Exact phylodynamics via structured Markov genealogy processes

Edward Ionides

University of Michigan, Department of Statistics

University of Waterloo, Department of Statistics and Actuarial Sciences Seminar, 28 October 2025

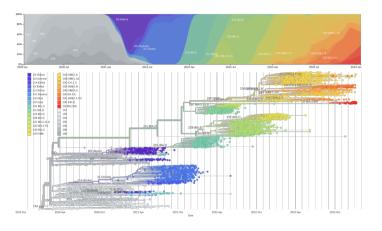
Acknowledgments

This talk is based on King A. A., Lin, Q., & Ionides, E. L. (2025). Exact phylodynamic likelihood via structured Markov genealogy processes. *ArXiv:2405.17032*.

Aaron King, Michigan. Project leader and credit for these slides.
 To see him present the topic:
 https://www.youtube.com/watch?v=-KK7lTdYDYA

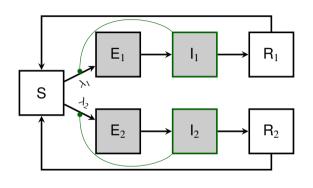
- Qianying Lin, Ohio State
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Example: surveillance for emerging SARS-CoV-2 variants



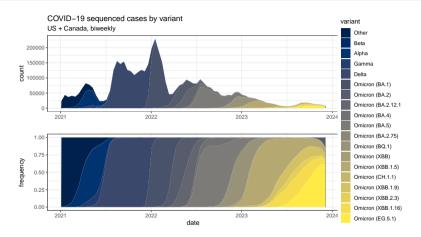
nextstrain.org (Hadfield et al., 2018)

Example: surveillance for emerging SARS-CoV-2 variants



$$\lambda_1 = \beta_1 \frac{I_1}{N} \qquad \lambda_2 = \beta_2 \frac{I_2}{N}$$

Example: surveillance for emerging SARS-CoV-2 variants



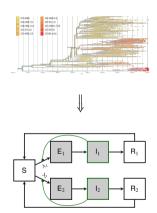
(Mathieu et al., 2020)

What is phylodynamics?

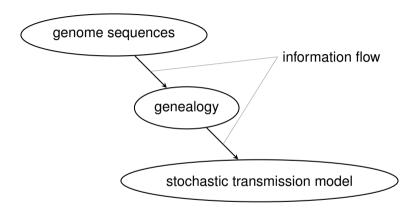
Broadly:

Phylodynamics is the project of inferring determinants of epidemic spread using genomic data from pathogen samples.

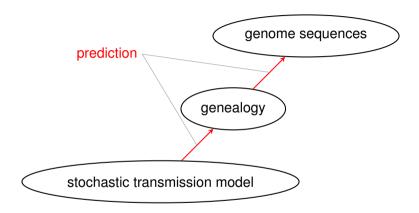
In this talk:
Phylodynamics means using
genomic data
to infer
stochastic dynamic transmission models.



Core problems of phylodynamics



Core problems of phylodynamics



Core problems of phylodynamics

```
S = set of genome sequences
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 $\Phi=$ genealogical tree relating the sequences

E = sequence evolution model

D =dynamic, stochastic transmission model

Y = other time series data

$$\mathcal{L} = f(S, Y|D, E) = \int f(S|\Phi, E) f(\Phi, Y|D) d\Phi$$

 $f(S|\Phi, E)$ = phylogenetic likelihood $f(\Phi, Y|D)$ = phylodynamic likelihood

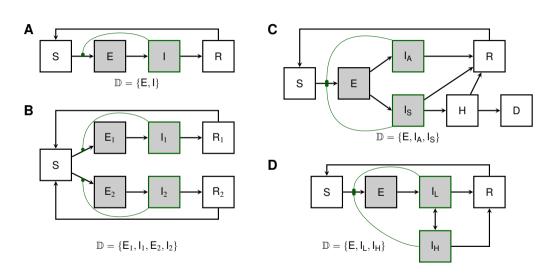
Current approaches

- Coalescent models
 - asymptotic large-population justification
 - naturally studied backwards in time
 - hard to relate formally to small-population models specified forwards in time, except in special cases.
- Linear birth-death processes
 - tractability stems from independence of lineages
 - simple branching models struggle to explain nonlinear phenomena such as susceptible depletion.
 - linearization is possible under large-population, small sample-fraction assumptions
- How can we investigate scientifically motivated nonlinear models?
- An exact likelihood-based method would be statistically efficient.

Overview

- We show how a given population process induces a unique genealogy process.
- Pruning and obscuration project a genealogy onto observable data.
- We derive the exact likelihood as the solution to a nonlinear filtering problem
- This equation can be solved by standard Monte Carlo methods.

Details on the arXiv (King et al., 2024)



- *Population process*: a non-explosive Markov jump process, $\mathbf{X}_t \in \mathbb{X}$, $t \in \mathbb{R}_+$.
- Initial-state distribution, p_0 :

$$\mathsf{Prob}\left[\mathbf{X}_0 \in \mathcal{E}\right] = \int_{\mathcal{E}} p_0(x) \, \mathrm{d}x$$

• Jump rates: $\alpha(t, x, x') = \text{rate of jump } x \to x'$

$$\alpha(t, x, x') \ge 0, \qquad \int_{\mathbb{X}} \alpha(t, x, x') dx' < \infty$$

Multiple events at each jump are allowed.

Kolmogorov forward equation (KFE):

lf

$$\frac{\partial w}{\partial t}(t,x) = \int w(t,x') \,\alpha(t,x',x) \,\mathrm{d}x' - \int w(t,x) \,\alpha(t,x,x') \,\mathrm{d}x'$$

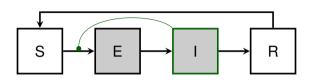
and

$$w(0,x) = p_0(x)$$

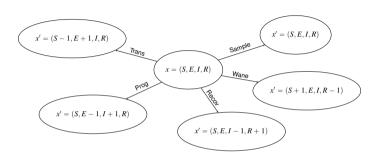
then

$$\int_{\mathcal{E}} w(t, x) \, \mathrm{d}x = \mathsf{Prob} \left[\mathbf{X}_t \in \mathcal{E} \right].$$

KFE is sometimes called the *master equation* for X_t .

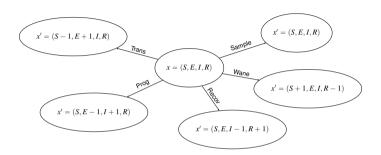


$$\frac{\partial w}{\partial t}(t,x) = \int w(t,x') \alpha(t,x',x) dx' - \int w(t,x) \alpha(t,x,x') dx'$$



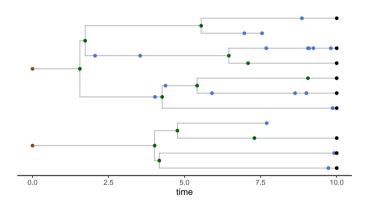
 $\mathbb{U} = \{ \text{Trans}, \text{Prog}, \text{Recov}, \text{Wane}, \text{Sample} \}$

$$\frac{\partial w}{\partial t}(t,x) = \sum_{u \in \mathbb{U}} \left\{ \int w(t,x') \, \alpha_u(t,x',x) \, \mathrm{d}x' - \int w(t,x) \, \alpha_u(t,x,x') \, \mathrm{d}x' \right\}$$

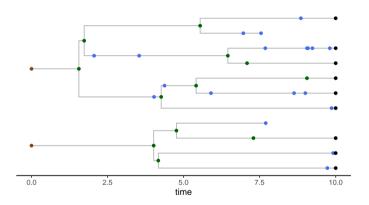


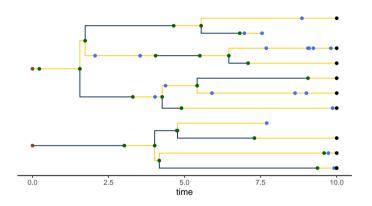
 $\mathbb{U} = \{ \text{Trans}, \text{Prog}, \text{Recov}, \text{Wane}, \text{Sample} \}$

$$\begin{split} \frac{\partial w}{\partial t}(t,S,E,I,R) &= \frac{\beta(t) \left(S+1\right) I}{N} \ w(t,S+1,E-1,I,R) - \frac{\beta(t) \, S \, I}{N} \ w(t,S,E,I,R) + \sigma \left(E+1\right) w(t,S,E+1,I-1,R) - \sigma \, E \, w(t,S,E,I,R) \\ &+ \gamma \left(I+1\right) w(t,S,E,I+1,R-1) - \gamma \, I \, w(t,S,E,I,R) + \omega \left(R+1\right) w(t,S-1,E,I,R+1) - \omega \, R \, w(t,S,E,I,R) \end{split}$$

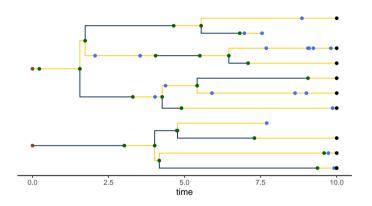


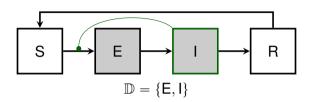
- L: countable set of labels
- partit(\mathbb{L}): set of collections of finite, mutually-disjoint subsets of \mathbb{L} .
- partition *fineness* defines a partial order, \leq , on partit(\mathbb{L}).
- The tree structure of a genealogy is a monotone, càdlàg map
 - $Z:[0,T] \to \mathsf{partit}(\mathbb{L}) \text{ such that } t_1 \leqslant t_2 \text{ implies } Z_{t_1} \leqslant Z_{t_2}.$

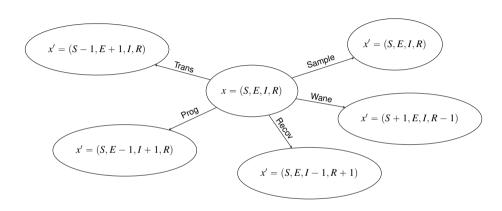




- A *coloring*, *Y*, is an assignment of a deme to each point of the genealogy.
- For $t \in [0,T]$, a a label, $Y_t(a) = (Y_t^{\mathsf{d}}(a), Y_t^{\mathsf{m}}(a)) \in \mathbb{D} \times \mathbb{Z}_+$
- $Y_t^{d}(a)$ is the deme in which the lineage of a is located at time t.
- $Y_t^{\mathsf{m}}(a)$ is the number of nodes encountered along the lineage a in going from time 0 to t.
- $Y_t^{\mathsf{m}}(a)$ is a simple counting process.
- Given a tree Z, let Y(Z) denote the set of colorings Y that are compatible with Z
- Formally, a genealogy is a triple, (T, Z, Y).







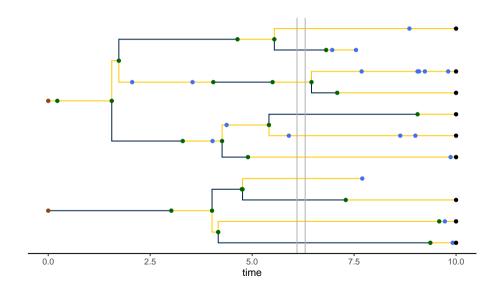
 $\mathbb{U} = \{\text{Trans}, \text{Prog}, \text{Recov}, \text{Wane}, \text{Sample}\}$

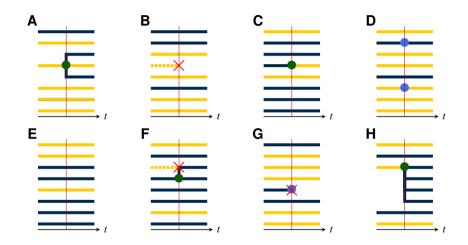
If we write

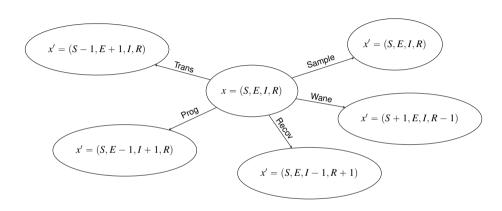
$$\alpha(t, x, x') = \sum_{u \in \mathbb{U}} \alpha_u(t, x, x'),$$

the KFE becomes

$$\frac{\partial w}{\partial t}(t,x) = \sum_{u} \int w(t,x') \,\alpha_{u}(t,x',x) \,\mathrm{d}x' - \sum_{u} \int w(t,x) \,\alpha_{u}(t,x,x') \,\mathrm{d}x'$$





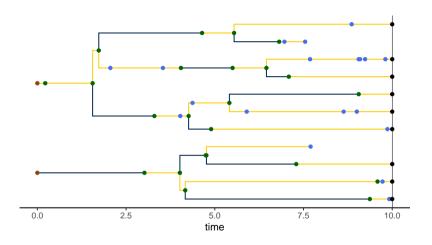


 $\mathbb{U} = \{\text{Trans}, \text{Prog}, \text{Recov}, \text{Wane}, \text{Sample}\}$

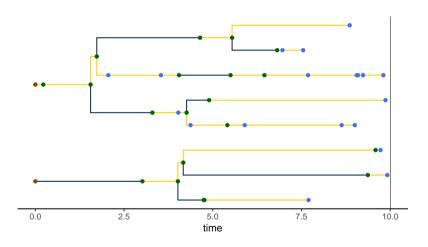
A population process induces a genealogy process

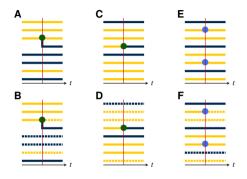
- \bullet G_t is a stochastic process on the space of genealogies.
- The map $X \mapsto G$ is random.
- **Key assumption:** Lineages within a deme are *exchangeable*. There is no more structure than is implied by the population process.
- Simulation code on github.com/kingaa/phylopomp
- Animations at https://kingaa.github.io/manuals/phylopomp/vignettes/

Full genealogy

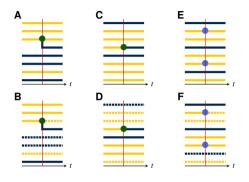


Pruned genealogy

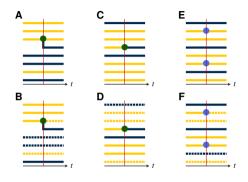




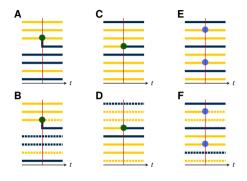
Top row shows the *unpruned genealogy* in neighborhood of an event. Bottom row shows the corresponding *pruned genealogy*.



For $x \in \mathbb{X}$, $i \in \mathbb{D}$, $n_i(x)$ is the *occupancy* of deme i when the system is in state x. In panel A $n = (n_{\text{blue}}, n_{\text{yellow}}) = (4, 4)$; in panel C n = (3, 5);

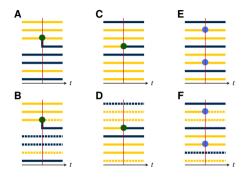


For $u \in \mathbb{U}$, $i \in \mathbb{D}$, r_i^u is the *production* of event u in deme i. In panel A, $r = (r_{\text{blue}}, r_{\text{yellow}}) = (1, 1)$; in panel E, r = (0, 2).



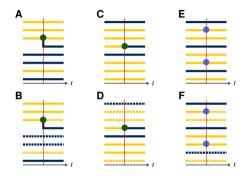
The *lineage count*, $\ell_i(t)$, is the number of unpruned lineages in deme i at time t. In this case, for all panels, $\ell=(2,2)$.

Local structure of a pruned genealogy



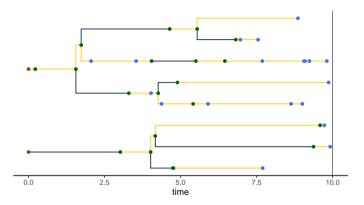
The *saturation*, s_i , is the number of unpruned lineages in deme i descending from the event. In panels B and D, s = (1,0); in panel F, s = (0,1).

Local structure of a pruned genealogy



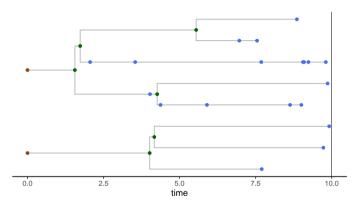
Obviously, $s_i \leqslant r_i \leqslant n_i$ and $s_i \leqslant \ell_i \leqslant n_i$.

Pruned genealogy



A pruned genealogy is specified by two functions of time, (Y,Z): Z_t gives the local topological structure; Y_t gives the local coloring.

Obscured genealogy



An obscured genealogy is specified by (T,Z).

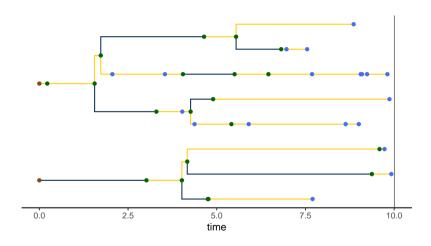
Binomial ratio

For $n, r, \ell, s \in \mathbb{Z}_+^{\mathbb{D}}$, define the *binomial ratio*

$$egin{pmatrix} egin{pmatrix} n & \ell \\ r & s \end{pmatrix} \coloneqq egin{cases} \prod_{i \in \mathbb{D}} rac{inom{n_i - \ell_i}{r_i - s_i}}{inom{n_i}{r_i}}, & ext{if } orall in it } \{\ell_i, r_i\} \geqslant s_i \geqslant 0, \\ 0, & ext{otherwise}. \end{cases}$$

Observe that $\binom{n}{r} \stackrel{\ell}{s} \in [0, 1]$. Moreover,

$$\sum_{s \in \mathbb{Z}_+^{\mathbb{D}}} \binom{n}{r} \binom{\ell}{s} \binom{\ell}{s} = 1.$$



Suppose that P=(Y,Z) is a given pruned genealogy with depth T. Define

$$\phi_u(x, y, y') := \begin{pmatrix} n(x) & \ell(y') \\ r^u & s(y, y') \end{pmatrix} Q_u(y, y').$$

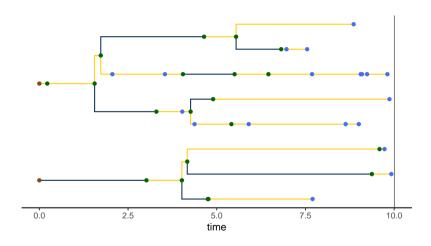
Here, Q=1 if the local structure of P is compatible with an event of type u at that time; Q=0 otherwise.

If w = w(t, x) satisfies the initial condition $w(0, x) = p_0(x)$ and the filter equation

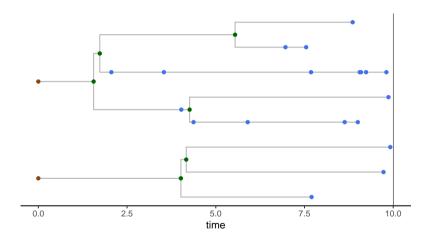
$$\begin{split} \frac{\partial w}{\partial t}(t,x) &= \sum_{u} \int w(t,x') \, \alpha_{u}(t,x',x) \, \phi_{u}(x,\widetilde{\mathbf{Y}}_{t},\mathbf{Y}_{t}) \, \mathrm{d}x' - \sum_{u} \int w(t,x) \, \alpha_{u}(t,x,x') \, \mathrm{d}x', \quad t \notin \operatorname{ev}(\mathbf{P}), \\ w(t,x) &= \sum_{u} \int \widetilde{w}(t,x') \, \alpha_{u}(t,x',x) \, \phi_{u}(x,\widetilde{\mathbf{Y}}_{t},\mathbf{Y}_{t}) \, \mathrm{d}x', \quad t \in \operatorname{ev}(\mathbf{P}), \end{split}$$

then the likelihood of P is

$$\mathcal{L} = \int w(\mathbf{T}, x) \, \mathrm{d}x.$$



Theorem: likelihood of an obscured genealogy



Theorem: likelihood of an obscured genealogy

Let (T,Z) be a given obscured genealogy. Then there are probability kernels π and q such that if

$$\beta_u(t, x, x', y, y') = \alpha_u(t, x, x') \, \pi_u(t, x, x', y, y'), \qquad \psi_u(t, x, x', y, y') = \frac{\phi_u(x', y, y')}{\pi_u(t, x, x', y, y')},$$

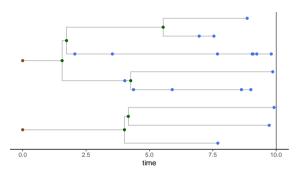
and if w = w(t, x, y) satisfies the initial condition $w(0, x, y) = p_0(x) \mathbb{1}\{q(x, y) > 0\}$ and the filter equation

$$\begin{split} \frac{\partial w}{\partial t} &= \sum_{uy'} \int w(t,x',y') \, \beta_u(t,x',x,y',y) \, \psi_u(t,x',x,y',y) \, \mathrm{d}x' - \sum_{uy'} \int w(t,x,y) \, \beta_u(t,x,x',y,y') \, \mathrm{d}x', \quad t \notin \mathrm{ev}(\mathbf{Z}), \\ w(t,x,y) &= \sum_i \int \widetilde{w}(t,x',y') \, \beta_u(t,x',x,y',y) \, \psi_u(t,x',x,y',y) \, \mathrm{d}x', \quad t \in \mathrm{ev}(\mathbf{Z}), \end{split}$$

then the likelihood of (T, Z) is

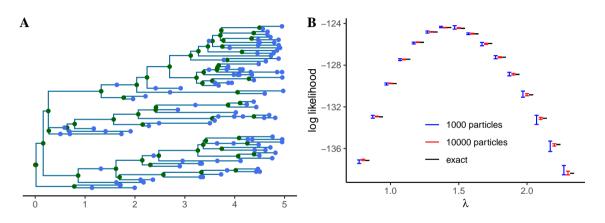
$$\mathcal{L} = \sum_{y} \int w(T, x, y) \, \mathrm{d}x.$$

Theorem: likelihood of an obscured genealogy



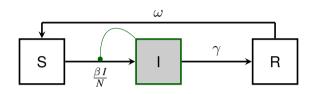
$$\begin{split} \frac{\partial w}{\partial t} &= \sum_{uy'} \int w(t,x',y') \, \beta_u(t,x',x,y',y) \, \psi_u(t,x',x,y',y) \, \mathrm{d}x' - \sum_{uy'} \int w(t,x,y) \, \beta_u(t,x,x',y,y') \, \mathrm{d}x', \quad t \in \mathrm{ev}(\mathbf{Z}), \\ w(t,x,y) &= \sum_{uy'} \int \widetilde{w}(t,x',y') \, \beta_u(t,x',x,y',y) \, \psi_u(t,x',x,y',y) \, \mathrm{d}x', \quad t \in \mathrm{ev}(\mathbf{Z}), \end{split}$$

Linear birth-death model



Uniform sampling. Exact likelihoood is available in closed form.

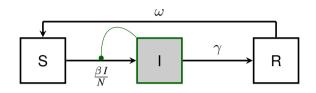
SIRS model



Between genealogical events:

$$\frac{\partial w}{\partial t} = \frac{\beta \left(S+1\right) \left(I-1\right)}{N} \left(1 - \frac{\binom{\ell}{2}}{\binom{I}{2}}\right) w(t, S+1, I-1, R) + \gamma \left(I+1\right) w(t, S, I+1, R-1) + \omega \left(R+1\right) w(t, S-1, I, R+1) - \left(\frac{\beta SI}{N} + \gamma I + \omega R + \psi I\right) w(t, S, I, R).$$

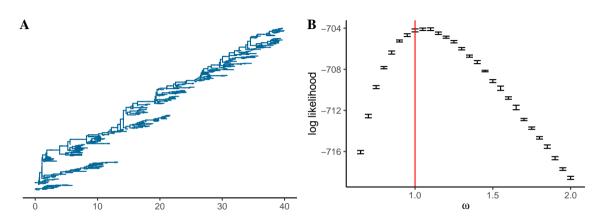
SIRS model



At genealogical events:

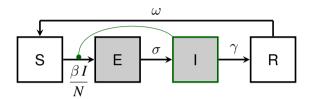
$$w(t,S,I,R) = \begin{cases} \frac{2\,\beta\,(S+1)}{I\,N}\,\widetilde{w}(t,S+1,I-1,R), & \text{branch point at } t, \\ \\ \psi\,\widetilde{w}(t,S,I,R), & \text{internal sample at } t, \\ \\ \psi\,\,(I-\ell)\,\,\widetilde{w}(t,S,I,R), & \text{terminal sample at } t. \end{cases}$$

SIRS model

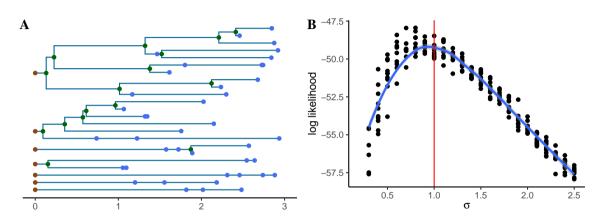


Uniform sampling. One deme only.

SEIRS model



SEIRS model



Concluding remarks

- The theory corrects and strictly extends all existing likelihood-based phylodynamic methods (e.g., Volz et al., 2009; Rasmussen et al., 2011; Stadler, 2010; Volz, 2012; Volz & Frost, 2014; Rasmussen et al., 2014; Vaughan et al., 2019).
- All computations can be carried out forward in time.
 This expands the class of models that can be entertained.
- There is great flexibility in the sampling model.
- Other data streams can be readily and simultaneously assimilated.
- Applications beyond infectious disease epidemiology.
- Full details in King et al. (2024).

Outstanding challenges

- There is some way to go before these results translate into algorithms.
- Key issues: scalability and expense
- Efficient choice of importance-sampling kernel (Borrowing information from future is allowed.)
- Phylogenetic uncertainty
- Efficient simulation algorithms
- Reassortment and recombination

Summary

- A discretely structured Markov population process uniquely induces a genealogy-valued Markov process.
- The likelihood of an observed genealogy satisfies a nonlinear filtering equation.
- Existing tree-based phylodynamic approaches are special cases.
- Various approaches to solving this equation are possible and have yet to be fully explored.
- These results liberate us to entertain models that more closely match our scientific questions, with less hindrance from inference methodology.

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