

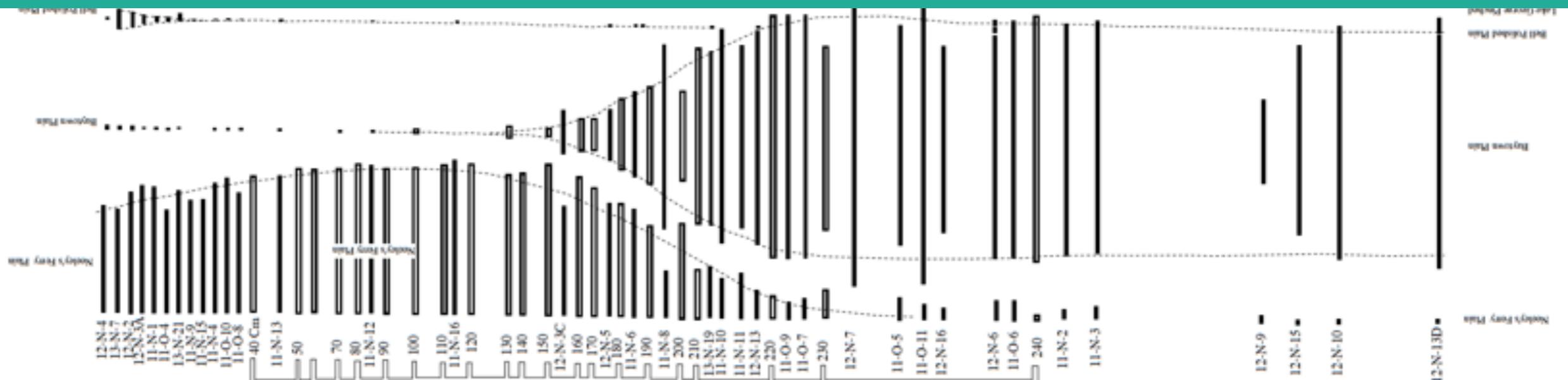
# Measuring Cultural Transmission At Archaeological Scales: How Can We Improve Empirical Sufficiency?

Mark E. Madsen

Dissertation Defense  
June 11, 2020



UNIVERSITY *of* WASHINGTON



# A bit of context...and plan

*Syst. Zool.*, 37(2):142–155, 1988

## Context

### HOMAGE TO CLIO, OR, TOWARD AN HISTORICAL PHILOSOPHY FOR EVOLUTIONARY BIOLOGY

ROBERT J. O'HARA

*Museum of Comparative Zoology, Harvard University,  
Cambridge, Massachusetts 02138*

Evolutionary archaeology addresses many questions

But it has a common core task:  
**documenting evolutionary history**

This means **tracing cultural transmission**

O'Hara (1988) -

**Chronicle:** Evidence for what/when

**History:** Explanation for chronicle

**Model:** A proposed **history**

## Plan

Dissertation comprised of 4 independent studies

Each is methodological

Goal is to improve empirical sufficiency for documenting CT

Tasks:

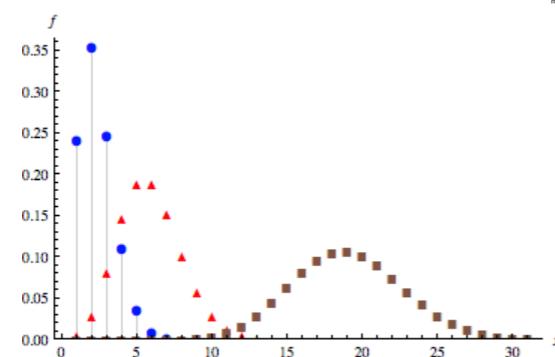
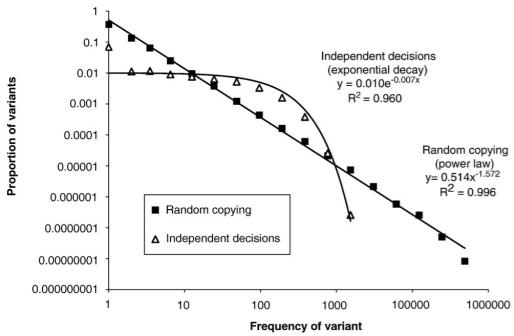
- Develop ways to study **equifinality**
- Develop **better chronicles** and better ways of fitting **models** against **chronicles**

Tools: simulation, machine learning

# Three scales of research in evolutionary archaeology

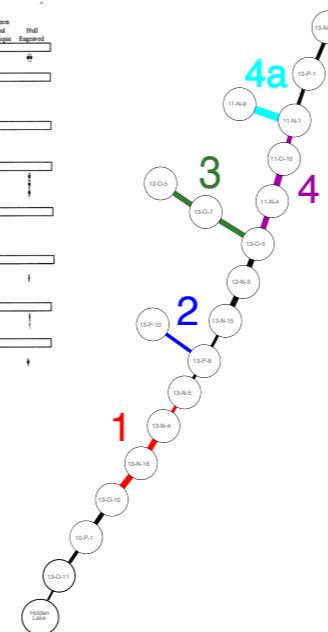
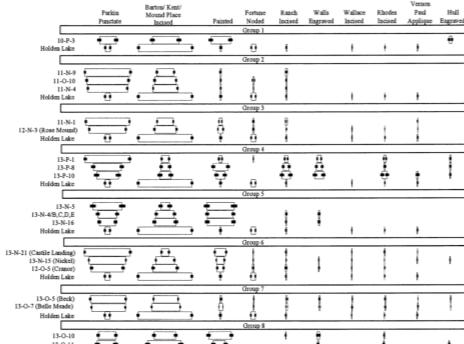
## Microevolutionary

- Ex: trait frequency distribution
- Neutrality tests, diversity stats
- Synchronic models
- **Equifinality problems!**



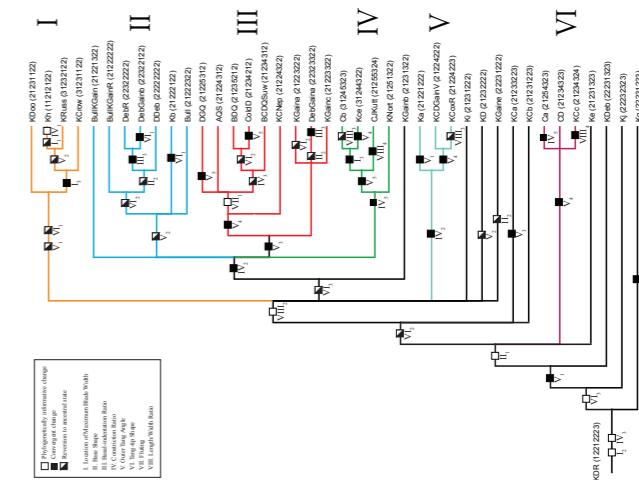
## “Mesoscopic”

- Ex: frequency seriation
- Orders units by frequency
- Regional scale, shorter time
- **Need methods and models!**



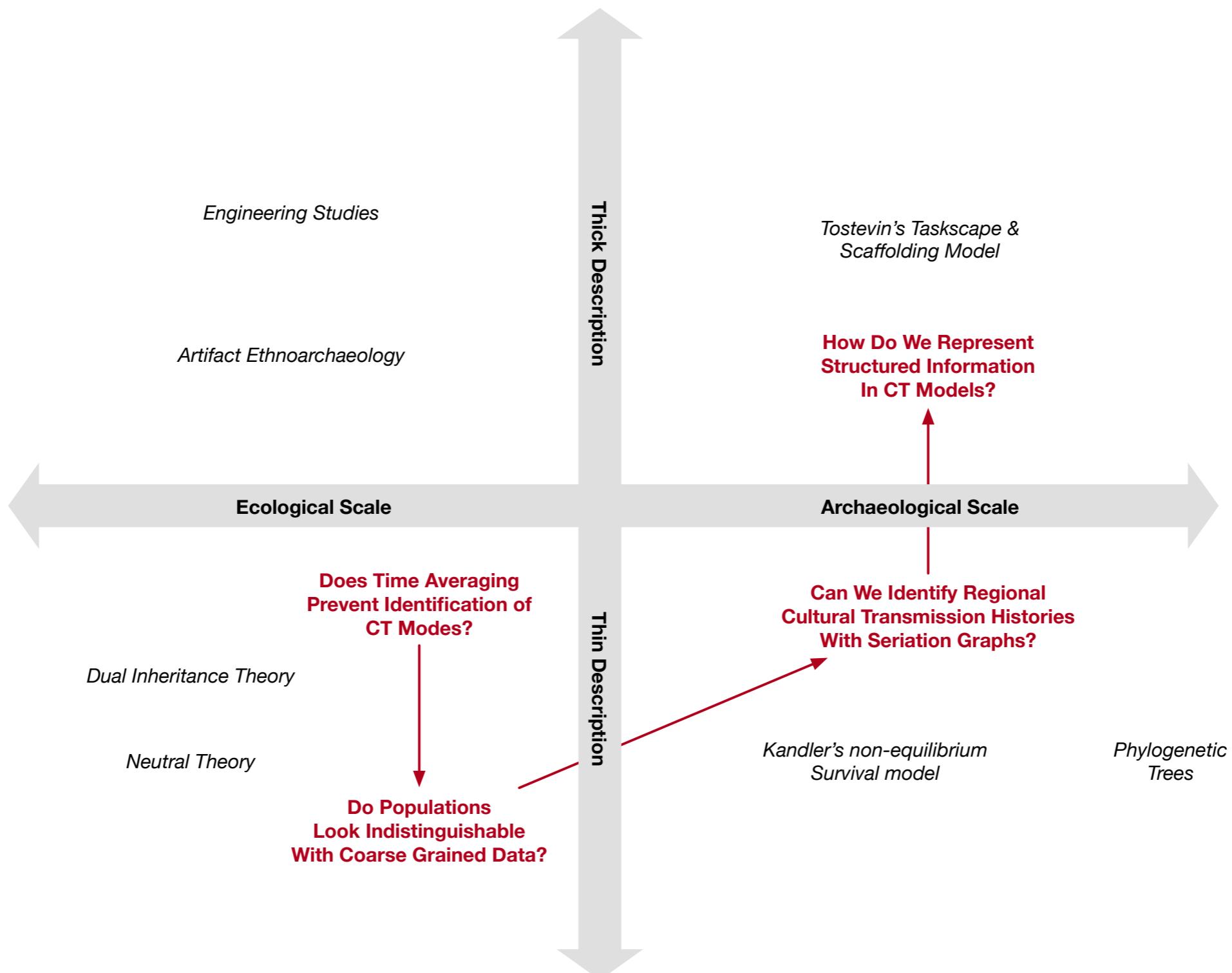
## Macroevolutionary

- Ex: phylogenetic methods
- Orders units by presence/absence
- Large scale, long term history
- Well developed methods and tools

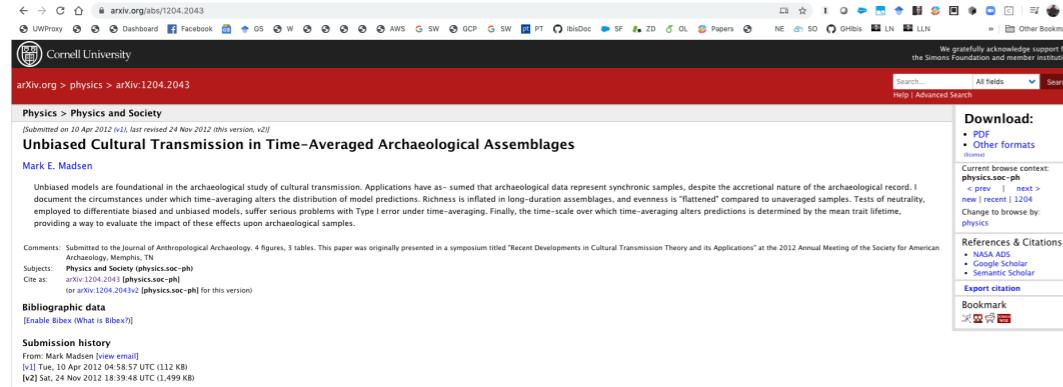


*Can we make the microevolutionary approach empirically work?  
If not, how do we build diachronic models at archaeological scales?*

# Context and Four Research Questions



# Does Time Averaging Prevent Identification of Cultural Transmission Modes? (Ch. 2)



## Methods

Simulation of unbiased CT (Wright Fisher infinite alleles) with 16 different innovation rates.

Simulator tracked unaggregated and aggregated trait counts (12 window sizes), trait lifetime.

Analysis looked at:

- Excess Type I error in Slatkin neutrality test
- Elevation in trait richness
- Ability to estimate innovation rate ( $\theta$ )
- Evenness among trait frequencies

Literature on identifying “biased” CT relies on departure from neutral expectations.

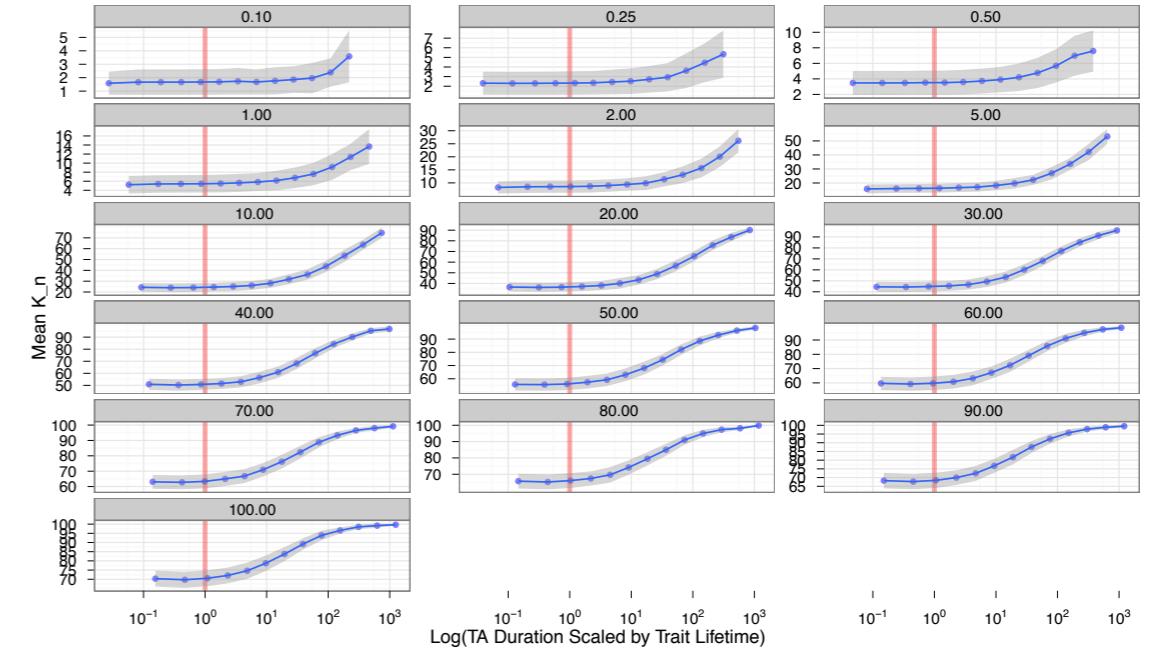
How does **temporal aggregation** affect statistical tests and diversity statistics used to test for departure from neutrality?

## Summary

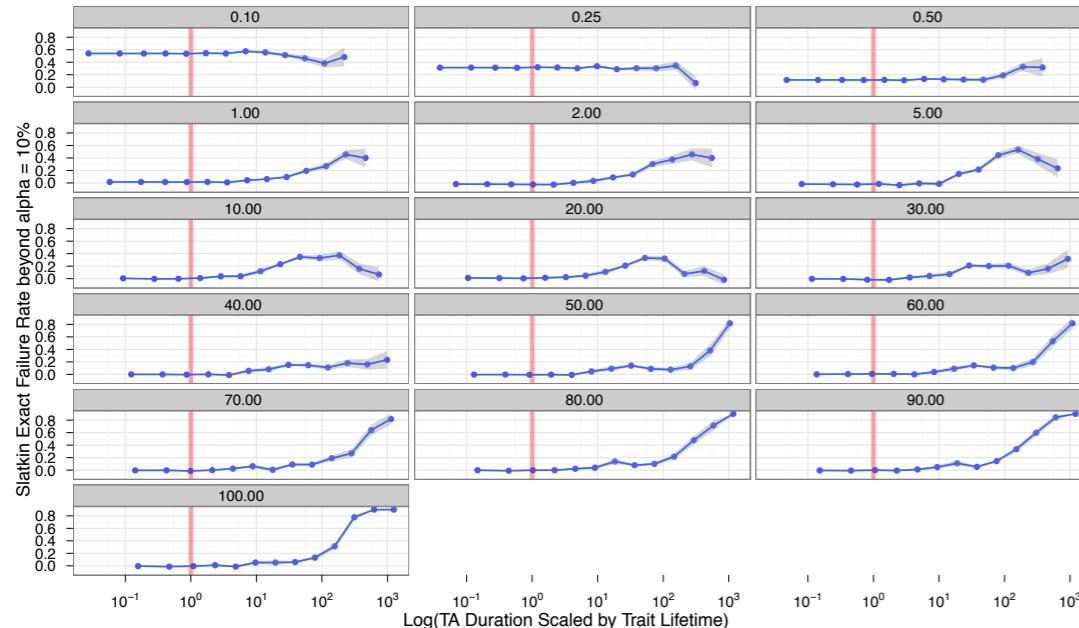
# Time averaging significantly affects microevolutionary modeling

- Time averaging leads to increased likelihood of finding "biased transmission"
- Effects manifest as **duration of samples > mean trait lifetime**

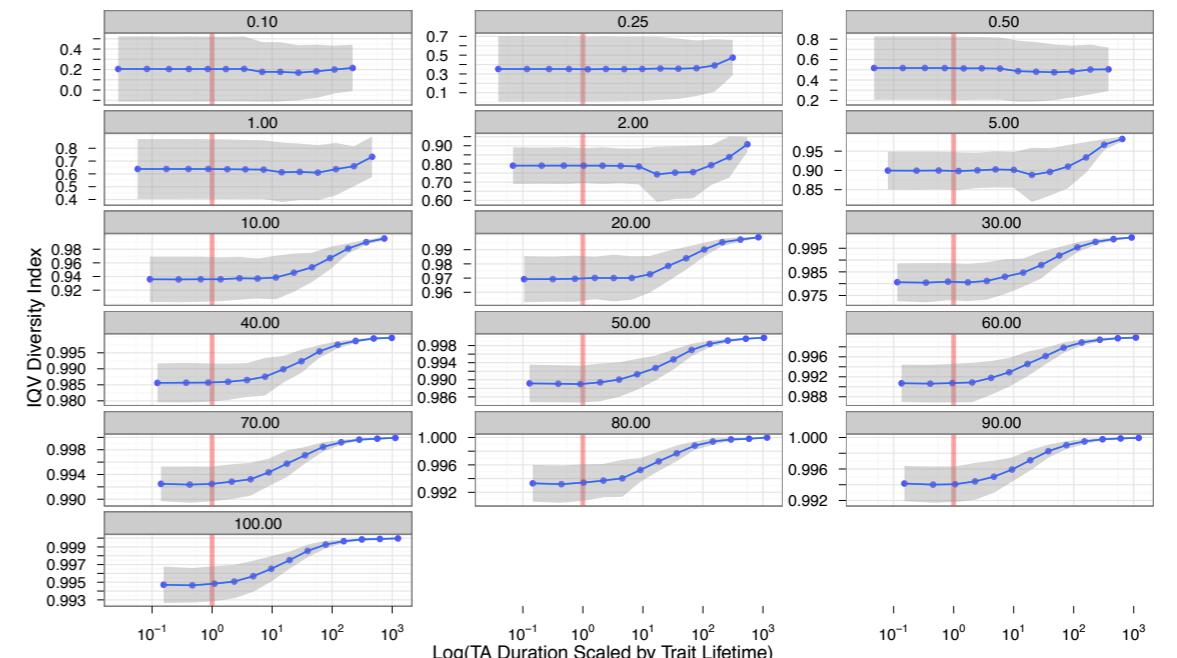
## Elevated trait richness



## Increased Type I error in tests



## Increased trait evenness



# Do Populations Look Indistinguishable With Coarse Grained Data ? (Ch. 3)

## Summary

Real populations are heterogeneous in their social learning modes and social vs. individual learning.

Do the effects of multiple CT modes “cancel” out in coarse grained, population level data? How do sampling and time averaging affect this?

These questions are about **detecting equifinality** when formulating sets of models. Can we statistically “screen” for equifinality?

## Methods

Simulation of mixtures of conformists, unbiased copiers, novelty seekers, and pure unbiased population.

Simulator tracked raw and time averaged trait counts, attribute vs. class, different sample sizes.

*Equifinality measured as approximation to Bayes error rate classifying samples compared to true DG process.*

Classifier used 23 summary statistics as predictor variables, measured on class and per-attribute counts.

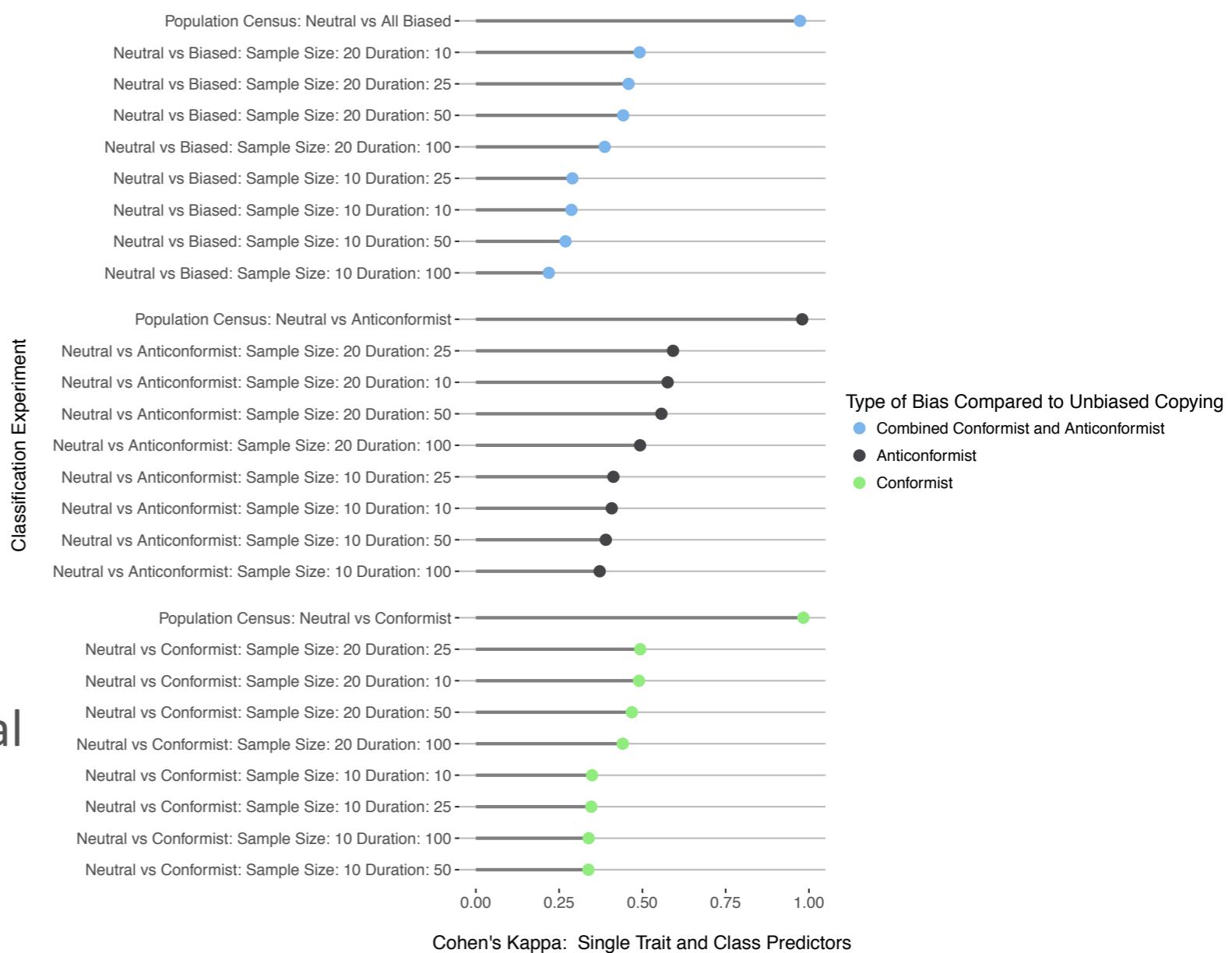
Coarse grained data have trouble identifying the details of social learning at archaeological scale

Employ Cohen's kappa as measure of classifier accuracy (good for unbalanced class counts)

Ability to identify the correct model from data is good with truly synchronous data and very large samples/census, because all the information is in the rare traits.

Time averaging and the ability to take only small samples rapidly create equifinality among theoretical models.

# Time to give up the microevolutionary program in archaeology?



# Can We Identify Regional Cultural Transmission Histories with Seriation Graphs? (Ch. 4-6)

## Summary

Mesoscopic scale: regional variation, assemblage durations of 10s or 100s years. How do we formalize **models** about evolutionary history at this scale?

What **chronicles** (units) can we fit to historical **models**?

Explored how modern **seriation graphs** provide the **chronicles**; time-varying graphs or “**temporal networks**” formalize a **model** of evolutionary history to test.

What kinds of histories can we distinguish (**equifinality**)?

## Methods

Interval temporal networks model a metapopulation; forms hypothesis about population structure and history.

Simulate CT on the ITN; perform TA and sampling; seriate results as graphs

Characterize seriation structure as Laplacian spectrum of the solution graph

Train classifier on seriation spectra from 4 regional models and evaluate equifinality

Use trained classifier on Mississippian ceramic seriations

# Seriation research employed in this dissertation

Lipo, Madsen, Dunnell, and Hunt

1997

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ARTICLE NO. AA970314

Population Structure, Cultural Transmission, and Frequency Seriation

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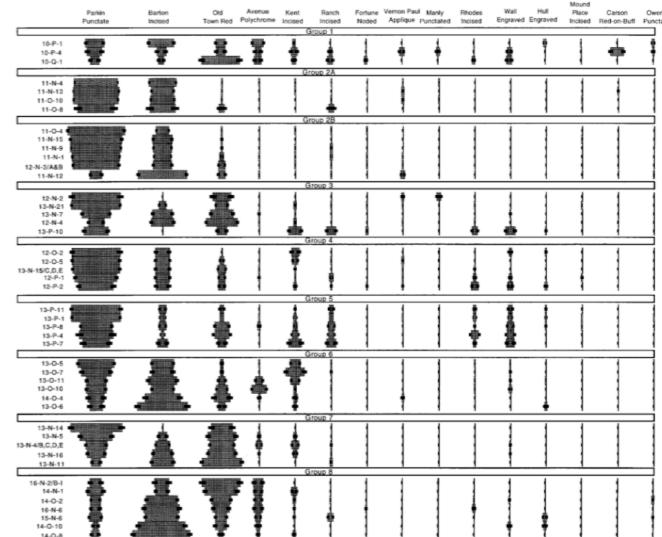
and

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*Multiple sub-solutions  
Seriation confidence intervals*



Lipo, Madsen, and Dunnell

2015

PLOS ONE

OPEN ACCESS

RESEARCH ARTICLE

A Theoretically-Sufficient and Computationally-Practical Technique for Deterministic Frequency Seriation

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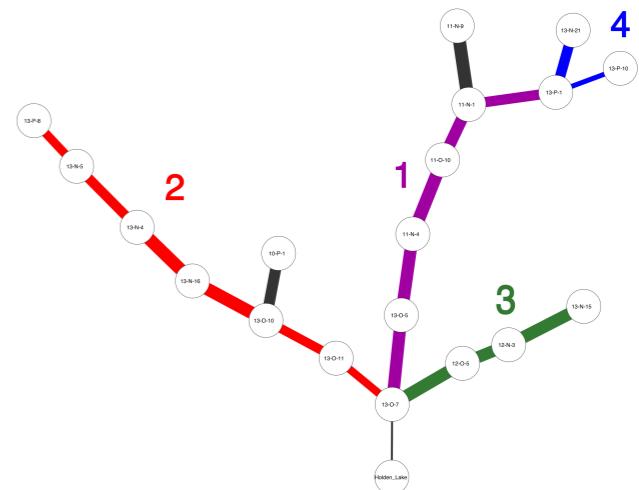
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*Seriation graphs unify  
sub-solutions*

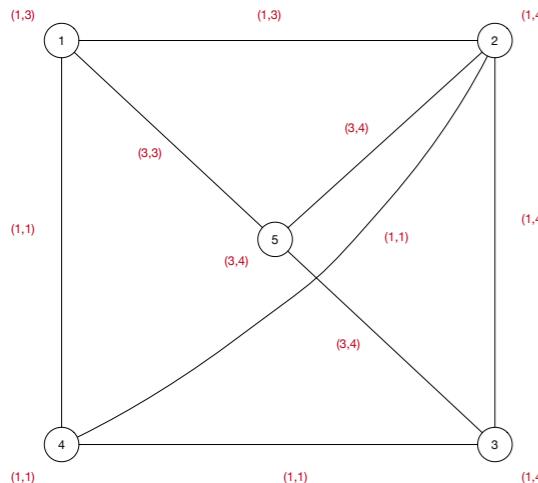
*Incorporate space and  
time*



# Temporal networks are hypotheses about evolutionary history

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Interval temporal graph “all in one view”



Historical models studied here:

## Complete Networks

Populations in a region all exchange traits, and migration among all populations

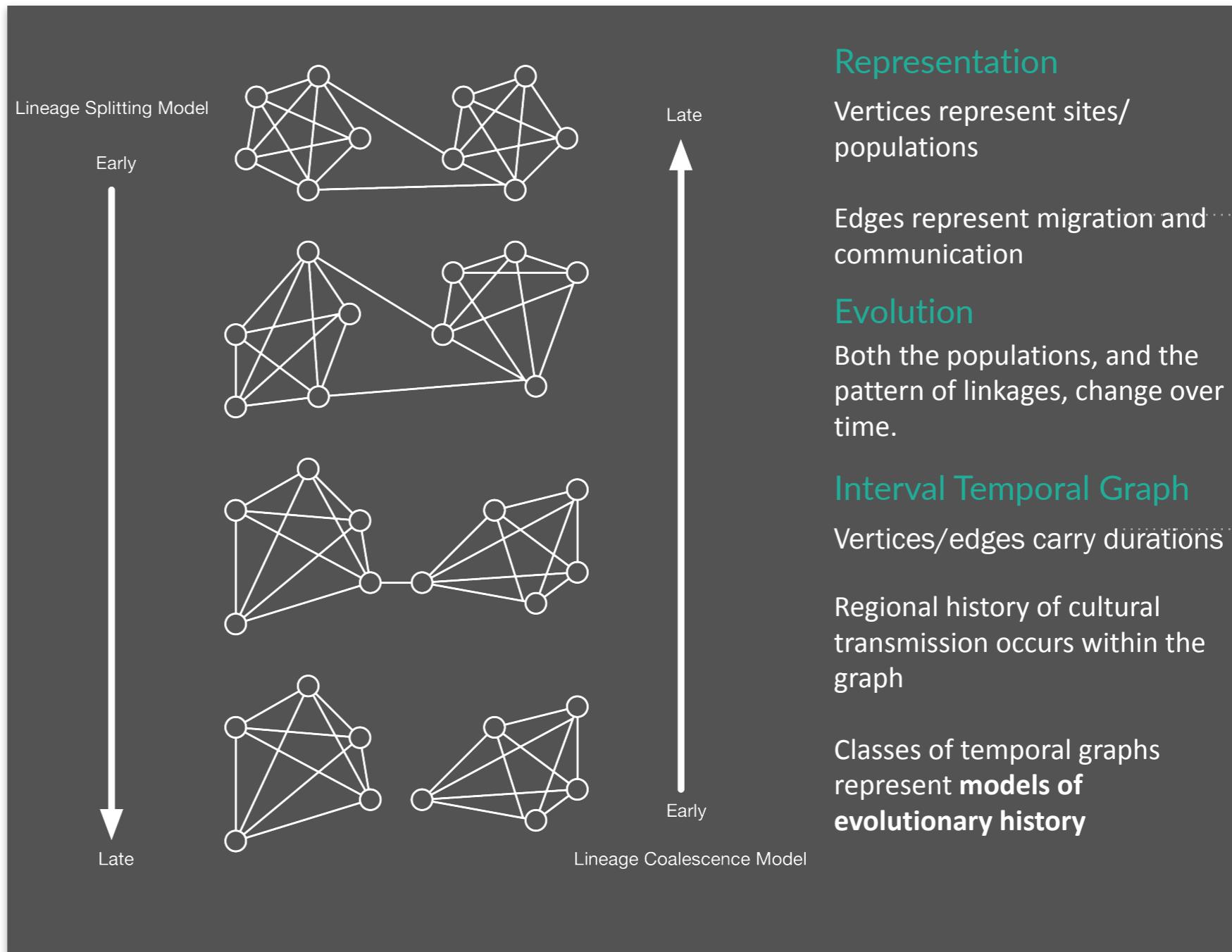
## “Lineage Splitting”

Sets of populations which formerly shared traits and migrants split into two or more groups which no longer communicate

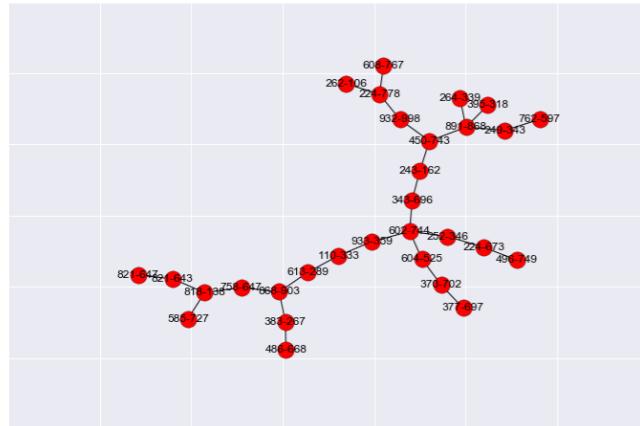
## “Nearest Neighbor” Bias

Interaction is biased toward neighbors, with smaller numbers of long distance links. Studied square and long regions (along river)

Interval temporal graph “unrolled” in slices for viewing



# Quantifying seriation graph structure



Example seriation solution from simulated cultural evolution on a social network which “split” into two lineages after evolving as one large lineage

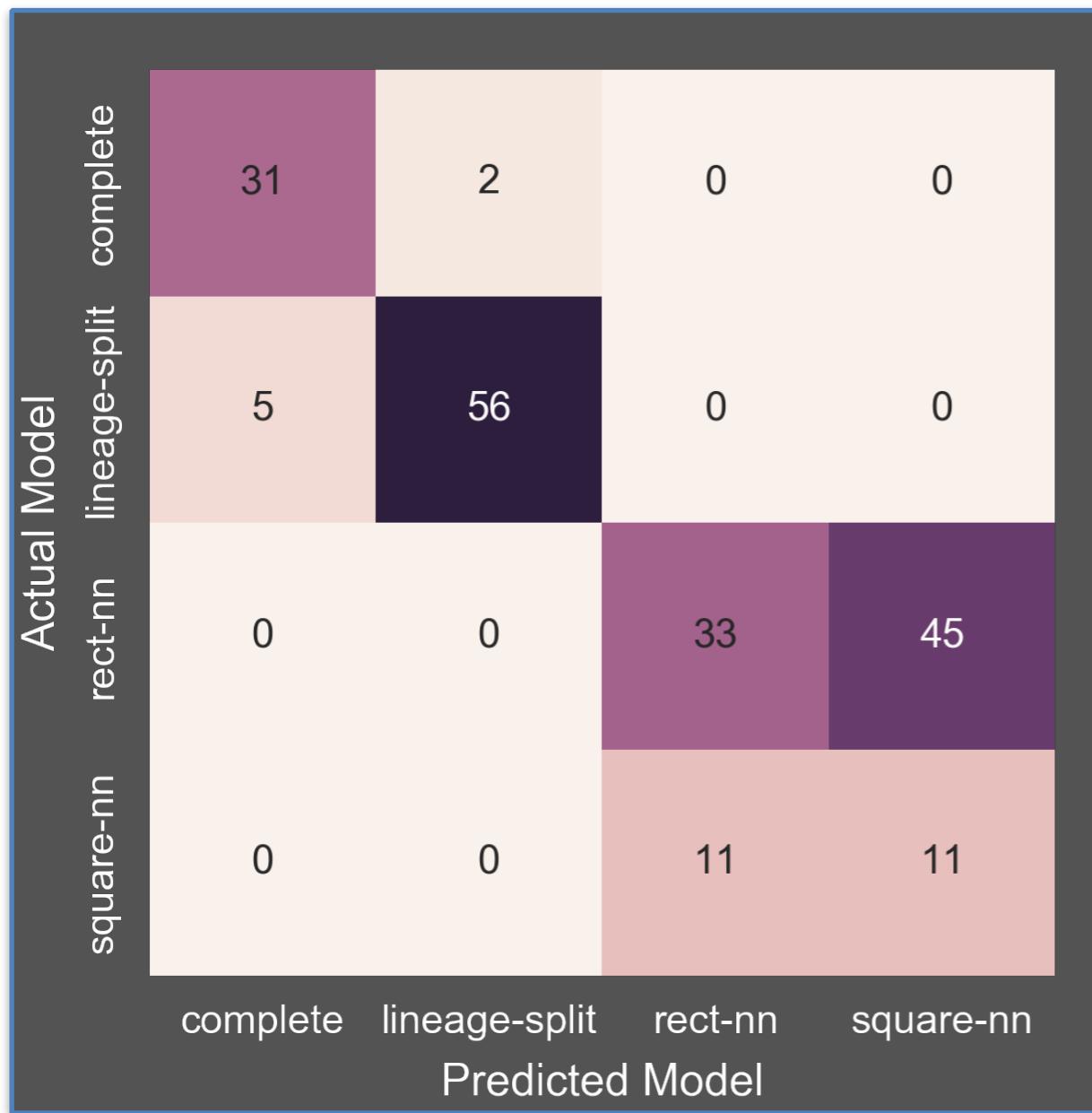
The “structure” of edges and vertices in a graph is given by its Laplacian matrix, which can be summarized by its eigenvalue spectrum

Labeled graph	Degree matrix	Adjacency matrix	Laplacian matrix
	$\begin{pmatrix} 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$	$\begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 2 & -1 & 0 & 0 & -1 & 0 \\ -1 & 3 & -1 & 0 & -1 & 0 \\ 0 & -1 & 2 & -1 & 0 & 0 \\ 0 & 0 & -1 & 3 & -1 & -1 \\ -1 & -1 & 0 & -1 & 3 & 0 \\ 0 & 0 & 0 & -1 & 0 & 1 \end{pmatrix}$

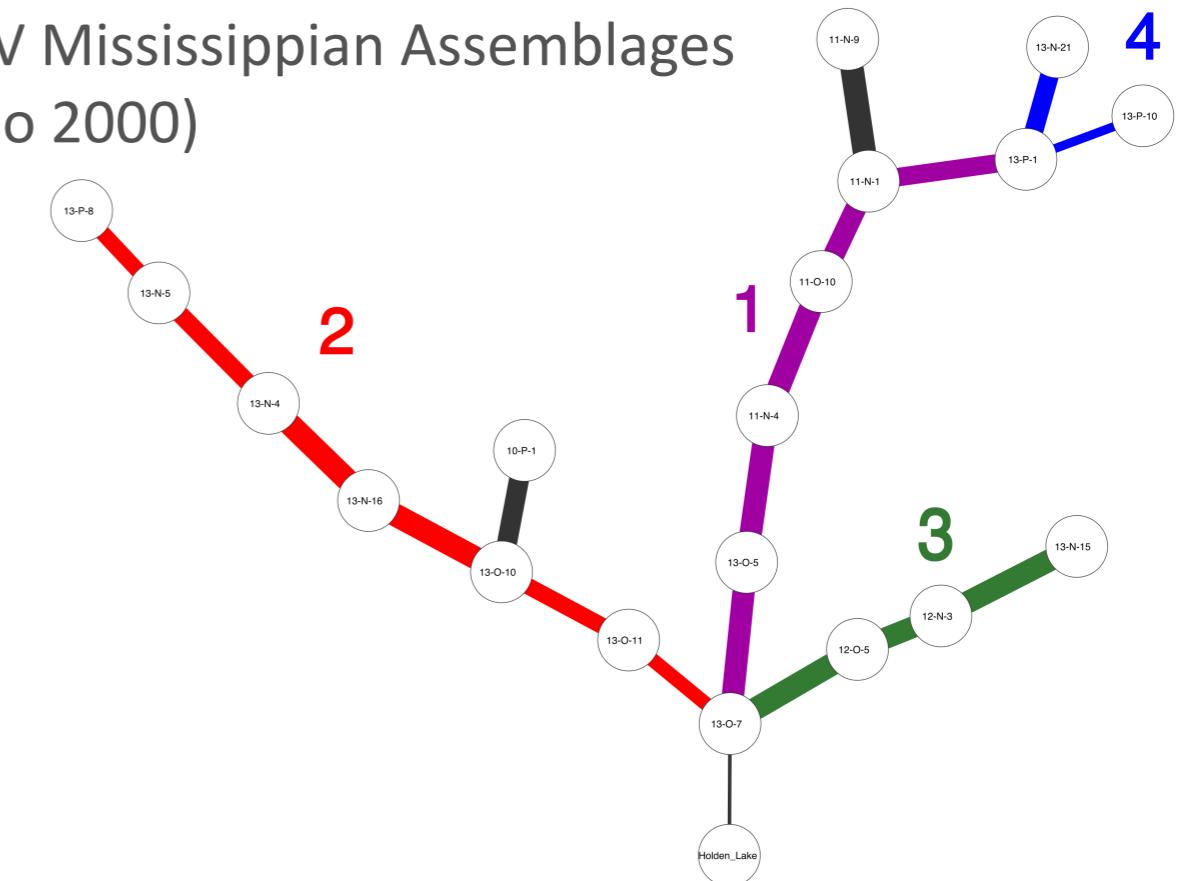
The eigenvalues are then used as predictor variables in a classifier model, to predict the correct evolutionary model.

# Results – promising but need more models!

Equifinality analysis: confusion matrix



LMV Mississippian Assemblages  
(Lipo 2000)



Trained classifier per-model probabilities:

<b>Complete:</b>	6.67%
<b>Lineage Split:</b>	93.32%
<b>Rect-NN:</b>	0%
<b>Square-NN:</b>	0.01%

# How Do We Represent Structured Information in Cultural Transmission Models? (Ch. 7)

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## Summary

How does teaching affect the richness of cultural repertoires, compared to individual learning with imitation?

**Shape of design space:** how to represent prerequisites/dependencies?

**Analysis:** how do empirical cases “fill” the theoretical design space

## Methods

Tree structures represent “prerequisites”; many trees represent the “design space” of a technology.

Learning follows prerequisite structure

Analysis looked at how much of design space is filled given learning rate, innovation rate

Behavioral Modernity and the Cultural Transmission of Structured Information: The Semantic Axelrod Model

Mark E. Madsen and Carl P. Lipo

### Abstract

Cultural transmission models are coming to the fore in explaining increases in the Paleolithic toolkit richness and diversity. During the later Paleolithic, technologies increase not only in terms of diversity but also in their complexity and interdependence. As Mesoudi and O’Hearn (Badoglio et al. 363–72, 2008) have argued, selection broadly favors social forms of information that is learned, copied, and imitated. We believe that teaching provides the necessary scaffolding for transmission of more complex cultural traits. Here, we introduce an extension of the Axelrod (J Confil Resolut 41:203–226, 1997) model of cultural differentiation in which traits have prerequisite relationships, and where social learning is dependent upon the ordering of those prerequisites. We examine the resulting structure of cultural repertoires as learning environments range from largely unstructured arenas to structured teachers of necessary prerequisites, and find that in combination with individual learning and imitation, high probabilities of teaching prerequisites leads to richer cultural repertoires. Our results point to ways in which we can build more comprehensive explanations of the archaeological record of the Paleolithic as well as other cases of technological change.

### Keywords

Structured trait model • Axelrod model • Unbiased transmission • Knowledge prerequisites • Sites • Cumulative cultural transmission

### 6.1 Introduction

Although humans and our hominin ancestors have been cultural animals throughout our evolutionary history, an important change occurred in our lineage during the Middle and Upper Paleolithic. For millennia our ancestors manufactured relatively small toolkits and their material culture was remarkably similar across continental distances and over many generations. Beginning in the Middle Paleolithic and continuing through the Upper Paleolithic, the archaeological record reflects an explosion in our cultural repertoire. Over tens of thousands of years, artificial toolkits shift from sets of relatively few items with multiple uses to large collections of highly specialized tools that were manufactured using complex technologies and that were manufactured from an enriched range of materials. The changes in artifacts suggest that human solutions to the problems of everyday life became regionalized and differentiated. Further, the economic basis of our lives began to broaden and also, in many areas, to become specialized (Bar-Yosef 2002; d’Errico and Stringer 2011; Straus 2005).

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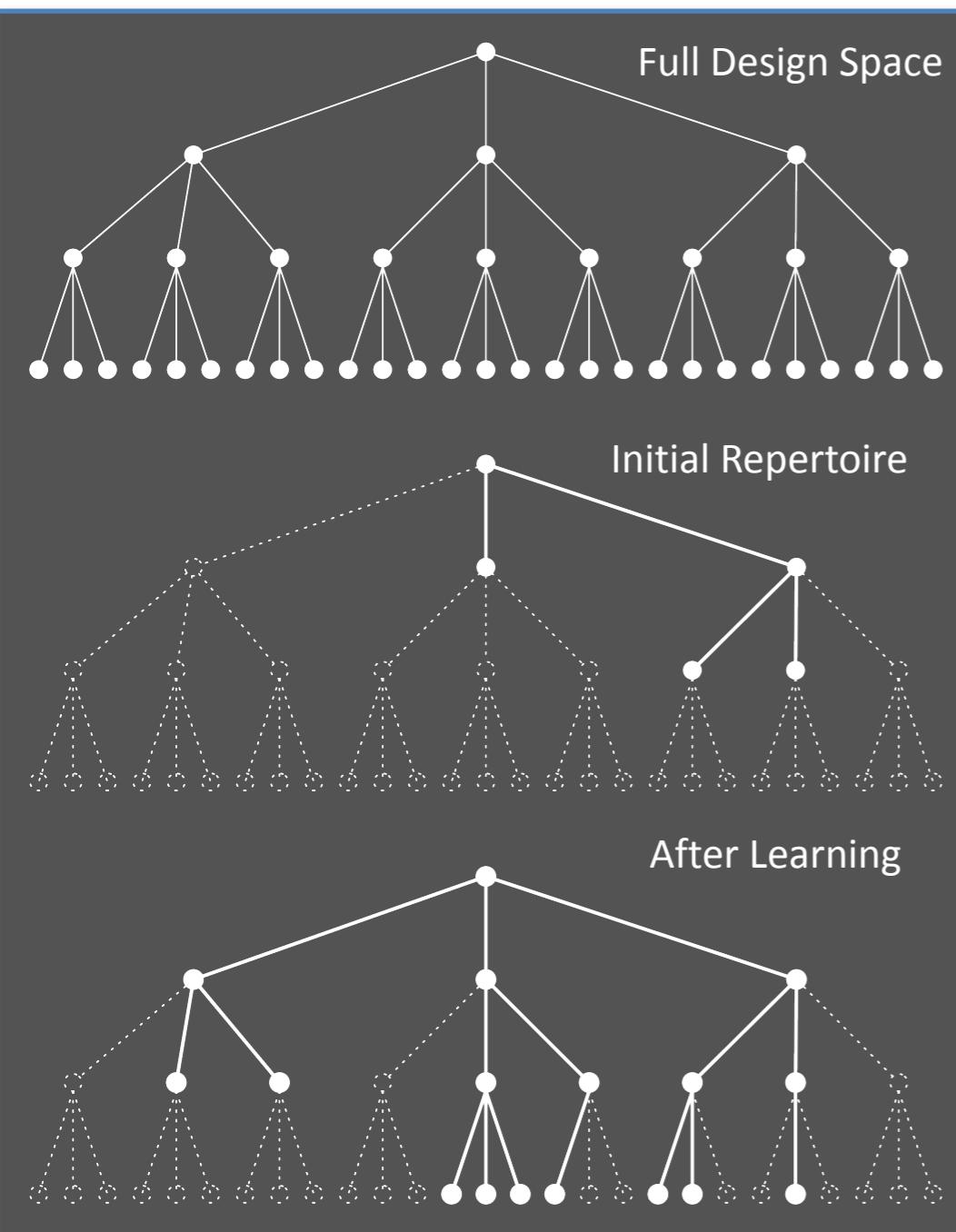
A. Mesoudi and K. Aoki (eds.) *Learning Strategies and Cultural Evolution during the Paleolithic*,  
Replacement of Neanderthals by Modern Humans Series, DOI 10.1007/978-4-431-55363-2\_6,  
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# Representing structured information in CT models

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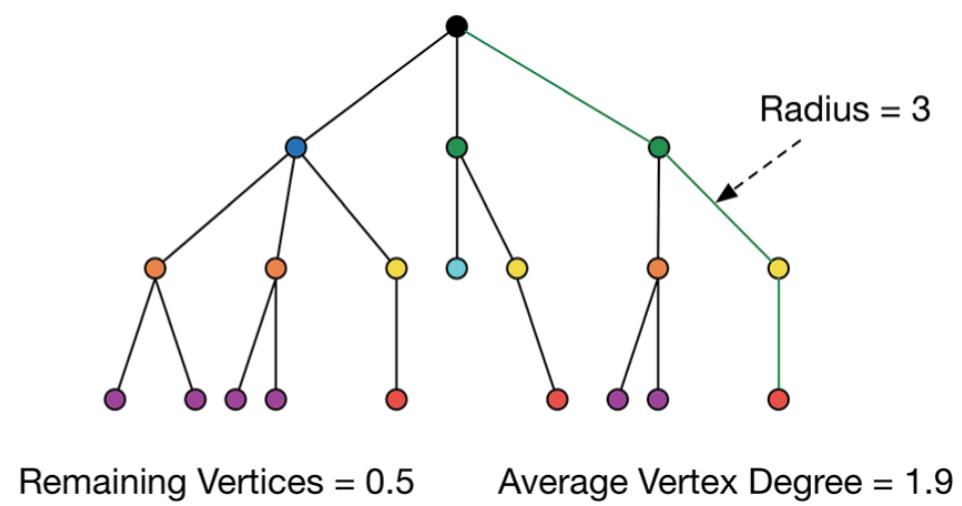
Modeling traits with prerequisite structure  
(inspired by Stout 2011 “action hierarchies”)



## “Semantic” Axelrod Model

- Individuals interact with neighbors with prob ~ trait overlap
- Copying sensitive to having prerequisite
- Probability of being taught a prerequisite
- Probability of individual innovation
- Moran dynamics
- Sample repertoires after  $10^4 - 10^5$  events

## Statistics for Measuring Repertoire Structure



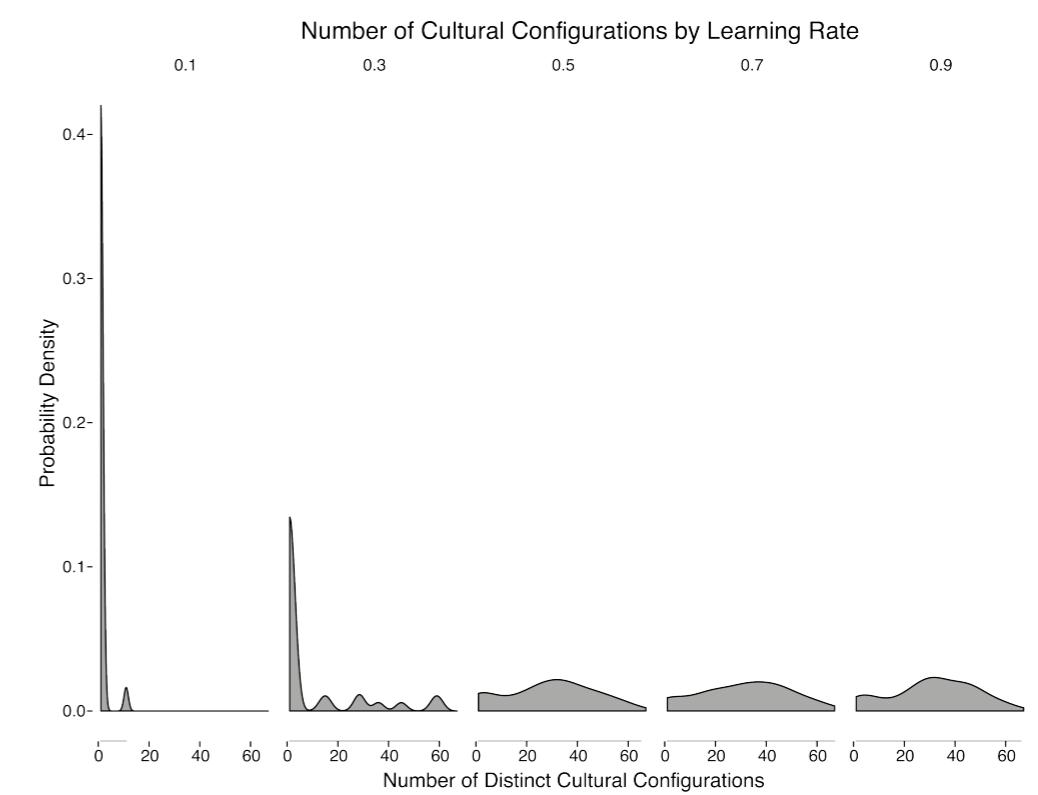
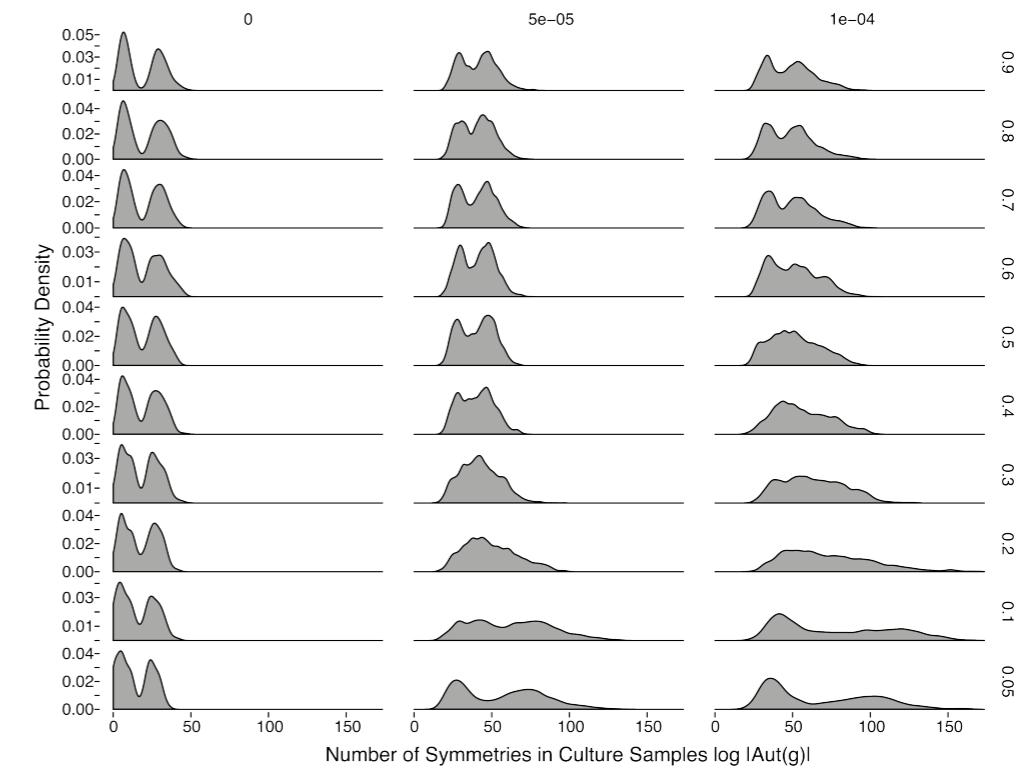
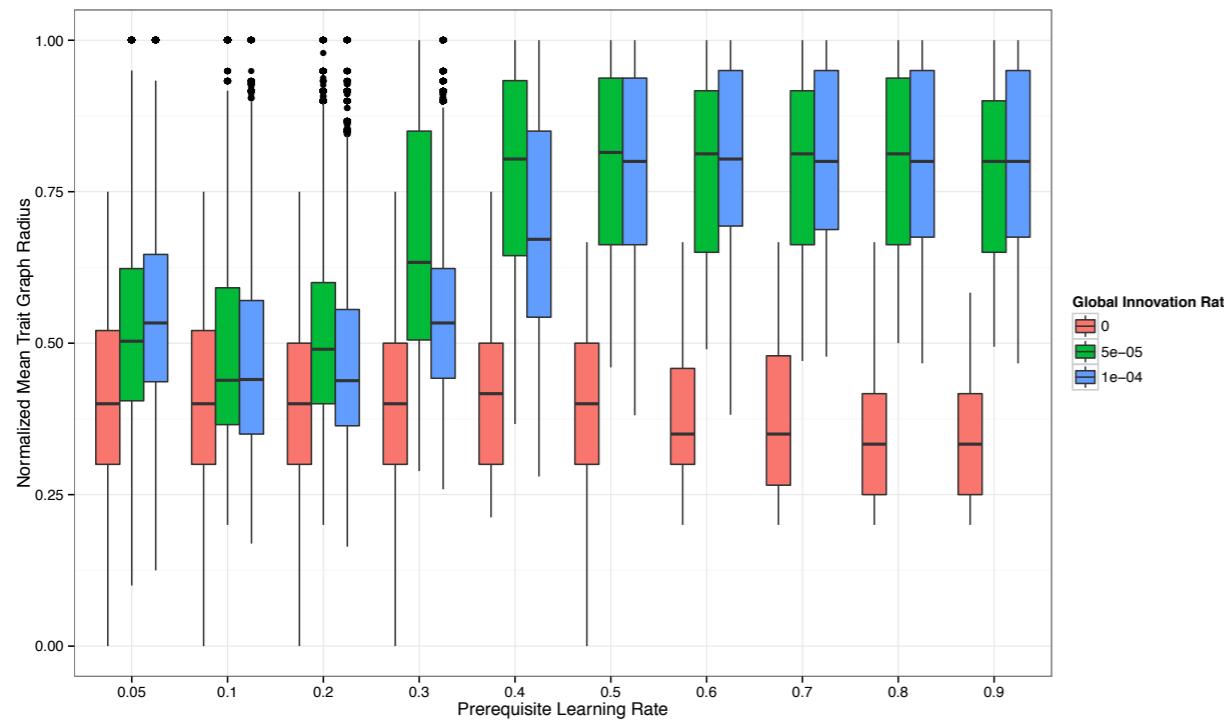
Also: measure “shape” of tree through # of symmetries - size of “automorphism group”

# Results

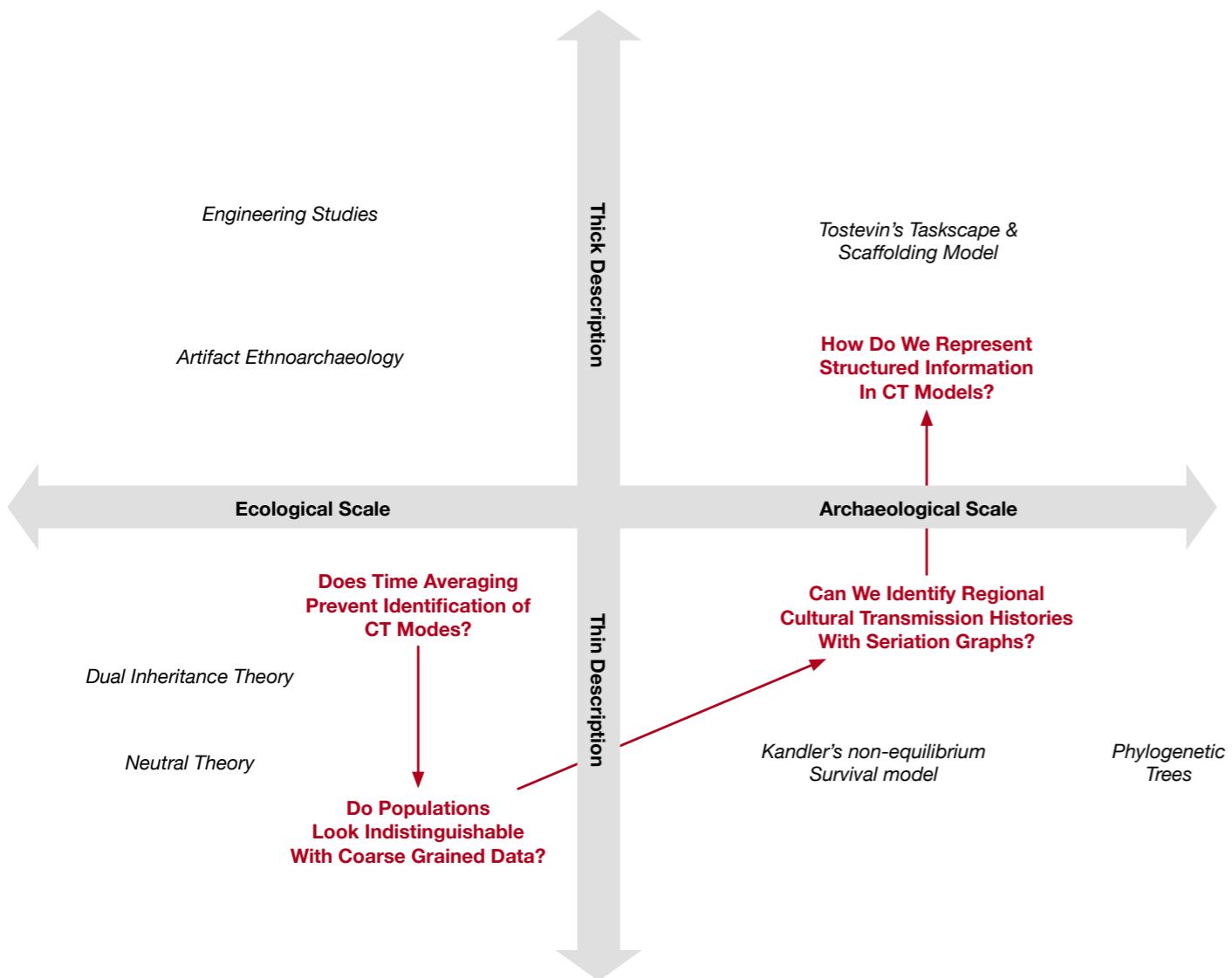
## How Are We Filling Design Space?

Even moderate amounts of “teaching” increase depth of repertoires but individual innovation is critical

Increasing depth means repertoires with more levels of prerequisites



# Conclusions and Contributions



- Effects of time averaging, particularly relationship to trait turnover
- Method for screening equifinality via classifier models and predictive data distributions
- Temporal networks as diachronic models for CT in space/time
- Seriation graphs as the diachronic observable at the mesoscale
- Dependency trees as the observable for content of transmitted traits

# Thank You!

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