

# Multi-state Models and the Survival package

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July 2019

# Changes

- ▶ survival 0.x: pre “white book”: (1986 – 1989)
- ▶ survival 1.x: Splus era (1989 – 2004)
  - ▶ Second International S Conference, 1992, Toulouse
- ▶ survival 2.x: R (2004 – 2019)
- ▶ survival 3.x: on github 7/3, CRAN on 9/1?

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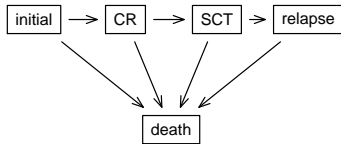
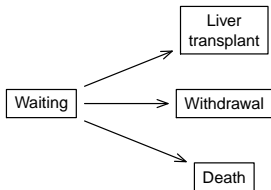
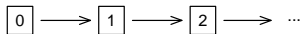
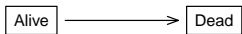
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- ▶ Book: end of 2020

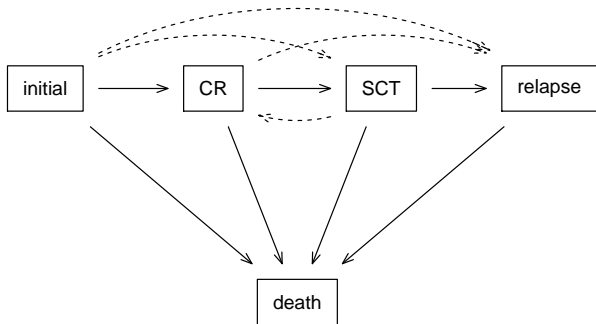
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- ▶ 701 packages depend on `survival` (as of 4 July)

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- ▶ I rarely change major versions – something must be up
- ▶ 701 packages depend on `survival` (as of 4 July)
- ▶ Major increments in multi-state modeling
- ▶ Why multi-state?





	id	trt	tstart	tstop	event
1	1	B	0	44	CR
2	1	B	44	113	relapse
3	1	B	113	235	death
4	2	A	0	200	SCT
5	2	A	200	286	death
6	3	A	0	38	CR
7	3	A	38	1983	censor



# Data

- ▶ event is a multi-level factor variable.
  - ▶ The first level must correspond to “no event at this time”
  - ▶ Otherwise unrestricted.
- ▶ An id variable identifies multiple rows per subject.
- ▶ Consistent
  - ▶ If at risk, you should be some state: (0,50,T) (90, 210,M)
  - ▶ But only one place at a time: (0,50,T) (30, 210,P)

	id	trt	tstart	tstop	event	e2
1	1	B	0	44	CR	-
2	1	B	44	113	relapse	Fail
3	1	B	113	235	death	-
4	2	A	0	200	SCT	SCT
5	2	A	200	286	death	Fail
6	3	A	0	38	CR	-
7	3	A	38	1983	cancel	-

```

> AJfit <- survfit(Surv(tstart, tstop, e2) ~ trt, id=id,
                  data=mydata, influence=TRUE)
> dim(AJfit)
strata states
      2      3
> print(AJfit, digits=2)
Call: survfit(formula = Surv(tstart, tstop, e2) ~ trt, data = my
              id = id, influence = TRUE)

```

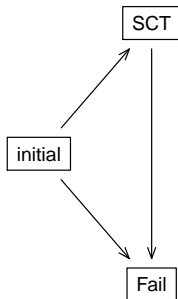
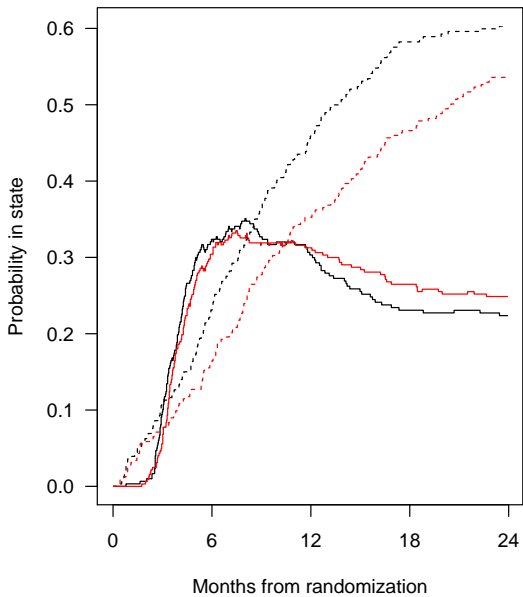
	n	nevent	rmean	std(rmean)*
trt=A, (s0)	759	0	527	47
trt=B, (s0)	821	0	651	49
trt=A, SCT	759	131	510	51
trt=B, SCT	821	134	569	52
trt=A, Fail	759	194	1382	59
trt=B, Fail	821	184	1198	58

\*mean time in state, restricted (max time = 2419 )

```

> plot(AJfit[, 2:3])

```



## Multi-state coxph models

```
> cfit <- coxph(Surv(tstart, tstop, e2) ~ trt, id=id, mydata)
> print(cfit, digits=2)
```

Call:

```
coxph(formula = Surv(tstart, tstop, e2) ~ trt, data = mydata,
      id = id)
```

1:2	coef	exp(coef)	se(coef)	robust se	z	p
trtB	-0.18	0.84	0.12	0.12	-1.4	0.2

1:3	coef	exp(coef)	se(coef)	robust se	z	p
trtB	-0.24	0.79	0.13	0.13	-1.9	0.06

2:3	coef	exp(coef)	se(coef)	robust se	z	p
trtB	-0.30	0.74	0.18	0.18	-1.7	0.08

States: 1= (s0), 2= SCT, 3= Fail

## Post coxph probability-in-state curves

```
> dummy <- data.frame(trt=c("A", "B"))
> csurv <- survfit(cfit, newdata=dummy)
> dim(csurv)
strata  data  states
      1     2     3
> plot(csurv[,2:3], col=1:2, lty=c(1,1,2,2))
```

# Goals

- ▶ Curves of  $P(\text{state} | t)$  are as easy as `survfit`
- ▶ Multi-state fits are as easy as `coxph`
- ▶ Secondary summaries  $E(\text{time in state})$ ,  $E(\text{visits to state})$ , ...
- ▶ Standardized data  $\rightarrow$  better data tools
  - ▶ Cannot be in two places at once
  - ▶ If at risk, must be someplace
  - ▶ Gaps and teleports are viewed with suspicion
  - ▶ Don't make the user break the rules
  - ▶ Immortal time bias is pernicious.
- ▶ Robust variance (dfbeta matrix) for all estimates
  - ▶ Correct variance with IP weights
  - ▶ Variance of derived quantities
- ▶ These are the tools that I use.

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- ▶ Don't bugger it up

## Data check

```
> check <- survcheck(Surv(tstart, tstop, event) ~ 1,
                      data=mydata, id=id)
> check$transitions
      to
from   CR SCT relapse death (censored)
(s0)  443 106    13    55         29
CR      0 159   168    17        110
SCT     11  0    45   149        158
relapse 0  99    0    99         28
death   0  0    0    0          0
> #
> check$flag
overlap      gap      jump teleport
      0          0          0          0
```

## Complex multi-state coxph models

```
temp <- list(Surv(tstart, tstop, event) ~ age + trt,  
            1:c("SCT", "Fail") ~ sex / common,  
            "SCT":"Fail" ~ hgb)  
fit2 <- coxph(temp, data=mdata, id=id, x=TRUE)
```

# Yet to do

- ▶ Nag level

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- ▶ Nag level
- ▶ Unnamed state
  - ▶ “ ”
  - ▶ ()
  - ▶ (s0)
- ▶ Methods: [, coef, plot, print, quantile, anova, vcov, extractAIC, ...
- ▶ More tests
- ▶ Check 500 other packages
- ▶ Submit to CRAN

# Hitchhiker's guide to survival

## Causal estimates

- ▶ A very important aspect of time-to-event data
- ▶ Properties:
  1. Prediction can be verified
    - ▶  $P(\text{alive at 2 years}) = 27\%$
    - ▶ I can watch you for 2 years and find out
  2. Prediction is additive over subjects
    - ▶  $p_1 = .27, p_2 = .83, p_3 = \dots$
    - ▶ population prediction =  $(1/n) \sum p$
  3. The HR does not satisfy this,  $P(\text{state})$  does.
- ▶ The HR does not satisfy this,  $P(\text{state})$  does.

