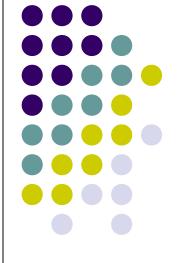
Algorithmic aspects of phylogenetic network construction*

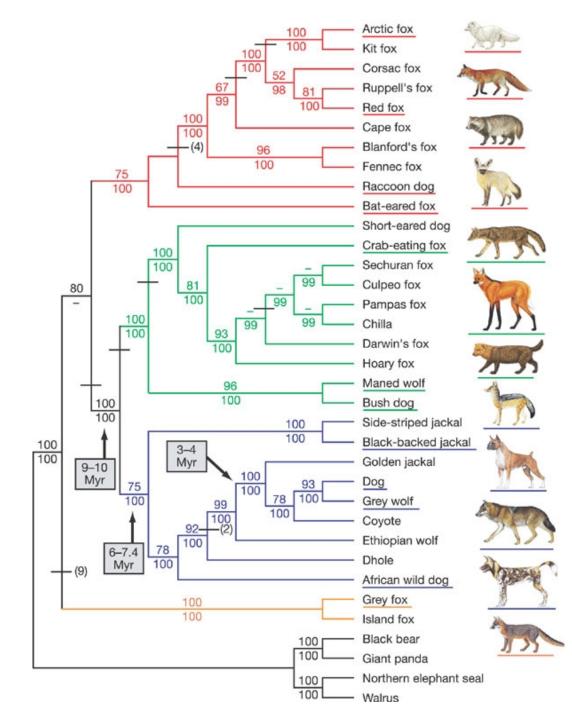
Steven Kelk

Networks and Strategic Optimization Department of Knowledge Engineering

Universiteit Maastricht



* On the elusiveness of optimal softwired phylogenetic networks



Genome sequence, comparative analysis and haplotype structure of the domestic dog

> Lindblad-Toh et al, Nature 2005

(Almost) everything begins with Multiple Sequence Alignment



	* .	: .	. *	: : : .	
Q5E940 BOVIN	MPREDRATWKSNYFLK	IIQLLDDYPKCFIVGADNVGS	K <mark>QMQ</mark> Q IRMS LRGK	- AVVLM <mark>GKNT</mark> MMR <mark>K</mark> AI <mark>RGHLE</mark> NNPALE	76
RLA0 HUMAN	MPREDRATWKSNYFLK	II <mark>Q</mark> LLDDY <mark>P</mark> KCFIV <mark>G</mark> ADNVGSI	K <mark>QMQ</mark> Q IRMS LRGK	- AVVLM <mark>GKNT</mark> MMR <mark>KAIRGHLE</mark> NN <mark>P</mark> ALE	76
RLA0 MOUSE	MPREDRATWKSNYFLK	II <mark>Q</mark> LLDDY <mark>P</mark> KCFIV <mark>G</mark> ADNVGS	K <mark>QMQ</mark> Q IRMS LRGK	-AVVLM <mark>GKNT</mark> MMR <mark>KAIRGHLE</mark> NNPALE	76
RLAO RAT	MPREDRATWKSNYFLK	II <mark>Q</mark> LLDDY <mark>P</mark> KCFIV <mark>G</mark> ADNVGS	K <mark>QMQ</mark> Q IRMS LRGK	-AVVLM <mark>GKNT</mark> MMR <mark>KAIRGHLE</mark> NN <mark>P</mark> ALE	76
RLA0 CHICK	MPREDRATWKSNYFMK	IIQLLDDY <mark>P</mark> KCFVV <mark>G</mark> ADNVGS	K <mark>QMQ</mark> Q IRMS LRGK	-AVVLM <mark>GKNT</mark> MMR <mark>KAIRGHLE</mark> NNPALE	76
RLA0 RANSY	MPREDRATWKSNYFLK	II <mark>Q</mark> LLDD <mark>YP</mark> KCFIV <mark>G</mark> ADNVGS	K <mark>QMQ</mark> Q IRMS LRGK	-AVVLM <mark>GKNT</mark> MMR <mark>KAIRGHLE</mark> NNSALE	76
Q7ZUG3 BRARE	MPREDRATWKSNYFLK	IIQLLDDY <mark>P</mark> KCFIV <mark>G</mark> ADNVGSI	K <mark>QMQ</mark> T IRLS LRGK	-AVVLM <mark>GKNT</mark> MMR <mark>KAIRGHLE</mark> NNPALE	76
RLA0 ICTPU	MPREDRATWKSNYFLK	II <mark>Q</mark> LLNDY <mark>P</mark> KCFIV <mark>G</mark> ADNVGS	K <mark>QMQ</mark> T IRLS LRGK	-AIVLM <mark>GKNT</mark> MMR <mark>KAIRGHLE</mark> NN <mark>P</mark> ALE	76
RLA0 DROME	MVRENK <mark>A</mark> AWKAQYFIK	VV <mark>E</mark> LFDEF <mark>P</mark> KCFIV <mark>G</mark> ADNVGSI	K <mark>QMQ</mark> N IRTS LRGL	-AVVLMGKNTMMRKAIRGHLENNPQLE	76
RLA0 DICDI	MSGAG-SKRKKLF <mark>I</mark> EK	ATKLFTT YDKMIV AE A <mark>D</mark> FV <mark>GS</mark>	S <mark>QLQ</mark> KIRKSIRGI	- <mark>GAVLMGKKTMIRKVIR</mark> DLADSK <mark>P</mark> ELD	75
Q54LP0_DICDI	FASGAG-SKRKNVF <mark>I</mark> EK	ATKLFTT YDKMIV AE A <mark>D</mark> FV <mark>GS</mark>	S <mark>QLQ</mark> KIRKSIRGI	- <mark>GAVLMGKKTMIRKVIR</mark> DLADSK <mark>P</mark> ELD	75
RLA0_PLAF8	MAKLSKQQK <mark>K</mark> QMY <mark>I</mark> EK	LSSLIQQ <mark>Y</mark> SKILIVHV <mark>D</mark> NV <mark>GS</mark> I	N <mark>QM</mark> AS VRKS LRGK	- A <mark>T I LMGKNT</mark> RIRTAL <mark>K</mark> KNLQAV <mark>P</mark> QIE	76
RLA0_SULAC					79
RLA0_SULTO	<mark>MRIM</mark> AVITQERK <mark>IA</mark> KW <mark>K</mark> IEEVKE	LE <mark>Q</mark> K LRE YHT IIIAN I <mark>EG</mark> F <mark>P</mark> AI	DK <mark>LHD IR</mark> KK <mark>MRG</mark> M	- AE I <mark>KVTKNT</mark> LF <mark>G</mark> IAAKNA <mark>G</mark> LDVS	80
RLA0_SULSO	<mark>M</mark> KR <mark>L</mark> ALALKQRK <mark>VA</mark> SW <mark>K</mark> LEEVKE	LT <mark>ELIKNSNTILIG</mark> NL <mark>EG</mark> FPAI	DKLHE IRKK LRGK	- A <mark>T I KVTKNT</mark> LFK IAAKNA <mark>G</mark> ID IE	80
_				- <mark>YPMMVAK</mark> KRIIL <mark>RAMK</mark> AA <mark>G</mark> LE LDDN	86
_				- <mark>gvikiikpt</mark> lfkiaftkvyggi <mark>p</mark> ae	85
_	~			- AVL <mark>KVSRNT</mark> LTERALNQL <mark>G</mark> ET IP	78
_	MAEERHHTEH IPQWKKDE IEN				78
_	MAAVRGSPPEYKVRAVEE				75
_				D <mark>TIIRMSRNT</mark> LMRIALEEKLDER <mark>P</mark> ELE	
_				-ALI <mark>RMSK</mark> K <mark>T</mark> LISLALEKA <mark>G</mark> RELENVD	74
_				TM <mark>TLKMSRNT</mark> LIE <mark>RAIKEVAE</mark> ETGN <mark>P</mark> EFA	82
—				QM <mark>TLKMSRNTLIKRAVEEVAE</mark> ETGN <mark>P</mark> EFA	82
RLA0_METJA				KVKL <mark>RMSRNTLIIR</mark> ALKEAAEELNN <mark>P</mark> KLA	81
RLA0_PYRAB			~	GGLLRVSRNTLIELAIKKAAQELGKPELE	דר
RLA0_PYRHO				GGLLRVSRNTLIE LAIKKAAKE LGKPELE	דר
RLA0_PYRFU				N <mark>gllrvsrnt</mark> lielaikkvaqelgkpele	רר
RLA0_PYRKO				KALL <mark>RVSRNT</mark> LIELAIKRAAQEL <mark>G</mark> QPELE	76
RLA0_HALMA				- AELRVSRNTLLE RALDDVDDGLE	79
RLA0_HALVO				- AAV RMSRNTLVN RALDE VN DGFE	79
RLA0_HALSA	MSAEEQRTTEEVPEWKRQEVAE				79
RLA0_THEAC				- <mark>INLKVIKKTLLFKALENLG</mark> DEKLS	72
				-VKIKVVKK <mark>T</mark> LLF <mark>K</mark> ALDSINDEKLT	72
_				-ARIKV <mark>SR</mark> ARLLRLAIEN <mark>IG</mark> KNNIV	72
ruler	1	.30	50	70 80 90	

There is more to life than trees

 \cdot All these methods assume that a (single) tree is the best way to model the underlying evolution.

• If this is not true, then we have a problem, because there is a high risk that the output of tree-building algorithms will then be **meaningless**.

· Sometimes there are clues about this:

- · Algorithms build very badly supported trees
- Extra knowledge about the underlying evolutionary mechanisms

• But in general it is **dangerously easy** to confuse non-treelike evolution with a **noisy tree signal**.

· Therefore critical to understand and model underlying mechanisms.



Why might we get weak support for a tree?



"Noisy tree"

Data *does* fit a single tree, weak support is only a consequence of "noise"

"Trees in trees" Data consists of multiple different tree signals...but both gene and species evolution are still ultimately treelike (e.g. due to incomplete lineage sorting, gene loss, gene duplication)

Other phenomena

Such as recombination (Meiotic, Sexual)

"Trees in networks"

Data consists of multiple different tree signals...gene evolution is treelike, but species evolution is no longer treelike (e.g. hybridization, horizontal gene transfer)

Why might we get weak support for a tree?



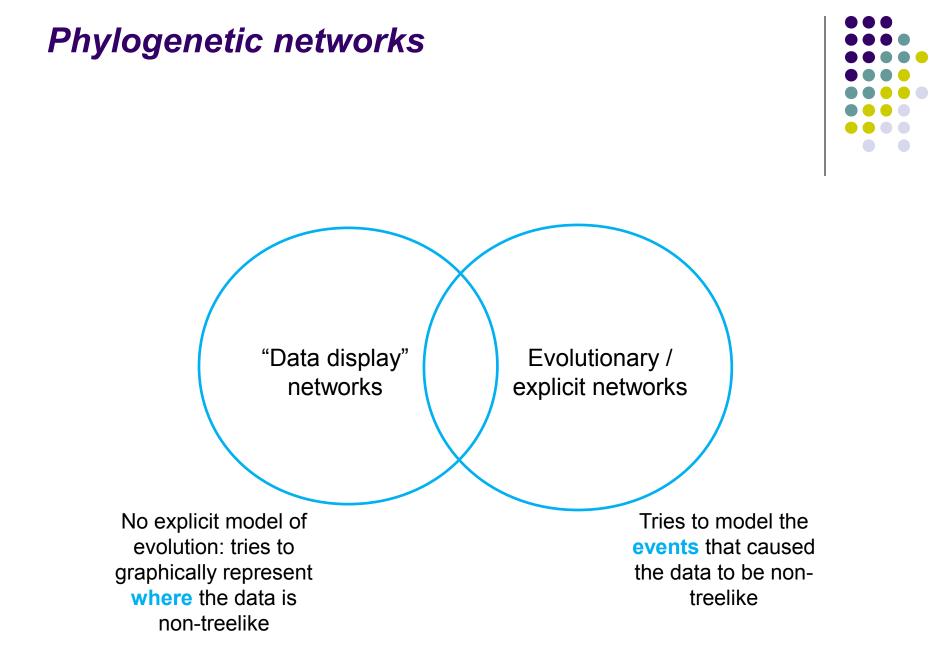
"Noisy tree" Data *does* fit a single tree, weak support is only a consequence of "noise" **"Trees in trees"** Data consists of multiple different tree signals...but both gene and species evolution are still ultimately treelike (e.g. due to incomplete lineage sorting, gene loss, gene duplication)

"Trees in networks"

Data consists of multiple different tree signals...gene evolution is treelike, but species evolution is no longer treelike (e.g. hybridization, horizontal gene transfer)

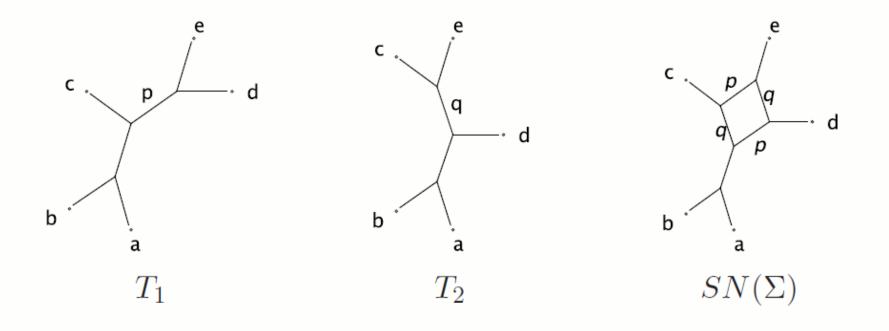
Other phenomena Such as recombination (Meiotic, Sexual)

"Reticulate" (i.e. non-treelike) evolutionary phenomena



Data-display networks (1)

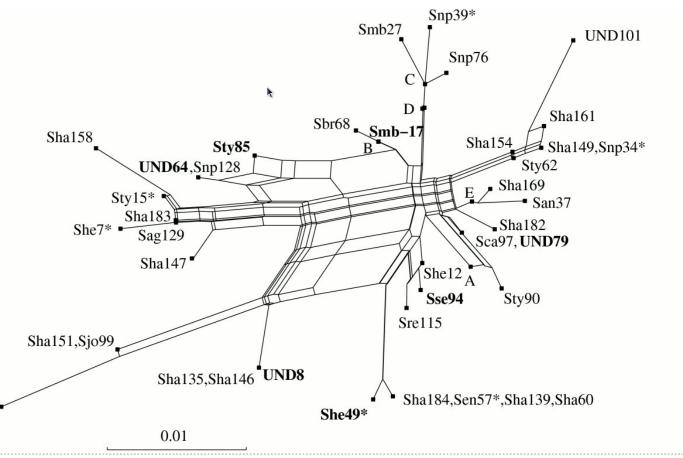




From: Daniel Huson, ISMB-Tutorial 2007: Introduction to Phylogenetic Networks

Data-display networks (2)





A phylogenetic network. The network was generated by Neighbor-Net for a sequence-based data set comprising of Salmonella isolates that originally appeared in [17]. A detailed network-based analysis of this data is presented in [2], where the strains indicated in bold-face are tested for the presence of recombination. Note that the network is planar (that is, it can be drawn in the plane without any crossing edges), and that parallel edges in the network represent bipartitions of the data.

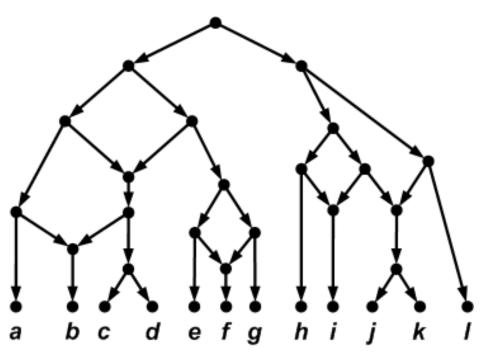
Bryant et al. Algorithms for Molecular Biology 2007 2:8 doi:10.1186/1748-7188-2-8

Sty19*

Evolutionary phylogenetic networks

· Can be used to explicitly model reticulate evolution:

- · Hybridization
- · Horizontal Gene Transfer (HGT)
- · Recombination
- · Reticulation vertices often have an explicit biological interpretation
- Rooted, with an explicit
 "direction" of evolution
- Underlying mathematical abstractions are often similar, despite different scale levels of interpretation

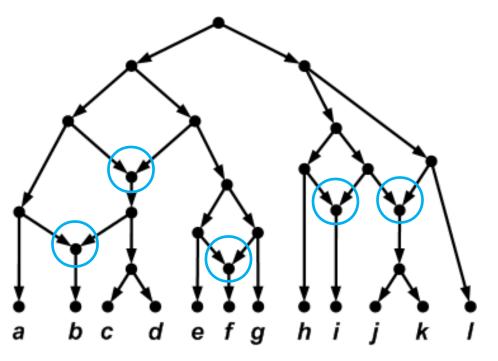




Evolutionary phylogenetic networks

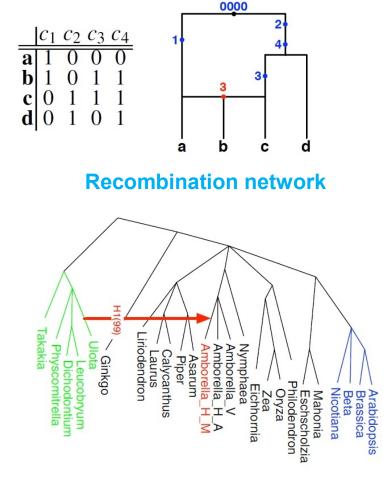
· Can be used to explicitly model reticulate evolution:

- · Hybridization
- · Horizontal Gene Transfer (HGT)
- · Recombination
- · Reticulation vertices often have an explicit biological interpretation
- Rooted, with an explicit
 "direction" of evolution
- Underlying mathematical abstractions are often similar, despite different scale levels of interpretation



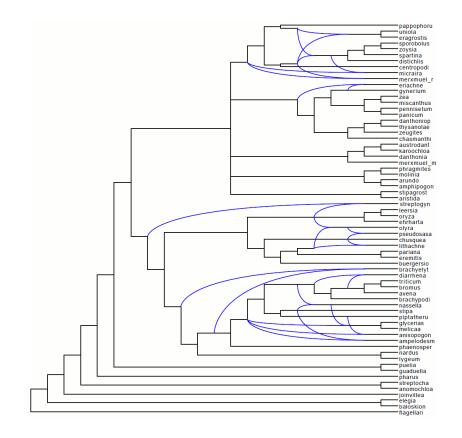
Different models and scales, always rooted, directed acyclic graphs (DAGs)





Horizontal Gene Transfer (HGT)

(f) nad7



"Softwired cluster" network

Constructing evolutionary phylogenetic *networks*



· It's important to ask ourselves several questions:

1. **MODEL**: What are we trying to **model** exactly? Is it biologically realistic?

2. **OBJECTIVE**: What do we consider to be an **optimal solution** within that model?

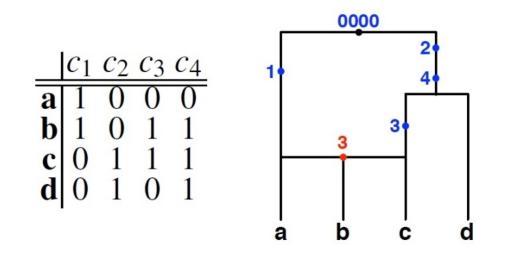
3. TRACTABILITY: Is there any hope of developing efficient algorithms to compute optimal solutions?

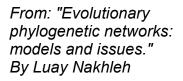
• Extremely challenging to simultaneously answer these questions well!

· In the meantime: many different models, algorithms, packages

Case study 1: constructing Recombination Networks







· Input is **binary character data** (i.e. strings of binary data)

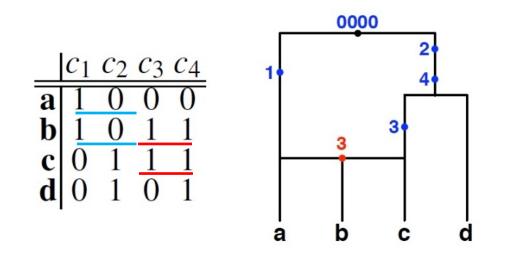
• Reticulations represent chromosomal crossover (mostly single crossover, sometimes multiple crossover). Sometimes also gene conversion.

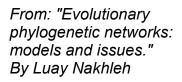
• Mutation model is the **"infinite sites**" model: at most one mutation per site (0 to 1, or 1 to 0).

 Goal is to construct a recombination network with a minimum number of reticulation events.

Case study 1: constructing Recombination Networks







Input is binary character data (i.e. strings of binary data)

• Reticulations represent chromosomal crossover (mostly single crossover, sometimes multiple crossover). Sometimes also gene conversion.

• Mutation model is the **"infinite sites**" model: at most one mutation per site (0 to 1, or 1 to 0).

 Goal is to construct a recombination network with a minimum number of reticulation events.

Case study 1: constructing Recombination Networks

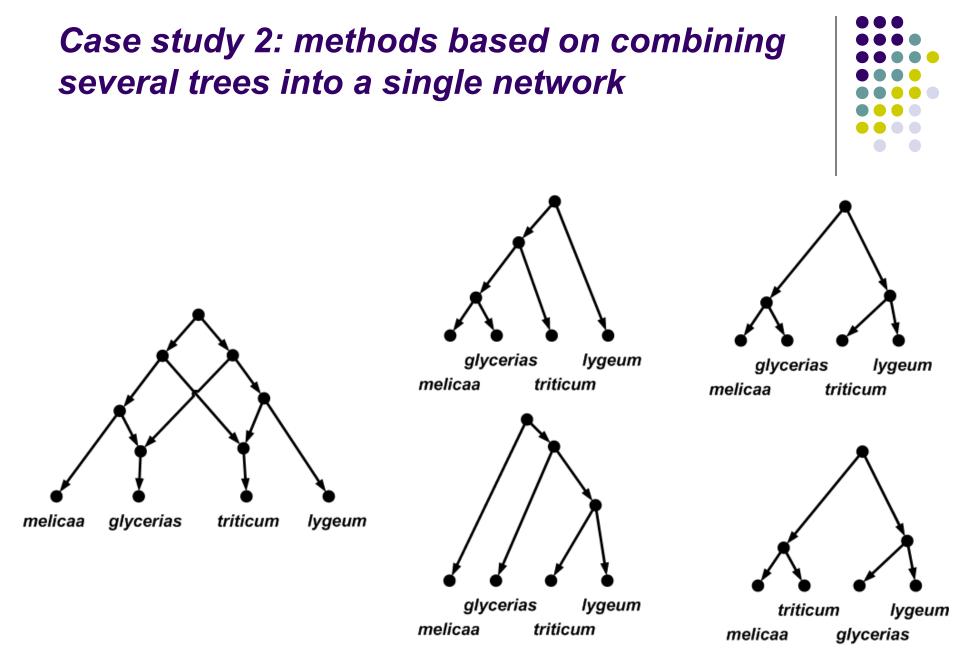
• Extensive interest and research from the theoretical computer science community: computing a network with a minimum number of recombinations is NP-hard.

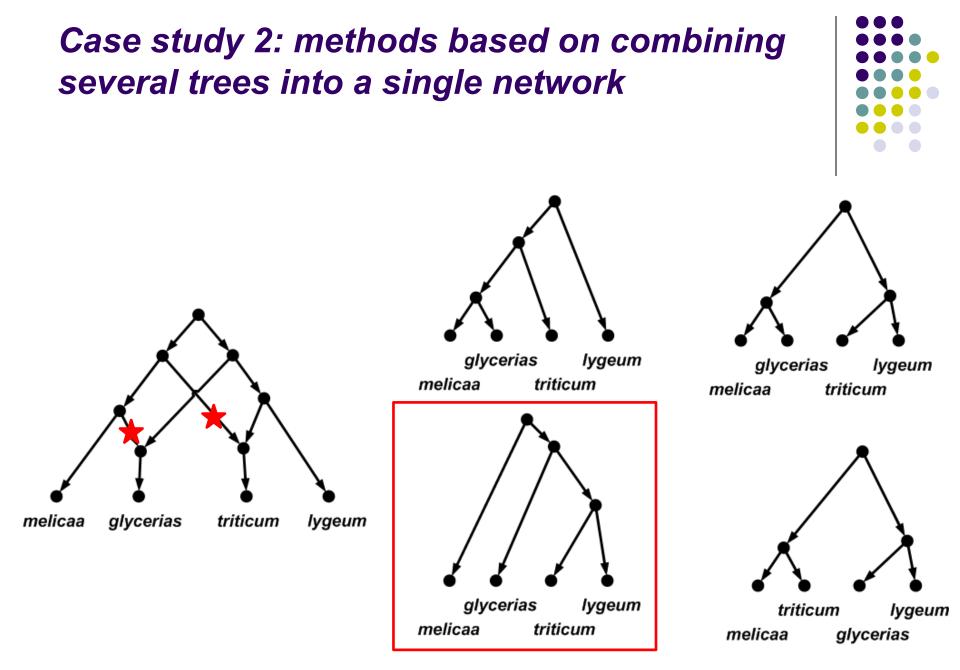
• The groups who worked on this problem (e.g. Dan Gusfield's group at UC Davis) mainly responded to this hardness by developing (computational) **lower and upper bounds** on the minimum number of reticulations required. Many of these bounds are also NP-hard to compute.

· Also: **branch and bound** techniques for computing optimal solutions for (very) small instances.

 Curiously there has been very little work on approximation algorithms i.e. fast algorithms that compute solutions that are within a certain multiplicative factor of optimality.

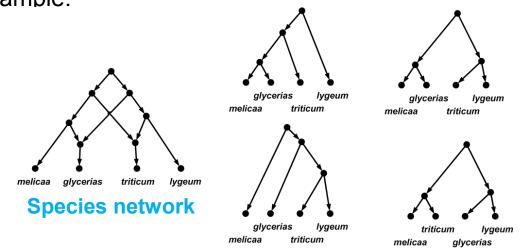












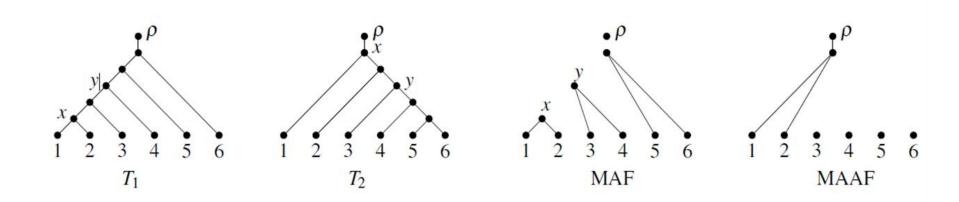
Four gene trees contained by the species network

· Input: a set of gene trees

· Output: a species network that contains all the input gene trees and which has a minimum number of reticulations

• There has been a huge amount of research from (a different wing of) the theoretical computer science community for this problem, mainly focusing on case when the input consists of exactly two binary gene trees.

• Most research has focused on the very close link with a problem called the Maximum Acyclic Agreement Forest problem (MAAF).

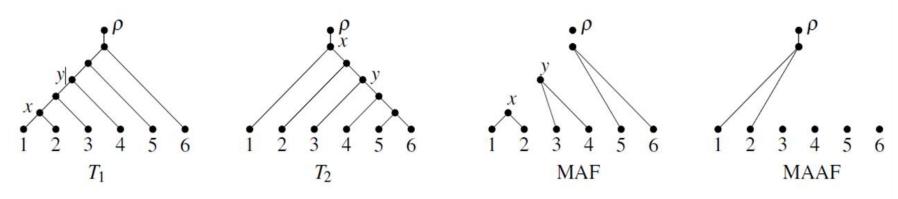


From: A UNIFYING VIEW ON APPROXIMATION AND FPT OF AGREEMENT FORESTS, Christopher Widden 2009 (Master's Thesis)



• The problem is **NP-hard** and **APX-hard** but despite these complexitytheoretic limitations algorithmic progress has been **considerable**.

- · Reduction rules (correctness of divide and conquer)
- · Fixed parameter tractability
- Integer linear programming solutions (exploiting the static nature of the MAAF problem)
- · Algorithms to enumerate all optimal solutions
- Approximation algorithms (...?)

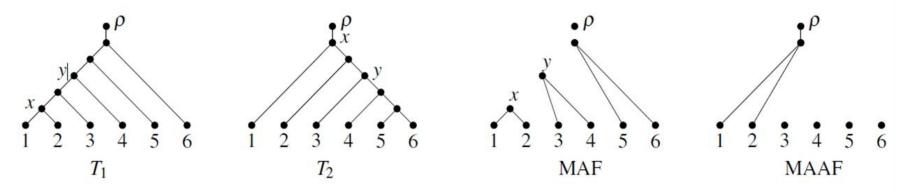




· However, people working on this problem have hit upon barrier.

• Much of the "MAAF theory" starts to break down when there are **more than two trees** in the input. In the absence of a rigorous theory for more than two trees, researchers are again seeking refuge in **lower/upper bound** computations. Approximation algorithms seem difficult to develop.

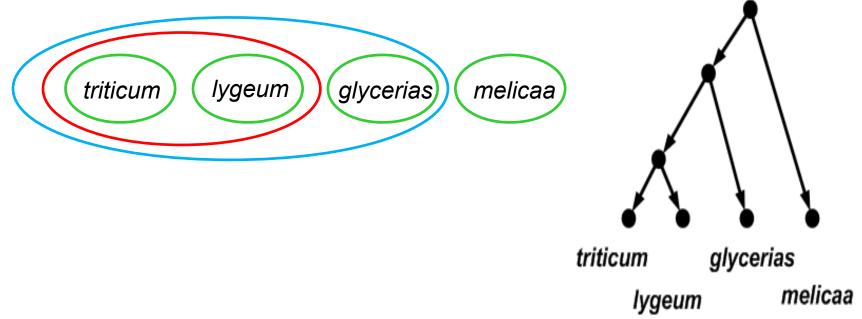
 Multiple research groups are moving towards a "beyond MAAFs" theory...who will get there first?



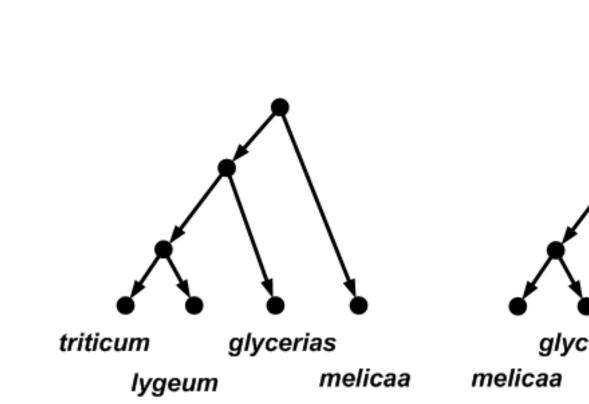
• Every edge (u,v) of a tree induces a **cluster**: the set of leaf descendants of v.

 \cdot The set of clusters induced by the edges of a tree, is a laminar family .

· A tree is completely characterised by its set of clusters.



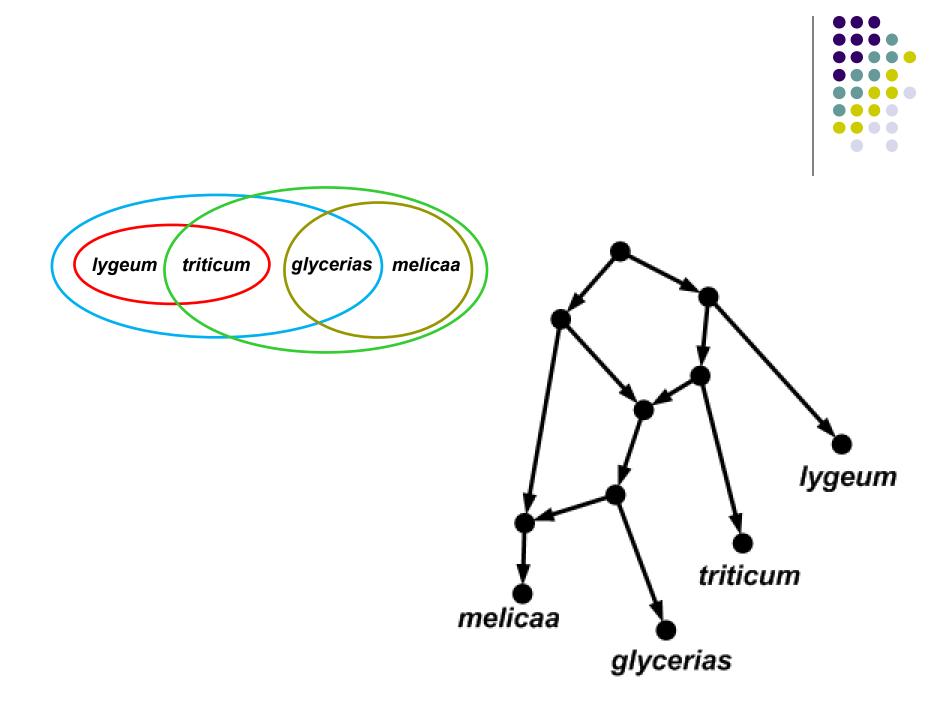




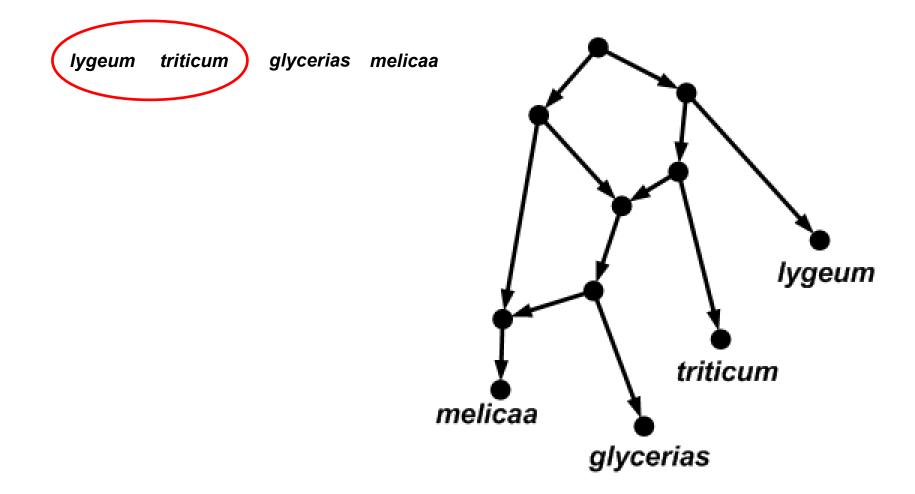
{triticum}, {lygeum}, {glycerias}, {melicaa}, {triticum, lygeum}, {triticum, lygeum, glycerias}. glycerias lygeum melicaa triticum

{triticum}, {lygeum}, {glycerias}, {melicaa}, {melicaa, glycerias}, {melicaa, glycerias, triticum}.

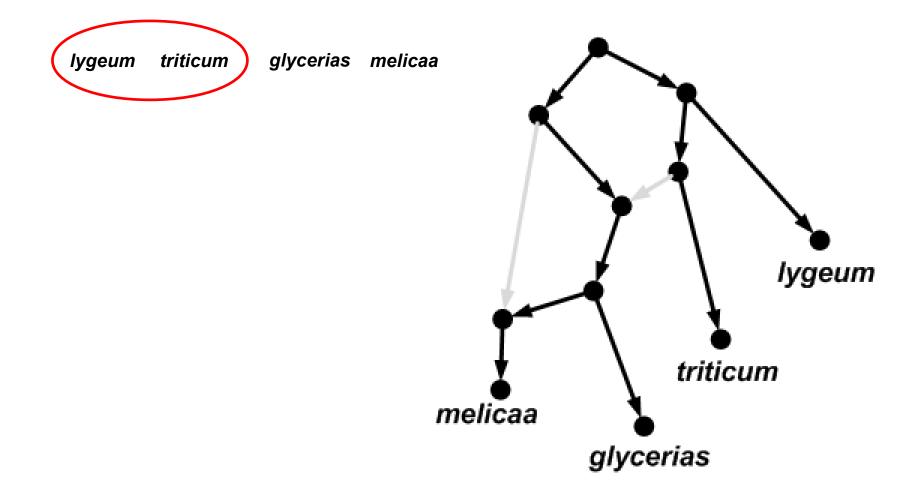
Union of clusters from both trees: {triticum}, {lygeum}, {glycerias}, {melicaa}, {triticum, lygeum}, {triticum, lygeum, glycerias}, {melicaa, glycerias, triticum}.



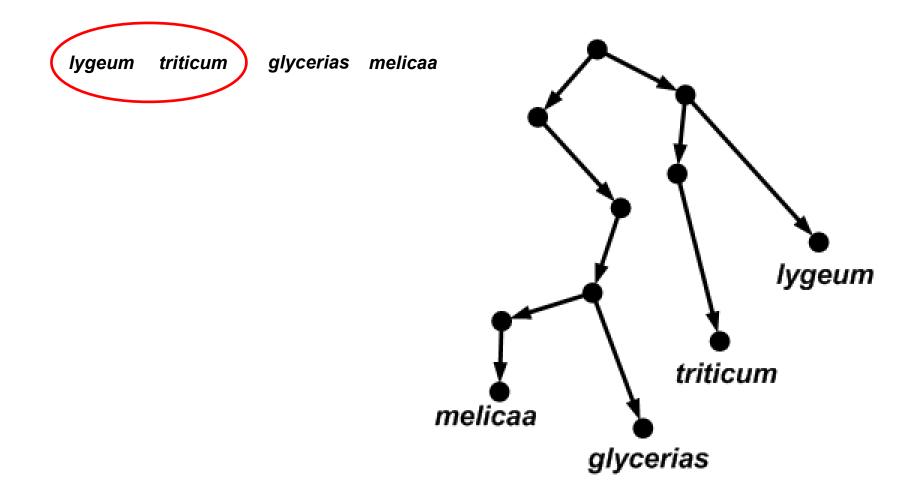




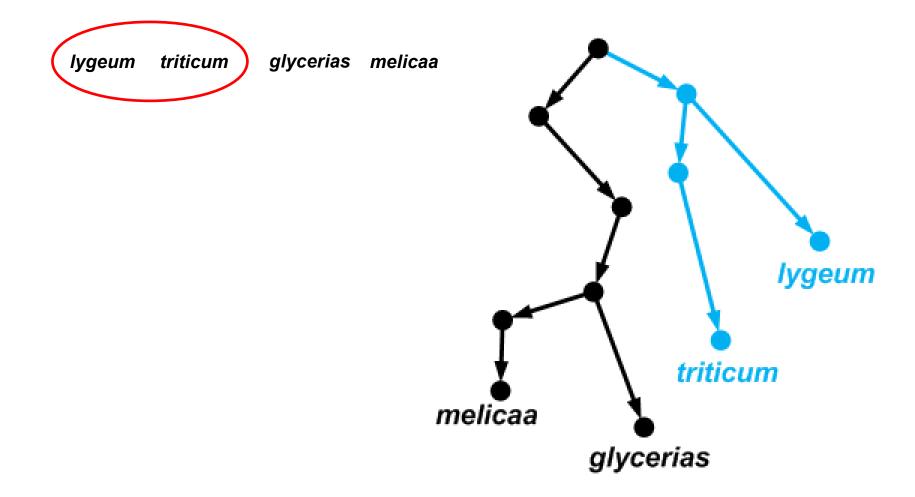


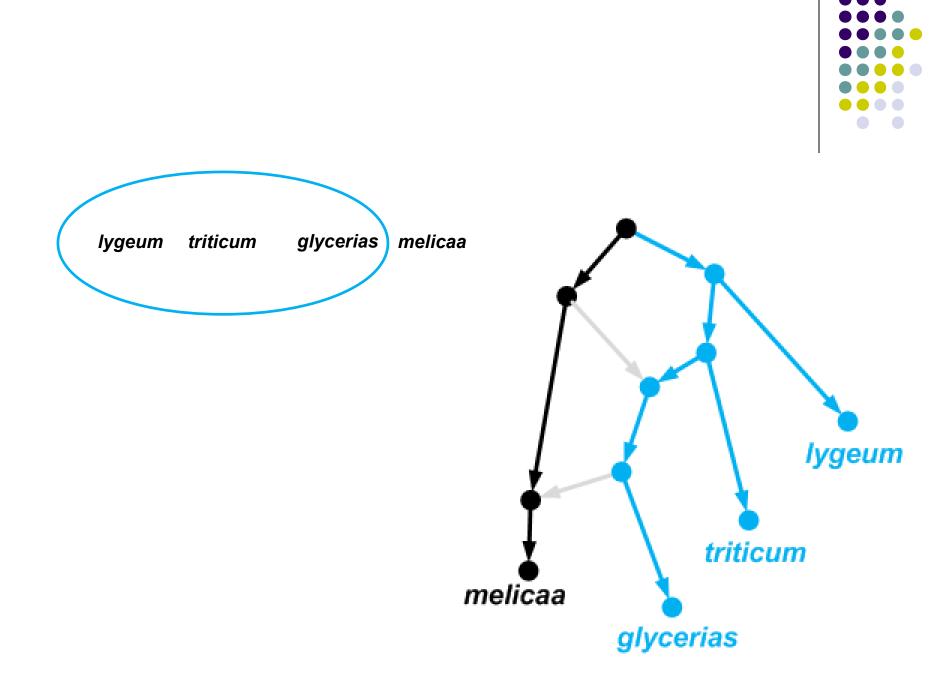


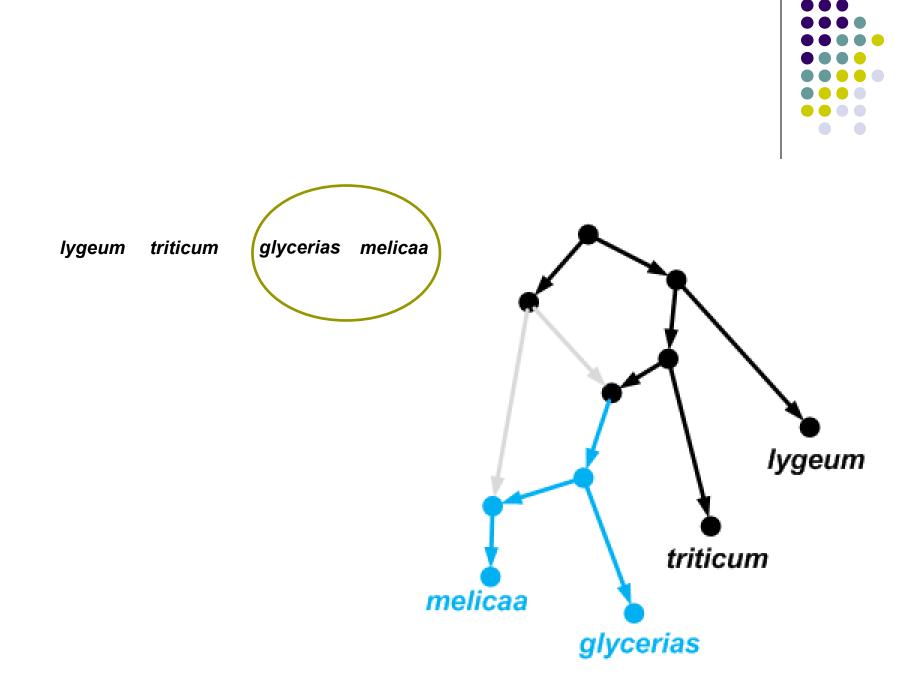


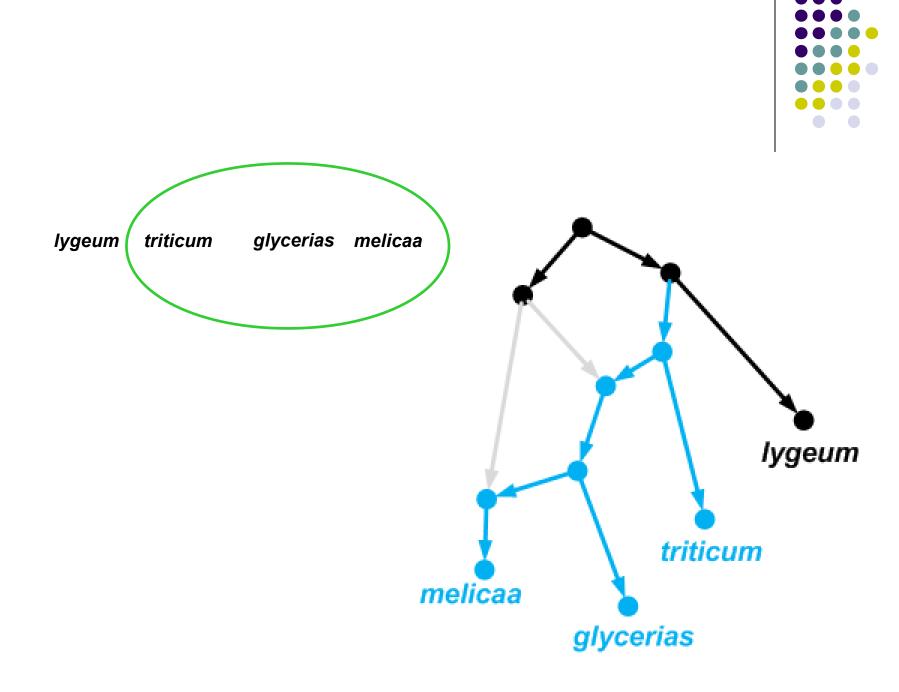












 \cdot There are multiple algorithms and software packages for constructing networks with a small number of reticulations that display all the clusters contained in a set of input trees, e.g.

- · CLUSTERNETWORK (2008)
- · GALLEDNETWORK (2009)
- · CASS (2010)
- · CLUSTISTIC (2011).



Dendroscope

by Daniel H. Huson with contributions from Tobias Dezulian, Markus Franz, Christian Rausch, Daniel C. Richter and Regula Rupp

www-ab.informatik.uni-tuebingen.de/software/dendroscope

 Producing solutions with a minimum number of reticulation is still NP-hard and APX-hard, even for clusters obtained from two trees but there has been positive algorithmic progress despite this. In particular: if we assume the minimum number of reticulations has been fixed as a constant.

• Advantage of using clusters, rather than the trees themselves, is that it allows a focus on only well-supported "clades" in the input trees. But...





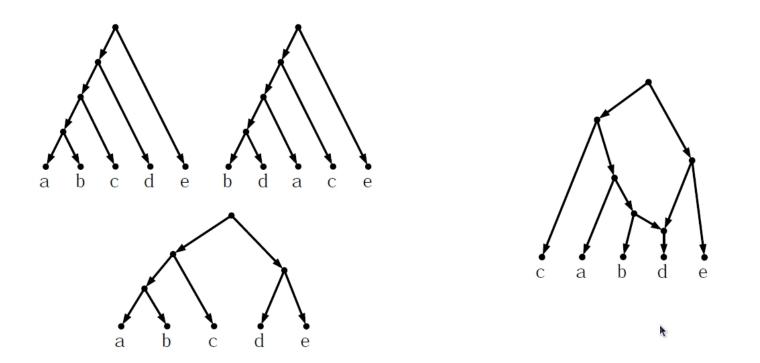
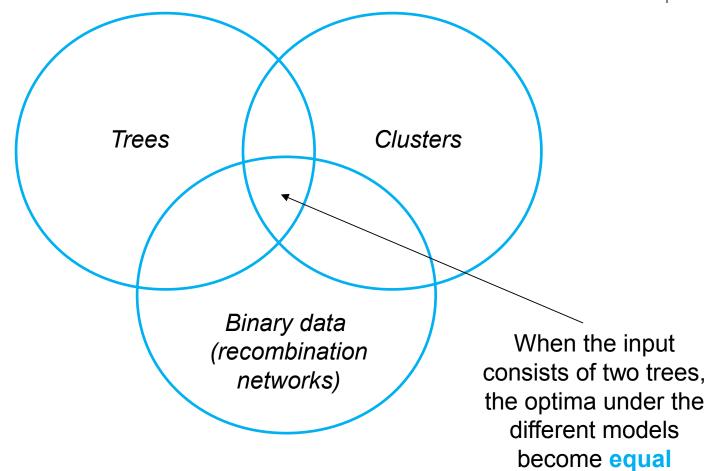


Figure 5. The level-1 network on the right with a single reticulation represents the union of the clusters (and triplets) obtained from the three trees on the left. However, any network that displays all three trees will have at least two reticulations and have level at least two.





Where does the future lie? 1: Unification

· We have seen three different techniques for constructing phylogenetic networks.

· All models suffer from hardness. Different groups tend to work on different models, and the groups have responded to the hardness in **different ways**.

- · (Computational) lower and upper bounds
- Maximum Acyclic Agreement Forest
- Fixed upper bound on the number of reticulations

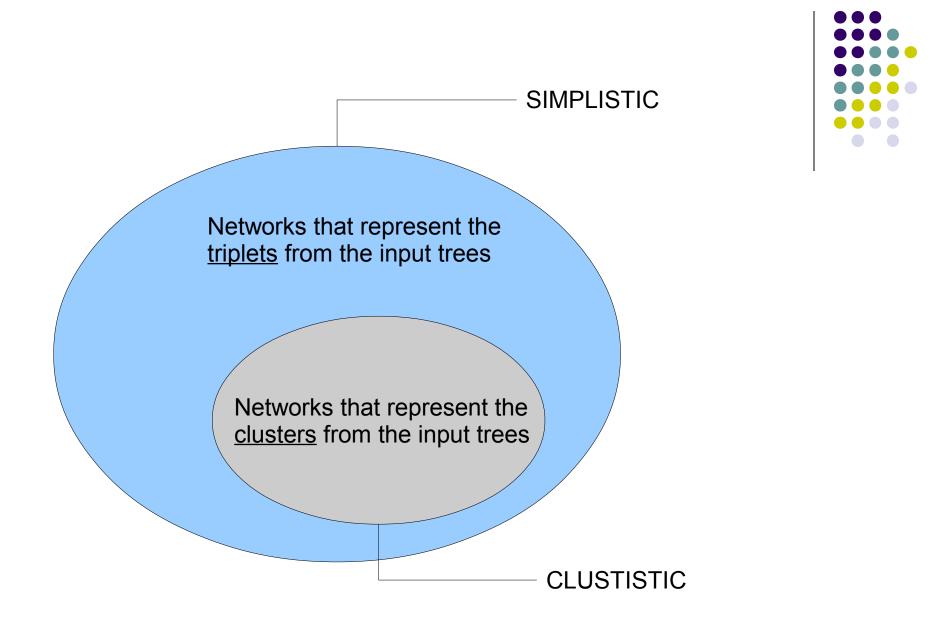
binary data trees clusters

· Using insights gained from model can lead to deeper structural insights in another, with the case of two trees being an extreme example.

· "When two trees go to war" (Van Iersel and Kelk 2010)

• "On the elusiveness of clusters" (Kelk, Scornavacca and Van Iersel 2011)

mber of reticulations clusters



CLUSTISTIC = SIMPLISTIC + filtering oracle

Where does the future lie? 2: Deepening

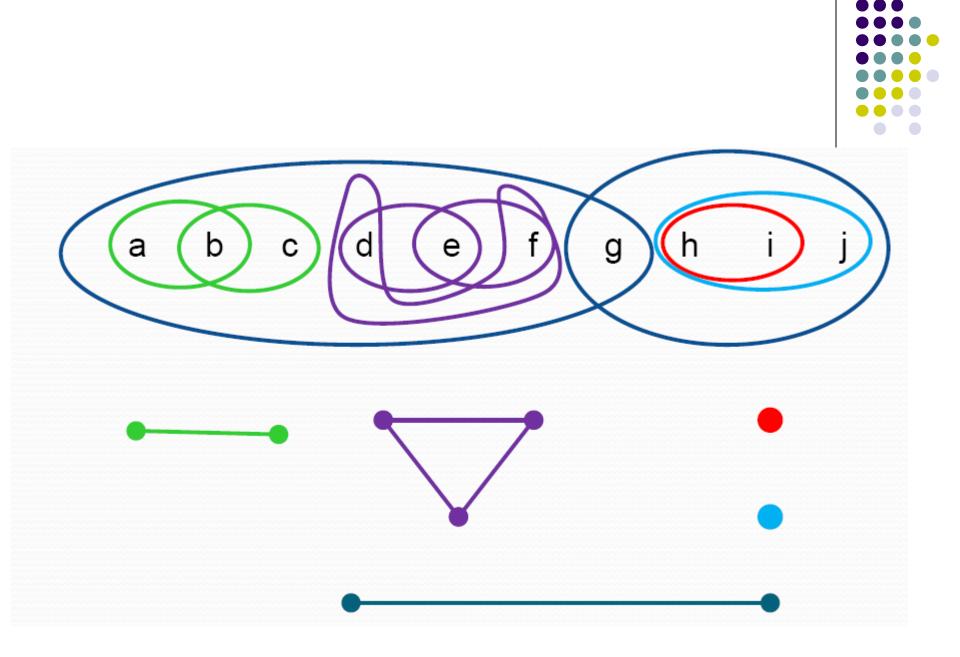


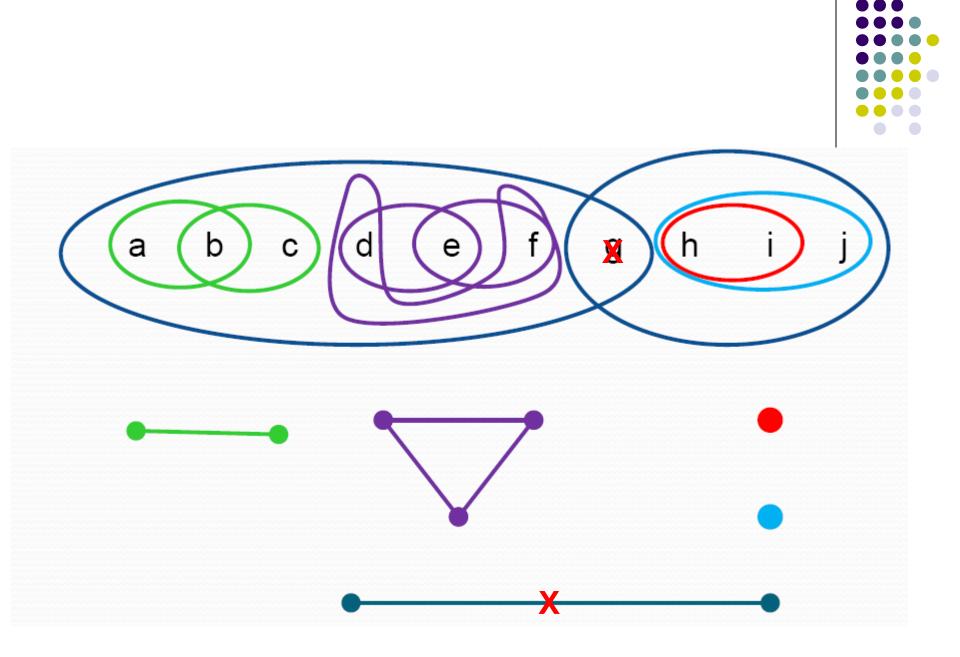
• All these different models produce **beautiful and novel combinatorial optimization problems**.

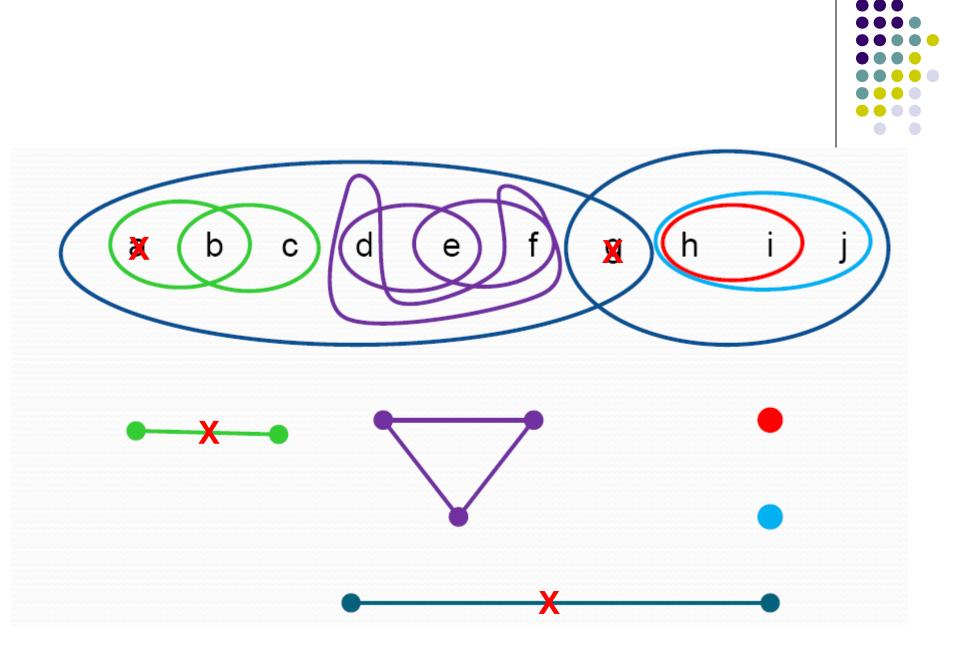
• For example, some of the softwired cluster problems can be thought of as a kind of "iterative, laminar" Hitting Set.

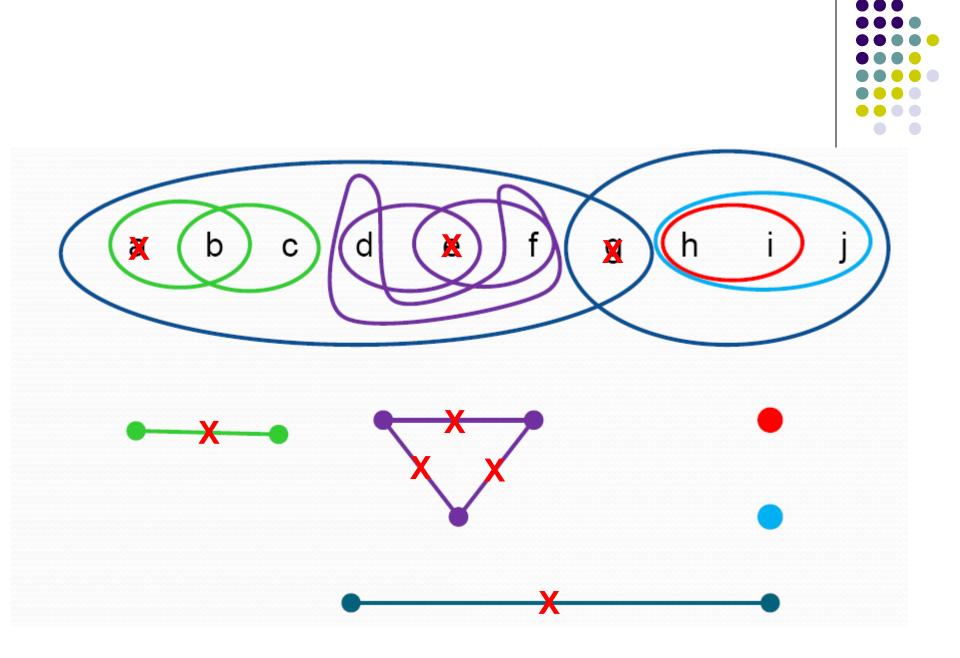
• However, these problems are not yet well-known to combinatorial optimization specialists, and advanced techniques from combinatorial optimization are not yet being used in the phylogenetic network literature.

• There is an enormous amount to be gained by strengthening contact between these two groups.









Where does the future lie? 3: Modeling



• Phylogenetic networks are a very good example of how attempting to model biological phenomena can lead to new mathematical problems.

• It is important to stay **close** to the biological problems that we are trying to solve. Biologists really do want to solve this problem so algorithms should be turned into easy-to-use **software**.

• There is still a huge amount of uncertainty regarding the best model for phylogenetic networks and what exactly we should be trying to "optimize".

• Algorithmic specialists need to actively get involved in this modelling debate. A challenging balancing act!

Finally...further reading

 Luay Nakhleh, "Evolutionary phylogenetic networks: models and issues." In: The Problem Solving Handbook for Computational Biology and Bioinformatics, L. Heath and N. Ramakrishnan (editors). Springer, 125-158, 2010.

 Daniel Huson, Regula Rupp and Celine Scornavacca, "Phylogenetic Networks", Cambridge University Press.

• David Morrison, *"An introduction to phylogenetic networks",* Dystenium LLC, New York, to appear shortly.





Concepts, Algorithms and Applications

Daniel H. Huson Regula Rupp Celine Scornavacca

CAMBRIDGE

Thanks for listening

PhD position available



• I currently have a PhD position available on this topic (algorithmic aspects of phylogenetic network construction). Focus is discrete maths, approximation algorithms, graph theory, fixed parameter tractability etc.

 Position is at the Department of Knowledge Engineering at the University of Maastricht.
 There will be collaboration with researchers based in Amsterdam (CWI/VU).



Het Vrijthof, Maastricht