

Reinventing Test and Trace

A Bayesian Approach For Estimating SARS-CoV-2 Setting-Specific Transmission Rates

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Overview

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Introduction - About Us

- Tim is a final-year Mathematics and Statistics student at the University of Warwick.
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Introduction - Motivation

- Ineffectiveness of Test and Trace programme
 - Escalating costs of over £22 million. (National Audit Office, 2020)
 - Failure to meet testing and contact tracing targets. (iSAGE, 2020)
 - Lack of data and analysis targeted at understanding setting-specific transmission.
- Ineffectiveness of the Tier system in the UK
 - Lockdown-induced economic losses of £355 billion. (OBR, 2021)
 - Unreasonable groupings of activities with disparate transmission risks.
- **Can we design a data-driven approach for studying setting-specific transmission?**

Introduction - Existing Work

- SIR-type models
 - Characterize epidemic evolution through dynamic compartment flows.
 - Calvetti et al. (2020), Kubinec et al. (2020), Flaxman et al. (2020).
 - Dynamic complexity increases estimate variance and error.
- Network-based modelling
 - Analyse mobility along a graph, with an overlaid SIR model.
 - Chang et al. (2020), Chang, Hradings, et al. (2020).
 - Difficult to calibrate with real data.
- Meta-analysis studies of setting-specific transmission
 - Pooled setting-specific SAR estimates from multiple scientific studies.
 - Thompson et al. (2020), Chian Koh et al.(2020).
 - Heterogeneity and practicality concerns.

Introduction - Our Approach

- Through the T&T programme, individuals fill out a survey detailing whether they visited each one of P locations in the last week: $\mathbf{x}_i \in \{0, 1\}^P$
- Survey data is combined with antigen test results for each individual: $y_i \in \{0, 1\}$
- We then employ a Bayesian inference model to estimate the individual transmission rates in each of the locations included in the survey: $\boldsymbol{\theta} \in [0, 1]^P$
- Full model description and code:  **THargreaves/reinventing-test-and-trace-r**

Bayesian Inference - Why and How?

- Properties of Bayesian Inference
 - Quantifies uncertainty in parameters by treating them as random variables.
 - Generative modelling approach can perform better with fewer training samples. (Ng, 2001)
 - Incorporates experimental estimates and expert opinion through 'priors'.
- Posterior sampling done using HMC algorithm (NUTS variant).
- Two implementations:
 - Stan - Probabilistic programming language compiled in C++ \implies fast!
 - TensorFlow Probability - offers support for GPU's and distributed computing setups.

Modelling - The Base Model

- Transmission for an individual depends on:
 - Places visited.
 - Specific transmission rates of said places.
 - Transmission could occur at some other setting not specified in the survey
 - We incorporate this possibility through the base transmission risk.
 - For an individual to become infected, all we need is for transmission to have occurred in at least one setting or base transmission.
- Transmission: $\mathbf{t}_i \sim \text{Ber}(\mathbf{x}_i \circ \boldsymbol{\theta})$
 - Base transmission: $b_i \sim \text{Ber}(\rho)$
 - Infection: $w_i = \mathbb{1}\{\mathbf{1}^\top \mathbf{t}_i + b_i > 0\}$

Modelling - Resampling

- We want to relax the random sampling assumption
 - Infected individuals are more likely to get tested.
 - Symptoms, time/effort involved in testing, etc...
- Solution: Gather data from T&T as well as a random survey.
- With this framework, we can now introduce conditional testing rate parameters.
- We then 'weight down' transmission likelihood by the testing rates for infected and non-infected individuals.

- Define $s_i = \begin{cases} 1, & \text{T\&T sample} \\ 0, & \text{otherwise} \end{cases}$
- Define also testing rates:
 - $\mathbb{P}(s_i = 1 | w_i = 1) = \gamma_+$
 - $\mathbb{P}(s_i = 1 | w_i = 0) = \gamma_-$

Modelling - Inaccurate testing

- We also want to model test inaccuracy
 - False Positive: Test wrongly indicates infected.
 - False Negative: Test wrongly indicates not infected.
 - Solution: Introduce parameters for the true positive and true negative rates.
 - Use these to 'weight down' transmission likelihood.
 - We can incorporate 'strong priors' for TP/TN rates
 - Calibrate targeting results from UK SARS-CoV-2 test development and validation cell. (PHE Porton Down et al., 2020)
- True positive rate:
 $\mathbb{P}(y_i = 1 | w_i = 1) = \lambda_+$
 - True negative rate:
 $\mathbb{P}(y_i = 0 | w_i = 0) = \lambda_-$
 - Priors: $\lambda_+, \lambda_- \sim \text{Beta}(\alpha_0, \beta_0)$
 - Calibrate α_0, β_0 to match experimental $\bar{\lambda}$ and s_{λ}^2 .

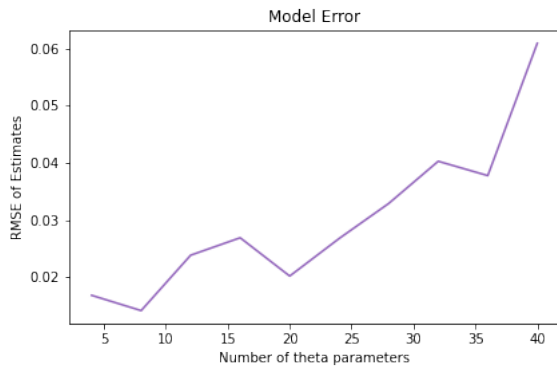
Modelling - Hierarchical Extension

- Question: How much riskier is the Dirty Duck relative to your average pub?
 - We want to model transmission risk relative to similar settings.
 - Split similar settings into "classes".
 - E.g// fast food locales - McDonald's, Subway, Domino's, etc.
 - Model setting-specific transmission rates as deviations from the average setting class transmission rate.
- Introduce K classes.
 - Denote the class of setting $p \in [P]$ by $c(p) : [P] \rightarrow [K]$.
 - Class transmission parameters:
 $\mu \in [0, 1]^K, \sigma^2 \in \mathbb{R}_{>0}^K$
 - $\theta_p \sim \text{Logitnormal}(\text{logit}(\mu_{c(p)}), \sigma_{c(p)}^2)$

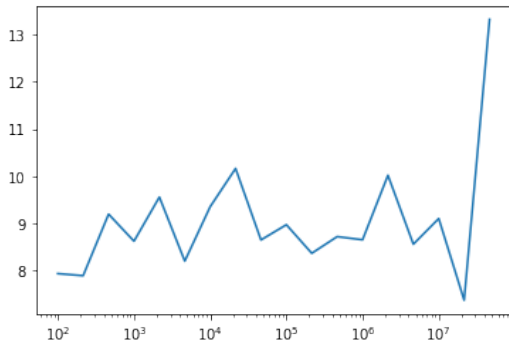
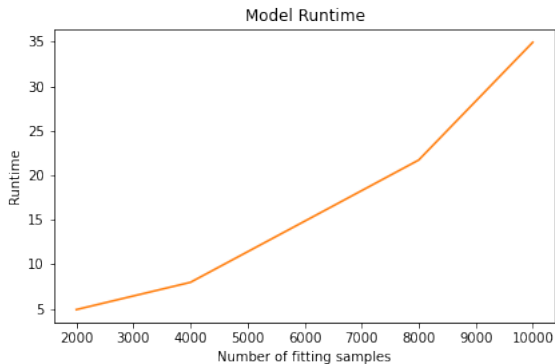
Modelling - Interventions

- Question: Does wearing a mask have the same impact everywhere?
 - We want to model setting-specific impact of mask-wearing.
 - Ask individuals if they wear masks.
 - Capture impact on likelihood through a parameter applying only to mask-wearing individuals
 - We model the multiplier effect on the transmission odds ratio for specific classes
 - *"You are X times more likely to become infected without a mask in Setting A"*
- Define $m_i = \begin{cases} 1, & \text{mask-wearing} \\ 0, & \text{otherwise} \end{cases}$
 - Define $\iota \in \mathbb{R}^K$ as the class-specific mask-wearing impact.
 - $\theta_p \sim \text{Logitnormal}(\text{logit}(\mu_{c(p)}), \sigma_{c(p)}^2) + \ln(\iota_{c(p)})$

Diagnostics - Estimation Error



Deployment and Scalability - Runtime



Further Research

- Modelling additional policy interventions
 - Social distancing measures, business closures, full lockdown.
- Reducing computational cost
 - Can we make more efficient code for both implementations?
- Incorporation into a hierarchical SIR
 - Use of particle filters given noise both in partial observations and dynamical system.

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