R code for implementing the methodology proposed in Patra and Sen (2013)

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In this article, we discuss the implementation of the techniques developed in Patra and Sen (2013). To run the codes, the user requires an installation of R (see R Core Team (2013)) including the *Iso* (see Turner (2013)) and the *fdrtool* (see Klaus and Strimmer (2013))package.

The following function takes as input the data and outputs $\gamma\ d_n(\hat{F}^{\gamma}_{s,n}, \check{F}^{\gamma}_{s,n})$ (see Patra and Sen (2013, Equation 7)) at equally spaced points. The *gridsize* determines the spacing between two consecutive points at which $\gamma\ d_n(\hat{F}^{\gamma}_{s,n}, \check{F}^{\gamma}_{s,n})$ is evaluated. In the sample code, we assume that F_b is the Uniform distribution.

```
EstMixMdl <- function(data,gridsize=200)
{
  n <- length(data)        ## Length of the data set
  data <- sort(data)       ## Sorts the data set
  data.1 <- unique(data)   ## Finds the unique data points
  Fn <- ecdf(data)         ## Computes the empirical DF of the data
  Fn.1 <- Fn(data.1)       ## Empirical DF of the data at the data points
  ## Calculate the known F_b at the data points
  ## Note: for Uniform(0,1) F_b(x) = x
  ## Usually would need to CHANGE this
  Fb <- data.1
  ## Compute the weights (= frequency/n) of the unique data values, i.e., dF_n
  Freq <- diff(c(0,Fn.1))
  distance <- rep(0,gridsize)
  distance[0]<- sqrt(t((Fn.1-Fb)^2)%*%Freq)
  for(i in 1:gridsize)
  {
    a <- i/gridsize               ## Assumes a value of the mixing proportion
    F.hat <- (Fn.1-(1-a)*Fb)/a     ## Computes the naive estimator of F_s
    F.is=pava(F.hat,Freq,decreasing=FALSE) ## Computes the Isotonic Estimator of F_s
    F.is[which(F.is<=0)]=0
    F.is[which(F.is>=1)]=1
    distance[i] <- a*sqrt(t((F.hat-F.is)^2)%*%Freq);
  }
  return(distance)
}
```

The following set of commands will give a plot of $\gamma\ d_n(\hat{F}^{\gamma}_{s,n}, \check{F}^{\gamma}_{s,n})$ for $\gamma \in [0, 1]$.

```
dist.alpha <- EstMixMdl(data,gridsize)
frame()
plot((1:gridsize)/gridsize,dist.alpha,type='l',xlab="x",ylab="Distance",col="blue")
```

We can compute the a lower confidence bound for α_0 using asymptotic quantiles of the Cramér-von Mises statistic, which are readily available (e.g., see Anderson and Darling (1952)). The 90%, 95%, and 99% quantiles are 0.5893, 0.6792, and 0.8622 respectively. The following computes the 95% lower confidence bound for α_0.

```
q <- 0.6792
Lower.Cfd.Bound <- sum(dist.alpha>q/sqrt(n))/gridsize
```

To find the estimator of α_0 discussed in Patra and Sen (2013, Section 3) with a particular choice of c_n, use the following lines of code.

```
#Here we have taken the choice of c_n to be log(log(n)).
c.n<-log(log(n))
Est<- sum(dist.alpha>c.n/sqrt(n))/gridsize
```

To find an heuristic estimator of α_0 as discussed in Patra and Sen (2013, Section 4.3), use the following lines of code.

```
## Numerically find the 2nd derivative of ‘dist.alpha’
dder <- Comp_2ndDer(dist.alpha, gridsize)
Est <- which.max(dder)/gridsize
## Overlaid plot of the normalized 2nd derivative
lines((1:gridsize)/gridsize ,dder*(max(dist.alpha)/max(dder)),col='red')
legend("topright",c("Distance","Scaled 2nd derivative"),
lty=c(1,1), col = c("blue","red") )
```

We can now estimate the distribution function F_s using the estimate of α_0 (see Patra and Sen (2013, Section 5.1)). The following function estimates the CDF. It takes as input an estimator of α_0 together with the ECDF (empirical cumulative distribution function) and F_b evaluated at data points. It outputs a matrix with naive and isotonised estimate of F_s evaluated at data points.

```
CDFEst <- function(Fn.1,Fb,Est)
{
## Compute the weights (= frequency/n) of the unique data values, i.e., dF_n
Freq <- diff(c(0,Fn.1))
## Computes the naive estimator of F_s
Est.CDF.naive <- (Fn.1-(1-Est)*Fb)/Est
## Computes the Isotonic Estimator of F_s
Est.CDF=pava(Est.CDF.naive,Freq,decreasing=FALSE)
Est.CDF[which(Est.CDF<=0)]=0
Est.CDF[which(Est.CDF>=1)]=1
return(cbind(Est.CDF.naive,Est.CDF))
}
```

Suppose now that F_s has density f_s. If we assume that f_s is non-increasing, then we can estimate it using techniques discussed in Patra and Sen (2013, Section 5.2). The following function estimates the density. It takes as input an estimator of α_0 together with the ECDF (empirical cumulative distribution function) and F_b evaluated at data points. The output is a matrix with the data points in the first column and the corresponding values of f_s in the second column.

```
DensEst <- function(Fn.1,Fb,Est)
{
F.hat <- (Fn.1-(1-Est)*Fb)/Est
Freq <- diff(c(0,Fn.1))
F.is <- pava(F.hat,Freq,decreasing=FALSE)
F.is[which(F.is<=0)] <- 0
F.is[which(F.is>=1)] <- 1
F.check <- F.is
x <- data.1
y <- F.check
ll <- gcmlcm(x,y, type="lcm")
xtemp=rep(ll$x.knots,each=2)                #data points for density
ytemp=c(0,rep(ll$slope.knots,each=2),0)     #value of density
ans<-rbind(t(xtemp),t(ytemp))
return(ans)
}
```

References

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