



Clinical and Epidemiological Virology
 Department of Microbiology
 and Immunology
 Rega Institute
 KU Leuven, Belgium

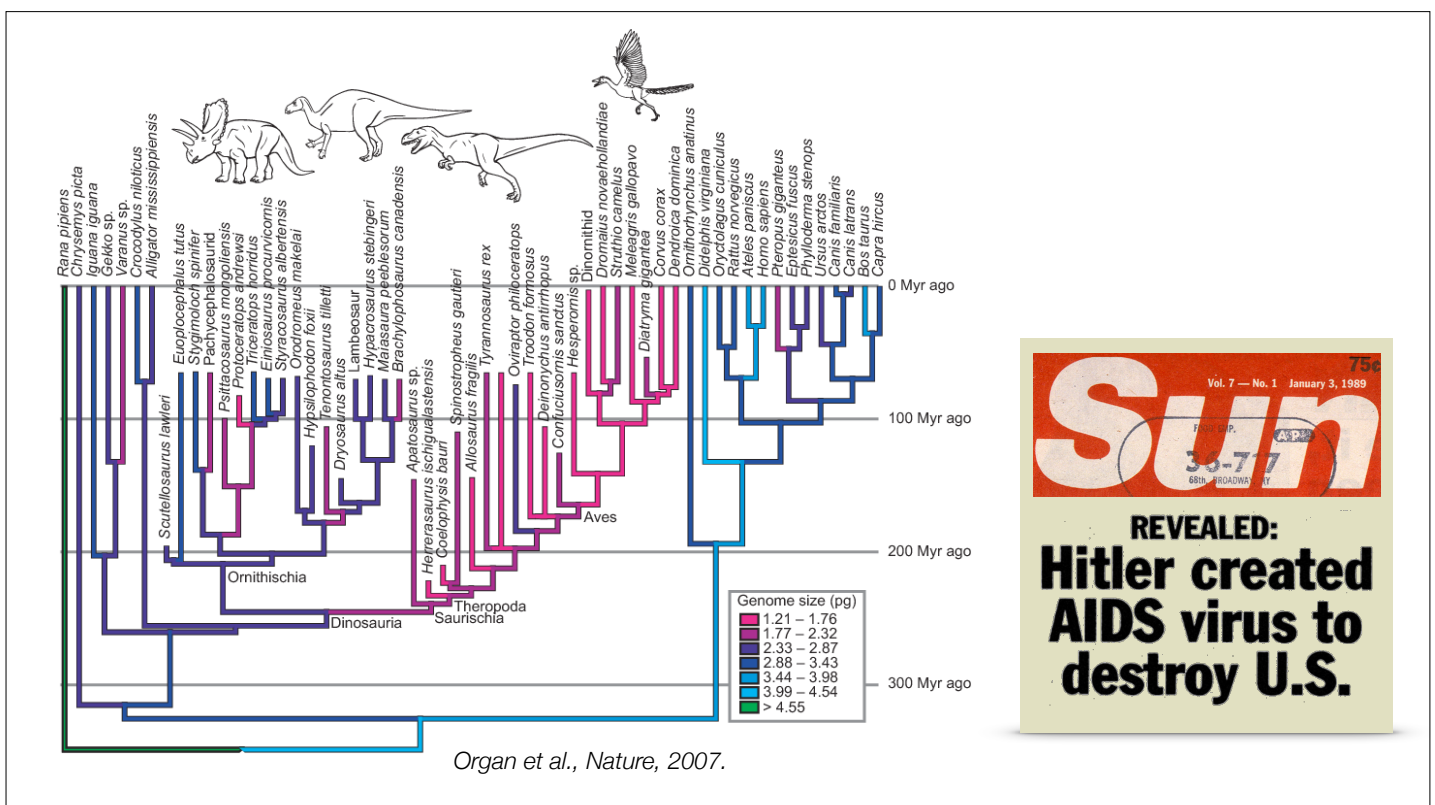


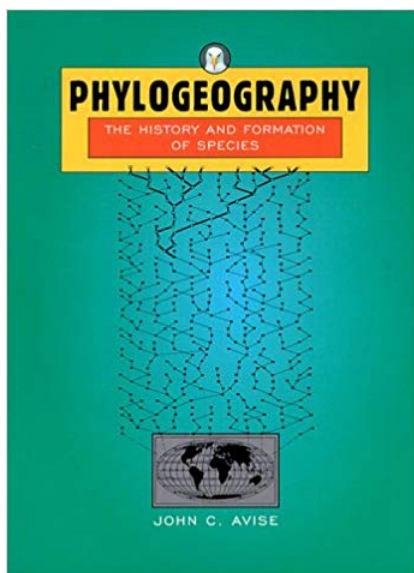
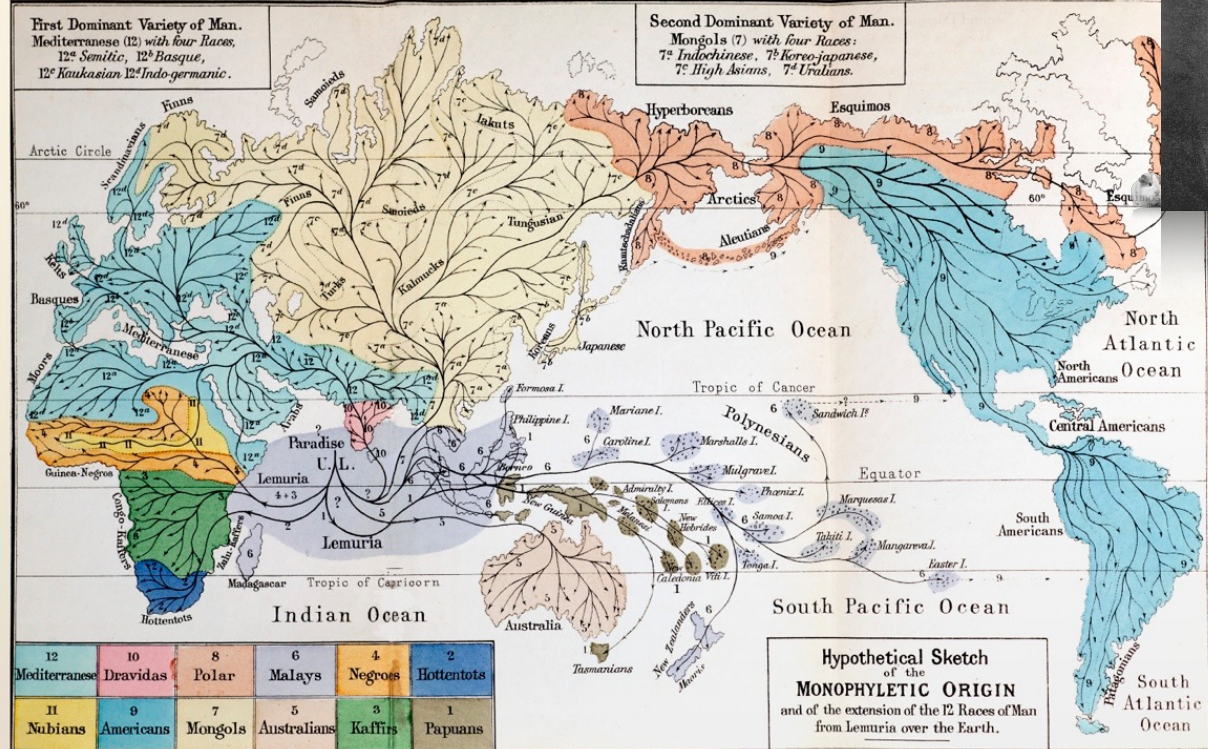
Phylogenetic diffusion models

Philippe Lemey¹ and Marc Suchard²

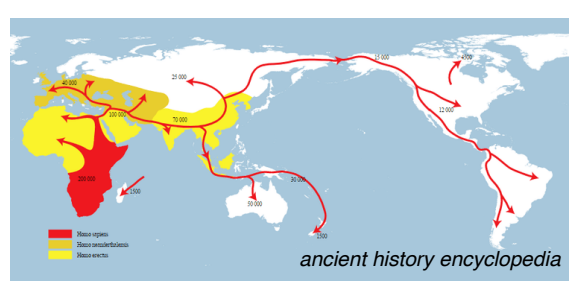
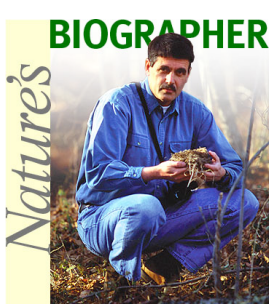
1. Rega Institute, Department of Microbiology and Immunology, K.U. Leuven, Belgium.
2. Departments of Biomathematics and Human Genetics, David Geffen School of Medicine at UCLA. Department of Biostatistics, UCLA School of Public Health

SISMID, Jul 10-12, 2019





“a field of study concerned with the principles and processes governing the geographic distribution of genealogical lineages, especially those within and among closely related species.” *Avise, 2000*

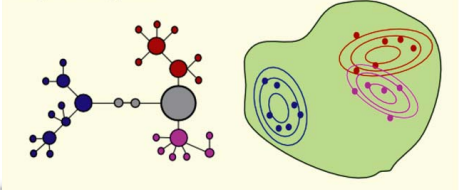


Three roads diverged? Routes to phylogeographic inference

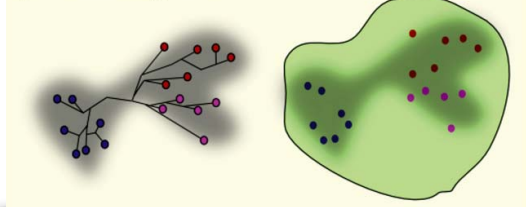
Erik W. Bloomquist¹, Philippe Lemey² and Marc A. Suchard^{3,4}

TRENDS in Ecology & Evolution

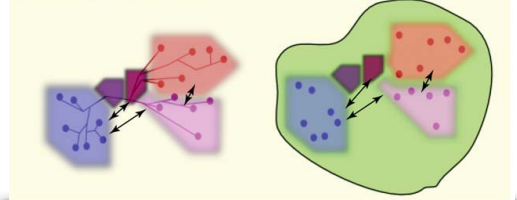
Comparative approach



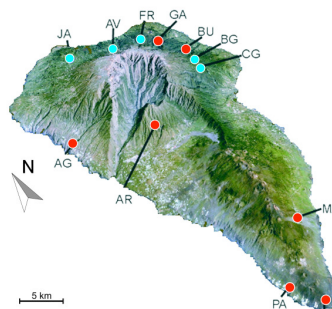
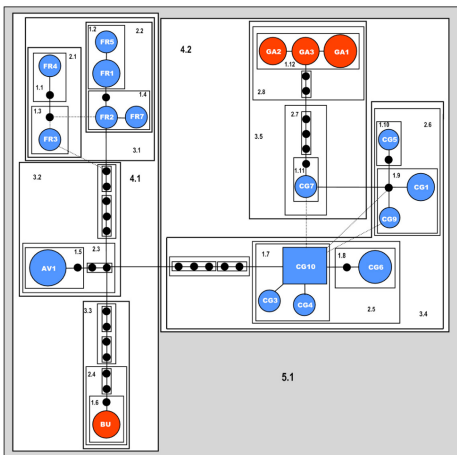
Spatial diffusion approach



Population genetics approach



Nested clade phylogeographic analysis (NCPA)

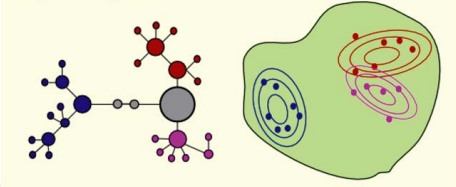


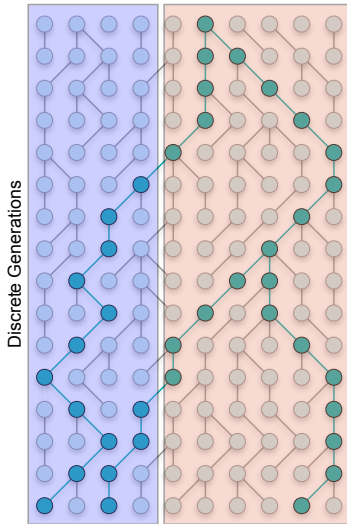
1. haplotype network
2. geographical structure test

3. interpretation through inference key

1. Are all clades within the nesting clade found in separate areas with no overlap?
 - NO - Go to step 2.
 - YES - Go to step 19.
2. Is at least one of the following conditions satisfied?
 - a. The D_i 's for one or more tips are significantly small and the D_i 's for one or more of the interiors are significantly large or non-significant.
 - b. The D_i 's for one or more tips are significantly small or non-significant and the D_i 's for some but *not* all of the interiors are significantly small.
 - c. The D_i 's for one or more interiors are significantly large and the D_i 's for the tips are either significantly small or non-significant.
 - d. The I-T D_i is significantly large.
 - NO - Go to step 11.
 - YES - Go to step 3.
 - Tip/Interior Status Cannot be Determined - **Inconclusive Outcome.**
3. Is at least one of the following conditions satisfied?
 - a. Some D_i and/or I-T D_i values are significantly reversed from the D_i values.
 - b. One or more tip clades show significantly large D_i 's.
 - c. One or more interior clades show significantly small D_i 's.
 - d. I-T has a significantly small D_i with the corresponding D_i value non-significant.
 - NO - Go to step 4.
 - YES - Go to step 5.
4. Are both of the following conditions satisfied?
 - a. The clades (or 2 or more subsets of them) with significantly small D_i or D_i values have ranges that are completely or mostly non-overlapping with the other clades in the nested group (particularly interiors), or if no clades have significantly small D_i or D_i values but an interior D_i or I-T D_i is significantly large, and that interior clade is completely or mostly non-overlapping with the other clades in the nested group.
 - b. The pattern of completely or mostly non-overlapping ranges in the above condition represents a break or reversal from lower level trends within the nested clade series (applicable to higher-level clades only).
 - **NO - Restricted Gene Flow with Isolation by Distance (Restricted Dispersal by Distance in Non-sexual species).** This inference is strengthened if the clades with restricted distributions are found in diverse locations, if the union of their ranges roughly corresponds to the range of one or more clades (usually interiors) within the same nested group (applicable only to nesting clades with many clade members or to the highest level clades regardless of number), and if the D_i values increase and become more geographically widespread with increasing clade level within a nested series (applicable to lower level clades only).
 - YES - Go to step 9.

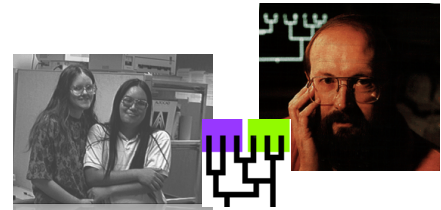
Comparative approach





Coalescent theory:

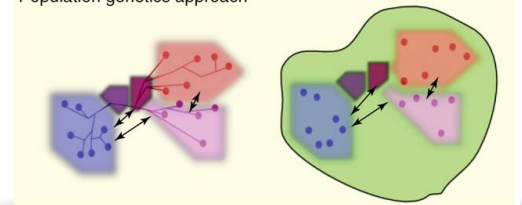
- is a statistical framework for the analysis of genetic polymorphism data
- is an extension of classical population-genetics theory and models
- one can estimate time (number of generations) for lineages to coalesce
- many applications (including migration analysis)



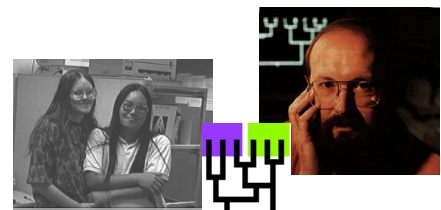
LAMARC - Likelihood Analysis with Metropolis Algorithm using Random Coalescence



Population genetics approach



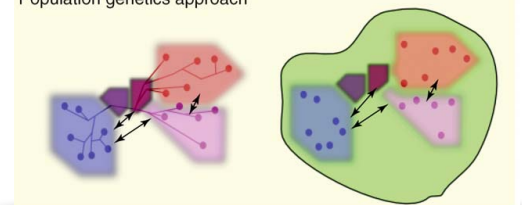
- Vaughan TG, Kühnert D, Poppinga A, Welch D, Drummond AJ. Efficient Bayesian inference under the **structured coalescent**. *Bioinformatics*. 2014 Aug 15;30(16):2272-9. doi: 10.1093/bioinformatics/btu201.
- De Maio N, Wu CH, O'Reilly KM, Wilson D. New Routes to Phylogeography: A Bayesian **Structured Coalescent** Approximation. *PLoS Genet*. 2015 Aug 12;11(8):e1005421. doi: 10.1371/journal.pgen.1005421.
- Müller NF, Rasmussen DA, Stadler T. The **Structured Coalescent** and Its Approximations. *Mol Biol Evol*. 2017 Nov 1;34(11):2970-2981. doi: 10.1093/molbev/msx186.
- Kühnert D, Stadler T, Vaughan TG, Drummond AJ. **PhyloDynamics** with Migration: A Computational Framework to Quantify Population Structure from Genomic Data. *Mol Biol Evol*. 2016 Aug;33(8):2102-16. doi: 10.1093/molbev/msw064.



LAMARC - Likelihood Analysis with Metropolis Algorithm using Random Coalescence



Population genetics approach

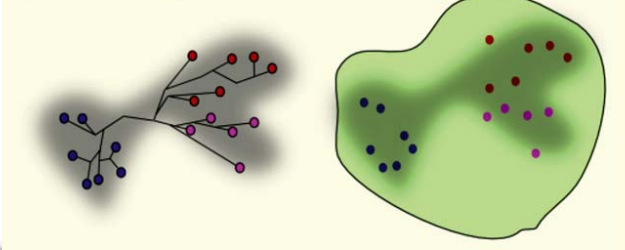


Beast2

Bayesian evolutionary analysis by sampling trees

Phylogenetic diffusion

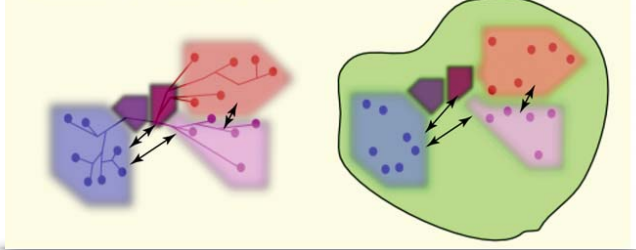
Spatial diffusion approach



- Samples are assumed to be collected in a manner that is blind to their location.
- Sample location used as data
- Just as for genetic data, non-random sampling procedures will bias results
- flexible and scalable

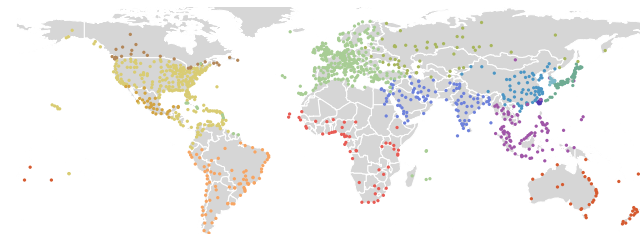
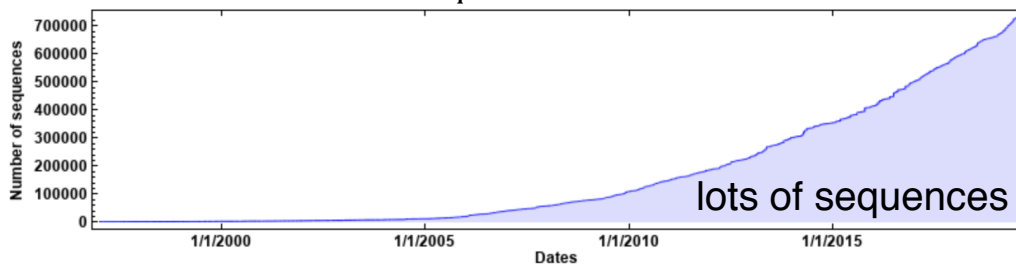
Structured coalescent

Population genetics approach

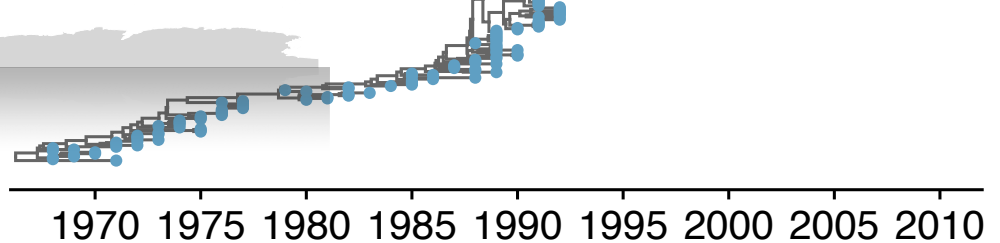


- no assumptions about the manner in which samples are collected with respect to location
- Sample distribution not used as data
- Uneven sampling can reduce inference power, but will not bias results
- Computationally prohibitive

Flu sequences in GenBank

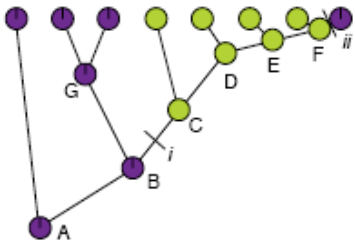


- flexible and scalable

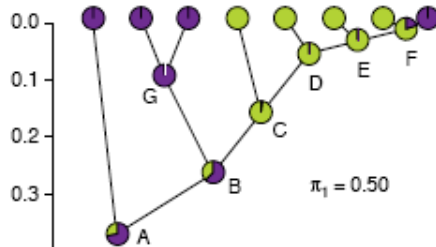


Discrete ancestral state reconstruction

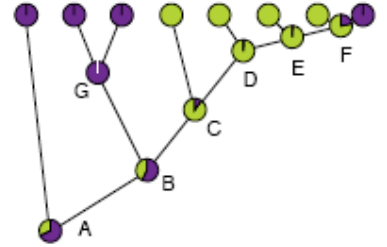
Parsimony analysis



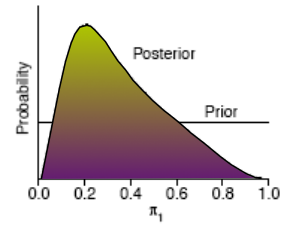
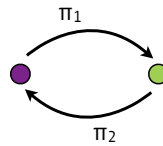
ML analysis



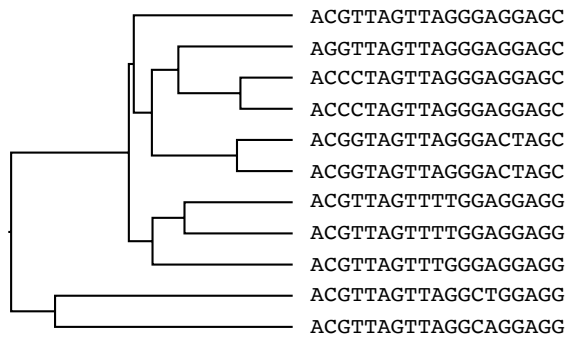
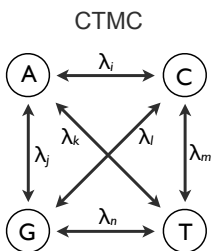
Bayesian analysis



● Location 1 ● Location 2

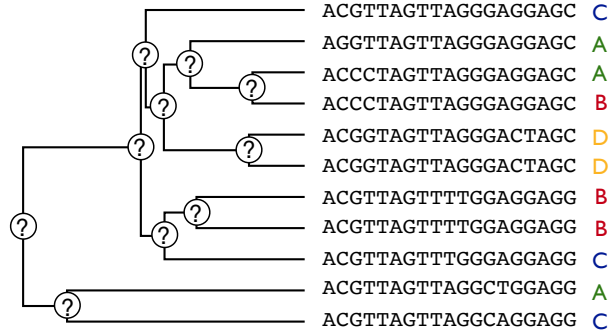
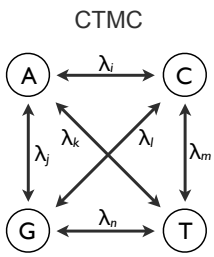


Discrete phylogenetic diffusion



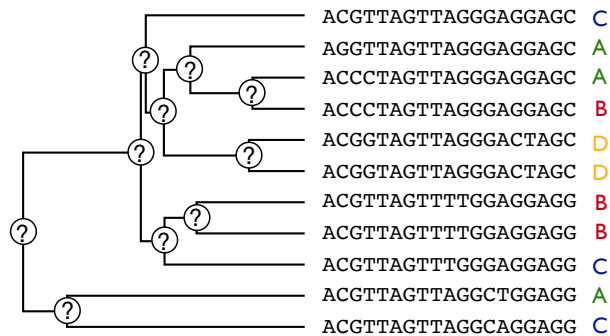
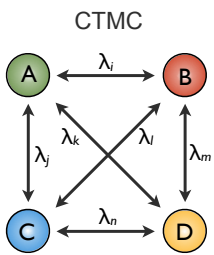
$$p(\text{ACGTTAGTTAGGCTGGAGG} \mid \text{ACGTTAGTTAGGCTGGAGG}, \text{ACGTTAGTTAGGCTGGAGG}, \text{ACGTTAGTTAGGCTGGAGG}, \text{ACGTTAGTTAGGCTGGAGG}, \text{CTMC})$$

Discrete phylogenetic diffusion



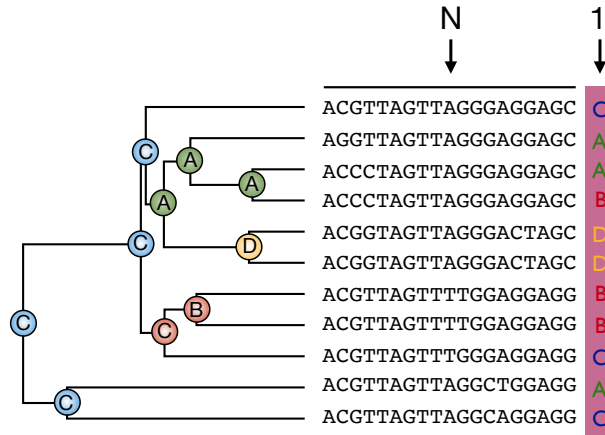
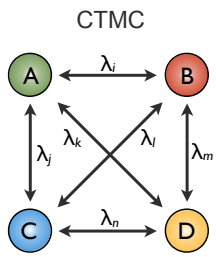
$$p \left(\begin{array}{c} \text{ACGTG} \\ \text{ACGTG} \\ \text{ACGTG} \\ \text{ACGTG} \end{array} \middle| \begin{array}{c} \text{[Tree]} \\ \text{[CTMC]} \end{array} \right)$$

Discrete phylogenetic diffusion: migration



$$p \left(\begin{array}{c} \text{ACGTG} \\ \text{ACGTG} \\ \text{ACGTG} \\ \text{ACGTG} \end{array} \middle| \begin{array}{c} \text{[Tree]} \\ \text{[CTMC]} \end{array} \right) \quad p \left(\begin{array}{c} \text{A} \\ \text{B} \\ \text{C} \\ \text{D} \end{array} \middle| \begin{array}{c} \text{[Tree]} \\ \text{[CTMC]} \end{array} \right)$$

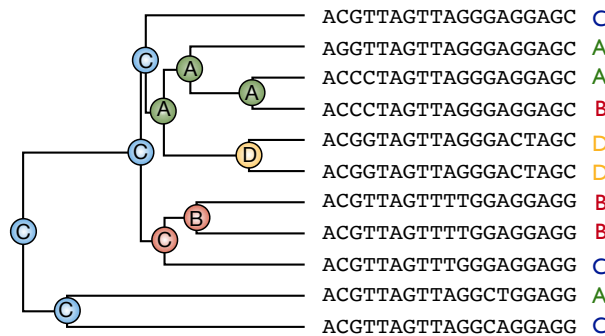
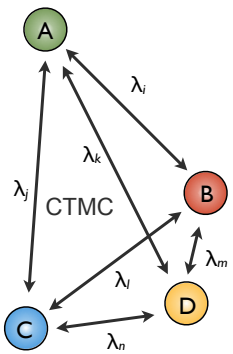
Discrete phylogenetic diffusion: *migration*



$$p(\text{ACGTG} \mid \text{ACGTG}, \text{ACGTG}, \text{ACGTG}, \text{ACGTG}) \quad p(\text{A B C D} \mid \text{A B C D}, \text{A B C D}, \text{A B C D}, \text{A B C D})$$

Discrete phylogenetic diffusion: *migration*

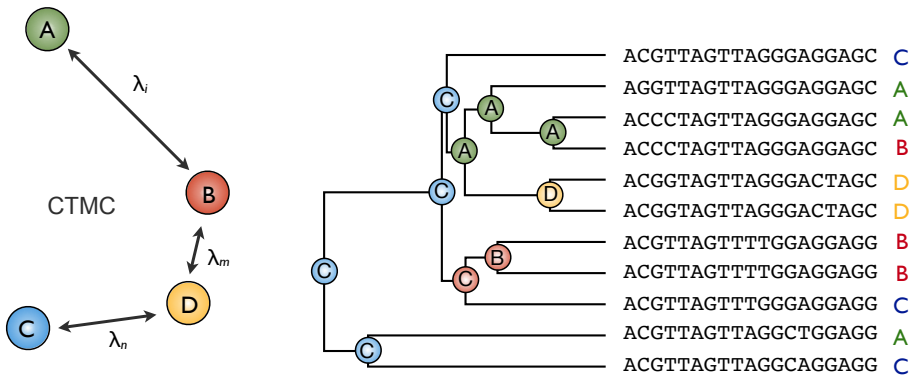
prior specification



$$p(\text{ACGTG} \mid \text{ACGTG}, \text{ACGTG}, \text{ACGTG}, \text{ACGTG}) \quad p(\text{A B C D} \mid \text{A B C D}, \text{A B C D}, \text{A B C D}, \text{A B C D})$$

Discrete phylogenetic diffusion: *mugration*

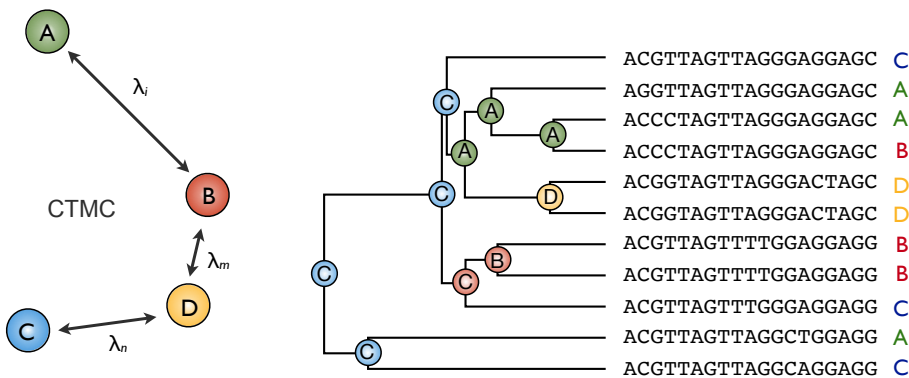
Bayesian variable selection - spike-and-slab



$$p(\text{ACGTG} \mid \text{ACGTG} \text{ tree}) \quad p(\text{ABCD} \mid \text{tree}, \text{matrix})$$

Discrete phylogenetic diffusion: *mugration*

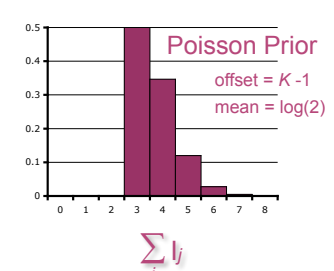
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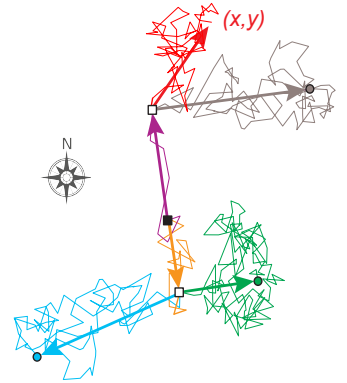
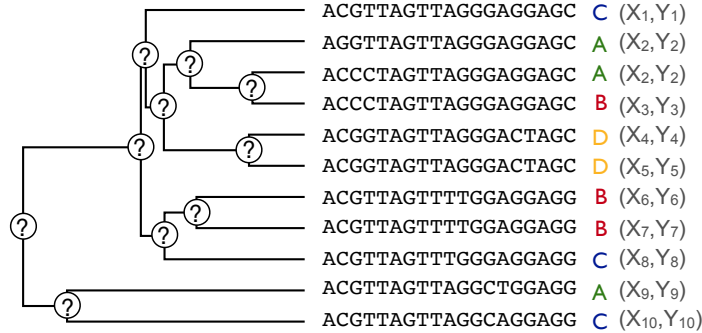
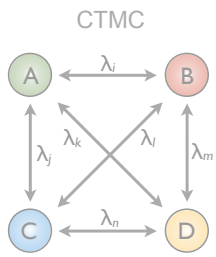
Rate Indicators $I_{[0,1]}$

	A	B	C	D
A	.	$\pi_{A i}$	$\pi_{C j}$	$\pi_{D k}$
B	$\pi_{A i}$.	$\pi_{C l}$	$\pi_{D m}$
C	$\pi_{A j}$	$\pi_{B l}$.	$\pi_{D n}$
D	$\pi_{A k}$	$\pi_{B m}$	$\pi_{C n}$.

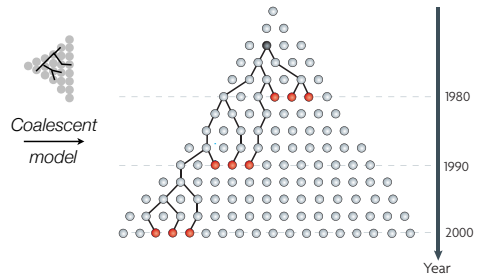
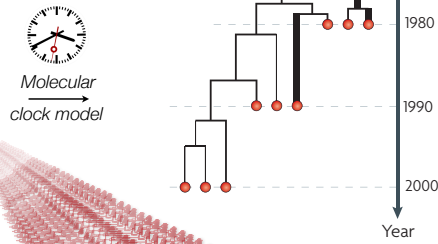
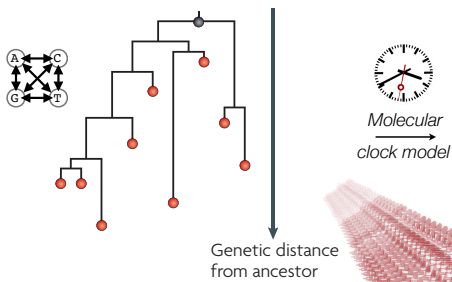


$$\text{Bayes factor} = \frac{\text{posterior odds}}{\text{prior odds}} = \frac{\Pr(I=1 \mid D) / (1 - \Pr(I=1 \mid D))}{\Pr(I=1) / (1 - \Pr(I=1))}$$

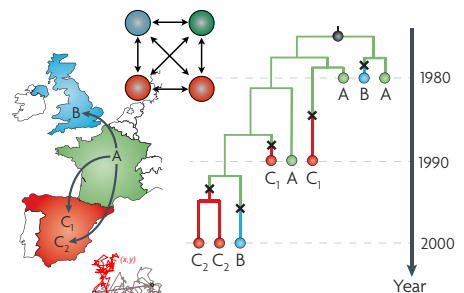
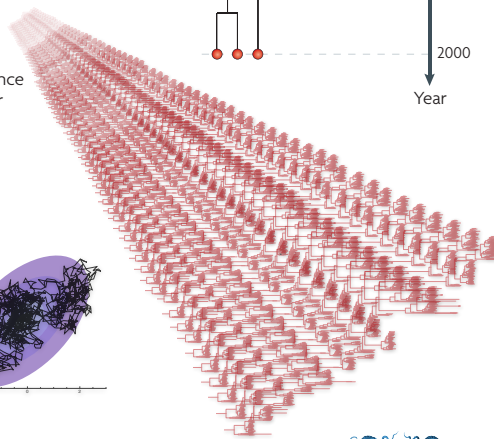
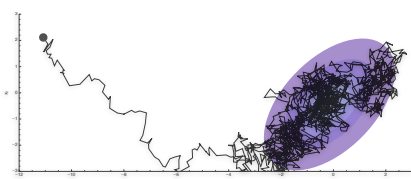
Continuous phylogenetic diffusion: Brownian motion process



$$p(\text{ACGTG} \mid \text{ACGTG}, \text{ACGTG}, \text{ACGTG}) \quad p(\text{ACGTG} \mid \text{ACGTG}, \text{ACGTG}, \text{ACGTG}) \quad p(\text{Y}_1 \mid \text{Y}_2, \text{Y}_3, \text{Y}_4)$$



Pybus and Rambaut, NRG, 2009.



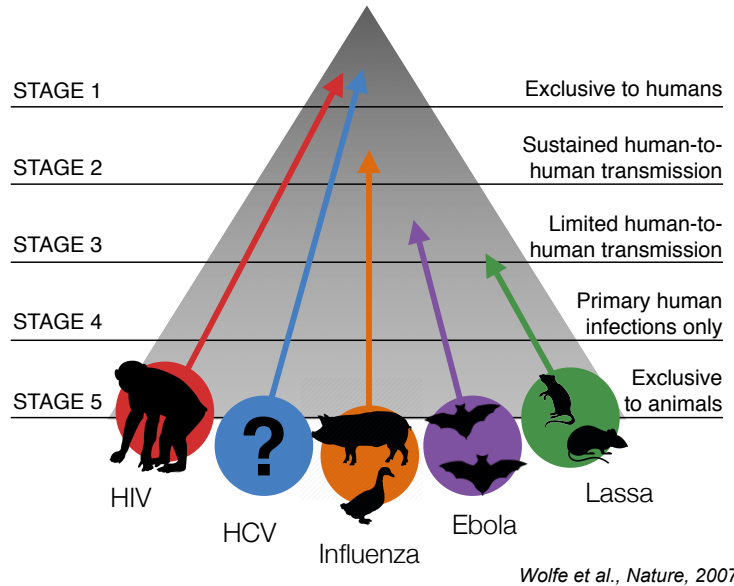
Suchard et al., VE., 2018.

$$p(\text{ACGTG} \mid \text{ACGTG}, \text{ACGTG}, \text{ACGTG}) \quad p(\text{Y}_1 \mid \text{Y}_2, \text{Y}_3, \text{Y}_4)$$



Phylodynamics of pathogen emergence and spread

- Where do they come from?
- How do they get established in humans
- What is the role of adaptation vs. epidemiology in shaping pathogen genetic diversity
- How to support public health interventions

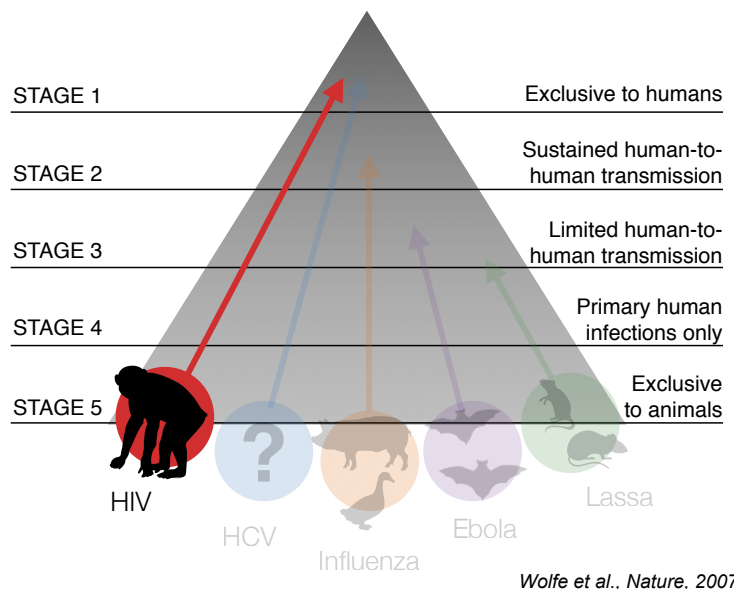


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adaptation
in shaping
diversity
public health



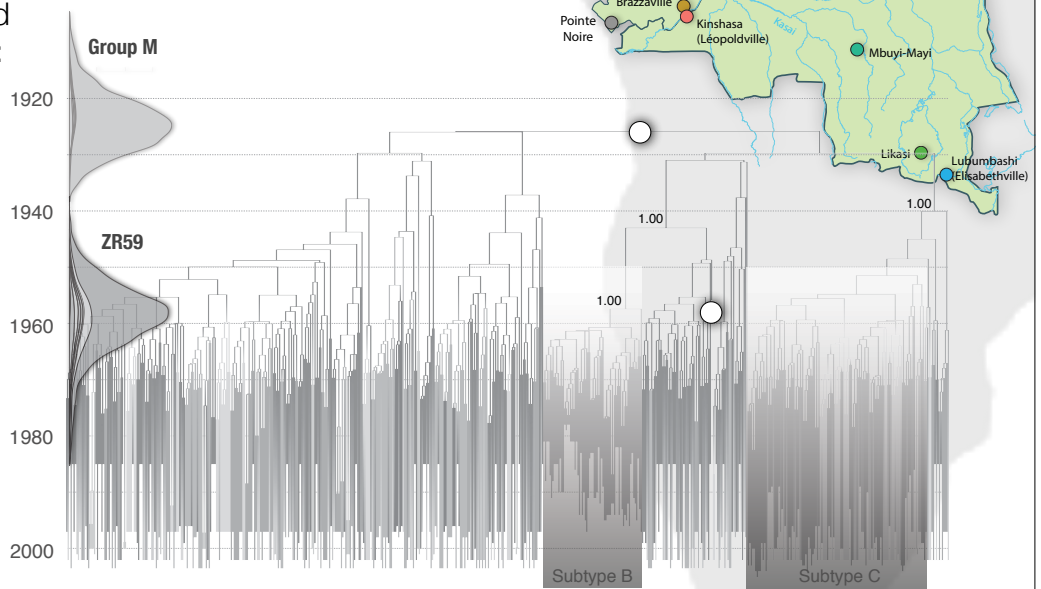
Phylodynamics of pathogen emergence and spread

HIV-1 group M emerged around 1920 (95% BCI: 1909-30)

Faria et al., Science, 2014.



HIV



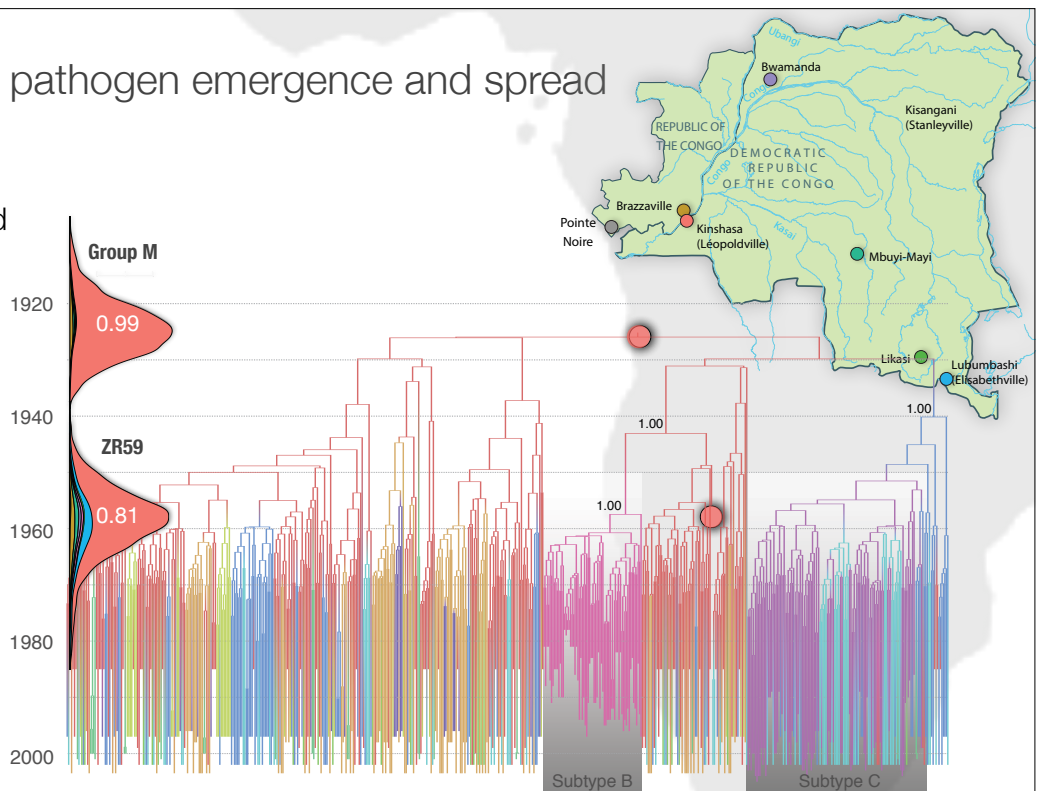
Phylodynamics of pathogen emergence and spread

HIV-1 group M emerged around 1920 (95% BCI: 1909-30) in Leopoldville

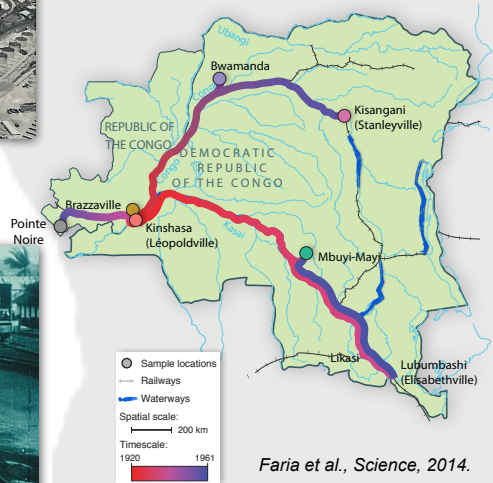
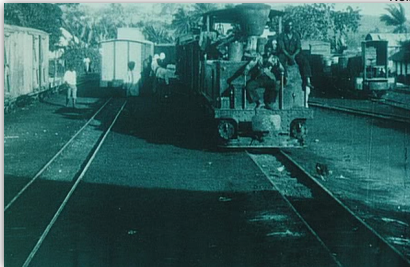
Faria et al., Science, 2014.



HIV

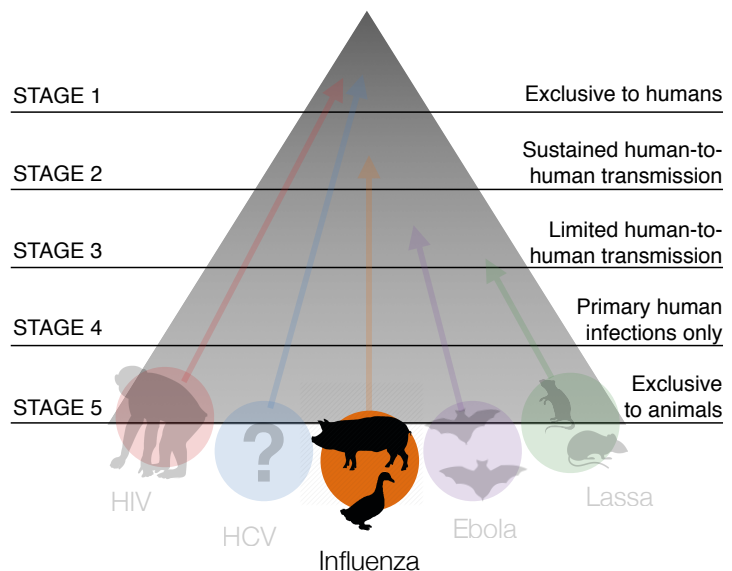


From early on, Kinshasa was the best connected city in central Africa



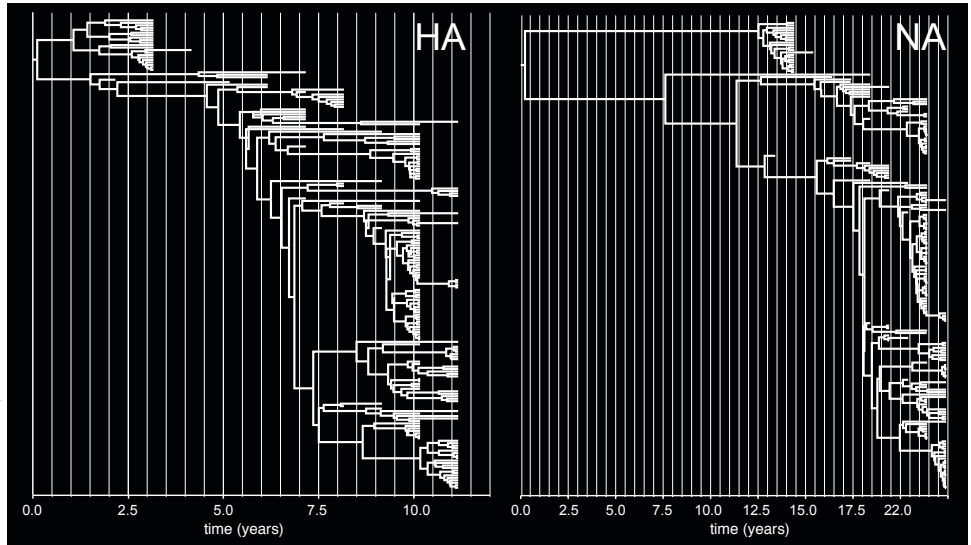
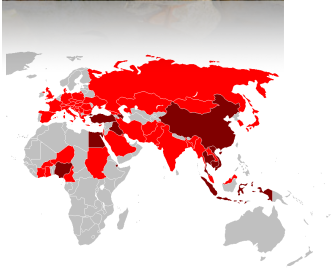
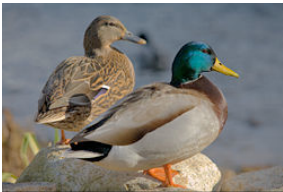
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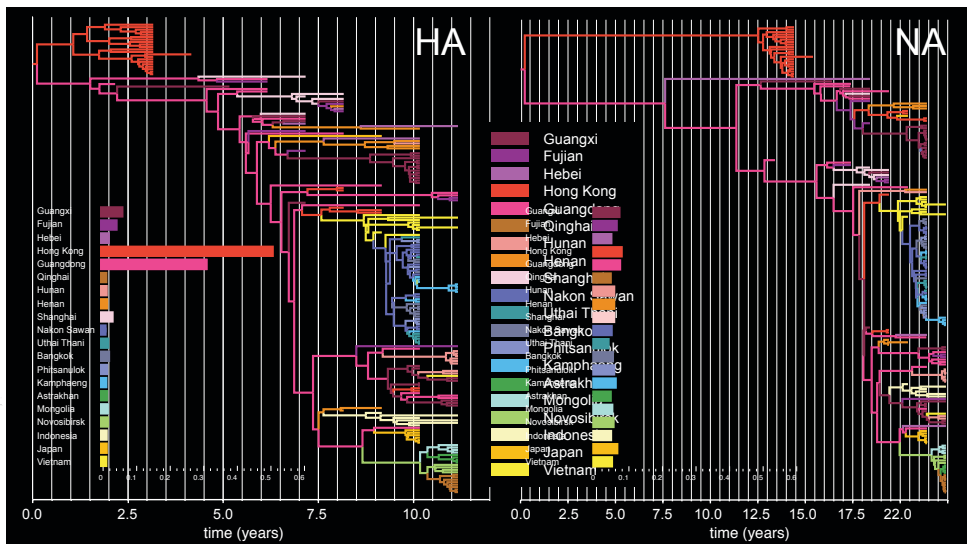
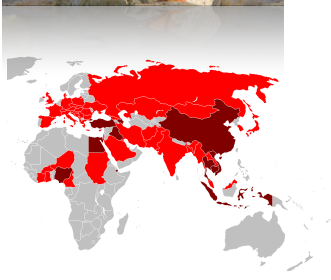
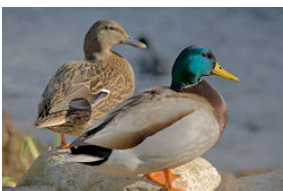
Wolfe et al., Nature, 2007.

Avian influenza H5N1



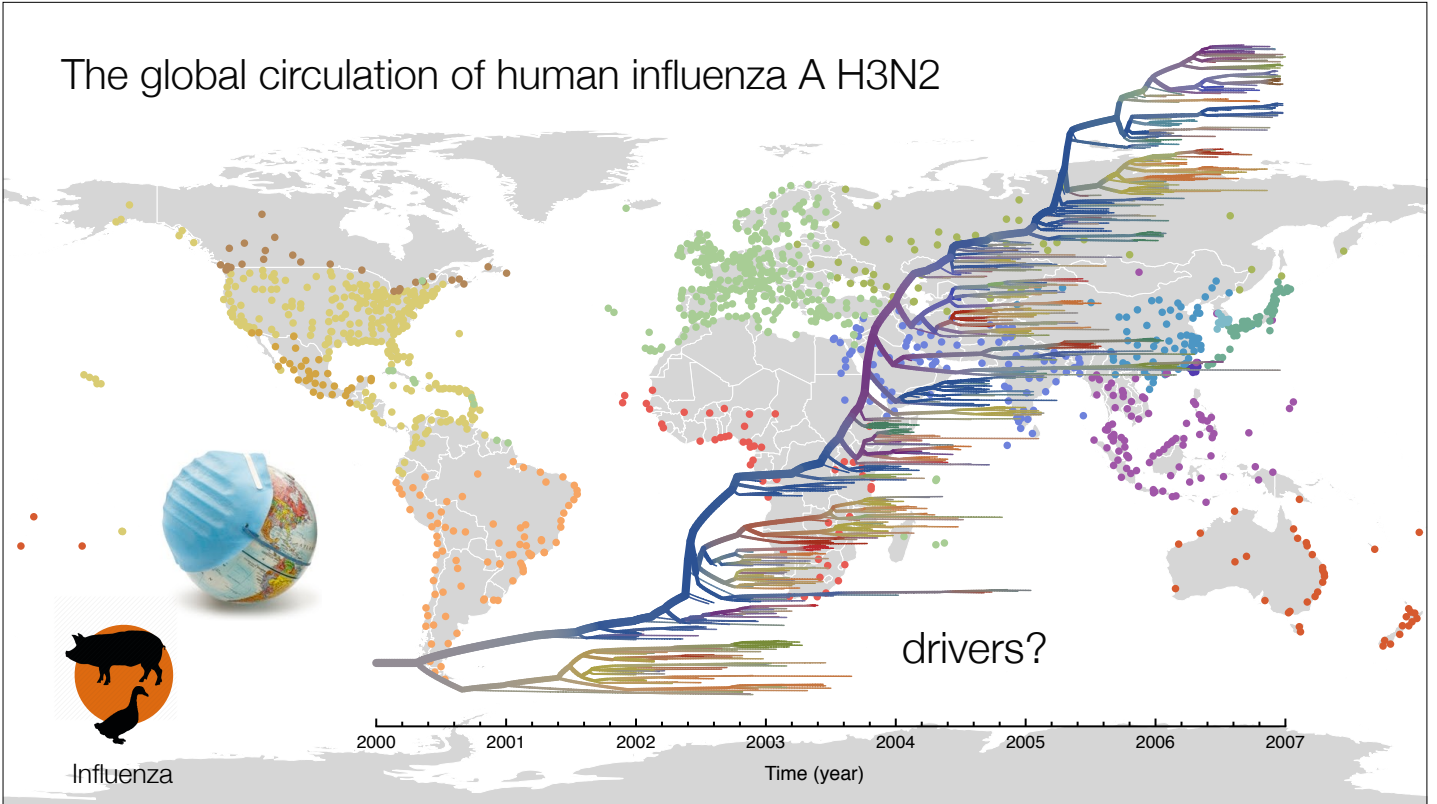
Wallace et al., PNAS, 2007

Avian influenza H5N1

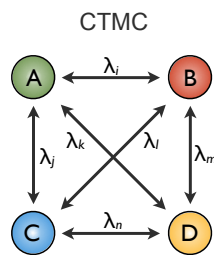
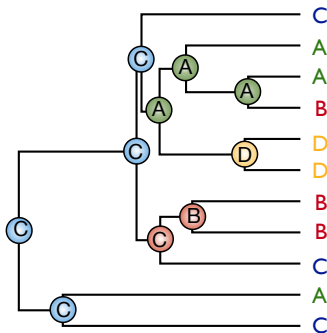


Wallace et al., PNAS, 2007

The global circulation of human influenza A H3N2



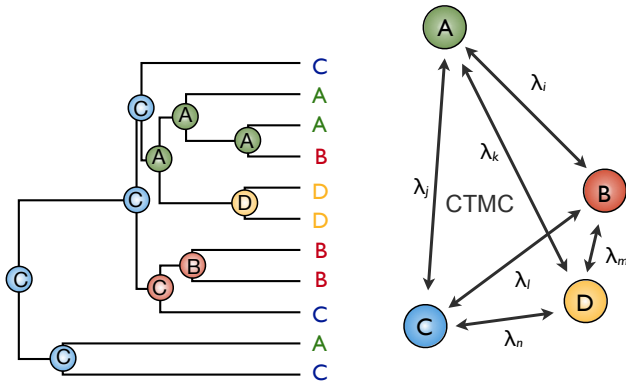
Discrete phylogenetic diffusion: *migration*



drivers?

$$p(\text{DMP} | \text{tree}, \text{matrix})$$

Discrete phylogenetic diffusion: *migration*

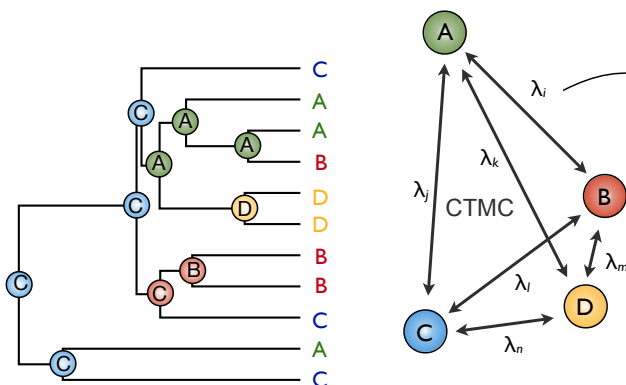


drivers?

$$p(\text{DTPP}, \text{Tree}, \text{Migration})$$

Lemey et al., PLoS Path, 2014

Discrete phylogenetic diffusion: *migration*

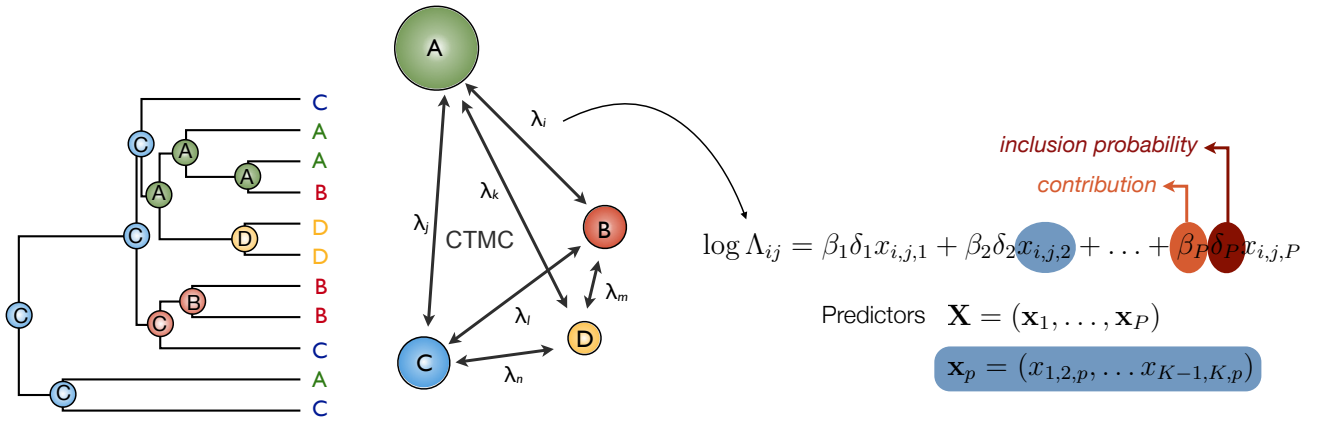


drivers?

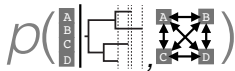
$$p(\text{DTPP}, \text{Tree}, \text{Migration})$$

Lemey et al., PLoS Path, 2014

Discrete phylogenetic diffusion: migration



drivers?



Lemey et al., PLoS Path, 2014

Predictors

Average distance

Minimum distance

Origin absolute latitude

Destination absolute latitude

Passenger flow

Origin population size

Destination population size

Origin population density

Destination population density

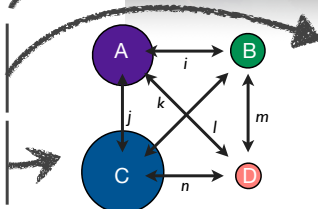
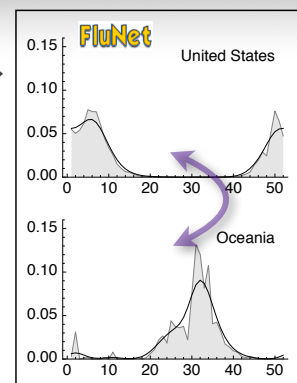
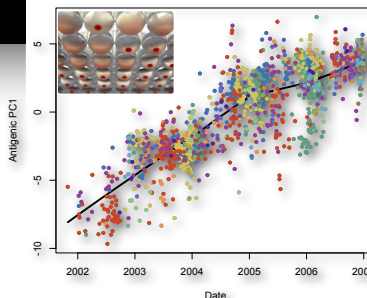
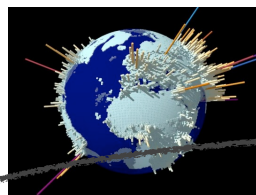
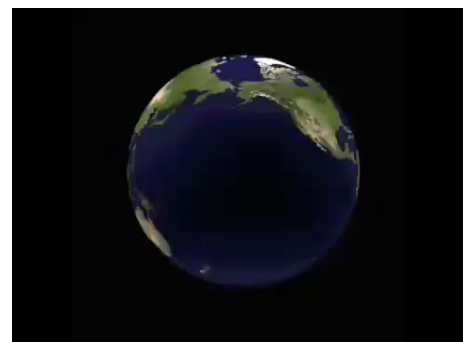
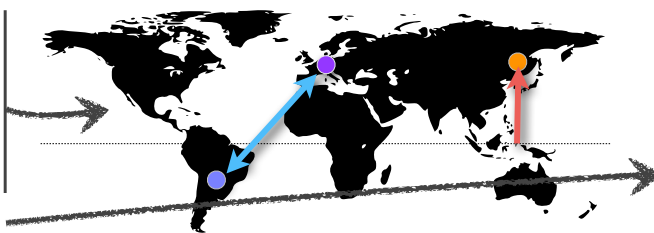
H3 incidence overlap

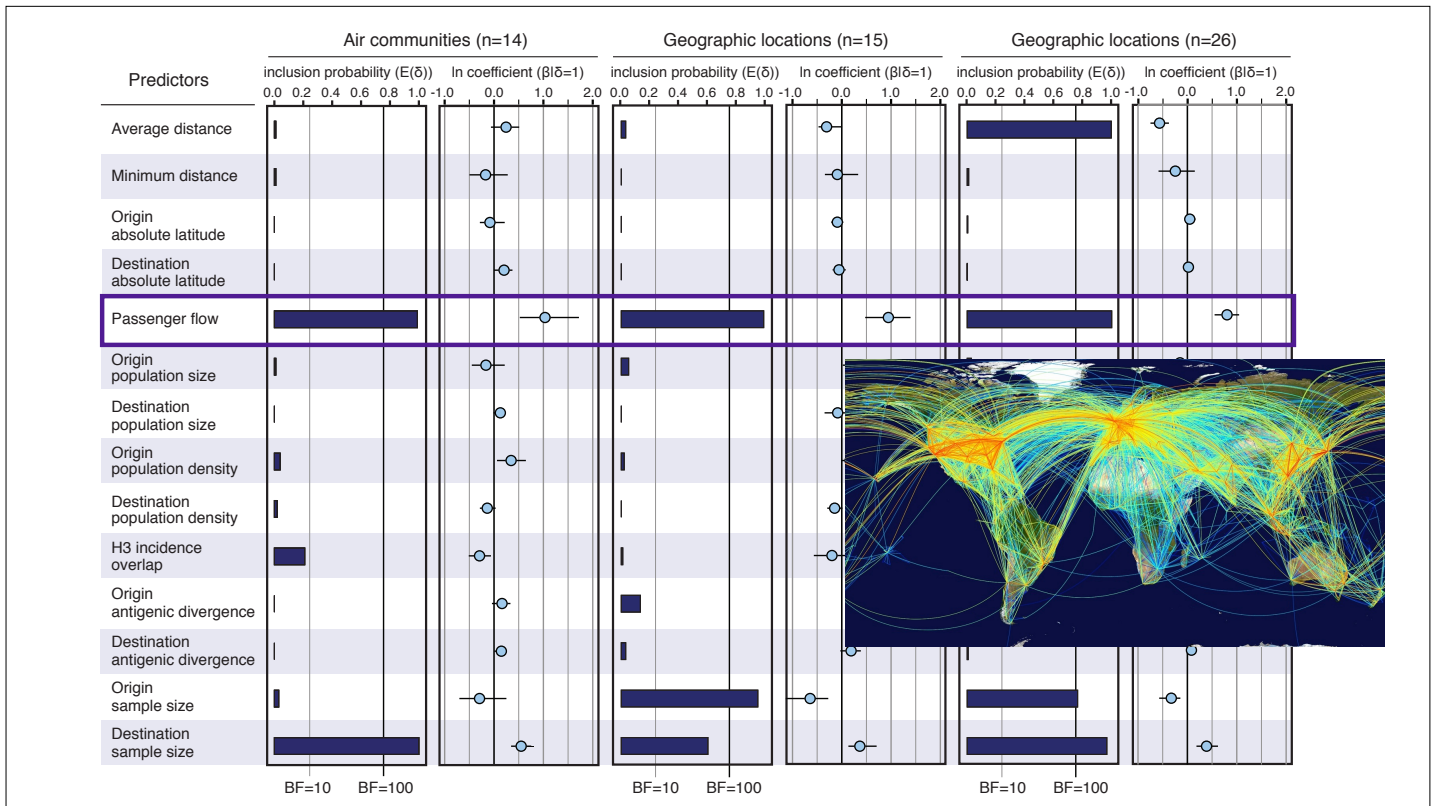
Origin antigenic divergence

Destination antigenic divergence

Origin sample size

Destination sample size





The global circulation of human influenza A and B

-Where do they come from?

-How do they get established in humans

-What is the role of adaptation vs, epidemiology in shaping pathogen genetic diversity

-How to support public health interventions

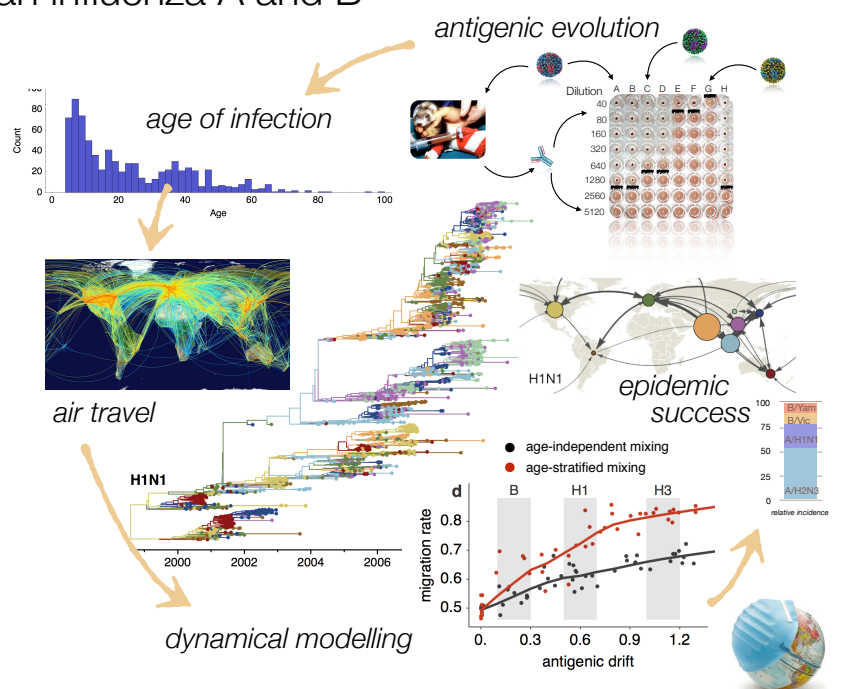


Influenza

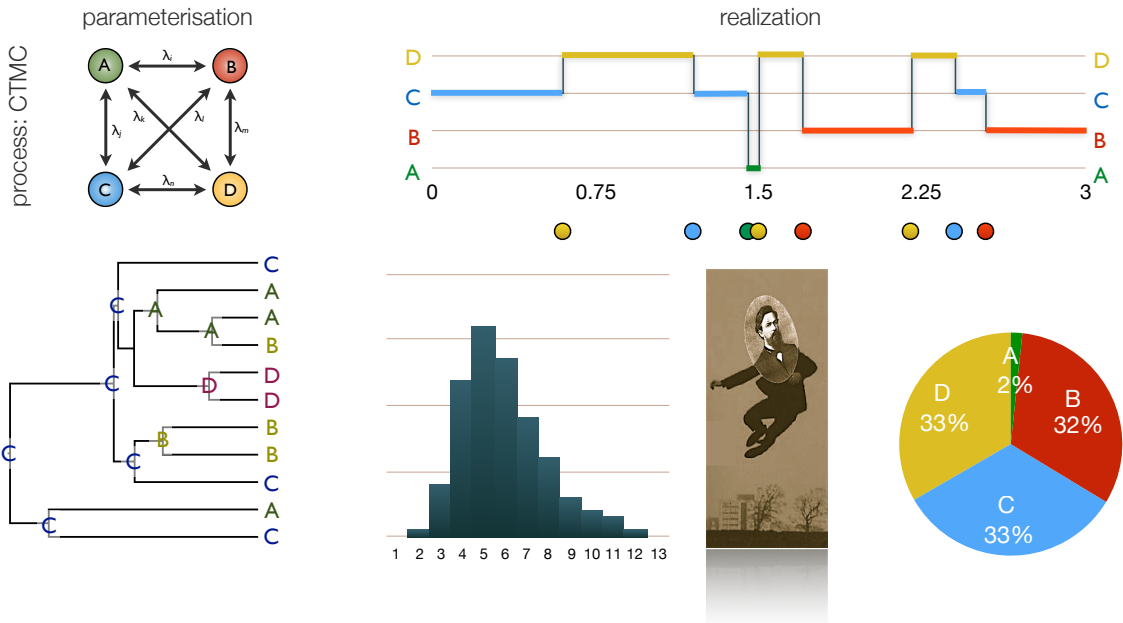


Bedford *et al.*,
eLife, 2014

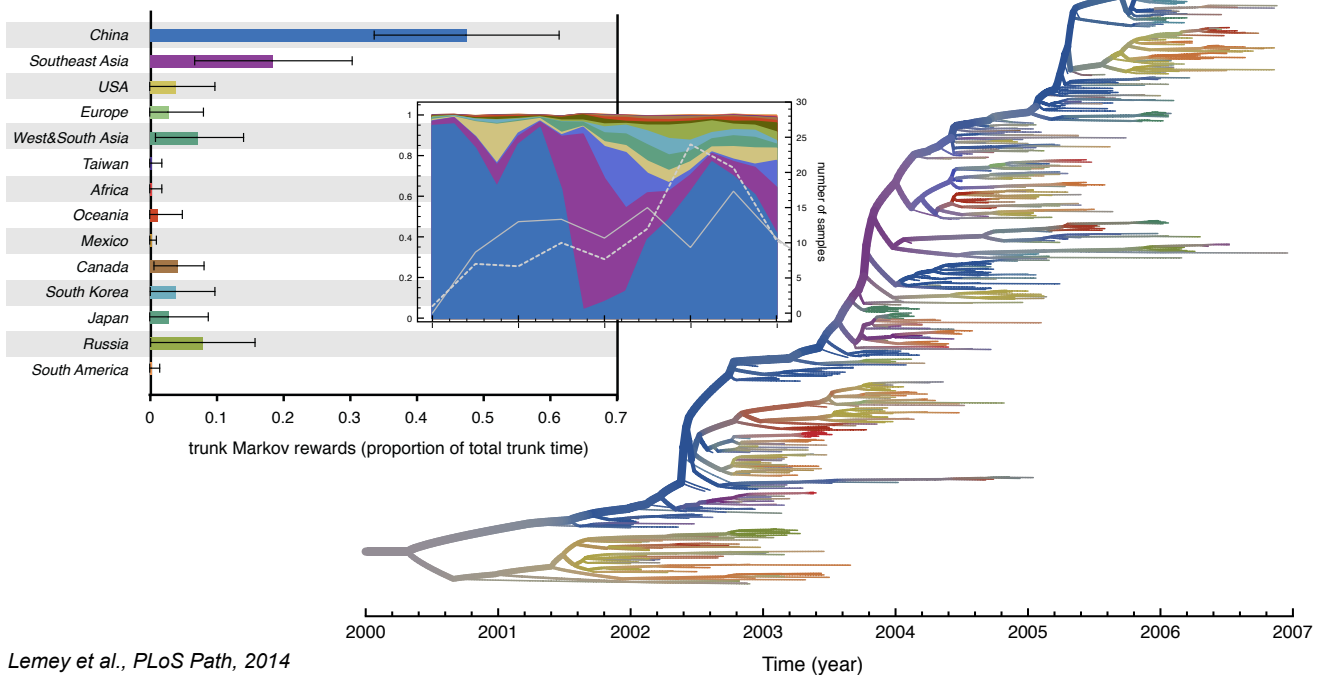
Bedford *et al.*,
Nature, 2015



From parameters to realisations: Markov jumps and rewards

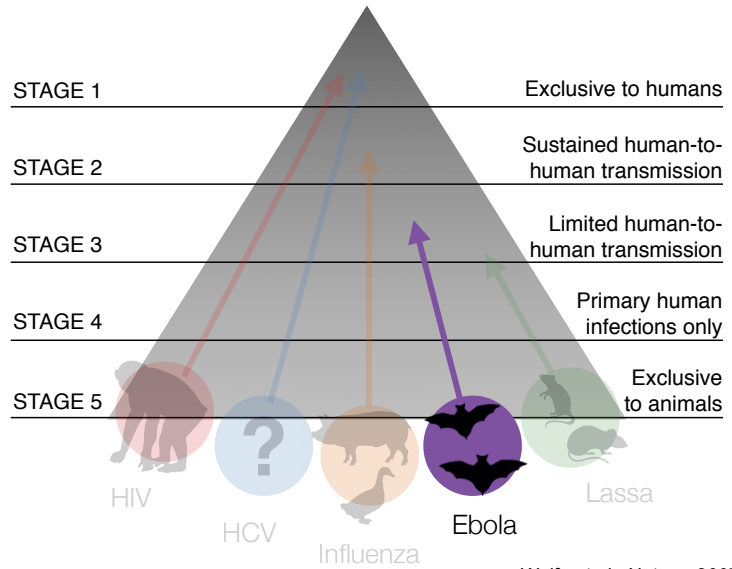


The 'trunk' source population of flu



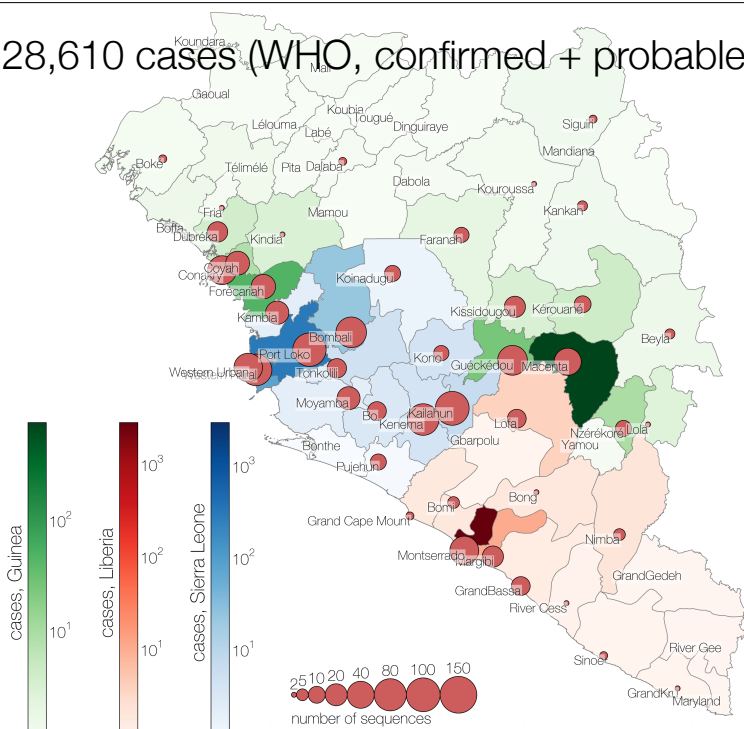
Phylodynamics of pathogen emergence and spread

- Where do they come from?
- How do they get established in humans
- What is the role of adaptation vs. epidemiology in shaping pathogen genetic diversity
- How to support public health interventions

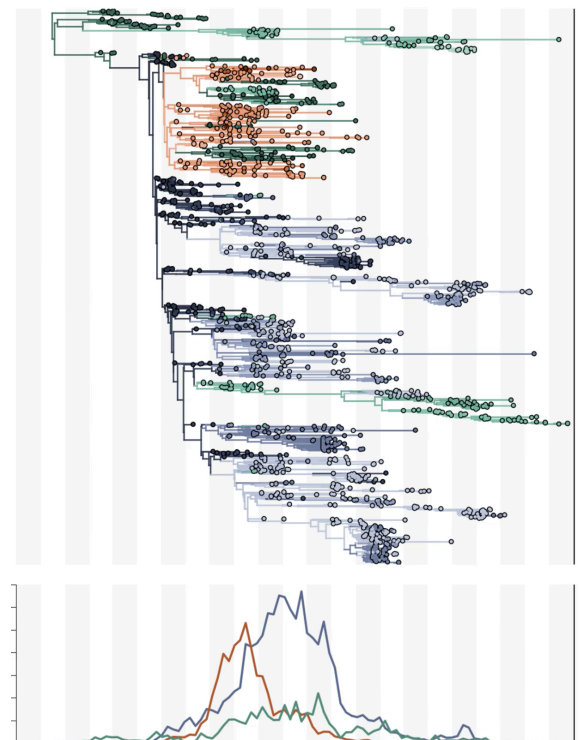


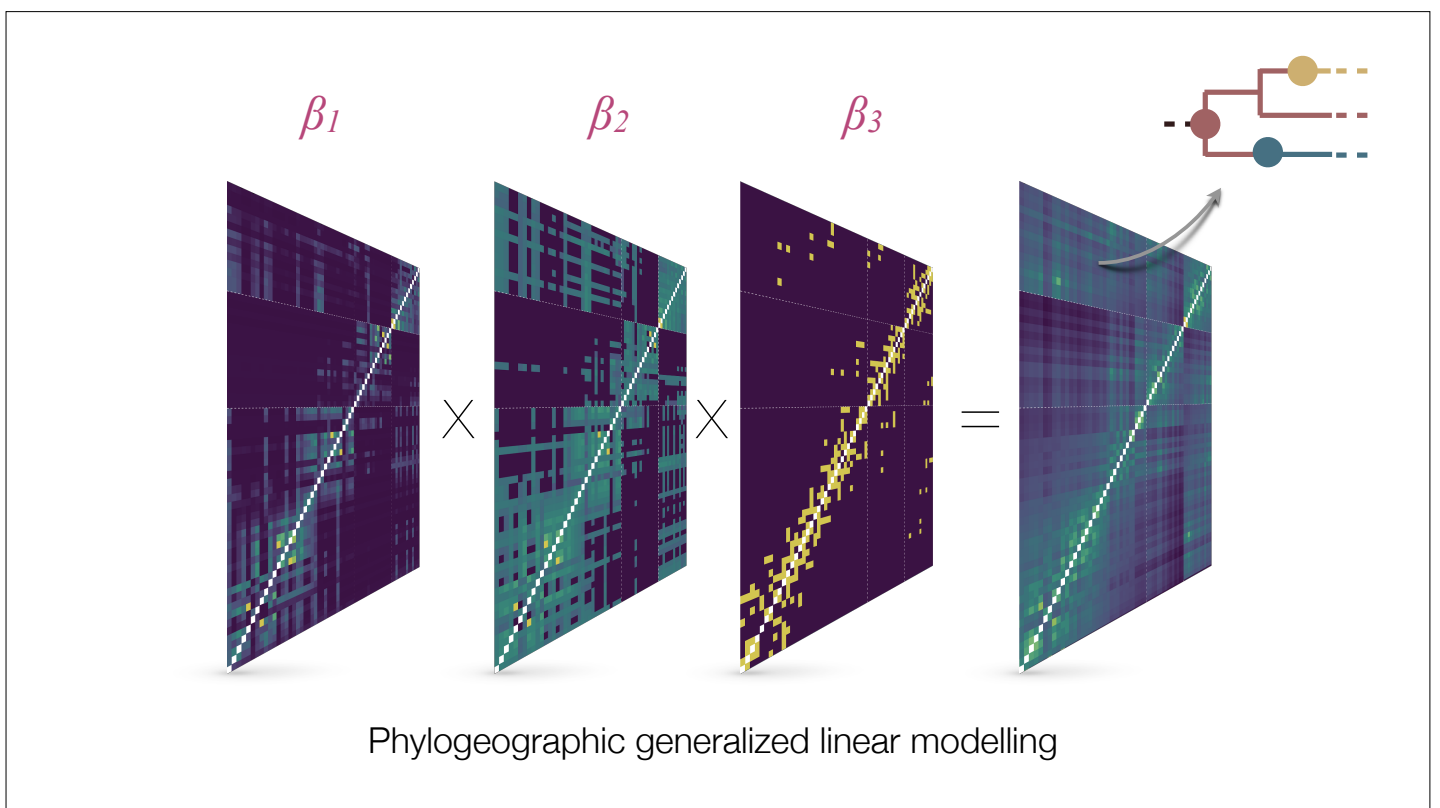
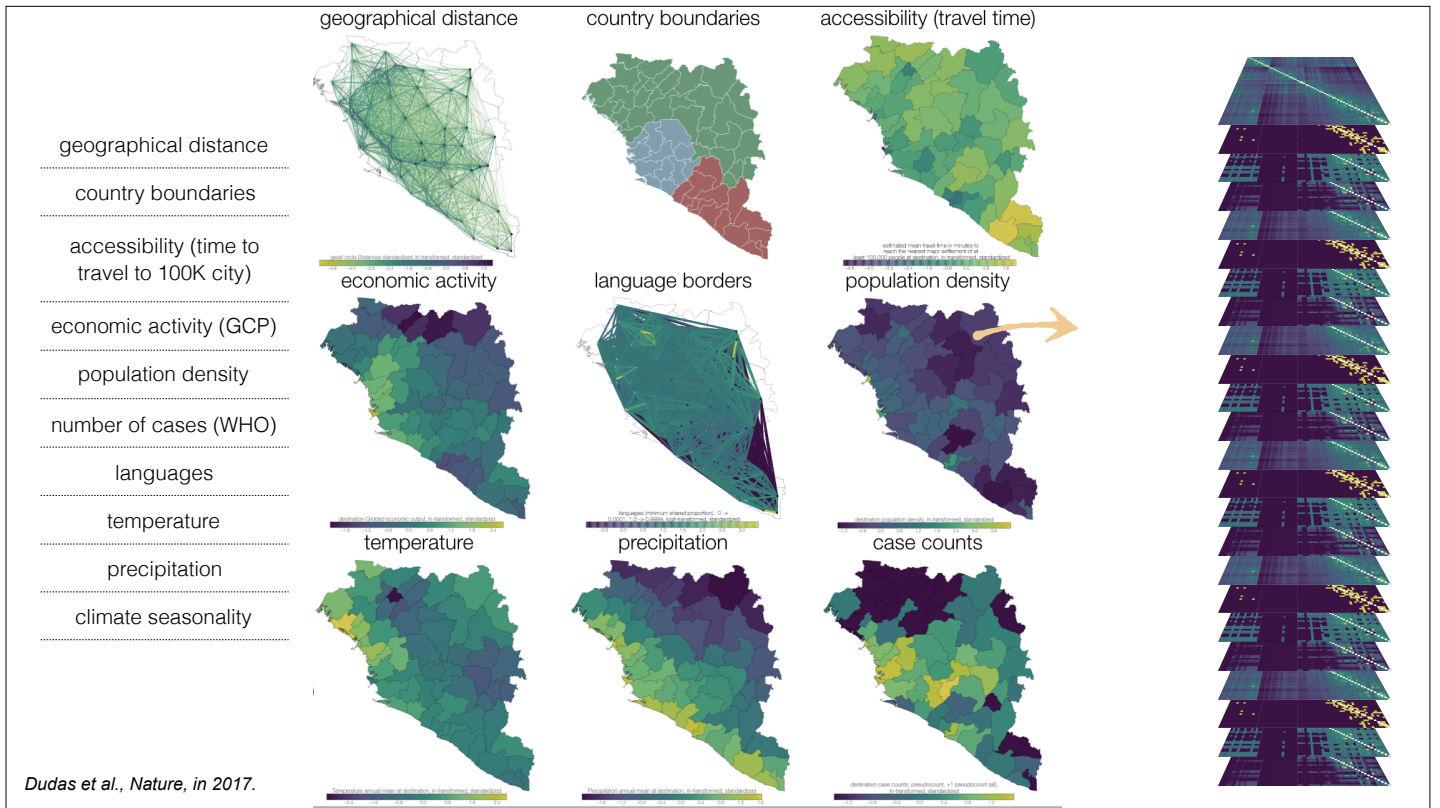
Wolfe et al., Nature, 2007.

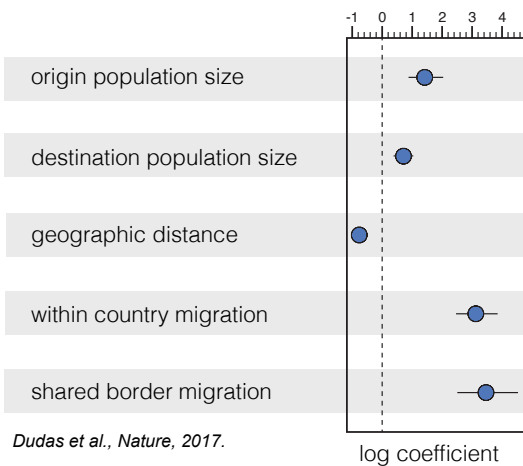
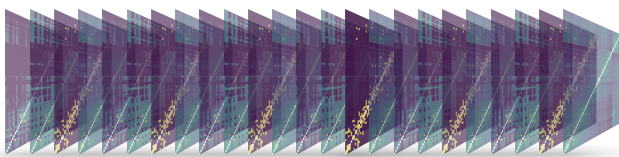
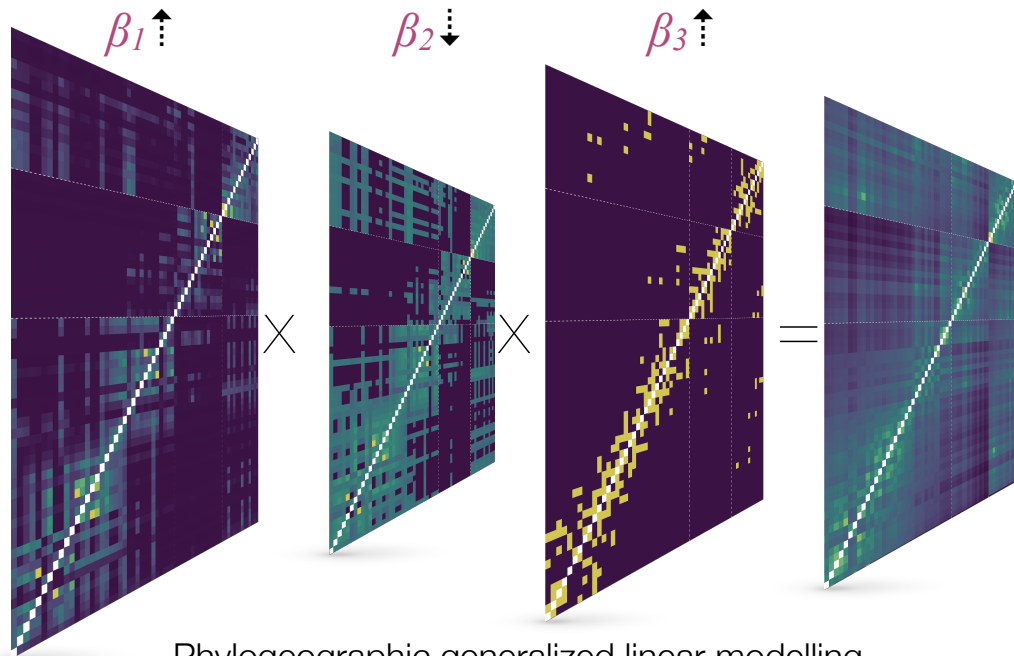
28,610 cases (WHO, confirmed + probable)



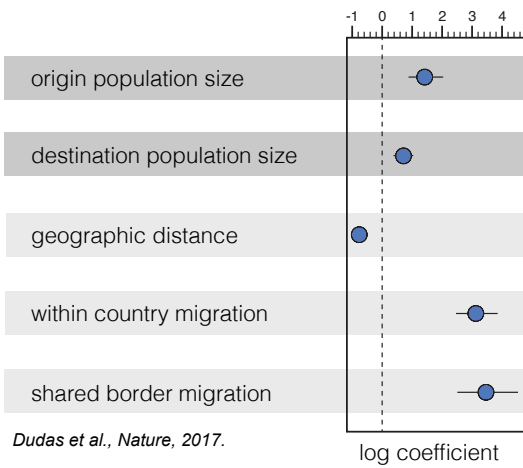
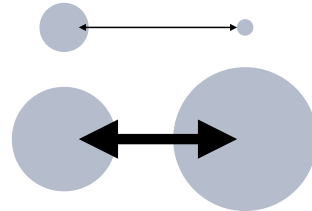
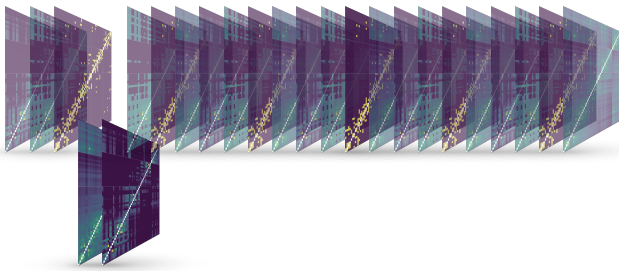
1610 EBOV genomes (>5% of cases)



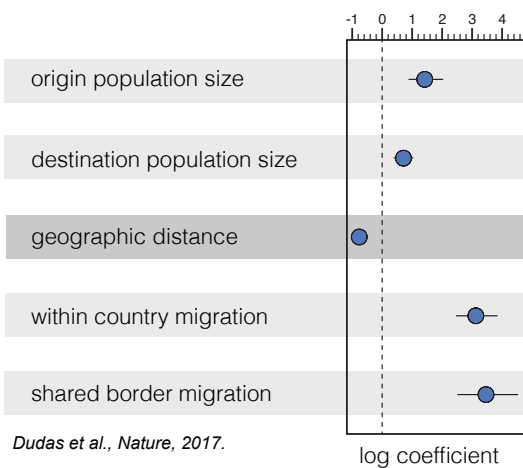
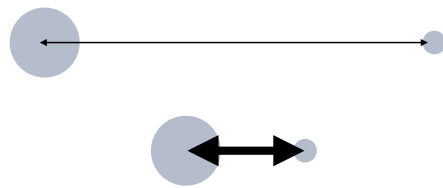
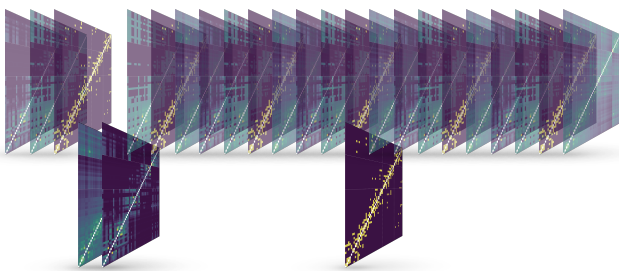




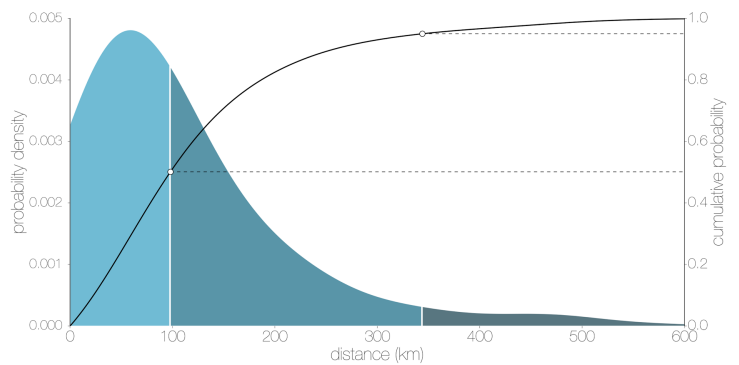
Dudas et al., Nature, 2017.

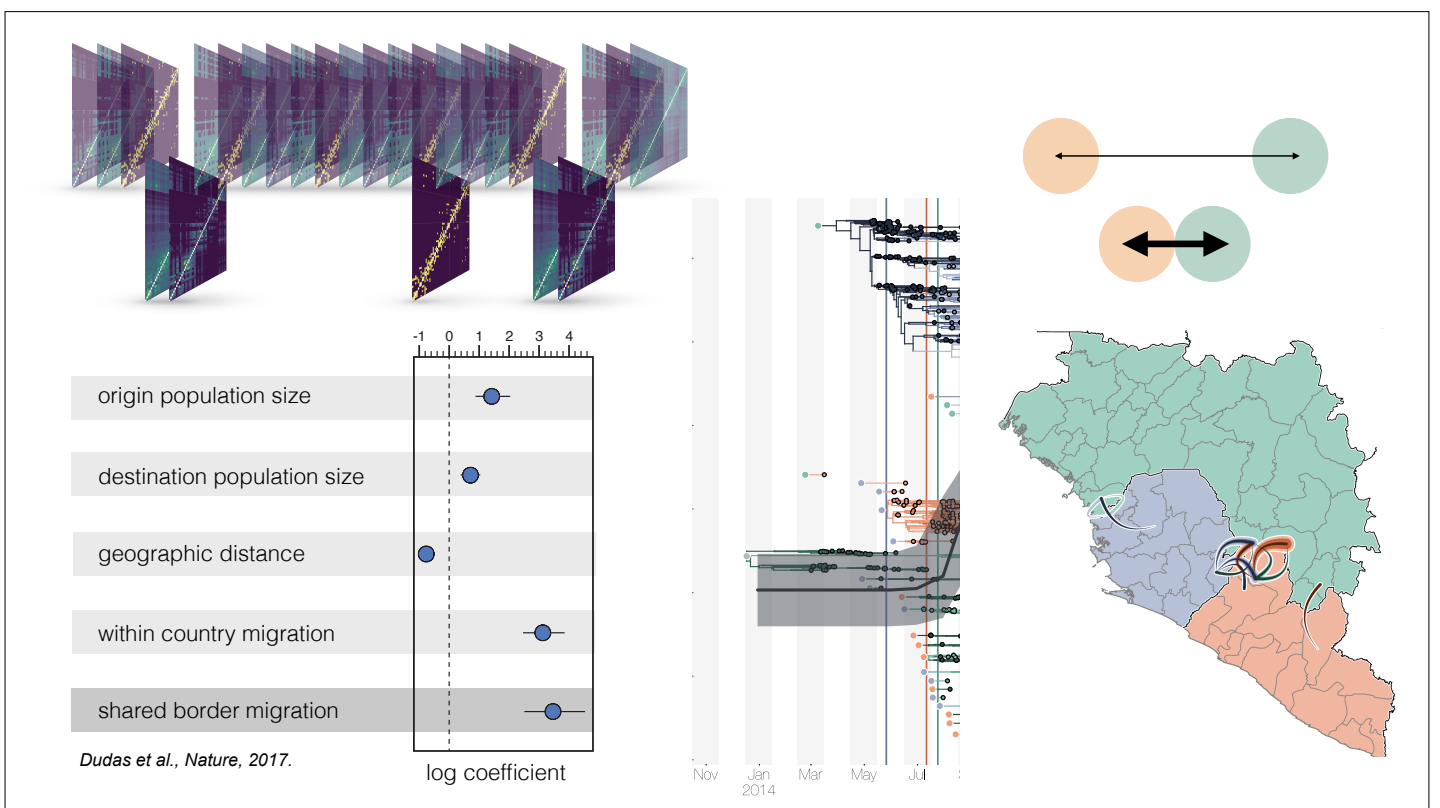
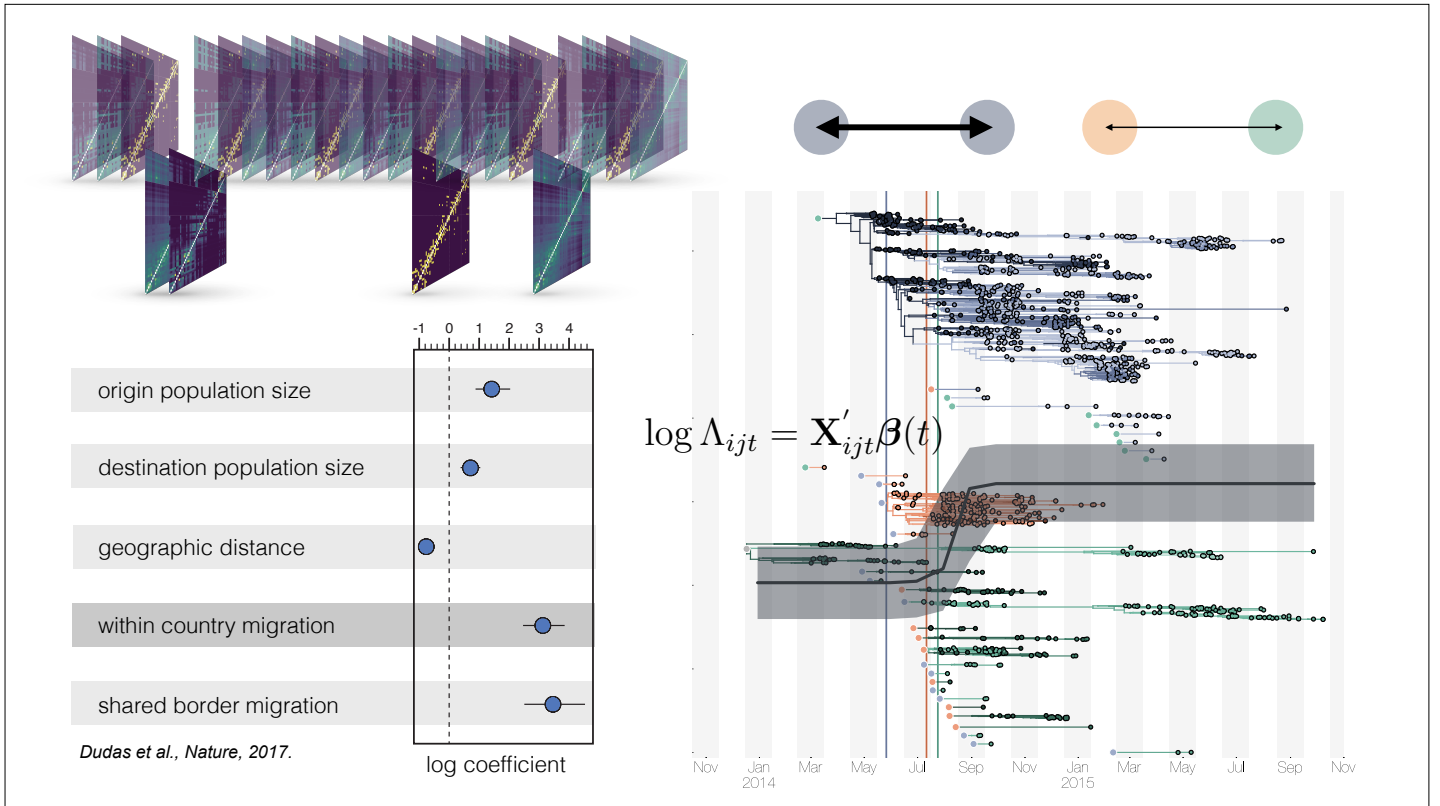


Dudas et al., Nature, 2017.



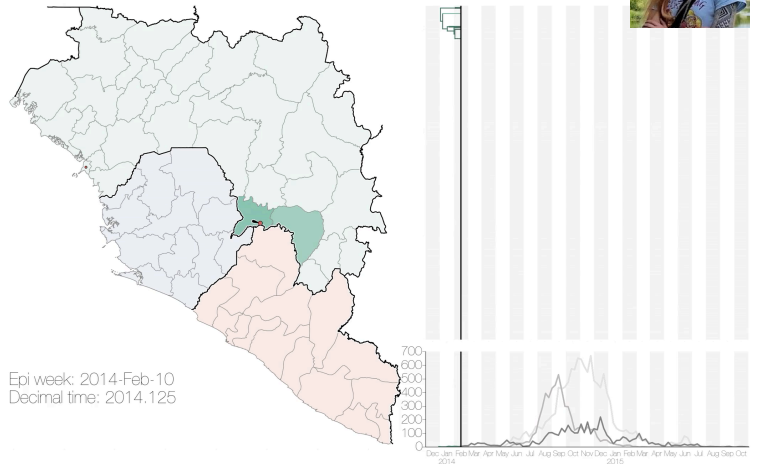
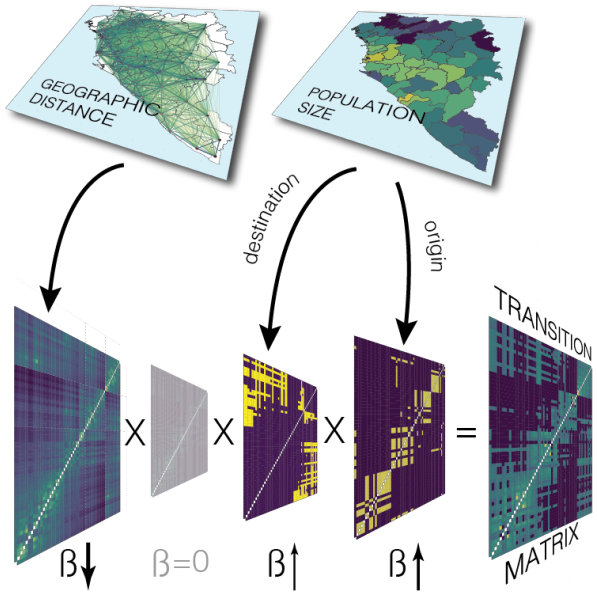
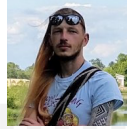
Dudas et al., Nature, 2017.





SciPy John Hunter Excellence in Plotting Contest

winning entry



Epi week: 2014-Feb-10
Decimal time: 2014.125

CTMC: parameters ~ (locations)²

GLM-CTMC: parameters ~ predictors

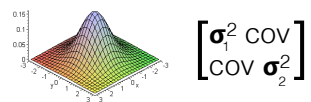
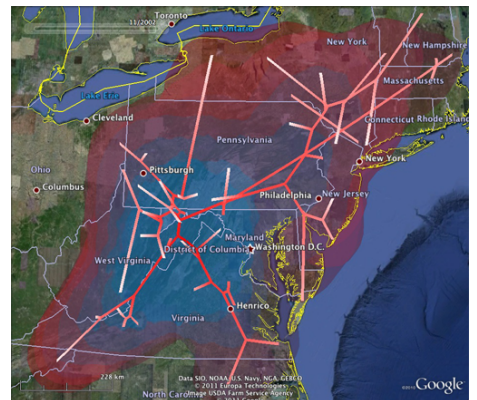
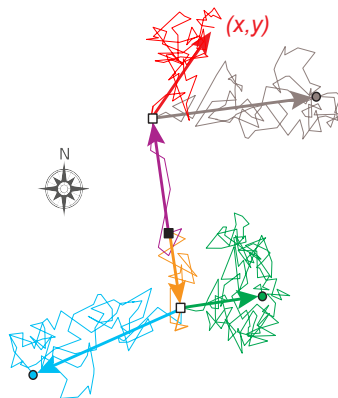
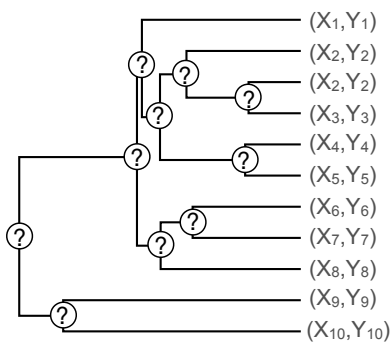
$$\text{overfitting: } \log \Lambda_{ij} = \mathbf{X}'_{ij} \delta \beta + \epsilon_i + \epsilon_j$$

computation: BEAGLE

Dudas et al., Nature, 2017.

Grubaugh et al., Nat Micr, 2019.

Continuous phylogenetic diffusion: Brownian motion process



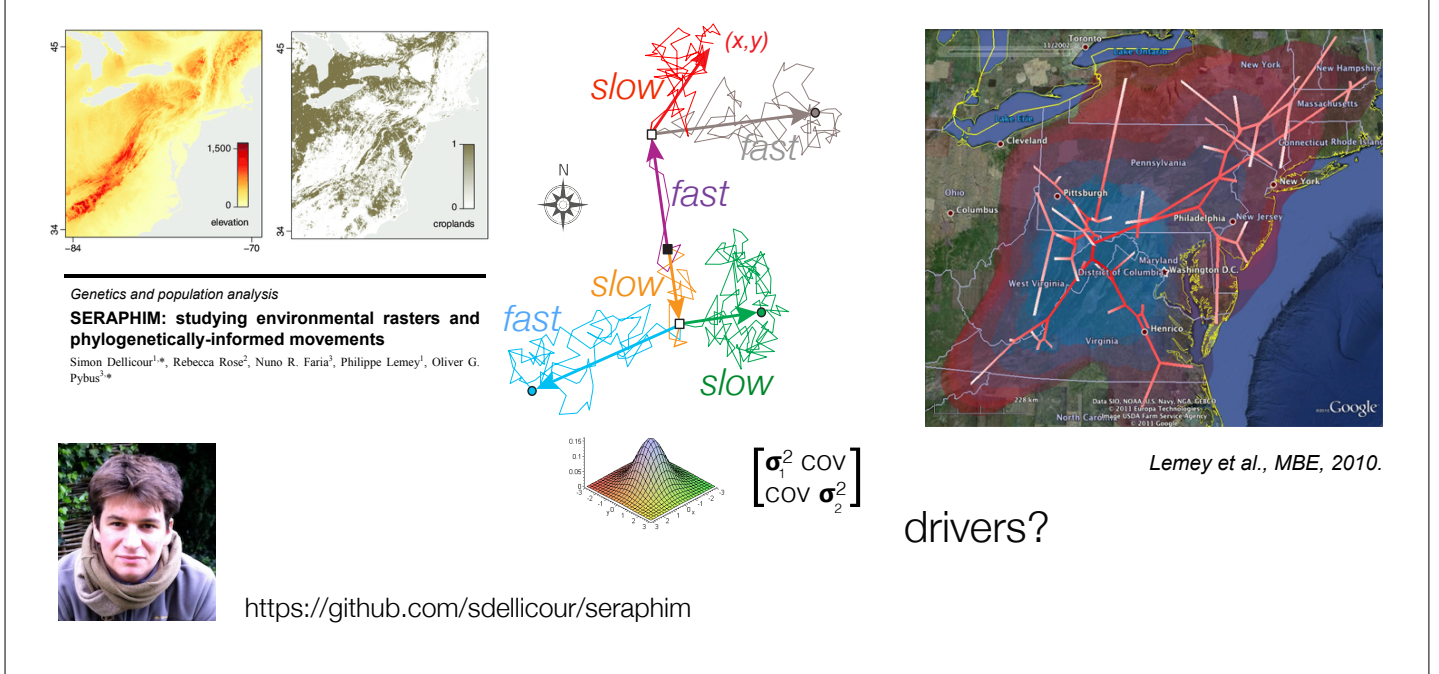
Lemey et al., MBE, 2010.

$$p(\mathbf{Y}_1, \mathbf{Y}_2, \mathbf{Y}_3, \mathbf{Y}_4 | \text{tree, BM})$$

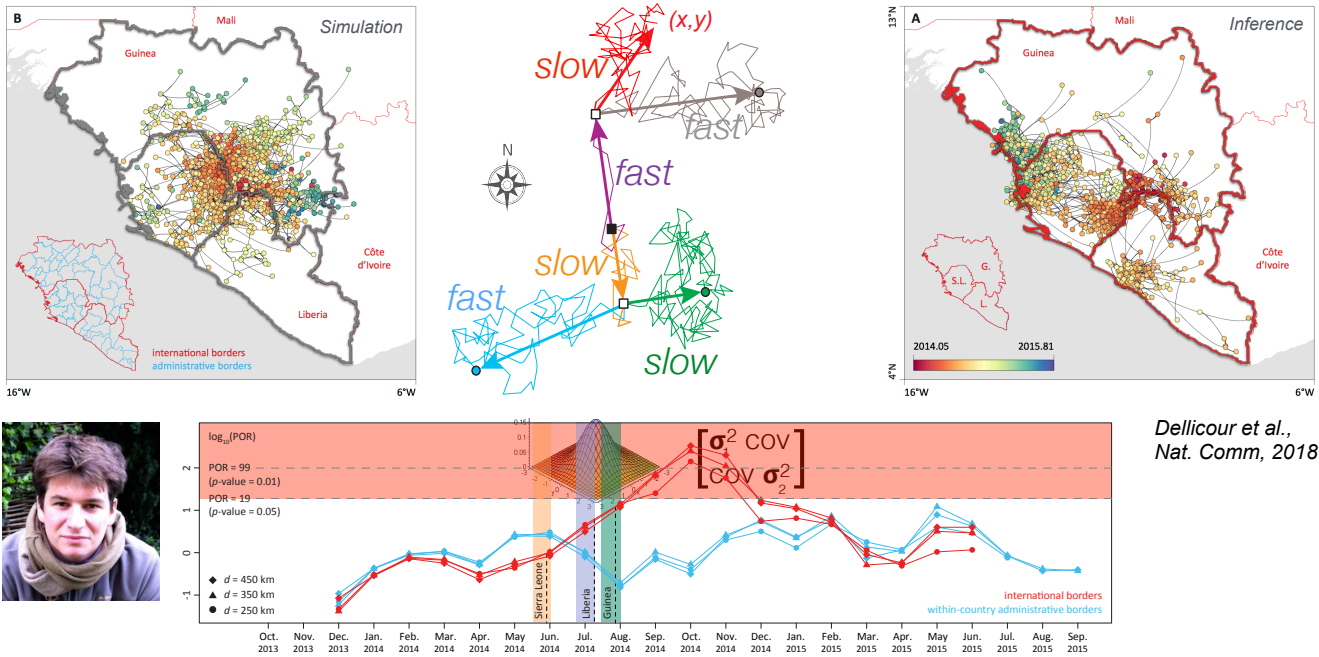
Continuous phylogenetic diffusion: *relaxed* Brownian motion process



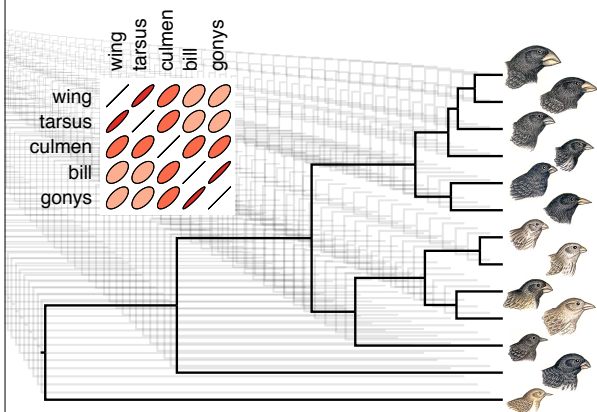
Continuous phylogenetic diffusion: landscape phylogeography



Continuous phylogenetic diffusion: landscape phylogeography

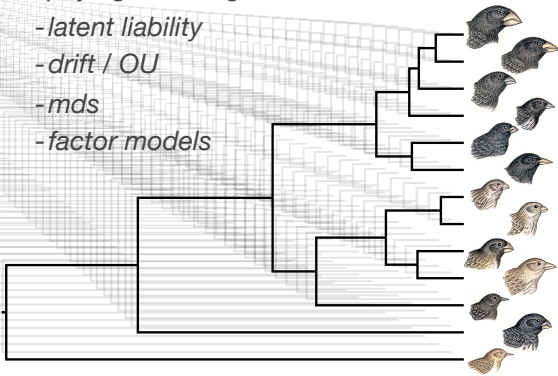


Continuous phylogenetic diffusion: comparative methods



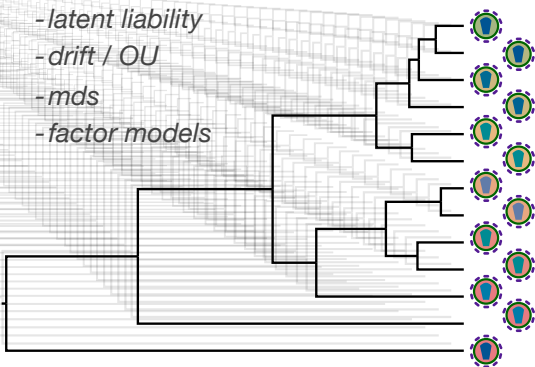
Continuous phylogenetic diffusion: comparative methods

- *missing data*
- *repeated measurements*
- *phylogenetic signal*
- *latent liability*
- *drift / OU*
- *mds*
- *factor models*



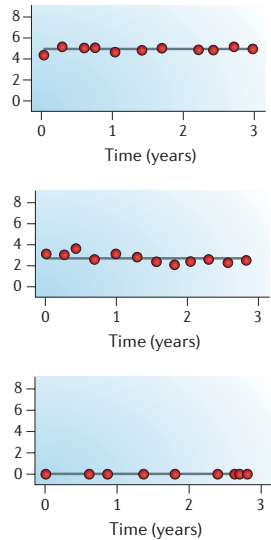
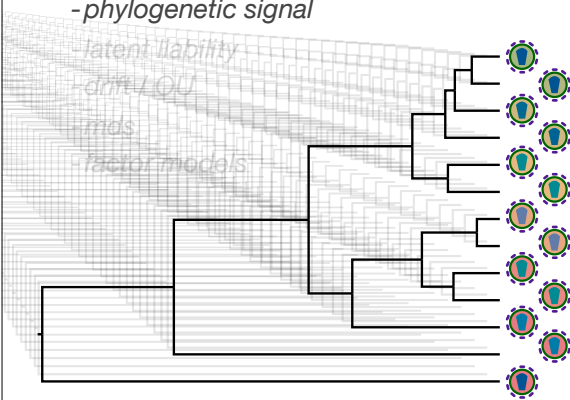
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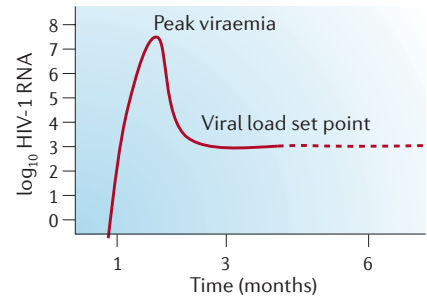


Continuous phylogenetic diffusion: comparative methods

- missing data
- repeated measurements
- phylogenetic signal
- latent liability
- drift/OU
- mds
- factor models



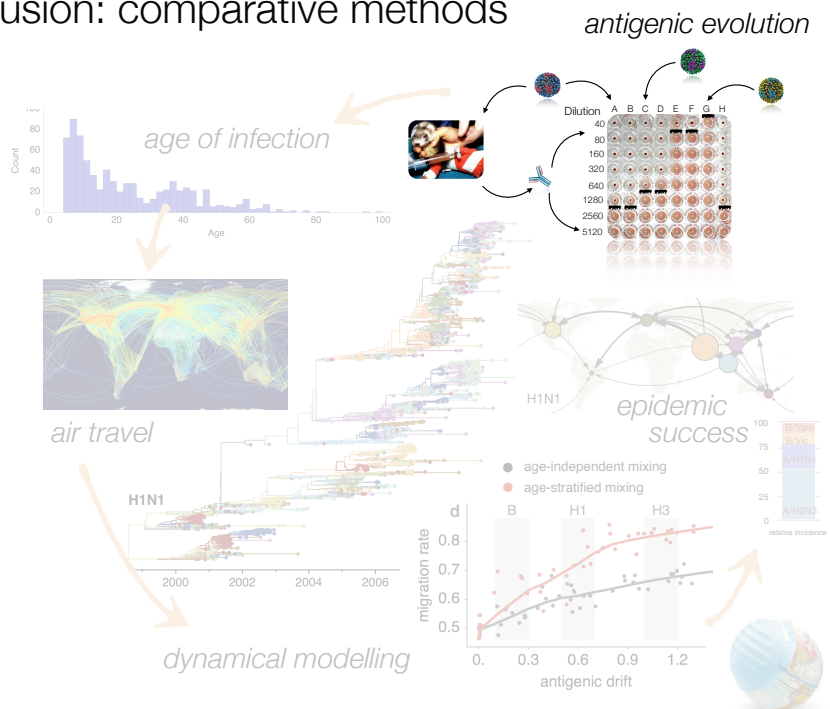
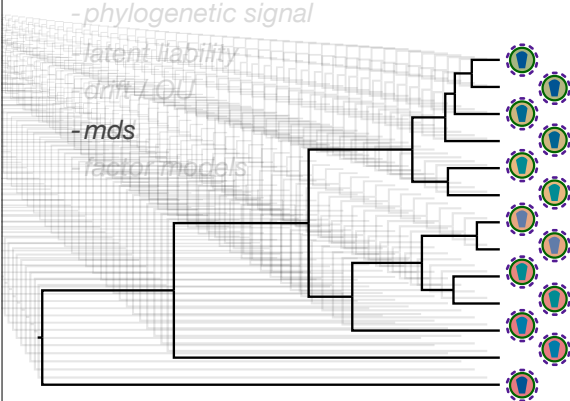
'heritability' of infection traits?



Vrancken et al., MEE, 2015

Continuous phylogenetic diffusion: comparative methods

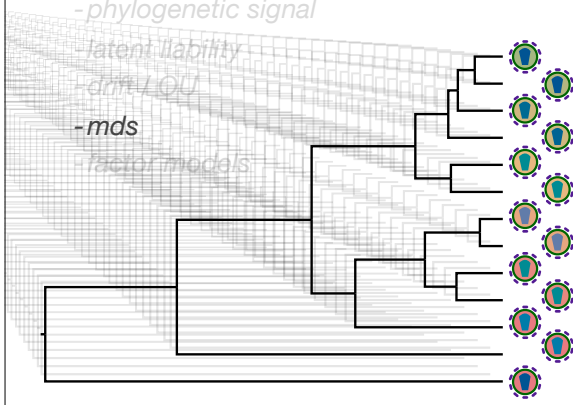
- missing data
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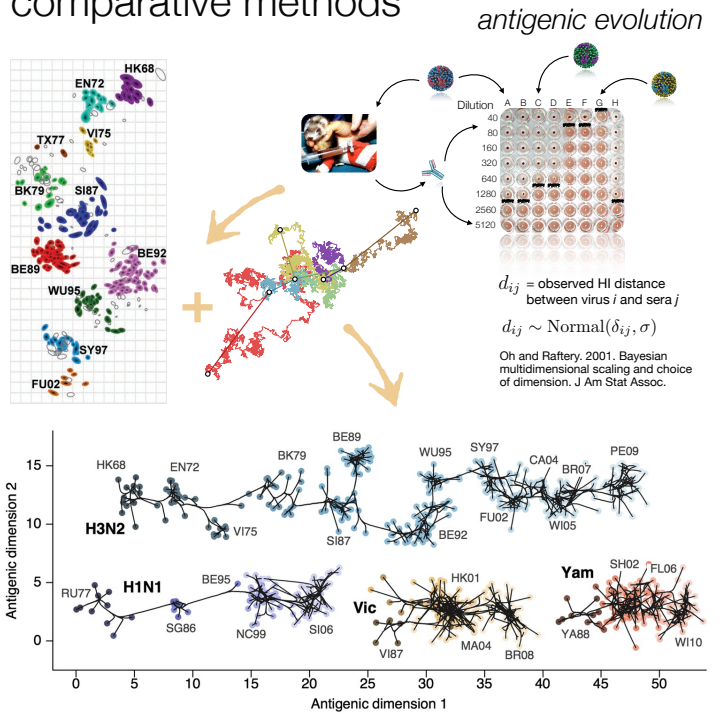
Bedford et al.,
eLife, 2014
Bedford et al.,
Nature, 2015

Continuous phylogenetic diffusion: comparative methods

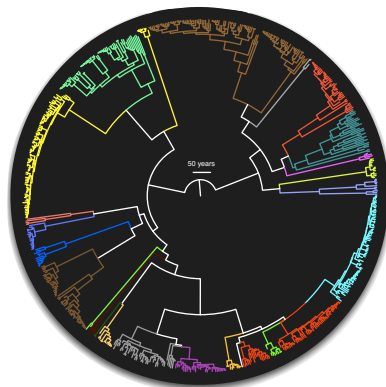
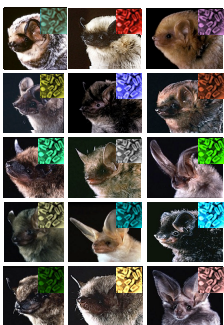
- missing data
- repeated measurements
- phylogenetic signal
- latent liability
- drift LOU
- mds
- factor models



Bedford et al., *elife*, 2014



discrete phylogenetic diffusion: other traits



$$\log \Lambda_{ij} = \beta_1 \delta_1 x_{i,j,1} + \beta_2 \delta_2 x_{i,j,2} + \dots + \beta_P \delta_P x_{i,j,P}$$

predictor **support**

host divergence 45.23

range overlap 0.35

roost structure overlap 1.45

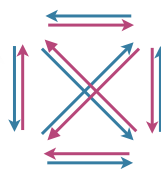
Δ wing aspect ratio 0.14

Δ wing loading 0.23

Δ body size 0.42



Streicker et al., *Science*, 2012
Faria et al., *Phil Roy Soc B*, 2014



Phylogeography: discrete or continuous?

sampling discrete \longleftrightarrow continuous



ancestral locations sampling locations

anywhere

geography abstraction flexible

dispersal $\sim f(\text{distance})$
distance = euclidean

hypothesis testing GLM

Dellicour,
Bioinformatics,
2016



Phylogeography: discrete or continuous?

sampling discrete \longleftrightarrow continuous

BIAS!!



ancestral locations sampling locations

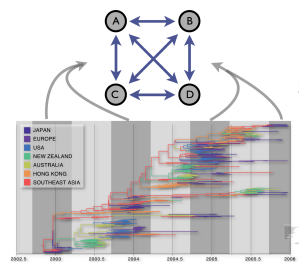
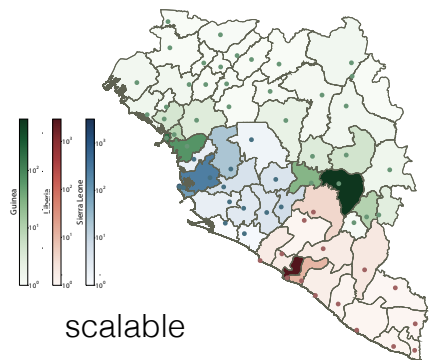
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geography abstraction flexible

dispersal $\sim f(\text{distance})$
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Dellicour,
Bioinformatics,
2016



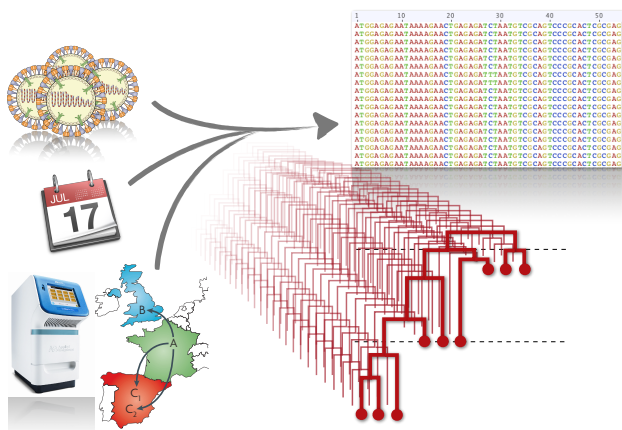
flexible

Bayesian phylogenetic and phylodynamic data integration using BEAST 1.10

Marc A Suchard , Philippe Lemey, Guy Baele, Daniel L Ayres, Alexei J Drummond , Andrew Rambaut  [Author Notes](#)

Virus Evolution, Volume 4, Issue 1, 1 January 2018, vey016,
<https://doi.org/10.1093/ve/vey016>

Published: 08 June 2018



website: beast.community

source code: <https://github.com/beast-dev/beast-mcmc>


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How-To Guides	▼
Advanced Tutorials	▼
Workshop Tutorials	▲
Estimating Rates and Dates	
Evolutionary Dynamics of Influenza	
Model Selection and Testing	
Phylogeographic Diffusion in Discrete Space	
Phylogeographic Diffusion in Continuous Space	
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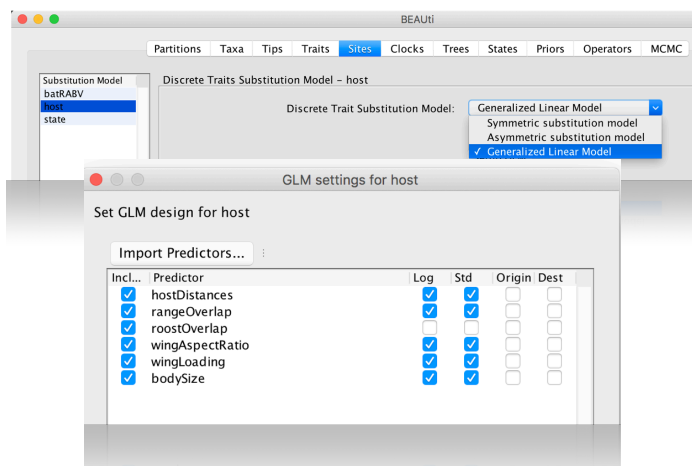
veme: <https://rega.kuleuven.be/cev/veme-workshop/2019>

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