TITLE

Ilia Kohanovski[a], Uri Obolski[b,c], and Yoav Ram[a,*]

[a]School of Computer Science, Interdisciplinary Center Herzliya, Herzliya 4610101, Israel
[b]School of Public Health, Tel Aviv University, Tel Aviv 6997801, Israel
[c]Porter School of the Environment and Earth Sciences, Tel Aviv University, Tel Aviv 6997801, Israel
[*]Corresponding author: yoav@yoavram.com

April 27, 2020

Abstract

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

Introduction

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

Nulla malesuada porttitor diam. Donec felis erat, congue non, volutpat at, tincidunt tristique, libero. Vivamus viverra fermentum felis. Donec nonummy pellentesque ante. Phasellus adipiscing semper elit. Proin fermentum massa ac quam. Sed diam turpis, molestie vitae, placerat a, molestie nec, leo. Maecenas lacinia. Nam ipsum ligula, eleifend at, accumsan nec, suscipit a, ipsum. Morbi blandit ligula feugiat magna. Nunc eleifend consequat lorem. Sed lacinia nulla vitae enim. Pellentesque tincidunt purus vel magna. Integer non enim. Praesent euismod nunc eu purus. Donec bibendum quam in tellus. Nullam cursus pulvinar lectus. Donec et mi. Nam vulputate metus eu enim. Vestibulum pellentesque felis eu massa.

Quisque ullamcorper placerat ipsum. Cras nibh. Morbi vel justo vitae lacus tincidunt ultrices. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. In hac habitasse platea dictumst. Integer tempus convallis augue. Etiam facilisis. Nunc elementum fermentum wisi. Aenean placerat. Ut imperdiet, enim sed gravida sollicitudin, felis odio placerat quam, ac pulvinar elit purus eget enim. Nunc vitae tortor. Proin tempus nibh sit amet nisl. Vivamus quis tortor vitae risus porta vehicula.

Models and Methods

Data. We use daily confirmed case data $\mathbf{X} = (X_1, \ldots, X_T)$ from several different countries. These incidence data summarize the number of individuals X_t tested positive for SARS-CoV-2 RNA (using RT-qPCR) at each day t. Data was retrieved for X regions, see Table 1 for details and references. In regions in which there were multiple sequences of days with zero confirmed cases (e.g. France), we cropped the data to begin with the last sequence so that our analysis focuses on the first community-transmitted outbreak rather then isolated imported cases.

Region	Start date	End date	Reference
Austria	X Feb		Flaxman et al. [1]
Wuhan, China	10 Jan	8 Feb	Pei and Shaman [5]

Table 1: Reference for confirmed cases incidence data. All dates in 2020.

SEIR model. We model SARS-CoV-2 infection dynamics by following the number of susceptible S, exposed E, reported infected I_r, and unreported infected I_u individuals in a population of size N. This model distinguishes between reported and unreported infected individuals: the reported infected are those that have enough symptoms to eventually be tested and thus appear in daily case reports, to which we fit the model.

Susceptible (S) individuals become exposed due to contact with reported or unreported infected individuals (I_r or I_u) at a rate β_t or $\mu\beta_t$. The parameter $0 < \mu < 1$ represents the decreased transmission rate from unreported infected individuals, who are often subclinical or even asymptomatic. The transmission rate $\beta_t \geq 0$ may change over time t due to behavioral changes of both susceptible and infected individuals. Exposed individuals, after an average incubation period of Z days, become reported infected with probability α_t or unreported infected with probability $(1 - \alpha_t)$. The reporting rate $0 < \alpha_t < 1$ may also change over time due to changes in human behavior. Infected individuals remain infectious for an average period of D days, after which they either recover, or becomes ill enough to be quarantined. They therefore no longer infect other individuals, and the model does not track their frequency. The model is described by the following equations:

$$\begin{aligned} \frac{dS}{dt} &= -\beta_t S \frac{I_p}{N} - \mu\beta_t S \frac{I_s}{N} \\ \frac{dE}{dt} &= \beta_t S \frac{I_p}{N} + \mu\beta_t S \frac{I_s}{N} - \frac{E}{Z} \\ \frac{dI_r}{dt} &= \alpha_t \frac{E}{Z} - \frac{I_r}{D} \\ \frac{dI_u}{dt} &= (1 - \alpha_t)\frac{E}{Z} - \frac{I_r}{D}. \end{aligned} \tag{1}$$

The initial numbers of exposed $E(0)$ and unreported infected $I_u(0)$ are considered model parameters, whereas the initial number of reported infected is assumed to be zero $I_r(0) = 0$, and the number of susceptible is $S(0) = N - E(0) - I_u(0)$. The vector θ of model parameters is

$$\theta = \Big(Z, D, \mu, \{\beta_t\}, \{\alpha_t\}, \{p_t\}, E(0), I_u(0)\Big). \tag{2}$$

This model is inspired by Li et al.[4] and Pei and Shaman[5], who used a similar model with multiple regions and constant transmission β and reporting rate α to infer COVID-19 dynamics in China and the continental US, respectively.

Likelihood function. The *expected* cumulative number of reported infected individuals until day t is

$$Y_t = \int_0^t \alpha_s \frac{E(s)}{Z}\, ds, \quad Y_0 = 0. \tag{3}$$

We assume that reported infected individuals are confirmed and therefore observed in the daily case report of day t with probability p_t (note that an individual can only be observed once, and that p_t may change over time, but t is a specific date rather than the time elapsed since the individual was infected). Hence, we assume that the number of confirmed cases in day t is binomially distributed,

$$X_t \sim Bin\big(n_t, p_t\big),$$

where n_t is the *realized* (rather than expected) number of reported infected individuals yet to appear in daily reports by day t. The cumulative number of confirmed cases until day t is

$$\tilde{X}_t = \sum_{i=1}^{t} X_i, \quad X_0 = 0.$$

Given $\tilde{X}_{t-1}$, we assume n_t is Poisson distributed,

$$\big(n_t \mid \tilde{X}_{t-1}\big) \sim Poi\Big(Y_t - \tilde{X}_{t-1}\Big), \quad n_1 \sim Poi(Y_1).$$

Therefore, $\big(X_t \mid \tilde{X}_{t-1}\big)$ is a binomial conditioned on a Poisson, which reduces to a Poisson with

$$\big(X_t \mid \tilde{X}_{t-1}\big) \sim Poi\Big(\big(Y_t - \tilde{X}_{t-1}\big) \cdot p_t\Big), \quad X_1 \sim Poi(Y_1 \cdot p_1). \tag{4}$$

For given vector θ of model parameters (Eq. (2)), we compute the expected cumulative number of reported infected individuals $\{Y_t\}_{t=1}^{T}$ for each day (Eq. (3)). Then, since $\tilde{X}_{t-1}$ is a function of $X_1, \ldots, X_{t-1}$, we can use Eq. (4) to write the probability to observe the confirmed case data $\mathbf{X} = (X_1, \ldots, X_T)$ as

$$\mathbb{L}(\theta \mid \mathbf{X}) = P(\mathbf{X} \mid \theta) = P(X_1 \mid \theta) P(X_2 \mid \tilde{X}_1, \theta) \cdots P(X_T \mid \tilde{X}_{T-1}, \theta). \tag{5}$$

This defines a *likelihood function* $\mathbb{L}(\theta \mid \mathbf{X})$ for the parameter vector θ given the data $\mathbf{X}$.

NPI model. To model non-pharmaceutical interventions (NPIs), we set the beginning of the NPIs to day τ and define

$$\beta_t = \begin{cases} \beta, & t < \tau \\ \beta\lambda, & t \geq \tau \end{cases}, \quad \alpha_t = \begin{cases} \alpha_1, & t < \tau \\ \alpha_2, & t \geq \tau \end{cases}, \quad p_t = \begin{cases} 1/9, & t < \tau \\ 1/6, & t \geq \tau \end{cases}, \tag{6}$$

where $0 < \lambda < 1$. The values for p_t follow Li et al.[4], who estimated the average time between infection and reporting in Wuhan, China, at 9 days before the start of NPIs (Jan 23, 2020) and 6 days after start of NPIs. The parameter τ is then added to the parameter vector θ (Eq. (2)).

Model fitting. To fit our model (Eq. (1)) to the data $\mathbf{X}$ and estimate the model parameters θ, we apply a Bayesian inference approach. We define the following flat priors on the model parameters $P(\theta)$:

$$\begin{aligned} Z &\sim Uniform(2, 5) \\ D &\sim Uniform(2, 5) \\ \mu &\sim Uniform(0.2, 1) \\ \beta &\sim Uniform(0.8, 1.5) \\ \lambda &\sim Uniform(0, 1) \\ \alpha_1, \alpha_2 &\sim Uniform(0.02, 1) \\ E(0) &\sim Uniform(0, 3000) \\ I_u(0) &\sim Uniform(0, 3000) \\ \tau &\sim Uniform(1, T-1), \end{aligned} \tag{7}$$

where T is the number of days in the data $\mathbf{X}$. Most priors follow Li et al.[4], except λ, which is used to enforce that the transmission rates are lower after the start of the NPIs ($\lambda < 1$). The likelihood function is defined in Eq. (5). The posterior distribution on the model parameters $P(\theta \mid \mathbf{X})$ is then estimated using an affine-invariant ensemble sampler for Markov chain Monte Carlo (MCMC) implemented in the `emcee` Python package[2].

Model selection. We perform model selection using DIC (deviance information criterion)[6],

$$\begin{aligned} DIC(\theta, \mathbf{X}) &= 2\mathbb{E}[D(\theta)] - D(\mathbb{E}[\theta]) \\ &= 2\log \mathcal{L}(\mathbb{E}[\theta] \mid \mathbf{X}) - 4\mathbb{E}[\log \mathcal{L}(\theta \mid \mathbf{X})], \end{aligned} \tag{8}$$

where $D(\theta)$ is the Bayesian deviance, and expectations $\mathbb{E}[\cdot]$ are taken over the posterior distribution $P(\theta \mid \mathbf{X})$. We compare models by reporting their relative DIC; lower is better.

Results

Several studies have described the effects of non-pharmaceutical interventions in several countries [1,3,4]. These studies have assumed that the parameters of the epidemiological model change at a specific date, as in Eq. (6), and set the change date τ to the official NPI date τ^*. They then fit the model once for $t < \tau^*$ and once for $t \geq \tau^*$ (see TABLE2 for a summary of official NPI dates.) For example, Li et al.[4] estimate the dynamics in China before and after τ^* at Jan 23. Thereby, they effectively estimate (β, α_1) and (λ, α_2) separately.

Here we estimate the posterior distribution of *effective* start date of the NPI, $P(\tau \mid \mathbf{X}$, as well as maximum a priori (MAP) estimates, $\hat{\tau}$, by jointly estimating $\tau, \beta, \lambda, \alpha_1, \alpha_2$ on the entire time series per region (e.g. Italy, Austria), rather than splitting the region time series at τ^*. In all examined cases the effect of an NPI is significant: the DIC of a model without NPI ($\beta_t \equiv \beta, \alpha_t \equiv \alpha, p_t \equiv p$ for all t) was higher than the DIC of a model with NPI (Eq. (6)) by at least Z. Therefore, FIGURE compares the official dates τ^* and our MAP estimates $\hat{\tau}$, with confidence intervals. It can be seen that un most regions $\hat{\tau}$ and τ^* differ significantly: that is, the effective start of NPI was either advanced or delayed compared to the official date. Do we want to report DIC of model with τ compared to model with fixed $\tau = \tau^*$? Or just that ($P(\tau \neq \tau^*) > zzz$) ? Or confidence intervals?

In the following, we describe our findings on delayed and advanced start of NPI.

Delayed effective start of NPI. We find that our MAP estimates $\hat{\tau}$ often differ significantly from the official dates tau^*. For example, in Italy, the first case officially confirmed on Feb 21, a lockdown was delayed in Northern Italy on Mar 8, with social distancing implemented in the rest of the country, and

the lockdown was extended to the entire nation on Mar 11[3]. That is, the official date τ^* is either Mar 8 or 11. However, we estimate the effective date $\hat{\tau}$ at Mar 16 (the posterior probability that τ is later than Mar 11 is $(P(\tau > \tau^*) = ???)$. Similarly, in Wuhan, China, lockdown was declared on Jan 23[4], but we estimate that the effective start of NPIs to be 3-4 days layer $(P(\tau > \tau^*) = ???)$.

Advanced effective start of NPIs. In contrast, in some regions we estimate an effective start of NPIs $\hat{\tau}$ that is *earlier* then the official date τ^*. For example, social distancing was encouraged starting on Mar 8[1], but mass gatherings still occurred on Mar 8, including a march of 120,000 people for the International Women's Day, and a football match between Real Betis and Real Madrid (2-1) with a crowd of 50,965 in Seville. A national lockdown was only announced on Mar 14 (τ^*)[1]. Nevertheless, we estimate the effective start of NPI $\hat{\tau}$ at Mar 8 or 9, rather than Mar 14 $(P(\tau < \tau^*) = ???)$.

Match between effective and official start of NPI. We have also found a single case in which the official and effective dates match: Switzerland ordered a national lockdown on Mar 20 (τ^*), after banning public evens and closing schools on Mar 13 and 14[1]. Indeed, our MAP estimate $\hat{\tau}$ is Mar 20, and the posterior distribution shows two density peaks: a smaller one between Mar 10 and Mar 14, and a taller one between Mar 17 and Mar 22. It's also worth mentioning that Switzerland was the first to mandate self isolation of confirmed cases[1].

Discussion

Quisque ullamcorper placerat ipsum. Cras nibh. Morbi vel justo vitae lacus tincidunt ultrices. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. In hac habitasse platea dictumst. Integer tempus convallis augue. Etiam facilisis. Nunc elementum fermentum wisi. Aenean placerat. Ut imperdiet, enim sed gravida sollicitudin, felis odio placerat quam, ac pulvinar elit purus eget enim. Nunc vitae tortor. Proin tempus nibh sit amet nisl. Vivamus quis tortor vitae risus porta vehicula.

Fusce mauris. Vestibulum luctus nibh at lectus. Sed bibendum, nulla a faucibus semper, leo velit ultricies tellus, ac venenatis arcu wisi vel nisl. Vestibulum diam. Aliquam pellentesque, augue quis sagittis posuere, turpis lacus congue quam, in hendrerit risus eros eget felis. Maecenas eget erat in sapien mattis porttitor. Vestibulum porttitor. Nulla facilisi. Sed a turpis eu lacus commodo facilisis. Morbi fringilla, wisi in dignissim interdum, justo lectus sagittis dui, et vehicula libero dui cursus dui. Mauris tempor ligula sed lacus. Duis cursus enim ut augue. Cras ac magna. Cras nulla. Nulla egestas. Curabitur a leo. Quisque egestas wisi eget nunc. Nam feugiat lacus vel est. Curabitur consectetuer.

Suspendisse vel felis. Ut lorem lorem, interdum eu, tincidunt sit amet, laoreet vitae, arcu. Aenean faucibus pede eu ante. Praesent enim elit, rutrum at, molestie non, nonummy vel, nisl. Ut lectus eros, malesuada sit amet, fermentum eu, sodales cursus, magna. Donec eu purus. Quisque vehicula, urna sed ultricies auctor, pede lorem egestas dui, et convallis elit erat sed nulla. Donec luctus. Curabitur et nunc. Aliquam dolor odio, commodo pretium, ultricies non, pharetra in, velit. Integer arcu est, nonummy in, fermentum faucibus, egestas vel, odio.

As several countries (e.g. Austria, Israel) begin to relieve lockdowns and ease restrictions, we expect similar delays and advances to occur: in some countries people will begin to behave as if restrictions were eased before the official date, and in some countries people will continue to self-restrict even after restrictions are officially removed. Such delays and advances could confuse analyses and lead to wrong conclusions about the effects of NPI removals.

Acknowledgements

This work was supported in part by the Israel Science Foundation 552/19 (YR) and XXX/XX (Alon Rosen)

References

[1] Flaxman, S., Mishra, S., Gandy, A., Unwin, J. T., Coupland, H., Mellan, T. A., Zhu, H., Berah, T., Eaton, J. W., Guzman, P. N. P., Schmit, N., Cilloni, L., Ainslie, K. E. C., Baguelin, M., Blake, I., Boonyasiri, A., Boyd, O., Cattarino, L., Ciavarella, C., Cooper, L., Cucunubá, Z., Cuomo-Dannenburg, G., Dighe, A., Djaafara, B., Dorigatti, I., Van Elsland, S., Fitzjohn, R., Fu, H., Gaythorpe, K., Geidelberg, L., Grassly, N., Green, W., Hallett, T., Hamlet, A., Hinsley, W., Jeffrey, B., Jorgensen, D., Knock, E., Laydon, D., Nedjati-Gilani, G., Nouvellet, P., Parag, K., Siveroni, I., Thompson, H., Verity, R., Volz, E., Gt Walker, P., Walters, C., Wang, H., Wang, Y., Watson, O., Xi, X., Winskill, P., Whittaker, C., Ghani, A., Donnelly, C. A., Riley, S., Okell, L. C., Vollmer, M. A. C., Ferguson, N. M. and Bhatt, S. 2020, 'Estimating the number of infections and the impact of non-pharmaceutical interventions on COVID-19 in 11 European countries', *Imp. Coll. London* (March), 1–35.
URL: *https://doi.org/10.25561/77731*

[2] Foreman-Mackey, D., Hogg, D. W., Lang, D. and Goodman, J. 2013, 'emcee : The MCMC Hammer ', *Publ. Astron. Soc. Pacific* **125**(925), 306–312.

[3] Gatto, M., Bertuzzo, E., Mari, L., Miccoli, S., Carraro, L., Casagrandi, R. and Rinaldo, A. 2020, 'Spread and dynamics of the COVID-19 epidemic in Italy: Effects of emergency containment measures', *Proc. Natl. Acad. Sci.* p. 202004978.
URL: *http://www.pnas.org/lookup/doi/10.1073/pnas.2004978*

[4] Li, R., Pei, S., Chen, B., Song, Y., Zhang, T., Yang, W. and Shaman, J. 2020, 'Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV2)', *Science (80-.).* p. eabb3221.
URL: *https://www.sciencemag.org/lookup/doi/10.1126/scienc*

[5] Pei, S. and Shaman, J. 2020, 'Initial Simulation of SARS-CoV2 Spread and Intervention Effects in the Continental US', *medRxiv* p. 2020.03.21.20040303.
URL: *http://medrxiv.org/content/early/2020/03/23/2020.03.2*

[6] Spiegelhalter, D. J., Best, N. G., Carlin, B. P. and Van Der Linde, A. 2002, 'Bayesian measures of model complexity and fit', *J. R. Stat. Soc. Ser. B Stat. Methodol.* **64**(4), 583–616.