# The real-time pandemic influenza model and its implementation(s)

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#### Introduction



- Two software packages, obtaining epidemic inference via:
  - MCMC using basic random-walk Metropolis updates.
  - SMC using particle learning (In development).
- In each package, model is implemented with bespoke, standalone C++ code for Bayesian inference from the real-time model.

#### Additionally...

- R version of the SMC code (Alice to discuss)
  - Parallelised using Rmpi.
  - Runs on BSU cluster.
  - Code slow, many speed-ups possible.
  - Reduced functionality.

## Compilation and Running



• Within each package, code can be compiled using the command

Creates two executable files, one 'fast', one debuggable.

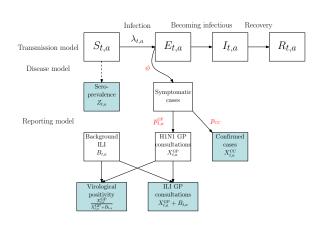
• Command line execution (personal preference), e.g.

```
nice -19 ./rtm_gnu > outputfile.txt &
```

#### What does the code do?



- SEIR model governing transmission.
- Disease model describing disease severity and healthcare seeking behaviours.
- Reporting model.
   Multiple sources of epidemic data, generated over
  - R parallel regions
  - A strata (usually age-groups)
  - T time points (days/weeks).



### Input files



Unless specified otherwise, the executable will look for two input files mod\_inputs.txt and mod\_pars.txt.

#### mod\_inputs.txt

#### Specification of:

- data structure
- likelihood
- regions (population, data files)
- contact model
- MCMC/SMC control

### Input files



Unless specified otherwise, the executable will look for two input files mod\_inputs.txt and mod\_pars.txt.

#### mod\_pars.txt

Specification of, for each parameter

- initial values (redundant for SMC)
- prior distributions
- dimension
- parameterisation
- proposal parameters

### Input files



Unless specified otherwise, the executable will look for two input files mod\_inputs.txt and mod\_pars.txt.

#### Changing the source of inputs

To change the names of either of these input files:

In a file names smc\_rtm\_inputs.txt, set the values of the following variables.

model\_parameters: mod\_pars\_alt.txt
model\_inputs: mod\_inputs\_alt.txt

Would it be preferred if there was the capability to specify these as command line inputs, rather than specified in a .txt file?

#### Data Structure & Likelihood



```
GP_consultation_flag 1
Hospitalisation_flag 0
Deaths_flag 0
Sero_data_flag 1
Viro_data_flag 1
gp_count_likelihood 1 ## 0 POISSON, 1 FOR NEGATIVE BINOMIAL DATA.
transmission kernel 0 ## 0 FOR THE REED-FROST 1 FOR MASS ACTION.
transmission_time_steps_per_day 2
reporting_time_steps_per_day 2
duration_of_runs_in_days 245
duration_of_previous_runs_in_days 164
num_regions 1
num_age_groups 7
                            Green text indicates new options in SMC code
Sero_likelihood_start_day 75
Sero_likelihood_end_day 245 ## SPECIFY A SUBSET OF THE DATA TO BE
INCLUDED IN LIKELIHOOD.. USEFUL TO AVOID ZEROS.
```

### Regions



```
study_region = { regions_used = London, WestMidlands, North, South; regions_population = 119967, 410926, 840309, 989473, 2747554, 1566445, 882256, 68285, 259069, 651598, 730409, 1443924, 1343723, 884837, 227677, 864277, 2217602, 2676783, 5101913, 4823469, 3093895, 224805, 863397, 2251281, 2415331, 5166801, 4927669, 3298357; An R × A array.
```

## Regions (cont'd)



### MCMC options - notation



- The MCMC algorithm aims to sample from a posterior distribution  $\pi_t(\theta|\mathbf{x}_t)$ .
- Suppose the parameter vector,  $\theta$  can be partitioned into  $(\theta_1, \dots, \theta_k)$ .
- Each parameter component  $\theta_j$  has a prior distribution  $\pi_0(\theta_j)$ .
- Start with an initial vector  $\theta^{(0)} = (\theta_1^{(0)}, \dots, \theta_k^{(0)})$
- At iteration, i, we have  $\theta^{(i)}$ .
- For j = 1, ..., k, make a proposal

$$\theta_j^{(*)} \sim N\left(\theta_j^{(i)}, \sigma_i^2 \mathbf{I}\right).$$
 (1)

- Then accept this proposal as  $\theta_j^{(i+1)}$  with the appropriate acceptance probability. Otherwise set  $\theta_j^{(i+1)} = \theta_j^{(i)}$ .
- Run until i = N.

# MCMC options (cont'd)



num\_iterations 700000

N number of iterations.

output\_type 0

0 or 1, for output as MCMC chains, or output as particles

thin\_output\_every 100

Stored chains are thinned to every 100<sup>th</sup> iteration (post burn-in only).

 $thin\_stats\_every$  5000

Summary statistics are output every 5000<sup>th</sup> iteration (post burn-in only).

adaptive\_phase 100000

No. of iterations within the burn-in over which the proposal variances are adaptated.

adapt\_every 100

Proposal variance adaptation occurs every 100<sup>th</sup> iteration (within the adaptive phase only).

burn\_in 200000

Length of burn-in. All of the first 200000 iterations are discarded.

## MCMC options (cont'd)



num\_progress\_reports 10

Number of updates produced during both the adaptive and posterior phases.

mixing\_threshold\_ub 0.3

During the adaptive phase, acceptance rates above 0.3 lead to a scale-up of proposal variances

mixing\_threshold\_lb 0.2

During the adaptive phase, acceptance rates below 0.2 lead to a reduction in proposal variances

prop\_var\_inflation 1.1

Proposal variance scale-up factor

prop\_var\_shrinkage 0.9

Proposal variance scale-down factor

maximum\_block\_size 9

Maximum number of components of the  $\theta^{(j)}$  that are proposed in any one go.

random\_seed 80
max\_threads 8

The number of parallel threads used in evaluating the model likelihood.

## SMC options - Reweighting



- We wish to evaluate a posterior density  $\pi_{t_1}(\theta|\mathbf{x}_{t_0})$ , starting from an initial posterior  $\pi_{t_0}(\theta|\mathbf{x}_{t_0})$ .
- Code will load in (or generate if  $t_0 = 0$ ) a particle set,  $\{\theta^{t_0,1},\ldots,\theta^{t_0,n}\}$  and weights  $\omega_{t_0}^{(1)},\ldots,\omega_{t_0}^{(n)}$ , representing a weighted sample from  $\pi_{t_0}$ .
- At general time t+1, assimilate new data in continuous time. This means we consider densities of the form  $\pi_{t,\delta}(\theta) = \pi_t(\theta) \{ p(\mathbf{x}_{t+1}|\theta) \}^{\delta}$ , for  $\delta \in [0,1]$ . At 'time'  $t + \delta$ , particle j carries weight

$$\tilde{\omega}_{t+\delta}^{(j)} = \omega_t^{(j)} \left\{ p \left( \mathbf{x}_{t+1} | \theta^{t,j} \right) \right\}^{\delta}$$

# SMC options - Detecting **Impoverishment**



Define the effective sample size

$$ESS\left(\left\{\omega^{(\cdot)}\right\}\right) = \frac{\left(\sum_{l=1}^{n} \omega^{(l)}\right)^{2}}{\sum_{j=1}^{n} \omega^{(j)}}.$$

- If, for some threshold  $\epsilon \in [0,1]$ :
  - $ESS(\{\tilde{\omega}_{t+1}^{(j)}\}) > \epsilon n$ . No particle set rejuvenation required. Set  $\theta^{t+1,j} = \theta^{t,j}$  and  $\omega_{t+1}^{(j)} = \omega_t^{(j)}, \forall i = 1, \ldots, n$ .
  - $ESS(\{\tilde{\omega}_{t+1}^{(j)}\}) \leq \epsilon n$ . The particle set is impoverished and requires rejuvenation. Pick  $\delta_0$ , such that  $ESS(\{\tilde{\omega}_{t+\delta_0}^{(j)}\}) = \epsilon n$ . The particle set is then rejuvenated (see next slide) and weights are reset  $\omega_{t+\delta_c}^{(j)}=1$ .
    - Define weights  $\tilde{\omega}_{t,\delta_0,\delta}^{(j)} = p(\mathbf{x}_{t+1}|\theta^{t+\delta_0,j})^{\delta-\delta_0}$ . Further rejuvenations will be required if this leads to an ESS calculation that once again drops below  $\epsilon n$  while  $\delta < 1$ .

### SMC options - Rejuvenation



Resampling, followed by population MCMC, using proposal distributions weakly dependent upon the starting states (i.e. the particle set requiring rejuvenation).

- Using the weighted sample, make estimates of  $\hat{\mu}$  and  $\hat{\Sigma}$ , the sample mean and covariance.
- Resample the particles according to the particle weights.
- Move the n particles. Effectively running n parallel MCMC chains... except
  - No requirement to attain convergence no burn-in phase.
  - No requirement to run long chains to harvest a sample. The parallel chains provide a sample.

# SMC options - Rejuvenation (2)



- Move(continued) Two types of move:
  - Correlated random-walk: Propose

$$heta^* | heta_k^{(j)} \sim \mathsf{N}\left( heta_k^{(j)}, \gamma ar{oldsymbol{\Sigma}}_k
ight).$$

Approximate Gibbs': Propose

$$heta^* | heta_k^{(j)} \sim \mathsf{N}\left(ar{ heta}_k, ar{oldsymbol{\Sigma}}_k
ight)$$

- Moves can be based on the above distributions or their conditionals if not using a full block update.
- Any number of the above types of proposal can be made per iteration, and they can be of a subset of parameter components and they can be full-block or componentwise.
- Parameter  $\gamma$  can be adapted between successive batches.
- gamma can also be vector-valued.

## SMC options - Rejuvenation (3)



- **Move**(continued) Repeat the process until the sample inter-class correlation coefficient,  $r_{\Delta}^*$  reaches some lower threshold.
  - After resampling,  $r_{\Delta}^* = 1$ .
  - Provides a measure of how well the chains have collectively forgotten their starting points.
  - Stop making proposals when  $r_A^* \leq r_{A,0}$ .

## SMC options (cont'd)



location\_particles /saved/

Where the 'current' cles are stored. Ignored if duration\_of\_previous\_runs\_in\_days = 0. Defaults to the current directory.

num\_particles 10000

Number of particles to use. If saved number is different, this will be the number resampled.

updaters 110

3 update steps: 0 for a correlated r-w proposal, 1 for an approx. Gibbs proposal.

block\_updates 110

One for each of the above. 0 for cpt-wise updates, 1 for a block update

## SMC options (cont'd)



ess\_threshold 0.5

 $\epsilon$ , the ESS threshold that triggers sample rejuvenation.

icc\_threshold 0.1

 $r_{A,0}$ , the threshold for stopping the move-step of the rejuvenation.

mixing\_threshold\_ub 0.3

For correlated r-w updates, acceptance rates above 0.3 lead to a scale-up of  $\gamma$ .

mixing\_threshold\_lb 0.2

As above, acceptance rates below 0.2 lead to a reduction in  $\gamma$ .

prop\_var\_inflation 1.1

 $\gamma$  scale-up factor

prop\_var\_shrinkage 0.9

γ scale-down factor

# Specifying model parameters - Initial Values



```
prop_symptomatic = { param_value = 0.1, 0.15, 0.2, 0.25; }
```

- Sets initial values for MCMC chain.
- In SMC, redundant, other than to determine the length of the parameter vector *i.e.* how many parameters govern the proportion symptomatic in the population (over time and ages).

# Specifying model parameters - Prior Choice(1)



- Value required for each parameter component.
- If first value indicates a multivariate proposal, it over-rides the rest.
- Values and distributions...
  - Fixed value.
  - Gamma distribution.
  - Beta distribution.
  - Normal distribution.
  - Multivariate normal distribution.
  - Malf-normal distribution.
  - Uniform distribution.

# Specifying model parameters - Prior Choice(1)



- Code knows how many parameters each distribution requires.
- Parameters are assigned as a queue the four parameters components above have prior distributions:

```
• \beta(0.5, 2)
• \beta(1, 1)
• \beta(20, 10)
• \beta(1, 1)
```

- A constant parameter component takes no prior parameter values.
- Gamma distribution is in shape/rate parameterisation.
- Multivariate normal  $(\mu, \Sigma)$  parameters are specified as a vector  $(\mu_1, \Sigma_{11}, \Sigma_{12}, \dots, \sigma_{1p}, \mu_2, \sigma_{21}, \dots, \sigma_{pp})$ , a p(p+1) length vector.

# Specifying model parameters -



# Parameterisation

Model parameters are parameters that specify the, for example, proportion symptomatic. We need not be specifying the actual parameter value. Instead the relation is via a generalised linear model set-up.

$$g\left(\underbrace{\theta}_{(r_0t_0a_0)\times 1}\right) = \underbrace{\mathbf{X}}_{(r_0t_0a_0)\times p}\underbrace{\beta}_{p\times 1}$$

- β The parameter vector of length p that we specify in the mod\_pars.txt file.
- **X** A  $(r_0t_0a_0 \times p)$  design matrix.
- $g(\cdot)$  A link function
- $\theta$  A vector of the calculated parameter values,  $(\theta_{111}, \theta_{112}, ..., \theta_{r_0t_0a_0})$ , with, for example,  $\theta_{rta}$  giving the proportion symptomatic in region r, time t and age a.

# Specifying model parameters - Parameterisation(2)



- Breakpoints: Specify breakpoints to avoid having to specify an  $RTA \times p$  design matrix where not necessary (also avoids large matrix multiplication).
- Example: As in regional papers, R = 4, T = 245, A = 7. Don't need to always have a matrix with 6860 rows.
- regional\_breakpoints: true/false. So  $r_0 \in \{1, R\}$ .
- age\_breakpoints: true/false or a integer-value vector, taking ascending values in 1,..., A. If age\_breakpoints = 3, say, then the first three age-classes can have a different value of the parameter at all times to the older age classes, and a<sub>0</sub> = 2. Again, true/false set a<sub>0</sub> = A or 1 respectively.
- time\_breakpoints: same as age\_breakpoints, although has no impact for parameters that specify an initial condition, e.g. exponential growth rate.

# Specifying model parameters - Parameterisation(3)



```
prop_symptomatic = { param_value = 0.1, 0.15, 0.2, 0.25;
    prior_distribution = 3, 3, 3, 3;
    prior_parameters = 0.5, 2, 1, 1, 20, 10, 1, 1;
    time_breakpoints = 83, 245; Upper bounds for the breakpoints
    age_breakpoints = 3, 7; are optional and are ignored
    regression_link = 2;
    regression_design = file.design.txt;
}
```

- regression\_link: the choice of the function  $g(\cdot)$ .

  - 2  $g(x) = \log(x/(1-x))$
- regression\_design: the location of a file specifying the design matrix. Elements are read in separated by spaces, in the order  $X_{11}$ ,  $X_{12}$ , .... Alternatively, can be specified as a numerical vector here.

# Specifying model parameters - SMC/MCMC



- proposal\_variance In MCMC, the random-walk proposal variances for each parameter component. In SMC, only the first value is used, it is the value of  $\gamma$  for any component-wise updates.
- update\_indicators In MCMC, a dummy variable. In SMC, this indicates whether this parameter component should be updated as part of each proposal mechanism, 1 for yes, 0 for no.

#### Model Parameters - What are they?



The  $\beta$ 's, that specify the  $\theta$ 's

$$g\left(\underbrace{\theta}_{(r_0t_0a_0)\times 1}\right) = \underbrace{\mathbf{X}}_{(r_0t_0a_0)\times p}\underbrace{\beta}_{p\times 1}$$

where  $\theta$  could represent:

Parameter name	Short Description	Variation
negbin_overdispersion	Over-dispersion parameter for Negative	$r \times t \times a$
	Binomially distributed primary care count	
	data.	
$latent\_period$	The mean duration of the latent period	$r \times t \times a$
${\tt infectious\_period}$	The mean duration of the infectious pe-	$r \times t \times a$
	riod	
relative_infectiousness The relative infectiousnesss of state $l_2$ to		$r \times t \times a$
	state / <sub>1</sub>	

### Model Parameters - What are they? (2)



Parameter name	Short Description	Variation
prop_symptomatic	Proportion of infections that lead to	$r \times t \times a$
	symptoms (typically ILI).	
${\tt contact\_parameters}$	Parameters used to scale specified entries	$r \times t \times a^*$
	of the contact matrices.	
RO_amplitude_kA	Amplitude of seasonal variation in the	r only.
	value of $R_0$ (as a fraction of the peak	
	value).	
RO_seasonal_peakday	Timing in the year of the peak value of	r only.
	$R_0$	
exponential_growth_rate	e Initial rate of growth of the epidemic,	r only.
	proxy of $R_0$ at epidemic time-0	
$log_p_lambda_0$	Log-initial rate of arrivals in consultation,	r only.
	a proxy for <i>I</i> * the initial number of infec-	
	tives.	

<sup>\*</sup>Time and age variation in the contact structure is specified in mod\_inputs.txt. Any time and age variation specified in mod\_pars.txt will be quietly ignored.

## Model Parameters - What are they? (3)



Parameter name	Short Description	Variation
prop_susceptible	Proportion of individuals susceptible to infection.	$r \times a$ .
prop_HI_32_to_HI_8	Proportion of immunity that would test positive with a HI of 32 (where immunity is defined by HI 8.	$r \times a$ .
<pre>prop_case_to_GP_ consultation</pre>	Proportion of symptomatic cases that consult with a GP (or other primary care provider).	$r \times t \times a$
prop_case_to_hosp	Proportion of symptomatic cases that will require hospitalisation.	$r \times t \times a$
prop_case_to_death	Proportion of symptomatic cases that lead to death.*	$r \times t \times a$

<sup>\*</sup>This data stream currently treated independently of hospitalisations. This may not be reasonable, but it may be possible to use for other count data, such as early case confirmation.

### Model Parameters - What are they? (4)



Parameter name	Short Description	Variation
importation_rates	Rate of inflow of new infections.	$r \times t \times a$ .
${\tt background\_GP}$	Rates of background GP consultation	$r \times t \times a$ .
	(measured in consultations per 100,000	
	people, per year).	
${ t test\_sensitivity}$	The test sensitivity of the virological	$t \times a$
	swabbing process, taking values in $[0,1]$ .	
${ t test\_specificity}$	The test specificity of the virological	$t \times a$
	swabbing process, taking values in $[0,1]$ .	
day_of_week_effects	Scaling factors for the expected number	$r \times t \times a$
	of primary care consultations per day.	