CONTACT-TRACING STRATEGIES FOR SARS-COV-2 ERADICATION **** DRAFT ****

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ABSTRACT

As of 5^{rd} April a large proportion of the global population are living under social distancing measures in order to control the spread of COVID-19. If these measures are successful, in a few weeks, prevalence will again be low in certain parts of the world. However, it is not clear what the best policy will be at that point. This paper investigates the feasibility of using contact tracing along with a combination of other measures in order to ease the social distancing measures while preventing a resurgence of the disease. We find that manual contact tracing alone is unlikely to achieve the speed or accuracy needed to contain the disease, and so suggest a technological solution based on tracing via mobile phone app. The proposed solution maintains user's privacy and conforms to European data protection laws. **** **This is a live document and is subject to change** ****

Keywords COVID-19, SARS-CoV-2

1 Introduction

Many countries in the world are now committed to a surge in incidence of COVID-19 and are practising social distancing in order to suppress its spread. If successful, these countries will soon be in a situation where prevalence is reducing. Once this is achieved there are a number of strategies:

- lift the social distancing measures and allow a second (and subsequent) waves until herd immunity is achieved(Ferguson et al., 2020).
- maintain low levels until a vaccine is available
- eradicate the virus locally and impose strict border controls and containment strategies until the virus is contained globally

Here we investigate the feasibility of the third option by slowly lifting social distancing measures while maintaining self isolation of symptomatic individuals and implementing an extensive testing and contact-tracing capability.

2 Description of the Model

The model we use is based on the stochastic branching model described in (Hellewell et al., 2020) but implemented as an agent-based, discrete event simulation. This allows us to implement more complex containment strategies with less effort. It also allows us to correctly capture the tracing of infected agents via a previously untraced mutual infector, which is not properly captured in a stochastic branching model. In the presence of many asymptomatic carriers, and very fast and accurate tracing, this is expected to be important. It also allows us to capture the workload on a central testing facility and the feedback of delays as workload increases.[2]

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[2]Although a discrete-event simulation takes longer to execute than a branching model, execution time is not a bottleneck so it is worthwhile in order to capture these dynamics.

The model consists of infected agents, each of which belongs to a household and a workplace/school. Once infected, an agent goes though an incubation period with duration drawn from a Weibull distribution with shape parameter 2.322737 and scale parameter 6.492272(Backer, Klinkenberg, & Wallinga, 2020). The transmission generation interval (i.e. time from exposure to transmission) is drawn from a skew normal distribution with location parameter equal to the clinical onset time (i.e. end of the incubation period), scale parameter of 2.0 and skew parameter of 1.95(Hellewell et al., 2020). This results in 15% of infections occurring before clinical onset(Hellewell et al., 2020). In order to avoid unrealistically early transmissions, the generation interval was bounded to a minimum of 1 day. At creation, 17.9% of agents are deemed to be asymptomatic(Mizumoto, Kagaya, Zarebski, & Chowell, 2020)[3]. Asymptomatic carriers are assumed to be $\frac{2}{3}$ as infectious as symptomatic carriers(Ferguson et al., 2020). The number of susceptible agents that an infected agent will infect if not isolated is drawn from a negative binomial distribution with overdispersion parameter 10.0(Zhuang et al., 2020)(Riou & Althaus, 2020) and mean of $\frac{3R_0}{3-\rho}$ for symptomatic agents and $\frac{2R_0}{3-\rho}$ for asymptomatic agents where $\rho = 0.179$ is the probability of being asymptomatic and R_0 is the basic reproductive number. At each transmission event a new infected agent is created, unless the agent is isolated, in which case the event has no effect.

Each transmission event occurs either in the household, at the workplace/school or in the community. This allows us to capture the differences in ease and speed of contact tracing in these three cases, as well as capturing the effect of closer and more frequent contact with household members compared to workplace and community. Distinguishing household contacts also allows us to simulate the effect of household-wide self-isolation policies such as those implemented in the UK. Finally, it allows us to capture any immunity in the population built up during a first wave of infections. After a first wave of infection we would expect there to be a correlation in immunity between members of the same household since during the peak, under "stay at home" rules, if one member of a household contracts the disease it is likely that all other members will also contract it, so we end up with immune and susceptible households. This means that only members of susceptible households can become infected during the contact-tracing stage. The relative probability of transmission in the household was 3 times greater in the household than in the other locations. This calibrated in order to obtain equal aggregate numbers of transmission events in each location under no intervention(Ferguson et al., 2020). The distribution of number of members in a household was calibrated against(Smith, 2014). A transmission event to an immune agent does not cause infection. Immunity is only applied to school/workplace and community transmissions for the reasons outlined above.

The source code of the model is available at https://github.com/danftang/Covid19

2.1 Contact tracing and isolation policy

3 Policy Scenarios

Various policy scenarios were simulated to find the probability that an initial population of 100 infected agents could be eradicated. Eradication was deemed to have been achieved if the cumulative number of cases remained below 5000 and there was no untraced infected population at 15 weeks into the simulation. It was assumed that 5% of the population was immune. The probability of eradication was estimated by performing a monte-carlo run of 300 simulations and counting the proportion that achieved eradication.

If not otherwise stated the following default values are used in the scenarios: 15% pre-symptomatic transmission, $R0 = 3.5$, 18% of infected are asymptomatic carriers, 5% of the population are immune. Swab tests take 24 hours to process and come back positive if the agent's infectiousness is above 2% per day in order to exclude positive results during the latent phase.

3.1 Manual contact tracing with household-wide quarantine

In this scenario, anyone who becomes symptomatic must immediately self-isolate along with all members of the household. The symptomatic person is tested and if positive close-contacts are traced, quarantined and tested. Further positive results are traced recursively.

In this scenario, the speed and accuracy of the contact tracing is of key importance. Figure 1 shows the probability of containment for a range of values of the time taken to trace a contact (i.e. perform a test on a suspected case, get results and trace the contact) and of the proportion of close contacts that are traced. This figure is based on the assumption that 75% of the public comply with the self-isolation policy. As can be seen, the contact tracing would need to be very fast and accurate to have a reasonable chance of containment. For this reason, it seems unlikely that manual contact-tracing, based on interviews with the infected person, will be fast or accurate enough to be effective.

3.2 Isolation of whole household and work-colleagues

In this scenario, we have household-wide quarantine as above, but in addition, we assume that companies are (perhaps legally) obliged to report symptomatic employees and have systems in place to record close contacts within the

[3] [TODO: Age weight this figure]

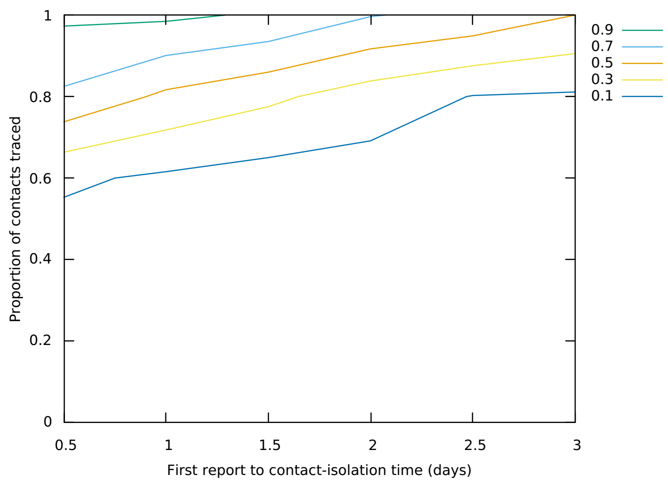

Figure 1: Probability of eradication under self-isolation and contact tracing. Assuming 95% compliance to self-isolation.

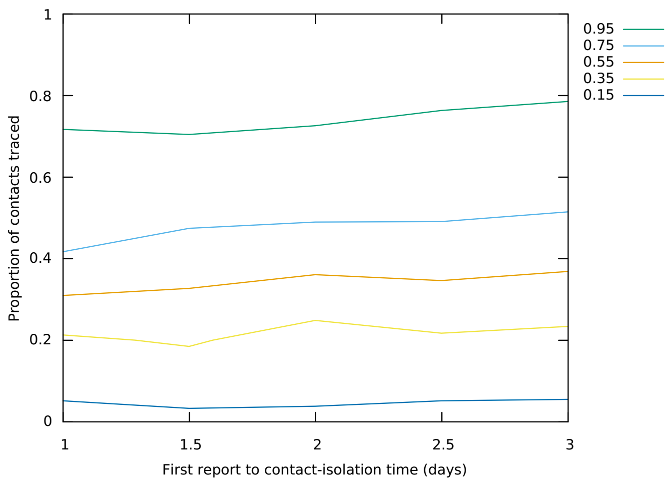

Figure 2: Probability of eradication under quarantine of whole household and workplace contacts assuming 90% enforcement in the workplace, 30% pre-symptomatic transmission and 30% of infections asymptomatic.

workplace. Under this scenario, we assume that 90% of close contacts within the workplace can be traced and 90% of non-compliant symptomatic cases are reported. The time from first report to isolation of workplace colleagues is taken to be 36 hours, representing the swab test time of 24 hours plus 12 hours delay.

Under this scenario, with the default parameters, all simulations are controlled even without any tracing in the community. With less optimistic values of 30% pre-symptomatic transmission and 30% of infections asymptomatic, the probability of control is as shown in figure 2.

In this case, we would need to trace upwards of 80% of contacts in the community in order to have a >95% chance of control.

3.3 Tracing with mobile phone app

The only practical way of tracing such a high proportion of contacts in the community is by using technology. Efforts to control the virus in China have demonstrated the use of community tracing technology, but implementation in western countries is more challenging because user privacy and data protection must be preserved. However, a privacy-protecting mobile phone app for contact tracing has been proposed(Tang, 2020), so in this scenario, we add the use of this mobile

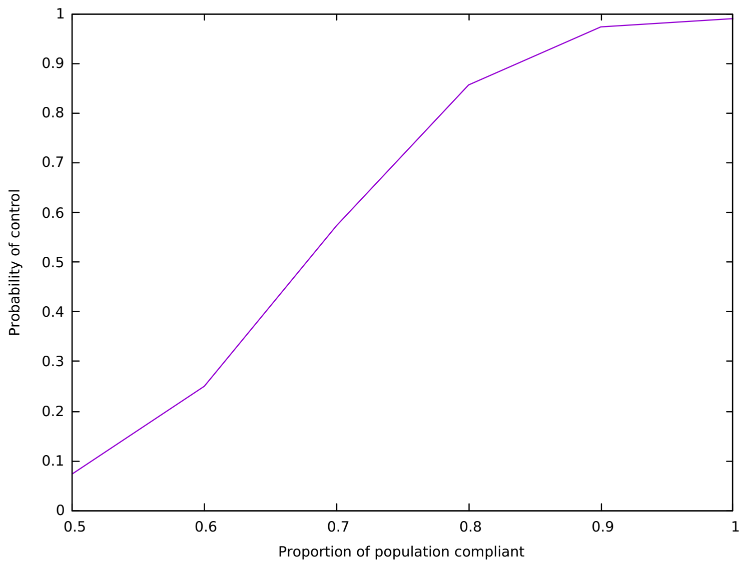

Figure 3: Probability of eradication under community tracing with mobile phone assuming 90% enforcement in the workplace, 30% pre-symptomatic transmission and 30% of infections asymptomatic.

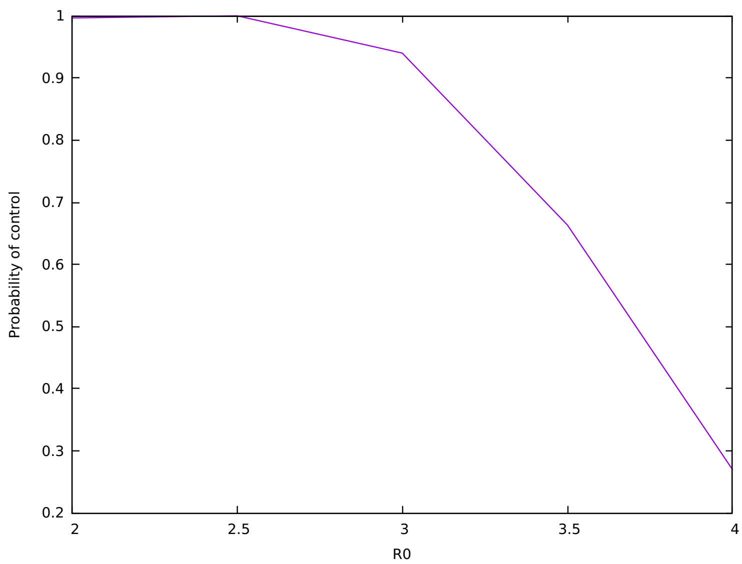

Figure 4: Probability of eradication under community tracing assuming 75% compliance, 90% enforcement in the workplace, 30% pre-symptomatic transmission and 30% of infections asymptomatic.

app in addition to household self-isolation and workplace enforcement. We assume that the phone app can track 90% of close contacts between users. As before, we take the pessimistic values of 30% pre-symptomatic transmission and 30% of infections asymptomatic.

In this scenario we assume compliance is an intrinsic property of the agent. A compliant agent will install the mobile phone app and self-isolate upon becoming symptomatic, whereas a non-compliant agent will do neither. This captures the expected correlation between these things, which is important because it makes it more likely that an infectious person in the community will not be using the mobile phone app, and cannot be traced.[4]

Figure 3 shows the probability of control for different probabilities of compliance in the population. Even under this scenario, we need >80% compliance in the community, in addition to enforcement at work, to have a >90% chance of control. However, a recent survey(Abeler, 2020) has shown that public support for an app is high in the UK and that around 74% of respondents would probably or definitely install a contact-tracing app.

Figure shows the probability of control for different values of $R0$ at 75% compliance.

[4][Non-compliants are more likely to be immune (what is the size of this effect?)]

4 Discussion

We have shown that a policy of household-wide isolation along with workplace enforcement and a mobile phone app for community contact tracing has a good chance of success even under quite pessimistic values of the parameters. However, under pessimistic values, a very high proportion of the population would have to install the app. In this case it may be necessary to offer strong incentives to use the app or even make it mandatory.

The range of uncertainty in the parameters is, however, very large. Under such large uncertainty, the probability of preventing a resurgence of infections can be minimised by adopting a policy of gradual loosening of social distancing measures along with close observation of the data. In this way, the effective R can be gradually increased while constantly using new observations to feed back into the policy by working out if further loosening is possible or more app uptake is necessary.

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