Threshold models

Friday Harbor Laboratories, 9 June 2017

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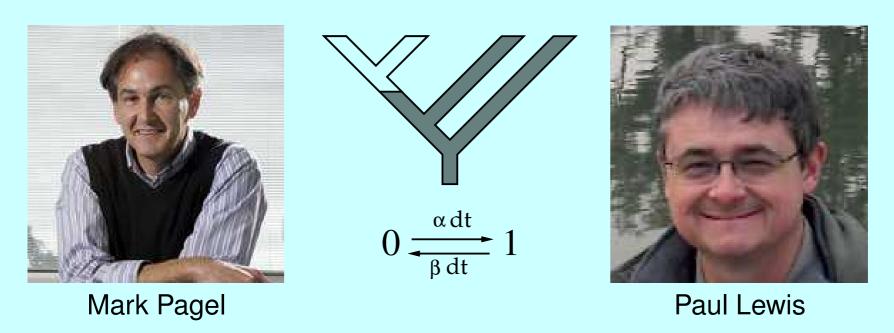
Evolutionary Quantitative Genetics Workshop

How to use phylogenies for morphology or behavior?

- Currently, most people use parsimony methods for these
- They code the characters discretely, which lead to what used to be called "the character coding problem"
- They have no statistical model and little way of knowing how uncertain are their inferences (except for some bootstrapping or jackknifing which assumes characters change independently)
- But is discrete coding necessary? No.
- Are there statistical models for these discrete phenotypes? Yes.

Current methods for statistical treatment of 0/1 characters

Pagel (1994) and Lewis (2001) treat such data with



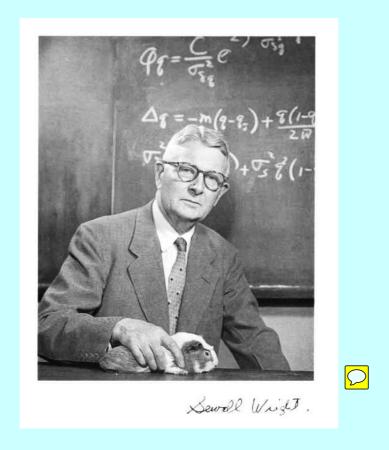
Pagel allows inference of whether changes in two characters are correlated, on a known tree.

Lewis uses a k-state "M_k" model to infer the tree, but does not allow for correlations among characters.

Neither takes into account contributions to a 0/1 character from multiple underlying loci.

Threshold models - p.3/30

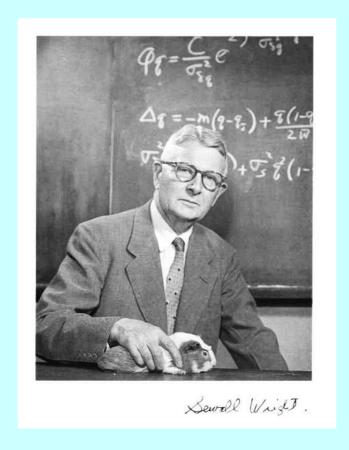
The threshold model A relevant model was invented in 1934 by



Sewall Wright (1889-1988) shown here in 1955

The threshold model

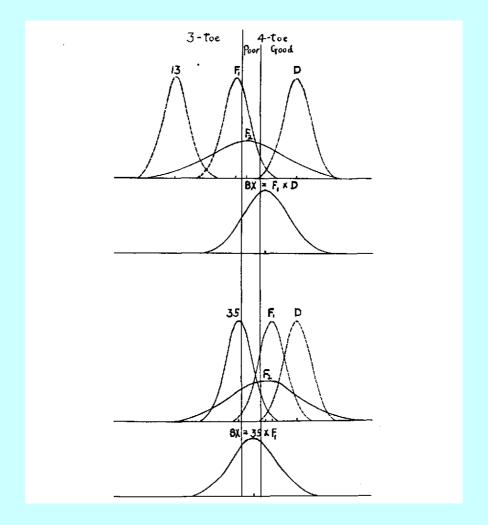
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Sewall Wright (1889-1988) shown here in 1955

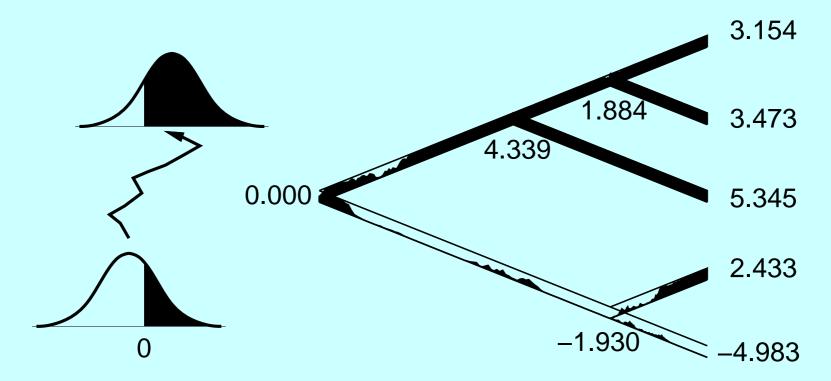
(The story goes that he then absent-mindedly started to erase the board with the guinea pig)

The threshold model, applied

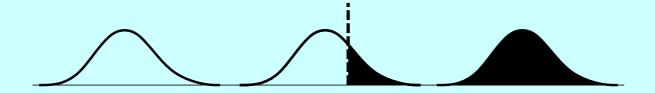


Sewall Wright (1934), guinea pig digit number (from Wright's follow-up 1934 second paper)

The threshold model on a tree



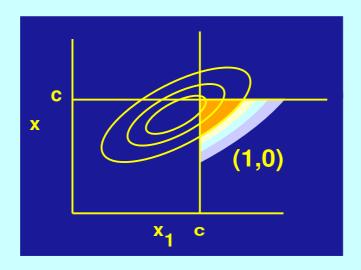
Biologically realistic properties



- Soon after the population crosses the threshold, crossing back is more likely than it is later on (when the population may have gotten further from the threshold). The M_k model does not predict this.
- The model predicts a phase of polymorphism (the M_k model makes no such prediction)
- The model very straightforwardly incorporates covariation between characters. For the M_k model, one needs to introduce vast numbers of new parameters.

Computing the likelihood

With two species, one character:



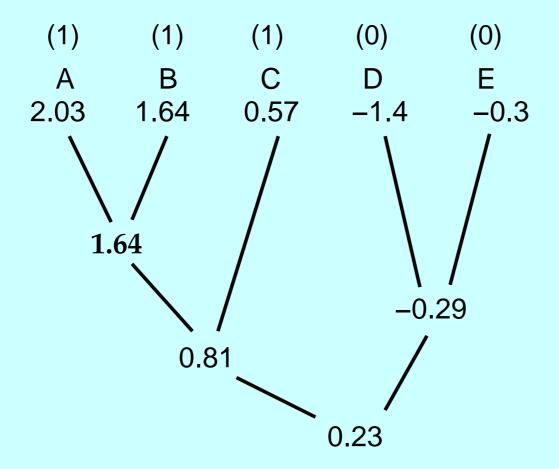
Disadvantages:

Quite hard to compute likelihoods: need to compute area in a corner of a correlated multivariate normal distribution.

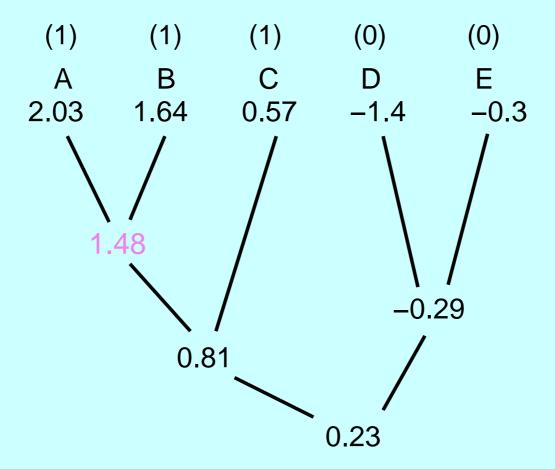
With 5 species, one character:

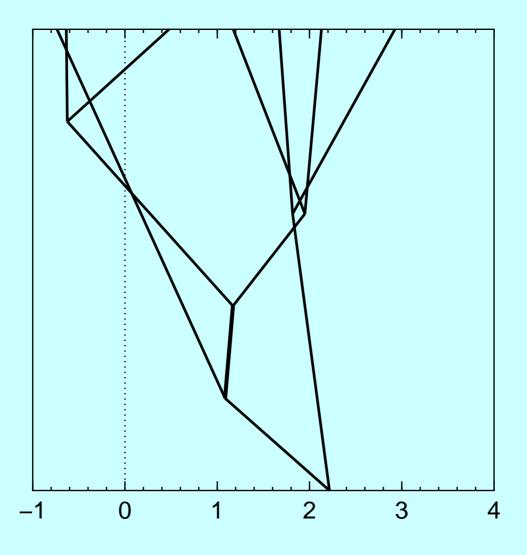
$$\begin{array}{lll} \mathsf{L} & = & \mathrm{Prob} \; (1,1,0,1,1) \\ & = & \int_0^\infty \int_0^\infty \int_0^\infty \int_0^\infty \int_0^\infty \varphi(\mathsf{x}_1,\mathsf{x}_2,\mathsf{x}_3,\mathsf{x}_4,\mathsf{x}_5 \mid \mathrm{Tree}) \; \mathsf{dx}_1 \; \mathsf{dx}_2 \; \mathsf{dx}_3 \; \mathsf{dx}_4 \; \mathsf{dx}_5 \\ \end{array}$$

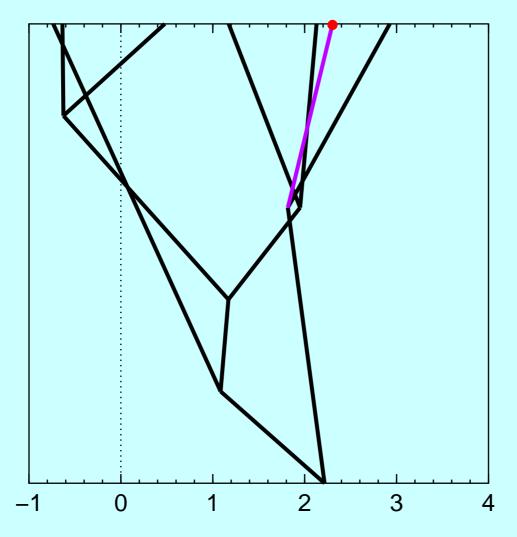
MCMC on liabilities



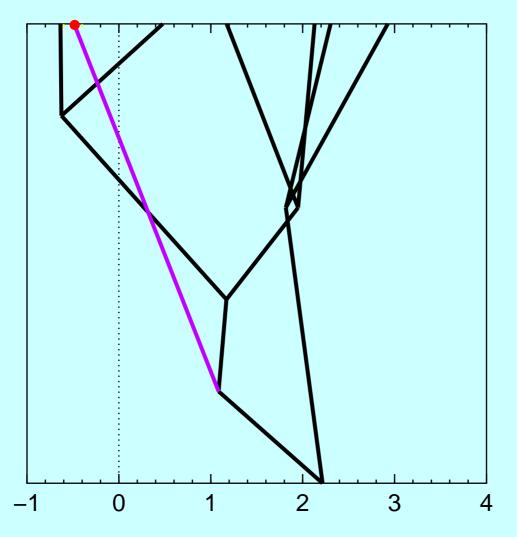
MCMC on liabilities: result of Gibbs sampling



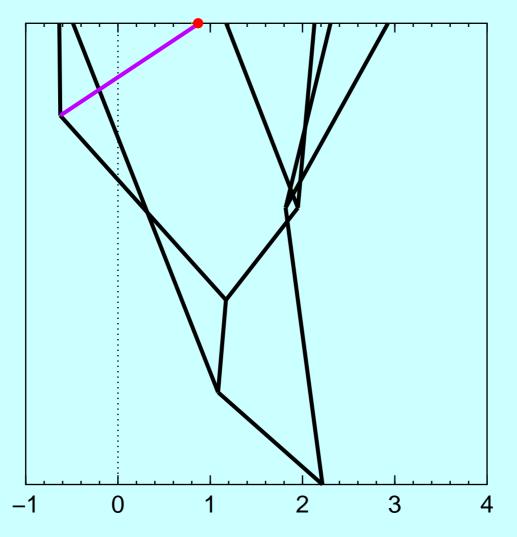




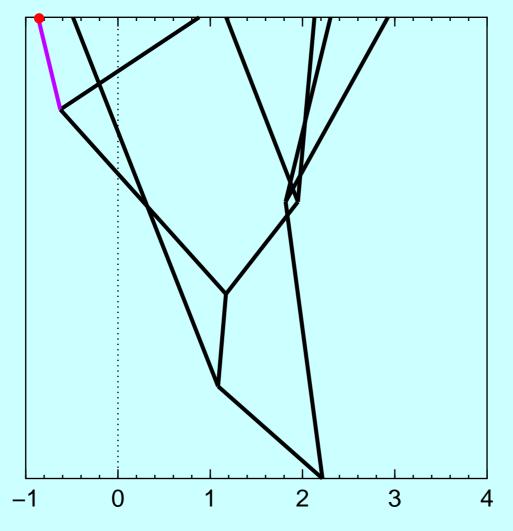
Updating a tip node's liability



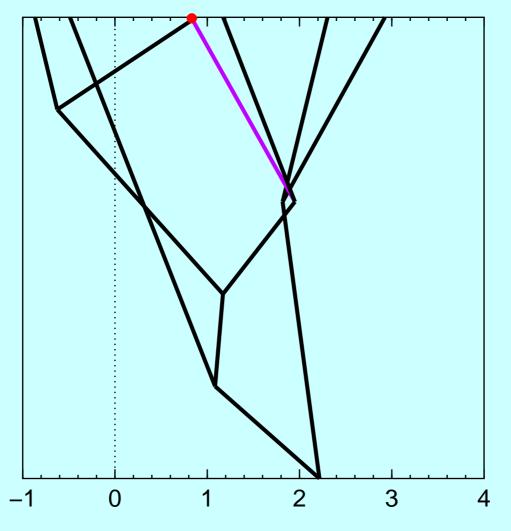
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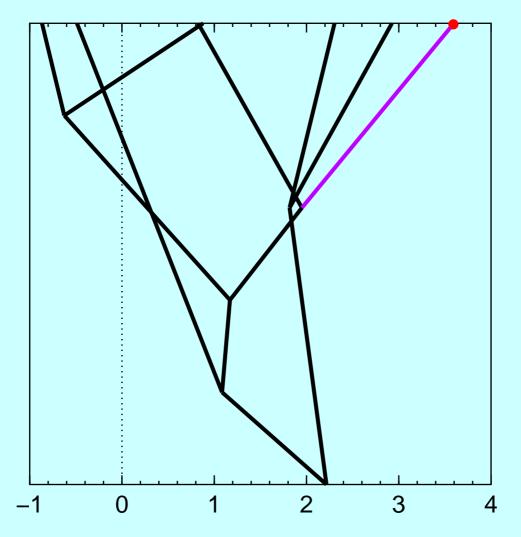
Updating a tip node's liability



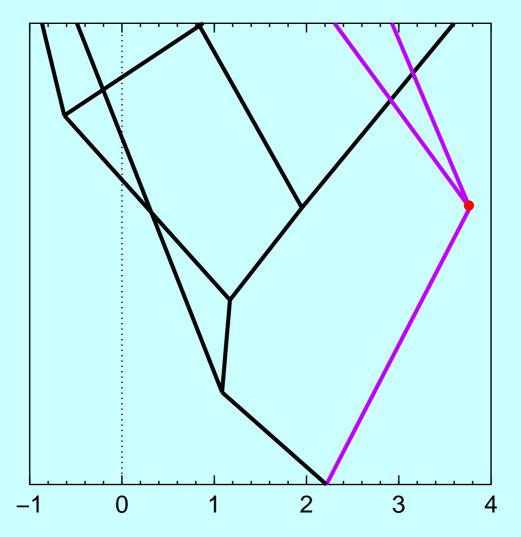
Updating a tip node's liability



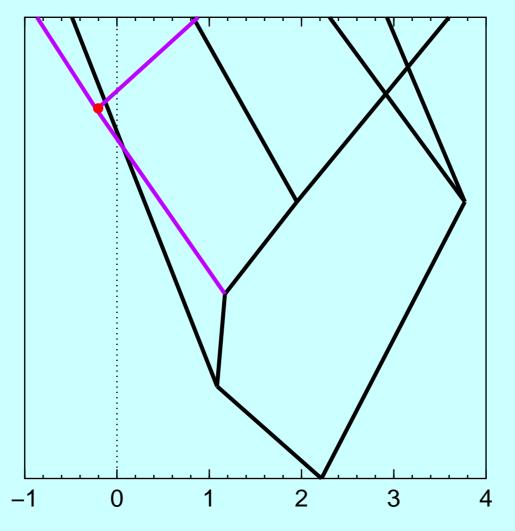
Updating a tip node's liability



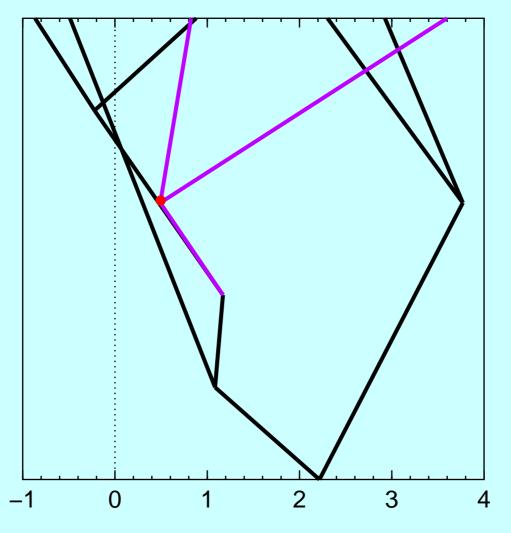
Updating a tip node's liability



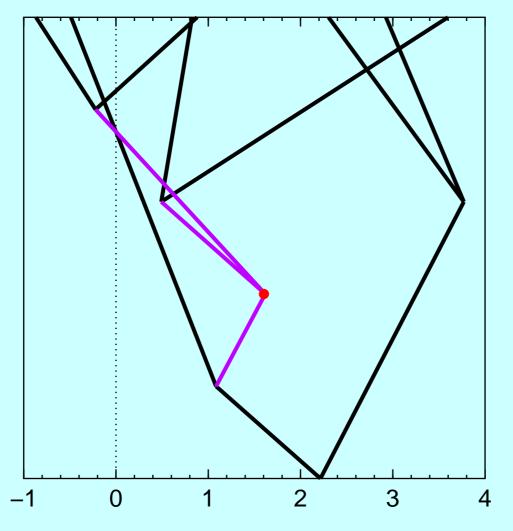
Updating an interior node's liability



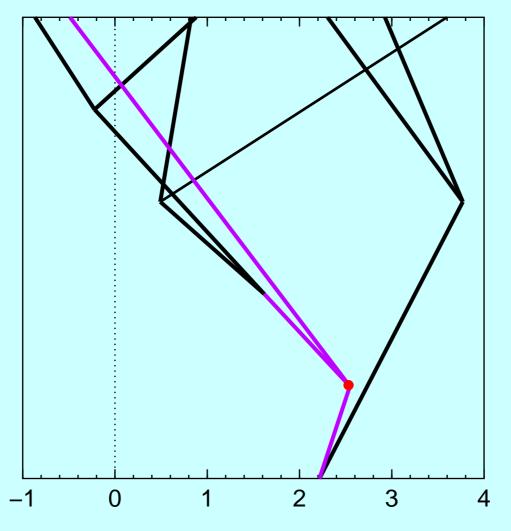
Updating an interior node's liability



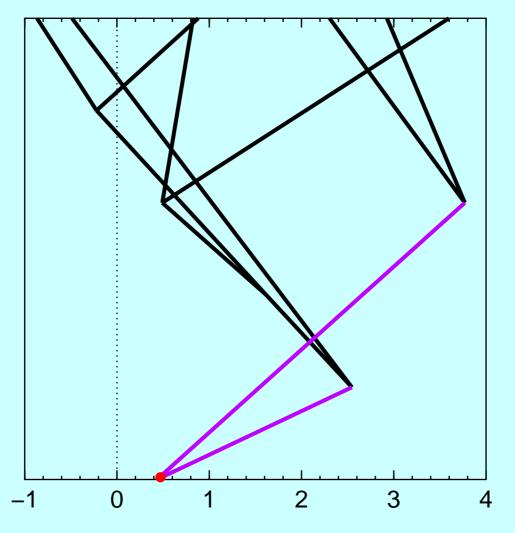
Updating an interior node's liability



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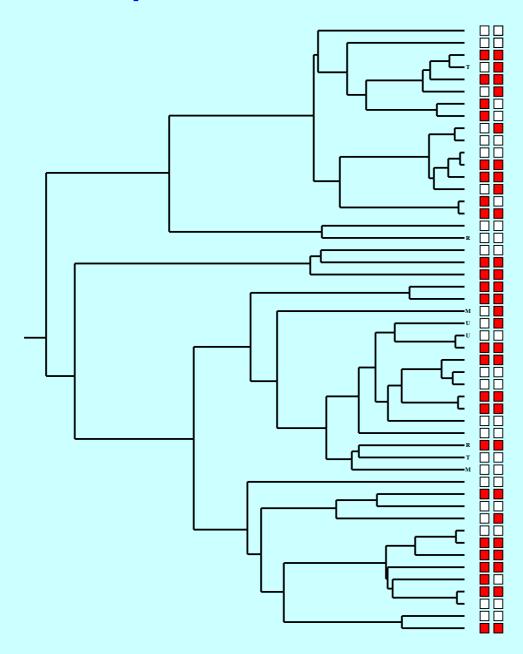


Updating an interior node's liability



... and one keeps doing this for tip and interior nodes, many times

A simulated example, with its true tree



A (very) small-scale simulation

True covariance matrix

1 0.8 0 0.8 1.64 -0.6 0 -0.6 1.36

One data set with 50 species on a the same tree:

For the same simulated data set

Run 1		Run 2	
1.70072 1.39356 0).39289 1.68	1.40056	0.40495
1.39356 1.65104 0).20923 1.40	056 1.67836	0.23021
0.39289 0.20923 1	0.40	495 0.23021	1.09550
	<u>.</u>		

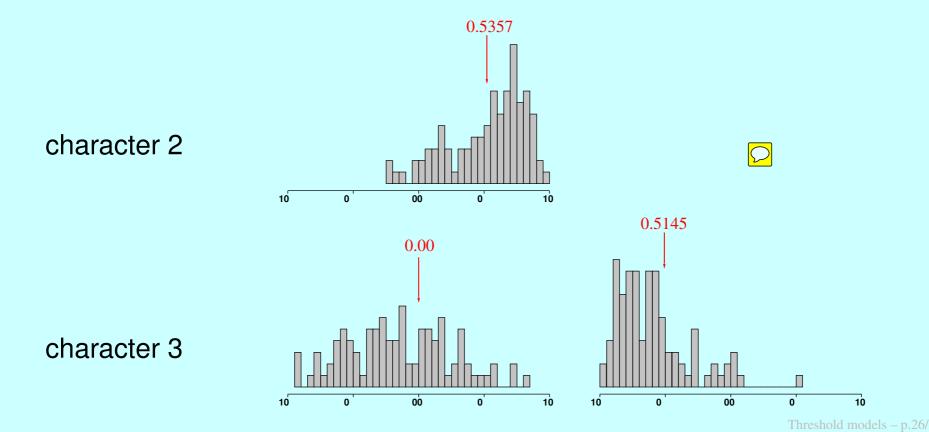


A simulation: inferred correlation coefficients

With 50 trees, each with 2 simulated data sets:

character 1 character 2

character 1



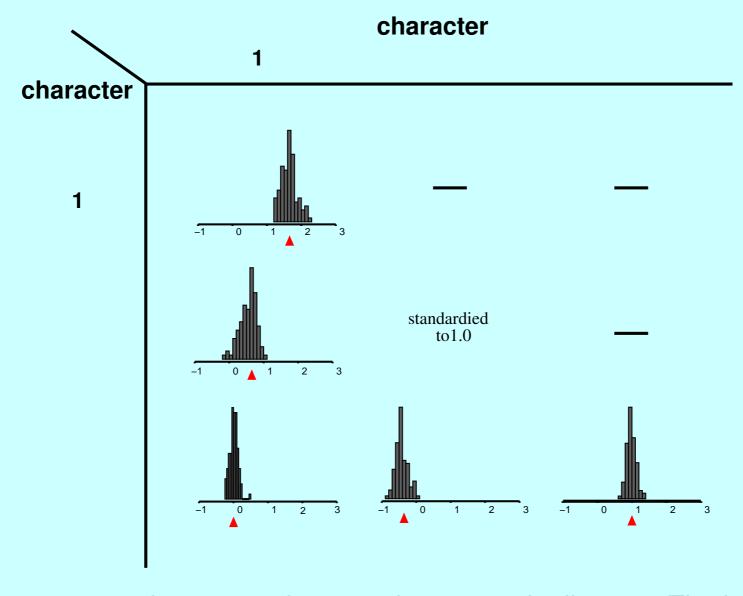
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- This would be a noisier version of what we can do exactly already, so there is no point to it, right?
- But ... we could do both discrete and continuous characters together in this way, with almost no extra effort.

Simulations with both discrete and continuous characters



Characters 1 and 3 are continuous, character 2 is discrete. The inferred covariances are shown for the 100 simulated data sets. Threshold models – p.28/30

References for threshold methods

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- Lewis, P. O. 2001. A likelihood approach to estimating phylogeny from discrete morphological character data. *Systematic Biology* 50: 913-925. [Uses 0/1 stochastic process to infer morphological phylogenies]

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