The OU model was created for optimality theory.

It works by things moving towards an optimum phenotype.

Most extensions of the original OU model have focused on locating regimes.

However, little attention has been given on how traits can influence regimes.

Here we jointly model the evolution of regimes.

Furthermore, by jointly modeling with an HMM we can discover things.

The Ornstein-Uhlnbeck model has received considerable attention since its original application to phylogenetic comparative datasets both empirically and theoretically (Hansen 1997).

When extending to multiple evolutionary optima, these regimes were assumed to be known a priori, informed by any biological insights (Butler and King, 2004). Since then, there have been many attempts to forego the a priori placement of regimes and instead infer their location based on the continuous traits of interest (surface, bayou, lasso). However, the nature of this inference leads to the small-p, large-n problem in which we are evaluating more hypotheses than there are data points. Furthermore, this forgoes attributing a model to the regimes themselves, instead finding the particular painting which best matches the chosen criterion. These approaches have value since they appropriately assume that there is heterogeneity in the evolutionary process. They utilize this heterogeneity to locate where regimes change and from that leave room for discovery. But, by placing regimes on the phylogeny without reference to the evolutionary process of the regimes themselves we fail to capture how the mutual information that the regimes and continuous traits contain about one another. Instead, our regime paintings simply reflect what’s best for the continuous trait.

We know that regimes and traits covary, that they contain information about one another, so why do we pretend this is a one way street?

Our method can be used in conjunction with other methods that infer the number and position of optima with predefined hypotheses. These methods can give insights into the amount of heterogeneity in the process and inform the number of hidden states that may be appropriate.

This is 1000 points for OUM where only sigma and alpha varied

10:04

Chart, scatter chart

Description automatically generated

10:04

I'll next check BMS

Brian O'Meara 10:06 AM

ooh -- not directly related to your stuff, but it's cool to see dentist putting so much effort at the ∆2 sampling

James Boyko:somethingsomething: 10:06 AM

I set it it delta10 :grimacing:

Brian O'Meara 10:07 AM

oh, so it is

James Boyko:somethingsomething: 10:28 AM

As expected, sigma1 is linear sloping towards 0

Brian O'Meara 10:29 AM

look at the curvature of the boundary between black and gray for sigma1 vs mk

Chart, scatter chart

Description automatically generated

10:30

seems to go almost horizontal at high mk

10:30

which is also consistent with the mk alone plot

10:31

basically, any value of mk can result in a good likelihood by shifting sigma. And at high mk, only need to shift sigma a little bit

James Boyko:somethingsomething: 10:32 AM

But those shifts are still kinda small

10:32

0.0001 units of sigma (edited)

Brian O'Meara 10:34 AM

true

10:34

but also, small CI

James Boyko:somethingsomething: 10:35 AM

Mm, ya I think I see what you're saying

10:35

This ran 1000 steps looking for all points within 2 negative log likelihood units of the best parameter values.

Parameters:

Mk sigma1

best 175.08401 0.0007190998

lower.CI 42.75232 0.0006931472

upper.CI 643.76385 0.0008813270

lowest.examined 18.03420 0.0006931472

highest.examined 680.02042 0.0010323681

Brian O'Meara 10:35 AM

the mk rate seems ridiculous. How many changes on a time interval from root to tip would that be?

James Boyko:somethingsomething: 10:36 AM

100s

10:37

It is absolutely ridiculous

Lynch (1991)