

Phylogenetic comparative methods: applying modern probabilistic methods to evolutionary biology

Krzysztof Bartoszek

Department of Mathematics
Uppsala University

Będlewo, 28 May 2015

Species proximity

Figs. 2 and 3 (J. Felsenstein. **Phylogenies and the comparative method.** *Am. Nat.*, 125(1): 1-15, 1985)

Figs. 5, 6 and 7 (J. Felsenstein. **Phylogenies and the comparative method.** *Am. Nat.*, 125(1): 1-15, 1985)

Evolutionary models — neutral evolution

- ▶ Independent contrasts, **Brownian motion** (Felsenstein 1985)
- ▶ $dX_t = \sigma dB_t, X_0 = X_0$
- ▶ $E[X](t) = X_0, \quad \text{Var}[X](t) = \sigma^2 t \rightarrow \infty$
- ▶ $\text{Cov}[X_i, X_j](t) = \sigma^2 t_{ij}$

Evolutionary models — adaptive evolution

- ▶ Adaptation, **Ornstein–Uhlenbeck** (Hansen 1997)

- ▶ $dX_t = -\alpha(X_t - \theta)dt + \sigma dB_t, X_0 = X_0$

- ▶ $E[X](t) = e^{-\alpha t}X_0 + (1 - e^{-\alpha t})\theta \rightarrow \theta$

- ▶ $\text{Var}[X](t) = \frac{\sigma^2}{2\alpha}(1 - e^{-2\alpha t}) \rightarrow \frac{\sigma^2}{2\alpha}$

- ▶ $\text{Cov}[X_i, X_j] = \frac{\sigma^2}{2\alpha}(e^{-2\alpha t_{ij}} - e^{-2\alpha t})$

Interacting traits — slouch

- ▶ Adaptation to a randomly fluctuating optimum
- ▶ Allometry $y = ax^b \rightarrow \log y = \log a + b \cdot \log x$
- ▶ Hansen, Pienaar, Orzack (2008)

▶

$$\begin{aligned}dY(t) &= -\alpha \left(Y(t) - \psi(t) - \sum_{l=1}^k b_l X_l(t) \right) dt \\ &\quad + \sigma_y dB_y(t) \\ dX_l(t) &= \sigma_l dB_l(t)\end{aligned}$$

Interacting traits — mvSLOUCH

- ▶ Coadaptation of traits
- ▶ Bartoszek, Pienaar, Mostad, Andersson, Hansen (2012)



$$d\vec{X}(t) = \Sigma d\vec{B}_x(t)$$



$$d\vec{Y}(t) = -\mathbf{A} \left(\vec{Y}(t) - \vec{\psi}(t) \right) dt + \Sigma_y d\vec{B}_y(t)$$



$$\begin{aligned} d\vec{Y}(t) &= -\mathbf{A} \left(\vec{Y}(t) - \vec{\psi}(t) - \mathbf{B}\vec{X}(t) \right) dt \\ &\quad + \Sigma_y d\vec{B}_y(t) \\ d\vec{X}(t) &= \Sigma d\vec{B}_x(t) \end{aligned}$$

Interacting traits — mvSLOUCH

- ▶ Eigenvalues of $\mathbf{A}$ — λ
- ▶ all $\lambda > 0$ — adaptation
- ▶ evolutionary regression $E[\vec{Y}|\vec{X}](t)$
- ▶ optimal regression $\mathbf{B}$
- ▶ $E[\vec{Y}|\vec{X}](t) \rightarrow \mathbf{B}$ in OUBM mode

Simpson's paradox

$$\text{Cov}[Y_i, Y_j](t)$$

Fig. E1 (K. Bartoszek, J. Pienaar, P. Mostad, S. Andersson, T.F. Hansen. **A phylogenetic comparative method for studying multivariate adaptation.** *J. Theor. Biol.*, 314:204–215, 2012)

Fig. 2A (K. Bartoszek, J. Pienaar, P. Mostad, S. Andersson, T.F. Hansen. **A phylogenetic comparative method for studying multivariate adaptation.** *J. Theor. Biol.*, 314:204–215, 2012)

- ▶ antler length, male and female body size
- ▶ breeding group size, mating strategy

Coadaptation — mvSLOUCH

Plard et. al. (2011) OLS explains the data best
i.e. *no* phylogenetic effects, but only compared to BM.

Figs. 1 and 3 ([K. Bartoszek](#), [J. Pienaar](#), [P. Mostad](#), [S. Andersson](#),
[T.F. Hansen](#). **A phylogenetic comparative method for studying
multivariate adaptation.** *J. Theor. Biol.*, 314:204–215, 2012)

mvSLOUCH analysis

Figs. 2C and 2D ([K. Bartoszek, J. Pienaar, P. Mostad, S. Andersson, T.F. Hansen](#). **A phylogenetic comparative method for studying multivariate adaptation.** *J. Theor. Biol.*, 314:204–215, 2012)

- ▶ antler length = female body size + breeding group size
- ▶ male body size = female body size + breeding group size
- ▶ female body size : BM

“Tree-free” methods

But what if we do not observe
the tree ?

Fig. 1 (S. Sagitov, K. Bartoszek **Interspecies correlation for
neutrally evolving traits.** *J. Theor. Biol.*, 309:11–19, 2012)

Gernhard (2008), Sagitov and KB (2012)

-

A horizontal sequence of dots representing a 1D lattice. The first dot on the left is blue. The subsequent dots are black. A green arrow points upwards to the fourth dot from the left, which is labeled $k=3$. Ellipses ($\dots$) are placed between the fourth and fifth dots, indicating the continuation of the lattice.

Conditioned Yule tree

$$H_{n,k} = \sum_{i=1}^n \frac{1}{i^k} \quad b_{n,x} = \prod_{i=1}^n \frac{i}{i+x}$$

- ▶ $E[T] = H_{n,1}/\lambda \sim \ln n/\lambda$
- ▶ $\text{Var}[T] = H_{n,2}/\lambda^2 \rightarrow \frac{\pi^2}{6\lambda^2}$
- ▶ $E[\tau] = \frac{n+1}{\lambda(n-1)}H_{n,1} - \frac{2n}{\lambda(n-1)} \sim \ln n/\lambda$
- ▶ $\text{Var}[\tau] = \frac{(n^2-1)H_{n,2} - 2(n+1)H_{n,1}^2 + 4(n+1)H_{n,1} - 4n}{\lambda^2(n-1)^2} \rightarrow \frac{\pi^2}{6\lambda^2}$
- ▶ $\text{Cov}[T, \tau] = \frac{1}{\lambda^2(n-1)}(2n - (n+1)H_{n,2}) \rightarrow \frac{1}{\lambda^2}(2 - \frac{\pi^2}{6})$
- ▶ $E[e^{-\gamma T}] = b_{n,\gamma}, \quad E[e^{-\gamma \tau}] = \frac{2-(n+1)(\gamma+1)b_{n,\gamma}}{(n-1)(\gamma-1)}$

Application: Interspecies correlation ($\lambda = 1$)

How similar do we expect two random species to be?

$$\rho_n = \frac{\text{Cov}[X_1, X_2]}{\text{Var}[X]}$$

Brownian motion

$$dX(t) = \sigma dB(t) \quad X(0) = X_0$$

$$\mathbb{E}[X(t)] = X_0 \quad \text{Var}[X(t)] = \sigma^2 t$$

$$\rho_n \sim 2(\ln n)^{-1}$$

Ornstein–Uhlenbeck process

$$dX(t) = -\alpha(X(t) - \theta)dt + \sigma dB(t) \quad X(0) = X_0$$

$$\mathbb{E}[X(t)] = e^{-\alpha t} X_0 + (1 - e^{-\alpha t})\theta \quad \text{Var}[X(t)] = \frac{\sigma^2}{2\alpha}(1 - e^{-2\alpha t})$$

$$\rho_n \sim \begin{cases} Cn^{-2\alpha} & 0 < \alpha < 0.5 \\ 2n^{-1} \ln n & \alpha = 0.5 \\ Cn^{-1} & \alpha > 0.5 \end{cases}$$

Application: Classical estimators ($\lambda = 1$)

$$\bar{X}_n := \frac{1}{n} \sum_{i=1}^n X_i \qquad S_n^2 := \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2$$

	$E[\bar{X}_n]$	$\text{Var}[\bar{X}_n]$	$E[S_n^2]$	$\text{Var}[S_n^2]$
$\alpha = 0$	X_0	$2\sigma^2$	$\sigma^2 \ln n + O(1)$	$(\frac{\pi^2}{6} + 1)\sigma^4$
$\alpha \in (0, \frac{1}{2})$	$\theta + O(n^{-\alpha})$	$c_\alpha n^{-2\alpha}$	$\frac{\sigma^2}{2\alpha} + O(n^{-2\alpha})$	$O(n^{-2\alpha})$
$\alpha = \frac{1}{2}$	$\theta + O(n^{-\alpha})$	$2 \frac{\ln n}{n}$	$\frac{\sigma^2}{2\alpha} + O(\frac{\ln n}{n})$	$O(\frac{\ln n}{n})$
$\alpha > \frac{1}{2}$	$\theta + O(n^{-\alpha})$	$c_\alpha n^{-1}$	$\frac{\sigma^2}{2\alpha} + O(n^{-2\alpha})$	$O(n^{-1})$

$$\text{Var} [S_n^2] \rightarrow 0$$

$$\mathbb{E} [S_n^2] \rightarrow \frac{\sigma^2}{2\alpha}$$

$$S_n^2 = \frac{1}{n} \sum_i X_i^2 - \frac{2}{n(n-1)} \sum_i \sum_{j>i} X_i X_j$$

$$\begin{aligned} \mathbb{E} [Z_1 Z_2 Z_3 Z_4] &= m^4 \\ &+ m^2 (c_{12} + c_{13} + c_{14} + c_{23} + c_{24} + c_{34}) \\ &+ c_{12} c_{34} + c_{13} c_{24} + c_{14} c_{23}. \end{aligned}$$

$$\text{Var} [S_n^2] \rightarrow 0$$

$$\begin{aligned} \mathbb{E} [(S_n^2)^2] &= \frac{1}{n^2} \left(\sum_i \mathbb{E} [X_i^4] + 2 \sum_i \sum_{j>i} \mathbb{E} [X_i^2 X_j^2] \right) \\ &\quad - \frac{4}{n^2(n-1)} \left(\sum_i \sum_{j>i} \mathbb{E} [X_i^3 X_j] \right. \\ &\quad \left. + \sum_i \sum_{j>i} \mathbb{E} [X_i X_j^3] + \sum_i \sum_{j>i} \sum_{k \neq i,j} \mathbb{E} [X_i^2 X_j X_k] \right) \\ &\quad + \frac{4}{n^2(n-1)^2} \left(\sum_i \sum_{j>i} \mathbb{E} [X_i^2 X_j^2] \right. \\ &\quad \left. + \sum_i \sum_{j>i} \sum_{k \neq i,j} \mathbb{E} [X_i^2 X_j X_k] \right. \\ &\quad \left. + \sum_i \sum_{j>i} \sum_{k \neq i,j} \mathbb{E} [X_i X_j^2 X_k] \right. \\ &\quad \left. + \sum_i \sum_{j>i} \sum_{k \neq i,j} \sum_{m>k; m \neq i,j} \mathbb{E} [X_i X_j X_k X_m] \right). \end{aligned}$$

$$b_{n,x} \sim \Gamma(x+1)n^{-x}$$

Application: weak convergence

Theorem

Let $\delta = \frac{X_0 - \theta}{\sqrt{\sigma_a^2/2\alpha}}$ be a normalized difference between the ancestral and optimal values. Consider the normalized sample mean $\bar{Y}_n = \frac{\bar{X}_n - \theta}{\sqrt{\sigma_a^2/2\alpha}}$ of the Yule-Ornstein-Uhlenbeck process with $\bar{Y}_0 = \delta$. As $n \rightarrow \infty$ the process $\bar{Y}_n$ has the following limit behaviour.

- (i) If $\alpha > 0.5$, then $\sqrt{n} \cdot \bar{Y}_n$ is asymptotically normally distributed with zero mean and variance $\frac{2\alpha+1}{2\alpha-1}$.
- (ii) If $\alpha = 0.5$, then $\sqrt{n/\ln n} \cdot \bar{Y}_n$ is asymptotically normally distributed with zero mean and variance 2.
- (iii) If $\alpha < 0.5$, then $n^\alpha \cdot \bar{Y}_n$ converges a.s. and in L^2 to a random variable $Y_{\alpha,\delta}$ with $E[Y_{\alpha,\delta}] = \delta\Gamma(1+\alpha)$ and $E[Y_{\alpha,\delta}^2] = \left(\delta^2 + \frac{4\alpha}{1-2\alpha}\right)\Gamma(1+2\alpha)$.

Weak convergence proof sketch

Lemma

Let $\mathcal{Y}_n$ be the σ -algebra containing information about our Yule tree. We have:



$$\mathbb{E} [\bar{Y}_n | \mathcal{Y}_n] = \delta e^{-\alpha T},$$

$$\begin{aligned} \mathbb{E} [\bar{Y}_n^2 | \mathcal{Y}_n] &= n^{-1} + (1 - n^{-1}) \mathbb{E} [e^{-2\alpha\tau} | \mathcal{Y}_n] \\ &\quad - e^{-2\alpha T} + \delta^2 e^{-2\alpha T}, \end{aligned}$$

$$\begin{aligned} \text{Var} [\bar{Y}_n | \mathcal{Y}_n] &= n^{-1} + (1 - n^{-1}) \mathbb{E} [e^{-2\alpha\tau} | \mathcal{Y}_n] \\ &\quad - e^{-2\alpha T}. \end{aligned}$$

- For all positive α we have $\text{Var} [\mathbb{E} [e^{-2\alpha\tau} | \mathcal{Y}_n]] = O(n^{-3})$ as $n \rightarrow \infty$.

Weak convergence proof sketch

Proof.

E.g.

$$\begin{aligned}\mathrm{Var} [Y_1 + \dots + Y_n | \mathcal{Y}_n] &= n(1 - e^{-2\alpha T}) \\ &\quad + 2 \sum_{i < j} (e^{-2\alpha \tau_{ij}} - e^{-2\alpha T}) \\ &= n - n^2 e^{-2\alpha T} \\ &\quad + n(n-1) \mathrm{E} [e^{-2\alpha \tau} | \mathcal{Y}_n] .\end{aligned}$$



Weak convergence proof sketch

Let $\mathcal{Y}_n$ be the σ -algebra about our Yule tree.

(i)

It suffices to show :

$$(\mu_n, \sigma_n^2) := (\sqrt{n} \mathbb{E} [\bar{Y}_n | \mathcal{Y}_n], n \operatorname{Var} [\bar{Y}_n | \mathcal{Y}_n]) \\ \xrightarrow{P} \left(0, \frac{2\alpha + 1}{2\alpha - 1}\right), \quad n \rightarrow \infty,$$

since then, due to the conditional normality of $\bar{Y}_n$, we will get the following convergence of characteristic functions

$$\mathbb{E} \left[e^{i\gamma \sqrt{n} \cdot \bar{Y}_n} \right] = \mathbb{E} \left[e^{i\mu_n \gamma - \sigma_n^2 \gamma^2 / 2} \right] \rightarrow e^{-\frac{2\alpha+1}{2(2\alpha-1)} \gamma^2}.$$

Weak convergence proof sketch

We can write,

$$\begin{aligned}\mu_n &= \sqrt{n}\delta e^{-\alpha T}, \\ \sigma_n^2 &= 1 + (n-1) \mathbb{E} [e^{-2\alpha\tau} | \mathcal{Y}_n] - ne^{-2\alpha T}.\end{aligned}$$

and further

$$\mathbb{E} [\sigma_n^2] = 1 - nb_{n,2\alpha} + \frac{2 - (n+1)(2\alpha+1)b_{n,2\alpha}}{2\alpha-1} \rightarrow \frac{2\alpha+1}{2\alpha-1}.$$

Due to fast enough decay of variances:

$$\begin{aligned}1 + (n-1) \mathbb{E} [e^{-2\alpha\tau} | \mathcal{Y}_n] &\xrightarrow{L^2} \frac{2\alpha+1}{2\alpha-1}, \\ ne^{-2\alpha T} &\xrightarrow{L^2} 0, \\ \mu_n &\xrightarrow{L^2} 0\end{aligned}$$

hence

$$(\mu_n, \sigma_n^2) \xrightarrow{P} (0, \frac{2\alpha+1}{2\alpha-1}).$$

Application: confidence interval

$$\mathbb{E} [S_n^2] \rightarrow \frac{\sigma_a^2}{2\alpha} \quad \text{Var} [S_n^2] \rightarrow 0$$

allows us to write confidence intervals

$$\text{for } \alpha > 0.5 \quad \bar{X}_n \pm z_{1-x/2} \cdot \sqrt{S_n^2} \cdot \frac{1}{\sqrt{n}} \cdot \sqrt{\frac{2\alpha + 1}{2\alpha - 1}},$$

$$\text{for } \alpha = 0.5 \quad \bar{X}_n \pm z_{1-x/2} \cdot \sqrt{S_n^2} \cdot \frac{\sqrt{2 \ln n}}{\sqrt{n}},$$

$$\text{for } \alpha < 0.5 \quad (\bar{X}_n - q_{x/2} \cdot \sqrt{S_n^2} \cdot n^{-\alpha}, \\ \bar{X}_n + q_{1-x/2} \cdot \sqrt{S_n^2} \cdot n^{-\alpha}).$$

Including jumps

Fig. 1 (K. Bartoszek **Quantifying the effects of anagenetic and cladogenetic evolution.** *Math. Biosc.*, 254:42–57, 2014)

- ▶ Jump has mean 0, variance σ_c^2
- ▶ Jumps decorrelate the contemporary sample
- ▶ Quadratic variation

$$\mathbb{E}[[X]] = \sigma_a^2 \mathbb{E}[T] + \sigma_c^2 \mathbb{E}[\Upsilon^*]$$

Including jumps

$$H_{n,k} = \sum_{i=1}^n \frac{1}{i^k} \quad b_{n,x} = \prod_{i=1}^n \frac{i}{i+x}$$

- ▶ $E[\Upsilon] = 2H_{n,1} - 2 \sim 2 \ln n$
- ▶ $\text{Var}[\Upsilon] = 2(H_{n,1} - 1 - 2(H_{n,2} - 1)) \sim 2 \ln n$
- ▶ $E[v] = \frac{4}{n-1}(n - H_{n,1}) - 2 \rightarrow 2 \quad \text{Var}[v] = 6 + O(n^{-1} \ln n)$
- ▶ $s > 0$, for v we need $n \geq 2$,

$$\begin{aligned} E[s^\Upsilon] &= \frac{1}{n} \frac{1}{b_{n-1,2s-1}} \\ E[s^v] &= \begin{cases} \frac{1}{(n-1)(3-2s)} \left((n+1) - \frac{2}{nb_{n-1,2s-1}} \right) \\ \frac{2(n+1)}{n-1} \left(H_{n+1} - \frac{5}{3} \right), s = 1.5 \end{cases} \end{aligned}$$

Network models

Joint work with G. Jones, B. Oxelman, S. Sagitov

Fig. 1 (K. Bartoszek, G. Jones, B. Oxelman, S.S. **Time to a single hybridization event in a group of species with unknown ancestral history.** *J. Theor. Biol.*, 322:1–6, 2013)

- ▶ speciation rate λ
- ▶ hybridization rate β
- ▶ if $\frac{\beta_n}{2\lambda_n}n \rightarrow 0$ then $\tau_n \xrightarrow{\mathcal{D}} \text{exponential}(2\lambda)$

and also working with S. Glemin, I. Kaj, M. Lascoux (UU)

Thank you !!!!

- ▶ S. Andersson, G. Jones, P. Mostad, B. Oxelman, S. Sagitov, M. Prager (GU, CTH)
- ▶ S. Glemin, I. Kaj, M. Lascoux (UU)
- ▶ V. Mitov, T. Stadler (ETH Zürich)
- ▶ T.F. Hansen, K. Voje (Oslo Univ.)
- ▶ P. Liò, H. Xiao (Cambridge Univ.)
- ▶ J. Pienaar (Alabama Univ.)

References

- ▶ K.B., J. Pienaar, P. Mostad, S. Andersson, T.F. Hansen. **A phylogenetic comparative method for studying multivariate adaptation.** *J. Theor. Biol.*, 314:204–215, 2012
- ▶ S.S., K.B. **Interspecies correlation for neutrally evolving traits.** *J. Theor. Biol.*, 309:11–19, 2012
- ▶ K.B., G. Jones, B. Oxelman, S.S. **Time to a single hybridization event in a group of species with unknown ancestral history.** *J. Theor. Biol.*, 322:1–6, 2013
- ▶ K.B., S.S. **Phylogenetic confidence intervals for the optimal trait value.** *J. Appl. Probab.*, 52, 2015
- ▶ K.B. **Quantifying the effects of anagenetic and cladogenetic evolution.** *Math. Biosc.*, 254:42–57, 2014
- ▶ K.B., S.S. **A consistent estimator of the evolutionary rate.** *J. Theor. Biol.*, 371:69–78, 2015