ANALYSIS OF SPREAD COVID-19 IN NIGERIA USING BAYESIAN INFERENCE

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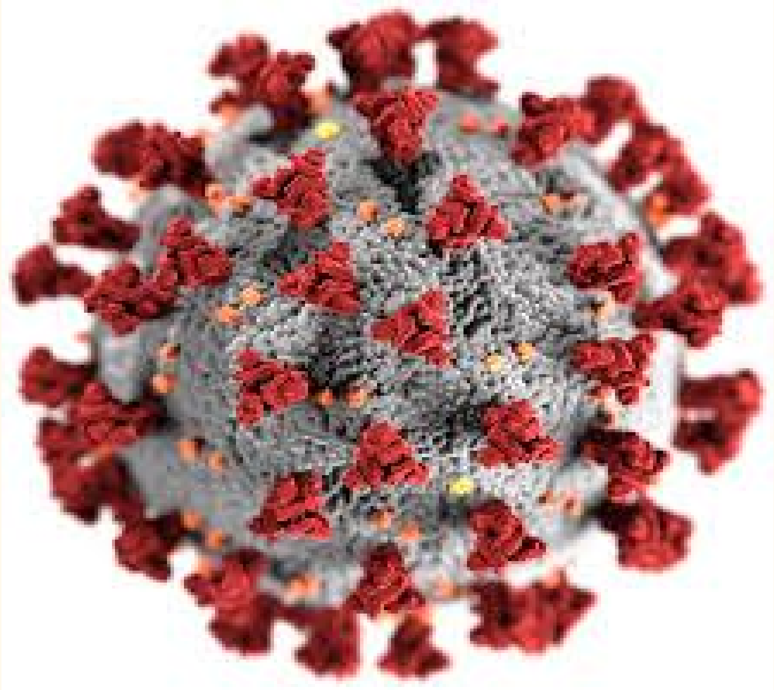

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INTRODUCTION

In Nigeria, the first COVID-19 case was announced around 1 am on Friday 28 February 2020, following the spread of this disease in Wuhan, late last year. Due to its spread across the globe and the severity of clinical outcomes, the World Health Organisation declared COVID-19 à pandemic. With a total population of about 200 million people, Nigeria had conducted just under 12,000 tests as of April 26. And as of 29 April 2020, Nigeria had recorded over 13000 cases with 40 deaths.

Various states such as Abuja, Lagos, and Ogun have attempted to minimize the growth in the number of COVID-19 infections. This majorly contributed to the rapid spread of this disease in the suburbs of these states. The attempts are largely based on non-pharmaceutical interventions (NPIs) aimed at separating the infectious population from the susceptible population.

These initiatives aim to strategically reduce the spread of the pandemic to a level where their healthcare systems stand a chance of reducing the total number of deaths. Some of the critical indicators for policymaker response planning include projections of the infected population, recovered population, and the effectiveness of NPI.

An important issue implied in calibrating localized models is inferring parameters of compartmental models such as susceptible-infectious-recovered (SIR) and the susceptible-exposed-infectious-recovered (SEIR) that are widely used in infectious disease projections. In the aspect of key policymakers and stakeholders, a critical aspect of measuring the projecting infections is the inference of parameters that align with the underlying trajectories in their jurisdictions. The spreading rate (lambda) is a parameter of particular interest which is subject to changes due to voluntary social distancing measures and government-imposed contact bans.

Shortfalls to be addressed.

The inability to forecast in employing the use of these models is compounded by the unavailability of the unlimited data in the initial phases and the rapidly changing dynamics due to rapid public policy changes.

To address this shortfall, we use the Bayesian Inferencing of epidemiological modeling in Nigeria. The Bayesian inference allows for incorporations of prior and likelihood parameters.

In this week's challenge, we(Team Nigeria) combine Bayesian inference with the compartmental SEIR model to infer time-varying spreading rates that enable measuring the effectiveness of government interventions in Nigeria.

METHODS

In this particular weekly challenge, we incorporate the use SEIR model, an epidemiological model that models susceptibility, exposure, infections, and recovery.

Why is the SEIR model the best fit?

- It models the total Nigerian population that is susceptible to the pandemic, those exposed to the virus,those already infected, and those who have recovered from the disease.
- This statistical modeling technique models asymptomatic individuals while splitting infection into symptomatic
- Also enables us to describe the time-dependent growth of COVID based on our model.
- Also models latent period; the period it takes on exposed to the disease to become infected

Bayesian Parameter Inference

We use this particular method to model parameters on the Nigerian COVID-19 Data extracted from the John Hopkins University database.

This method allows for the posterior parameters to be modeled. This inference obeys theorem invented by Thomas Bayes :

$$P(\theta|\text{Data},\text{Model}) = P(\text{Data}|\theta,\text{Model})P(\theta)$$

Where $P(\theta|\text{Data}, \text{Model})$ is the posterior of θ given Model and observed data(Data).The likelihood is $P(\text{Data}|\theta, \text{Model})$and evidence $P(\text{Data}|\text{Model})$

Prior

Incorporates expected value such as different spread ate(lambda), recovery rate(mu), and different change points based on NPI. We use log-normal prior to calculating the recovery rate (mu).

We use the government interventions to set priors on change points in spreading rate(lambda).

The prior on change points include :

- 30th March 2020 corresponds with the inter-state lockdown.
- 4th May 2020 enacting face masks and social distancing measures.
- 2nd June 2020 start of lockdown easing for economic recovery.

Likelihood

This indicates the probability of observing the reported cases(data) given a particular model.

In this week's challenge, we adopt the Student-t likelihood.

Why use Student-t likelihood?

It allows us to model parameter updates that are few or rare in discrepancies between predicted cases and reported cases.

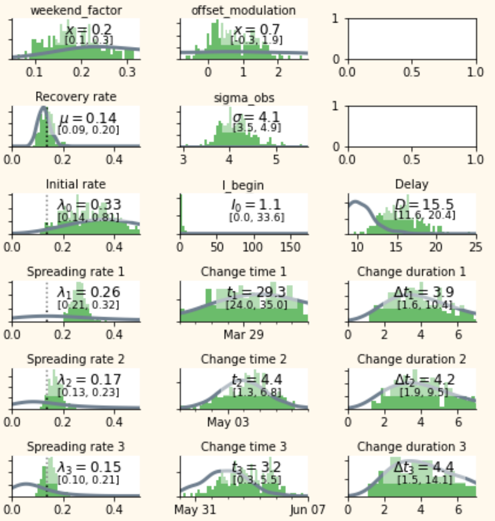
Markov Chain Monte Carlo(MCMC)

We use MCMC sampling to sample from the posterior distribution of parameters. .MCMC methods have been widely used to sample COVID-19 inferences.

In particular, we use this sampling method to calibrate our SEIR model on daily cases from 29 March 2020 up to 5th August.

RESULTS

Our SEIR model parameters inference was performed using the data (29 March - 1 Aug)



Interpretation

The main goal of enforcing NPI by the Nigerian Government was to reduce the (effective) spread rate λ* which is the **λ(spreading rate) - μ(recovery rate)**. To get a decline in the number of new infections, **λ must be < 0**

According to the paper, we saw that if the growth rate is greater than zero($\lambda > \mu$), the reported case grows exponentially; and if, however, the growth rate is smaller than zero ($\lambda < \mu$), then recovery dominates and new cases decrease.

From our above graph, we see that the initial spreading rate was $\lambda 0 = 0.33$, and our recovery rate $\mu=0.14$. Therefore our initial growth rate $\lambda 0 = 0.33 - 0.14 = 0.19$

After the enforcement of the first intervention by the federal government on the 30th of March, we see that the spreading rate decreased to $\lambda 1=0.26$ and our recovery rate is $\mu=0.14$. our first growth rate $\lambda 1 = 0.26 - 0.14 = 0.12$ which decreases by 0.07 from the initial, it was still a positive value. Hence, it implies there's still an exponential growth of new cases.

After the second intervention by the federal government on the 4th of May, we see that the spreading rate decreased from $\lambda 1=0.26$ to $\lambda 2=0.17$ and our recovery rate is $\mu=0.14$. our second growth rate $\lambda 1 = 0.17 - 0.14 = 0.03$ which decreased drastically by 0.09, it still remained positive. Hence, it implies the exponential growth of new cases.

After the third intervention by the federal government on the 2nd of June, we see that the spreading rate decreased from $\lambda 2=0.17$ to $\lambda 3=0.15$ which was just a little different from the what the second spreading point was(0.17) and our recovery rate is $\mu=0.14$. From subtracting the two of them, we get our third growth rate $\lambda 1 = 0.15 - 0.14 = 0.01$ which we can approximate to be 0.

Limitation of this analysis

Given the data , above we are only able to model this particular disease, we make a biased assumption that asymptomatic cases become symptomatic when exposed to COVID 19. There might be a correlation between COVID-19 and other respiratory diseases that needs to be addressed.

CONCLUSION

The NPI enforced by the federal government, mitigated the spread of COVID-19 in Nigeria by drastically reducing the spread rate, but did most likely not lead to a sustained decline of new infections

Above all, no model can be perfect enough to predict the future correctly but a good one is sufficient enough to be useful for public policy.