

Non And Semi Parametric Survival Analysis - DrPH(Epid)

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Cox proportional hazard model

Introduction

The coxph function

The Cox proportional-hazards regression model can be fit in R with the `survival::coxph` function.

The argument *method* indicates how to handle observations that have tied (i.e., identical) survival times. The default “efron” method is generally preferred to the once-popular “breslow” method.

Initial preparation

Prepare folder and file

Set the working directory to store all the working datasets and also the outputs.

```
setwd("E:/Epi_Stat_Matters/LectureNotes2015/Survival-Analysis/survival-analysis-DrPH-epid-2015/Practicals")  
list.files()
```

```
## [1] "addicts.dta"  
## [2] "NonAndSemipara.pdf"  
## [3] "NonAndSemipara.Rmd"  
## [4] "NonAndSemipara_DrPH_Epid.html"  
## [5] "NonAndSemipara_DrPH_Epid.md"  
## [6] "NonAndSemipara_DrPH_Epid.pdf"  
## [7] "NonAndSemipara_DrPH_Epid.Rmd"  
## [8] "NonAndSemipara_DrPH_Epid_files"  
## [9] "NonAndSemiParametricSurvivalAnalysis.Rproj"
```

Read data

We can use `foreign::read.dta` to read stata format data.

```
library(foreign)  
data1<-read.dta('addicts.dta',convert.factors = T)
```

Load library

The popular package to run survival analysis in R is `survival` package. We can load the package using the `library` function

```
library(survival)
```

Preliminary analysis

Declare file as a survival data format

It is important to tell R that the data for survival analysis is in the time-to-event format. We need to specify:

1. variable time
2. variable event. What would be the event of interest. The rest will be censored observations.

When can see the summary of the data

```
datas <- Surv(time = data1$survt,event = data1$status == 1)
summary(datas)
```

```
##           time           status
## Min.      : 2.0    Min.      :0.0000
## 1st Qu.: 171.2    1st Qu.:0.0000
## Median : 367.5    Median :1.0000
## Mean   : 402.6    Mean    :0.6303
## 3rd Qu.: 585.5    3rd Qu.:1.0000
## Max.    :1076.0    Max.     :1.0000
```

Overview of data

Let us see the first 50 observations for the

1. time-to-event data
2. the original data

```
head(datas,50)
```

```
## [1] 428 275 262 183 259 714 438 796+ 892 393 161+ 836 523 612
## [15] 212 399 771 514 512 624 209 341 299 826+ 262 566+ 368 302
## [29] 602+ 652 293 564+ 394 755 591 787+ 739 550 837 612 581+ 523
## [43] 504 785 774 560 160 482 518 683
```

```
head(data1,50)
```

```
##    id clinic status survt      prison dose
## 1   1 clinic1     1   428      no record  50
## 2   2 clinic1     1   275 has_previous_rec 55
## 3   3 clinic1     1   262      no record  55
## 4   4 clinic1     1   183      no record  30
## 5   5 clinic1     1   259 has_previous_rec 65
## 6   6 clinic1     1   714      no record  55
## 7   7 clinic1     1   438 has_previous_rec 65
## 8   8 clinic1     0   796 has_previous_rec 60
## 9   9 clinic1     1   892      no record  50
## 10 10 clinic1     1   393 has_previous_rec 65
## 11 11 clinic1     0   161 has_previous_rec 80
## 12 12 clinic1     1   836 has_previous_rec 60
## 13 13 clinic1     1   523      no record  55
## 14 14 clinic1     1   612      no record  70
## 15 15 clinic1     1   212 has_previous_rec 60
## 16 16 clinic1     1   399 has_previous_rec 60
## 17 17 clinic1     1   771 has_previous_rec 75
## 18 18 clinic1     1   514 has_previous_rec 80
## 19 19 clinic1     1   512      no record  80
## 20 21 clinic1     1   624 has_previous_rec 80
## 21 22 clinic1     1   209 has_previous_rec 60
## 22 23 clinic1     1   341 has_previous_rec 60
## 23 24 clinic1     1   299      no record  55
```

```
## 24 25 clinic1      0   826      no record   80
## 25 26 clinic1      1   262 has_previous_rec 65
## 26 27 clinic1      0   566 has_previous_rec 45
## 27 28 clinic1      1   368 has_previous_rec 55
## 28 30 clinic1      1   302 has_previous_rec 50
## 29 31 clinic1      0   602      no record   60
## 30 32 clinic1      1   652      no record   80
## 31 33 clinic1      1   293      no record   65
## 32 34 clinic1      0   564      no record   60
## 33 36 clinic1      1   394 has_previous_rec 55
## 34 37 clinic1      1   755 has_previous_rec 65
## 35 38 clinic1      1   591      no record   55
## 36 39 clinic1      0   787      no record   80
## 37 40 clinic1      1   739      no record   60
## 38 41 clinic1      1   550 has_previous_rec 60
## 39 42 clinic1      1   837      no record   60
## 40 43 clinic1      1   612      no record   65
## 41 44 clinic1      0   581      no record   70
## 42 45 clinic1      1   523      no record   60
## 43 46 clinic1      1   504 has_previous_rec 60
## 44 48 clinic1      1   785 has_previous_rec 80
## 45 49 clinic1      1   774 has_previous_rec 65
## 46 50 clinic1      1   560      no record   65
## 47 51 clinic1      1   160      no record   35
## 48 52 clinic1      1   482      no record   30
## 49 53 clinic1      1   518      no record   65
## 50 54 clinic1      1   683      no record   50
```

- sign is for censored observation

Estimation of the survival based on non-parametric method

To estimate the expected survival probability, we can use the non-parametric method. The most popular one is the Kaplan-Meier survival estimate.

Estimate the crude (unadjusted) survival functions for all

Using the intercept-only model to obtain Kaplan-Meier survival estimates for all event times.

```
surv.fit<-survfit(datas~1, data = data1)
summary(surv.fit)
```

```
## Call: survfit(formula = datas ~ 1, data = data1)
##
##   time n.risk n.event survival std.err lower 95% CI upper 95% CI
##    7     236      1    0.996 0.00423    0.9875    1.000
##   13     235      1    0.992 0.00597    0.9799    1.000
##   17     234      1    0.987 0.00729    0.9731    1.000
##   19     233      1    0.983 0.00840    0.9667    1.000
##   26     232      1    0.979 0.00937    0.9606    0.997
##   29     229      1    0.975 0.01026    0.9546    0.995
##   30     228      1    0.970 0.01107    0.9488    0.992
##   33     227      1    0.966 0.01182    0.9431    0.989
```

##	35	226	2	0.957	0.01317	0.9320	0.984
##	37	224	1	0.953	0.01379	0.9265	0.981
##	41	223	2	0.945	0.01493	0.9158	0.974
##	47	221	1	0.940	0.01546	0.9105	0.971
##	49	220	1	0.936	0.01597	0.9053	0.968
##	50	219	1	0.932	0.01646	0.9001	0.965
##	59	216	1	0.927	0.01694	0.8949	0.961
##	62	215	1	0.923	0.01740	0.8897	0.958
##	67	213	1	0.919	0.01785	0.8845	0.954
##	75	211	1	0.914	0.01829	0.8793	0.951
##	79	210	1	0.910	0.01871	0.8742	0.948
##	84	209	1	0.906	0.01913	0.8691	0.944
##	90	207	1	0.901	0.01953	0.8639	0.940
##	95	206	1	0.897	0.01992	0.8588	0.937
##	96	205	1	0.893	0.02029	0.8537	0.933
##	109	202	1	0.888	0.02067	0.8486	0.930
##	117	200	1	0.884	0.02104	0.8435	0.926
##	122	199	1	0.879	0.02140	0.8384	0.922
##	126	198	1	0.875	0.02174	0.8333	0.919
##	127	197	1	0.870	0.02208	0.8282	0.915
##	129	196	1	0.866	0.02241	0.8232	0.911
##	136	194	1	0.862	0.02274	0.8181	0.907
##	143	193	1	0.857	0.02305	0.8131	0.903
##	145	192	1	0.853	0.02336	0.8080	0.900
##	147	190	1	0.848	0.02366	0.8030	0.896
##	149	188	1	0.844	0.02396	0.7979	0.892
##	150	187	1	0.839	0.02426	0.7929	0.888
##	157	185	1	0.835	0.02455	0.7878	0.884
##	160	184	1	0.830	0.02483	0.7828	0.880
##	161	183	1	0.826	0.02510	0.7777	0.876
##	167	181	1	0.821	0.02538	0.7727	0.872
##	168	180	1	0.816	0.02564	0.7676	0.868
##	170	179	1	0.812	0.02590	0.7626	0.864
##	175	178	1	0.807	0.02615	0.7576	0.860
##	176	176	1	0.803	0.02640	0.7526	0.856
##	180	175	2	0.794	0.02689	0.7425	0.848
##	181	173	1	0.789	0.02712	0.7375	0.844
##	183	172	1	0.784	0.02735	0.7325	0.840
##	190	171	1	0.780	0.02757	0.7275	0.836
##	192	170	1	0.775	0.02779	0.7226	0.832
##	193	169	1	0.771	0.02800	0.7176	0.827
##	204	168	1	0.766	0.02821	0.7127	0.823
##	205	166	1	0.761	0.02841	0.7077	0.819
##	207	165	1	0.757	0.02861	0.7027	0.815
##	209	164	1	0.752	0.02881	0.6978	0.811
##	212	162	2	0.743	0.02919	0.6878	0.802
##	216	160	2	0.734	0.02955	0.6779	0.794
##	223	157	1	0.729	0.02973	0.6729	0.790
##	231	156	1	0.724	0.02991	0.6679	0.785
##	232	155	1	0.720	0.03008	0.6630	0.781
##	237	154	1	0.715	0.03024	0.6580	0.777
##	244	153	1	0.710	0.03040	0.6531	0.772
##	247	152	1	0.706	0.03056	0.6481	0.768
##	257	151	1	0.701	0.03071	0.6432	0.764

##	258	150	1	0.696	0.03086	0.6383	0.759
##	259	149	1	0.692	0.03101	0.6333	0.755
##	262	148	2	0.682	0.03128	0.6235	0.746
##	268	146	2	0.673	0.03154	0.6138	0.738
##	275	144	1	0.668	0.03167	0.6089	0.733
##	280	143	1	0.663	0.03179	0.6040	0.729
##	286	141	1	0.659	0.03191	0.5991	0.724
##	293	140	1	0.654	0.03203	0.5942	0.720
##	294	139	1	0.649	0.03214	0.5893	0.716
##	299	138	1	0.645	0.03225	0.5844	0.711
##	302	137	1	0.640	0.03236	0.5796	0.707
##	314	136	1	0.635	0.03246	0.5747	0.702
##	322	134	1	0.631	0.03256	0.5698	0.698
##	337	131	1	0.626	0.03267	0.5648	0.693
##	341	129	1	0.621	0.03277	0.5598	0.689
##	348	126	1	0.616	0.03288	0.5547	0.684
##	350	125	1	0.611	0.03298	0.5496	0.679
##	358	124	1	0.606	0.03308	0.5446	0.675
##	366	122	1	0.601	0.03318	0.5395	0.670
##	367	121	1	0.596	0.03328	0.5343	0.665
##	368	119	1	0.591	0.03338	0.5292	0.660
##	376	118	1	0.586	0.03347	0.5241	0.656
##	386	117	1	0.581	0.03355	0.5189	0.651
##	389	116	1	0.576	0.03364	0.5138	0.646
##	393	115	1	0.571	0.03371	0.5087	0.641
##	394	114	1	0.566	0.03379	0.5036	0.636
##	399	112	1	0.561	0.03386	0.4984	0.631
##	428	109	1	0.556	0.03394	0.4932	0.627
##	434	108	1	0.551	0.03401	0.4879	0.622
##	438	107	1	0.546	0.03408	0.4827	0.617
##	450	105	1	0.540	0.03415	0.4774	0.612
##	452	104	1	0.535	0.03422	0.4722	0.607
##	457	102	1	0.530	0.03428	0.4668	0.602
##	460	101	1	0.525	0.03434	0.4615	0.597
##	465	99	1	0.519	0.03440	0.4562	0.591
##	482	96	1	0.514	0.03447	0.4507	0.586
##	489	95	1	0.509	0.03453	0.4452	0.581
##	496	94	1	0.503	0.03458	0.4398	0.576
##	504	92	1	0.498	0.03463	0.4342	0.570
##	512	91	1	0.492	0.03468	0.4287	0.565
##	514	90	1	0.487	0.03473	0.4232	0.560
##	517	89	1	0.481	0.03476	0.4178	0.554
##	518	87	1	0.476	0.03480	0.4122	0.549
##	522	86	1	0.470	0.03483	0.4067	0.544
##	523	85	2	0.459	0.03488	0.3956	0.533
##	532	80	1	0.453	0.03491	0.3899	0.527
##	533	78	1	0.448	0.03495	0.3841	0.522
##	540	77	1	0.442	0.03497	0.3783	0.516
##	546	74	1	0.436	0.03501	0.3723	0.510
##	550	73	1	0.430	0.03503	0.3664	0.504
##	560	70	1	0.424	0.03507	0.3603	0.498
##	563	69	1	0.418	0.03509	0.3542	0.492
##	581	62	1	0.411	0.03517	0.3474	0.486
##	591	59	1	0.404	0.03525	0.3404	0.479

##	612	54	2	0.389	0.03550	0.3252	0.465
##	624	51	1	0.381	0.03561	0.3175	0.458
##	646	48	1	0.373	0.03574	0.3095	0.450
##	652	47	1	0.365	0.03586	0.3015	0.443
##	661	46	1	0.357	0.03595	0.2935	0.435
##	667	45	1	0.350	0.03601	0.2856	0.428
##	679	44	1	0.342	0.03606	0.2777	0.420
##	683	43	1	0.334	0.03609	0.2699	0.412
##	708	39	1	0.325	0.03616	0.2614	0.404
##	714	37	1	0.316	0.03623	0.2527	0.396
##	739	35	1	0.307	0.03631	0.2437	0.387
##	749	34	1	0.298	0.03635	0.2348	0.379
##	755	33	1	0.289	0.03635	0.2260	0.370
##	760	32	1	0.280	0.03632	0.2173	0.361
##	771	28	1	0.270	0.03638	0.2075	0.352
##	774	27	1	0.260	0.03638	0.1978	0.342
##	785	26	1	0.250	0.03633	0.1882	0.332
##	821	20	2	0.225	0.03675	0.1635	0.310
##	836	17	1	0.212	0.03690	0.1506	0.298
##	837	16	1	0.199	0.03689	0.1380	0.286
##	857	14	1	0.184	0.03688	0.1246	0.273
##	878	13	1	0.170	0.03667	0.1116	0.260
##	892	10	1	0.153	0.03675	0.0958	0.245
##	899	9	1	0.136	0.03639	0.0807	0.230

And also for a specific time for example the expected survival at time 100.

```
summary(surv.fit, times = 100)
```

```
## Call: survfit(formula = datas ~ 1, data = data1)
##
##   time n.risk n.event survival std.err lower 95% CI upper 95% CI
##   100    203     25    0.893  0.0203    0.854    0.933
```

Estimate crude (unadjusted) survival functions for strata

For each clinic

```
surv.clin<-survfit(datas~clinic, data = data1)
summary(surv.clin)
```

```
## Call: survfit(formula = datas ~ clinic, data = data1)
##
##               clinic=clinic1
##   time n.risk n.event survival std.err lower 95% CI upper 95% CI
##    7    162     1    0.9938 0.00615    0.98184    1.000
##   17    161     1    0.9877 0.00868    0.97080    1.000
##   19    160     1    0.9815 0.01059    0.96094    1.000
##   29    157     1    0.9752 0.01223    0.95155    0.999
##   30    156     1    0.9690 0.01366    0.94258    0.996
##   33    155     1    0.9627 0.01493    0.93390    0.992
##   35    154     1    0.9565 0.01609    0.92545    0.989
##   37    153     1    0.9502 0.01716    0.91719    0.984
##   41    152     1    0.9440 0.01815    0.90907    0.980
##   47    151     1    0.9377 0.01907    0.90107    0.976
```

##	49	150	1	0.9315	0.01994	0.89319	0.971
##	50	149	1	0.9252	0.02077	0.88540	0.967
##	59	147	1	0.9189	0.02156	0.87763	0.962
##	62	146	1	0.9126	0.02231	0.86993	0.957
##	67	144	1	0.9063	0.02304	0.86224	0.953
##	75	143	1	0.9000	0.02373	0.85462	0.948
##	84	142	1	0.8936	0.02440	0.84706	0.943
##	90	141	1	0.8873	0.02503	0.83955	0.938
##	95	140	1	0.8809	0.02564	0.83209	0.933
##	96	139	1	0.8746	0.02623	0.82467	0.928
##	117	135	1	0.8681	0.02683	0.81711	0.922
##	126	134	1	0.8616	0.02740	0.80959	0.917
##	127	133	1	0.8552	0.02795	0.80211	0.912
##	129	132	1	0.8487	0.02848	0.79467	0.906
##	136	130	1	0.8422	0.02899	0.78721	0.901
##	145	129	1	0.8356	0.02950	0.77978	0.895
##	147	128	1	0.8291	0.02998	0.77238	0.890
##	150	126	1	0.8225	0.03045	0.76495	0.884
##	157	124	1	0.8159	0.03092	0.75748	0.879
##	160	123	1	0.8093	0.03138	0.75004	0.873
##	167	121	1	0.8026	0.03182	0.74256	0.867
##	168	120	1	0.7959	0.03225	0.73512	0.862
##	175	119	1	0.7892	0.03267	0.72770	0.856
##	176	117	1	0.7824	0.03308	0.72023	0.850
##	180	116	2	0.7690	0.03385	0.70539	0.838
##	181	114	1	0.7622	0.03422	0.69801	0.832
##	183	113	1	0.7555	0.03458	0.69065	0.826
##	192	112	1	0.7487	0.03492	0.68331	0.820
##	193	111	1	0.7420	0.03525	0.67601	0.814
##	204	110	1	0.7352	0.03557	0.66872	0.808
##	205	108	1	0.7284	0.03589	0.66138	0.802
##	207	107	1	0.7216	0.03619	0.65406	0.796
##	209	106	1	0.7148	0.03648	0.64676	0.790
##	212	104	2	0.7011	0.03705	0.63207	0.778
##	216	102	1	0.6942	0.03732	0.62476	0.771
##	223	101	1	0.6873	0.03758	0.61747	0.765
##	237	100	1	0.6804	0.03783	0.61020	0.759
##	244	99	1	0.6736	0.03807	0.60295	0.752
##	247	98	1	0.6667	0.03829	0.59571	0.746
##	257	97	1	0.6598	0.03851	0.58850	0.740
##	258	96	1	0.6530	0.03872	0.58131	0.733
##	259	95	1	0.6461	0.03892	0.57413	0.727
##	262	94	2	0.6323	0.03928	0.55984	0.714
##	275	92	1	0.6255	0.03945	0.55272	0.708
##	293	90	1	0.6185	0.03962	0.54553	0.701
##	294	89	1	0.6116	0.03978	0.53836	0.695
##	299	88	1	0.6046	0.03993	0.53120	0.688
##	302	87	1	0.5977	0.04007	0.52406	0.682
##	314	86	1	0.5907	0.04020	0.51694	0.675
##	337	83	1	0.5836	0.04035	0.50964	0.668
##	341	81	1	0.5764	0.04049	0.50226	0.661
##	348	78	1	0.5690	0.04063	0.49468	0.654
##	350	77	1	0.5616	0.04077	0.48712	0.647
##	358	76	1	0.5542	0.04090	0.47958	0.640

##	367	75	1	0.5468	0.04102	0.47207	0.633
##	368	74	1	0.5394	0.04112	0.46457	0.626
##	376	73	1	0.5321	0.04122	0.45710	0.619
##	386	72	1	0.5247	0.04130	0.44964	0.612
##	393	71	1	0.5173	0.04138	0.44221	0.605
##	394	70	1	0.5099	0.04144	0.43480	0.598
##	399	69	1	0.5025	0.04149	0.42741	0.591
##	428	66	1	0.4949	0.04156	0.41978	0.583
##	434	65	1	0.4873	0.04161	0.41217	0.576
##	438	64	1	0.4797	0.04165	0.40459	0.569
##	452	62	1	0.4719	0.04169	0.39688	0.561
##	457	61	1	0.4642	0.04172	0.38921	0.554
##	465	59	1	0.4563	0.04175	0.38140	0.546
##	482	56	1	0.4482	0.04179	0.37331	0.538
##	489	55	1	0.4400	0.04182	0.36524	0.530
##	496	54	1	0.4319	0.04183	0.35719	0.522
##	504	53	1	0.4237	0.04183	0.34918	0.514
##	512	52	1	0.4156	0.04181	0.34120	0.506
##	514	51	1	0.4074	0.04177	0.33325	0.498
##	517	50	1	0.3993	0.04173	0.32532	0.490
##	518	48	1	0.3910	0.04168	0.31724	0.482
##	522	47	1	0.3826	0.04161	0.30918	0.474
##	523	46	2	0.3660	0.04143	0.29317	0.457
##	532	44	1	0.3577	0.04132	0.28521	0.449
##	533	43	1	0.3494	0.04119	0.27729	0.440
##	546	40	1	0.3406	0.04107	0.26894	0.431
##	550	39	1	0.3319	0.04094	0.26062	0.423
##	560	38	1	0.3232	0.04078	0.25235	0.414
##	563	37	1	0.3144	0.04060	0.24412	0.405
##	581	33	1	0.3049	0.04048	0.23505	0.396
##	591	31	1	0.2951	0.04035	0.22570	0.386
##	612	29	2	0.2747	0.04005	0.20644	0.366
##	624	26	1	0.2641	0.03988	0.19649	0.355
##	646	25	1	0.2536	0.03966	0.18664	0.345
##	652	24	1	0.2430	0.03939	0.17688	0.334
##	667	23	1	0.2325	0.03907	0.16722	0.323
##	679	22	1	0.2219	0.03869	0.15765	0.312
##	683	21	1	0.2113	0.03827	0.14818	0.301
##	714	20	1	0.2008	0.03778	0.13882	0.290
##	739	19	1	0.1902	0.03724	0.12957	0.279
##	749	18	1	0.1796	0.03664	0.12042	0.268
##	755	17	1	0.1691	0.03598	0.11140	0.257
##	760	16	1	0.1585	0.03525	0.10249	0.245
##	771	15	1	0.1479	0.03444	0.09372	0.233
##	774	14	1	0.1374	0.03357	0.08508	0.222
##	785	13	1	0.1268	0.03260	0.07660	0.210
##	821	10	2	0.1014	0.03062	0.05613	0.183
##	836	7	1	0.0869	0.02948	0.04474	0.169
##	837	6	1	0.0725	0.02790	0.03406	0.154
##	857	4	1	0.0543	0.02615	0.02116	0.140
##	892	3	1	0.0362	0.02286	0.01052	0.125
##	899	2	1	0.0181	0.01717	0.00283	0.116
##							
##				clinic=clinic2			

##	time	n.risk	n.event	survival	std.err	lower 95% CI	upper 95% CI
##	13	74	1	0.986	0.0134	0.961	1.000
##	26	73	1	0.973	0.0189	0.937	1.000
##	35	72	1	0.959	0.0229	0.916	1.000
##	41	71	1	0.946	0.0263	0.896	0.999
##	79	68	1	0.932	0.0294	0.876	0.991
##	109	66	1	0.918	0.0321	0.857	0.983
##	122	65	1	0.904	0.0346	0.838	0.974
##	143	64	1	0.890	0.0368	0.820	0.965
##	149	62	1	0.875	0.0389	0.802	0.955
##	161	61	1	0.861	0.0408	0.785	0.945
##	170	60	1	0.847	0.0426	0.767	0.934
##	190	59	1	0.832	0.0442	0.750	0.924
##	216	58	1	0.818	0.0457	0.733	0.913
##	231	56	1	0.803	0.0472	0.716	0.901
##	232	55	1	0.789	0.0486	0.699	0.890
##	268	54	2	0.759	0.0510	0.666	0.866
##	280	52	1	0.745	0.0520	0.650	0.854
##	286	51	1	0.730	0.0530	0.633	0.842
##	322	50	1	0.716	0.0539	0.617	0.830
##	366	47	1	0.700	0.0549	0.601	0.817
##	389	45	1	0.685	0.0558	0.584	0.804
##	450	43	1	0.669	0.0568	0.566	0.790
##	460	41	1	0.653	0.0577	0.549	0.776
##	540	35	1	0.634	0.0590	0.528	0.761
##	661	23	1	0.606	0.0625	0.495	0.742
##	708	19	1	0.575	0.0669	0.457	0.722
##	878	10	1	0.517	0.0812	0.380	0.703

For time = 100

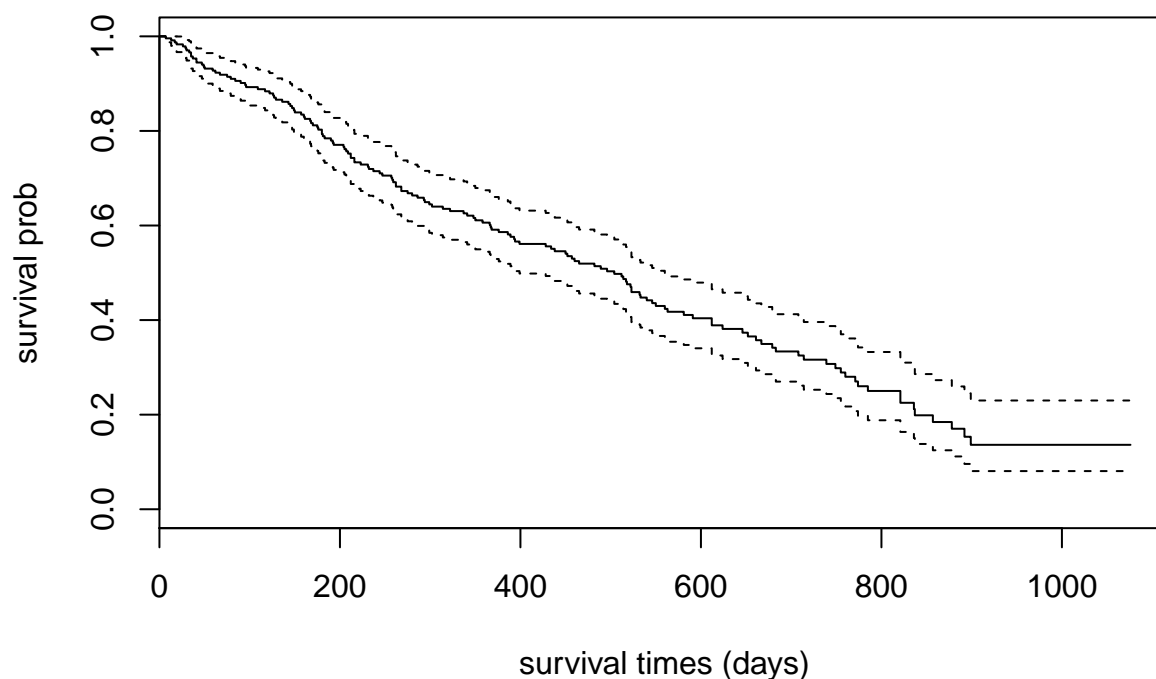
```
summary(surv.clin,times = 100)
```

```
## Call: survfit(formula = datas ~ clinic, data = data1)
##
##               clinic=clinic1
##      time      n.risk      n.event      survival      std.err
## 100.0000    137.0000    20.0000      0.8746      0.0262
## lower 95% CI upper 95% CI
##    0.8247      0.9276
##
##               clinic=clinic2
##      time      n.risk      n.event      survival      std.err
## 100.0000     66.0000      5.0000      0.9320      0.0294
## lower 95% CI upper 95% CI
##    0.8762      0.9914
```

Kaplan-Meier survival plots

We will plot the survival probability against time for all observations

```
plot(surv.fit, xlab='survival times (days)', ylab='survival prob')
```



We will plot the survival probability against time for observations based on clinic.

```
str(data1$clinic)
```

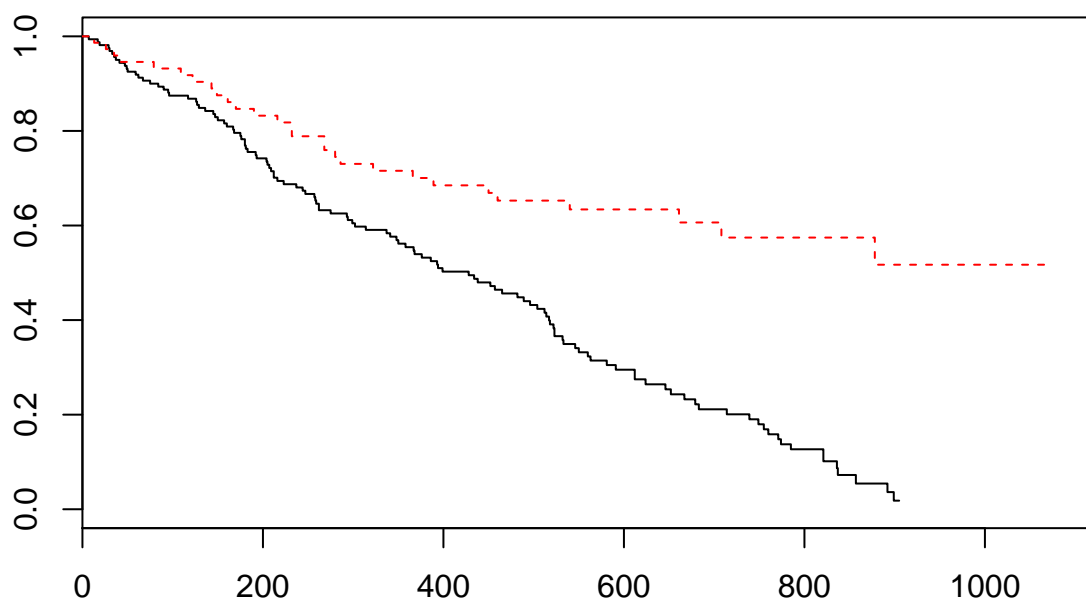
```
## Factor w/ 2 levels "clinic1","clinic2": 1 1 1 1 1 1 1 1 1 ...
```

```
str(data1$prison)
```

```
## Factor w/ 2 levels "no record","has_previous_rec": 1 2 1 1 2 1 2 2 1 2 ...
```

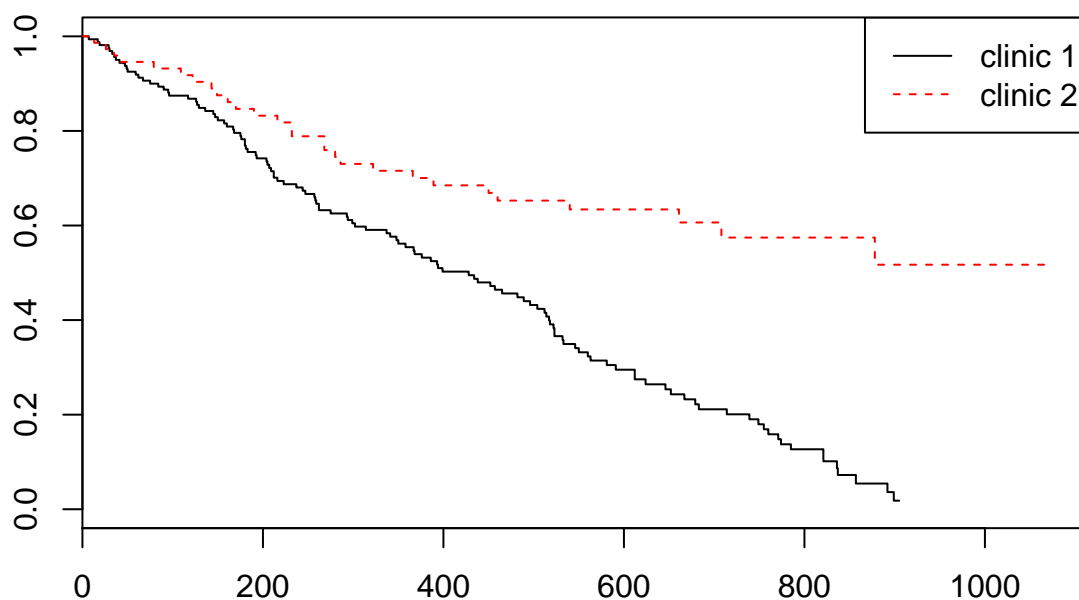
Let us plot. Note that the *solid* line and *black* color belong to clinic1 and the *dashed* line with *red* color belong to clinic2

```
plot(surv.clin, lty=c('solid','dashed'), col=c('black','red'))
```



Now, we add legend

```
plot(surv.clin, lty=c('solid','dashed'), col=c('black','red'))  
legend('topright',c('clinic 1','clinic 2'),lty=c('solid','dashed'), col=c('black','red'))
```



Inferences based on Kaplan-Meier survival estimates

The log rank test

To test for the difference in the estimated survival times by the Kaplan-Meier, the default is the log-rank test

```
survdifff(datas~clinic, data = data1)
```

```
## Call:
## survdiff(formula = datas ~ clinic, data = data1)
##
##               N Observed Expected (O-E)^2/E (O-E)^2/V
## clinic=clinic1 163      122    90.9      10.6      27.9
## clinic=clinic2  75       28    59.1      16.4      27.9
##
##  Chisq= 27.9  on 1 degrees of freedom, p= 1.28e-07
```

Estimation using the Semi-parametric method

The most common semi-parametric method to estimate the survival probability is the Cox proportional hazard regression model

The Cox PH model

Efron is default method in R to estimate the survival based on the Cox PH model

```
data1.cox <- coxph(datas ~ prison + dose + clinic, data = data1)
summary(data1.cox)
```

```
## Call:
## coxph(formula = datas ~ prison + dose + clinic, data = data1)
##
##      n= 238, number of events= 150
##
##              coef exp(coef)  se(coef)      z Pr(>|z|)
## prisonhas_previous_rec  0.326555  1.386184  0.167225  1.953  0.0508 .
## dose                    -0.035369  0.965249  0.006379 -5.545 2.94e-08 ***
## clinicclinic2           -1.009896  0.364257  0.214889 -4.700 2.61e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##              exp(coef) exp(-coef) lower .95 upper .95
## prisonhas_previous_rec  1.3862    0.7214    0.9988    1.9238
## dose                    0.9652    1.0360    0.9533    0.9774
## clinicclinic2           0.3643    2.7453    0.2391    0.5550
##
## Concordance= 0.665  (se = 0.026 )
## Rsquare= 0.238  (max possible= 0.997 )
## Likelihood ratio test= 64.56  on 3 df,   p=6.228e-14
## Wald test               = 54.12  on 3 df,   p=1.056e-11
## Score (logrank) test = 56.32  on 3 df,   p=3.598e-12
```

column **z** is the ratio between each regression coefficient to its SE. It is a Wald statistic which is asymptotically standard normal under the hypothesis that the corresponding beta is 0.

Other alternatives = Breslow , Exact

Exponentiated coefficients in the second column of the first panel (and in the first column of the second panel) of the output are interpretable as multiplicative effects on the hazard or simply as **Hazard Ratio**

Estimated distribution of survival times based on Cox PH model

The survfit function estimates $S(t)$, by default at the **mean values of the covariates**.

```
survfit(data1.cox)
```

```
## Call: survfit(formula = data1.cox)
##
##      n  events  median 0.95LCL 0.95UCL
##    238    150    518    452    591
```

```
summary(survfit(data1.cox))
```

```
## Call: survfit(formula = data1.cox)
##
##   time n.risk n.event survival std.err lower 95% CI upper 95% CI
##    7     236      1   0.9967 0.00334    0.9901      1.000
##   13     235      1   0.9933 0.00475    0.9840      1.000
##   17     234      1   0.9899 0.00582    0.9786      1.000
```

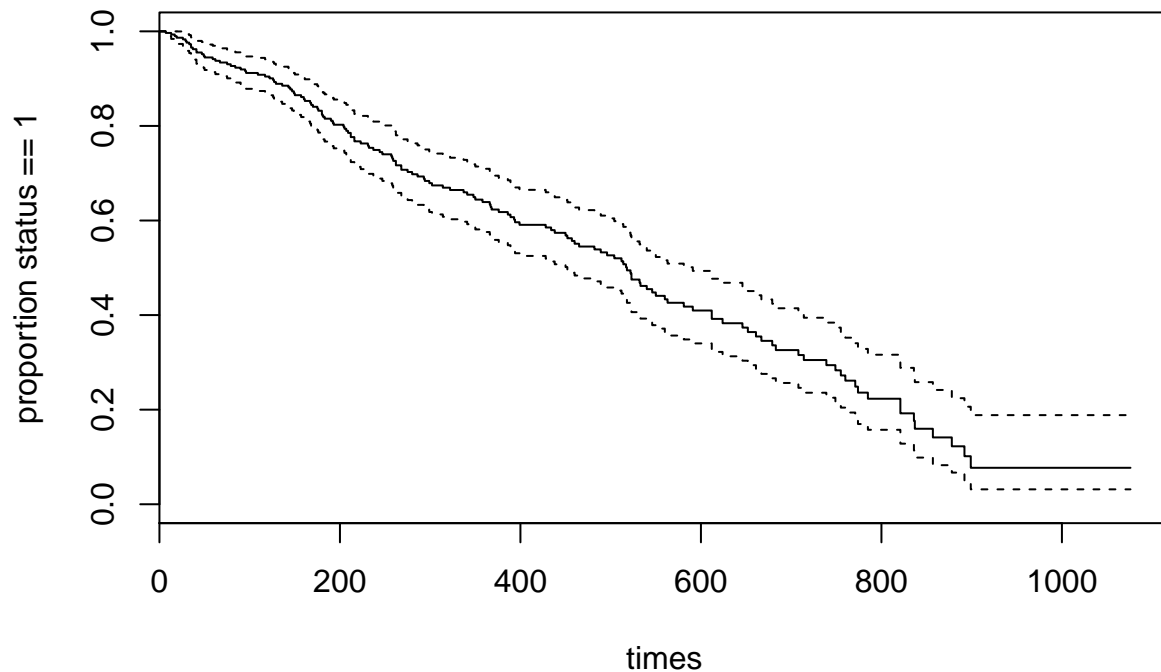
##	19	233	1	0.9865	0.00673	0.9734	1.000
##	26	232	1	0.9831	0.00755	0.9684	0.998
##	29	229	1	0.9797	0.00830	0.9635	0.996
##	30	228	1	0.9762	0.00899	0.9587	0.994
##	33	227	1	0.9727	0.00964	0.9540	0.992
##	35	226	2	0.9658	0.01081	0.9448	0.987
##	37	224	1	0.9623	0.01135	0.9403	0.985
##	41	223	2	0.9553	0.01237	0.9314	0.980
##	47	221	1	0.9518	0.01284	0.9270	0.977
##	49	220	1	0.9483	0.01331	0.9226	0.975
##	50	219	1	0.9448	0.01375	0.9182	0.972
##	59	216	1	0.9413	0.01419	0.9139	0.970
##	62	215	1	0.9377	0.01462	0.9095	0.967
##	67	213	1	0.9341	0.01505	0.9051	0.964
##	75	211	1	0.9305	0.01548	0.9006	0.961
##	79	210	1	0.9268	0.01589	0.8962	0.958
##	84	209	1	0.9231	0.01629	0.8918	0.956
##	90	207	1	0.9194	0.01669	0.8873	0.953
##	95	206	1	0.9157	0.01708	0.8829	0.950
##	96	205	1	0.9120	0.01747	0.8784	0.947
##	109	202	1	0.9082	0.01785	0.8739	0.944
##	117	200	1	0.9044	0.01823	0.8694	0.941
##	122	199	1	0.9006	0.01861	0.8648	0.938
##	126	198	1	0.8968	0.01898	0.8603	0.935
##	127	197	1	0.8929	0.01933	0.8558	0.932
##	129	196	1	0.8890	0.01969	0.8513	0.928
##	136	194	1	0.8851	0.02006	0.8466	0.925
##	143	193	1	0.8811	0.02041	0.8420	0.922
##	145	192	1	0.8771	0.02076	0.8373	0.919
##	147	190	1	0.8731	0.02110	0.8327	0.915
##	149	188	1	0.8691	0.02145	0.8280	0.912
##	150	187	1	0.8650	0.02178	0.8234	0.909
##	157	185	1	0.8610	0.02211	0.8187	0.905
##	160	184	1	0.8569	0.02243	0.8141	0.902
##	161	183	1	0.8528	0.02276	0.8094	0.899
##	167	181	1	0.8487	0.02308	0.8047	0.895
##	168	180	1	0.8446	0.02339	0.8000	0.892
##	170	179	1	0.8405	0.02370	0.7953	0.888
##	175	178	1	0.8363	0.02400	0.7906	0.885
##	176	176	1	0.8322	0.02430	0.7859	0.881
##	180	175	2	0.8238	0.02490	0.7764	0.874
##	181	173	1	0.8196	0.02519	0.7717	0.870
##	183	172	1	0.8154	0.02547	0.7669	0.867
##	190	171	1	0.8111	0.02576	0.7621	0.863
##	192	170	1	0.8068	0.02604	0.7574	0.860
##	193	169	1	0.8026	0.02631	0.7526	0.856
##	204	168	1	0.7983	0.02658	0.7479	0.852
##	205	166	1	0.7940	0.02685	0.7431	0.848
##	207	165	1	0.7896	0.02712	0.7382	0.845
##	209	164	1	0.7853	0.02738	0.7334	0.841
##	212	162	2	0.7764	0.02791	0.7235	0.833
##	216	160	2	0.7674	0.02843	0.7136	0.825
##	223	157	1	0.7629	0.02868	0.7087	0.821
##	231	156	1	0.7583	0.02893	0.7036	0.817

##	232	155	1	0.7537	0.02918	0.6986	0.813
##	237	154	1	0.7492	0.02942	0.6937	0.809
##	244	153	1	0.7446	0.02966	0.6887	0.805
##	247	152	1	0.7400	0.02989	0.6837	0.801
##	257	151	1	0.7354	0.03012	0.6787	0.797
##	258	150	1	0.7308	0.03035	0.6737	0.793
##	259	149	1	0.7261	0.03057	0.6686	0.789
##	262	148	2	0.7167	0.03101	0.6584	0.780
##	268	146	2	0.7073	0.03143	0.6483	0.772
##	275	144	1	0.7026	0.03163	0.6432	0.767
##	280	143	1	0.6978	0.03183	0.6382	0.763
##	286	141	1	0.6931	0.03203	0.6331	0.759
##	293	140	1	0.6884	0.03222	0.6280	0.755
##	294	139	1	0.6836	0.03241	0.6230	0.750
##	299	138	1	0.6789	0.03259	0.6179	0.746
##	302	137	1	0.6742	0.03277	0.6129	0.742
##	314	136	1	0.6694	0.03295	0.6078	0.737
##	322	134	1	0.6645	0.03313	0.6027	0.733
##	337	131	1	0.6596	0.03331	0.5974	0.728
##	341	129	1	0.6546	0.03349	0.5921	0.724
##	348	126	1	0.6494	0.03369	0.5866	0.719
##	350	125	1	0.6442	0.03388	0.5811	0.714
##	358	124	1	0.6390	0.03406	0.5756	0.709
##	366	122	1	0.6338	0.03424	0.5701	0.705
##	367	121	1	0.6285	0.03442	0.5645	0.700
##	368	119	1	0.6232	0.03460	0.5590	0.695
##	376	118	1	0.6179	0.03477	0.5533	0.690
##	386	117	1	0.6125	0.03494	0.5477	0.685
##	389	116	1	0.6071	0.03511	0.5420	0.680
##	393	115	1	0.6017	0.03526	0.5364	0.675
##	394	114	1	0.5963	0.03542	0.5308	0.670
##	399	112	1	0.5909	0.03557	0.5251	0.665
##	428	109	1	0.5852	0.03573	0.5192	0.660
##	434	108	1	0.5796	0.03589	0.5134	0.654
##	438	107	1	0.5739	0.03604	0.5075	0.649
##	450	105	1	0.5682	0.03619	0.5015	0.644
##	452	104	1	0.5625	0.03633	0.4956	0.638
##	457	102	1	0.5568	0.03646	0.4897	0.633
##	460	101	1	0.5509	0.03660	0.4836	0.628
##	465	99	1	0.5450	0.03674	0.4775	0.622
##	482	96	1	0.5389	0.03688	0.4712	0.616
##	489	95	1	0.5326	0.03703	0.4648	0.610
##	496	94	1	0.5264	0.03716	0.4583	0.604
##	504	92	1	0.5201	0.03729	0.4519	0.599
##	512	91	1	0.5137	0.03742	0.4454	0.593
##	514	90	1	0.5074	0.03753	0.4389	0.587
##	517	89	1	0.5011	0.03763	0.4325	0.581
##	518	87	1	0.4946	0.03774	0.4259	0.574
##	522	86	1	0.4881	0.03784	0.4193	0.568
##	523	85	2	0.4752	0.03800	0.4062	0.556
##	532	80	1	0.4684	0.03810	0.3994	0.549
##	533	78	1	0.4617	0.03820	0.3926	0.543
##	540	77	1	0.4549	0.03828	0.3857	0.536
##	546	74	1	0.4478	0.03837	0.3786	0.530

##	550	73	1	0.4407	0.03845	0.3714	0.523
##	560	70	1	0.4334	0.03854	0.3640	0.516
##	563	69	1	0.4260	0.03861	0.3567	0.509
##	581	62	1	0.4179	0.03875	0.3485	0.501
##	591	59	1	0.4096	0.03888	0.3401	0.493
##	612	54	2	0.3919	0.03922	0.3221	0.477
##	624	51	1	0.3828	0.03939	0.3129	0.468
##	646	48	1	0.3735	0.03954	0.3035	0.460
##	652	47	1	0.3641	0.03967	0.2941	0.451
##	661	46	1	0.3548	0.03976	0.2848	0.442
##	667	45	1	0.3455	0.03982	0.2756	0.433
##	679	44	1	0.3360	0.03986	0.2663	0.424
##	683	43	1	0.3260	0.03991	0.2565	0.414
##	708	39	1	0.3155	0.03997	0.2461	0.404
##	714	37	1	0.3049	0.04001	0.2358	0.394
##	739	35	1	0.2941	0.04004	0.2252	0.384
##	749	34	1	0.2832	0.04001	0.2147	0.374
##	755	33	1	0.2724	0.03992	0.2043	0.363
##	760	32	1	0.2613	0.03979	0.1939	0.352
##	771	28	1	0.2487	0.03985	0.1816	0.340
##	774	27	1	0.2360	0.03981	0.1696	0.328
##	785	26	1	0.2231	0.03969	0.1574	0.316
##	821	20	2	0.1922	0.03980	0.1281	0.288
##	836	17	1	0.1764	0.03954	0.1137	0.274
##	837	16	1	0.1596	0.03917	0.0987	0.258
##	857	14	1	0.1413	0.03869	0.0826	0.242
##	878	13	1	0.1225	0.03778	0.0669	0.224
##	892	10	1	0.1016	0.03671	0.0500	0.206
##	899	9	1	0.0771	0.03516	0.0315	0.188

The plot method for objects returned by `survfit` graphs the estimated survival function, along with a point-wise 95-percent confidence band.

```
plot(survfit(data1.cox),
     xlab = 'times', ylab = 'proportion status == 1')
```



Checking the PH assumption

Tests and graphical diagnostics for proportional hazards may be based on the scaled Schoenfeld residuals; these can be obtained directly as `residuals(model, "scaledsch")`, where `model` is a `coxph` model object. The matrix returned by `residuals` has one column for each covariate in the model. More conveniently, the `cox.zph` function calculates tests of the proportional-hazards assumption for each covariate, by correlating the corresponding set of scaled Schoenfeld residuals

Using graphical methods

We will use `cox.zph`

It computes a test for each covariate, along with a global test for the model as a whole

```
cox.zph(data1.cox)
```

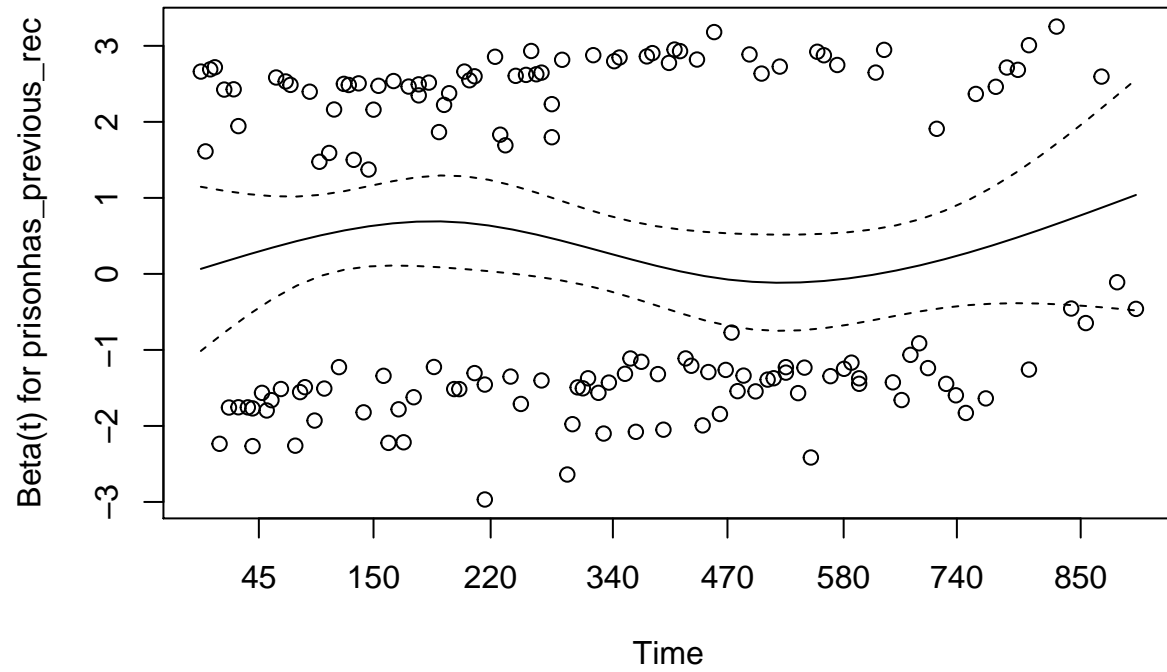
```
##               rho chisq      p
## prisonhas_previous_rec -0.0382  0.22 0.639369
## dose                   0.0724  0.70 0.402749
## clinicclinic2         -0.2578 11.19 0.000824
## GLOBAL                 NA 12.62 0.005546
```

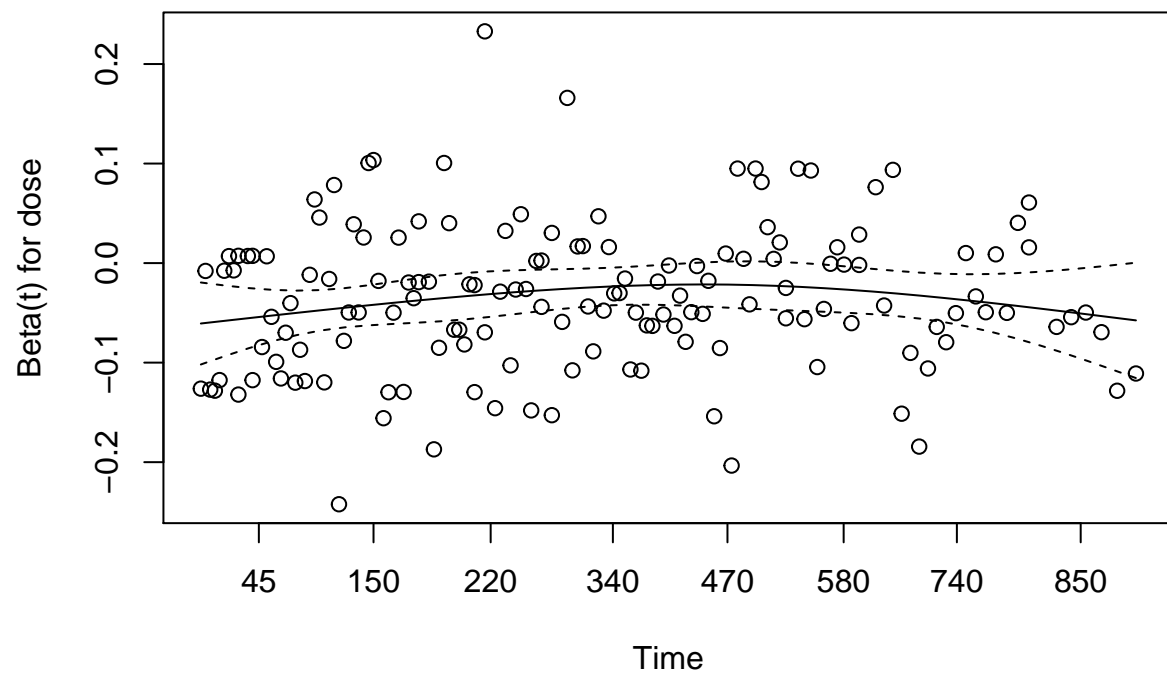
Strong evidence of non-proportional hazards for the whole model and for covariate `age`

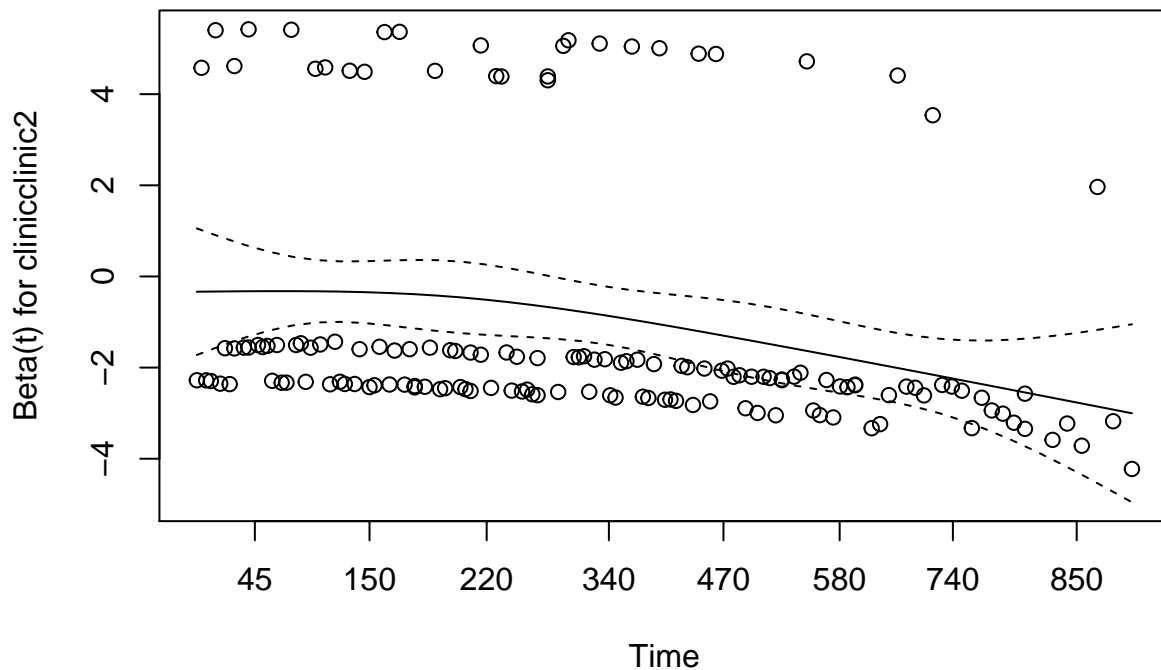
Get the detailed plots after `cox.zph`. Plotting the object returned by `cox.zph` produces graphs of the scaled Schoenfeld residuals against transformed time. Systematic departures from a horizontal line are indicative of

non-proportional hazards.

```
plot(cox.zph(data1.cox))
```







Modification if a model violates PH assumption

An alternative to incorporating an interaction in the model is to divide the data into strata based on the value of one or more covariates. Each stratum is permitted to have a different baseline hazard function, while the coefficients of the remaining covariates are assumed to be constant across strata. An advantage of this approach is that we do not have to assume a particular form of interaction between the stratifying covariates and time. A disadvantage is the resulting inability to examine the effects of the stratifying covariates. Stratification is most natural when a covariate takes on only a few distinct values, and when the effect of the stratifying variable is not of direct interest

Run, the strata argument for clinic (which has threaten the proportionality)

```
str.cox <- coxph(datas ~ prison + dose + strata(clinic),
                 data = data1)
summary(str.cox)
```

```
## Call:
## coxph(formula = datas ~ prison + dose + strata(clinic), data = data1)
##
##   n= 238, number of events= 150
##
##               coef exp(coef)  se(coef)      z Pr(>|z|)
## prisonhas_previous_rec  0.389605  1.476397  0.168930  2.306  0.0211 *
## dose                    -0.035115  0.965495  0.006465 -5.432 5.59e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
##               exp(coef) exp(-coef) lower .95 upper .95
## prisonhas_previous_rec  1.4764    0.6773    1.0603    2.0559
## dose                    0.9655    1.0357    0.9533    0.9778
##
## Concordance= 0.651  (se = 0.034 )
## Rsquare= 0.133   (max possible= 0.994 )
## Likelihood ratio test= 33.91  on 2 df,   p=4.322e-08
## Wald test            = 32.66  on 2 df,   p=8.076e-08
## Score (logrank) test = 33.33  on 2 df,   p=5.774e-08
```

Any existing violation of PH assumption

```
cox.zph(str.cox)
```

```
##               rho  chisq    p
## prisonhas_previous_rec -0.0205 0.0628 0.802
## dose                   0.0860 0.9953 0.318
## GLOBAL                  NA 1.0186 0.601
```

Nope. All are good. All fulfill PH assumption.

Cox PH model with interaction term

Read page 197 and 198 Applied Survival Analysis by Hosmer and Lemeshow.

Prediction

Predict relative risk

We use `predict.coxph` to predict the outcomes after running the Cox PH model. For example to obtain the relative risk; that is the risk of population of interest (with a set of covariates) against the population average, we can use these:

```
pred_risk <- predict(data1.cox, type = 'risk')
cbind(head(data1[, c('prison', 'dose', 'clinic')]),
      head(pred_risk))
```

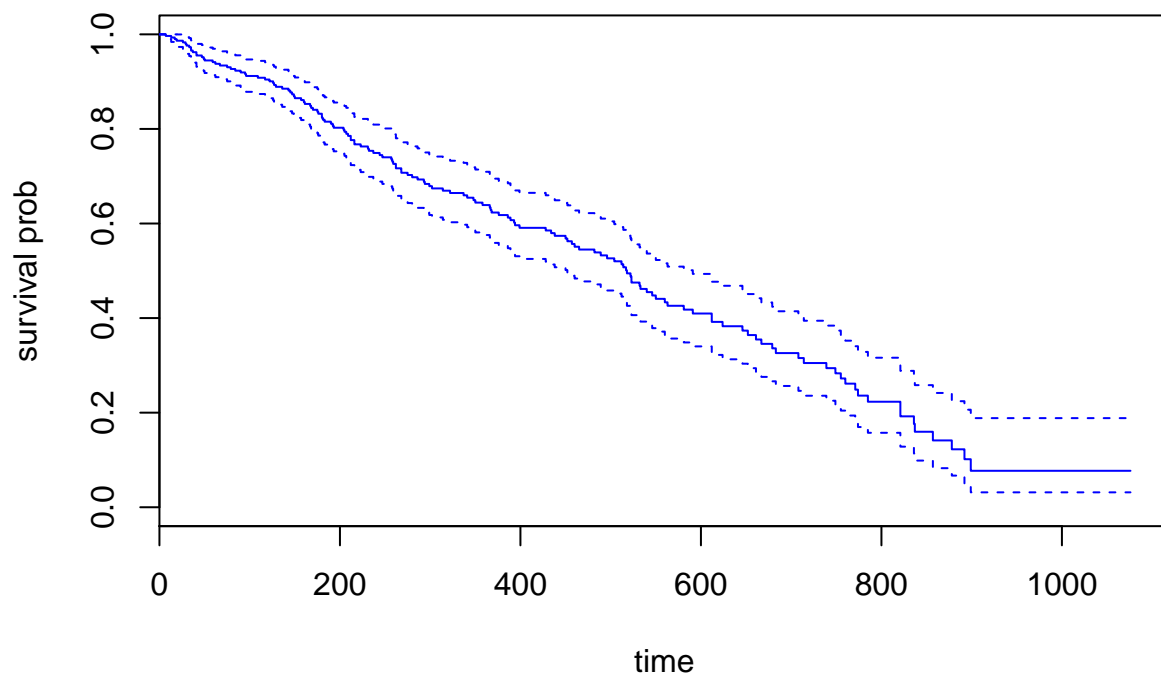
```
##           prison dose  clinic head(pred_risk)
## 1          no record  50 clinic1          1.705322
## 2 has_previous_rec  55 clinic1          1.980725
## 3          no record  55 clinic1          1.428904
## 4          no record  30 clinic1          3.459550
## 5 has_previous_rec  65 clinic1          1.390649
## 6          no record  55 clinic1          1.428904
```

Plot the expected survival probability after Cox model

We can plot the survival probability against time based on the Cox PH model

```
plot(survfit(data1.cox), col=4,
     xlab = 'time', ylab = 'survival prob', main = 'survival prob against time based on Cox model')
```

survival prob against time based on Cox model

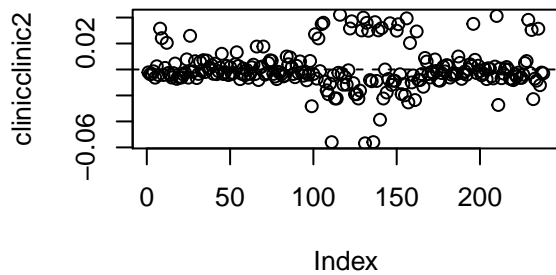
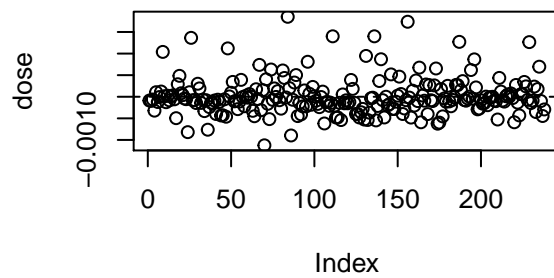
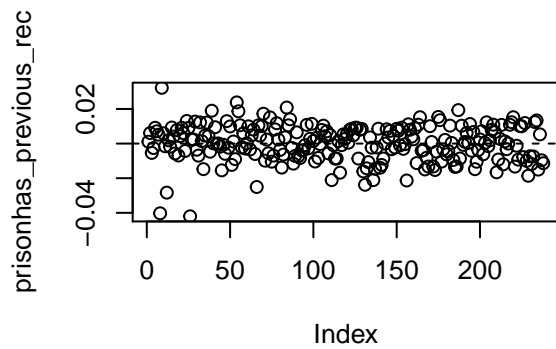


Model assessment

Influential observation

Check the dfbeta values

```
dfbeta <- residuals(data1.cox, type="dfbeta")
par(mfrow=c(2, 2))
for (j in 1:3) {plot(dfbeta[, j], ylab=names(coef(data1.cox))[j])
abline(h=0, lty=2)
}
```



Summarize the dfbetas values

```
names(coef(data1.cox))
```

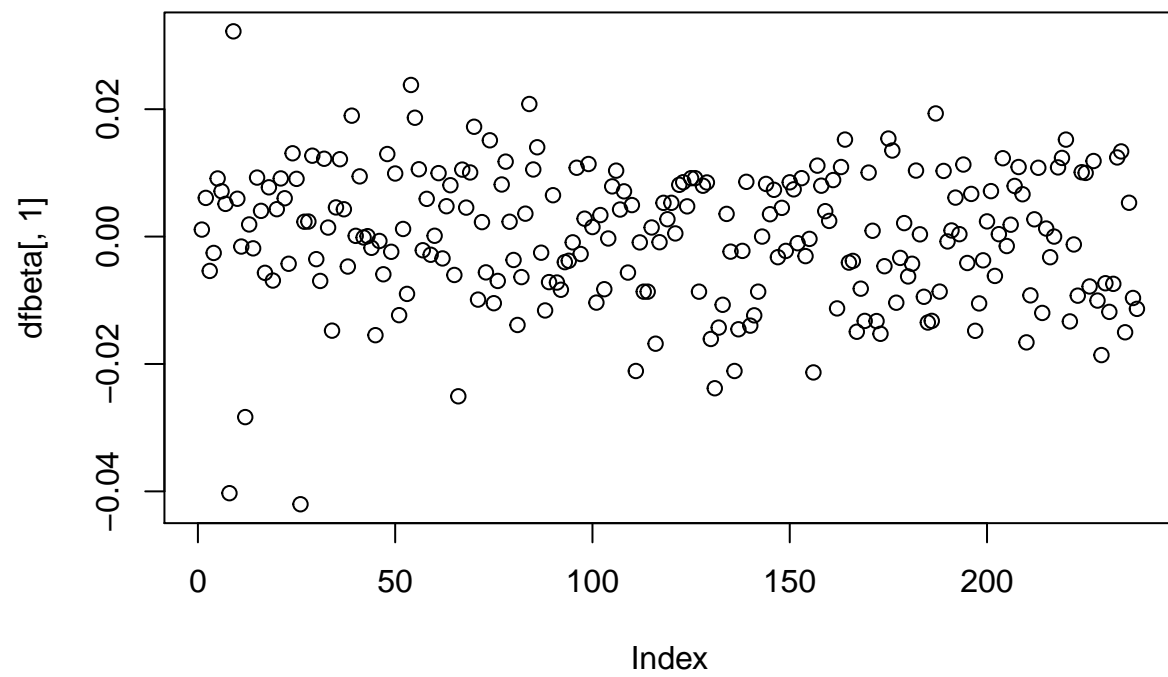
```
## [1] "prisonhas_previous_rec" "dose"
## [3] "clinicclinic2"
```

```
summary(dfbeta)
```

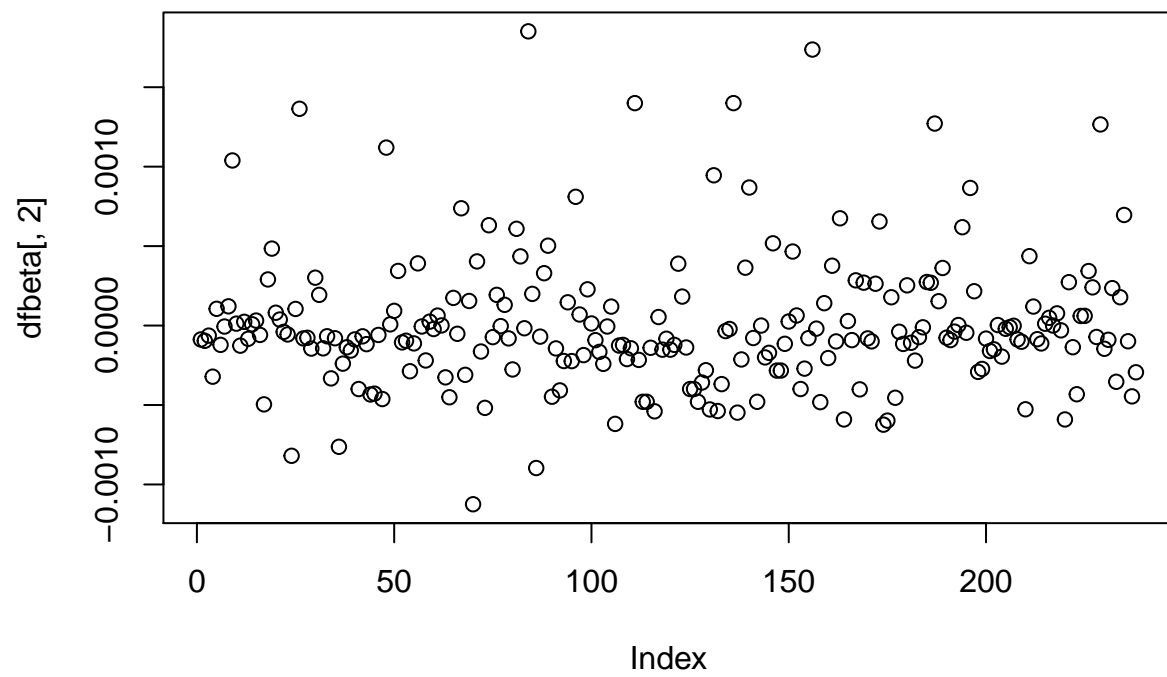
##	V1	V2	V3
## Min.	:-0.0420194	Min. :-1.124e-03	Min. :-0.056857
## 1st Qu.	:-0.0069652	1st Qu.: -2.093e-04	1st Qu.: -0.006397
## Median	: 0.0004387	Median : -7.285e-05	Median : -0.002787
## Mean	: 0.0000000	Mean : 0.000e+00	Mean : 0.000000
## 3rd Qu.	: 0.0081117	3rd Qu.: 1.282e-04	3rd Qu.: 0.003349
## Max.	: 0.0322183	Max. : 1.851e-03	Max. : 0.042105

Plot the dfbetas values

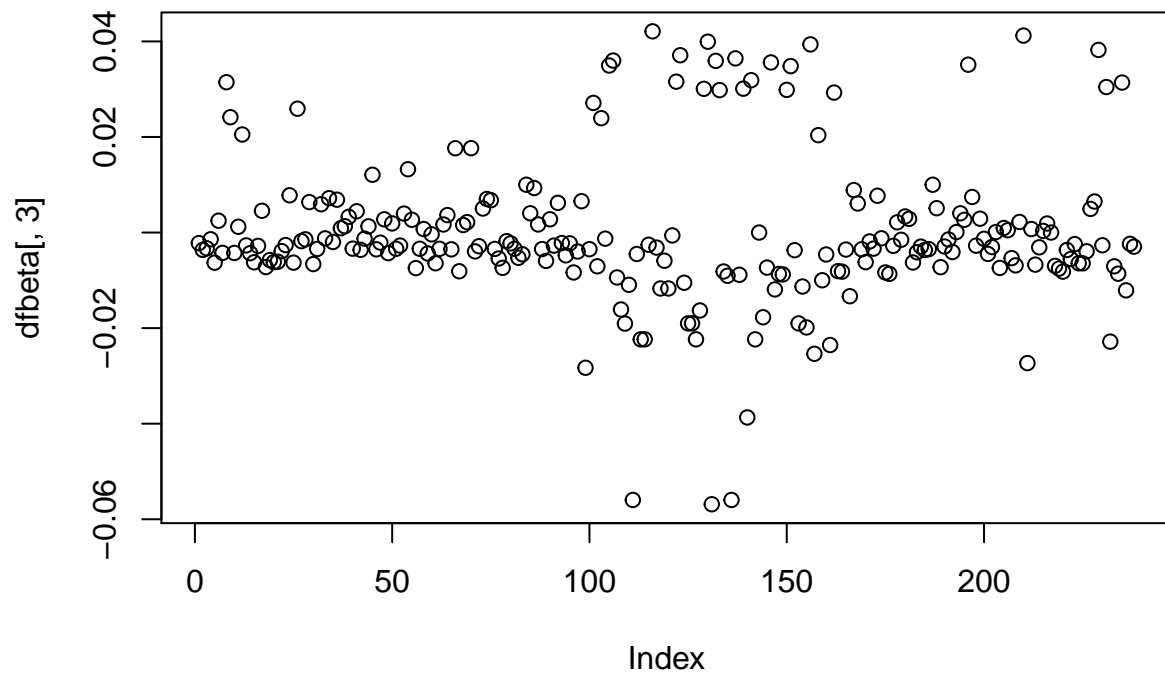
```
plot(dfbeta[,1]) #prison
```

```
plot(dfbeta[,2]) #dose
```



```
plot(dfbeta[,3]) #clinic
```

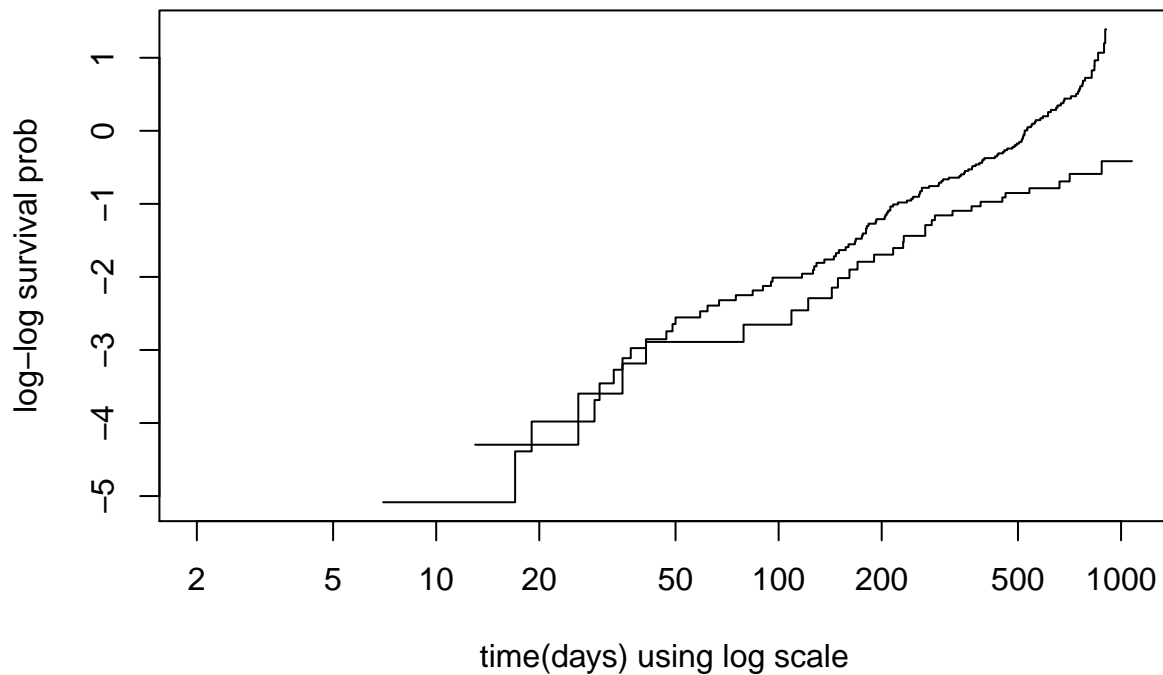


Additional tutorial

method 1

```
plot(surv.clin, fun='cloglog',  
     xlab='time(days) using log scale', ylab='log-log survival prob',  
     main='log-log curves by clinics')
```

log-log curves by clinics



Looks the curves cross each other. This indicate model violate PH assumption

Using statistical test

```
test.ph <- coxph(datas ~ prison + dose + clinic, data = data1)
test.ph2 <- cox.zph(test.ph, transform = rank)
test.ph2
```

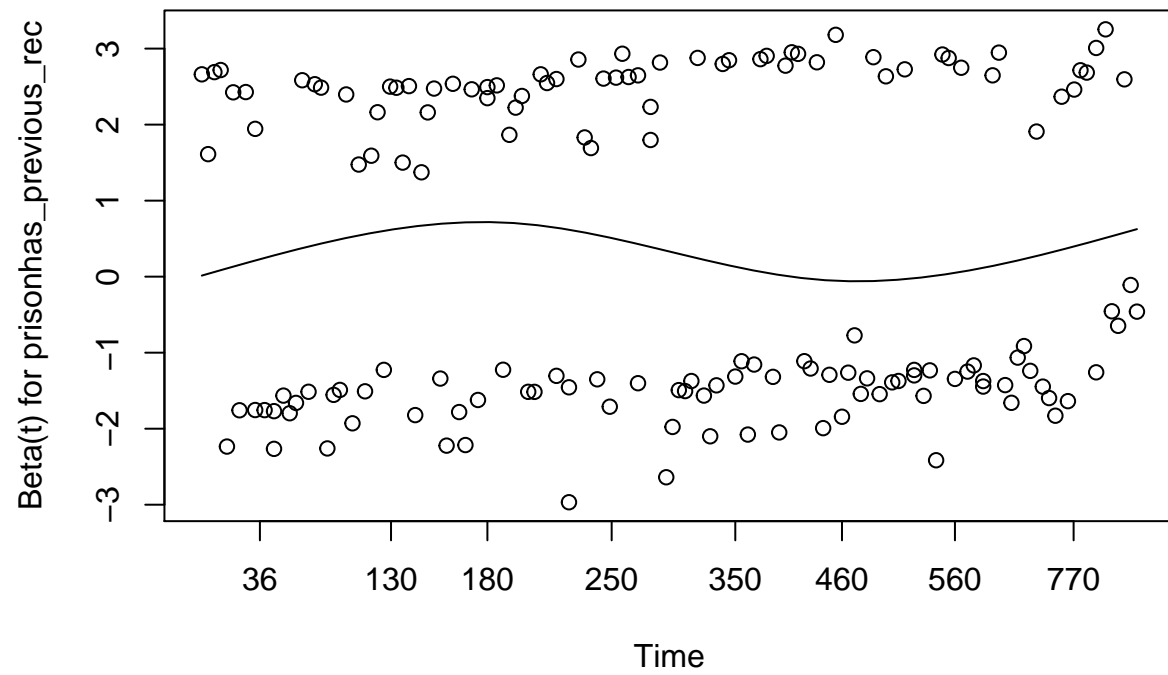
```
##               rho  chisq      p
## prisonhas_previous_rec -0.0462  0.322 0.57068
## dose                   0.0905  1.096 0.29521
## clinicclinic2          -0.2498 10.495 0.00120
## GLOBAL                 NA 12.425 0.00606
```

```
# var = clinic means residuals should pertain to the variable clinic
plot(test.ph2, se=FALSE, vsr = "clinic")
```

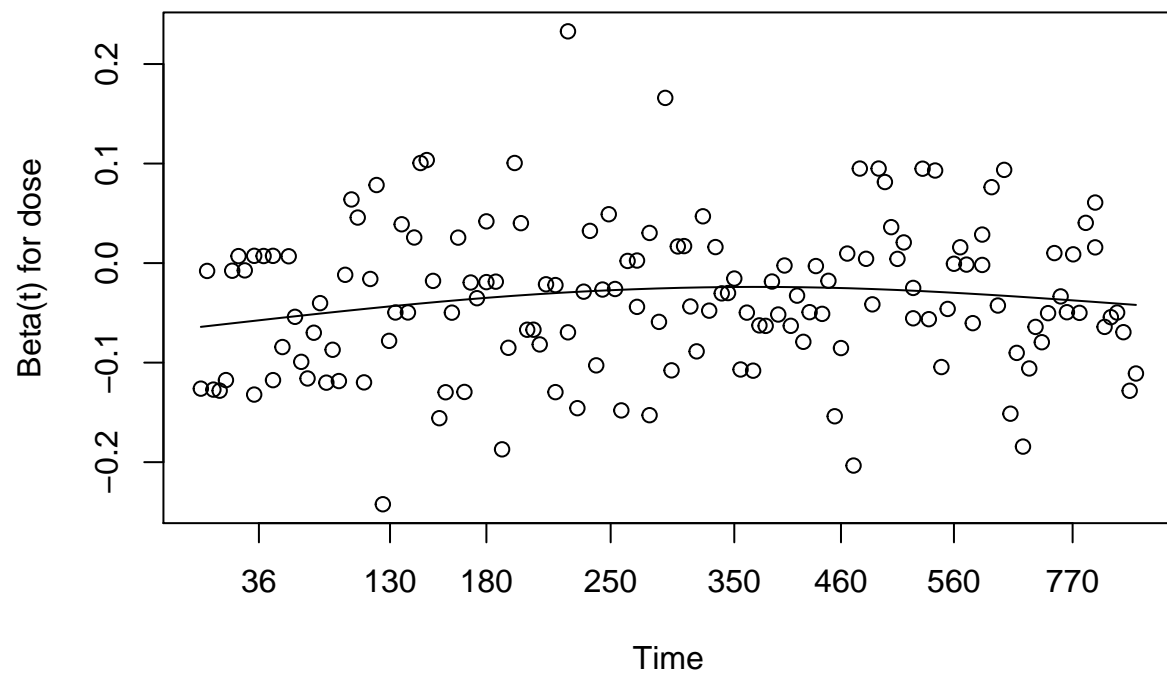
```
## Warning in plot.window(...): "vsr" is not a graphical parameter
```

```
## Warning in plot.xy(xy, type, ...): "vsr" is not a graphical parameter
```

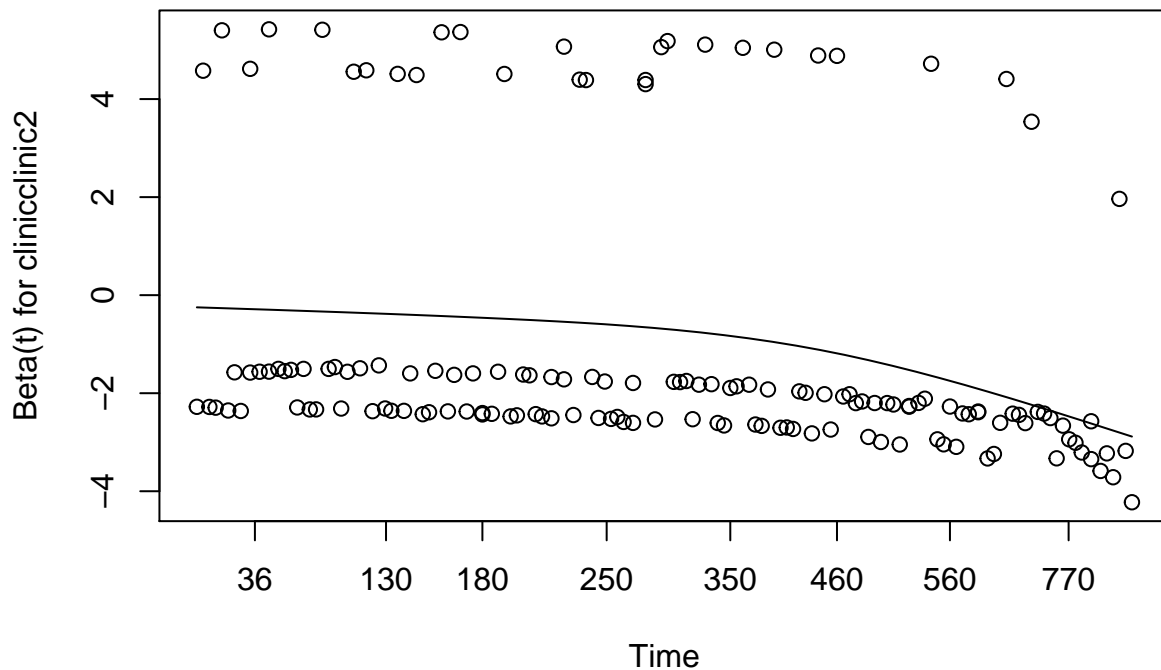
```
## Warning in title(...): "vsr" is not a graphical parameter
```



```
## Warning in plot.window(...): "vsr" is not a graphical parameter
## Warning in plot.xy(xy, type, ...): "vsr" is not a graphical parameter
## Warning in title(...): "vsr" is not a graphical parameter
```



```
## Warning in plot.window(...): "vsr" is not a graphical parameter
## Warning in plot.xy(xy, type, ...): "vsr" is not a graphical parameter
## Warning in title(...): "vsr" is not a graphical parameter
```



Running stratified Cox model

When models violate PH assumption. in our case, 'clinic' does violate PH assumption but others are not. So we do stratified Cox model

```
surv.strata <- coxph(datas ~ prison + dose + strata(clinic), data = data1)
summary(surv.strata)
```

```
## Call:
## coxph(formula = datas ~ prison + dose + strata(clinic), data = data1)
##
##   n= 238, number of events= 150
##
##               coef exp(coef)  se(coef)      z Pr(>|z|)
## prisonhas_previous_rec  0.389605  1.476397  0.168930  2.306   0.0211 *
## dose                   -0.035115  0.965495  0.006465 -5.432 5.59e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##               exp(coef) exp(-coef) lower .95 upper .95
## prisonhas_previous_rec    1.4764    0.6773    1.0603    2.0559
## dose                      0.9655    1.0357    0.9533    0.9778
##
## Concordance= 0.651  (se = 0.034 )
## Rsquare= 0.133   (max possible= 0.994 )
```

```
## Likelihood ratio test= 33.91 on 2 df, p=4.322e-08
## Wald test = 32.66 on 2 df, p=8.076e-08
## Score (logrank) test = 33.33 on 2 df, p=5.774e-08
```

Running stratified Cox model with interaction

```
surv.strata.ia <- coxph(datas ~ prison + dose + clinic:dose + clinic:prison + strata(clinic), data=data1)
summary(surv.strata.ia)
```

```
## Call:
## coxph(formula = datas ~ prison + dose + clinic:dose + clinic:prison +
##       strata(clinic), data = data1)
##
## n= 238, number of events= 150
##
##               coef exp(coef) se(coef)      z
## prisonhas_previous_rec      0.502846  1.653421  0.188706  2.665
## dose                    -0.035799  0.964834  0.007738 -4.626
## dose:clinicclinic2      -0.001164  0.998837  0.014570 -0.080
## prisonhas_previous_rec:clinicclinic2 -0.582989  0.558227  0.428135 -1.362
##
##               Pr(>|z|)
## prisonhas_previous_rec      0.00771 **
## dose                    3.72e-06 ***
## dose:clinicclinic2      0.93632
## prisonhas_previous_rec:clinicclinic2  0.17329
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##               exp(coef) exp(-coef) lower .95
## prisonhas_previous_rec      1.6534      0.6048      1.1422
## dose                    0.9648      1.0364      0.9503
## dose:clinicclinic2      0.9988      1.0012      0.9707
## prisonhas_previous_rec:clinicclinic2  0.5582      1.7914      0.2412
##
##               upper .95
## prisonhas_previous_rec      2.3934
## dose                    0.9796
## dose:clinicclinic2      1.0278
## prisonhas_previous_rec:clinicclinic2  1.2919
##
## Concordance= 0.649 (se = 0.034 )
## Rsquare= 0.14 (max possible= 0.994 )
## Likelihood ratio test= 35.77 on 4 df, p=3.222e-07
## Wald test = 34.09 on 4 df, p=7.138e-07
## Score (logrank) test = 34.97 on 4 df, p=4.706e-07
```

Calculating the HR

If we want to calculate the HR between PRISON=1 vs PRISON=0 for CLINIC=2, then one way is by making CLINIC equals 0. So when CLINIC==2, then CLINIC2==0.

```
data1$clinic2<- (as.numeric(data1$clinic)) - 1
summary(data1$clinic2)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
```



```
## 0.0000 0.0000 0.0000 0.3151 1.0000 1.0000
head(as.numeric(data1$clinic))

## [1] 1 1 1 1 1 1

surv.strata.ia2 <- coxph(datas ~ prison + dose + clinic2:dose + clinic2:(as.numeric(prison)) +
                        strata(clinic2),data=data1)
summary(surv.strata.ia2)

## Call:
## coxph(formula = datas ~ prison + dose + clinic2:dose + clinic2:(as.numeric(prison)) +
##       strata(clinic2), data = data1)
##
##      n= 238, number of events= 150
##
##              coef exp(coef)    se(coef)      z Pr(>|z|)
## prisonhas_previous_rec    0.502846  1.653421  0.188706  2.665  0.00771
## dose                    -0.035799  0.964834  0.007738 -4.626 3.72e-06
## dose:clinic2             -0.001164  0.998837  0.014570 -0.080  0.93632
## clinic2:as.numeric(prison) -0.582989  0.558227  0.428135 -1.362  0.17329
##
## prisonhas_previous_rec    **
## dose                      ***
## dose:clinic2
## clinic2:as.numeric(prison)
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##              exp(coef) exp(-coef) lower .95 upper .95
## prisonhas_previous_rec    1.6534    0.6048    1.1422    2.3934
## dose                    0.9648    1.0364    0.9503    0.9796
## dose:clinic2             0.9988    1.0012    0.9707    1.0278
## clinic2:as.numeric(prison) 0.5582    1.7914    0.2412    1.2919
##
## Concordance= 0.649 (se = 0.034 )
## Rsquare= 0.14 (max possible= 0.994 )
## Likelihood ratio test= 35.77 on 4 df,  p=3.222e-07
## Wald test               = 34.09 on 4 df,  p=7.138e-07
## Score (logrank) test = 34.97 on 4 df,  p=4.706e-07
```

References:

1. <https://socserv.socsci.mcmaster.ca/jfox/Books/Companion/appendix/Appendix-Cox-Regression.pdf>
2. Reference for calculating the relative risk <http://stats.stackexchange.com/questions/44896/how-to-interpret-the-output-of-predict-coxph>
3. Another reference for predicting the outcomes after Cox model <http://datamining.togaware.com/survivor/Lung1.html>