

The predictive individual effect distribution for survival data: Appendix

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The appendix provides some methodological details and explains the code that has been used for the three examples.

1 The Lehmann-Doksum model

To derive the predictive distribution of the individual effect, we use a model introduced by Lehmann (Lehmann 1974) and investigated by Doksum (Doksum 1974). The Lehmann-Doksum model relates the outcomes X and Y as follows:

$$\begin{aligned} &\text{Lehmann-Doksum model:} \\ &X + \Delta(X) \text{ has the same distribution as } Y \end{aligned} \tag{1}$$

Because the shift function is not assumed constant, this looks like an assumption-free construction. Unfortunately, however, $\Delta(X)$ is not unique. A simple example is $X \sim N(0, 1)$ and $Y \sim N(\delta, 1)$: besides the natural $\Delta_1(X) = \delta$, $\Delta_2(X) = -2X + \delta$ also satisfies the above requirement.

Doksum defines the *shift function* as the minimum horizontal distance between F and G (see Figure 1) and gives the solution for $\Delta(x)$:

$$\Delta(x) = G^{-1}\{F(x)\} - x \tag{2}$$

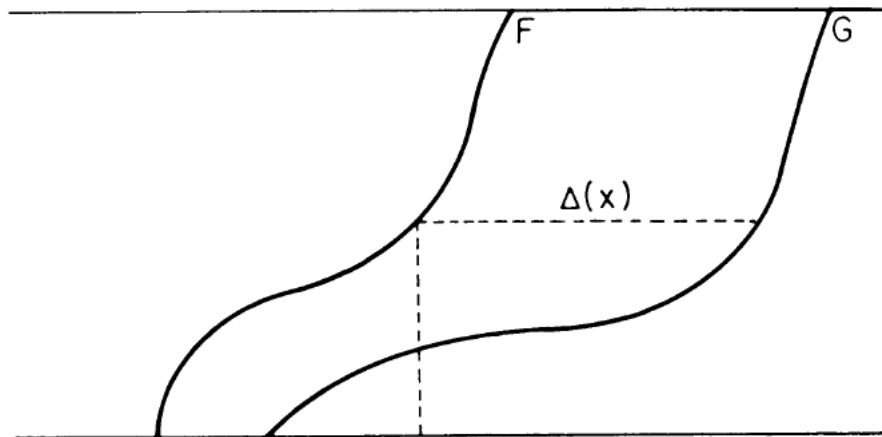


Figure 1: The Doksum distance (Doksum 1974)

2 Implementation

2.1 Main function: `pie_surv`

The main function is `pie_surv`. For help, see the file `pie_surv.r`.

The data set passed to `pie_surv` must contain the following variables:

- `time`: observed survival or censoring times
- `event`: event indicator, 1 for survival and 0 for censoring times
- `trt`: treatment indicator, 1 for treatment and 0 for control

2.2 Required libraries

In addition to the main library **clinpredict**, the following libraries are needed: **survival**, **ggplot2**, **tidyverse**, **mvtnorm**, **survminer**

```
# required libraries
library(clinpredict)

library(ggplot2)
library(survival)
library(tidyverse)
library(mvtnorm)
library(survminer)

options(digits=2)

# Simulation sample size for example
# 1000 sample is too small: default is 10000
n.pred = 2000
```

3 Example 1: CM141 trial

3.1 Analysis

```
# Example data file
data("CM141.r")
ds = CM141

ds = data(CM141)
ds = CM141

C.label = "standard of care"
T.label = "nivolumab"

yC.cond = 1:15
gain.cutoffs = -1:12

gain.label = "survival gain in months (nivolumab-standard)"

out1 = pie_surv(
  data = ds,
  n.pred = n.pred,
  yC.cond = yC.cond,
  pie.gain.cutoffs = gain.cutoffs,
  time.unit = "months",
  gain.label = gain.label,
  C.label = C.label,
  T.label = T.label
)
```

3.2 Outputs

3.2.1 Predictive individual effect distribution

```
# output object has the following elements...
```

```
names(out1)
```

```
.. [1] "rank.pres"      "int"           "coxPH"         "logrank"
.. [5] "pwexp"          "sim"           "marg"           "pie"
.. [9] "pie.gain"       "pie.cond"      "tables_knitr"  "figures"
```

```
# 1) main results
```

```
out1$pie
```

```
..      mean  sd  2.5% 50% 97.5%   <0   >=0
.. [1,]      4 5.3 -0.56 2.5    19 0.17 0.83
```

```
out1$pie.gain
```

```
..  <=-1  <=0   >0   >1   >2   >3   >4   >5   >6   >7   >8   >9
.. 0.008 0.168 0.832 0.619 0.538 0.466 0.391 0.315 0.257 0.205 0.167 0.138
..  >10  >11  >12
.. 0.112 0.085 0.066
```

```
# conditional pie (for fixed value control times)
```

```
out1$pie.cond
```

```
..      mean  sd  2.5%   50% 97.5%      <0   >=0
.. standard of care=1 -0.0914 0.33 -0.62 -0.13 0.62 0.6425 0.36
.. standard of care=2 -0.0043 0.29 -0.49 -0.03 0.69 0.5500 0.45
.. standard of care=3 0.2352 0.73 -0.90 0.19 1.88 0.3995 0.60
.. standard of care=4 1.0046 1.03 -0.89 0.95 3.22 0.1635 0.84
.. standard of care=5 2.8785 1.32 0.57 2.77 5.84 0.0050 0.99
.. standard of care=6 4.7524 1.79 1.59 4.61 8.73 0.0000 1.00
.. standard of care=7 5.5472 2.01 2.12 5.35 10.02 0.0000 1.00
.. standard of care=8 6.0476 2.22 2.27 5.89 10.98 0.0000 1.00
.. standard of care=9 6.5480 2.48 2.32 6.34 12.12 0.0005 1.00
.. standard of care=10 7.0485 2.79 2.36 6.76 13.28 0.0010 1.00
.. standard of care=11 7.5489 3.13 2.33 7.23 14.44 0.0010 1.00
.. standard of care=12 8.0493 3.49 2.31 7.68 15.63 0.0010 1.00
.. standard of care=13 8.5498 3.87 2.19 8.15 16.97 0.0015 1.00
.. standard of care=14 9.0502 4.26 2.04 8.60 18.52 0.0030 1.00
.. standard of care=15 9.5506 4.65 1.88 9.03 19.72 0.0055 0.99
```

3.2.2 Additional output

```
# interval boundaries
```

```
out1$int
```

```
.. $intC
.. 10% 50% 80%
.. 1.1 3.9 6.2
..
.. $intT
.. 20% 40%
.. 1.6 2.4
```

```
# Cox and log-rank results
out1$coxPH
```

```
.. Call:
.. coxph(formula = Surv(time, event) ~ trt, data = data)
..
..      coef exp(coef) se(coef)  z      p
.. trt1 -0.4      0.7      0.1 -3 0.007
..
.. Likelihood ratio test=7 on 1 df, p=0.008
.. n= 361, number of events= 218
```

```
out1$logrank
```

```
.. [1] 0.0034
```

```
# summaries of marginal predictive distributions
out1$marg
```

```
..              mean   sd 2.5% 50% 97.5%
.. standard of care  7.8  8.4 0.38 4.9    31
.. nivolumab        11.9 12.5 0.37 7.8    47
```

```
# results from pweexp analysis for control and treatment
# out1$pweexp
```

```
# simulated predictive values
head(out1$sim)
```

```
.. [1] "simulated values not saved: set *save.sim=TRUE*"

```

3.2.3 Tables and figures

```
# knitr tables: out1$tables_knitr
names(out1$tables_knitr)
```

```
.. [1] "marg"      "pie"      "pie.cond" "pie.gain"
```

```
out1$tables_knitr$marg
```

Table 1: : predictive standard of care and nivolumab survival times

	mean	sd	2.5%	50%	97.5%
standard of care	7.8	8.4	0.38	4.9	31
nivolumab	11.8	12.5	0.37	7.8	47

```
out1$tables_knitr$pie
```

Table 2: : predictive individual effect (T-C)

mean	sd	2.5%	50%	97.5%	<0	>=0
4	5.3	-0.56	2.5	19	0.17	0.83

```
out1$tables_knitr$pie.gain
```

Table 3: : cumulative predictive individual effect distribution

	x
<=-1	0.01
<=0	0.17
>0	0.83
>1	0.62
>2	0.54
>3	0.47
>4	0.39
>5	0.32
>6	0.26
>7	0.21
>8	0.17
>9	0.14
>10	0.11
>11	0.08
>12	0.07

```
# ggplot figures: out1$figures
names(out1$figures)
```

```
.. [1] "km"          "km.pwexp" "pie.gain" "pie.cond"
```

```
fig1.km = out1$figures$km
fig1.km.pwexp = out1$figures$km.pwexp
fig1.gain = out1$figures$pie.gain
fig1.cond = out1$figures$pie.cond

pdf("appfig1km.pdf", onefile=FALSE)
fig1.km
dev.off()
```

```
.. pdf
.. 2

pdf("appfig1kmpwexp.pdf",onefile=FALSE)
fig1.km.pwexp
dev.off()
```

```
.. pdf
.. 2

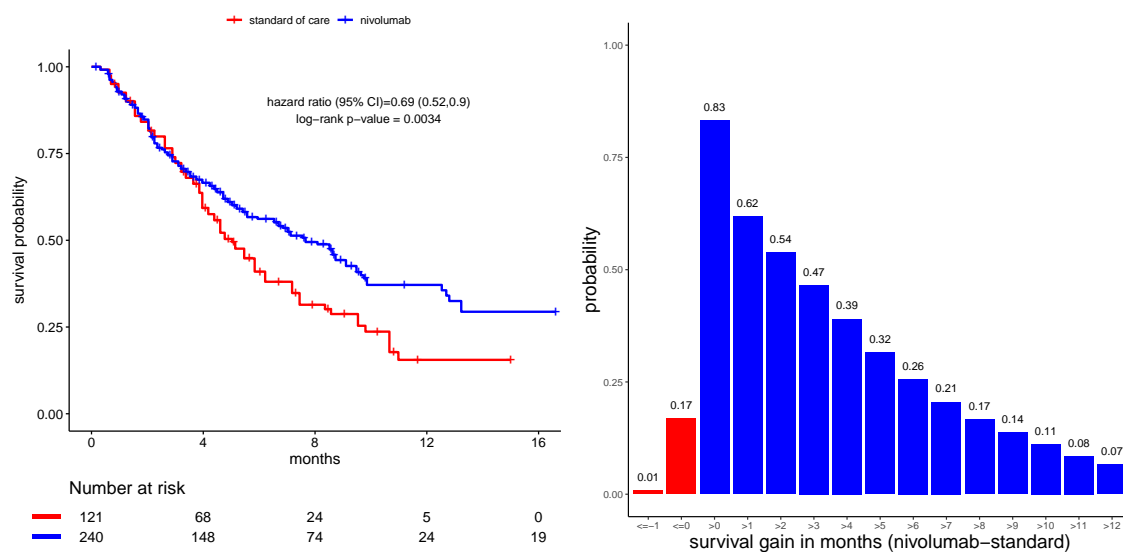
pdf("appfig1gain.pdf",onefile=FALSE)
fig1.gain
dev.off()
```

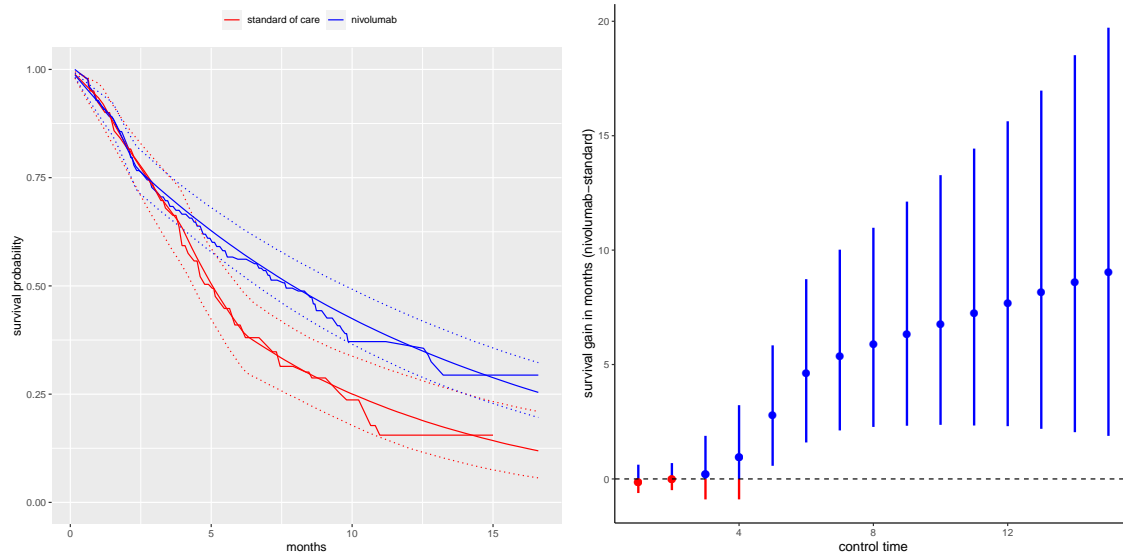
```
.. pdf
.. 2

pdf("appfig1cond.pdf",onefile=FALSE)
fig1.cond
dev.off()
```

```
.. pdf
.. 2
```

Figure 2: Kaplan-Meier curves, piecewise exponential distributions, survival gain, and conditional survival gain for CM141 trial





4 Example 2: CM057 trial with differential treatment effect for biomarker subgroup

The following analysis shows the predictive individual effect distribution for biomarker-negative and biomarker-positive patients in the CM057 trial (Borghaei et al. 2015).

```
data(CM057)
ds = CM057

# biomarker: group variable

# biomarker-negative
ds0 = ds[ds$group == 0, ]
# biomarker-positive
ds1 = ds[ds$group == 1, ]

C.label = "docetaxel"
T.label = "nivolumab"

gain.cutoffs = seq(-3, 24, by = 3)
gain.label = "survival gain in months (nivolumab-docetaxel)"

out2.0 = pie_surv(
  ds0,
  n.pred = n.pred,
  C.label = C.label,
  T.label = T.label,
  gain.label = gain.label,
  pie.gain.cutoffs = gain.cutoffs
)

out2.1 = pie_surv(
  ds1,
```



```

n.pred = n.pred,
C.label = C.label,
T.label = T.label,
gain.label = gain.label,
pie.gain.cutoffs = gain.cutoffs
)

labels = c("biomarker-negative", "biomarker-positive")

out.pie = rbind(out2.0$pie, out2.1$pie)
rownames(out.pie) = labels

out.piegain = rbind(out2.0$pie.gain, out2.1$pie.gain)
rownames(out.piegain) = labels

cap = "Summary of predictive individual effect distribution"
knitr::kable(out.pie, cap=cap)

```

Table 4: Summary of predictive individual effect distribution

	mean	sd	2.5%	50%	97.5%	<0	>=0
biomarker-negative	-0.56	4.2	-10.14	-0.48	5.9	0.62	0.38
biomarker-positive	10.60	9.8	-0.86	11.10	30.3	0.08	0.92

```

cap = "Probabilities of survival gains for nivolumab vs. docetaxel"
knitr::kable(rbind(out.piegain), cap=cap)

```

Table 5: Probabilities of survival gains for nivolumab vs. docetaxel

	<=-3	<=0	>0	>3	>6	>9	>12	>15	>18	>21	>24
biomarker-negative	0.10	0.62	0.38	0.11	0.02	0.0	0.00	0.00	0.00	0.00	0.00
biomarker-positive	0.01	0.08	0.92	0.76	0.69	0.6	0.43	0.25	0.15	0.09	0.06

```

fig20.km = out2.0$figures$km
fig21.km = out2.1$figures$km

fig20.gain = out2.0$figures$pie.gain
fig21.gain = out2.1$figures$pie.gain

dev.off()

```

```

.. null device
..          1

```

```

pdf("appfig20km.pdf", onefile=FALSE)
fig20.km
dev.off()

```

```
.. null device
..      1
```

```
pdf("appfig21km.pdf",onefile=FALSE)
fig21.km
dev.off()
```

```
.. null device
..      1
```

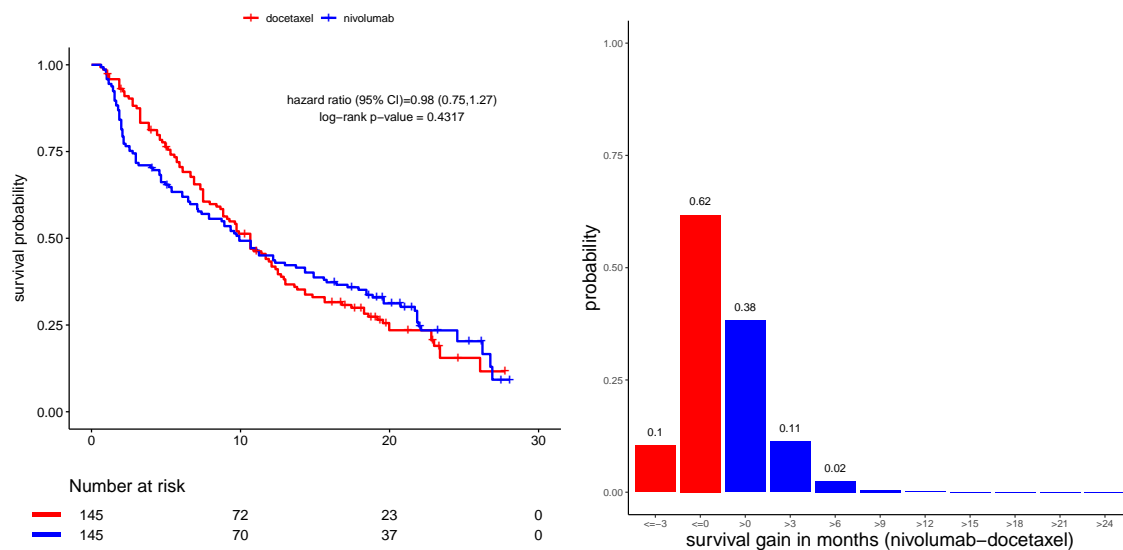
```
pdf("appfig20gain.pdf",onefile=FALSE)
fig20.gain
dev.off()
```

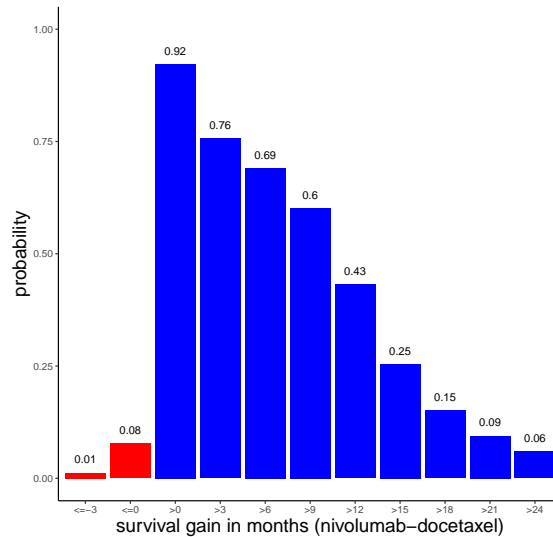
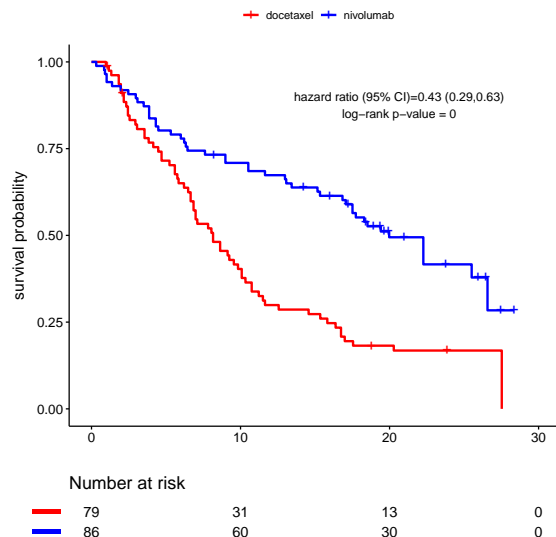
```
.. null device
..      1
```

```
pdf("appfig21gain.pdf",onefile=FALSE)
fig21.gain
dev.off()
```

```
.. null device
..      1
```

Figure 3: Kaplan-Meier curves and probabilities for survival gain for biomarker-negative (top) and biomarker-positive patients.





```
sessionInfo()
```

```
.. R version 3.6.0 (2019-04-26)
.. Platform: x86_64-w64-mingw32/x64 (64-bit)
.. Running under: Windows 10 x64 (build 18363)
..
.. Matrix products: default
..
.. locale:
.. [1] LC_COLLATE=German_Switzerland.1252 LC_CTYPE=German_Switzerland.1252
.. [3] LC_MONETARY=German_Switzerland.1252 LC_NUMERIC=C
.. [5] LC_TIME=German_Switzerland.1252
..
.. attached base packages:
.. [1] stats      graphics  grDevices  utils      datasets  methods    base
..
.. other attached packages:
.. [1] survminer_0.4.9  ggpubr_0.4.0    mvtnorm_1.0-10
.. [4] forcats_0.5.0    stringr_1.4.0    dplyr_1.0.5
.. [7] purrr_0.3.4      readr_1.3.1      tidyr_1.1.3
.. [10] tibble_3.0.1     tidyverse_1.3.0  survival_3.2-3
.. [13] ggplot2_3.3.3    clinpredict_0.1.2
..
.. loaded via a namespace (and not attached):
.. [1] httr_1.4.1        jsonlite_1.6     splines_3.6.0
.. [4] carData_3.0-4     modelr_0.1.8     assertthat_0.2.1
.. [7] highr_0.8         cellranger_1.1.0 yaml_2.2.0
.. [10] pillar_1.4.4      backports_1.1.4  lattice_0.20-41
.. [13] glue_1.4.2        digest_0.6.19    gridtext_0.1.4
.. [16] ggsignif_0.6.1    rvest_1.0.0      colorspace_1.4-1
.. [19] htmltools_0.4.0   Matrix_1.2-17    pkgconfig_2.0.2
.. [22] broom_0.7.6       haven_2.2.0      xtable_1.8-4
.. [25] scales_1.0.0      km.ci_0.5-2      openxlsx_4.2.3
.. [28] rio_0.5.26        KMsurv_0.1-5     generics_0.0.2
.. [31] car_3.0-10        ellipsis_0.3.0   withr_2.4.1
```

.. [34]	cli_1.1.0	magrittr_1.5	crayon_1.3.4
.. [37]	readxl_1.3.1	ggtext_0.1.1	evaluate_0.14
.. [40]	fs_1.3.2	rstatix_0.7.0	xml2_1.3.2
.. [43]	foreign_0.8-71	tools_3.6.0	data.table_1.12.2
.. [46]	hms_0.5.3	lifecycle_1.0.0	munsell_0.5.0
.. [49]	reprex_1.0.0	zip_2.1.1	compiler_3.6.0
.. [52]	rlang_0.4.10	grid_3.6.0	rstudioapi_0.10
.. [55]	labeling_0.3	rmarkdown_2.1	gtable_0.3.0
.. [58]	abind_1.4-5	DBI_1.1.0	curl_4.3
.. [61]	markdown_1.1	R6_2.4.0	gridExtra_2.3
.. [64]	zoo_1.8-8	lubridate_1.7.10	knitr_1.24
.. [67]	survMisc_0.5.5	stringi_1.4.3	Rcpp_1.0.6
.. [70]	vctrs_0.3.6	dbplyr_2.1.0	tidyselect_1.1.0
.. [73]	xfun_0.22		

References

Borghaei, H., L. Paz-Ares, L. Horn, and others. 2015. “Nivolumab Versus Docetaxel in Advanced Nonsquamous Non-small-Cell Lung Cancer.” *The New England Journal of Medicine* 373 (17): 1627–39.

Doksum, K. 1974. “Empirical probability plots and statistical inference for nonlinear models in the two-sample case.” *Annals of Statistics* 2 (2): 267–77.

Lehmann, E.L. 1974. *Nonparameterics: Statistical Methods Based on Ranks*. Holden Day, San Francisco.