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

Alexander Kreiß, Ingrid Van Keilegom

December 28, 2020

Abstract

Comments and explanations to the R-Code used in our paper 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. This file contains the functions which are necessary to implement the estimation procedure outlined in our paper 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.

If you find any mistakes in the implementation or have any 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.

• $inc_likelihood$ The Syntax is:

```
\begin{array}{l} \text{inc\_likelihood} < & \textbf{function}\,(\,x1\,,x2\,,w,\,theta1\,\_polar\,\,,\\ & \text{theta2\_polar}\,\,,N=500) \end{array}
```

This function computes the likelihood as specified in the paper for one single observation $(S_1, S_2, \widetilde{W})$. These three values are specified in x1, x2 and w, respectively. The tested model is specified in $theta1_polar$ and $theta2_polar$. Note that their coordinates need to be specified in polar format without the radius (which is always equal to 1). So, only the angles are specified. In particular, it is not possible to specify $m_1 = 0$ and $\theta_1 = 1$.

The likelihood is computed by approximating the integrals through Riemann sums. The number of terms in the Riemann sums is specified via N. The default value is 500.

• laguerre_density_pos The syntax is

```
laguerre_density_pos <- function(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.

• laguerre_polynomial The syntax is

```
laguerre_polynomial <- function(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 \leftarrow function(theta, x1, x2, w, m1, m2, N=500, cluster=FALSE)
```

This function computes the negative log-likelihood for a given set of observations $(S_{1,i}, S_{2,i}, \widetilde{W_i})_{i=1,\dots,n}$. The three types of observations are specified in the vectors x1, x2 and w, respectively. Thus, they must all 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 is passed to $inc_likelihood$. Finally, cluster can contain a cluster identifier as returned from makeCluster. Then, the computations are done in a parallel fashion by using the foreach framework. Thus the packages doParallel and froeach are required in this case.

 \bullet laguerre_approx The syntax is

```
laguerre_approx <- function(fdens,m,...)
```

This function can be used to compute the closest Laguerre type density of degreee 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.

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 reproduceable results.

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

```
library (Spherical Cubature) set . seed (2020)
```

 $trials \leftarrow 5$

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.

```
 \begin{array}{lll} n <& -10 \ \# \ Number \ of \ observations \\ \# \ Generate \ Data \\ w <& -\mathbf{rexp}(n, rate=0.3820225) \\ & \text{first\_infection} <& -\mathbf{runif}(n, \mathbf{min}=0, w) \\ & \text{second\_infection} <& -\mathbf{first\_infection}+\mathbf{rweibull}(n, shape=2.826, \\ & \mathbf{scale}=5.665) \\ & \text{S1} <& -\mathbf{first\_infection} \ +\mathbf{rlnorm}(n, meanlog=1.644, \mathbf{sd}=0.363) \\ & \text{S2} <& -\mathbf{second\_infection}+\mathbf{rlnorm}(n, meanlog=1.644, \mathbf{sd}=0.363) \\ & \text{w} <& -\mathbf{pmin}(w, S1) \\ \end{array}
```

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. At first we specify the informations which are necessary for the optimizer and start a cluster.

In order to make sure that the optimizer does not get stuck due to a bad choice of starting value, we do the estimation starting from trials many random starting values. We also prepare a list which shall contain the estimation results

```
lowest <- i
    currmin <- out [[i]] $objective
}
cat("Trial_",i,".\n")
}
stopCluster(cl)</pre>
```

The for-loop above repeats the same optimisation task for different random starting values (note that the starting values are specified in polar coordinates). The optimisation itself is performed using nloptr. The variable lowest contains in the end the index of the run which yielded the smallest result (i.e. the largest likelihood). We can now extract the estimates and transfer them to Cartesian coordinates.

```
\begin{array}{lll} \text{estimate} & \leftarrow & \text{out} \left[ \left[ \text{lowest} \right] \right] \$ \text{solution} \\ \text{theta1\_est} & \leftarrow & \text{polar2rect} \left( 1, \text{estimate} \left[ & 1: (\text{m1}) \right] \right) \\ \text{theta2\_est} & \leftarrow & \text{polar2rect} \left( 1, \text{estimate} \left[ (\text{m1+1}): (\text{m1+m2}) \right] \right) \end{array}
```

In the next step we use the functions <code>laguerre_density_post</code> and <code>laguerre_approx</code> 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.

```
## 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 a last step this file illustrates model selection. Here, certain maximal values of the degrees m_1 and m_2 are specified. For all lower degree combination the best model is fit (in the same way as above). Afterwards, it is direct to compute BIC and AIC.

```
## Set Information
trials <- 5
m1_max \leftarrow 4
m2_max <- 4
out_matrix <- matrix(0,nrow=m1_max,ncol=m2_max)
opts <- list (algorithm="NLOPT_LN_SBPLX", print_level=3,
                  xtol_rel = 0.001, maxeval = 10000)
out <- vector (mode="list", length=trials)
\#\# Set-Up Cluster
noc \leftarrow detectCores()-1
cl <- makeCluster(noc, outfile="progress")</pre>
registerDoParallel(cl)
## Do the estimation for all allowed pairs of degrees
for (m1 in 1:m1_max) {
  for(m2 in 1:m2\_max) {
     for(i in 1:trials) {
       currmin <- Inf
       lowest <\!\!- 0
       out [[i]] <- nloptr(x0=runif(m1+m2,min=0,max=pi),
                           eval_f=whole_inc_likelihood,
                           1b = rep(0, m1+m2), ub = rep(pi, m1+m2),
                           opts=opts, x1=S1, x2=S2, w=w, m1=m1,
                           m2=m2, N=500, cluster=c1)
        if(out[[i]] $objective < currmin) {</pre>
          lowest ← i
          currmin <- out [[i]] $ objective
       \mathbf{cat}\,(\,\text{``Trial}\,\,\text{\_''}\,\,,i\,\,,\,\text{``}\,\,.\,\backslash\,n\,\text{''}\,\,)
     out_matrix[m1,m2] <- out[[lowest]] $objective
  }
}
stopCluster(cl)
## Compute AIC and BIC
BIC <- matrix (0, ncol=m2_max, nrow=m1_max)
AIC \leftarrow \mathbf{matrix}(0, \mathbf{ncol} = m2 - max, \mathbf{nrow} = m1 - max)
\mathbf{for} (\mathbf{m1} \ \mathbf{in} \ 1:\mathbf{m1}_{-}\mathbf{max})  {
  for (m2 in 1:m2_max) {
     BIC[m1,m2] \leftarrow (m1+m2+2)*log(n)-2*(-out\_matrix[m1,m2])
     AIC[m1, m2] \leftarrow (m1+m2+2)
                                           -2*(-\text{out}_{-\mathbf{matrix}}[\text{m1},\text{m2}])
  }
```