

# DTDA: An Updated and Expanded R Package for the Statistical Analysis of Doubly Truncated Data

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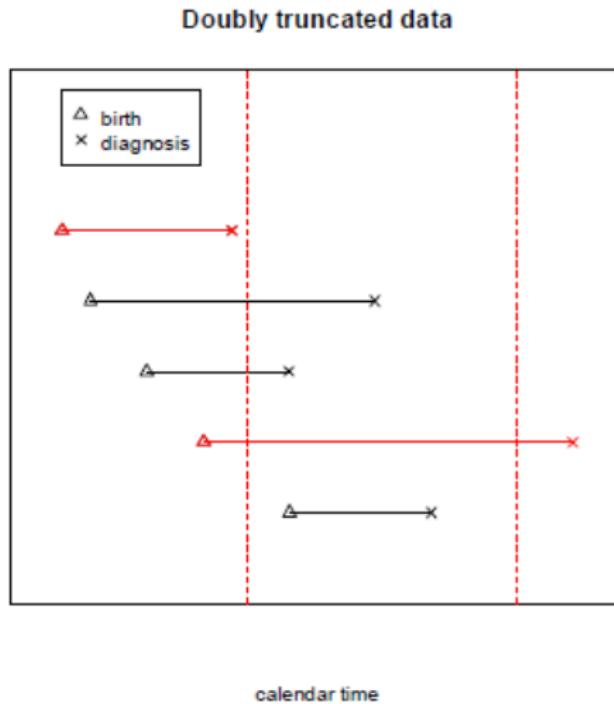
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Santiago de C., Oct 14, 2021

## Double truncation: definition

- Target variable  $X$  observed only when  $U \leq X \leq V$
- In that case truncation couple  $(U, V)$  observed too
- Prominent example: interval sampling of time-to-event data:  
Subjects with event within  $[d_0, d_1]$  recruited  
 $X$ : time-to-event  
 $\tau = d_1 - d_0$ : interval width  
 $V$ : time from birth to  $d_1$   
 $U = V - \tau$
- Sample: iid triplets  $(X_i, U_i, V_i)$ ,  $1 \leq i \leq n$
- $(X_1, U_1, V_1)$  follows the cond cdf of  $(X, U, V)$  given  $U \leq X \leq V$

# Doubly truncated data: interval sampling



Red segments are not observed

# Doubly truncated data: fields of application

- **Astronomy:** quasar luminosities
- **Epidemiology:** AIDS, cancer, Parkinson's Disease, Acute Coronary Syndrome, *autopsy-confirmed* neurodegenerative diseases
- **Engineering:** time to failure after installation of a device
- **Social Sciences/Finance:** marriage lengths, age at insolvency for companies
- (...)

## Doubly truncated data: sampling bias

- Sampling probability for  $X$ :

$$G(x) = P(U \leq X \leq V | X = x) = P(U \leq x \leq V)$$

(last equality requires  $(U, V) \perp X$ )

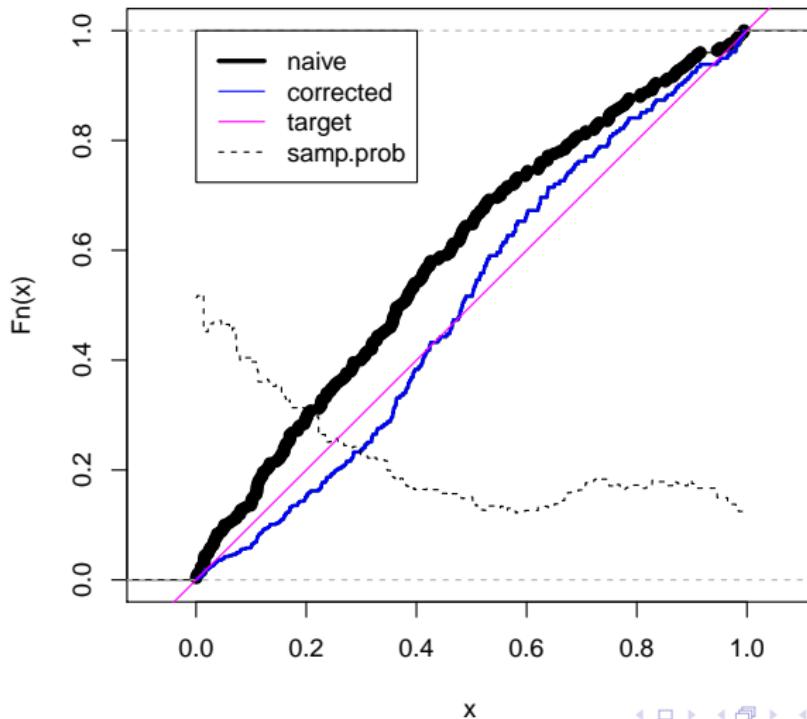
- $G(x)$  may be constant, or may be not
- NPMLE  $G_n(x)$  can be computed from the  $(X_i, U_i, V_i)$ 's
- NPMLE  $F_n(x)$  of the target cdf  $F(x) = P(X \leq x)$  is an IPWE:

$$F_n(x) = \sum_{i=1}^n I(X_i \leq x) G_n(X_i)^{-1} / \sum_{j=1}^n G_n(X_j)^{-1}$$

Weight attached to  $X_i$ :  $W_i = G_n(X_i)^{-1} / \sum_{j=1}^n G_n(X_j)^{-1}$

- Iterative methods to compute  $G_n$  (and  $F_n$ ) **needed** (DTDA)

# Doubly truncated data: simulated example



# DTDA package v3.0

- Maintainer: Carla Moreira
- Launched on April 11, 2021
- Update and expansion of the original DTDA (September 21, 2009)
- Main improvements:
  - Computational savings through parallel computing (bootstrapping!)
  - Smoothing methods to estimate density and hazard functions
  - New real datasets
  - Simulation of doubly truncated data (interval sampling)

- 46K downloads, 593 last month:

<https://cranlogs.r-pkg.org/badges/grand-total/DTDA>

<https://cranlogs.r-pkg.org/badges/DTDA>

## DTDA package v3.0: available functions

- Three iterative algorithms to compute  $F_n$ :

```
efron.petrosian(X, U = NA, V = NA, wt = NA, error = NA,  
nmaxit = NA, boot = TRUE, B = NA, alpha = NA, display.F  
= FALSE, display.S = FALSE)
```

```
lynden(X, U = NA, V = NA, error = NA, nmaxit = NA, boot  
= TRUE, B = NA, alpha = NA, display.F = FALSE,  
display.S = FALSE)
```

```
shen(X, U = NA, V = NA, wt = NA, error = NA, nmaxit =  
NA, boot = TRUE, boot.type = "simple", B = NA, alpha =  
NA, display.FS = FALSE, display.UV = FALSE, plot.joint  
= FALSE, plot.type = NULL)
```

- Function `shen()` computes and returns  $G_n$  too

## DTDA package v3.0: available functions (cont.)

- Smoothing methods for density and hazard functions:

```
densityDT(X, U, V, bw = "DPI2", from, to, n, wg = NA)
```

```
hazardDT(X, U, V, bw = "LSCV", from, to, n, wg = NA)
```

- Alternatively, use

```
density(X, bw = "nrd0", weights = W)
```

with

```
W <- shen(...)$biasf^-1  
W <- W / sum(W)
```

but if so take care with bandwidth selection!

## DTDA package v3.0: available functions (cont.)

- Random generation of doubly truncated data (interval sampling):

```
rsim.DT(n, tau, model = NULL)
```

- ...and many real datasets:

Quasars

AIDS

ChildCancer

AIDS.DT

EquipSRounded

PDearly, PDlate

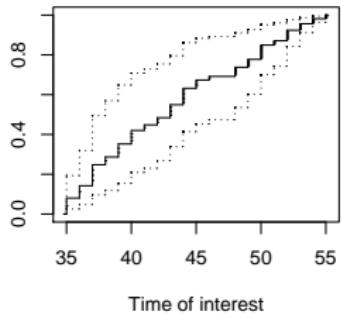
ACS, ACSred

## DTDA in practice: Parkinson's Disease (Clark et al. 2011)

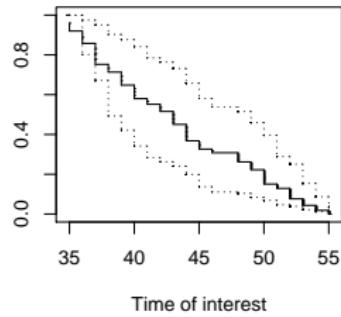
```
> library(DTDA)
> head(PDearly)    #two cases with missing info for V
  X  U  V SNP_A10398G SNP_PGC1a
  1 37 30 38          A          G
  2 46 39 47          A          AG
  3 36 34 42          A          G
  4 54 49 57          A          AG
> PDearly <- na.omit(PDearly)
> attach(PDearly)
> shen(X, U, V, display.FS=TRUE, display.UV=TRUE) -> res
  n.iterations 56
  S0 9.716169e-07
  events 97
  B 500
  alpha 0.05
  Boot simple
```

# DTDA in practice: Parkinson's Disease (Clark et al. 2011)

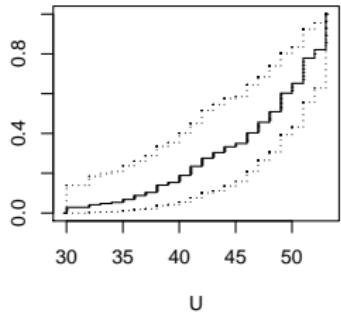
**Shen estimator**



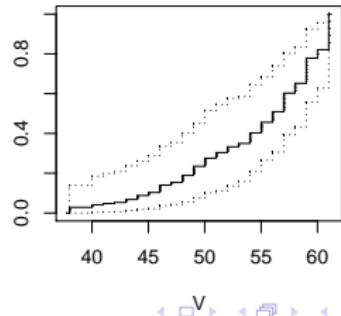
**Survival**



**Marginal U**



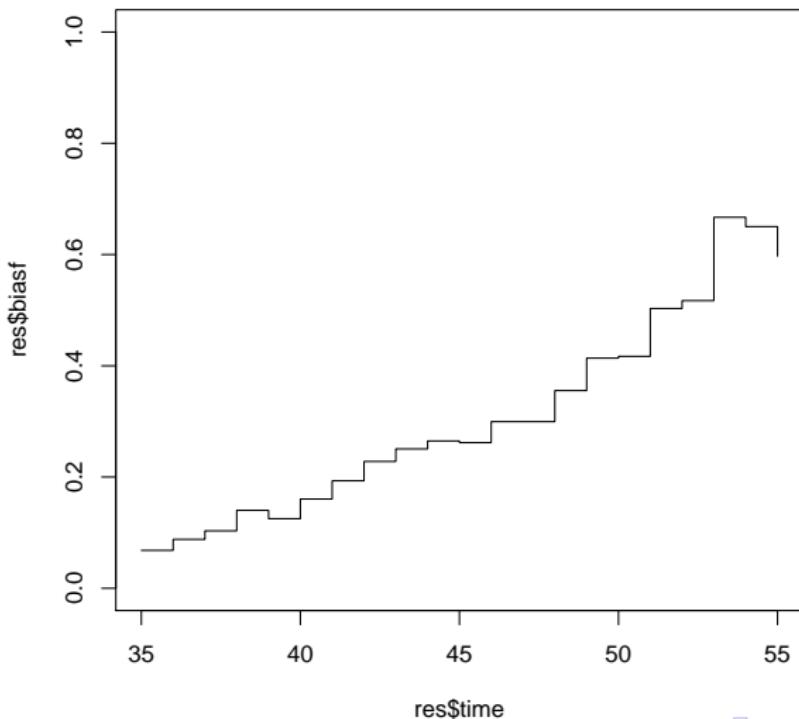
**Marginal V**



## DTDA in practice: Parkinson's Disease (Clark et al. 2011)

```
> #sampling probability:  
> plot(res$time, res$biasf, type = "s", ylim = c(0,1))  
  
> #save the weights  
> #useful to construct consistent estimators later:  
> W <- res$biasf^-1  
> W <- W / sum(W)  
  
> #estimation of the mean:  
> mean(X) #naive  
[1] 46.97938  
> sum(W * res$time) #correct  
[1] 43.20277
```

# DTDA in practice: Parkinson's Disease (Clark et al. 2011)



## DTDA in practice: Parkinson's Disease (Clark et al. 2011)

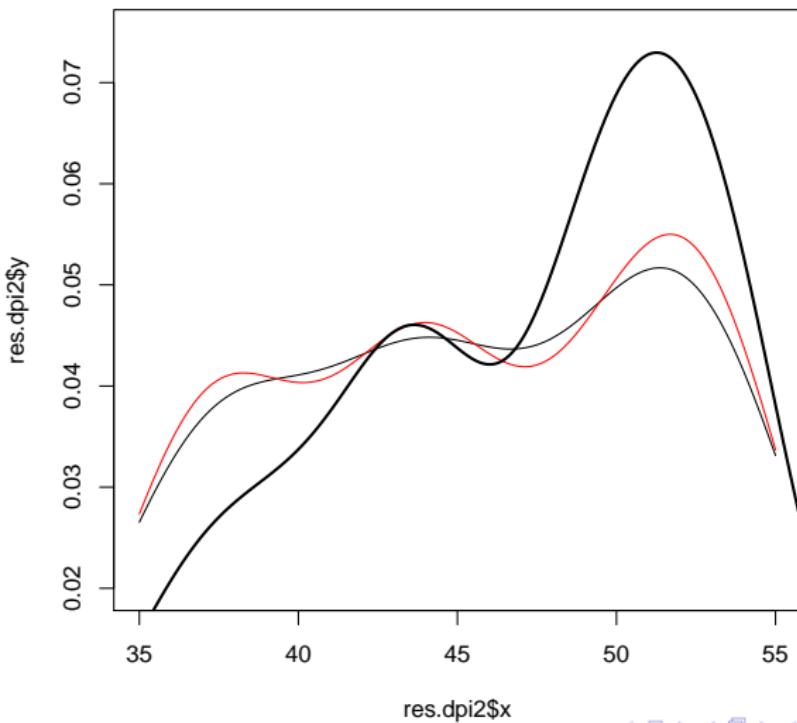
```
> densityDT(X, U, V, from = min(X), to = max(X),
+ n = 500) -> res.dpi2    #bw default is DPI2
> plot(res.dpi2, type = "l", ylim = c(.02, .075))

> densityDT(X, U, V, bw = "DPI1", from = min(X), to = max(X),
+ n = 500) -> res2.dpi1
> lines(res2.dpi1$x, res2.dpi1$y, col = 2)

> res.dpi2$bw; res2.dpi1$bw
[1] 2.855729
[1] 2.470739

> density(X) -> resn.d    #naive approach
> lines(resn.d$x, resn.d$y, lwd = 2)
> resn.d$bw    #ordinary rule-of-thumb undersmooths
[1] 2.046491
```

# DTDA in practice: Parkinson's Disease (Clark et al. 2011)



## DTDA in practice: AIDS (Kalbfleisch and Lawless 1989)

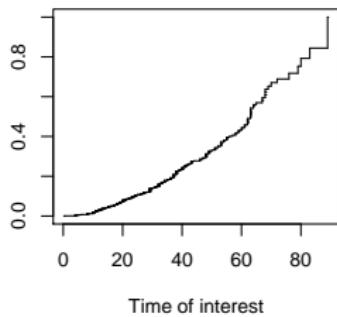
```
> head(AIDS.DT)
X      U      V AGE
1 0.5 -17.5 36.5 63
2 4.0 -18.5 35.5  1
3 4.0 -18.5 35.5 29
4 4.0 -33.5 20.5 46
```

```
> attach(AIDS.DT)
> res <- shen(X, U, V, boot = F, display.F = T,
+ display.UV = T)
n.iterations 23
S0 6.280252e-07
events 295
```

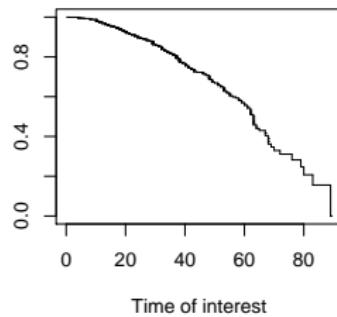
```
> plot(res$time, res$biasf, type = "s", ylim = c(0, 1))
```

# DTDA in practice

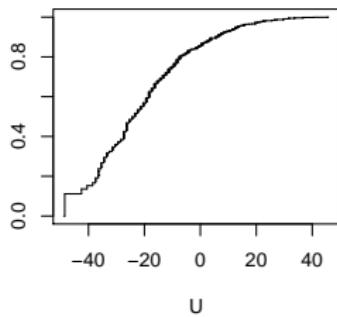
**Shen estimator**



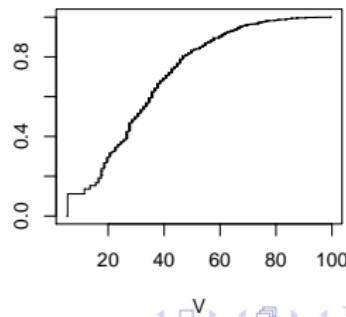
**Survival**



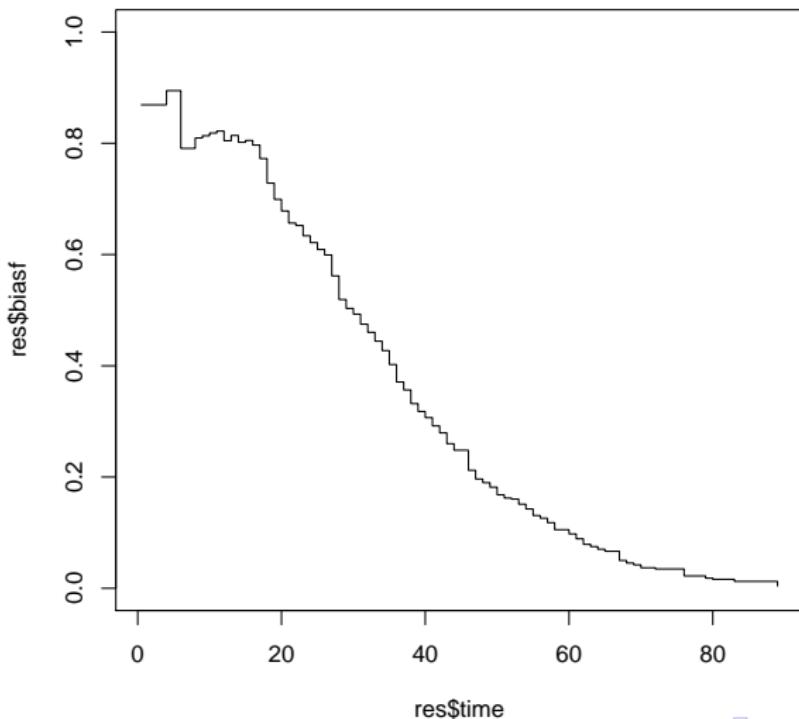
**Marginal U**



**Marginal V**



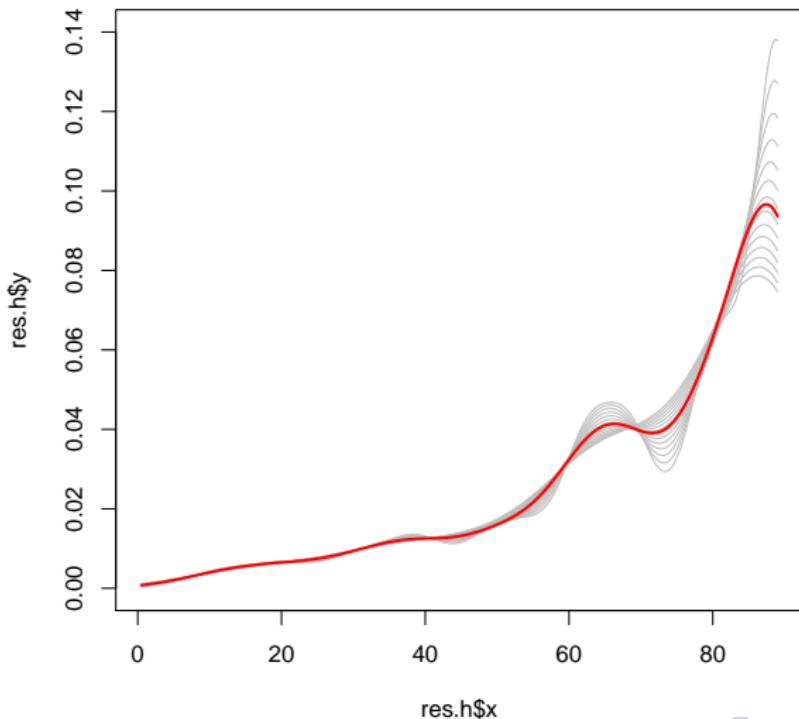
# DTDA in practice: AIDS (Kalbfleisch and Lawless 1989)



## DTDA in practice: AIDS (Kalbfleisch and Lawless 1989)

```
> #hazard function:  
> res.h <- hazardDT(X, U, V, bw = 5, from = min(X),  
+ to = max(X), n = 500)  
> plot(res.h$x, res.h$y, type = "l", ylim = c(0, .14))  
  
> b <- seq(3, 7, length = 14)  
> for (i in 1:k){  
+ res.hb <- hazardDT(X, U, V, bw = b[i], from = min(X),  
+ to = max(X), n = 500)  
+ lines(res.hb$x, res.hb$y, col = "gray")  
+ }  
> lines(res.h$x, res.h$y, col = 2, lwd = 2)
```

# DTDA in practice: AIDS (Kalbfleisch and Lawless 1989)



## DTDA in practice: simulating double truncation

- Simulating interval sampling:

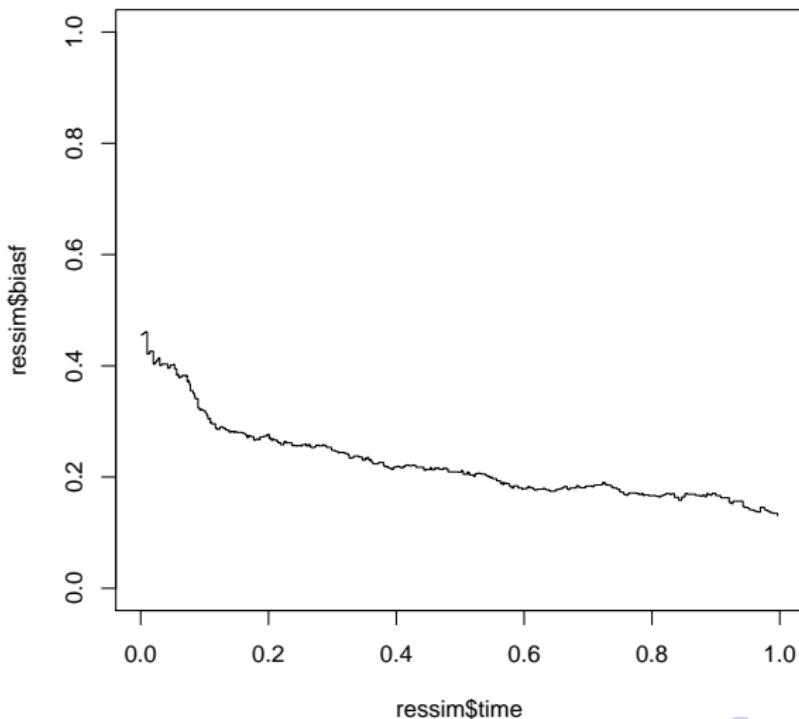
$$X \sim U(0, 1)$$

$U \sim U(-\tau, 1)$ ,  $V = U + \tau$  in model 1 (no sampling bias)

$U \sim \text{uniform squared (Beta)}$  in model 2 (sampling bias)

```
> set.seed(1234)
> rsim.DT(500, tau = 1/3, model = 2) -> mysim
> str(mysim)
'data.frame': 500 obs. of 3 variables:
$ X: num 0.11 0.622 0.145 0.443 0.58 ...
$ U: num -0.1687 0.5222 -0.0967 0.3343 0.5005 ...
$ V: num 0.165 0.856 0.237 0.668 0.834 ...
> ressim <- shen(mysim$X, mysim$U, mysim$V, boot = F)
> plot(ressim$time, ressim$biasf, type = "s", ylim = c(0, 1))
```

# DTDA in practice: simulating double truncation



## Further use of the sampling probabilities W

- Linear (multiple, polynomial) regression:

```
lm(formula, data, subset, weights = W, na.action, ...)
```

- Nonparametric regression (local linear smoothers):

```
sm.regression(x, y, h, design.mat = NA, model = "none",  
weights = W, group = NA, ...)
```

- Proportional hazards (Cox) regression: add `+offset(-log(W))` as an extra covariate in `formula`:

```
coxph(formula, data=, weights, subset, na.action, ...)
```

- **Remark:** standard errors must be updated (use e.g. bootstrapping)

## Further use of the sampling probabilities W (cont.)

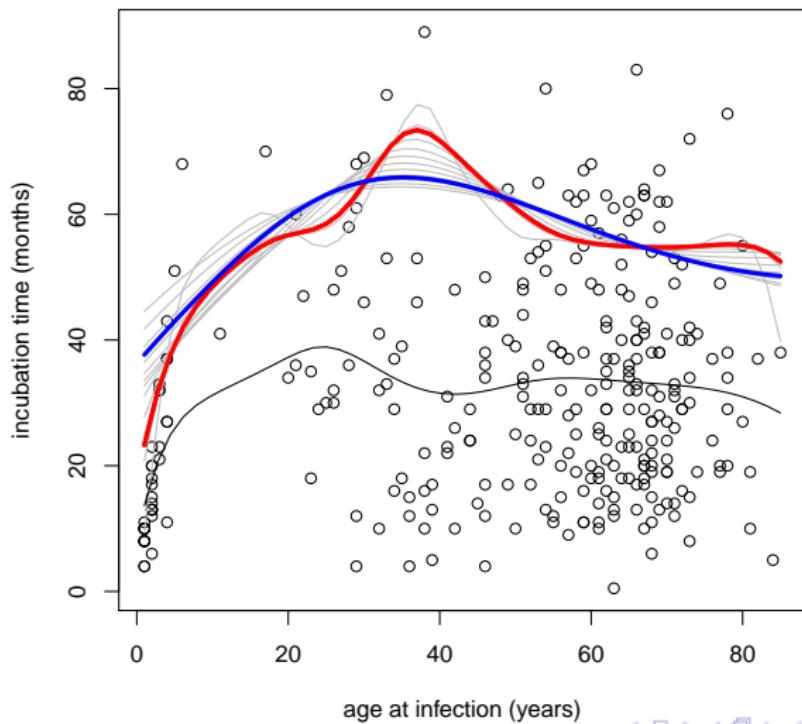
- Local linear smoothing:

```
> attach(AIDS.DT)
> W <- res$biasf^-1
> W <- W / sum(W)

> library(sm)
> res.LL <- sm.regression(AGE, X, h = 20, weights = W)
> res.LL2 <- sm.regression(AGE, X, h = 7.59, weights = W)

#naive estimator:
> res.LL2n <- sm.regression(AGE, X, h = 7.59)
```

## Further use of the sampling probabilities W (cont.)



## Further use of the sampling probabilities W (cont.)

- Proportional hazards (Cox) regression:

```
> library(survival)
> coxph(Surv(X) ~ AGE + I(AGE^2) + offset(-log(W)),
+ data = AIDS.DT) -> rescox
> coef(rescox)
            AGE      I(AGE^2)
-0.0290770914  0.0002863366
```

- Same for proportional cause-specific hazards model (competing risks)
- Linear regression:

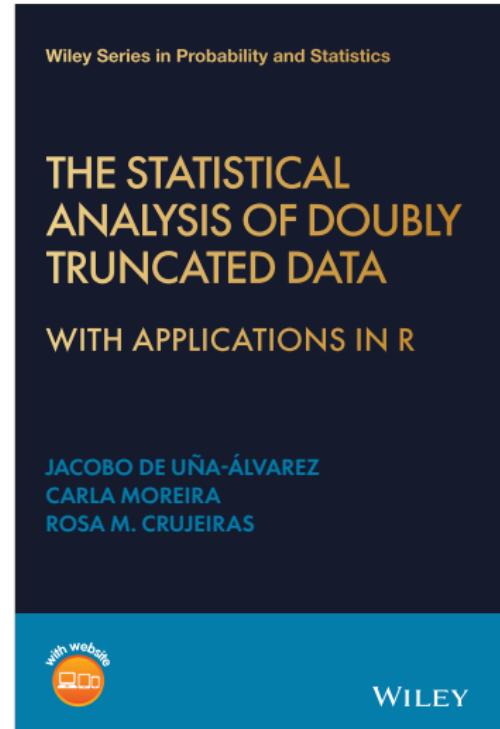
```
> lm(X ~ AGE + I(AGE^2), data = AIDS.DT,
+ weights = W) -> reslm
> coef(reslm)
(Intercept)          AGE      I(AGE^2)
36.11955323   1.48368927 -0.01785602
```

# DTDA package v3.0: discussion

- Three iterative algorithms implemented: `efron.petrosian()`, `lynden()`, `shen()`
- Other packages:
  - `double.truncation` by Takeshi Emura
  - `SurvTrunc` by Lior Rennert
  - `DTDA.cif`, `DTDA.ni` by José Carlos Soage
- Advantages of DTDA:
  - Sampling probabilities  $G_n(X_i)$  returned (`shen()`)
  - Simple and obvious bootstrap available
  - Confidence intervals for the truncation cdf, automatic plots
  - Faster computational times
  - Smoothing methods

# Thanks for your attention!

Forthcoming (January 2022):



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