

# Deep Learning to Improve Breast Cancer Detection on Screening Mammography - A summary



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Problem Description

Model

Results

Discussion

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Bayesian inference for the rescue!

Model

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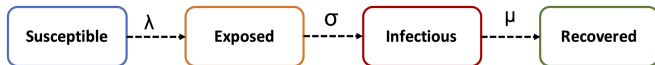


Figure: SEIR model [MM20]



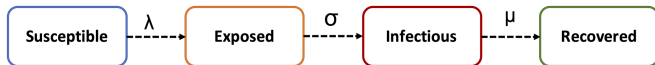


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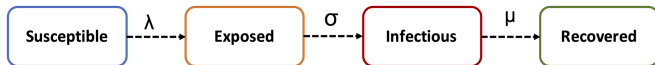


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- ▶ Basic reproductive number  $R_0 = \frac{\lambda}{\mu}$
- ▶ Delay  $D$  in becoming infected ( $I^{\text{new}}$ ) and being reported
- ▶  $\lambda$  time-varying with change points corresponding to NIPs

Parameter	Prior Distribution
Spreading rate $\lambda_0$	LogNormal(log(0.4),0.5)
Spreading rate $\lambda_1$	LogNormal(log(0.4),0.7)
Spreading rate $\lambda_2$	LogNormal(log(0.4),0.7)
Incubation to infectious rate $\sigma$	LogNormal(log(1/5),0.5)
Recovery rate $\mu$	LogNormal(log(1/8),0.2)
Reporting Delay $D$	LogNormal(log(8),0.2)
Initial Infectious $I_0$	Half-Cauchy(20)
Initial Exposed $E_0$	Half-Cauchy(20)
Change Point $t_1$	Normal(2020/03/18,1)
Change Point $t_2$	Normal(2020/03/28,1)

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- ▶ Likelihood function Student-T distribution
- ▶ Initial  $R_0 = 3.278$  (CI[2.715, 3.73])
- ▶ Hamiltonian Monte Carlo (HMC) method to sample from posterior distribution
  - ▶ No-U-Turn Sampling (NUTS)
  - ▶ 5000 samples with 1000 burn-in

Model	Change Points	LOO	Effective Parameters
SIR	2	448.00	10.27
SEIR	1	457.77	11.60
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SIR	1	463.03	8.51
SEIR	0	464.69	16.14
SIR	0	517.72	4.72

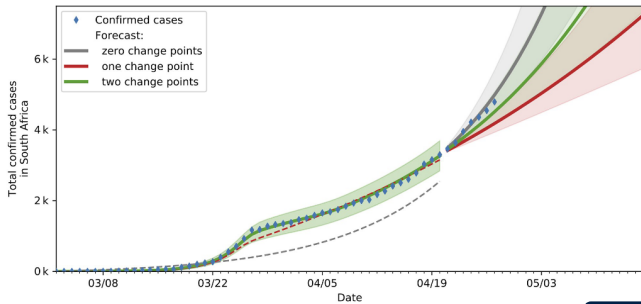
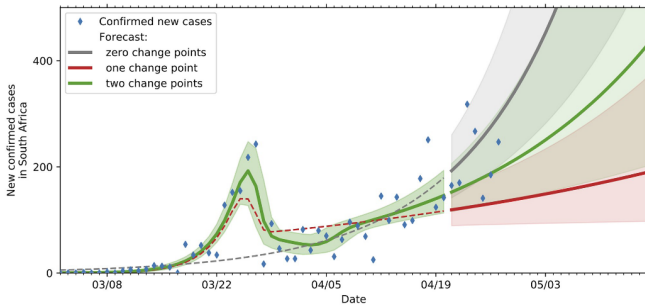
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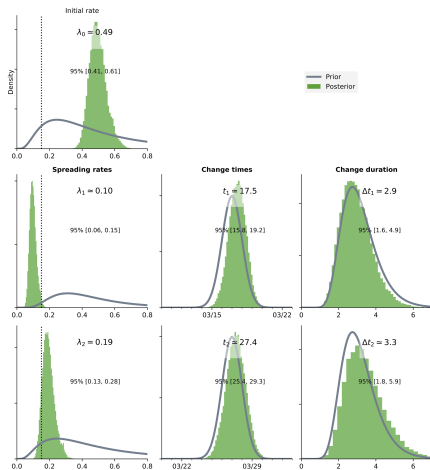
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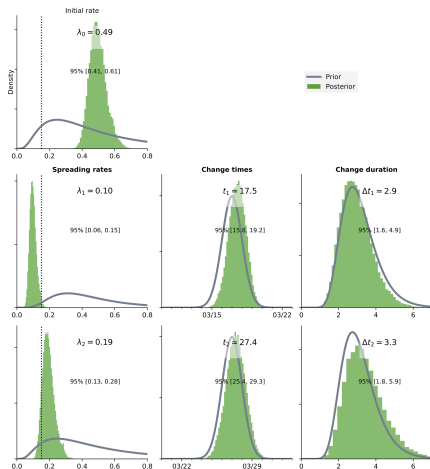
- SIR model with two change points yields lowest LOO cross entropy loss

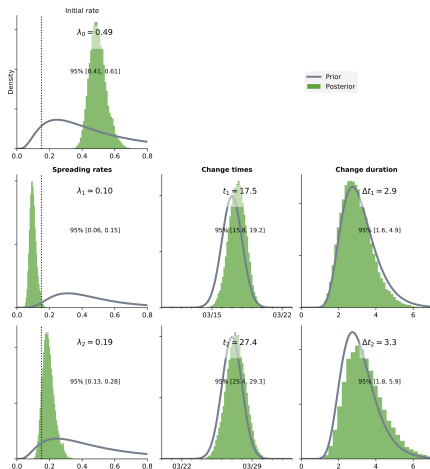




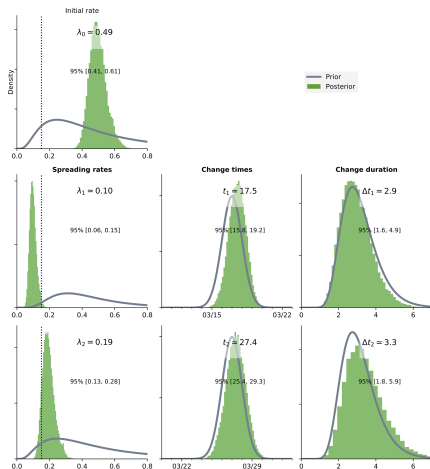


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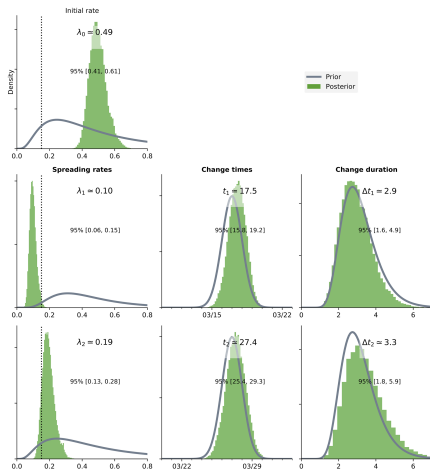




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- Recovery rate  $\mu \approx 0.151$  implies mean infectious period of 6.62 days

# Discussion

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- ▶ Parameter estimates help quantify the dynamic of the pandemic and account for uncertainty
- ▶ Assumptions on prior distributions?
- ▶ Take into account local, provincial developments



Rendani Mbuyha and Tshilidzi Marwala.  
Bayesian inference of covid-19 spreading rates in south  
africa.  
04 2020.