Introduction to the rstpm2 package

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Abstract

This vignette outlines the methods and provides some examples for link-based survival models as implemented in the R rstpm2 package.

Keywords: survival, splines.

1. Theory

Currently, the best description of the theory is in draft paper by Liu, Pawitan and Clements.

2. Mean survival

This has a useful interpretation for causal inference.

$$E_Z(S(t|Z, X = 1)) - E_Z(S(t|Z, X = 0))$$

```
fit <- rstpm()
predict(fit,type="meansurvdiff",newdata=data)</pre>
```

3. Cure models

For cure, we use the melanoma dataset used by Andersson and colleagues for cure models with Stata's stpm2 (see http://www.pauldickman.com/survival/).

Initially, we merge the patient data with the all cause mortality rates.

```
exityear <- floor(yydx+tm)</pre>
   ##year8594 <- (year8594=="Diagnosed 85-94")
+
+ })
> colon2 <- merge(colon2,popmort2)</pre>
For comparisons, we fit the relative survival model without and with cure.
> fit0 <- stpm2(Surv(tm,status %in% 2:3)~I(year8594=="Diagnosed 85-94"),</pre>
                        data=colon2,
                        bhazard=colon2$rate, df=5)
+
> summary(fit <- stpm2(Surv(tm, status %in% 2:3)~I(year8594=="Diagnosed 85-94"),
                        data=colon2,
                        bhazard=colon2$rate,
                        df=5,cure=TRUE))
Maximum likelihood estimation
Call:
mle2(minuslog1 = neg11, start = coef, eval.only = TRUE, vecpar = TRUE,
    gr = function (beta, kappa = 1)
        eta <- as.vector(pars$X %*% beta)
        etaD <- as.vector(pars$XD %*% beta)
        h <- link$h(eta, etaD)</pre>
        gradh <- link$gradh(eta, etaD, pars)</pre>
        gradH <- link$gradH(eta, etaD, pars)</pre>
        gconstraint <- colSums((kappa * h * pars$wt * gradh)[h <</pre>
            0, ])
        h[h < 0] < -1e-16
        g <- colSums(pars$wt * (-gradH + ifelse(pars$event, 1/h,
            0) * gradh)) - gconstraint
        if (delayed) {
            eta <- as.vector(pars0$X %*% beta)
            etaD <- as.vector(pars0$XD %*% beta)</pre>
            gradH <- link$gradH(eta, etaD, pars0)</pre>
            g <- g + colSums(gradH * pars0$wt)</pre>
        return(-g)
    \}, control = list(parscale = c(0.1, 0.1, 0.1, 0.1, 0.1, 0.1,
    0.1), maxit = 300), lower = -Inf, upper = Inf)
Coefficients:
                                        Estimate Std. Error z value
(Intercept)
                                       -3.977326 0.054778 -72.6078 < 2.2e-16
I(year8594 == "Diagnosed 85-94")TRUE -0.155613 0.025088 -6.2027 5.551e-10
nsx(log(tm), df = 5, cure = TRUE)1 3.323188 0.053166 62.5062 < 2.2e-16
```

```
nsx(log(tm), df = 5, cure = TRUE)2
                                      3.628637
                                                 0.053160 68.2592 < 2.2e-16
nsx(log(tm), df = 5, cure = TRUE)3
                                                 0.022465 72.7742 < 2.2e-16
                                      1.634854
nsx(log(tm), df = 5, cure = TRUE)4
                                      6.592018
                                                 0.111504 59.1190 < 2.2e-16
nsx(log(tm), df = 5, cure = TRUE)5
                                      3.371806
                                                 0.042788 78.8025 < 2.2e-16
(Intercept)
I(year8594 == "Diagnosed 85-94")TRUE ***
nsx(log(tm), df = 5, cure = TRUE)1
nsx(log(tm), df = 5, cure = TRUE)2
nsx(log(tm), df = 5, cure = TRUE)3
nsx(log(tm), df = 5, cure = TRUE)4
                                     ***
nsx(log(tm), df = 5, cure = TRUE)5
                                     ***
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
-2 log L: 42190.77
> predict(fit,head(colon2),se.fit=TRUE)
   Estimate
                lower
                          upper
1 0.8610835 0.8542905 0.8675849
2 0.7934666 0.7850118 0.8016323
3 0.6967422 0.6863213 0.7068947
4 0.8610835 0.8542905 0.8675849
5 0.8221253 0.8143237 0.8296344
6 0.8610835 0.8542905 0.8675849
```

The estimate for the year parameter from the model without cure is within three significant figures with that in Stata. For the predictions, the Stata model gives:

	+-			+
	1	surv	surv_lci	surv_uci
	-			
1.		.86108264	.8542898	.8675839
2.		.79346526	.7850106	.8016309
3.		.69674037	.6863196	.7068927
4.		.86108264	.8542898	.8675839
5.		.82212425	.8143227	.8296332
	-			
6.	1	.86108264	.8542898	.8675839
	+-			+

We can estimate the proportion of failures at the end of follow-up using:

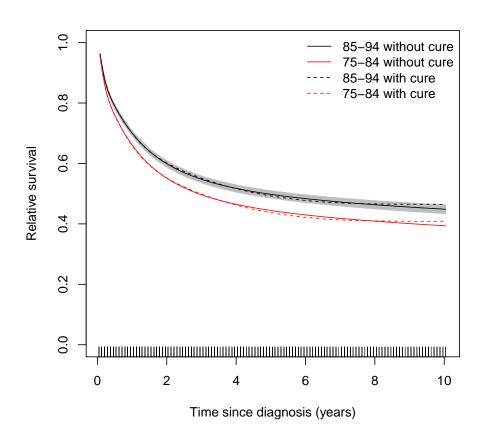
```
> newdata.eof <- data.frame(year8594 = unique(colon2$year8594),
+ tm=max(colon2$tm))
> 1-predict(fit0, newdata.eof, type="surv", se.fit=TRUE)
```

```
Estimate lower upper 1 0.6063672 0.6211721 0.5916026 2 0.5515138 0.5661327 0.5370117
```

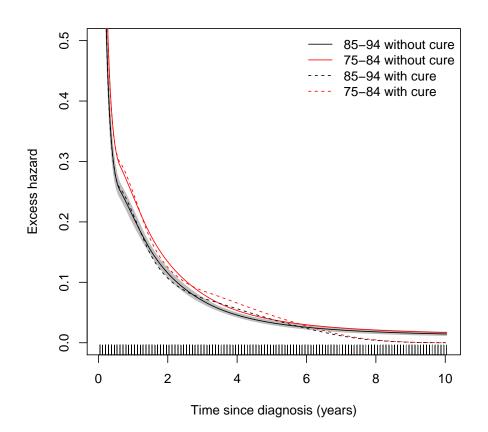
> 1-predict(fit, newdata.eof, type="surv", se.fit=TRUE)

```
Estimate lower upper 1 0.5913307 0.6055015 0.5772173 2 0.5350813 0.5485372 0.5217434
```

We can plot the predicted survival estimates:



And the hazard curves:



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