

# The statistical and informatics challenges posed by ascertainment biases in phylogenetic data collection

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# Ascertainment bias

a bias in parameter estimation or testing caused by non-random sampling of the data.

This talk will focus on analyses of filtered data.

Filtered data  $\rightarrow$  Some types of data will never be sampled.

# Correcting for filtered data in tree estimation

Use:

$$\mathbb{P}(\text{Data} \mid \text{Tree, not excluded})$$

as the likelihood instead of:

$$\mathbb{P}(\text{Data} \mid \text{Tree})$$

$$\mathbb{P}(\text{Data} \mid \text{Tree, not excluded}) = \frac{\mathbb{P}(\text{Data} \mid \text{Tree})}{\mathbb{P}(\text{not excluded} \mid \text{Tree})}$$

# Conclusions

- Analyzing variable-only data with Lewis'  $Mk_v$  model is consistent
- Inferring trees from parsimony-informative-only data:
  - can be consistent if the tree is not tiny.
  - can be feasible for multi-state data using new algorithms
- Treating gaps as missing data:
  - does not lead to inconsistency if indel process is independent of the substitution process.
  - can be positively misleading under mild violations of this independence assumption.
- “rules” for character encoding need to be linked to the data.  $? \neq$  – in molecular data.

# Filtering data: retain variable patterns

Taxon	Character					
	1	2	3	4	5	6
t1	0	1	1	0	0	0
t2	0	1	0	0	1	0
t3	0	1	0	1	1	1
t4	0	0	0	1	0	1

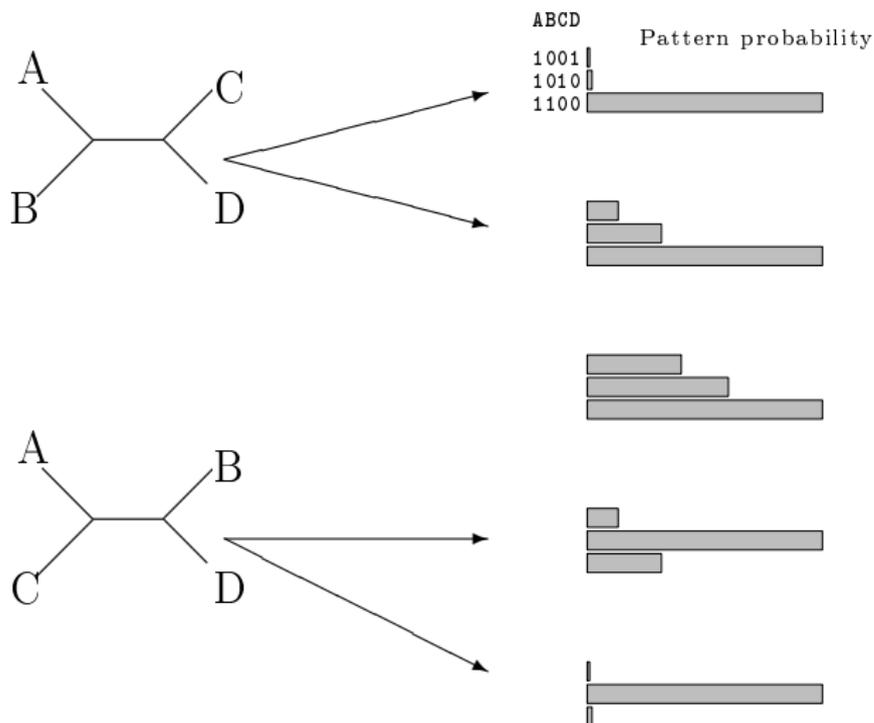
→

Taxon	Character				
	1	2	3	4	5
t1	1	1	0	0	0
t2	1	0	0	1	0
t3	1	0	1	1	1
t4	0	0	1	0	1

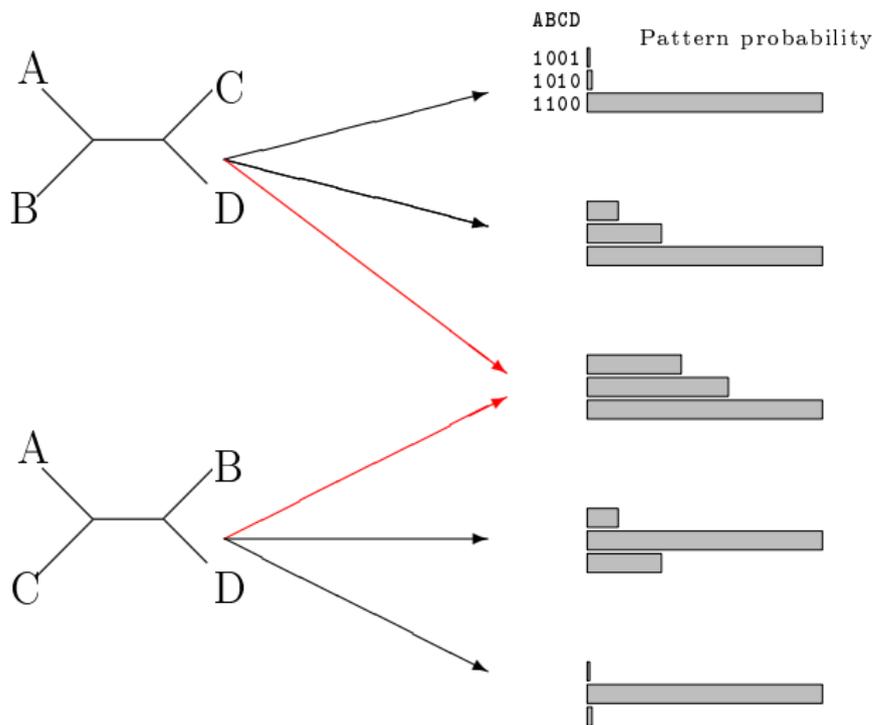
# Filtering data: retain parsimony-informative patterns

Taxon	Character						→	Taxon	Char.		
	1	2	3	4	5	6			1	2	3
t1	0	1	1	0	0	0	t1	0	0	0	
t2	0	1	0	0	1	0	t2	0	1	0	
t3	0	1	0	1	1	1	t3	1	1	1	
t4	0	0	0	1	0	1	t4	1	0	1	

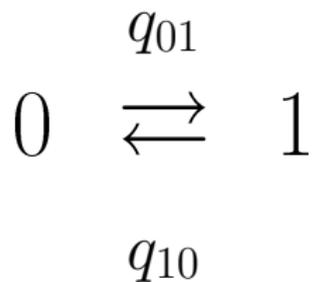
# Identifiability of the tree



# Partial identifiability of the tree



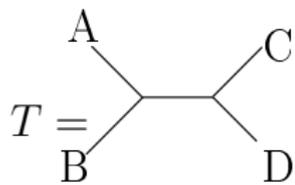
# A Markov model for character evolution



*Mk*:  $q_{10} = q_{01}$

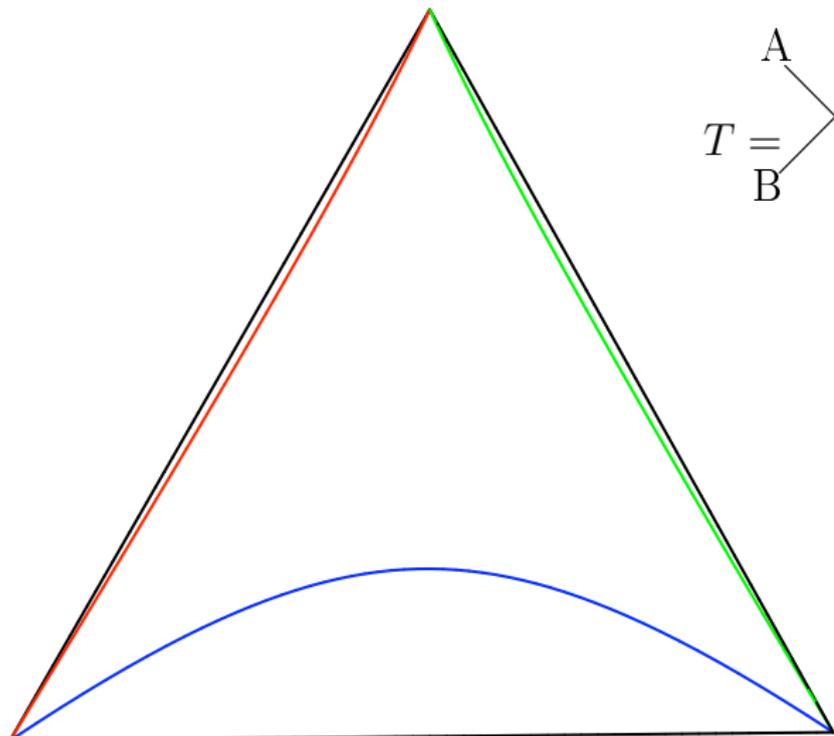
*GMk*:  $q_{10} \neq q_{01}$

$\mathbb{P}(1100|T)$



$\mathbb{P}(1010|T)$

$\mathbb{P}(1001|T)$



# Extending identifiability results

Filtering	Model	Identifiable?
None	$GMk$	Yes. (Steel, 1994)
Variable	$GMk_v$	Yes
Pars-inf	$Mk_{p-i}$	Part. (Steel et al., 1993)
	$GMk_{p-i}$	$N = 4$ No $N \geq 8$ Yes $5 < N \leq 7$ ?

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results in red: (Allman et al., 2010), extending (Allman and Rhodes, 2008) for  $GMk_v$

# Analyzing filtered data

<b>Analysis</b>	Filtering	
	Variable	Pars-inf.
$\mathbf{M}k$	Pos. Misleading	Pos. Misleading
$\mathbf{M}k_v$	Consistent	Pos. Misleading
$\mathbf{M}k_{p-i}$	-	Consistent $N \geq 8$

# Calculating the probability of not being excluded

$$\mathbb{P}(\text{not excluded} \mid \text{Tree}) = 1 - \mathbb{P}(\text{excluded} \mid \text{Tree})$$

For variable-only, binary data:

$$\mathbb{P}(\text{Var. pat} \mid \text{Tree}) = 1 - \mathbb{P}(\text{all 0 pat.} \mid \text{Tree}) - \mathbb{P}(\text{all 1 pat.} \mid \text{Tree})$$

# Calculating the probability of a parsimony-uninformative pattern

For multi-state character ( $k > 2$ ), and parsimony-informative-only data, there are lots of patterns:

$$\mathcal{O} \left( 2^{k-1} \binom{N}{k-1} \right)$$

JMK and MTH have implemented parsimony-uninformative specializations of an algorithm for calculating the prob. of classes of patterns.

Koch and Holder (2012)  
<https://github.com/mtholder/PhyPatClassProb>

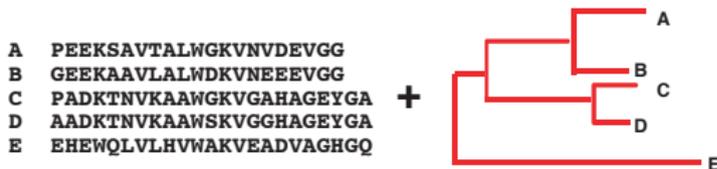
# Informatics implications

To correct for ascertainment bias we need to know what form of data filtering was used.

If a character was chosen because it was variable in a related group, it is difficult to correct of the ascertainment bias.

A	PEEKSAVTALWGKVNVDVEVGG	pairwise alignment →	A	-				
B	GEEKAAVLALWDKVNNEEVGG		B	.17	-			
C	PADKTNVKAAWGKVGAHAGEYGA		C	.59	.60	-		
D	AADKTNVKAAWSKVGGHAGEYGA		D	.59	.59	.13	-	
E	EHEWQLVLHVWAKVEADVAGHGQ		E	.77	.77	.75	.75	-

tree inference



alignment stage

A	PEEKSAVTALWGKVN--VDEVGG
B	GEEKAAVLALWDKVN--EEEVGG
C	PADKTNVKAAWGKVGAHAGEYGA
D	AADKTNVKAAWSKVGGHAGEYGA
E	EHEWQLVLHVWAKVEADVAGHGQ

gaps to missing

A	PEEKSAVTALWGKVN??VDEVGG
B	GEEKAAVLALWDKVN??EEEVGG
C	PADKTNVKAAWGKVGAHAGEYGA
D	AADKTNVKAAWSKVGGHAGEYGA
E	EHEWQLVLHVWAKVEADVAGHGQ

# Gaps-as-missing-data ML (SML) on the correct alignment

- Clearly ignores information from indels,
- Warnow (2012) argues that the method is inconsistent - but her proof only works when there are no substitutions on the tree.

Holder, Heath, Lewis, Swofford, and Bryant (*in prep*):

1. Proof of consistency if indel process is independent of substitution process,
2. Example of the method being positively misleading under a +I model for indels and substitutions.

# Theorem 1

The tree and parameter pair,  $\hat{T}_M, \hat{\theta}_M$ , estimated via SML will yield a consistent estimator of the tree,  $T$ , if:

- (a) the time-reversible substitution model,  $\theta$ , results in consistent estimation of the  $T$  in the absence of indels;
- (b) the indel process,  $\phi$ , acts independently of substitution process and the sequence states;
- (c) the probability distribution for newly inserted states is identical to the the equilibrium state frequency of the substitution process; and
- (d) there is non-zero probability of generating a site without gaps under  $\phi$ .

# What if rates of indels are correlated with rates of substitutions?

- Substitution: Jukes-Cantor + a proportion of invariant sites
- Indel: invariant sites will not experience indels. All sites that are free to have substitutions are also free to experience indels.

The result:

If we calculate the expected pattern frequency spectra for extreme “Felsenstein-zone” trees, and mimic infinite character sampling the software using “gaps-as-missing-data” approach (ML and Bayesian) prefers the wrong tree.

We still need to verify that this is not an artifact of local optima being found in software.

# Positively misleading behavior from treating gaps as missing data

- Long-branch attraction if the rate of the indel process is correlated with the rate of the substitution process.
- Non-random filtering of data  $\rightarrow$  long branches underestimated.

The result could have implications for the (long-standing) debates in systematics about the effect of missing data and inapplicable character states.

# Informatics implications

- Gaps aren't missing data, we really should be using models of the indel process.
- Terminal gaps in alignments often *are* the result of missing data. Software should not use the same symbol for gaps caused by indels and gaps caused by incomplete sequencing.

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Tandy J. Warnow. Standard maximum likelihood analyses of alignments with gaps can be statistically inconsistent. *PLOS Currents Tree of Life*, Mar 12:[last modified: 2012 Apr 3] Edition 1, 2012. doi: 10.1371/currents.RRN1308. URL <http://currents.plos.org/treeoflife/article/standard-maximum-likelihood-analyses-of-alignments-with-gaps>