

Simulated examples for the survival ensemble methods

Select data type

ELSA_Diabetes_Study2 ▼

Time point for event prediction:

10

Random seed for calibration and validation

42

K_Outer loop CV (for validation)

3

K_inner CV folds (model tuning)

3

Simulated data: random seed (generation):

4242

Sample size:

150

Observation time

5

Expected event prevalence by study end

0.5

Expected drop out rate

0.3

Custom data: path to data file

~/Desktop/Study_KCL/PhD P

Predictors to use in the model

"baseline_age_", "genderdun

Time variable name

time

Event indicator variable name

event

Sample statistics

CoxPH

SRF

Ens1: CoxPH->SRF

Ens2: CoxPH in clusters

Ens3: extended CoxPH

Summary

Conclusions

Internally cross-validated results:

Show 25 entries

Search:

	AUCROC	BS	BS_scaled	C_score	Calib_slope	Calib_alpha	T
test	0.778	0.0769	0.1017	0.7468	1.0648	0.046	10
train	0.7909	0.0754	0.1195	0.7567	1.1225	0.045	10

Showing 1 to 2 of 2 entries

Previous

1

Next

Internally cross-validated Test results for each CV fold:

Show 25 entries

Search:

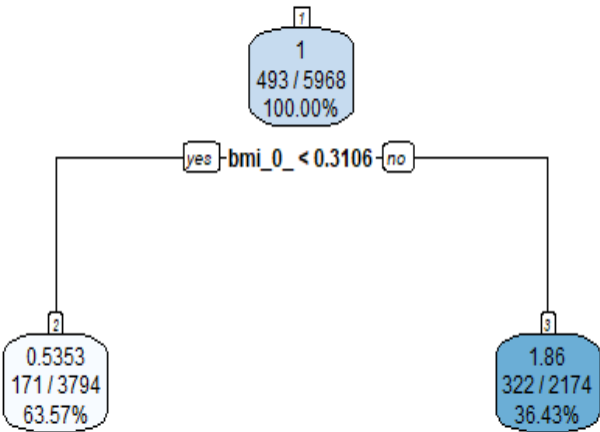
	AUCROC	BS	BS_scaled	C_score	Calib_slope	Calib_alpha	T
test.1	0.7693	0.086	0.1027	0.7404	1.069	0.0743	10
test.2	0.7625	0.0756	0.0767	0.7236	0.9232	0.0365	10
test.3	0.8023	0.0691	0.1258	0.7765	1.2022	0.0273	10

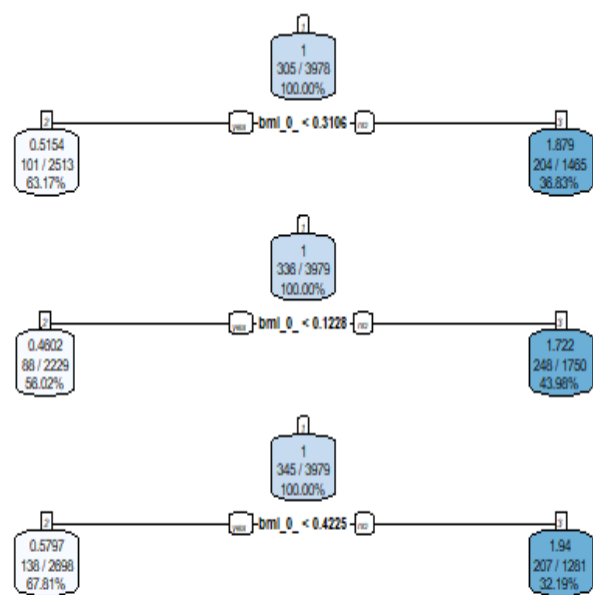
Showing 1 to 3 of 3 entries

Previous

1

Next





Show 10 entries

Search:

	coef	exp(coef)	se(coef)	z	Pr(> z)
sz20_	0.0314	1.0319	0.0454	0.6925	0.4886
pc1_	0.0212	1.0214	0.0453	0.4673	0.6403
pc2_	-0.0651	0.9369	0.0452	-1.4404	0.1498
pc3_	0.0072	1.0072	0.0472	0.1528	0.8786
pc4_	-0.0105	0.9896	0.0444	-0.2357	0.8137
age_	0.1754	1.1917	0.0563	3.1128	0.0019
sex	-0.3062	0.7363	0.1029	-2.9766	0.0029
bmi_0_	0.3085	1.3614	0.0604	5.109	0
hyp_0	0.4904	1.6329	0.0941	5.2111	0
cvd_0	-0.0331	0.9674	0.1327	-0.2499	0.8027

```

$test
  T      AUCROC      BS BS_scaled  C_score
1 10 0.7693149 0.08599898 0.10270605 0.7403549
2 10 0.7624956 0.07564321 0.07669279 0.7235991
3 10 0.8022541 0.06909455 0.12579893 0.7764802
  Calib_slope Calib_alpha test cv_n
1  1.0689787  0.07425385    1    1
2   0.9231891  0.03649639    1    2
3  1.2021587  0.02730576    1    3

$train
  T      AUCROC      BS BS_scaled  C_score
1 10 0.7982134 0.07084518 0.1236720 0.7581750
2 10 0.7982208 0.07649145 0.1272103 0.7687648
3 10 0.7763923 0.07894850 0.1075090 0.7432108
  Calib_slope Calib_alpha test cv_n
1  1.144057  0.04176389    0    1
2  1.110478  0.04582521    0    2
3  1.113096  0.04752583    0    3

$testaverage
      T      AUCROC      BS  BS_scaled
10.00000000 0.77802152 0.07691225 0.10173259
  C_score Calib_slope Calib_alpha      test
0.74681141 1.06477551 0.04601867 1.00000000

$trainaverage
      T      AUCROC      BS  BS_scaled
10.00000000 0.79094217 0.07542838 0.11946377
  C_score Calib_slope Calib_alpha      test
0.75671687 1.12254366 0.04503831 0.00000000

$model_list
$model_list[[1]]
$model_list[[1]]$treemodel
n= 3978

node), split, n, deviance, yval
  * denotes terminal node

1) root 3978 2090.3410 1.0000000
  2) bmi_0_< 0.310594 2513 856.6503 0.5153783 *
  3) bmi_0_>=0.310594 1465 1109.4060 1.8792320 *

$model_list[[1]]$modcoxmodel
Call:
coxph(formula = as.formula(paste("Surv(df_train$time, df_train$event) ~",
  paste(predict.factors, collapse = "+"))), data = df_train,
  x = TRUE)

              coef exp(coef) se(coef)
sz20_         -0.031330  0.969156  0.055656
pc1_           0.016134  1.016265  0.057637
pc2_          -0.093042  0.911155  0.057887
pc3_          -0.024301  0.975992  0.060319

```

pc4_	-0.038358	0.962369	0.058286
age_	0.144791	1.155798	0.071801
sex	-0.353514	0.702216	0.131318
bmi_0_	0.252468	1.287199	0.082062
hyp_0	0.538283	1.713064	0.120599
cvd_0	-0.025864	0.974468	0.168937
B_dep_0	0.340963	1.406301	0.151434
trig_0	0.096417	1.101218	0.035706
baseline_hdl	-0.297892	0.742381	0.197442
stroke_0	0.315922	1.371523	0.303216
B_smokstatus_0	0.409015	1.505334	0.151475
exercise_light	-0.003738	0.996269	0.244836
exercise_vig	-0.330648	0.718458	0.145688
EduLevel_low	0.332327	1.394208	0.220431
EduLevel_med	0.160220	1.173769	0.209952
wealth_med	0.060801	1.062687	0.159759
wealth_low	0.234254	1.263965	0.161578
t2dm_	0.321573	1.379296	0.059779
cluster_tree1.879232	0.690132	1.993978	0.176159

	z	p
sz20_	-0.563	0.57349
pc1_	0.280	0.77954
pc2_	-1.607	0.10799
pc3_	-0.403	0.68704
pc4_	-0.658	0.51048
age_	2.017	0.04374
sex	-2.692	0.00710
bmi_0_	3.077	0.00209
hyp_0	4.463	8.07e-06
cvd_0	-0.153	0.87832
B_dep_0	2.252	0.02435
trig_0	2.700	0.00693
baseline_hdl	-1.509	0.13136
stroke_0	1.042	0.29746
B_smokstatus_0	2.700	0.00693
exercise_light	-0.015	0.98782
exercise_vig	-2.270	0.02323
EduLevel_low	1.508	0.13165
EduLevel_med	0.763	0.44539
wealth_med	0.381	0.70352
wealth_low	1.450	0.14712
t2dm_	5.379	7.47e-08
cluster_tree1.879232	3.918	8.94e-05

Likelihood ratio test=273.3 on 23 df, p=< 2.2e-16
n= 3978, number of events= 305

```
$model_list[[1]]$clusters
[1] 1.879232 0.515378
```

```
$model_list[[2]]
$model_list[[2]]$treemodel
n= 3979
```

```
node), split, n, deviance, yval
```

* denotes terminal node

```
1) root 3979 2236.1680 1.0000000
  2) bmi_0_ < 0.1228089 2229 743.9276 0.4601545 *
  3) bmi_0_ >= 0.1228089 1750 1358.8730 1.7221500 *
```

```
$model_list[[2]]$modcoxmodel
```

Call:

```
coxph(formula = as.formula(paste("Surv(df_train$time, df_train$event) ~",
  paste(predict.factors, collapse = "+"))), data = df_train,
  x = TRUE)
```

	coef	exp(coef)	se(coef)	z
sz20_	0.056481	1.058107	0.056765	0.995
pc1_	0.021115	1.021339	0.054847	0.385
pc2_	-0.013904	0.986193	0.055185	-0.252
pc3_	0.036449	1.037122	0.059384	0.614
pc4_	0.034536	1.035140	0.052262	0.661
age_	0.243151	1.275261	0.067700	3.592
sex	-0.265403	0.766897	0.124144	-2.138
bmi_0_	0.322843	1.381048	0.068618	4.705
hyp_0	0.557509	1.746316	0.114264	4.879
cvd_0	-0.044285	0.956681	0.159025	-0.278
B_dep_0	0.331283	1.392754	0.148077	2.237
trig_0	0.104463	1.110114	0.031824	3.282
baseline_hdl	-0.566958	0.567249	0.192600	-2.944
stroke_0	0.519228	1.680729	0.251577	2.064
B_smokstatus_0	0.375297	1.455424	0.148538	2.527
exercise_light	0.003652	1.003659	0.234295	0.016
exercise_vig	-0.215276	0.806319	0.133434	-1.613
EduLevel_low	0.396542	1.486675	0.222224	1.784
EduLevel_med	0.331270	1.392735	0.210705	1.572
wealth_med	0.001424	1.001425	0.149084	0.010
wealth_low	0.167137	1.181916	0.152430	1.096
t2dm_	0.307085	1.359456	0.056194	5.465
cluster_tree1.72215	0.613150	1.846237	0.161722	3.791

p

sz20_	0.319731
pc1_	0.700258
pc2_	0.801084
pc3_	0.539358
pc4_	0.508717
age_	0.000329
sex	0.032528
bmi_0_	2.54e-06
hyp_0	1.07e-06
cvd_0	0.780644
B_dep_0	0.025271
trig_0	0.001029
baseline_hdl	0.003243
stroke_0	0.039028
B_smokstatus_0	0.011517
exercise_light	0.987564
exercise_vig	0.106668
EduLevel_low	0.074354
EduLevel_med	0.115905

```

wealth_med      0.992379
wealth_low      0.272869
t2dm_           4.64e-08
cluster_tree1.72215 0.000150

```

```

Likelihood ratio test=325 on 23 df, p=< 2.2e-16
n= 3979, number of events= 336

```

```

$model_list[[2]]$clusters
[1] 1.722150 0.460155

```

```

$model_list[[3]]
$model_list[[3]]$treemodel
n= 3979

```

```

node), split, n, deviance, yval
      * denotes terminal node

```

```

1) root 3979 2275.804 1.0000000
  2) bmi_0_< 0.422484 2698 1074.604 0.5797049 *
  3) bmi_0_>=0.422484 1281 1076.318 1.9398860 *

```

```

$model_list[[3]]$modcoxmodel

```

```
Call:
```

```

coxph(formula = as.formula(paste("Surv(df_train$time, df_train$event) ~",
  paste(predict.factors, collapse = "+"))), data = df_train,
  x = TRUE)

```

	coef	exp(coef)	se(coef)	z
sz20_	0.06340	1.06545	0.05533	1.146
pc1_	0.02630	1.02665	0.05463	0.481
pc2_	-0.08886	0.91497	0.05411	-1.642
pc3_	0.01407	1.01417	0.05469	0.257
pc4_	-0.04171	0.95914	0.05374	-0.776
age_	0.14376	1.15461	0.06817	2.109
sex	-0.31699	0.72834	0.12434	-2.549
bmi_0_	0.31586	1.37143	0.07165	4.408
hyp_0	0.40267	1.49581	0.11239	3.583
cvd_0	-0.02466	0.97565	0.16111	-0.153
B_dep_0	0.24557	1.27835	0.14924	1.645
trig_0	0.10870	1.11483	0.04025	2.700
baseline_hdl	-0.42387	0.65451	0.18952	-2.237
stroke_0	0.45491	1.57604	0.28328	1.606
B_smokstatus_0	0.39766	1.48834	0.14121	2.816
exercise_light	-0.14408	0.86582	0.24121	-0.597
exercise_vig	-0.20064	0.81821	0.12899	-1.556
EduLevel_low	0.38005	1.46236	0.21311	1.783
EduLevel_med	0.31994	1.37704	0.20092	1.592
wealth_med	-0.05387	0.94755	0.14335	-0.376
wealth_low	0.09223	1.09662	0.14809	0.623
t2dm_	0.29383	1.34156	0.05609	5.239
cluster_tree1.939886	0.56730	1.76350	0.15965	3.554
p				
sz20_	0.25188			
pc1_	0.63017			

```
pc2_          0.10052
pc3_          0.79700
pc4_          0.43764
age_          0.03496
sex           0.01079
bmi_0_        1.04e-05
hyp_0         0.00034
cvd_0         0.87837
B_dep_0       0.09988
trig_0        0.00693
baseline_hdl  0.02532
stroke_0      0.10830
B_smokstatus_0 0.00486
exercise_light 0.55029
exercise_vig  0.11983
EduLevel_low  0.07453
EduLevel_med  0.11131
wealth_med    0.70706
wealth_low    0.53339
t2dm_         1.62e-07
cluster_tree1.939886 0.00038
```

Likelihood ratio test=270.2 on 23 df, p=< 2.2e-16
n= 3979, number of events= 345

```
$model_list[[3]]$clusters
[1] 1.939886 0.579705
```

```
$time
Time difference of 35.42474 secs
```