# Learning to Count: Tests for Evolutionary Innovation and Robust Sequence Distance Estimation

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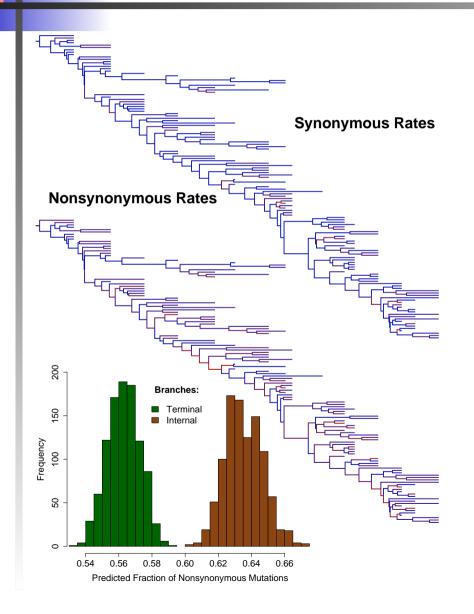
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# Classic Problem: Detecting Adaptation in Intrahost HIV Evolution



- Data: 129 HIV variants from one patient
- Question: Does adaptation occur along the backbone of evolution? (Suggests violations of neutrality)
- Difficulty:
  - Branch/time-specific synonymous/non-synonymous rate models are too unwieldy
- Solution?: Count the expected
   # of labeled transitions

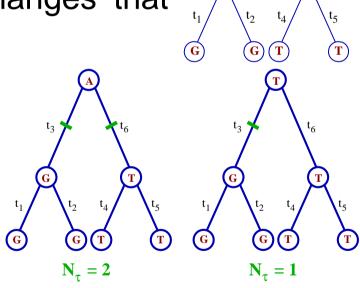
# **Evolutionary Counting Processes: Current Approaches**

Model trait evolution as a continuous-time Markov chain  $\Lambda$ , and

Infer the number  $N_{\tau}$  of state-changes that occur along the tree  $\tau$  via

Stochastic Mapping (Nielsen, 2002):

- Simulation-based
- Uses rejection sampling



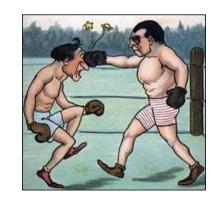
Can do one better? Analytic solutions for  $\Pr(N_{\tau} = n | \mathbf{Y})$  and  $\mathsf{E}(N_{\tau}^{k} | \mathbf{Y})$  enable (computationally) efficient statistical tests.

### Punch-Line: Simulation Methods ... Could Be Better

#### Computational efficiency / accuracy Comparison:

Simulants	Slow Evolving Site $N_{ au}pprox 4$		Fast Evolving Site $N_{ au} \approx 15$	
	Rejections/Simulant	Error	Rejections/Simulant	Error
100	100	0.0598	38845	0.4624
500	105	0.0255	39247	0.3319
1000	102	0.0259	42075	0.2905
10000	106	0.0205	40805	0.2809

- 61-state Markov chain (codon model) on 129-tip tree (HIV evolution)
- Counting labeled subsets of changes (synonymous/non-synonymous) on "internal" vs. "external" branches

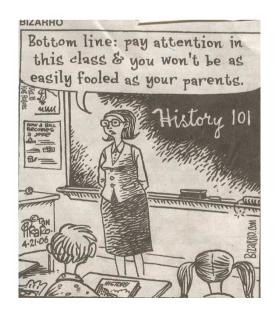


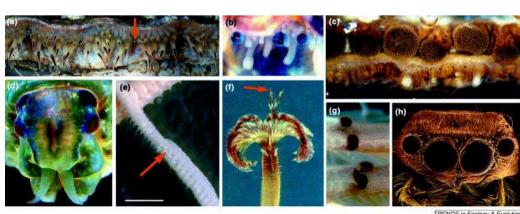
1 min vs. 10 hrs

# Those Who Forget Their History . . .

#### **Three Major Approaches**:

- Examine process at stationarity/no conditioning on start/end points: Ball, Neuts (ion channel physics)
- Label only one specific transition: Guttorp, Bruno, Hobolth
- Via uniformization: Siepel





## **General Framework: Labeled Changes**

Counting 1  $\rightarrow$  3 and 2  $\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\infty \\ \hline $0.0 \\ \hline \end{tabular} \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\infty \\ \hline \end{tabular} \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\infty \\ \hline \end{tabular} \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\infty \\ \hline \end{tabular} \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\infty \\ \hline \end{tabular} \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\infty \\ \hline \end{tabular} \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 <math>\rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  1 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  2 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  2 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  3 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  3 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  3 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  3 Transitions  $X_t: \begin{tabular}{c} $\text{Counting 1} $\rightarrow$ 3 and 2 \rightarrow$  3 Transitions  $X_t: \begin{tabu$ 

- ullet R is a set of ordered index pairs that label transitions
- ullet  $\Lambda$  generator,  $\Lambda_R=\{\lambda_{ij} imes 1_{\{(i,j)\in R\}}\}$ , and  $\Lambda_{\overline{R}}=\Lambda-\Lambda_R$



- Matrix  $\mathbf{Q}(n,t)$  of probabilities  $(N_t = n, X_t = j \mid X_0 = i)$
- Matrix  $\mathbf{M}^{[k]}(t)$  of restricted, factorial moments  $(N_t^{[k]} 1_{\{X_t=j\}} \mid X_0=i)$

### Derivation Sketch: A Moment's Reflection on One Branch

Start with Kolmogorov's Forward equation:

$$\frac{d}{dt}\mathbf{Q}(n,t) = \mathbf{Q}(n,t)\mathbf{\Lambda}_{\overline{R}} + \mathbf{Q}(n-1,t)\mathbf{\Lambda}_{R}$$

and the matrix probability generating function:

$$\mathbf{G}(r,t) = \sum_{n=0}^{\infty} r^n \mathbf{Q}(n,t)$$

Then  $\frac{\partial}{\partial t}\mathbf{G}(r,t) = \mathbf{G}(r,t) \left(\mathbf{\Lambda}_{\overline{R}} + r\mathbf{\Lambda}_{R}\right) \Rightarrow \mathbf{G}(\mathbf{r},\mathbf{t}) = \mathbf{e}^{(\mathbf{\Lambda}_{\overline{\mathbf{R}}} + \mathbf{r}\mathbf{\Lambda}_{\mathbf{R}})\mathbf{t}}$  and  $\mathbf{M}^{[k]}(t) = \frac{\partial^{k}}{\partial r^{k}}\mathbf{G}(r,t)|_{r=1}$  - hard unless  $\mathbf{\Lambda}$  and  $\mathbf{\Lambda}_{R}$  commute!

Use integration instead  $\mathbf{M}^{[k]}(t)=k\int_0^t \mathbf{M}^{[k-1]}(t)\mathbf{\Lambda}_R e^{\mathbf{\Lambda}(t-\theta)}d\theta$ 

$$\mathbf{M}^{[1]}(t) = \sum_{i,j} \mathbf{B}_i \mathbf{\Lambda}_R \mathbf{B}_j I_{ij}(t), \quad I_{ij}(t) = \begin{cases} te^{d_i t} & \text{if } d_i = d_j, \\ \frac{e^{d_i t} - e^{d_j t}}{d_i - d_j} & \text{if } d_i \neq d_j. \end{cases}$$

### Reaping the Rewards of **Counting over Trees**

Let  $\mathbf{H} = \sum_{b} h(X_t^{(b)})$  be an additive summary, where  $h(\cdot)$  counts/rewards (on possibly select branches), e.g.,





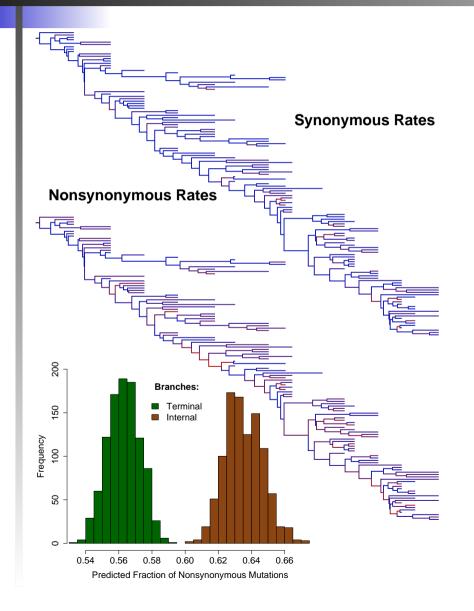


Then E(H) also has an analytic solution  $\Rightarrow$  no simulation of internal-node states or conditioning on ancestral reconstruction.



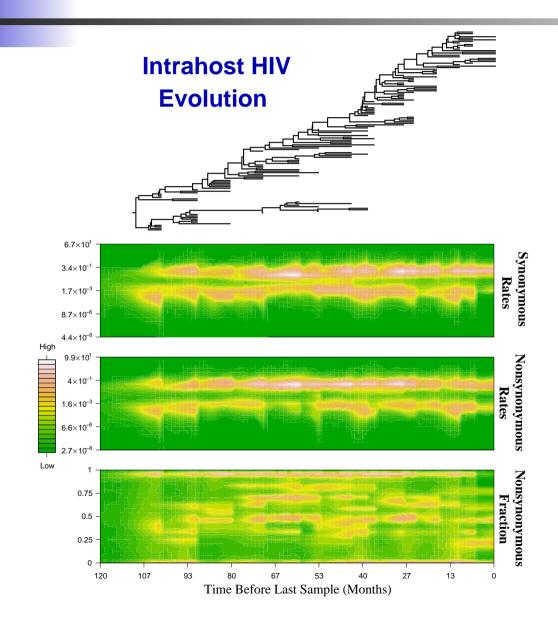
Noteworthy: Integrating H generalizes Felsenstein's Pruning Algorithm, the work-horse of modern phylogenetics.

## **Detecting Adaptation in Intrahost HIV Evolution**



- Data: 129 HIV variants from one patient
- Question: Does adaptation occur along the backbone of evolution? (Suggests violations of neutrality)
- Difficulty: Branch-specific synonymous/non-synonymous rate change models are too unwieldy
- Key: Requires posterior simulation from only a simple, homogeneous rate model

## Temporal Rate Variation in Intrahost HIV Evolution

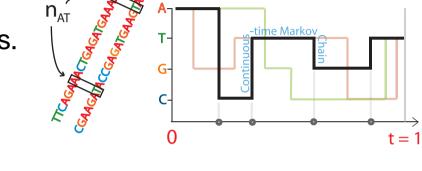


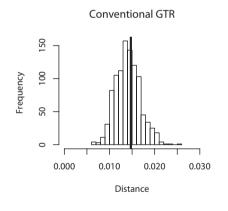
- Branch-specific counts enable rate projection onto real time
- Bimodality of both synonymous and non-synonymous distributions
- Early adaptation, followed by weakening selection

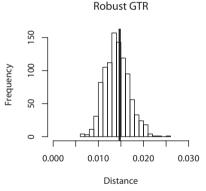
### Pair-wise Robust Distance Estimation

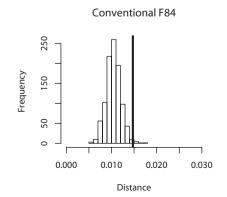
Pairwise distance = E(N) w.r.t.

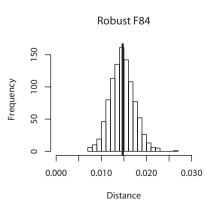
- Stationary( $\pi_i \times p_{ij}$ ) distribution, vs.
- Empirical $(f_{ij})$  distribution (robust) further straight-forward to label











#### **Nucleotide simulation:**

- True model = GTR
- Robust estimator using F84

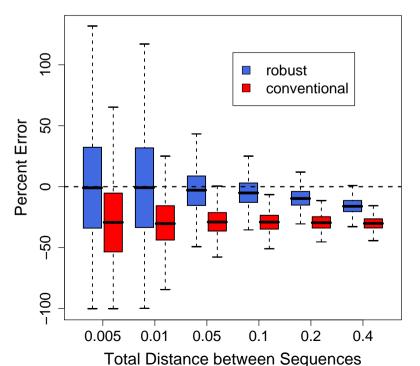
   (analytic calculations)
   performs as well as
   estimators under GTR

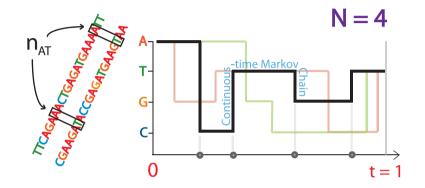
N = 4

### Pair-wise Robust Distance Estimation - II

Pairwise distance = E(N) w.r.t.

- Stationary( $\pi_i \times p_{ij}$ ) distribution, vs.
- Empirical $(f_{ij})$  distribution (robust) further straight-forward to label Robust vs Conventional Distances





#### Nucleotide simulation:

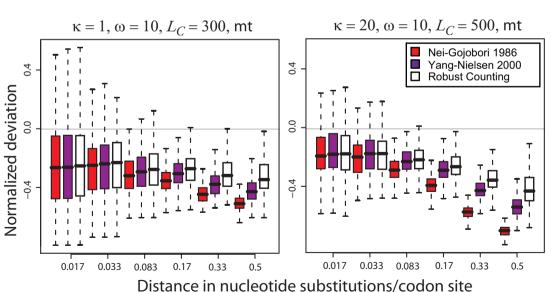
- Vary "true" sequence distance from 0.005 to 0.4
- Robust inference decreases
   bias caused by model
   misspecification

### Robust Labeled Distance Estimation

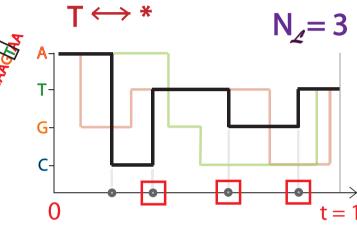
Labeled distance =  $E(N_{\mathcal{L}})$ 

Go robust with a silly codon model:

- Composition 3×F84s
- No numerical optimization



"Neutral" reconstruction possible?



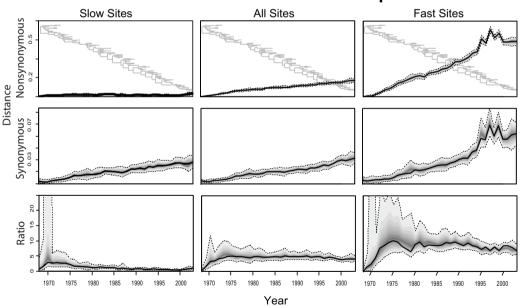
Synonymous distance estimation outperforms:

- Nei and Gojobori (1986)
- Yang and Nielsen (2000) - specially tailored estimator

# **Arbitrarily Sophisticated Distances: Codon Volatility Change in Influenza A H3N2**

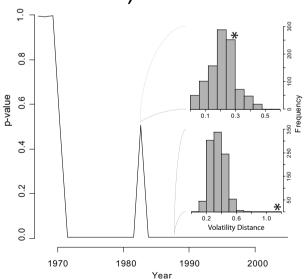
Hypothesis: Codon volatility correlates with selective pressures (Plotkin and Dushoff, 2003)

S/N distances for 96 HA sequences:



Question: Do volatility changes differ in the antibody interaction sites (consistent with the volatility hypothesis)?

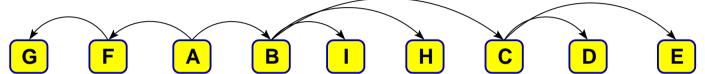
Distribution (epitope vs. elsewhere):



Antigenic shift in 1982

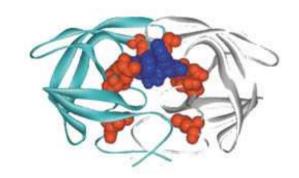
### Handling Convergent Evolution in HIV

#### **Transmission Network**



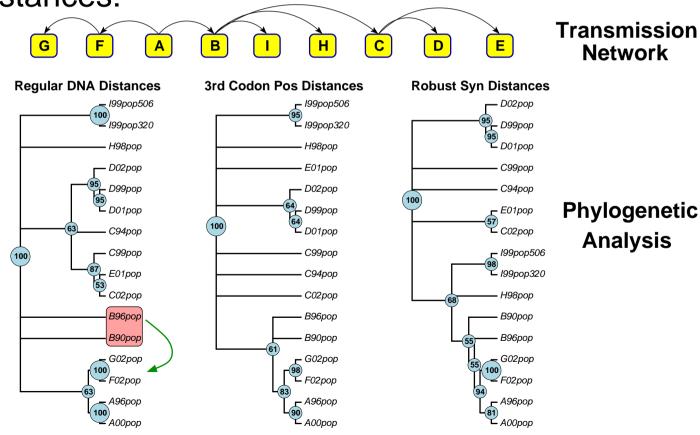
- Lemey et al. (2005) examine the genetic signature of a known HIV transmission network in the face of convergent evolution
- HIV pol and env sequences from 9 subjects
- Distance-based reconstructions using NG86 measures
- Trouble: pol phylogenies conflict with network





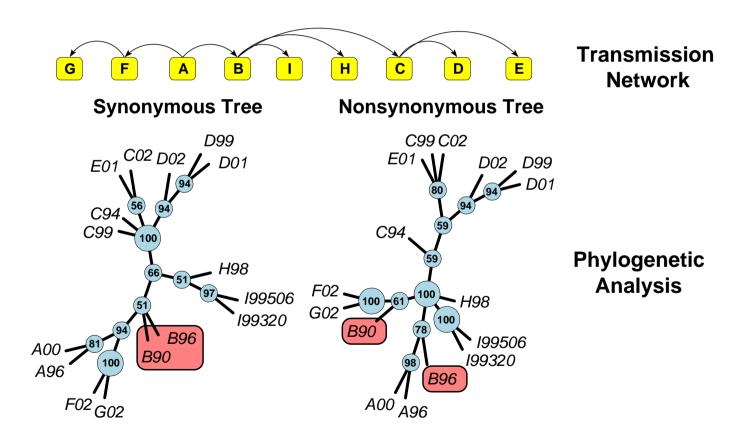
### **HIV Convergent Evolution-II**

 Compare "synonymous tree" estimates using 3rd codon positions (throw away data) vs our robust synonymous distances:



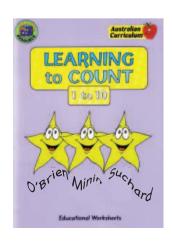
### **HIV Convergent Evolution-III**

Compare "synonymous" and "nonsynonymous" trees:



### **A Few Summary Comments**

- Analytic expressions for evolutionary counting processes are derivable and flexible to use:
  - For moderate  $|\Lambda|$ : substantial increase in computational efficiency over simulation-based methods
  - For large  $|\Lambda|$ : now tractable
- Complex posterior p-value tests require simulation only under the null (simple) model for which standard software exists

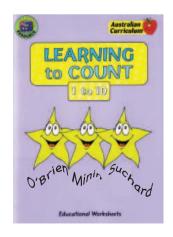


- Minin and Suchard, Journal of Mathematical Biology, 2008
- Minin and Suchard, Proceedings of the Royal Society B, 2008

## A Few (More) Summary Comments

- We introduce a general framework for computing abitrary labeled distances; appears robust to model misspecification
- How robust??? ⇔ an open question
- O'Brien, Minin and Suchard, *Molecular Biology and Evolution*, 2009





- R package markovjumps
- Recently integrated into BEAST and ready for release; anyone want to try it?