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# Intraspecific gene genealogies: trees grafting into networks 

## David Posadaand Keith A. Crandall

Intraspecific gene evolution cannot always be represented by a bifurcating tree. Rather, population genealogies are often multifurcated, descendant genes coexist with persistent ancestors and recombination events produce reticulate relationships. Whereas traditional phylogenetic methods assume bifurcating trees, several networking approaches have recently been developed to estimate intraspecific genealogies that take into account these populationlevel phenomena.
take advantage of the unique characteristics of intraspecific data. In this article, wesummarize some population genetics principles, explain why networks areappropriaterepresentations of intraspecific genetic variation, describe and compareavailable methods and softwarefor network estimation, and giveexamples of their application.

## Gene genealogies

Given a sample of genes, the relationships among them can betraced back in time to a common ancestral gene. The geneal ogical pathways interconnecting the current sampletothe common ancestor constitutea gene tree or genegenealogy. A genetree is the pedigree of a set of genes and exists independently of potential mutations. Theonly portion of a gene tree that can generally be estimated with genetic data is that portion marked by the (potential) mutational events that definethedifferent alleles (Box 1). This lower resolution tree is theallele

## Glossary

Additive tree: a tree on which the pairwise distances between haplotypes are equal to the sum of the lengths of the branches on the path between the members of each pair.
Coalescent event: the time inverse of a DNA replication event; that is, the event leading to the common ancestor of two sequences ooking back in time.
Gene: a segment of DNA.
Gene tree: the representation of the evolutionary history of a group of genes.
Haplotype or allele: a unique combination of genetic markers present in a sample.
Haplotype space: the collection of points representing the possible different haplotypes. The dimension of this space is the number of characters ( $L$ ). The number of points (haplotypes) included in the haplotype space is the number of states raised to the number of characters (i.e. for DNA sequences $4^{L}$ ).
Homoplasy: a similarity that is not a result of common history. It is caused by parallel, convergent or reverse mutations
Interior haplotypes: those haplotypes that have more than one mutational connection.
Minimum-spanning tree: graph theory construct that connects the $n$ haplotypes, thus a complete network of $n$ - 1 branches is built.The tree is 'minimal' when the total length of the branches is the minimum necessary to connect all the haplotypes.
Missing intermediate: an extant haplotype that was not sampled or an extinct ancestral haplotype.
Network: a connected graph with cycles (Fig. la).
Patristic or phyletic distances: the distance between haplotypes as inferred from the network. It does not have to be equal to the actual distance (number of differences) between haplotypes.
Phylogeny: hierarchical genetic relationships among species. Arising by speciation.
Robinsonian distance matrix: a matrix with the property that, for any
or hapLotype tree. Genegenealogies areapproximated by theestimation of haplotype or alleletrees. Given theabundance of methods availablefor phylogenetic estimation ${ }^{1}$, which ones are most appropriatefor estimating haplotypetrees?

## Problems with interspecific methods at the intraspecific

 levelEvolutionary relationships aboveand below the species level aredifferent in nature. Relationships between genes sampled from individuals bel onging to different species (phylogeny sensu stricto) arehierarchical. This is becausethey are the product of reproductive isolation and population fission over longer timescales, during which mutation combined with population divergence led tothefixation of different alle es and, ultimately, to nonoverlapping genepools.

By contrast, relationships between genes sampled fromindi viduals within a species (sometimes called toкоgen ${ }^{2}$ ) are not hierarchical, because they arethe result of sexual reproduction, of smaller numbers of relatively recent mutations and, frequently, of recombination (Fig. 1). Moretraditional methods developed toestimateinterspecific relationships, such as maximum likelihood, maximum parsimony and minimum evolution, cannot properly take account of thefact that, at the population level, several phenomena violatesome of their assumptions. This leads to poor resolution or inadequately portrays geneal ogical relationships.
ordered triplet of sequences $i, j$ and $k$, any distance $\mathrm{d}_{i k} \geq \max \left(\mathrm{d}_{i j}, \mathrm{~d}_{j k}\right)$. Singletons: haplotypes represented by a single sequence in the sample.
Species tree: the representation of the evolutionary history of a group of species.
Split: the division of the haplotypes into two exclusive sets. For $n$ sequences, there are $2 n$-1 possible splits.
Tip haplotypes: those haplotypes that have only a single mutational connection to the other haplotypes within the network.
Tokogeny: nonhierarchical genetic relationships among individuals. Arising by sexual reproduction.
Tree: a connected graph without cycles (cycles are commonly called reticulations or loops by evolutionary biologists) (Fig. lb,c).
I (a)


Network
(b)


Multifurcate tree
(c)


## Low divergence

By necessity, conspecificindividuals diverge later than individuals from different species. Consequently, within-species data sets havefewer characters for phylogenetic analysis, diminishing the statistical power of traditional phylogenetic methods.

## Extant ancestral nodes

In natural populations, most haplotypes in thegene pool exist as sets of multiple, identical copies that originated by DNA replication. When one of these copies mutates to a new haplotype, it is extremely unlikely that other copies of theancestral haplotype al so mutate or that all copies of the ancestral haplotype rapidly becomeextinct. Thus, the ancestral haplotypes are expected to persist in the population and to besampled together with their descendants. Traditional phylogenetic methods, based on a bifurcating tree, can detect and artificially represent persistent ancestral haplotypes as occupying a branch of zerolength at the basal node of a cluster. However, this approach relies on modifying (e.g. by estimation of branch lengths) an inappropriate model - a bifurcating tree with all haplotypes occupyingtips or terminal branches.

## Multifurcations

A fact related tothe persistence of ancestral haplotypes in thepopulation is that a singleancestral haplotype will often giverisetomultipledescendant haplotypes,

## Box 1 Gene trees, haplotype trees and population trees

## Gene trees versus haplotype trees

Genetrees are independent of the (neutral) mutation process. They depend on demographic factors such as population size and geographical structure. Because, by definition, neutral mutations do not affect the number of offspring or migration patterns, they do notaffect the gene genealogy. Gene trees precisely represent the genegenealogy of a given sample. However, such precise information is usually unknown or even impossible to extract from a sample of extant genes. For example, in Fig. I, there is no way to know that geneA1 is more closely related to A4than either is to A2. Unless detailed pedigree information is available, which usually is not the case, the only branches of the gene tree that we can estimate are those marked by a mutation and that therefore define haplotypes.

We must be able to seegenetic differences (mutations) to determine relationships; therefore, we use haplotype trees most often. With haplotypetrees, we cannotsee all the coalescentevents and can only group genes by their similarities and haplotype classes.Whereas traditional methods often lack the power to solve intraspecific relationships, network approaches offer an appropriate representation of the haplotype relationships, including extinct (Fig. I, haplotype D) or unsampled (Fig. I, haplotype B) haplotype variants.

## Haplotype trees versus population trees

It is often assumed that the haplotype trees represent exactly the history of the populations sampled. However,
haplotypes do not, in general, have the same evolutionary history as population lineages ${ }^{\text {a }}$. Disagreement among haplotype trees and population trees can arise from recombination (Fig. Ila) and
deep coalescence or lineage sorting (Fig. Ilb).

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II (a)

| Pop. A | Pop. B | Pop. C | Pop. D |
| :--- | :--- | :--- | :--- |
| (hap. A | (hap. | (hap. E) | (hap. E) |
| and B) | C and D) |  |  |


(b)

| Pop. A | Pop. B | Pop. C | Pop. D |
| :--- | :--- | :--- | :--- |
| (hap. A | (hap. | (hap. E) | (hap. E) |
| and B) | C and D) |  |  | and B) C and D)

Population tree Haplotype tree

- Mutation
x Extinct or not sampled
R Recombination
Pop. Population
Hap. Haplotype
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yielding a haplotypetreewith truemultifurcations. Indeed, population genetics theory predicts that the older thehaplotype, the moredescendant haplotypes will be associated with it (Box 2 ).


## Reticulation

Evol utionary processes commonly acting at the population level, such as recombination between genes and hybridization between lineages, and HOMOPLASY (Box 1), generatereticulaterelationships within the population. Traditional methods, based on bifurcating trees, makenoexplicit allowancefor such reticulations. Instead, for instance, maximum parsimony deals with ambiguities arising from homoplasy by simply sel ecting a treethat minimizes the number of assumptions of parallel, convergent or reversing mutations without showing wherethese
might haveoccurred. Recombinants arealsotypically forced intoa nonreticulating treetopology, in which, in somefortunate instances, they might occupy positions intermediate between two clusters. In other cases, the recombinant will beplaced in a basal lineagetothe cladethat includes its most derived parent ${ }^{3,4}$.

## Large sample sizes

Appropriatesampling can becrucial to phylogenetic studies ${ }^{5}$. Typically, intraspecificstudies involvemany individuals for comparison, whereas many interspecific phylogenetic studies tend to bebased on one representative individual per species. Because of thedensity of sampling, especially when coupled with low divergence, intraspecific data sets reach considerablesamplesizes (>100). Theselargesample sizes would requireexcessivecomputational timefor

$\overline{T R E N D S ~ i n ~ E c o l o g y ~ \& ~ E v o l u t i o n ~}$

Fig. 1. Tokogeny versus phylogeny. (a) Processes occurring among sexual species (phylogenetic processes) are hierarchical.That is, an ancestral species gives rise to two descendant species. (b) Processes occurring within sexual species (tokogenetic processes) are nonhierarchical.That is, two parentals combine their genes to give rise to the offspring. (c)The split of two species defines a phylogenetic relationship among species (thick lines) but, at the same time, relationships among individuals within the ancestral species (species 1) and within the descendant species (species 2 and 3 ) are tokogenetic (arrows).
most methods that have been devel oped for interspecific comparisons.

## Solution: network methods

Phylogeneticmethods that allow for persistent ancestral nodes, multifurcations and reticulations are needed totake these population phenomena into account. The advantage of networks over strictly bifurcating trees for estimating within-species relationships now becomes obvious. Networks can account effectively for processes acting at the species level and they might beabletoincorporate predictions from population genetics theory (Box 2). In addition, networks providea way of representing more of the phylogeneticinformation present in a data set (Fig. 2). For example, the presence of loops in a network might indicaterecombination. In other cases, loops arethe product of homopl asies and precisely indicatethe occurrence of reverse or parallel mutations. Most network methods aredistance methods, with the common idea of minimizing (with
some specific restrictions) the distances (number of mutations) among haplotypes. In other cases, the likelihood function is maximized.

## Pyramids

Thepyramids technique ${ }^{6}$ is an extension of the hierarchical clustering framework. Whereas traditional hierarchical methods such as Unweighted Pair Group with Arithmetic Means (UPGAM) represent a nested set of nonoverlapping clades, pyramids represent a set of clades that can overlap without necessarily being nested. Theinput data is a (Robinsonian) distancematrix (Box 1). Thepyramid is obtained by using agglomerative algorithms. By allowing overlapping clusters, pyramids can beused to represent reticulate events, although these events are only allowed to be placed among terminal nodes that are sister taxa.

## Statistical geometry

This was one of the first network approaches for intraspecific phylogenetics to be developed 7 . In this method, haplotypes are considered as geometric configurations in the haplotype space. Numerical invariants (somefunction of the data whose value remains constant) related to the length of the connections (pairwise differences) among haplotypes are assigned tothehaplotypes and statistical averages of these invariants are then calculated. Given thevaluefor theinvariants, theoptimal network connecting the four haplotypes in each quartet is derived. Finally, an averagequartet geometry representative of thewhol e data set is constructed by integrating all the quartet networks. This geometry and the associated statistics can be used, for example, to deduce the degree of treelikeness of the data, to detect varying positional substitution rates in sequences or to estimatethe relativetemporal order of haplotypedivergence. However, they do not offer an estimate of the sequencegeneal ogy. Thestatistical geometry incorporates a model of nud eotide substitution through the estimation of haplotypedistances and its statistical natureallows a reliable assessment of the derived conclusions.

## Split decomposition

Any data set can be partitioned into sets (not necessarily of equal size) of sequences or 'splits'. A network can bebuilt by taking in turn those splits defined by the characters and combining them successively ${ }^{8}$. Each split will define a branch connectingthetwo partitions delimited by thesplit. When splits are incompatible (i.e. they define contradictory groupings) a loop is introduced to indicate that there are alternativesplits. Thesplit decomposition method is fast, which means that a reasonablenumber of haplotypes ( $>50$ ) can be analyzed; that it can be applied to nud eotideor protein data; and that it allows for the inclusion of

## Box 2. Predictions from coalescent theory and application to intraspecific phylogenetics

The ancestry of a random sample of $n$ genes is often modeled by a stochastic process known as the coalescent. Coalescent theory describes the genealogical process of a sample of selectively neutral genes from a population, looking backwards in time ${ }^{\text {a }}$. Several results from coalescent theory related to the frequency and geographical distribution of the haplotypes are relevant to intraspecific phylogenetics.

There is a direct relationship between haplotype frequencies and the ages of the haplotypes ${ }^{\text {b,c. }}$. Specifically, the probability that an allele represented $n_{i}$ times in a sample of size $n$ is the oldest allele in the sample is $n_{i} / n$, and the expected rank of the alleles by age is the same as the rank of alleles by frequency.Therefore, highfrequency haplotypes have probably been present in the population for a long time. Consequently, most of the new mutants are derived from common haplotypes, implying that rarer variants represent more recent mutations and are more likely to be related to common haplotypes than to other rare variants ${ }^{\text {d }}$. The expectation for the number of alleles in common between the samplese implies that the immediate descendents of a new mutation are more likely to remain in the original population than to move to a distant population, unless high levels of gene flow occur. These results can be summarized in five explicit predictions.

- Older alleles (those of higher frequency in the population) have a greater
probability of becoming interior haplotypes (those haplotypes that have more than one mutational connection) than younger haplotypes.
- On average, older alleles will be more broadly distributed geographically
- Haplotypes with greater frequency will tend to have more mutational connections.
- Singletons are more likely to be connected to nonsingletons than to other singletons.
- Singletons are more likely to be connected to haplotypes from the same population than to haplotypes from different populations.
These theoretical predictions make intuitive sense and have been shown to be valid in empirical data setsf. However, they assume neutral evolution (and lack of population subdivision) and might not be

accurate in the presence of selection. These predictions can also be used to root the network. Some loops or reticulations in the networks can be the result of homoplasies, thus representing the consequence of a lack of power to decide among alternative connections.These loops could be broken at any place, resulting in different networks.

The above predictions can be used to establish which one of the alternative networks is more plausiblef.g. For example, in Fig. I, if the frequency of haplotype 2 is lower than the frequency of the other haplotypes, resolutions a and b are favored because they result in haplotype 2 as a tip. (Dotted lines represent ambiguous connections.)

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models of nucleotidesubstitution or aminoacid replacement. Themethod is suitableal so to bootstrap evaluation.

## Median networks

In the median-network approach ${ }^{9,10}$, sequences are first converted to binary data and constant sites are eliminated. E ach split is encoded as a binary character with states 0 and 1 . Sites that support the same split aregrouped in one character, which is weighted by the number of sites grouped. This leads to therepresentation of haplotypes as 0-1 vectors. Median or consensus vectors are cal culated for each triplet of vectors until the median network is finished. For >30 haplotypes, the resulting median networks areimpractical to display, owing tothe presence of high-dimensional hypercubes. F ortunately, the network can bereduced (i.e. some loops can be solved) using predictions from
coalescent theory (Box 2). All the most parsimonious trees are guaranteed to be represented in a median network. Although mainly aimed at mtDNA data, median networks can beestimated from other kinds of data, as long as thedata arebinary or can be reduced to binary data.

## Median-joining networks

Themedian-joining network method ${ }^{11,12}$ begins by combiningtheminimum-Spanning trees (MSTs) within a singlenetwork. With a parsimony đriterion, median vectors (which represent missing intermediates) are added tothenetwork. Median-joining networkscan handlelargedata sets and multistatecharacters. It is an exceptionally fast method that can analyzethousands of haplotypes in a reasonableamount of timeand can also beapplied toaminoadd sequences. However, it requires theabsence of recombination, which restricts the application of this method at the population level.
(a)

(d)

(g)



Fig. 2. Phylogenetic estimation. Different phylogenetic reconstruction techniques, including network techniques, were applied to the data set described in Box 1, Fig. I. (a) UPGMA.
(b) Maximum parsimony. (c) Pyramid. (d) Statistical geometry (provides an estimate of average quartet topology rather than of the actual genealogy). (e) Split decomposition. (f) Minimum spanning network. (g) Medianjoining network. (h) Statistical parsimony. (i) Reticulogram.

Statistical parsimony
Thestatistical parsimony al gorithm ${ }^{13}$ begins by estimating the maximum number of differences among haplotypes as a result of singlesubstitutions (i.e. thosethat arenot theresult of multiple substitutions at a singlesite) with a $95 \%$ statistical confidence. This number is called the parsimony limit (or parsimony connection limit). After this, haplotypes differing by onechange are connected, then thosediffering by two, by three and so on, until all thehaplotypes areincluded in a singlenetwork or the parsimony connection limit is reached. The statistical parsimony method emphasizes what is shared among haplotypes that differ minimally rather than the differences among the haplotypes and provides an empirical assessment of deviations from parsimony. This method allows the identification of putativerecombinants by looking at the spatial
distribution in the sequence of thehomoplasies defined by thenetwork ${ }^{14}$.

## Molecular-variance parsimony

Theoverall strategy in the molecular-variance parsimony technique ${ }^{15}$ is to use some population statistics as criteria for the choi ce of theoptimal network. Each competing MST is translated into a matrix of PATRISTIC DISTANCES among haplotypes.
Thesematrices are used to compute a set of relevant population statistics: functions of haplotype frequencies, squared patristic distances among haplotypes and geographic partitioning of populations. The optimal MSTs arethosefrom which optimum estimates of population statistics are obtained (e.g. minimizing the molecular variance or the sum of square deviations). This method makes explicit use of sampled hapl otypefrequencies and geographic subdivisions, and presents the solution in theform of a set of (near) optimal networks.

## Netting

This is a distancemethod that represents all the equally most parsimonious trees for a given data set in a singlenetwork ${ }^{16}$. The underlying idea is tojoin the closest pair of sequences (the pair with thefewest differences). Thenext sequence that is closest tothe first two is joined sothat the threepairwisedifferences aresatisfied. Thus, patristic distances necessarily equal thenumber of differences. If a homoplasy is encountered, a new spatial dimension is added to the graph. Gaps and invariant positions areexcluded from the analysis. Because the method tries to satisfy all the distances among haplotypes, the number of dimensions might behigh and the display of the network thus becomes complex and difficult. This problem becomes worse as data sets become larger.

## Likelihood network

Thelikelihood-network procedure ${ }^{17}$ is based on a directed graphical model for theevol ution of sequences along a network. Graphical models are graphs in which nodes arestochastic variables, whereas branches indicate correl ations between these

Table 1 Properties of networking algorithms

| Methods | Category ${ }^{\text {a }}$ | Software | Speed | Input data | Model of evolution | Reticulations | Statistical assessment |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Pyramids | Distance | Pyramids | Fast | Distances | Yes | Yes | No |
| Statistical geometry | Distance invariants | Geometry, Statgeom | Fast | Multistate | Yes | Yes | Yes |
| Split decomposition | Distance parsimony | SplitsTree | Fast | Multistate | Yes | Yes | Yes |
| Median networks | Distance | No | Slow | Binary | No | Yes | No |
| Median-joining networks | Distance | Network | Very fast | Multistate | No | No | No |
| Statistical parsimony | Distance | TCS | Fast | Multistate | No | Yes | Yes |
| Molecular-variance parsimony | Distance | Arlequin | Fast | Multistate | Yes | Yes | Yes |
| Netting | Distance | No | Slow | Multistate | No | Yes | No |
| Likelihood network | Likelihood | PAL | Slow | Multistate | Yes | Yes | Yes |
| Reticulogram | Least squares | T-rex | Fast | Distances | No | Yes | Yes |
| Reticulate phylogeny | Least squares | No | Slow | Distances ${ }^{\text {b }}$ | Yes | Yes | Yes |
| ${ }^{\text {a }}$ Details of software programs given in Box 3 ; bDistances estimated from gene frequency data. |  |  |  |  |  |  |  |

## Box 3. Softwareavailability

Several software packages implement some of the networkmethods described in this article.

- PYRAMIDS estimates pyramids from distance matrices. Executables for Windows and Unix are available (http://genome.genetique.uvsq.fr/Pyrami ds/).There is also a convenient online implementation (http://www.bioweb. pasteur.fr/seqanal/interfaces/pyramids. html). PYRAMIDS was written by J .C.Aude etal. (INRA, France).
- STATGEOM calculates the statistical geometry in distance and in sequence space of a set of aligned DNA, RNA, amino acid or binary sequences. Source code with documentation and a Sun SPARC executable are available (http:// gwdu17.gwdg.de/-kniesel/statgeom.html). STATGEOM was written by K. NieseltStruwe (Dept of Physics, University of Auckland, New Zealand).
- GEOMETRY is a package for nucleotide sequence analysis using the method of statistical geometry in sequence space ${ }^{\text {a }}$. The program is available as a DOS executable (http://molevol.bionet.nsc.ru/ soft.htm; ftp://ftp.bionet.nsk.su/incoming/
molevol/; ftp:/ftp.ebi.ac.uk/pub/software/ dos/).
- SPLITSTREE implements the split decomposition method ${ }^{\text {b }}$.This program is currently available as a Mac executable or as a Unix version (ftp://ftp.unibielefeld.de/pub/math/splits/).
- NETWORK is a program for estimating median-joining networks.The program is available as a DOS executable (http://www.fluxusengineering.com/shar enet. htm ) and was written by A. Röhl (Mathematisches Seminar, Universität Hamburg, Germany).
- ARLEQUIN is aJ ava program that implements the method of molecular variance parsimony (http://lgb.unige.ch/ arlequin/index.php3).ARLEQUIN was written by S. Scheneider etal. (Dept of Anthropology, University of Geneva, Switzerland).
- TCS is aj ava program for estimating statistical parsimony networks ${ }^{\text {( }}$ (http:// bioag.byu.edu/zoology/crandall_lab/tcs. $\mathrm{htm})$. It allows the estimation of root probabilities.
- PAL is an open-sourceJ avalibrary for molecular evolution and phylogenetics
(http://www.pal-project.org/). Its >120 modules allow the fast prototyping of special-purpose analysis programs. PAL has been used to compute likelihoods for networks.The PAL project is led by K. Strimmer (Dept of Zoology, University of Oxford, UK) andA. Drummond (School of Biological Science, University of Auckland, New Zealand).
- T-REX is a C++ program implementing the reticulogram estimationd. Windows, Macintosh and DOS executables are available(http://www.fas.umontreal.ca/biol/ casgrain/en/labo/t-rex/index.html).


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variables. A graph might be directed by rooting the network at a specific nodeand directing all branches away from this node. A given network can beturned into directed acydic graphs, which allows the computation of its likelihood. Arbitrary phylogenetic networks areevaluated by likel ihood and the network with the best likelihood is chosen as thefinal solution.

Within this framework, the use of ancestral recombination graphs ${ }^{18}$ when recombination is present has recently been suggested ${ }^{19}$. Thelikelihoodnetwork algorithmalsoallows the simultaneous estimation of parameters (e.g. therecombination rate). The use of a likelihood framework offers the possibility of hypothesis testing, and thestatistical comparison of both trees and networks. However, a difference compared with theother methods is that theamount of computing time can beexcessively large. Effectivesearch strategies need to be devised before large data sets can beanalyzed.

## Reticulogram

This procedure ${ }^{20}$ is based on theaddition of reticulationstoa bifurcating tree. Themethod uses as input a distancematrix and an ADDITIVE TREE inferred from the samedistancematrixusing one of thedassical reconstruction algorithms. An optimality criterion is used to estimatetheminimum number of reticulations required tomaximizethefit of thenetwork tothedata -
a least squares loss function computed as the sum of the squared differences between theoriginal and the patristic distances. Theminimum of this criterion provides a stopping rulefor the addition of reticulation. Thecomputations arerepeated recursively for all pairs of nodes (except thoseal ready connected) in the network to obtain a gl obally optimal solution.

## Reticulate phylogenies from gene frequencies

This method infers reticulatephylogenies using genetics distances estimated fromgenefrequency data ${ }^{21}$. Themean squared error (MSE) of a least squares function is used as theoptimality criterion to select among possiblereticulatephylogenies. Theoretically, all possible phylogenies must be evaluated, and theinferred phylogeny is the onethat has theminimum MSE. The use of a least-squares function allows theestimation of the branch lengths in the phylogeny. Two models are defined: a drift model and an extended model with mutation. Thedrift model is best used in short-term evolution, in which mutation has not played an important role, whereas the mutation model is applicabletolong-term evolution.

## Strengths and weaknesses of network methods

The comparison of different networking strategies is not straightforward. Comprehensive simulation studies areneeded to evaluate the

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accuracy and robustness of different methods. In general, distancemethods might imply a loss of information by summarizing the difference between haplotypes with onevalue. Optimality criterion methods (likelihood and least squares) offer a reliable statistical assessment, hypotheses testing and, in some cases, parameter estimation. M ost of these methods are conveniently implemented in computer programs, which are in some cases capable of handl ing many sequences. Several properties of different methods aresummarized in Table1.

## Rooting intraspecific phylogenies

In many cases, the problem of biol ogical interest requires a root, or at least someknowledge of the relativeages of haplotypes ${ }^{22}$. Rooting networks is especially difficult becauseoutgroups are often separated from the ingroup by many mutational steps and becauseindividuals within a species aresimilar to each other. This leads toa lack of power to decide where therootingshould takeplace. However, predictions from coal escent theory can be applied in intraspecific phylogeny reconstruction toroot thenetwork. By definition, theoldest ancestral hapl otype is the root of the phylogeny. Given coalescent criteria, this ancestral haplotype is identified as themost frequent. The number of connections and the position of a haplotype in thenetwork can al so beused to assign root probabilities. Thelikelihood-network method provides a way to root a phylogenetic network by choosing a nodethat produces the most likely network.

## Conclusions and future directions

Traditional methods for estimating phylogenies were not designed and might not be adequatefor
within-species phylogeny. Network approaches can incorporate population processes in the construction or refinement of haplotype relationships. Moreover, networks allow a more detailed display of populational information than strictly bifurcating trees. Although we have focused on the application of networks to sequence data, most methods described here can be applied to proteins or restriction-fragment length polymorphism data. In general, the main interest of intraspecific phylogenies is not in themselves but rather in their applications. They have been used for detecting recombination ${ }^{23,24}$, delimiting species ${ }^{25}$, inferring modes of speciation ${ }^{26}$, partitioning population history and structure ${ }^{27}$, and studying genotype and phenotype associations ${ }^{28}$.

The devel opment of networks in a likelihood framework, which allows hypothesis testing with a sound statistical basis, is particularly interesting. However, the computational tractability of likelihood networks remains a drawback. Coalescent theory is an activearea of research that is likely toyield new predictions that could beused in the devel opment of morerefined network approaches, which currently arenot based on the coalescent. Most of the methods described here are implemented in computer programs (вох 3), and other network methods have been reviewed recently ${ }^{29}$. Given the recent interest in intraspecific phylogenies and their applications, we expect to seeincreased interest in the development and application of intraspecific phylogenetics using network approaches to depict geneal ogi cal relationships. Futurework will involvecomparing methods and testing the robustness of their assumptions.

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# Ecology of sprouting in woody plants: the persistence niche 

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#### Abstract

Many woody plants can resprout and many ecosystems are dominated by resprouters. They persist in situthrough disturbance events such as fire, flooding or wind stoms. However, the importance of 'persistence' in plant demography has been neglected in favour of 'recruitment': Thus much research on plant regeneration, conservation and evolution has focused on the importance of safe sites, seed and seedling banks, dispersal and gemmination with the implied importance of de novo replacement rather than persistence. Recent research shows a growing appreciation forthe role of sprouting as a form of persistence in a diversity of ecosystems and tradeoffs between the two regeneration modes.


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In a seminal paper in 1977, Peter Grubb ${ }^{1}$ introduced the concept of the'regeneration niche' to help explain the coexistence of similar species. Grubb noted that species that share much the same lifeform, phenology and habitat range might nevertheless have different seedling requirements. F or example, 'when a wholelarge tree is blown over'thelarge gap thus formed would favour light-demanding seedlings, whereas smaller gaps would favour shadetol erant recruits. Theliterature on theecol ogy of seeds and seedlings has expanded enormously since this time. Seed ecology is widely studied because of its assumed importance in the population growth of plants. Seed traits are included in general systems for dassifying plant functional types ${ }^{2,3}$. The same broad recognition has not been given to the mode of persistence of established plants. When a tree is blown over, gaps might not befilled by seedlings but by shoots sprouting from the fallen tree. Sprouts grow much faster than seedlings and can quickly reoccupy their own gaps. Sprouting ability can have major impacts on plant populations: turnover of populations is reduced; the effects of disturbanceare minimized; and dependence on seeds for population maintenancemight becomenegligible. Species differ in their sprouting ability, and both strong and weakly sprouting species occur in diverse ecosystems ${ }^{4,5}$. Here, wereview studies of the phenomenon emphasizing emerging generalizations and implications for the population biology of woody plants.

The ecology of sprouting has anal ogies to clonality ${ }^{6}$. However, although donal plants generally sprout, only a small fraction of woody sprouters are clonal and capable of vegetative spread. Sprouting response is difficult to quantify partly becausethere is a continuum of responses to disturbances of varying severity ${ }^{7}$. This could partly account for its absence from general plant strategy schemes (B ox 1). After theleast severedisturbance, such as damage caused by caterpillar feeding, plants replace lost tissues by sprouting from buds. As the severity of disturbance increases, plants diverge in their ability to recover by sprouting (Fig. 1). Most interest has been in disturbances that can potentially kill plants such as fire, hurricane damage, drought, flooding, herbivory and landslides, as well as anthropogenic disturbance such as forest clearing. In Mediterranean type shrublands, where crown fires arerel atively frequent, shrub species areoften either killed outright by burning (nonsprouters or 'seeders') or recover vegetatively from roots or stems (sprouters) ${ }^{4,8}$. Classifying sprouting behaviour is harder in forests and woodlands because species often di verge in their sprouting responseat different lifehistory stages ${ }^{5,7,9}$. Some species never sprout; in some species, sprouting ability increases with sizeto reach a maximum in adult stages, although in other species sprouting is common in juveniles but adults are unabletosprout (Fig. 2). Someforest trees retain a bud bank, sprouting continuously with or without disturbance and thus come d ose to immortality. E xamples include Tilia cordata (small-leaved lime) in Britain, whose northern populations havesurvived by sprouting since dimates cooled and reproduction ceased 5000 years ago ${ }^{10}$. Ginkgo biloba (maidenhair tree) might oweits survival in China to the extraordinary persistence of trees that resprout from specialized basal swellings on thetrunk ${ }^{11}$.

Sprouting is common, and might be the ancestral state, in woody angiosperms ${ }^{12}$. Most conifers do not sprout although thereareexceptions in several unrelated lineages, including species of Pinus in the

