

TITLE

Ilia Kohanovski^a, Uri Obolski^{b,c}, and Yoav Ram^{a,*}

^aSchool of Computer Science, Interdisciplinary Center Herzliya, Herzliya 4610101, Israel

^bSchool of Public Health, Tel Aviv University, Tel Aviv 6997801, Israel

^cPorter 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, consectetur adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetur 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.

18 Introduction

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

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

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

38 Models and Methods

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

Region	Start date	End date	Reference
Austria	X Feb		Flaxman et al. (2020)
Wuhan, China	10 Jan	8 Feb	Pei & Shaman (2020)

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

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

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

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

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

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

65 This model is inspired by Li et al. (2020) and Pei & Shaman (2020), who used a similar model with
 66 multiple regions and constant transmission β and reporting rate α to infer COVID-19 dynamics in
 67 China and the continental US, respectively.

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

$$70 \quad Y_t = \int_0^t \alpha_s \frac{E(s)}{Z} ds, \quad Y_0 = 0. \quad (3)$$

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,

$$X_t \sim \text{Bin}(n_t, p_t),$$

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,

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

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

$$72 \quad (X_t \mid \tilde{X}_{t-1}) \sim \text{Poi}((Y_t - \tilde{X}_{t-1}) \cdot p_t), \quad X_1 \sim \text{Poi}(Y_1 \cdot p_1). \quad (4)$$

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

$$77 \quad \mathbb{L}(\theta \mid \mathbf{X}) = P(\mathbf{X} \mid \theta) = P(X_1 \mid \theta) P(X_2 \mid \tilde{X}_1, \theta) \cdots P(X_T \mid \tilde{X}_{T-1}, \theta). \quad (5)$$

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

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

$$81 \quad \beta_t = \begin{cases} \beta, & t < \tau \\ \beta\lambda, & t \geq \tau \end{cases}, \quad \alpha_t = \begin{cases} \alpha_1, & t < \tau \\ \alpha_2, & t \geq \tau \end{cases}, \quad p_t = \begin{cases} 1/9, & t < \tau \\ 1/6, & t \geq \tau \end{cases}, \quad (6)$$

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

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

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

88 where T is the number of days in the data \mathbf{X} . Most priors follow Li et al. (2020), except λ , which
 89 is used to enforce that the transmission rates are lower after the start of the NPIs ($\lambda < 1$). The
 90 likelihood function is defined in Eq. (5). The posterior distribution on the model parameters $P(\theta | \mathbf{X})$
 91 is then estimated using an affine-invariant ensemble sampler for Markov chain Monte Carlo (MCMC)
 92 implemented in the `emcee` Python package (Foreman-Mackey et al. 2013).

93 Results

94 Several studies have described the effects of non-pharmaceutical interventions in several countries
 95 (Flaxman et al. 2020, Gatto et al. 2020). These studies have assumed that the epidemiological
 96 dynamics change at a specific date, as in Eq. (6), set the change date τ to the official NPI date τ^* ,
 97 and fit the model once for $t < \tau^*$ and once for $t \geq \tau^*$ (see [TABLE2](#) for a summary of official NPI
 98 dates.) For example, Li et al. (2020) estimate the dynamics in China before and after τ^* at Jan 23.
 99 Thereby, they effectively estimate (β, α_1) and (λ, α_2) separately.

100 Here we estimate the posterior distribution of *effective* start date of the NPI, $P(\tau | \mathbf{X})$, as well as
 101 maximum a priori (MAP) estimates, $\hat{\tau}$, by jointly estimating $\tau, \beta, \lambda, \alpha_1, \alpha_2$ on the entire time series
 102 per region (e.g. Italy, Austria), rather than splitting the region time series at τ^* . [FIGURE](#) shows a
 103 comparison the official dates τ^* and our MAP estimates $\hat{\tau}$, with confidence intervals. In most cases
 104 analyses, we find that $\hat{\tau}$ and τ^* differ significantly: that is, the effective start of NPI was either advanced
 105 or delayed compared to the official date. In the following, we describe our findings on delayed and
 106 advanced start of NPI.

107 **Delayed effective start of NPI.** We find that our MAP estimates $\hat{\tau}$ often differ significantly from
 108 the official dates τ^* . For example, in Italy, the first case officially confirmed on Feb 21, a lockdown
 109 was delayed in Northern Italy on Mar 8, with social distancing implemented in the rest of the country,
 110 and the lockdown was extended to the entire nation on Mar 11 (Gatto et al. 2020). That is, the official
 111 date τ^* is either Mar 8 or 11. However, we estimate the effective date $\hat{\tau}$ at Mar 16 (the posterior
 112 probability that τ is later than Mar 11 is $(P(\tau > \tau^*) = ???)$. Similarly, in Wuhan, China, lockdown was
 113 declared on Jan 23 (Li et al. 2020), but we estimate that the effective start of NPIs to be 3-4 days later
 114 $(P(\tau > \tau^*) = ???)$.

115 **Advanced effective start of NPIs.** In contrast, in some regions we estimate an effective start of
 116 NPIs $\hat{\tau}$ that is *earlier* than the official date τ^* . For example, social distancing was encouraged starting
 117 on Mar 8 (Flaxman et al. 2020), but mass gatherings still occurred on Mar 8, including a march of
 118 120,000 people for the [International Women's Day](#), and a football match between [Real Betis and Real](#)
 119 [Madrid](#) (2-1) with a crowd of 50,965 in Seville. A national lockdown was only announced on Mar 14

120 (τ^*) (Flaxman et al. 2020). Nevertheless, we estimate the effective start of NPI $\hat{\tau}$ at Mar 8 or 9, rather
121 than Mar 14 ($P(\tau < \tau^*) = ???$).

122 **Match between effective and official start of NPI.** We have also found a single case in which the
123 official and effective dates match: Switzerland ordered a national lockdown on Mar 20 (τ^*), after
124 banning public events and closing schools on Mar 13 and 14 (Flaxman et al. 2020). Indeed, our MAP
125 estimate $\hat{\tau}$ is Mar 20, and the posterior distribution shows two density peaks: a smaller one between
126 Mar 10 and Mar 14, and a taller one between Mar 17 and Mar 22. It's also worth mentioning that
127 Switzerland was the first to mandate self isolation of confirmed cases (Flaxman et al. 2020).

128 Discussion

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

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

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

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

152 **Acknowledgements**

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

- 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., Whitaker, C., Ghani, A., Donnelly, C. A., Riley, S., Okell, L. C., Vollmer, M. A. C., Ferguson, N. M. & 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>
- Foreman-Mackey, D., Hogg, D. W., Lang, D. & Goodman, J. (2013), ‘emcee : The MCMC Hammer ’, *Publ. Astron. Soc. Pacific* **125**(925), 306–312.
- Gatto, M., Bertuzzo, E., Mari, L., Miccoli, S., Carraro, L., Casagrandi, R. & 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.2004978117>
- Li, R., Pei, S., Chen, B., Song, Y., Zhang, T., Yang, W. & 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/science.abb3221>
- Pei, S. & 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/2020/03/23/2020.03.21.20040303>