

Estimation of the incubation time distribution for COVID-19

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Abstract: We consider nonparametric estimation of the incubation time distribution of COVID-19.

1. Introduction

The Dutch Centre for Infectious Disease Control (Dutch: RIVM) analyzes in [1] a data set of 88 travelers who are assumed to have picked up the COVID-19 virus in Wuhan. The distribution of their incubation times is estimated using certain simple distributions, like Weibull, log-normal and gamma. If the only thing we know about the start of the incubation time is that it belongs to an interval $[0, E_i]$, the log likelihood for one observation is:

$$\log \int_{t \in [0, E_i]} g(S_i - t) dF_i(t).$$

Here E_i would be the upper bound of an interval for the infection interval, for which we take (looking back) 0 as the left point for the i th individual (see [2]), $S_i \geq E_i$ is the time where the person becomes symptomatic (note that $S_i = E_i$ is possible), and F_i would be the distribution function of the time of a possible contact with an infector. The exit times and times of becoming symptomatic of the 88 Wuhan travelers are shown in Table 1.

It is clear that, without further assumptions, g and F_i are not identifiable. To remedy this, we assume, as in [1] (see also [9]), that F_i is the uniform distribution on $[0, E_i]$. If we want to use maximum likelihood, we have to maximize

$$\sum_{i=1}^n \log \left\{ \int_{t=0}^{E_i} g(S_i - t) dt / E_i \right\},$$

and since the E_i do not matter in the maximization problem, we end up with the problem of maximizing

$$\sum_{i=1}^n \log \left\{ \int_{t=0}^{E_i} g(S_i - t) dt \right\} = \sum_{i=1}^n \log \{G(S_i) - G(S_i - E_i)\} \quad (1)$$

where G is the incubation time distribution function.

The algorithms we used for analyzing the data set can be found on [3]. We describe the data files given there. The original data file is `data_Wuhan_tsv`, which gives details on persons in the sample and which can be found in [1]. This was transformed into a data file `transformed_data_Wuhan.txt`, consisting of three columns, giving, respectively, the arrivals in and departures from Wuhan and the time the person became symptomatic. If the arrival time was unknown, this time was set to -18 , which means 18 days before December 31, 2019, which is the zero on the time scale. For traveler number 67, who apparently had a connecting flight, the duration of stay in Wuhan was changed from 0 to 1 day. This, in turn, was transformed into the input file `inputdata_Wuhan.txt`, where the time, spent in Wuhan, was shifted making the left point equal to zero, and consists of two columns: the first column contains the data $S_i - E_i$ (time of becoming symptomatic minus exit time from Wuhan) and S_i , time of becoming symptomatic, where all times are shifted to have entrance time zero. If the person became symptomatic in Wuhan we put $S_i - E_i = 0$.

Assuming that the distribution of the possible time of infection is uniform on the exposure interval, and estimating the distribution function G by the Weibull distribution, parametrized as

$$G(x) = G_{a,b}(x) = 1 - \exp \{-bx^a\}, \quad x > 0, \quad (2)$$

i	E_i	S_i		i	E_i	S_i
1	5	5		45	39	40
2	30	33		46	35	42
3	21	22		47	2	6
4	1	4		48	36	37
5	1	6		49	38	39
6	8	8		50	1	8
7	4	4		51	38	41
8	3	3		52	38	41
9	33	34		53	38	39
10	33	34		54	11	11
11	8	8		55	36	39
12	1	4		56	11	11
13	20	21		57	40	41
14	20	28		58	36	37
15	30	32		59	36	41
16	35	38		60	36	39
17	3	7		61	27	31
18	35	37		62	38	40
19	36	38		63	36	42
20	31	38		64	40	43
21	34	35		65	41	43
22	29	31		66	37	43
23	36	37		67	1	7
24	3	8		68	40	42
25	7	9		69	40	42
26	38	39		70	31	39
27	30	36		71	40	41
28	28	36		72	40	41
29	35	36		73	41	42
30	33	34		74	41	43
31	3	8		75	4	5
32	2	4		76	4	5
33	2	5		77	40	41
34	5	5		78	36	40
35	36	37		79	36	40
36	31	35		80	40	42
37	41	42		81	36	42
38	41	42		82	38	43
39	3	4		83	2	9
40	38	39		84	38	43
41	39	41		85	37	43
42	39	41		86	41	42
43	39	41		87	40	43
44	33	39		88	40	43

TABLE 1

Exit times and times of becoming symptomatic of the 88 Wuhan travelers after shifting the entrance times to 0.

we get as our maximum likelihood estimators of the parameters a and b :

$$\hat{a} = 3.03514, \quad \hat{b} = 0.002619. \quad (3)$$

Using the Weibull maximum likelihood method, the estimate was computed by two methods. One is a very simple method using `Weibull.cpp`, which is used in `analysis_EM.R` and `analysis_ICM.R`, where also the nonparametric estimate to be discussed in the next sections is computed. For this “pattern search” algorithm for looking for the parameters of the Weibull distribution one does not have to compute the derivatives of the log likelihood. It is based on the Hooke-Jeeves algorithm. The other one can be found in `R_Weibull_Estimation.R`, where we use the R package `lbfgs`, and where the gradient (derivatives of the log likelihood) has to be provided.

The results obtained for the Weibull distribution approach of the two algorithms are remarkably similar. The values in (3) were produced by the R script in [3], using the Hooke-Jeeves algorithm. For a convergence proof of the Hooke-Jeeves algorithm and interesting further discussion of the pattern search algorithms, see [8] and [11].

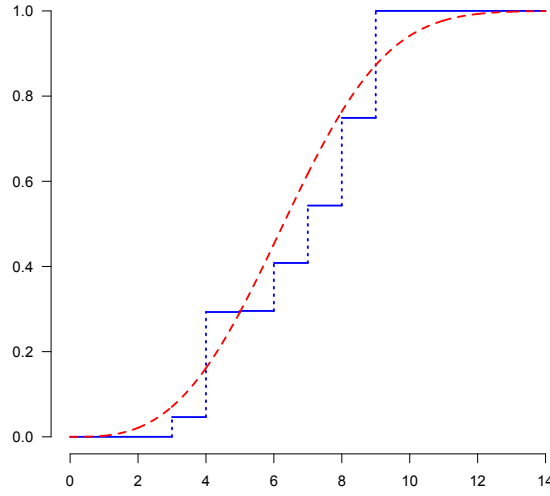


Fig 1: The nonparametric maximum likelihood estimate (MLE) \hat{G}_n of the incubation time distribution function (blue), and the MLE using the Weibull distribution (red, dashed), for the data set analyzed in [1].

2. Algorithms for computing the nonparametric maximum likelihood estimator

The EM iterations for the MLE maximizing (1), without making this parametric restriction, are in this case given by:

$$p'_j = p_j n^{-1} \sum_{i=1}^n 1_{\{j \in (S_i - E_i, S_i]\}} \bigg/ \sum_{k \in (S_i - E_i, S_i]} p_k, \quad (4)$$

where the ratios are zero if the denominators are zero. The implementation of this algorithm for the present situation can be found in `analysis_EM.R` in [3].

The EM iterations were started with the discrete uniform distribution on the 43 points $1, \dots, 43$, which corresponds to the range of values (days) in Table 1, but withdrew its mass after 10,000 iterations to the 7 points $3, \dots, 9$, which leads to the discrete distribution function, shown in Figure 1. A bar chart of the

Number of days	p_i
3	0.0463850922
4	0.2466837048
5	0.0024858945
6	0.1126655228
7	0.1347501680
8	0.2058210187
9	0.2512085991

TABLE 2
Probability masses of the nonparametric MLE.

corresponding probability masses is shown in Figure 2. It is seen that this is a bimodal discrete probability distribution with modes at resp. 4 and 9 days, with the highest value at the second mode. This discrete probability distribution is also given in Table 2.

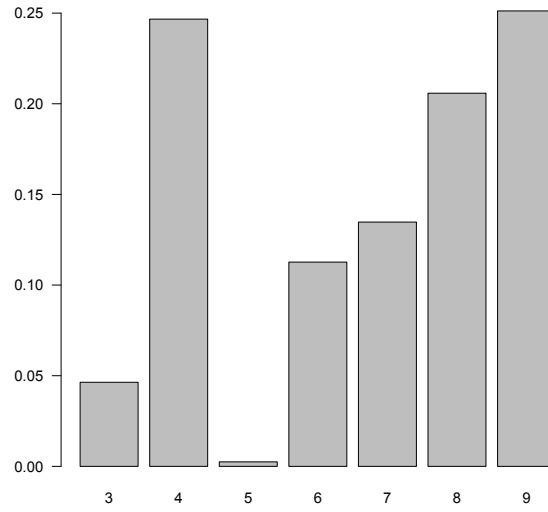


Fig 2: Bar chart of the probability masses of the nonparametric MLE

The iteration steps (4) follow from the so-called self-consistency equations, which are derived by differentiating the criterion function

$$n^{-1} \sum_{i=1}^n \log \left\{ \sum_{j \in (S_i - E_i, S_i]} p_j \right\} - \lambda \left\{ \sum_{j=1}^m p_j - 1 \right\}, \quad (5)$$

w.r.t. p_i , where in this case $m = 43$, and λ is a nonnegative Lagrange multiplier, chosen in such a way that

$$\sum_{j=1}^m p_j = 1. \quad (6)$$

This yields

$$n^{-1} \sum_{i=1}^n 1_{\{j \in (S_i - E_i, S_i]\}} \Big/ \sum_{k \in (S_i - E_i, S_i]} p_k = \lambda, \quad j = 1, \dots, m, \quad (7)$$

and multiplying these relations with p_j and summing over j yields $\lambda = 1$, using the side condition (6). But the relations (7) only hold for the *active* (in this case 7) parameters $p_i > 0$ of the solution; in the iterations (4) the inactive parameters p_i will tend to zero. For more details, see, e.g., [7], Section 7.2.

Because of the monotonicity of the distribution function G , maximizing the log likelihood over all distribution functions G is an isotonic regression problem, which can be solved by specific isotonic methods. In the present case we can apply the *iterative convex minorant algorithm*, discussed in [7], Section 7.3.

The log likelihood is of type:

$$f(\mathbf{y}) = \sum_{i=1}^m k_i \log (G(U_i) - G(T_i)), \quad (8)$$

where k_i is the number of observations (T_i, U_i) , and where

$$(T_i, U_i) = (0, V_i + W_i) 1_{\{V_i + W_i \leq E_i\}} + (V_i + W_i - E_i, V_i + W_i) 1_{\{V_i + W_i > E_i\}} \quad i = 1, \dots, n, \quad (9)$$

where $n = 88$, and where V_i is the infection time, W_i the incubation time and, as before, E_i the exit time of the travelers from Wuhan, where all observations are centred by subtracting the entrance time.

We first make the so-called preliminary reduction to reduce the problem to a maximization problem in the interior of a convex cone of type

$$\{\mathbf{y} = (y_1, \dots, y_m)^T : 0 < y_1 \leq \dots \leq y_m\}.$$

For the Wuhan data set it can be checked that, without loss of generality, $G(i) = 0$, $i \leq 2$, and $G(i) = 1$, $i \geq 9$, since in this case values strictly between 0 and 1 can only make the likelihood smaller. If we make this preliminary reduction, the log likelihood for the ordered parameters y_i , representing the values of the distribution function G at the observation points, becomes:

$$f(\mathbf{y}) = \sum_{0 \leq i < j \leq 7} N_{ij} \log (y_j - y_i), \quad (10)$$

where $y_i = G(i + 2)$, $i = 0, \dots, 7$, $y_0 = 0$, $y_7 = 1$, and where the triangular array (N_{ij}) , $0 \leq i < j \leq 7$, is given by:

$$\begin{array}{ccccccc} 1 & 3 & 4 & 0 & 0 & 2 & 0 \\ & 2 & 1 & 0 & 0 & 0 & 9 \\ & & 0 & 1 & 1 & 0 & 4 \\ & & & 1 & 0 & 2 & 3 \\ & & & & 1 & 0 & 6 \\ & & & & & 1 & 3 \\ & & & & & & 3 \end{array}$$

We have to maximize (8) under the restriction $0 < y_1 \leq \dots \leq y_6$; by the preliminary reduction, we lost the additional condition $y_6 < 1$. Let $\mathbf{y} = (y_1, \dots, y_6)^T$. The (Fenchel) sufficient and necessary conditions for the solution are:

$$\sum_{j=i}^6 \frac{\partial}{\partial y_j} f(\mathbf{y}) \leq 0, \quad i = 1, \dots, 6, \quad (11)$$

and

$$\sum_{i=1}^6 y_i \frac{\partial}{\partial y_i} f(\mathbf{y}) = 0, \quad (12)$$

where f is defined by (8). Since the values y_i are strictly between 0 and 1, (12) can only hold if also

$$\sum_{i=1}^6 \frac{\partial}{\partial y_i} f(\mathbf{y}) = 0,$$

and we can therefore turn (11) into

$$\sum_{j=1}^i \frac{\partial}{\partial y_j} f(\mathbf{y}) \geq 0, \quad i = 1, \dots, 6. \quad (13)$$

The resulting (nonparametric) MLE \hat{F}_n is shown in Figure 1, together with the MLE assuming that G is a Weibull distribution. The EM algorithm and the iterative convex minorant (ICM) algorithm give exactly the same solutions, but the ICM algorithm needs less iterations (106 in this case; the EM algorithm needs between 1000 and 10,000 iterations).

To compute the MLE via the iterative convex minorant algorithm, we have to construct so-called cusum (cumulative sum) diagrams. The cusum diagram consists of the point $(0, 0)$ and the points

$$\sum_{j=1}^i \left(w_j, \frac{\partial}{\partial y_j} f(\mathbf{y}) + w_j y_j \right), \quad i = 1, \dots, 6, \quad (14)$$

where

$$w_j = -\frac{\partial^2}{\partial y_j^2} f(\mathbf{y}). \quad j = 1, \dots, 6. \quad (15)$$

At each iteration step the left derivative vector \mathbf{y}' of the greatest convex minorant of the cusum diagram is computed on the basis of the current value \mathbf{y} , and the stationary point of this iteration is the solution of the optimization problem. We perform line search in case the full step to \mathbf{y}' would not lead to improvement or would go out of bounds (which does not happen in the present case). For more theory, see [7].

As in [7], section 1.2, we can compute the smoothed maximum likelihood estimator (SMLE) and also an estimate of the density. The SMLE is defined by

$$\tilde{G}_{nh}(t) = \int \mathbb{K}((t - y)/h) d\hat{G}_n(y), \quad (16)$$

where $h > 0$ and \mathbb{K} is an integrated kernel

$$\mathbb{K}(x) = \int_{-\infty}^x K(u) du. \quad (17)$$

Here K is a symmetric kernel with support $[-1, 1]$, for example the triweight kernel

$$K(u) = \frac{35}{32} (1 - u^2)^3 1_{[-1, 1]}(u). \quad (18)$$

We estimate the density by

$$\tilde{g}_{nh}(t) = h^{-1} \int K((t - y)/h) d\hat{G}_n(y). \quad (19)$$

For the present analysis we took $h = 3.6$ in (16) and $h = 4.6$ in (19); these bandwidths were chosen by a bootstrap method, explained in Section 3. The resulting estimates are shown in Figure 3.

3. Data-adaptive bandwidth choice for the density estimate and the SMLE

Let the random variables E_i with values on the integers (“days”) on the interval $[1, 42]$ represent the exit times (“length of stay in Wuhan”). Furthermore, let V_i denote the (unknown) infection time, which we take, conditionally on E_i , to be uniform on $[0, E_i]$, and let W_i denote the (again unknown) incubation time. Our observations are the pairs (9).

To determine the bandwidth h of our density estimator

$$\hat{g}_{nh}(t) = \int K_h(t - y) d\hat{G}_n(y), \quad (20)$$

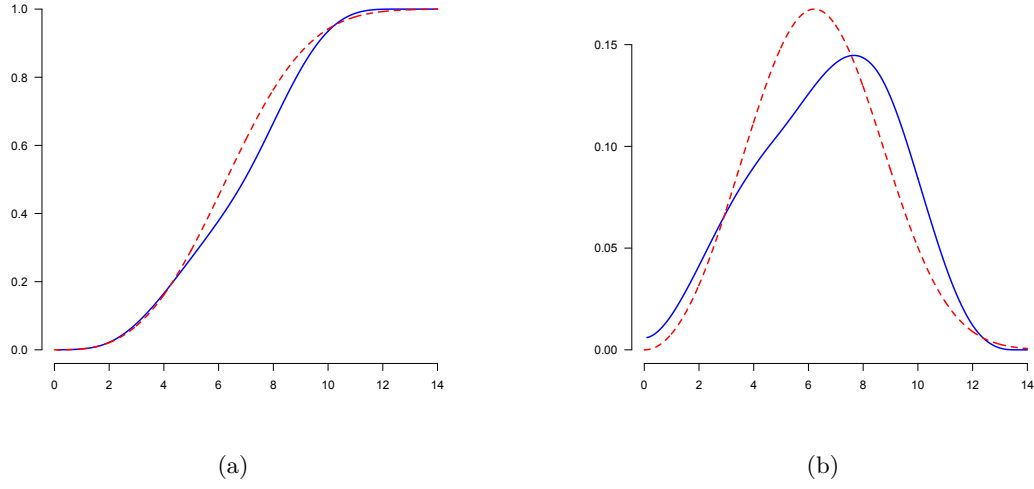


Fig 3: (a): The smoothed nonparametric maximum likelihood estimate (SMLE) of the incubation time distribution function (blue), and the MLE using the Weibull distribution (red, dashed), for the data set analyzed in [1] and (b): the smoothed nonparametric maximum likelihood estimate of the incubation time density function (blue), and the MLE of the density using the Weibull distribution (red, dashed), for the data set analyzed in [1].

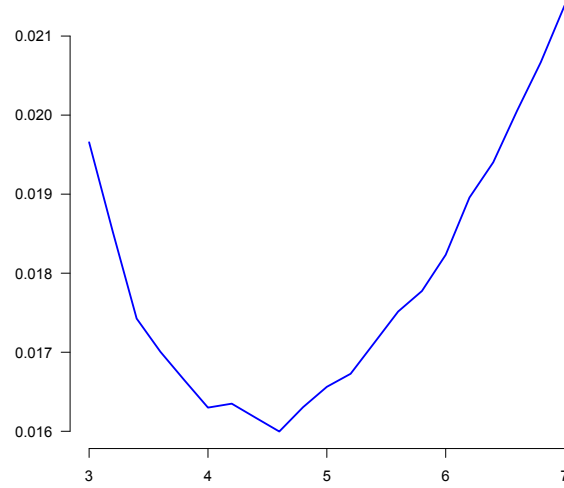


Fig 4: $\text{MSE}_g(h)$, given by (21), as function of h .

where \hat{F}_n is the MLE of the distribution function F of the incubation time, we follow a method somewhat similar to the method used in [10].

We take $B = 10,000$ bootstrap samples of observations (E_i, U_i^*) , corresponding to the observations (E_i, U_i) , where the E_i are the (actual) exit times if $E_i < S_i$, and where $E := S_i$ if the person got symptoms when still in Wuhan. The U_i^* are generated as the sums (rounded to the nearest integer) of a $\text{Uniform}(0, E_i)$ random variable V_i^* and a random variable W_i^* , generated from the density \hat{f}_{nh_0} by rejection sampling for a

fixed h_0 , for which we took $h_0 = 4$ in the present case. Note that we keep the E_i the same as in the original sample, somewhat analogously to the procedure followed in [10], which relieves us from the duty to estimate the exit time distribution.

Next we computed

$$\text{MSE}_g(h) = B^{-1} \sum_{b=1}^B \int \{\hat{g}_{nh}^*(x) - \hat{g}_{nh_0}(x)\}^2 dx. \quad (21)$$

The resulting loss function $\text{MSE}_f(h)$ is shown in Figure 4, which gave as the minimizing bandwidth $\hat{h} \approx 4.6$. Taking $h_0 = 3$ in our function of reference \hat{g}_{nh_0} gave the same minimizing value. The (approximate) independence of the starting value h_0 was also observed for the analogous bandwidth selection procedure in [10].

Similarly, we computed

$$\text{MSE}_G(h) = B^{-1} \sum_{b=1}^B \int \{\hat{G}_{nh}^*(x) - \hat{G}_{nh_0}(x)\}^2 dx, \quad (22)$$

as a function of h by the same bootstrap procedure, where \hat{G}_{nh}^* was computed for the bootstrap samples. The integrals were approximated by Riemann sums with step size 0.1 on the interval $[0, 14]$. The R scripts for this procedure can again be found on [3].

The method used here is called the “smoothed bootstrap”. Another option is to use the ordinary bootstrap with smaller sample sizes (since otherwise for this method the bias is not estimated in the right way). This method was for example applied in [6] and implemented in the R package `curstatCI` ([5]) for the current status model. We tried this method out, but found its behavior not to be satisfactory in the present case, possibly because of the small sample size.

4. The continuous model

Applying the method of the preceding section to the discrete data, where one only uses days on the time axis, is somewhat dubious, since, in fact, we do not have information on a finer scale, which would allow us to let the bandwidth (and therefore the bias) tend to zero. It is conceivable that we have information on a finer scale, for example the time of the outgoing flight or the time of day of becoming symptomatic. Presently both times are interval censored (where one day is the interval). We could therefore introduce another assumption, for example that the time of becoming symptomatic is uniformly distributed over a day. In any case, there seems enough reason to study the continuous model, where one would have (approximately) continuous observations, and to analyze what can be expected in this case.

We define the indicator Δ by

$$\Delta = 1_{\{S \leq E\}}, \quad (23)$$

where E is again the exit time and S is the time of becoming symptomatic. We consider the following simulation experiment. E_i is uniform $[0, M]$, the time of infection V_i is a Uniform random variable on $[0, E_i]$, conditionally on E_i , and the incubation time W_i is a truncated Weibull(a, b) distribution, where a and b have the same values as the estimates \hat{a} and \hat{b} in (3), respectively, and where the truncation interval $[0, M_1]$ is contained in the interval $[0, M]$. In the present simulation, we took $M_1 = 20$ and $M = 30$. In this way the upper bound for the observations S_i is equal to 50, which is somewhat comparable with the upper bound 43 of the observations S_i for the Wuhan travelers. This means that $S_i = V_i + W_i$, where we assume that V_i and W_i are independent, and that our observations are the triples (E_i, S_i, Δ_i) .

The MLE of the incubation time, where E_i and S_i are known, looks rather different from the MLE based on the discrete observations shown in Figure 1. An example of such an MLE is shown in Figure 5 for a sample of $n = 1000$. Since in this case the MLE can have more jumps, it has the possibility to be much closer to the continuous distribution function. It maximizes again expression (1), but this time the variables E_i and S_i are not discretized.

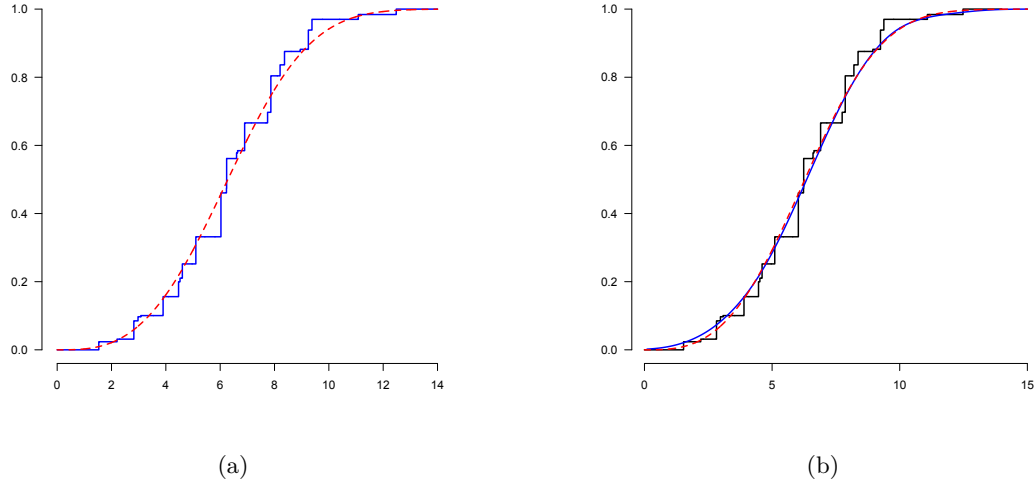


Fig 5: (a): The nonparametric maximum likelihood estimate (MLE) \hat{G}_n of the incubation time distribution function (blue) for a sample of size $n = 1000$, and the truncated Weibull distribution function (red, dashed) with parameters a and b , in the simulation model where the variables are not discretized. (b): The MLE (black) and the SMLE (blue), for the same sample, and the truncated Weibull distribution function (red, dashed). The bandwidth of the SMLE is $h = 3$.

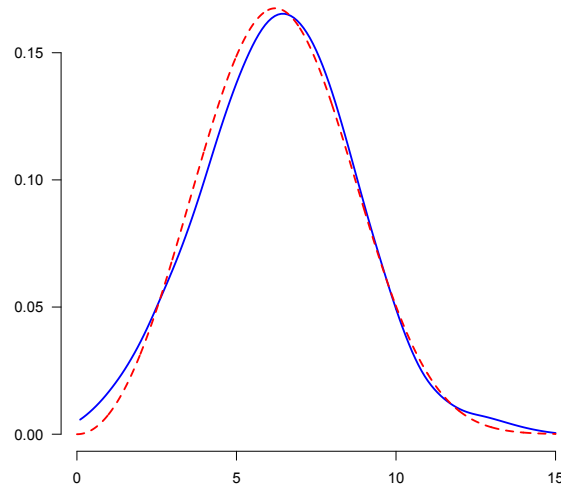


Fig 6: The nonparametric estimate of the density of the incubation time (blue, solid), based on a sample of size $n = 1000$ and bandwidth $h = 3.4$. The red dashed curve is the truncated Weibull density with parameters a and b of (3).

In this setup, the SMLE will, in the interior of the interval $[0, M]$, pointwise have the $n^{2/5}$ rate and the corresponding nonparametric density estimate the $n^{2/7}$ rate of convergence, and the pointwise limit distributions will be normal in both cases (see Section 6 of the present paper and [7], section 11.4). This means that we can apply the same techniques as in [6] and the R-package [5], and for example compute

pointwise bootstrap confidence intervals for the density. The bandwidth was determined by taking bootstrap subsamples of size $m = 100$, using bandwidths of size $cm^{-1/7}$ and using the optimal constant \hat{c} over the LS criterion in the bandwidth $\hat{c}n^{-1/7} = 3.598428$ for the density in the original sample, where we compare with the density estimate with bandwidth $h = 3$ in the original sample. This follows the procedure shown in the vignette of the R-package [5]. Since we have a simulation model here, we can also compute the real minimizing h , in a comparison with the truncated Weibull density, which is $h = 3.4$ in this case, which is not far from the bandwidth found by the bootstrap subsampling. In the pictures of this section, we took $h = 3.4$.

The bootstrap 95% confidence intervals for the density are shown for a sample of size $n = 1000$ in Figure 7. These computations can again be checked on [3]. For these intervals just 1000 bootstrap samples were taken, resampling with replacement from the original sample of triples (E_i, S_i, Δ_i) , computing the density estimate again in the bootstrap samples and determining the 2.5% and 97.5% percentiles of the values of the density estimates in the 1000 bootstrap samples. To get really good intervals it will be necessary to use an asymptotic pivot though, based on the theory, developed in Section 6 of the present paper.

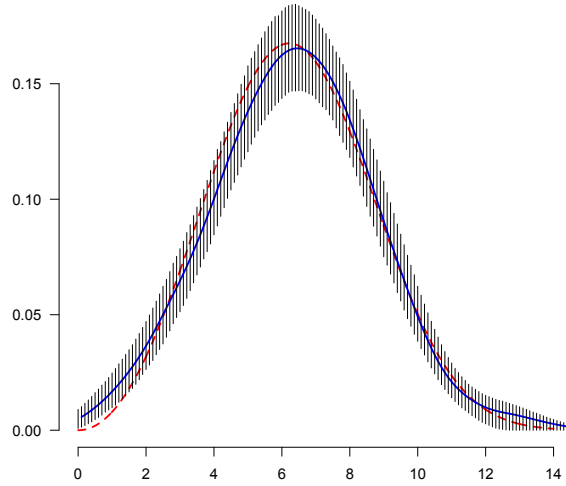


Fig 7: Density estimate (blue) and pointwise bootstrap 95% confidence intervals for the density of the incubation time distribution for a sample of size $n = 1000$ (same sample as in Figures 5 and 6). The truncated Weibull density is given by the red dashed curve.

5. Concluding remarks

We offered an alternative nonparametric approach to the estimation of the incubation time distribution which was estimated by parametric methods in [1] for a data set of travelers from Wuhan. In this way we do not have to choose a parametric distribution, like the Weibull, log-normal or gamma, as in [1], but compute a nonparametric maximum likelihood estimate instead which does not need the arbitrary choice of parameters at all.

However, to give a smooth estimate of the distribution function and (continuous) density, we have to choose a bandwidth parameter. For this choice a smoothed bootstrap approach was suggested. We also considered the models where the observations are not discretized at days and discussed rates of convergence and bootstrap confidence intervals in that case. The present paper can be considered to be the technical companion of the column [4]. All numerical computations are given as R scripts in [3].

6. Appendix

Using the notation of p. 330 of [7], we define the score function $\theta_{t,h,G}$ by:

$$\begin{aligned}\theta_{t,h,G}(e, v, \delta) &= E[a(W)|(E, S, \Delta) = (e, s, \delta_1, \delta_2)] \\ &= \delta \frac{\int_{w \leq s} a(w) dG(w)}{G(s)} + (1 - \delta) \frac{\int_{w \in (s-e, s]} a(w) dG(w)}{G(s) - G(s-e)},\end{aligned}\quad (24)$$

where $\delta = 1_{\{s \leq e\}}$. We assume $G(M_1) = 1$, where G is the distribution function of the incubation time and M_1 is the upper bound of the support of the distribution (taken to be $M_1 = 20$ in the simulations).

Defining, as in for example the interval censoring model,

$$\phi(u) = \int_{y \leq u} a(y) dG(y),$$

we get:

$$\theta_{t,h,G}(e, s, \delta) = \delta \frac{\phi(s)}{G(s)} + (1 - \delta) \frac{\phi(s) - \phi(s-e)}{G(s) - G(s-e)}, \quad (25)$$

where we define $0/0 = 0$. Note that ϕ is absolutely continuous w.r.t. G and that $\phi(s) = 0$, $s \geq M_1$, since we assume, as usual, $a \in L_2^0(G)$.

In the present model, the infection time is uniform on $[0, E]$ and E is Uniform $[0, M]$. So we get the following integral equation for the estimation of the density if $w \in [0, M]$,

$$\begin{aligned}E[\theta_{t,h,G}(E, S, \Delta)|W = w] &= \int_{e \in [w, M]} \frac{1}{Me} \left\{ \int_{s \in [w, e]} \frac{\phi(s)}{G(s)} ds \right\} de + \int_{e \in [w, M]} \frac{1}{Me} \left\{ \int_{s \in [w, w+e]} \frac{\phi(s) - \phi(s-e)}{G(s) - G(s-e)} ds \right\} de \\ &\quad + \int_{e \in (0, w]} \frac{1}{Me} \left\{ \int_{s \in [w, w+e]} \frac{\phi(s) - \phi(s-e)}{G(s) - G(s-e)} ds \right\} de \\ &= K_h(w - t).\end{aligned}\quad (26)$$

Differentiation w.r.t. w yields for the density estimate:

$$\begin{aligned}-\frac{\phi(w)}{MG(w)} \log(M/w) + \frac{1}{M} \int_{e \leq w} \frac{1}{e} \left\{ \frac{\phi(w+e) - \phi(w)}{G(w+e) - G(w)} - \frac{\phi(w) - \phi(w-e)}{G(w) - G(w-e)} \right\} de \\ + \frac{1}{Mw} \int_{s \in [w, 2w]} \frac{\phi(s) - \phi(s-w)}{G(s) - G(s-w)} ds - \frac{1}{Mw} \int_{s \geq w} \frac{\phi(s) - \phi(s-w)}{G(s) - G(s-w)} ds \\ = \frac{\partial}{\partial w} K_h(w - t),\end{aligned}\quad (27)$$

So we get the representation

$$\int K_h(t - y) d(\hat{G}_n - G_0)(y) = \int \theta_{t,h,\hat{G}_n}(e, s, \delta) dP_0(e, s, \delta),$$

where \hat{G}_n is the MLE and ϕ solves (26) for $G = \hat{G}_n$ (compare to (11.44), p. 331 of [7]).

This leads to

$$n^{2/7} \int K_h(t - y) d(\hat{G}_n - G_0)(y) \sim n^{2/7} \int \theta_{t,h,G_0}(e, s, \delta) (\mathbb{P}_n - P_0)(e, s, \delta), \quad (28)$$

where θ_{t,h,G_0} is defined by (25), where $G = G_0$, and ϕ is the solution of the equation (26) and satisfies $\phi(M_1) = 0$. Moreover, (28) would imply:

$$n^{2/7} \int K_h(t - y) d(\hat{G}_n - G_0)(y) \xrightarrow{\mathcal{D}} N(0, \sigma^2), \quad (29)$$

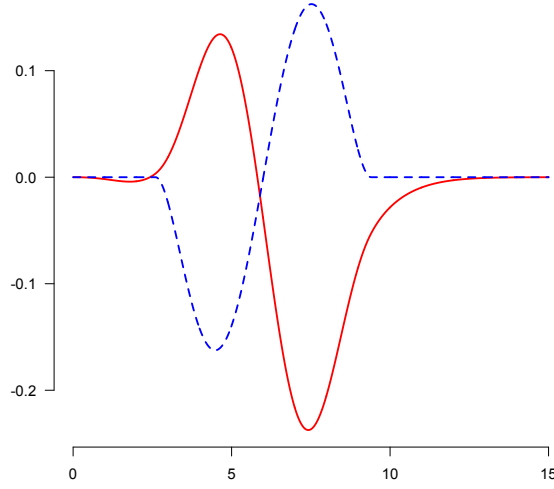


Fig 8: The function ϕ (red, solid), for $h = 3.4$, the triweight kernel K , and $t = 6$. The blue dashed curve is the function $w \mapsto \frac{\partial}{\partial w} K_h(w - t)$.

where

$$\sigma^2 = \lim_{n \rightarrow \infty} \text{var} \left(n^{2/7} \int \theta_{t, h_n, G_0}(e, s, \delta) \mathbb{P}_n(e, s, \delta) \right),$$

and $n^{1/7} h_n \rightarrow c > 0$. A picture of the function ϕ , solving (26), is shown in Figure 8. This was found by a simple iteration procedure for the integral equation (27), which can also be found in [3].

Note that, letting $\Phi(s) = \int_0^s \phi(u) du$, and defining $0/0 = 0$.

$$\begin{aligned} E \theta_{t, h, G}(E, S, \Delta) &= \frac{1}{M} \int_{s \leq e} \frac{1}{e} \frac{\phi(s)}{G(s)} G(s) de ds + \frac{1}{M} \int_{e < s} \frac{1}{e} \left\{ \frac{\phi(s) - \phi(s-e)}{G(s) - G(s-e)} \right\} \{G(s) - G(s-e)\} de ds \\ &= \frac{1}{M} \int_{s \leq e} \frac{1}{e} \phi(s) de ds + \frac{1}{M} \int_{e < s} \frac{1}{e} \{\phi(s) - \phi(s-e)\} de ds \\ &= \frac{1}{M} \int_{e=0}^M \frac{1}{e} \Phi(e) de + \frac{1}{M} \int_{e=0}^M \frac{1}{e} \{\Phi(M_1) - \Phi(e) - \Phi(M_1) + \Phi(0)\} de \\ &= \frac{1}{M} \int_{e=0}^M \frac{1}{e} \Phi(e) de - \frac{1}{M} \int_{e=0}^M \frac{1}{e} \Phi(e) de = 0, \end{aligned}$$

using $\phi(s) = 0$, $s \geq M_1$, where M_1 is the upper bound of the support of the density of the incubation time. Note that we use $M \geq M_1$, where $[0, M]$ is the interval containing the exit times (assumed to be uniformly distributed on $[0, M]$ in the simulation experiment). In Figure 8 we have $M_1 = 20$ and $M = 30$. For the asymptotic variance, we get:

$$\begin{aligned} E \theta_{t, h, G}(E, S, \Delta)^2 &= \frac{1}{M} \int_{s \leq e} \frac{1}{e} \frac{\phi(s)^2}{G(s)^2} G(s) de ds + \frac{1}{M} \int_{s > e} \frac{1}{e} \left\{ \frac{\phi(s) - \phi(s-e)}{G(s) - G(s-e)} \right\}^2 \{G(s) - G(s-e)\} de ds \\ &= \frac{1}{M} \int_{s \leq e} \frac{\phi(s)^2}{e G(s)} de ds + \frac{1}{M} \int_{s > e} \frac{\{\phi(s) - \phi(s-e)\}^2}{e \{G(s) - G(s-e)\}} de ds. \end{aligned} \tag{30}$$

t	simulation variances	$n^{-3/7} E \theta_{t,h,G}(E, S, \Delta)^2$
2	0.001524376	0.001008841
3	0.002652881	0.002154957
4	0.003535091	0.003396062
5	0.004193696	0.004055300
6	0.004351735	0.003954826
7	0.004238654	0.003850127
8	0.004073332	0.004037629
9	0.003385165	0.003609779
10	0.002352065	0.002530755
11	0.001402003	0.001405228

TABLE 3

A comparison of variances, given by a simulation of 1000 samples of size $n = 1000$ and the right-hand side of (30). The bandwidth $h = 3.4$ and G is the distribution function of the Weibull distribution, truncated on the interval $[0, 20]$.

Note that:

$$\begin{aligned} \text{var} \left(n^{2/7} \int K_h(t-y) d\hat{G}_n(y) \right) &\sim \text{var} \left(n^{2/7} \int \theta_{t,h,G_0}(e, s, \delta) d\mathbb{P}_n(e, s, \delta) \right) \\ &= n^{-3/7} E \theta_{t,h,G}(E, S, \Delta)^2. \end{aligned}$$

A table for the variances of the density estimates at $t = 2, 3, \dots, 11$, as computed from 1000 samples of size $n = 1000$ and from $n^{-3/7} E \theta_{t,h,G}(E, S, \Delta)^2$, as given by (30). The table is given graphically in Figure 9.

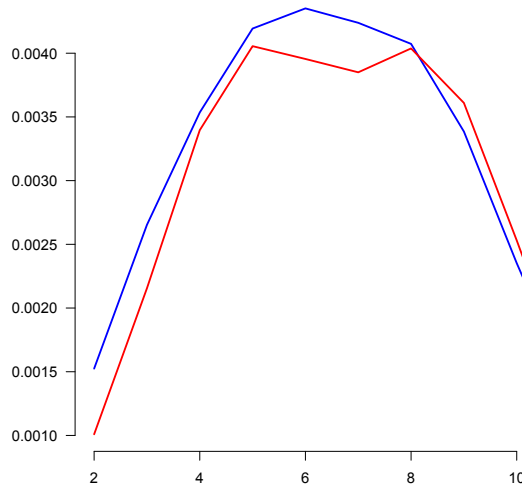


Fig 9: Plot of Table 3. The variances from the simulation are given by the blue curve and the red curve gives the values $n^{-3/7} E \theta_{t,h,G}(E, S, \Delta)^2$, for $t = 2, 3, \dots, 11$, $h = 3.4$ and G the truncated Weibull distribution function.

References

- [1] Jantien A. Backer, Don Klinkenberg, and Jacco Wallinga. Incubation period of 2019 novel coronavirus (2019-nCov) infections among travellers from Wuhan, China, 20-28 january 2020. *Euro Surveill.*, 25, 2020. URL <https://www.eurosurveillance.org/content/10.2807/1560-7917.ES.2020.25.5.2000062>.
- [2] Tom Britton and Gianpaolo Scalia Tomba. Estimation in emerging epidemics: bases and remedies. *J. R. Soc. Interface*, 16, 2019.

- [3] Piet Groeneboom. Incubationtime. <https://github.com/pietg/incubationtime>, 2020.
- [4] Piet Groeneboom. The Netherlands in Times of Corona (in Dutch). *Nieuw Archief voor Wiskunde*, 21:181–184, 2020. URL <http://www.nieuwarchief.nl/serie5/pdf/naw5-2020-21-3-181.pdf>.
- [5] Piet Groeneboom and Kim Hendrickx. curstatCI. R package, 2017. URL <https://cran.r-project.org/web/packages/curstatCI/index.html>. Version 0.1.1.
- [6] Piet Groeneboom and Kim Hendrickx. The nonparametric bootstrap for the current status model. *Electron. J. Stat.*, 11(2):3446–3484, 2017. ISSN 1935-7524. .
- [7] Piet Groeneboom and Geurt Jongbloed. *Nonparametric Estimation under Shape Constraints*. Cambridge Univ. Press, Cambridge, 2014.
- [8] Tamara G. Kolda, Robert Michael Lewis, and Virginia Torczon. Optimization by direct search: new perspectives on some classical and modern methods. *SIAM Rev.*, 45(3):385–482, 2003. ISSN 0036-1445. . URL <https://doi.org/10.1137/S003614450242889>.
- [9] Nicholas G. Reich, Justin Lessler, Derek A. T. Cummings, and Ron Brookmeyer. Estimating incubation period distributions with coarse data. *Stat. Med.*, 28(22):2769–2784, 2009. ISSN 0277-6715. . URL <https://doi.org/10.1002/sim.3659>.
- [10] Bodhisattva Sen and Gongjun Xu. Model based bootstrap methods for interval censored data. *Comput. Statist. Data Anal.*, 81:121–129, 2015. ISSN 0167-9473. . URL <http://dx.doi.org/10.1016/j.csda.2014.07.007>.
- [11] Virginia Torczon. On the convergence of pattern search algorithms. *SIAM J. Optim.*, 7(1):1–25, 1997. ISSN 1052-6234. . URL <http://dx.doi.org/10.1137/S1052623493250780>.