Regime shifts in

ecology & evolution

@cboettig

1. Fluctuation Domains
2. Evolutionary Regime Shifts
3. Limits of Information
4. Programmatic data access
5. Early Warning Signals

Two story lines

Two story lines

- Polished, linear, thematic progression

Two story lines

- Polished, linear, thematic progression (faculty)

Two story lines

- Polished, linear, thematic progression (faculty)
- How things actually happened

Two story lines

- Polished, linear, thematic progression (faculty)
- How things actually happened (students)

Mean Trait Path
Variance Between Paths
Snapshot of Path Distribution
Mean Trait, $\hat{x}$
Trait Var, σ^2
Density
Time, t
Trait, x

(a) Implicit resource. (b) Chemostat. (c) Branching.

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Fluctuation domains in adaptive evolution

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ABSTRACT

We derive an expression for the variation between parallel trajectories in phenotypic evolution, extending the well known result that predicts the mean evolutionary path in adaptive dynamics or quantitative genetics. We show how this expression gives rise to the notion of fluctuation domains – parts of the fitness landscape where the rate of evolution is very predictable (due to fluctuation dissipation) and parts where it is highly variable (due to fluctuation enhancement). These fluctuation domains are determined by the curvature of the fitness landscape. Regions of the fitness landscape with positive curvature, such as

1. Numerics aren't always wrong

1. Numerics aren't always wrong
2. stochastic phenomenon, not present in deterministic model

1. Numerics aren't always wrong
2. stochastic phenomenon, not present in deterministic model
3. Emergence of *regimes* of behavior

f(x) dt

Ornstein-Uhlenbeck
Brownian
confused
methods
Felsenstein
landscapes
wrong
what
noisy
fuzzy
peaks
comparative
adaptive
evolution
stochastic

Detecting evolutionary regime shifts with

comparative phylogenetics

Once upon a time…

Phylogeny was a nuisance.

Phylogeny was a nuisance.

something we “corrected for”

Then we turned our attention to the parameters

Then we turned our attention to the parameters

σ^2	Diversification
α	Stabilizing selection
θ	Adaptive Optimum
λ	phylogenetic signal
κ	speciational change
δ	accelerating / decelerating rates

The parameters were allowed to change,

The parameters were allowed to change, we became interested in where the *changes* occur.

Regime

Shifts

The Phylogeny of Phylogenetic Models

A key innovation?

A key innovation?

This guy

A key innovation?

This guy

These fish

Epinephelus polyphekadion
Platax orbicularis
Diagramma pictum
Kyphosus vaigiensis
Etroplus maculatus
Ptychochromis oligacanthus
Thorichthys meeki
Amphistichus argenteus
Rhacochilus vacca
Embiotoca jacksoni
Dascyllus trimaculatus
Abudefduf saxatilis
Dischistodus chrysopoecilus
Ambliglyphidodon leucogaster
Lachnolaimus maximus
Achoerodus viridis
Pseudodax moluccanus
Bodianus mesothorax
Semicossyphus pulcher
Bodianus rufus
Clepticus parrae
Neoodax balteatus
Odax acroptilus
Xiphocheilus typus
Choerodon anchorago
Choerodon schoenleinii
Iautoga onitis
Tautogolabrus adspersa
Chlorurus sordidus
Scarus dimidiatus
Scarus frenatus
Sparisoma chrysopterum
Cryptotomus roseus
Nicholsina usta
Epibulus insidiator
Oxycheilinus bimaculatus
Cheilinus oxycephalus
Cheilinus undulatus
Cheilinus fasciatus
Wetmorella nigropinnata
Oxycheilinus unifasciatus
Oxycheilinus celebicus
Cirrhilabrus lubbocki
Pseudocheilinus octotaenia
Pteragogus enneacanthus
Pteragogus cryptus
Malapterus reticulatus
Cheilio inermis
Novaculichthys taeniourus
Novaculoides macrolepidotus
Xyrichtys martinicensis
Iniistius aneitensis
Cymolutes praetextatus
Cymolutes torquatus
Austrolabrus maculatus
Pictilabrus laticlavia
Notolabrus gymnogenis
Pseudolabrus gayi
Coris aygula
Hologymnosus doliatus
Coris gaimaird
Pseudocoris yamashiroi
Hemigymnus melapterus
Oxyjulis californica
Halichoeres nicholsi
Halichoeres notospilus
Halichoeres bivittatus
Halichoeres radiatus
Stethojulis bandenensis
Stethojulis trilineata
Gomphosus varius
Thalassoma bifasciatum
Thalassoma lunare
Labrichthys unilineatus
Diproctacanthus xanthurus
Labropsis australis
Larabicus quadrilineatus
Labroides dimidiatus
Labroides bicolor
Labroides rubrolabiatus
Ophthalmolepis lineolata
Halichoeres hartzfeldi
Leptojulis cyanopleura
Anampses caeruleopunctatus
Anampses neoguinaicus
Pseudojuloides atavai
Pseudojuloides cerasinus
Halichoeres hortulanus
Halichoeres scapularis
Macropharyngodon geoffroy
Macropharyngodon meleagris
Coris batuensis
Halichoeres margaritaceus
Halichoeres miniatus
Halichoeres solorensis
Halichoeres papilionaceus
Halichoeres marginatus
Halichoeres argus
Hypsigenyines
Labrines
Scarines
Cheilines
Pseudocheilines
Novaculines
Pseudolabrines
Julidines
Labrichthyines
Po
Ej
As
Lm
Pm
Bm
Oa
Ca
To
Sf
Sc
Ei
Co
Cl
Pc
Mr
Ci
Xa
Nt
Pg
Cg
Pc
Tl
Gv
Hm
St
Oc
Hb
Dx
La
Ld
Hh
Lc
An
Hh
Mm
Hma
Hm
Ha

Fish Suck

Fish Suck

Nc
EB4
UPJ
Di
LPJ

These fish don't suck

Nc
Di
UPJ
EB4
LPJ

UPJ
LPJ

1
5 cm

Did this innovation release the constraints

of suction feeding?

. . . and release a burst of jaw evolution?

An evolutionary regime shift?

a large change in the model parameters

An evolutionary regime shift?

a large change in the model parameters
In which parameters?

Candidate models

Unconstrained Evolution

Constrained Evolution

Release of constraint

Accelerating rates

Brownian Motion
Ornstein-Uhlenbeck
Accelerated Evolution
Release of Constraint
trait value
time
2
1
0
-1
-2
0
20
40
60
80
100

THE FOLLOWING **PREVIEW** HAS BEEN APPROVED FOR

ALL AUDIENCES

THE **MATH** ADVERTISED HAS BEEN RATED

R RESTRICTED

MAY REDUCE CITATION COUNTS ®

Fawcett & Higginson (2012) PNAS

$$X_{T_1} = \underbrace{X_0}_{\text{where you start}} e^{-\alpha_1 T_1} + \underbrace{\theta_1 \left(1 - e^{-\alpha_1 T_1}\right)}_{\text{Where you are going}} + \underbrace{\int_0^{T_1} \sigma_1 e^{\alpha_1 (s - T_1)} \mathrm{d}W_s}_{\text{Random shocks along the way}}$$

$$X_{T_1} = \underbrace{X_0}_{\text{where you start}} e^{-\alpha_1 T_1} + \underbrace{\theta_1 \left(1 - e^{-\alpha_1 T_1}\right)}_{\text{Where you are going}} + \underbrace{\int_0^{T_1} \sigma_1 e^{\alpha_1 (s - T_1)} \mathrm{d}W_s}_{\text{Random shocks along the way}}$$

$$X_{T_2} = \underbrace{X_1}_{\text{where you were}} e^{-\alpha_2 T_2} + \underbrace{\theta_2 \left(1 - e^{-\alpha_2 T_2}\right)}_{\text{possibly new optimum}} + \underbrace{\int_{T_1}^{T_2} \sigma_2 e^{\alpha_2 (s - T_2)} \mathrm{d}W_s}_{\text{possibly new shocks}}$$

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$$\gamma_i = -\sum_{j=i+1}^{n} \alpha_j t_j$$

Generalized OU model

$$X_N = \sum_{i=0}^{n} e^{\gamma_i} \left[\theta_i \left(1 - e^{\alpha_i t_i}\right) + \int_0^{t_i} \sigma_i e^{\alpha_i (s - t_i)} \mathrm{d}W_s^i \right]$$

Some Mathematical Conveniences

Some Mathematical Conveniences

- Gaussian process!

Some Mathematical Conveniences

- Gaussian process! Need only $\mathrm{E}(X_i)$ and $\mathrm{Cov}(X_i, X_j)$

Some Mathematical Conveniences

- Gaussian process! Need only $\mathrm{E}(X_i)$ and $\mathrm{Cov}(X_i, X_j)$
- Evolution on different branches is *independent*

Averaging removes the random shocks

Averaging removes the random shocks

$$\mathrm{E}(X_i) \quad = \quad \sum_{i=0}^{n} e^{\gamma_i} \left[\theta_i \left(1 - e^{\alpha_i t_i} \right) \right]$$

Averaging removes the random shocks

$$\mathrm{E}(X_i) \quad = \quad \sum_{i=0}^{n} e^{\gamma_i} \left[\theta_i \left(1 - e^{\alpha_i t_i} \right) \right]$$

Itô Isometry makes stochastic integrals into regular integrals!

Averaging removes the random shocks

$$\mathrm{E}(X_i) \quad = \quad \sum_{i=0}^{n} e^{\gamma_i} \left[\theta_i \left(1 - e^{\alpha_i t_i} \right) \right]$$

Itô Isometry makes stochastic integrals into regular integrals!

$$\mathrm{E}(\int f(X_i) dW_i \times \int f(X_j) dW_j)$$

Averaging removes the random shocks

$$\mathrm{E}(X_i) \quad = \quad \sum_{i=0}^{n} e^{\gamma_i} \left[\theta_i \left(1 - e^{\alpha_i t_i} \right) \right]$$

Itô Isometry makes stochastic integrals into regular integrals!

$$\mathrm{E}(\int f(X_i) dW_i \times \int f(X_j) dW_j)$$

$$\mathrm{Cov}(X_i, X_j) =$$
$$\sum_{i=1}^{n} \left[e^{\gamma_i} \int_0^{t_i} \sigma_i e^{\alpha_i (u - t_i)} \mathrm{d}W_u^i \right] \times$$
$$\sum_{j=1}^{m} \left[e^{\gamma'_j} \int_0^{s_j} \sigma'_j e^{\alpha'_j (v - s_j)} \mathrm{d}W_v^j \right]$$

Covariance matrix determines the likelihood

$$\mathrm{Cov}(X_i, X_j) = \sum_{s=0}^{k} \left[e^{\gamma_s + \gamma'_s} \frac{\sigma_s^2}{2\alpha_s} \left(1 - e^{-2\alpha_s t_s}\right) \right]$$

Rooting our model

Some comparative physiology: Brownian models

$$\underbrace{\mathrm{d}X}_{\text{trait change}} = \underbrace{\sigma}_{\text{rate}} \times \underbrace{\mathrm{d}B_t}_{\text{Brownian}}$$

Some comparative physiology: Brownian models

$$\underbrace{\mathrm{d}X}_{\text{trait change}} = \underbrace{\sigma}_{\text{rate}} \times \underbrace{\mathrm{d}B_t}_{\text{Brownian}}$$

Some comparative physiology: OU models

$$\mathrm{d}X = \alpha(\underbrace{\theta}_{\text{optimum}} - X)\mathrm{d}t + \sigma \mathrm{d}B_t$$

Some comparative physiology: OU models

$$\mathrm{d}X = \alpha(\underbrace{\theta}_{\text{optimum}} - X)\mathrm{d}t + \sigma \mathrm{d}B_t$$

How about:

$$\mathrm{d}X = \underbrace{\alpha}_{\text{selection}} (\theta - X)\mathrm{d}t + \sigma \mathrm{d}B_t$$

How about:

$$\mathrm{d}X = \underbrace{\alpha}_{\text{selection}} (\theta - X)\mathrm{d}t + \sigma \mathrm{d}B_t$$

Combine both:

$$\mathrm{d}X = \alpha(\underbrace{\theta}_{\text{optimum}} - X)\mathrm{d}t + \underbrace{\sigma}_{\text{divers. rate}} \mathrm{d}B_t$$

Combine both:

$$\mathrm{d}X = \alpha(\underbrace{\theta}_{\text{optimum}} - X)\mathrm{d}t + \underbrace{\sigma}_{\text{divers. rate}} \mathrm{d}B_t$$

Many other combinations:

$$\mathrm{d}X = \underbrace{\alpha}_{\text{selection}} \left(\underbrace{\theta}_{\text{optimum}} - X \right) \mathrm{d}t + \sigma \mathrm{d}B_t$$

Many other combinations:

$$\mathrm{d}X = \underbrace{\alpha}_{\text{selection}} \left(\underbrace{\theta}_{\text{optimum}} - X \right)\mathrm{d}t + \sigma \mathrm{d}B_t$$

One model to rule them all?

$$\mathrm{d}X = \underbrace{\alpha}_{\text{selection}} \left(\underbrace{\theta}_{\text{optimum}} - X \right) \mathrm{d}t + \underbrace{\sigma}_{\text{divers. rate}} \mathrm{d}B_t$$

One model to rule them all?

$$\mathrm{d}X = \underbrace{\alpha}_{\text{selection}} \left(\underbrace{\theta}_{\text{optimum}} - X \right)\mathrm{d}t + \underbrace{\sigma}_{\text{divers. rate}} \mathrm{d}B_t$$

σ_1 σ_2

θ_1 θ_2

α_1 α_2

One model to rule them all?

$$\mathrm{d}X = \underbrace{\alpha}_{\text{selection}} \Big(\underbrace{\theta}_{\text{optimum}} - X \Big)\mathrm{d}t + \underbrace{\sigma}_{\text{divers. rate}} \mathrm{d}B_t$$

One model to rule them all?

$$\mathrm{d}X = \underbrace{\alpha}_{\text{selection}} \left(\underbrace{\theta}_{\text{optimum}} - X \right) \mathrm{d}t + \underbrace{\sigma}_{\text{divers. rate}} \mathrm{d}B_t$$

Beaulieu et al 2012, Evolution

But do you have the power to wield it?

But do you have the power to wield it?

Do you have . . . the complete time-calibrated tree of life?

But do you have the power to wield it?

Do you have . . . the complete time-calibrated tree of life?

Or is your data a hobbit?

Can our data support so many parameters?

Where the sidewalk ends

How do we choose between multiple complex models?

Before we can ask which is the right model,

How do we choose between multiple complex models?

Before we can ask which is the right model,
we must ask if we have enough data to tell.

How do we choose between multiple complex models?

Before we can ask which is the right model,
we must ask if we have enough data to tell.

Information citeria don't address this.

How do we choose between multiple complex models?

Before we can ask which is the right model,
we must ask if we have enough data to tell.

Information citeria don't address this.

AIC scores for four model comparisons

AIC scores for four model comparisons

Phylogenetic Monte Carlo

Simulate from simple model →

Phylogenetic Monte Carlo

Phylogenetic Monte Carlo

LogLik(complex) — **LogLik(simple)**

Phylogenetic Monte Carlo

LogLik(complex) — **LogLik(simple)**

Phylogenetic Monte Carlo

LogLik(complex) — LogLik(simple)

Phylogenetic Monte Carlo

LogLik(complex) — LogLik(simple)

Phylogenetic Monte Carlo

Phylogenetic Monte Carlo

LogLik(complex) — **LogLik(simple)**

ORIGINAL ARTICLE

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IS YOUR PHYLOGENY INFORMATIVE? MEASURING THE POWER OF COMPARATIVE METHODS

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Data Archived: Dryad doi:10.5061/dryad.m6r6hc12

Phylogenetic comparative methods may fail to produce meaningful results when either the underlying model is inappropriate or the data contain insufficient information to inform the inference. The ability to measure the statistical power of these methods

and what about the Parrotfish?
Was it a release of constraint after all?

and what about the Parrotfish?
Was it a release of constraint after all?

Of course!

Richer models, deeper holes

DATA

Adopt a theorist

“Getting data is hard. . .

“Getting data is hard. . .
even after it has already been collected!

Software has made comparative methods ubiquitous. . .

So how about data?

Duncan Temple Lang

Duncan Temple Lang

Duncan Temple Lang

Programmatic Access to data

TreeBASE

FishBase

Methods in Ecology and Evolution

APPLICATION

Treebase: an R package for discovery, access and manipulation of online phylogenies

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Summary

Journal of FISH BIOLOGY

Journal of Fish Biology (2012) 81, 2030–2039
doi:10.1111/j.1095-8649.2012.03464.x, available online at wileyonlinelibrary.com

rfishbase: exploring, manipulating and visualizing FishBase data from R

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(Received 23 April 2012, Accepted 22 August 2012)

This article introduces a package that provides interactive and programmatic access to the FishBase repository. This package allows interaction with data on over 30 000 fish species in the rich statistical

Programmatic access for everyone

Scott Chamberlain

Karthik Ram

Programmatic access for everyone

Scott Chamberlain

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RopenSci

Programmatic access for everyone

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ROpenSci

Programmatic access for everyone

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ROpenSci

Programmatic access for everyone

About 30 packages for different data repositories

Mendeley/PLoS API Binary Battle

Build an application with our data, make science more open

http://ropensci.org

Regime shifts in

ecology

Ecological Regime Shifts

Coral Bleaching

Eutrophication

Are there early warning signs of regime shifts?

Early Warnings of Regime Shifts: A Whole-Ecosystem Experiment
Early-warning
LETTER
REVIEWS
nature
Early warning signals of extinction in deteriorating environments
LETTER
Recovery rates reflect distance to a tipping point in a living system

A simple theory built on the mechanism of bifurcations

Scheffer *et al.* 2009

Early warning indicators

Let's give it a try. . .

Abundance
0
200
400
600
800
0
500
1000
1500
Time
CV
0.5
1.5
2.5
Autocor
-0.2
0.1
0
500
1000
1500
Time

Abundance
0
200
400
600
800
0
500
1000
1500
Time
CV
1.0
2.0
Autocor
-0.4
0.2
0
500
1000
1500
Time

Abundance
0
200
400
600
800
0
500
1000
1500
Time
CV
1.2
1.8
Autocor
0.1
0.3
0
500
1000
1500
Time

Abundance
0
200
400
600
800
0
500
1000
1500
Time
CV
1.5
2.5
3.5
Autocor
0.0
0.3
0.6
0
500
1000
1500
Time

Abundance
0
200
400
600
800
0
500
1000
1500
Time
CV
1.5
2.5
Autocor
0.0
0.4
0
500
1000
1500
Time

Abundance
0
200
400
600
800
0
500
1000
1500
Time
CV
2.0
3.0
4.0
Autocor
0.0
0.3
0.6
0
500
1000
1500
Time

Abundance
0
200
400
600
800
0
500
1000
1500
Time
CV
2.5
3.5
Autocor
0.0
0.3
0.6
0
500
1000
1500
Time

Abundance
0
200
400
600
800
0
500
1000
1500
Time
CV
3
5
7
Autocor
0.2
0.5
0
500
1000
1500
Time

Abundance
0
200
400
600
800
0
500
1000
1500
Time
CV
4
6
8
Autocor
0.40
0.60
0
500
1000
1500
Time

Abundance
0
200
400
600
800
0
500
1000
1500
Time
CV
20
60
Autocor
0.5
0.7
0
500
1000
1500
Time

Prediction Debrief. . .

Prediction Debrief...

- So what's an increase?

Prediction Debrief...

- So what's an increase?
- Do we have enough data to tell?

Prediction Debrief...

- So what's an increase?
- Do we have enough data to tell?
- Which indicators to trust most?

Empirical examples of early warning

Have relied on comparison to a *control system:*

Drake & Griffen 2010

Carpenter *et al.* 2011

We don't have a control system...

All we have is a squiggle

All we have is a squiggle

Making predictions from squiggles is *hard*

A pattern isn't enough

We need a framework

A framework for predicting catastrophe

A framework for predicting catastrophe

A statistic

τ

A framework for predicting catastrophe

A statistic

τ

Not approaching transition

A framework for predicting catastrophe

A statistic

τ

Not approaching transition

Approaching transition

A framework for predicting catastrophe

A statistic

τ

Not approaching transition

Approaching transition

Select a threshold

What's an increase?

What's an increase?

$\tau \in [-1, 1]$ quantifies the trend.

Unfortunately…

Both patterns come from a *stable* process!

Typical?

False alarm!

Typical?

False alarm!

How often do we see false alarms?

Often. τ can take any value in a stable system

Another way to be wrong

Warning Signal?

Failed Detection?

Another way to be wrong

Warning Signal?

Failed Detection?

τ can take any value in a collapsing system

Comparison to a system approaching transition
(100 data pts)
Density
0.0
0.2
0.4
0.6
0.8
1.0
-1.0
-0.5
0.0
0.5
1.0
Kendall's τ

Estimating distributions from generalized models

Beyond the Squiggles

Beyond the Squiggles

- general models by likelihood: stable and critical

Beyond the Squiggles

- general models by likelihood: stable and critical
- simulated replicates for null **and** test cases

Beyond the Squiggles

- general models by likelihood: stable and critical
- simulated replicates for null **and** test cases
- Use model *likelihood ratio* as an indicator

So how are we doing?

False Alarm?

Failed Detection?

Do we have enough data to tell?

Receiver-operator characteristics (ROCs):

Visualize the trade-off between
false alarms and failed detection

False Pos (93%)
True Pos (99.4%)
Density
0.0
0.2
0.4
2
4
6
8
10
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

False Pos (81.3%)
True Pos (97.5%)
Density
0.0
0.2
0.4
2
4
6
8
10
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

False Pos (63.9%)
True Pos (92.2%)
Density
0.0
0.2
0.4
2
4
6
8
10
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

False Pos (42.9%)
True Pos (80.6%)
Density
0.0
0.2
0.4
2
4
6
8
10
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

False Pos (23.3%)
True Pos (61.1%)
Density
0.0
0.2
0.4
2
4
6
8
10
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

False Pos (11.5%)
True Pos (36.9%)
Density
0.0
0.2
0.4
2
4
6
8
10
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

False Pos (4.3%)
True Pos (18.6%)
Density
0.0
0.2
0.4
2
4
6
8
10
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

False Pos (0.9%)
True Pos (7.9%)
Density
0.0
0.2
0.4
2
4
6
8
10
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

False Pos (0.3%)
True Pos (2.4%)
Density
0.0
0.2
0.4
2
4
6
8
10
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

False Pos (0.1%)
True Pos (0.4%)
Density
0.0
0.2
0.4
2
4
6
8
10
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

Density
0.0
0.1
0.2
0.3
2
4
6
8
10
12
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

Density
0.0
0.1
0.2
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0.4
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12
Test Statistic

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0.0
0.4
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Test Statistic

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12
Test Statistic

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0.8

Density
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0.1
0.2
0.3
2
4
6
8
10
12
Test Statistic

True Positive
0.0
0.4
0.8
0.0
0.4
0.8

abundance
Correlation test, τ = 0.807
CV
time

Comparison to a system approaching transition
Density
Kendall's τ

True Positive
False Postive
AUC = 0.63

Correlation test, τ = 0.096
CV
time

Comparison
(1000 data pts)
Density
Kendall's τ

True Positive
False Postive
AUC = 0.95

(a) Stable
(b) Deteriorating
(c) Daphnia
(d) Glaciation III
Data
Var
Autocor
Skew
CV
τ = -0.7
(p = 1e-05)
τ = 0.22
(p = 0.18)
τ = 0.72
(p = 0.0059)
τ = 0.93
(p = <2e-16)
τ = 0.7
(p = 1.6e-06)
τ = -0.15
(p = 0.35)
τ = 0
(p = 1)
τ = 0.64
(p = 3.6e-13)
τ = 0.72
(p = 5.6e-06)
τ = -0.15
(p = 0.35)
τ = 0.61
(p = 0.025)
τ = -0.54
(p = 9.2e-10)
τ = -0.67
(p = 2.3e-05)
τ = 0.31
(p = 0.049)
τ = 0.72
(p = 0.0059)
τ = 0.11
(p = 0.21)
Time

(b) Daphnia
True Positive
0.0
0.2
0.4
0.6
0.8
1.0
Likelihood, 0.87
Variance, 0.59
Autocorr, 0.56
Skew, 0.56
CV, 0.65

Simulation
Daphnia
Glaciation
True Positive
False Positive
Increasing Amount of Data
Likelihood
Variance
Autocorr
Skew
CV

Limits to the detection of early warning signals

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Quantifying limits to detection of early warning for critical transitions

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Catastrophic regime shifts in complex natural systems may be averted through advanced detection. Recent work has provided a proof-of-principle that many systems approaching a catastrophic transition may be identified through the lens of early warning indicators such as rising variance or increased return times. Despite widespread appreciation of the difficulties and uncertainty involved in such forecasts, proposed methods hardly ever characterize their expected error rates. Without the benefits of replicates, controls or hindsight, applications of these approaches must quantify how reliable different indicators are in avoiding false alarms, and how sensitive they are to missing subtle warning signs. We propose a

Evaluating shifts from historical data

The prosecutor's fallacy

(a) Birth rate and death rate functions used in the model

(b) Trajectory of a chance transition from a stable system

(c) Trajectory during an underlying parameter shift

The prosecutor's fallacy

The prosecutor's fallacy

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Early warning signals and the prosecutor's fallacy

Carl Boettiger[1,*] and Alan Hastings[2]

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Early warning signals have been proposed to forecast the possibility of a critical transition, such as the eutrophication of a lake, the collapse of a coral reef or the end of a glacial period. Because such transitions often unfold on temporal and spatial scales that can be difficult to approach by experimental manip-

Conclusions

1. Need for skepticism: Our models are frequently pushing the limits of our data
2. Cause for optimism: ambitious inferences of regime shifts can be made from weak signals given: (1) sufficiently constrained set of models and (2) ample data
3. Way forward involves better understanding of our models, more diverse data, better data infastructure, high performance and widely available software, synthetic and interdisciplinary approaches.

Conclusions

1. Talk to your faculty and colleagues!

Conclusions

1. Talk to your faculty and colleagues! (may be fatal to your existing research program)
2. Present in CPB seminar

Conclusions

1. Talk to your faculty and colleagues! (may be fatal to your existing research program)
2. Present in CPB seminar
3. Exploit your naiveté

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- Wainwright lab members
- Pop Bio cohort (6th yrs)

DOE CSGF

http://carlboettiger.info

addendum: the open laboratory notebook

- Was looking for an example notebook to track my research
- Stumbled on Cameron Neylon's LaBlog: "Open Science"
- tags for each project. Some take 100s of entries.
- some entries follow unpublished work, dead ends, and null results
- reproducible results with knitr/dynamic documents

Use and goals

- explore communication technology. (Blog, RSS, social media integration)
- explore scientific infrastructure. (Search, text mine, semantic RDFa links.)
- provide an educational resource.
- Archive research process.