Cigniti

# To Extend or Not to Extend – That is the Question

## A Tech Brief

# Introduction

With the COVID-19 pandemic raging across India, we have been under lockdown since March 25th, 2020. It is widely welcomed by close to 1.3 billion people, even though this has bought their lives to a standstill. The 800-pound gorilla in the room, of course, are the questions **"When should this lockdown be relaxed and how do we know that we are making progress?"**.

In any epidemic, **Rt** is the measure known as the **effective reproduction number.** It is the average number of people who become infected by an infectious person at a time t. The most well-known version of this number is the basic reproduction number: **R0** when t = 0. However, **R0** is a single measure that does not adapt with changes in behavior and restrictions.

As a pandemic evolves, increasing restrictions (or potential relaxing of restrictions) changes Rt. Knowing the current Rt is essential for policy-based decision-making. When Rt>1, the pandemic will spread through the entire population. The lower Rt, the more manageable the situation.

The value of Rt helps us in:

- Understanding how effective the non-pharmaceutical interventions have been in controlling the outbreak.
- Giving vital information, regarding whether we should increase or reduce restrictions, based on our competing goals of economic prosperity and saving human lives.[1]

Somehow this particular insight has been mainly missed by the world. Except for Hongkong[2], no one seems to be tracking this, at least on a real-time basis. This number is generally not that useful at the national level. The key aspect is to understand this number at the state or district level, where decisions regarding tightening or relaxing the non-pharmaceutical interventions are implemented.

In this tech brief, let's try and discuss a framework for this solution for the Indian states of Telangana (where I am based), Maharashtra, and Tamil Nadu, where the number of COVID cases seems to be growing at the fastest rate in India.

As part of future work, we will be trying to do the same at the district/city level for a better understanding of Rt at the ground level.

This borrows heavily from the work of Betterncourt and Riberio[3] and also from Kevin's GithubRepository[4].

# Approach

We have an estimate of the number of new COVID-19 patients daily. We can use this to estimate the current value of Rt. We can also see that the value of Rt will depend on Rt-1 (yesterday's value) and for every previous value of Rt-n.

We can use Bayes Rule to update our belief about Rt, based on the new infection data that we are seeing each day.

$$P(R_t \mid k) = [P(R_t) \cdot \text{Likelihood}(R_t \mid k)] / P(k)$$

The above equation can be interpreted as, having seen k cases, the distribution of Rt is equal to:

- The prior belief of the value Rt is assumed to be P(Rt)
- Times the likelihood of Rt given that we have seen k cases
- Divided by the probability of seeing k cases under all hypotheses of Rt.

Importantly, since P(k) is a constant, the numerator is proportional to the posterior. As all probabilities sum to 1.0, we can ignore P(k) and normalize the posterior sum to 1.0

$$P(R_t \mid k)\ P(R_t) \cdot \text{Likelihood}\ (R_t \mid k)$$

Of course, this is for one day. Generalizing this across all the previous days we have measurements for, we can write the same as

$$P(R_t \mid k)\ P(R_0) \cdot \text{Likelihood}\ (R_n \mid k_n) \cdot \text{Likelihood}\ (R_{n-1} \mid k_{n-1}) \ldots\ldots\ldots \text{Likelihood}\ (R_1 \mid k_1)$$

With a uniform prior P(R0), this reduces to:

$$P(R_t \mid k_t) \prod \text{Likelihood}\ (R_t \mid k_t)$$

One of the potential issues with this Bayesian approach is that the posterior is equally influenced by events in the distant past as much as in the recent past. In our case, this would mean that if Rt> 1 for a long period, and has come under control (Rt< 1) recently, the posterior will get stuck at values > 1 for a long time.

**Of course, this would not work for us, because the entire purpose of this exercise is to see when Rt has dipped below 1.**

One way to resolve this would be to just use the previous "m" days for calculating the likelihood function, rather than the entire history.

**LIKELIHOOD FUNCTION:**

We will be using Poisson Distribution as the likelihood function for this analysis, as this is the preferred model for understanding the "number of arrivals" in a given time period. Given an average arrival rate of 'λ' new cases per day, the probability of seeing k new cases are distributed according to the Poisson distribution:

$$P(k \mid \lambda) = (\lambda k e-\lambda) / k!$$

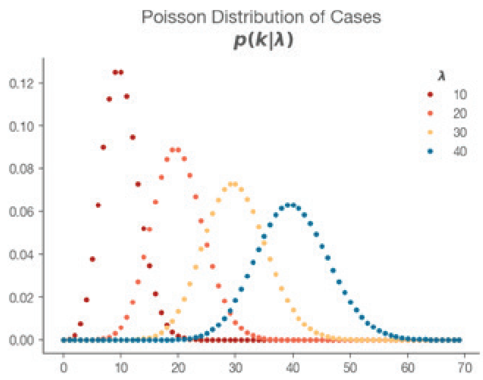


**Figure 1: Poisson Distribution**

**DERIVING Rt FROM λ**

The most important feature of this work is to connect Rt to λ. The derivation is itself out of the scope of this blog post, but the derivation can be found here.

**Derivation = λ = kt-1eY(Rt-1)**

The Y is taken as the reciprocal of the serial interval (5 days for COVID-19).

The problem can now be written as

**Likelihood(Rt|k) = (λke-λ) / k!**

In the next steps, we just have to perform the Bayesian update on the most likelihood function, which in this case we have chosen to be Poisson.

# Just to Summarize

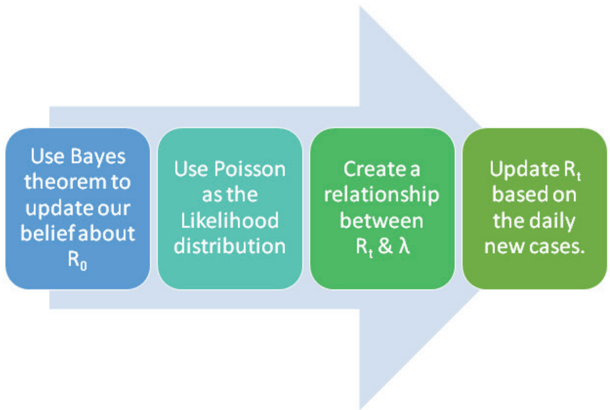


**Figure 2: Approach Summary**

# Data for the Real World

We have used data from the COVID-19 India Tracker website (https://www.covid19india.org/). We have extracted the data for the states of Telangana, Maharashtra, and Tamil Nadu for the period 14th March 2020 to 14th April 2020.

We are in the process of collecting more data, but the present analysis is limited to the above-mentioned three states.

# Analysis

The analysis has been conducted for each of the three states of Telangana, Maharashtra, and Tamil Nadu.

**Telangana**

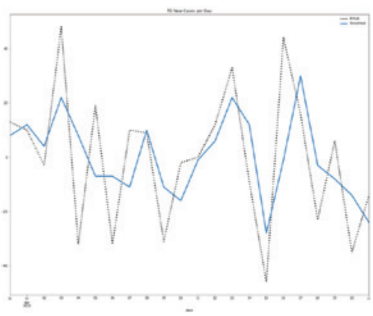

**Figure 3: Gaussian Smoothed new cases for Telangana**

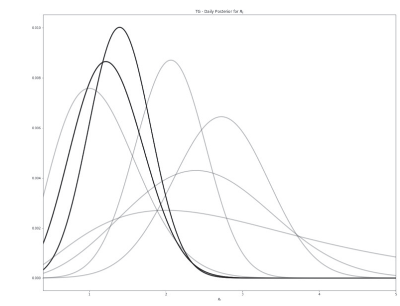

**Figure 4: Bayesian Update showing an increase in confidence**

| Date | Most Likely $R_t$ | Low @ 90% confidence | High @ 90% confidence |
|---|---|---|---|
| 2020-03-31 | 2.00 | 0.50 | 5.54 |
| 2020-04-05 | 1.22 | 0.52 | 1.99 |
| 2020-04-10 | 1.22 | 0.52 | 1.99 |
| 2020-04-15 | 1.4 | 0.78 | 2.08 |
| 2020-04-21 | 1.4 | 0.78 | 2.08 |

**Table 1: Confidence Intervals for Rt for Telangana**

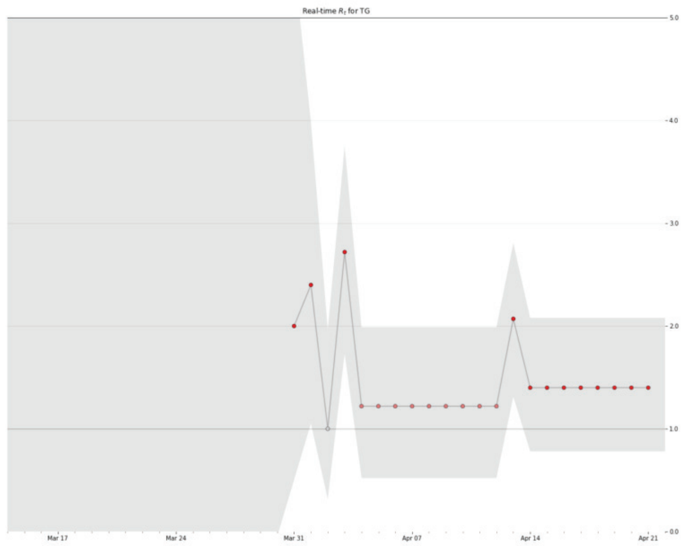


**Figure 5: Pictorial Representation of Confidence Intervals**

**Maharashtra**

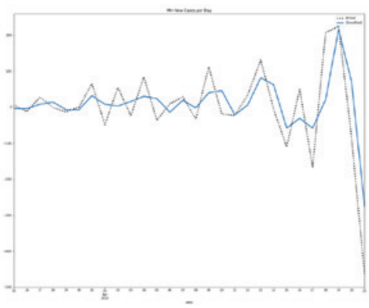

**Figure 6: Gaussian Smoothed new cases for Maharashtra**

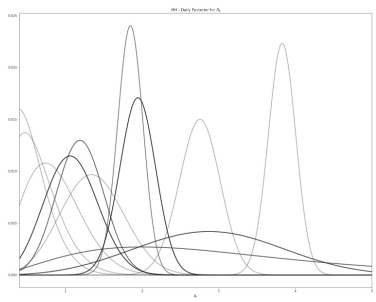

**Figure 7: Bayesian Update showing an increase in confidence**

| Date | Most Likely $R_t$ | Low @ 90% confidence | High @ 90% confidence |
|---|---|---|---|
| 2020-03-31 | 2.87 | 1.39 | 4.43 |
| 2020-04-05 | 1.06 | 0.55 | 1.68 |
| 2020-04-10 | 1.19 | 0.72 | 1.73 |
| 2020-04-15 | 1.95 | 1.57 | 2.34 |
| 2020-04-21 | 1.85 | 1.58 | 2.13 |

**Table 2: Confidence Intervals for Rt for Maharashtra**

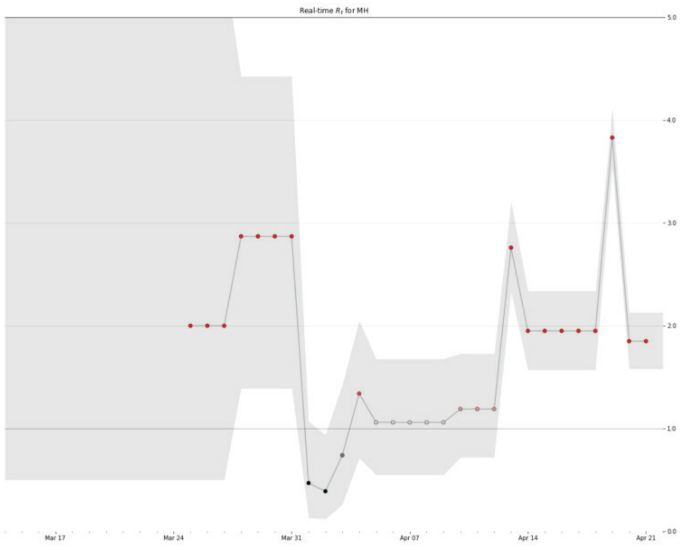

Figure 8: Pictorial Representation of Confidence Intervals

**Tamil Nadu**

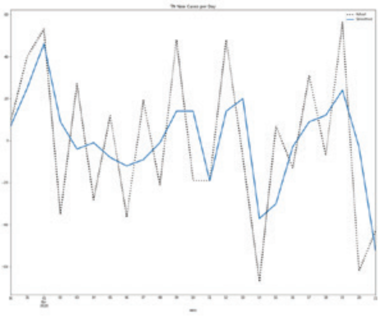

Figure 9: Gaussian Smoothed new cases for Tamil Nadu

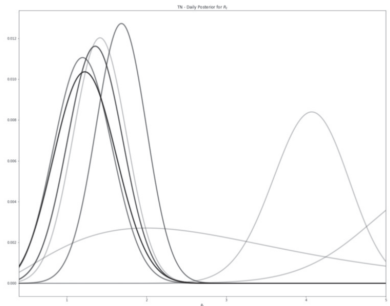

Figure 10: Bayesian Update showing an increase in confidence

| Date | Most Likely $R_t$ | Low @ 90% confidence | High @ 90% confidence |
|---|---|---|---|
| 2020-03-31 | 5.66 | 4.26 | 6.99 |
| 2020-04-05 | 1.23 | 0.64 | 1.89 |
| 2020-04-10 | 1.20 | 0.63 | 1.80 |
| 2020-04-15 | 1.36 | 0.83 | 1.96 |
| 2020-04-21 | 1.69 | 1.17 | 2.20 |

Table 3: Confidence Intervals for Rt for Tamil Nadu

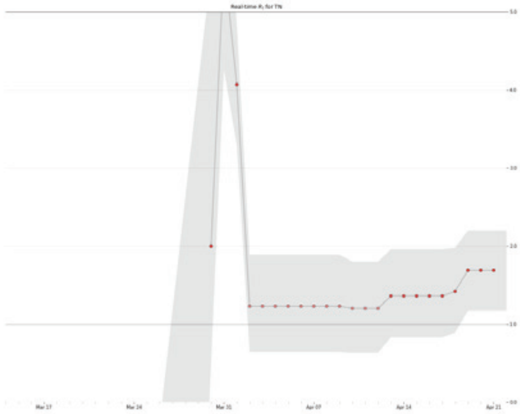

Figure 11: Pictorial Representation of Confidence Intervals

# Implications

**There is a general decline in Rt among the states and there is relatively a higher confidence level. But we are still not at that level where it is less than 1.**

# Future Work

We have planned to work on the following in the next few weeks:

- Real-time Rt for all the States and UTs. Given the availability of data, it can be extended to other countries.
- Publish the real Rt for each district in the country.
- An integrated dashboard that is updated automatically to aid decision-making around relaxing/tightening the lockdown.

### References

[1] Gabriel Leung (2020) Lockdown Can't Last Forever. Here's How to Lift It. Retrieved from https://www.nytimes.com/2020/04/06/opinion/coronavirus-end-social-distancing.html

[2] School of Public Health, The University of Hong Kong (2020). Retrieved from https://covid19.sph.hku.hk/dashboard

[3] Luís M. A. Bettencourt, Ruy M. Ribeiro (2008) Real Time Bayesian Estimation of the Epidemic Potential of Emerging Infectious Diseases. Retrieved from https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0002185

[4] Kevin Systrom (2020) Estimating COVID-19's Rt in Real-Time. Retrieved from https://github.com/k-sys/covid-19/blob/master/Realtime%20R0.ipynb

[5] John K. Kruschke (2015) Highest Density Interval. Retrieved from https://www.sciencedirect.com/topics/mathematics/highest-density-interval

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