecification by accounting for large-scale heterogeneity in rates and substitution patterns.

In a dataset of hundreds of genes and with dozens of models to choose from, it is not simple to assign models to genes or to construct a partitioning strategy. Automated model selection methods typically assume a fixed tree topology and try to maximize the likelihood of the data by altering the substitution models per gene (for example, REFS[93,140,141]). Some tools combine the process of model selection with the evaluation of alternative partition schemes, in which case genes that fit the same model are merged into one larger partition. For large datasets, the combined task of partition selection and model optimization is computationally intensive. Phylogenetic inference using empirical data under different substitution schemes may, however, result in differences in topology, branch lengths and statistical support[142,143]. Simulations show that optimized partitioning schemes are similar to partitioning based on biological common sense (for example, by gene or by codon) and that both approaches are substantially better than unpartitioned data[143,144].

Mixture models. Mixture models may also accommodate among-site heterogeneity in substitution rates and patterns (FIG. 4). In a mixture model, instead of assigning each site to a specific partition, the model averages overall possible assignments of a site to the site classes. The gamma model of variable rates among sites discussed above is a typical mixture model. When biological knowledge is available to assign sites to well-defined partitions (for example, to assign sites of a gene to the three codon positions), it is natural to use partition models; when such knowledge is lacking, mixture models offer a flexible alternative.

In the analysis of protein data, different parts of a protein may have very different substitution rates as well as having preferences for different amino acids dictated by local selective constraints. A one-size-fits-all empirical substitution matrix or even a partitioning approach is unlikely to capture these subtleties in the process of evolution. A mixture model may then be natural for accommodating the among-site heterogeneity in the rate and mode of amino acid substitution. A mixture model involves far more computation than a partition model, because without the knowledge of which component each site is from, one has to average overall components in the likelihood calculation (FIG. 6).

Mixture models can be used to account for site heterogeneity in both the rate and pattern of substitution. The model may assume multiple substitution matrices[145–147] or multiple sets of amino acid frequencies[148,149]. Profile mixture models use multiple components that differ in the frequencies of the 20 amino acids, while assuming a single set of exchangeability rates among them[148,150–152]. The C10–C60 (REF.[148]) empirical models, for example, include empirically estimated amino acid frequencies from known protein sequences. These models are implemented in both Bayesian[103] and ML frameworks[148,152,153]. The 'CAT' (categories) model, implemented in PhyloBayes[103], is the broadest generalization of the profile models. The CAT model treats the mixture components as free parameters and estimates the amino acid frequencies as well as the mixing proportions from the data (FIG. 4b). Importantly, the CAT model and other mixture models appear to be much less prone to underestimating branch lengths and more robust against LBA artefacts in analyses of distantly related species than site-homogeneous models[154].

Genealogical heterogeneity across genes

Concatenating all genes into a supermatrix and inferring a single tree assumes that one single gene tree underlies all genes and that it corresponds to the species tree. However, due to multiple biological processes — such as polymorphism in ancestral species, gene duplication and loss, and horizontal gene transfer — different genes or proteins may have different histories or gene trees[155,156].

Ancestral polymorphism means that orthologous genes from different species may not coalesce as soon as they reach the common ancestral species when we trace their history backwards in time; as a result, the genes

Mixture models
Models that assume different substitution rates or processes across sites of the alignment.

Profile mixture models
Models that assume multiple sets of state frequencies for sites (for example, CAT, C10–C60).

Coalescence
The process of lineage joining when one traces the history of a sample of sequences backwards in time.

Genetic drift
The process of random changes in allele frequencies over generations due to the stochastic nature of reproduction.

may not track the species phylogeny and may have a different tree topology from the species tree (FIG. 7). The phenomenon is variously termed incomplete lineage sorting (ILS), deep coalescence or gene-tree–species-tree incongruence. Incongruence is more likely to occur if the interior branches of the species tree are short and if the ancestral species had large population sizes. Phylogenetic relationships represented by long interior branches in the species tree will most likely be resolved confidently even if the analytical method ignores ILS. However, for species that arose through a radiative speciation process (which generates short interior branches in the species tree), ILS may pose serious challenges to species tree estimation[157].

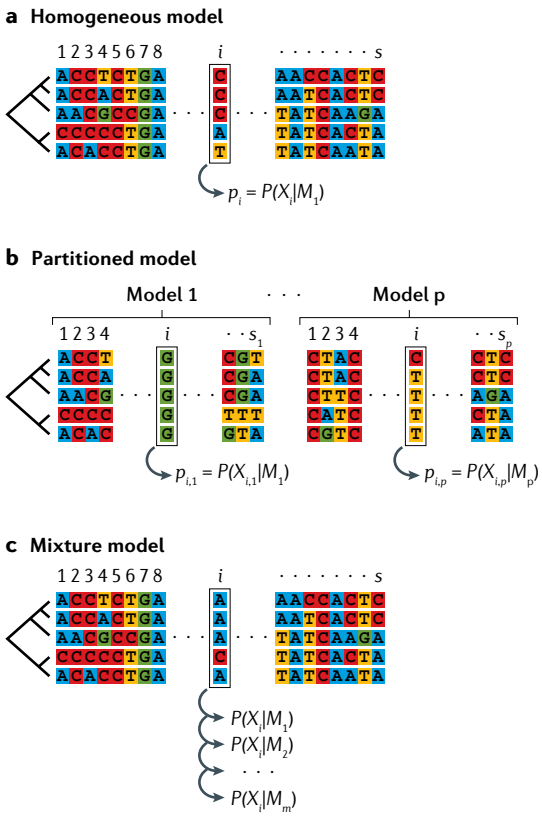


Fig. 6 | **Homogeneous partition and mixture models.** All the three types of models assume that sites (X_i, $i = 1, \ldots, s$, where s is the alignment size) evolve independently so that the likelihood (or the probability of all data) is the product of the probabilities for different sites given a model (M), that is, $L = \prod_{i=1}^{s} p_i$. **a** | The site-homogeneous model assumes the same substitution rate and process for all the sites in the alignment. The probability p_i of each site X_i is calculated under the shared model (M_1). **b** | In a partitioned model, each site is assigned to a partition, with sites in the same partition evolving according to the same model, whereas different partitions have different models or model parameters. Therefore, the probability of observing each site X_i is calculated under the model it is assigned to (M_j, $j = 1, \ldots, p$). **c** | In a mixture model, the sites in the alignment are a mixture of m classes, but we do not know a priori which class each site is from. The probability of observing data at a site i is then an average over the m site classes $p_i = \sum_{k=1}^{m} w_k P(X_i|M_k)$, where w_k is the proportion for class k.

The framework for accommodating ILS is the multispecies coalescent (MSC) model[158,159], an extension of the single-population coalescent[160] to the case of multiple species. Under the MSC model, the gene trees (topologies and branch lengths) vary among genes or genomic regions due to the coalescent process in the ancestral species: they have a statistical distribution specified by the species tree and by parameters such as the species divergence times and population sizes[161]. Thus, the MSC process is a natural consequence of reproduction and genetic drift. The simple MSC model has been extended to incorporate cross-species gene flow, leading to models such as MSC with migration (the isolation-with-migration or IM model)[162–164] and MSC with introgression (the MSCi or multispecies network coalescent or MSNC model)[165–167]; see REFS[161,168,169] for recent reviews.

There are two major classes of species tree methods that incorporate the MSC model. The summary or two-step methods use phylogenetic programs to infer the gene trees for individual loci, and then use the estimated gene trees as data to construct the species tree. Popular two-step programs include ASTRAL[170] and MP-EST[171]. These methods are computationally efficient and can analyse thousands of genes but may suffer from errors in reconstructed gene trees.

By contrast, the full likelihood methods calculate the likelihood of the sequence alignments and therefore accommodate the uncertainties in the gene trees. Commonly used programs implementing the MSC model include *BEAST[172,173] and BPP[174,175]; both are MCMC algorithms[176] and involve heavy computation, although algorithmic improvements have made it possible to analyse datasets of 10,000 loci[175,177,178].

Analyses of both simulated and empirical data suggest that full likelihood methods are superior to the approximate coalescent methods and to concatenation[177–179]. A number of coalescent-based methods have been applied and evaluated in relatively shallow divergences, but the effectiveness of these methods in reconstructing deep phylogenies is poorly understood. However, the root cause of ILS is the short internal branches in the species tree, rather than the shallowness of the nodes: deep phylogenies are just as affected by ILS as shallow phylogenies[157]. We expect that the next few years will see much effort in evaluating and overcoming the impact of ILS in deep parts of the tree of life.

Conclusions and perspectives

We have discussed a phylogenomic pipeline for accurate tree building, from careful data compilation including orthologue identification and contamination avoidance, via multiple sequence alignment, to selection of tree reconstruction methods and substitution models to avoid systematic errors in phylogenetic reconstruction. For challenging phylogenies — in particular deep phylogenies involving distant species — the choice of likelihood-based methods and the selection of adequate models to accommodate heterogeneities in the process of molecular evolution across sites, taxa and time (FIGS 3,4,5) appears to be as important as the generation of the underlying data. Here, we discuss a few areas in phylogenetic research that may see progress in the next few years.

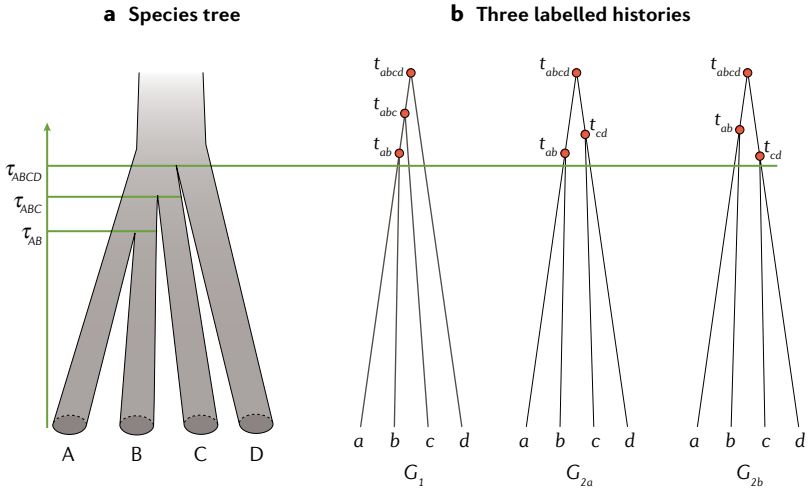


Fig. 7 | **Gene-tree–species-tree incongruence.** Ancestral polymorphism and deep coalescence may cause the most common gene tree to have a different topology from the species tree. The species tree is then said to be in the anomaly zone and the gene trees are called anomalous gene trees[159]. Anomaly zones do not exist for three species but exist for four or more species. **a** | Here, the four species A, B, C and D arose through rapid speciation events, with the speciation times τ_{AB}, τ_{ABC} and τ_{ABCD} nearly equal. **b** | When we sample one sequence from each species and trace the genealogical history of the four sequences *a*, *b*, *c* and *d*, there will be little chance for coalescence events to happen in the ancestral species AB or ABC because of the very short time interval. All four sequences are very likely to trace back to the common ancestor ABCD, in which coalescent events occur in a random order. As a result, each sequence of coalescent events will occur with the same probability. Each sequence of coalescent events generates a unique labelled history or ranked gene tree, which is a rooted tree with internal nodes ordered by age. There are 18 possible ranked gene trees and each has probability 1/18. Thus, the unbalanced gene tree G_1, which matches the species tree, has probability 1/18 as it represents one sequence of coalescent events (*a* and *b* joining first, then their ancestor joining with *c*, then their ancestor joining with *d*). The balanced gene tree ((*ab*),(*cd*)), which does not match the species tree, has probability 2/18, as it represents two distinct sequences of coalescent events or two labelled histories: G_2 in which $t_{ab} < t_{cd}$ and G_3 in which $t_{ab} > t_{cd}$. When the speciation times (τ_{AB}, τ_{ABC} and τ_{ABCD}) are close but not exactly the same, the mismatching balanced gene tree may still have a probability greater than for the matching unbalanced gene tree, even if not twice as large. For such speciation times, the species tree of part **a** is in the anomaly zone. In the anomaly zone, the majority-vote method of species tree estimation, which uses the most common gene tree as the species tree estimate, is inconsistent and will approach a wrong species tree when more and more loci or gene trees are used. The problem of the anomaly zone (and in general the problem of incomplete lineage sorting) is more serious the shorter the internal branches in the species tree are or the larger the ancestral populations.

One approach that has so far received little attention is the development of computationally tractable models for accommodating heterogeneity across clades. Besides compositional bias, amino acid exchangeabilities have also been reported to vary across the tree of life[180,181]. The strategy adopted to address this issue so far has been to remove data (taxa or genes) or to attempt to reduce other related problems such as among-site heterogeneity. Nevertheless, directly modelling tree heterogeneity should provide more accurate tree estimates.

Species radiations and the resulting short branches in the species phylogeny are responsible for many of the challenges in resolving the tree of life. This is particularly true for species radiations in deep time (examples within the animal kingdom include the divergences of mammals and birds, and the spirally cleaving phyla within the Lophotrochozoa). With deep radiations, the problem of ILS is exacerbated by the erosion of the phylogenetic signal resulting from substitutional saturation on the terminal branches. The performance of the MSC methods in deep divergences, when the molecular clock is seriously violated, needs careful study. Recent work shows that existing approximate methods may be vulnerable to LBA artefacts[182], and research is needed to evaluate the performance of coalescent approaches under relaxed-clock models in inference of deep divergences.

Phylogenomic datasets pose enormous computational burdens, in particular when complex models (for example, heterogeneous or MSC models) are used to reduce systematic errors. Great progress has been made in computational phylogenetics by the development of algorithms for speeding up[183] and parallelizing[184] the likelihood calculation, and the implementation of software making use of modern multi-processor multi-core computer architecture[92,103,185–187]. Additional improvements have been achieved in the mixing efficiency of MCMC sampling methods in Bayesian inference[188–190]. Yet, there appears to be much room for further improvement in the computational efficiency of those algorithms. Such advances will enhance the biological realism of phylogenomic models and will improve the overall phylogenetic accuracy.

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