Documentation to R-Code for Semi-Parametric Estimation Using Laguerre Polynomials

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Abstract

Comments and explanations to the R-Code used in our paper Kreiss and Van Keilegom [1]. The code itself can be download from the author's github account (akreiss).

1 General Remarks

In this documentation we explain the basic functionalities of the R code in the files functions.R and example.R. The file functions.R contains the functions which are necessary to implement the estimation procedure outlined in our paper Kreiss and Van Keilegom [1]. Afterwards we show how the functions can be applied by going through the code provided in example.R. For theoretical properties and justifications we refer to our paper. In this documentation we use the same notation as in the paper. The code relies on some c-code. A compiled version of the code is part of the repository. If you work on windows, you might be able to download $c_-function.dll$ and load it as in the example provided below. Otherwise you need to compile the c code in $c_-function.c$ yourself.

If you find any mistakes in the implementation or have any other questions or comments to the code, please contact us (contact details can be found on https://agkreiss.uber.space/)

2 The functions in functions.R

This file contains the following functions.

• fit_laguerre The syntax is:

```
 \begin{array}{ll} \text{fit\_laguerre} \leftarrow & \textbf{function} \, (\, \text{S1} \,, \text{S2} \,, \text{w,rC} \,, \text{x0=NULL,m1,m2}, \\ & \text{glob\_repeats} \,, \text{xtol\_rel} = & 0.0001 \,, \text{maxeval} = & 10000 \,, \\ & \text{int\_prec} = & 500 \,, \textbf{print} = & \texttt{TRUE}) \end{array}
```

This function fits the Laguerre model to the observations: Symptom onset times of the index cases S1, symptom onset times of the secondary cases S2, end of exposure windows w and the exponential growth parameters rC. All of these are vectors and they must have the same length. The degrees of the approximation are given in m1 (for the incubation time) and m2 (for the generation time).

The internal optimisation is based on the nloptr package. At first there will be $glob_repeats$ many global optimisations, the first of which starts from $x\theta$ if provided or a random value if $x\theta=NULL$. The other instances will always be started from random locations. The parameters used by nloptr are $xtol_rel=1000*xtol_rel$ and maxeval=maxeval. The used algorithm is $NLOPT_GN_CRS2_LM$. The best value from all these optimisation tasks is subsequently provided to a local optimizer $(NLOPT_LN_SBPLX)$ which uses $xtol_rel$ and maxeval as provided by the user. Finally, the value in int_prec gives the length of the Riemann sum which is used to approximate the integrals in the likelihood and print can be set to FALSE to avoid status messages.

The function returns a list with elements $theta1_est$ and $theta2_est$ which contain the estimators for the incubation time and the generation time, respectively. Furthermore the list contains the output of the best global optimizer in $glob_opt$ and of the local optimizer in loc_opt .

• model_selection_laguerre The syntax is:

```
model_selection_laguerre(S1,S2,w,rC,m1_max,m2_max, print=TRUE, glob_repeats=5,xtol_rel=0.0001, maxeval=10000,int_prec=500,cluster=FALSE)
```

This function computes the optimal fits for all pairs of degrees (m_1, m_2) for which $m_1 \leq m_1 max$ and $m_2 \leq m_2 max$. The data is provided in S1, S2, w, rC in the same way as for fit-laguerre. The values of print, glob-repeats, xtol-rel, maxeval and int-prec have the same meaning as for fit-laguerre. If you have previously started a cluster using make-Cluster, you can provide the cluster object here to have the optimisations for different degrees of approximation carried out in parallel. If cluster=FALSE (the default) the computations are carried out serially.

The function returns a list which contains the matrix L_matrix which contains the optimal negative log-likelihoods for all combinations (m_1, m_2) with $m_1 \leq m1_max$ and $m_2 \leq m2_max$. More precisely, the element $L_matrix[m_1, m_2]$ contains the negative optimal log-likelihood corresponding to the approximating degrees m_1 and m_2 . The output contains furthermore the elements $fit_results$, dim_list and $index_matrix$ which can be used as follows to access the specific estimators: For a given pair of degrees (m_1, m_2) find the value $r = index_matrix[m_1, m_2]$, the returned object of $fit_laguerre$ for the degrees (m_1, m_2) can be found in $fit_results[[r]]$. The two-columned matrix dim_list has the property that $dim_list[r,] = (m_1, m_2)$, where m_1, m_2 and r are as before. Finally, the elements $m1_max$ and $m2_max$ are also contained in the list as a reminder.

Note lastly that the optimisations are carried out independently from each other. Therefore it can happen due to numerical issues that a strictly larger model does not yield a larger likelihood. In order to solve this issue, we recommend to call force_monotonicity after each call of model_selection_laguerre.

• force_monotonicity The syntax is:

```
 \begin{array}{l} \texttt{force\_monotonicity} \, (\texttt{MSL}, \texttt{S1}\,, \texttt{S2}\,, \texttt{w}, \texttt{rC}\,, \texttt{xtol\_rel} = 0.0001\,, \\ \texttt{maxeval} = 10000\,, \texttt{int\_prec} = 500\,, \textbf{print} = \texttt{TRUE}) \end{array}
```

With this function the output of *model_selection_laguerre* can be post-processed to guarantee an increase in the likelihood for larger models. This is achieved by

looking for inconsistencies in the output of $model_selection_laguerre$ which is specified in MSL. When an inconsistency is found, it is resolved by calling $fit_laguerre$ with one global optimisation starting from the smaller model which causes the inconsistency. The remaining parameters are identical to the ones in $fit_laguerre$ and in particular the dataset provided in S1, S2, w and rC has to be the same as the one used in the call of $model_selection_laguerre$ to provide meaningful results. The output has the same format as the output of $model_selection_laguerre$.

• laguerre_density_pos The syntax is

```
laguerre_density_pos(z, theta)
```

The function simply computes the density specified by the parameter theta evaluated at z. Here theta is specified in Cartesian coordinates and must have Euclidean norm equal to one.

• laquerre_distr_pos The syntax is

```
laguerre_distr_pos(z, theta)
```

This function computes $\int_0^z f_{theta}(x)dx$ where f_{θ} is a Laguerre density which can be computed by the previous function $laguerre_density_pos$. Hence, the output is the distribution function of the corresponding Laguerre density evaluated at the values in z. The Laguerre density is specified through theta which has the same format as for $laguerre_density_pos$.

• laguerre_R0 The syntax is

```
laguerre_R0(theta,r)
```

This function computes the basic reproduction number R_0 when the distribution of the generation time is a Laguerre density specified through theta (cf. laguerre_density_pos for a description). The value of r equals the growth rate of the expected incidence.

• laguerre_quantile The syntax is

```
laguerre_quantile(theta,tau,ub=20,L=10000)
```

This function computes the quantiles specified in tau of a given Laguerre density (specified through theta, cf. $laguerre_density_pos$). This is done by numerically evaluating the density between 0 and a user specified upper bound ub on an equidistant grid of length L. The returned value equals the average of those two grid points which lie just above and below of the target quantile. Thus, it is necessary that ub is larger than the true value of the quantile.

• laguerre_polynomial The syntax is

```
laguerre_polynomial(z,k)
```

This function computes the Laguerre polynomial (which may not be confused with the corresponding Laguerre density) of a given degree k. The vector z contains the points at which the polynomial is supposed to be evaluated. The output of the function is a vector of the same length containing the values of the polynomial at the corresponding places.

• whole_inc_likelihood The syntax is

```
whole_inc_likelihood (theta, x1, x2, w, rC, m1, m2, N=500)
```

This function computes the negative log-likelihood for a given set of observations $(S_{1,i}, S_{2,i}, \widetilde{W}_i, C_i)_{i=1,\dots,n}$. The four types of observations are specified in the vectors x1, x2, w and rC, respectively. Note that the vector rC has to contain the exponential growth coefficients of the respective locations rather than the locations themselves. Thus, all four vectors must have the same length. The first parameter theta contains both parameter sets, for the incubation period in the entries 1 to m1 and for the generation time in the entries m1+1 to m1+m2. Both parameters have to be specified in polar coordinates (only the angles). The value of N has the same meaning as int_prec in other functions, e.g. $fit_laguerre$.

The output of this function is the un-normalized (i.e. not divided by the number of observations) negative log-likelihood corresponding to the given observations and models.

• laguerre_approx The syntax is

```
laguerre_approx(fdens,m,...)
```

This function can be used to compute the closest Laguerre type density of degree m to a given density fdens. The function fdens is required to allow as a first argument a vector of evaluation points and it must return the values of the density evaluated at these points. The additional arguments ... are passed to fdens. The output of this function is a normalized vector of length m+1 which contains the Cartesian coordinates of the parameter specifying the closest density.

 \bullet hellinger_distance The syntax is:

```
hellinger_distance(theta,td,...)
```

The function returns the squared Hellinger distance between a Laguerre density specified through theta and an arbitrary density specified in td. The format of td needs to be the same as the format of fdens in $laguerre_approx$.

• hellinger_distance_lag The syntax is:

```
hellinger_distance_lag(theta1, theta2)
```

The function returns the squared Hellinger distance between the two Laguerre densities given through theta1 and theta2.

3 Example

In this section we illustrate the usage of the functions by going through the code provided in *example.R*. In this example the following packages are required. Also we set the seed to get reproducible results.

```
## Libraries
library(doParallel)
library(foreach)
```

```
library(nloptr)
library(SphericalCubature)

## Load functions
dyn.load("c_function.dll")
source('./functions.R')

## Set seed for reproducability
set.seed(2020)
```

We begin by generating an example data set which we will work with. This requires no functions specific to our methodology. We decide here to restrict to a small dataset with n = 10 observations to obtain an example which runs quickly on most systems.

```
## Set information
n <- 10 # Number of observations
r \leftarrow log(2)/5 \# Exponential growth rate
## Generate Data
w \leftarrow rexp(n, rate = 0.3820225)
location < - sample(c(0,1), n, replace = TRUE, prob = c(26/40, 14/40))
rC \leftarrow \mathbf{rep}(0,n)
rC[location == 1] \leftarrow r
no_exp_growth <- which (location == 0)
exp_growth
                 \leftarrow which (location ==1)
first_infection \leftarrow \mathbf{rep}(0,n)
first_infection[no_exp_growth] <- runif(length(no_exp_growth),
          \min = 0, \max = w[\text{no}_e \exp_g \text{rowth}])
first_infection[
                       exp_growth] <- w[exp_growth]-
          rexp(length(exp_growth), rate=r) %% w[exp_growth])
second_infection <- first_infection
          +rweibull (n, shape = 2.826, scale = 5.665)
S1 \leftarrow first\_infection + rlnorm(n, meanlog = 1.644, sd = 0.363)
S2 \leftarrow second\_infection+rlnorm(n, meanlog=1.644, sd=0.363)
w \leftarrow pmin(w, S1)
```

Next we perform estimation for given degrees of the Laguerre polynomials. In this example we choose $m_1 = m_2 = 2$. Below, we discuss model selection too. Here we let the optimizer start from 10 random starting locations and stick otherwise with the default choices.

```
m1 \leftarrow 2

m2 \leftarrow 2

model_fit \leftarrow fit_laguerre(S1,S2,w,rC,NULL,m1,m2,10,0.0001,
```

```
10000,500,TRUE)
```

In the next step we use the functions laguerre_density_post and laguerre_approx in order to compute the estimated density as well as that Laguerre type density which come closest to the true model which we used in the simulations.

```
## Extract Estimate
theta1_est <- model_fit $theta1
theta2_est \leftarrow model_fit $theta2
## Compute estimated densities
x \leftarrow seq(from = 0, to = 15, length.out = 1000)
inc_est <- laguerre_density_pos(x, theta1_est)
gen_est <- laguerre_density_pos(x, theta2_est)
## Compute true density
inc \leftarrow dlnorm(x, meanlog=1.644, sd=0.363)
gen \leftarrow dweibull (x, shape=2.826, scale=5.665)
## Compute the best Laguerre approximation to the truth
best_theta_inc <- laguerre_approx(dlnorm, m=m1, meanlog=1.644,
                  sd = 0.363)
best_theta_gen <- laguerre_approx(dweibull,m=m2, shape=2.826,
                  scale = 5.665)
best_inc <- laguerre_density_pos(x, best_theta_inc)
best_gen <- laguerre_density_pos(x, best_theta_gen)
  Finally, all results are plotted.
dev.new()
\mathbf{par} (\mathbf{mfrow} = \mathbf{c} (1, 2))
plot(x, inc, main="Incubation_Period", type="l")
lines(x, inc_est, lty=2)
lines (x, best_inc, lty=3)
plot(x,gen,main="Generation_Time",type="l")
lines(x, gen_est, lty=2)
lines(x, best\_gen, lty=3)
```

As an example of feature estimation, we show next how quantiles and reproduction numbers can be obtained from the estimates. We begin with quantiles. Our interests lies in the following quantiles

```
tau \leftarrow c(0.3, 0.5, 0.7, 0.9)
```

The true quantiles are found through the corresponding R-functions

```
\begin{array}{l} true\_quant\_inc <- & \mathbf{qlnorm}(tau, meanlog=1.644, \mathbf{sd}=0.363) \\ true\_quant\_gen <- & \mathbf{qweibull}(tau, shape=2.826, \mathbf{scale}=5.665) \end{array}
```

In order to get the quantiles of the best Laguerre approximation and the quantiles of the estimated Laguerre approximation, the function *laguerre_quantile* can be used as follows:

```
## Quantiles of the best Laguerre Approximation
best_quant_inc <- rep(0,length(tau))
best_quant_gen <- rep(0,length(tau))
for(k in 1:length(tau)) {
   best_quant_inc[k] <- laguerre_quantile(best_theta_inc,tau[k])
   best_quant_gen[k] <- laguerre_quantile(best_theta_gen,tau[k])
}

## Estimated Quantiles
est_quant_inc <- rep(0,length(tau))
est_quant_gen <- rep(0,length(tau))

for(k in 1:length(tau)) {
   est_quant_inc[k] <- laguerre_quantile(theta1_est,tau[k])
   est_quant_gen[k] <- laguerre_quantile(theta2_est,tau[k])
}</pre>
```

Let us now compute the basic reproduction numbers. The true R_0 can be found by using the equation from the paper:

```
helpf <- function(x) {
   return(exp(-r*x)*dweibull(x,shape=2.826,scale=5.665))
}
R0 <- 1/integrate(helpf,lower=0,upper=Inf)$value
```

The estimated R_0 can be found by supplying the Laguerre approximation to the function $laguerre_R0$

```
R0_est <- laguerre_R0(theta2_est,r)
```

for (m1 in 1:8) {

As a last step this file illustrates model selection. Here, we try all degrees m_1 and m_2 which are lower than or equal to 8. For all degree combinations (m_1, m_2) the corresponding model is fit. This is dine by using the function $model_selection_laguerre$. In order to save time, we use here parallel computations as well. Afterwards we call $force_monotonicity$ to have a decrease in the negative log-likelihoods.

```
\begin{array}{ll} & \textbf{for}\,(m2\ in\ 1:8)\ \{ \\ & BIC\,[m1\,,m2]\ <-\ (m1\!+\!m2\!+\!2)\!*\! \textbf{log}\,(n)\!-\!2\!*\!(-MSLmon\$L\_\textbf{matrix}\,[m1\,,m2]\,) \\ & AIC\,[m1\,,m2]\ <-\ (m1\!+\!m2\!+\!2) \\ & -2\!*\!(-MSLmon\$L\_\textbf{matrix}\,[m1\,,m2]\,) \\ \} \end{array}
```

References

[1] A. Kreiss and I. Van Keilegom. Semi-parametric estimation of incubation and generation times by means of Laguerre polynomials. *arxiv*, 2020. URL https://arxiv.org/abs/2012.15611.