Risk-Evaluation: Breast Cancer Royston-Altman

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1 Evaluation of RISK survival models

This document highlights the use of

- RRPlot(),
- CoxRiskCalibration(), and
- CalibrationProbPoissonRisk(),

for the evaluation (RRPlot), and calibration of cox models (CoxRiskCalibration) or logistic models (CalibrationProbPoissonRisk) of survival data.

Furthermore, it can be used to evaluate any Risk index that reruns the probability of a future event on external data-set.

This document will use the survival::rotterdam, and survival::gbsg data-sets to train and predict the risk of cancer recurrence after surgery. Both Cox and Logistic models will be trained and evaluated.

Here are some sample plots returned by the evaluated functions:

1.1 The libraries

```
library(survival)
library(FRESA.CAD)

## Loading required package: Rcpp

## Loading required package: stringr
```

Loading required package: Hmisc

Loading required package: miscTools

```
##
## Attaching package: 'Hmisc'
## The following objects are masked from 'package:base':
##
##
       format.pval, units
## Loading required package: pROC
## Type 'citation("pROC")' for a citation.
##
## Attaching package: 'pROC'
## The following objects are masked from 'package:stats':
##
##
       cov, smooth, var
op <- par(no.readonly = TRUE)
pander::panderOptions('digits', 3)
pander::panderOptions('table.split.table', 400)
pander::panderOptions('keep.trailing.zeros',TRUE)
```

1.2 Breast Cancer Royston-Altman data

1.2.1 data(gbsg, package="survival") and data(rotterdam, package="survival")

```
gbsgdata <- gbsg
rownames(gbsgdata) <- gbsgdata$pid</pre>
gbsgdata$pid <- NULL</pre>
odata <-rotterdam
rownames(odata) <- odata$pid
odata$pid <- NULL
odata$rfstime <- odata$rtime
odata$status <- odata$recur
odata$rtime <- NULL
odata$recur <- NULL
odata <- odata[,colnames(odata) %in% colnames(gbsgdata)]</pre>
odata$size <- 10*(odata$size=="<=20") +
  35*(odata\$size=="20-50") +
  60*(odata$size==">50")
data <- as.data.frame(model.matrix(Surv(rfstime,status)~.*.,odata))</pre>
data$`(Intercept)` <- NULL</pre>
dataBrestCancerTrain <- cbind(time=odata[rownames(data), "rfstime"], status=odata[rownames(data), "status"]
colnames(dataBrestCancerTrain) <-str_replace_all(colnames(dataBrestCancerTrain),":","_")</pre>
colnames(dataBrestCancerTrain) <-str_replace_all(colnames(dataBrestCancerTrain)," ","")</pre>
colnames(dataBrestCancerTrain) <-str_replace_all(colnames(dataBrestCancerTrain),"\\.","_")</pre>
\verb|colnames| (\texttt{dataBrestCancerTrain})| < -\texttt{str\_replace\_all} (\texttt{colnames} (\texttt{dataBrestCancerTrain}), "-", "\_")|
colnames(dataBrestCancerTrain) <-str replace all(colnames(dataBrestCancerTrain),">"," ")
dataBrestCancerTrain$time <- dataBrestCancerTrain$time/365 ## To years
```

```
pander::pander(table(odata[rownames(data), "status"]), caption="rotterdam")
```

Table 1: rotterdam

0	1
1464	1518

1.2.2 data(gbsg, package="survival") data conditioning

```
gbsgdata <- gbsgdata[,colnames(odata)]
data <- as.data.frame(model.matrix(Surv(rfstime,status)~.*.,gbsgdata))

data$`(Intercept)` <- NULL

dataBrestCancerTest <- cbind(time=gbsgdata[rownames(data),"rfstime"],status=gbsgdata[rownames(data),"st

colnames(dataBrestCancerTest) <-str_replace_all(colnames(dataBrestCancerTest),":","_")
colnames(dataBrestCancerTest) <-str_replace_all(colnames(dataBrestCancerTest),"","")
colnames(dataBrestCancerTest) <-str_replace_all(colnames(dataBrestCancerTest),"\\.","_")
colnames(dataBrestCancerTest) <-str_replace_all(colnames(dataBrestCancerTest),"\\.","_")
colnames(dataBrestCancerTest) <-str_replace_all(colnames(dataBrestCancerTest),"-","_")
dataBrestCancerTest$time <- dataBrestCancerTest$time/365

pander::pander(table(odata[rownames(data),"status"]), caption="gbsg")</pre>
```

Table 2: gbsg

0	1
499	183

1.3 Cox Modeling

```
ml <- BSWiMS.model(Surv(time, status)~., data=dataBrestCancerTrain, loops=1, NumberofRepeats = 5)</pre>
```

```
sm <- summary(ml)
pander::pander(sm$coefficients)</pre>
```

Estimalewer HR upperu.Acc	una <i>e</i> yccurauch.	Accumaty CAUGull.AUOI NRI z.IDI z.NRIDelta.AUQuenc
age_node\$00716001 1.001 1.001 0.626	0.600 0.63	32 0.630 0.601 0.634 0.03040.459412.81 14.37 0.0330561
$\mathbf{size} \underline{\hspace{0.1cm}} \mathbf{gradde} 0564 \underline{0.005} 1.006 1.006 0.598$	0.623 0.63	0.599 0.626 0.634 0.0186 0.39149.82 11.29 0.0079471
$\mathbf{nodes} 0.0865820821.0901.0990.637$	0.642 0.64	43 0.640 0.643 0.644 0.0074 5 .05648.33 1.66 0.0001481
size 0.0068880051.0071.0090.595	0.641 0.64	0.5950.6420.6440.0144 0.0144 $0.35878.059.970.0013221$
$size_nodes$ 1.000 1.000 1.000 0.624	0.643 0.64	43 0.629 0.644 0.644 0.00346.34307.25 9.57 - 1
0.000378		0.000377
$age_size - 1.0001.0001.0000.567$	0.627 0.63	32 0.568 0.630 0.634 0.0063 5 .19355.95 5.36 0.0040781
0.000149		
grade 0.2049341461.2271.3140.565	0.637 0.64	43 0.561 0.638 0.644 0.00926.20695.88 6.31 0.0053441

	Estim	na te wer HR	upperu.Accı	ına <i>e</i> yccu	r aul t.Aco	cumaAyCAUGull.A	UMO I NRI	z.IDl	I z.NR	IDelta.A	₩ ��quency
age	-	0.9960.997	7 0.998 0.513	0.628	0.643	0.5130.6280.644	0.00416.093	175.27	2.51	0.01546	51
_	0.003										
${f grade}_{-}$	_nodes	0.9810.986	60.9920.635	0.645	0.643	0.6390.6460.644	0.00207 -	5.03	-	-	1
	0.013	784					0.093	10	2.55	0.002609	9

1.4 Cox Model Performance

Here we evaluate the model using the RRPlot() function.

1.4.1 The evaluation of the raw Cox model with RRPlot()

Here we will use the predicted event probability assuming a baseline hazard for events withing 5 years

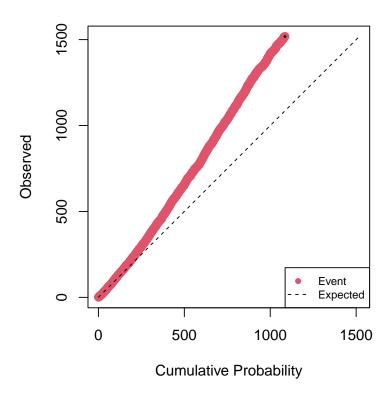
```
timeinterval <- 5 # Five years

h0 <- sum(dataBrestCancerTrain$status & dataBrestCancerTrain$time <= timeinterval)
h0 <- h0/sum((dataBrestCancerTrain$time > timeinterval) | (dataBrestCancerTrain$status==1))
pander::pander(t(c(h0=h0,timeinterval=timeinterval)),caption="Initial Parameters")
```

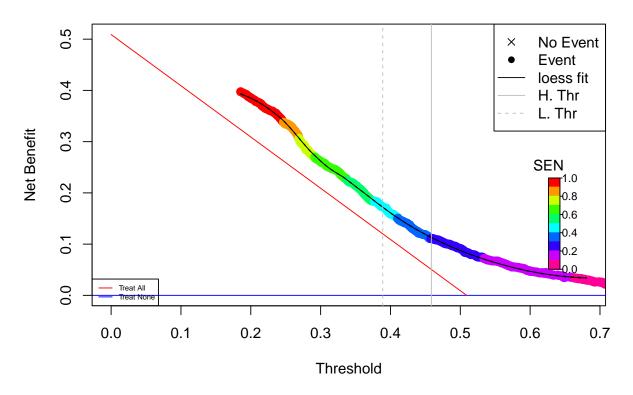
Table 4: Initial Parameters

h0	timeinterval
0.429	5

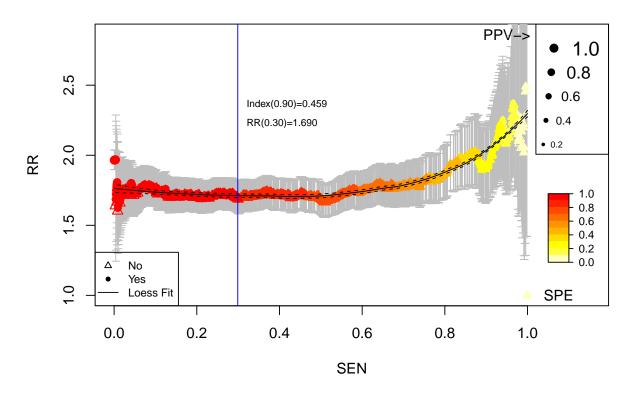
Cumulative vs. Observed: Train: Breast Cancer



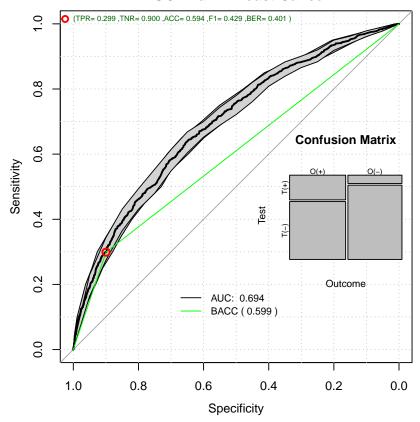
Decision Curve Analysis: Train: Breast Cancer



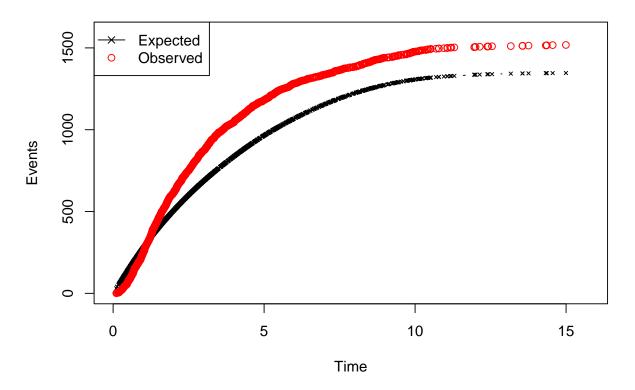
Relative Risk: Train: Breast Cancer



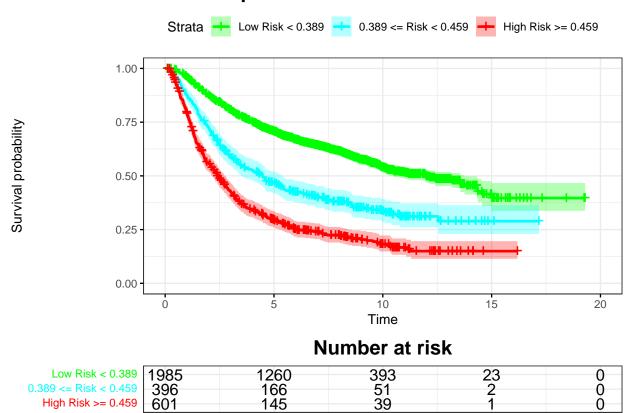
ROC: Train: Breast Cancer



Time vs. Events: Train: Breast Cancer



Kaplan-Meier: Train: Breast Cancer

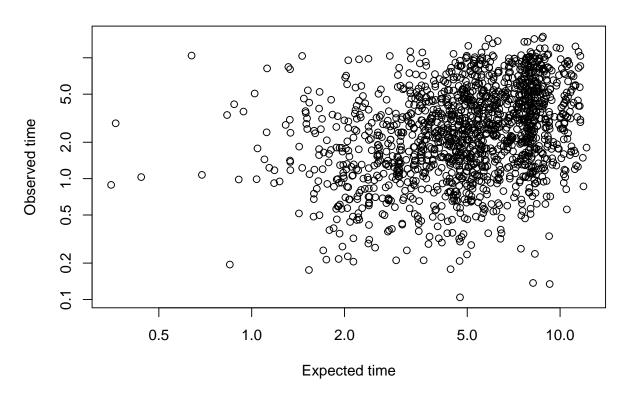


1.4.2 Time to event

High Risk >= 0.459

```
timetoEvent <- meanTimeToEvent(rdata[rdata[,1]==1,2],timeinterval)</pre>
obstime <- dataBrestCancerTrain[rdata[,1]==1,"time"]</pre>
plot(timetoEvent,obstime,xlab="Expected time",ylab="Observed time",main="Expected vs. Observed",log="xy
```

Expected vs. Observed



pander::pander(cor.test(timetoEvent,obstime,method="spearman"))

Table 5: Spearman's rank correlation rho: timetoEvent and obstime

Test statistic	P value	Alternative hypothesis	rho
3.95e + 08	5.22e-38 * * *	two.sided	0.322

MADerror <- mean(abs(timetoEvent-obstime))
pander::pander(MADerror)</pre>

3.12

The Time vs. Events are not calibrated. Lets do the calibration

1.4.3 Uncalibrated Performance Report

pander::pander(t(rrAnalysisTrain\$keyPoints),caption="Threshold values")

Table 6: Threshold values

	@:0.9	@:0.8	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr RR	$0.459 \\ 1.690$	0.389 1.713	$0.320 \\ 1.799$	$0.214 \\ 2.376$	0.18549 1.00000	0.4996 1.7255

	@:0.9	@:0.8	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
RR_LCI	1.586	1.603	1.666	1.869	0.00000	1.6196
RR_UCI	1.802	1.830	1.942	3.019	0.00000	1.8383
\mathbf{SEN}	0.299	0.462	0.644	0.965	1.00000	0.2464
\mathbf{SPE}	0.900	0.798	0.646	0.125	0.00137	0.9310
\mathbf{BACC}	0.599	0.630	0.645	0.545	0.50068	0.5887
${\bf Net Benefit}$	0.110	0.172	0.246	0.374	0.39742	0.0916

pander::pander(t(rrAnalysisTrain\$0ERatio\$estimate),caption="0/E Ratio")

Table 7: O/E Ratio

O/E	Low	Upper	p.value
1.13	1.07	1.19	4.66e-06

pander::pander(t(rrAnalysisTrain\$0E95ci),caption="0/E Mean")

Table 8: O/E Mean

mean	50%	2.5%	97.5%
1.16	1.16	1.15	1.17

pander::pander(t(rrAnalysisTrain\$0Acum95ci),caption="0/Acum Mean")

Table 9: O/Acum Mean

mean	50%	2.5%	97.5%
1.35	1.35	1.35	1.35

pander::pander(rrAnalysisTrain\$c.index\$cstatCI,caption="C. Index")

mean.C Index	median	lower	upper
0.676	0.677	0.663	0.69

pander::pander(t(rrAnalysisTrain\$ROCAnalysis\$aucs),caption="ROC AUC")

Table 11: ROC AUC

est	lower	upper
0.694	0.675	0.713

pander::pander((rrAnalysisTrain\$ROCAnalysis\$sensitivity), caption="Sensitivity")

Table 12: Sensitivity

est	lower	upper
0.299	0.276	0.323

pander::pander((rrAnalysisTrain\$ROCAnalysis\$specificity), caption="Specificity")

Table 13: Specificity

est	lower	upper
0.9	0.883	0.915

pander::pander(t(rrAnalysisTrain\$thr_atP),caption="Probability Thresholds")

Table 14: Probability Thresholds

90%	80%
0.459	0.389

pander::pander(rrAnalysisTrain\$surdif,caption="Logrank test")

Table 15: Logrank test Chisq = 465.079317 on 2 degrees of freedom, p = 0.000000

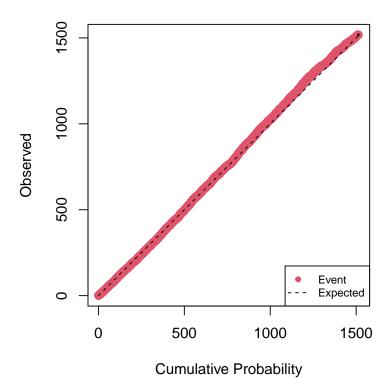
	N	Observed	Expected	$(O-E)^2/E$	$(O-E)^2/V$
class=0	1985	816	1144	93.9	385.7
class=1	396	248	177	28.0	31.8
class=2	601	454	197	336.3	391.3

1.4.4 Cox Calibration

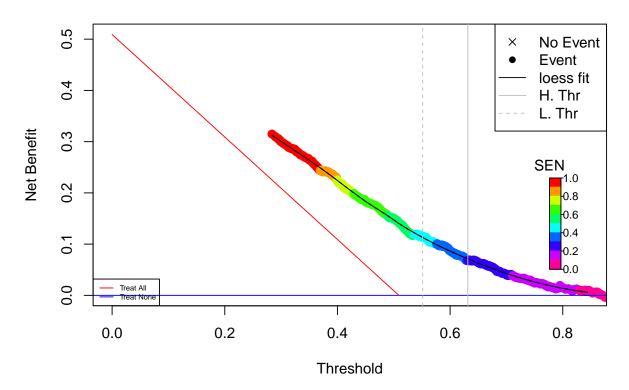
h0	Gain	DeltaTime
0.698	1.35	6.97

1.4.5 The RRplot() of the calibrated model

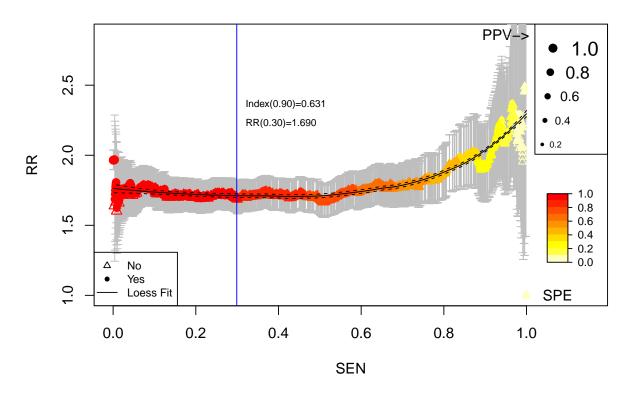
Cumulative vs. Observed: Cal. Train: Breast Cancer



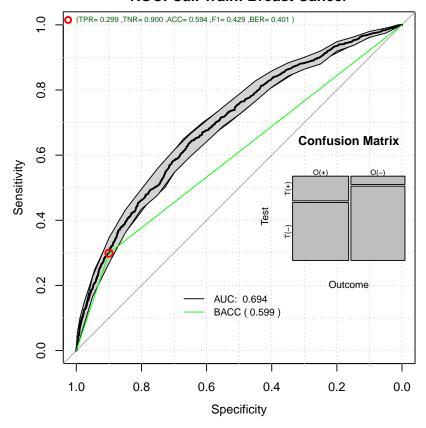
Decision Curve Analysis: Cal. Train: Breast Cancer



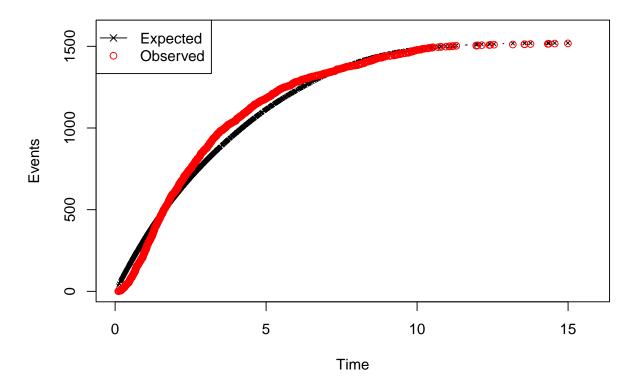
Relative Risk: Cal. Train: Breast Cancer



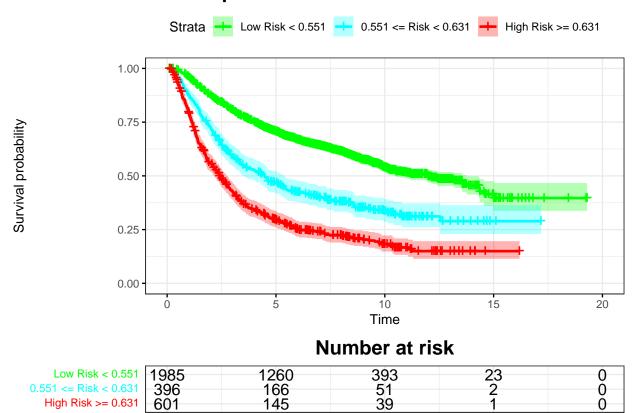
ROC: Cal. Train: Breast Cancer



Time vs. Events: Cal. Train: Breast Cancer



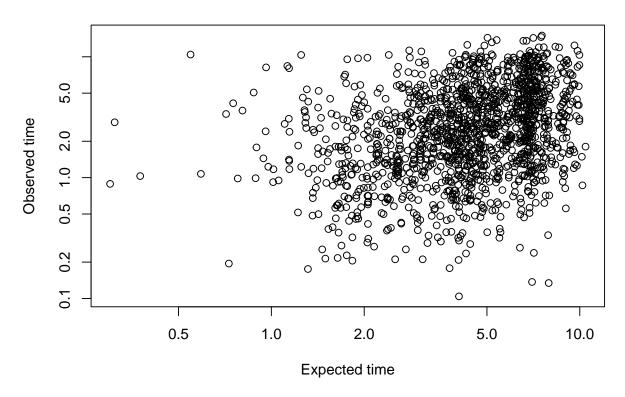
Kaplan-Meier: Cal. Train: Breast Cancer



1.4.6 Time to event after calibration

```
timetoEvent <- meanTimeToEvent(rdata[rdata[,1]==1,2],timeinterval)
obstime <- dataBrestCancerTrain[rdata[,1]==1,"time"]
plot(timetoEvent,obstime,xlab="Expected time",ylab="Observed time",main="Expected vs. Observed",log="xy")</pre>
```

Expected vs. Observed



pander::pander(cor.test(timetoEvent,obstime,method="spearman"))

Table 17: Spearman's rank correlation rho: timetoEvent and obstime

Test statistic	P value	Alternative hypothesis	rho
3.95e + 08	5.22e-38 * * *	two.sided	0.322

MADerror <- mean(abs(timetoEvent-obstime))
pander::pander(MADerror)</pre>

2.63

1.4.7 Calibrated Train Performance

pander::pander(t(rrAnalysisTrain\$keyPoints),caption="Threshold values")

Table 18: Threshold values

	@:0.9	0:0.8	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.6318	0.551	0.466	0.324	0.28381	0.500
RR	1.6904	1.713	1.799	2.376	1.00000	1.758
RR_LCI	1.5860	1.603	1.666	1.869	0.00000	1.636

	@:0.9	@:0.8	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
RR_UCI	1.8018	1.830	1.942	3.019	0.00000	1.889
\mathbf{SEN}	0.2991	0.462	0.644	0.965	1.00000	0.580
\mathbf{SPE}	0.8996	0.798	0.646	0.125	0.00137	0.706
\mathbf{BACC}	0.5993	0.630	0.645	0.545	0.50068	0.643
${\bf Net Benefit}$	0.0677	0.114	0.176	0.286	0.31480	0.150

pander::pander(t(rrAnalysisTrain\$0ERatio\$estimate),caption="0/E Ratio")

Table 19: O/E Ratio

O/E	Low	Upper	p.value
0.998	0.949	1.05	0.959

pander::pander(t(rrAnalysisTrain\$0E95ci),caption="0/E Mean")

Table 20: O/E Mean

mean	50%	2.5%	97.5%
1	1	0.996	1.01

pander::pander(t(rrAnalysisTrain\$OAcum95ci),caption="0/Acum Mean")

Table 21: O/Acum Mean

mean	50%	2.5%	97.5%
1.01	1.01	1.01	1.01

pander::pander(rrAnalysisTrain\$c.index\$cstatCI,caption="C. Index")

mean.C Index	median	lower	upper
0.676	0.676	0.662	0.69

pander::pander(t(rrAnalysisTrain\$ROCAnalysis\$aucs),caption="ROC AUC")

Table 23: ROC AUC

est	lower	upper
0.694	0.675	0.713

pander::pander((rrAnalysisTrain\$ROCAnalysis\$sensitivity),caption="Sensitivity")

Table 24: Sensitivity

est	lower	upper
0.299	0.276	0.323

pander::pander((rrAnalysisTrain\$ROCAnalysis\$specificity), caption="Specificity")

Table 25: Specificity

est	lower	upper
0.9	0.883	0.915

pander::pander(t(rrAnalysisTrain\$thr_atP),caption="Probability Thresholds")

Table 26: Probability Thresholds

90%	80%
0.631	0.551

pander::pander(rrAnalysisTrain\$surdif,caption="Logrank test")

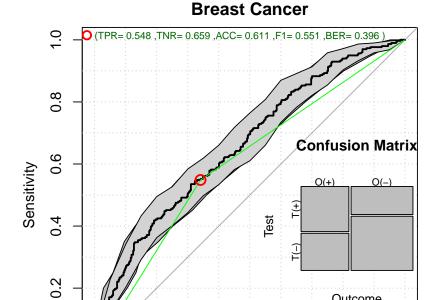
Table 27: Logrank test Chisq = 465.079317 on 2 degrees of freedom, p = 0.000000

	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	1985	816	1144	93.9	385.7
class=1	396	248	177	28.0	31.8
class=2	601	454	197	336.3	391.3

1.5 Performance on the external data set

index <- predict(ml,dataBrestCancerTest)</pre>

pp <- predictionStats_binary(cbind(dataBrestCancerTest\$status,index),plotname="Breast Cancer")</pre>



0.0

1.0

Outcome

0.2

0.0

AUC: 0.660 BACC (0.604)

0.4

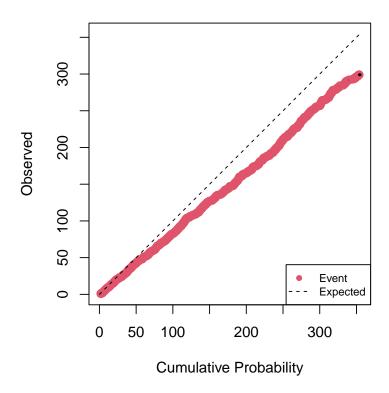
```
par(op)
prob <- ppoisGzero(index,h0)</pre>
rdata <- cbind(dataBrestCancerTest$status,prob)</pre>
rrCoxTestAnalysis <- RRPlot(rdata,atThr=rrAnalysisTrain$thr_atP,</pre>
                       timetoEvent=dataBrestCancerTest$time,
                      title="Test: Breast Cancer",
                      ysurvlim=c(0.00,1.0),
                      riskTimeInterval=timeinterval)
```

0.6

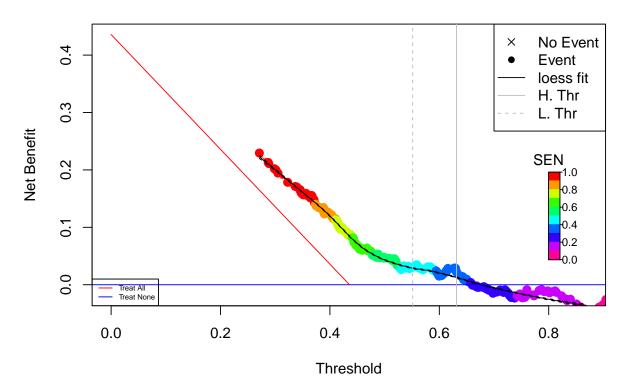
Specificity

8.0

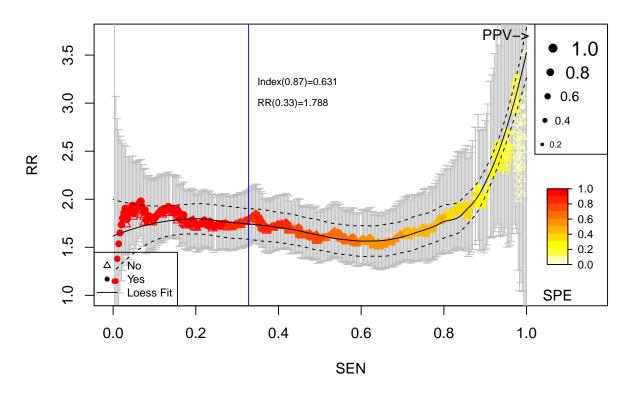
Cumulative vs. Observed: Test: Breast Cancer



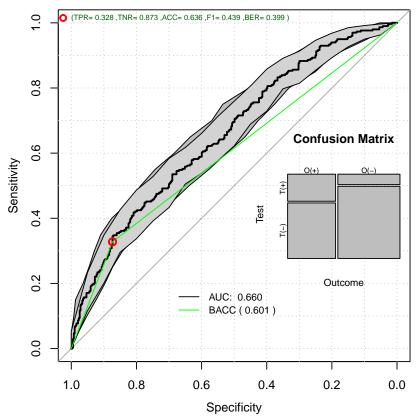
Decision Curve Analysis: Test: Breast Cancer



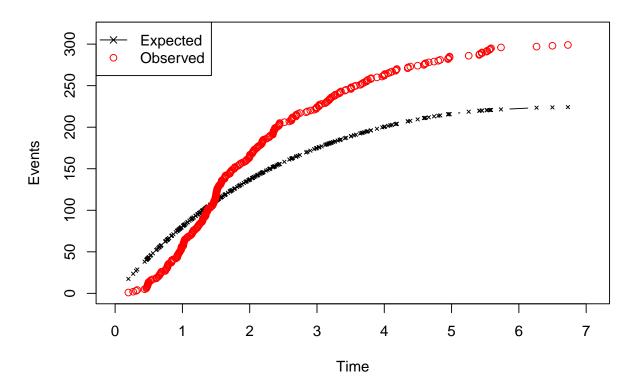
Relative Risk: Test: Breast Cancer



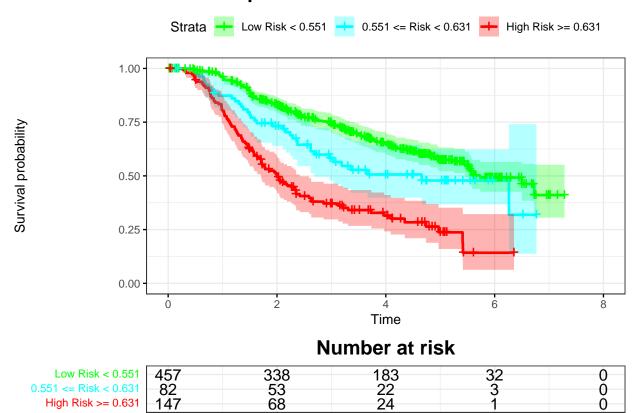




Time vs. Events: Test: Breast Cancer



Kaplan-Meier: Test: Breast Cancer



par(op)

1.5.1 External Data Report

pander::pander(t(rrCoxTestAnalysis\$keyPoints),caption="Threshold values")

Table 28: Threshold values

	@:0.631	@:0.551	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.6312	0.5516	0.5834	0.337	2.71e-01	0.4996
$\mathbf{R}\mathbf{R}$	1.7994	1.6427	1.7581	3.279	2.64e + 01	1.5937
RR_LCI	1.5366	1.3951	1.4980	1.641	5.65 e-02	1.3435
RR_UCI	2.1071	1.9343	2.0632	6.552	1.23e + 04	1.8906
\mathbf{SEN}	0.3311	0.4515	0.4181	0.977	1.00e+00	0.5518
\mathbf{SPE}	0.8734	0.7571	0.8088	0.111	1.55e-02	0.6537
\mathbf{BACC}	0.6022	0.6043	0.6134	0.544	5.08e-01	0.6028
NetBenefit	0.0221	0.0283	0.0312	0.171	2.29e-01	0.0455

pander::pander(t(rrCoxTestAnalysis\$0ERatio\$estimate),caption="0/E Ratio")

Table 29: O/E Ratio

O/E	Low	Upper	p.value
1.33	1.19	1.49	1.74e-06

pander::pander(rrCoxTestAnalysis\$c.index,caption="C. Index")

• C Index: 0.664

Dxy: 0.328S.D.: 0.0311

• n: 686

• missing: θ

• uncensored: 299

• Relevant Pairs: 266144

• Concordant: 176737

• Uncertain: 203702

• cstatCI:

mean.C Index	median	lower	upper
0.664	0.663	0.632	0.692

pander::pander(t(rrCoxTestAnalysis\$ROCAnalysis\$aucs),caption="ROC AUC")

Table 31: ROC AUC

est	lower	upper
0.66	0.619	0.7

pander::pander((rrCoxTestAnalysis\$ROCAnalysis\$sensitivity), caption="Sensitivity")

Table 32: Sensitivity

est	lower	upper
0.328	0.275	0.384

pander::pander((rrCoxTestAnalysis\$ROCAnalysis\$specificity)), caption="Specificity")

Table 33: Specificity

est	lower	upper
0.873	0.836	0.905

pander::pander(t(rrCoxTestAnalysis\$thr_atP),caption="Probability Thresholds")

Table 34: Probability Thresholds

90%	80%
0.631	0.551

pander::pander(rrCoxTestAnalysis\$surdif,caption="Logrank test")

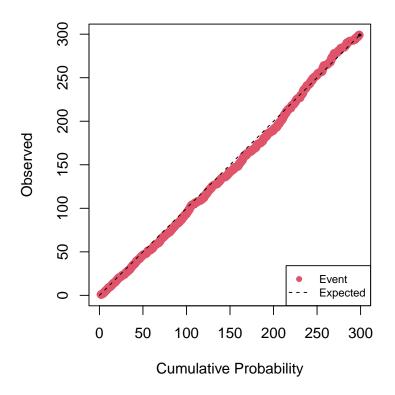
Table 35: Logrank test Chisq = 81.471750 on 2 degrees of freedom, p = 0.000000

	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	457	164	221.4	14.888	58.181
class=1	82	37	33.2	0.438	0.494
class=2	147	98	44.4	64.710	77.254

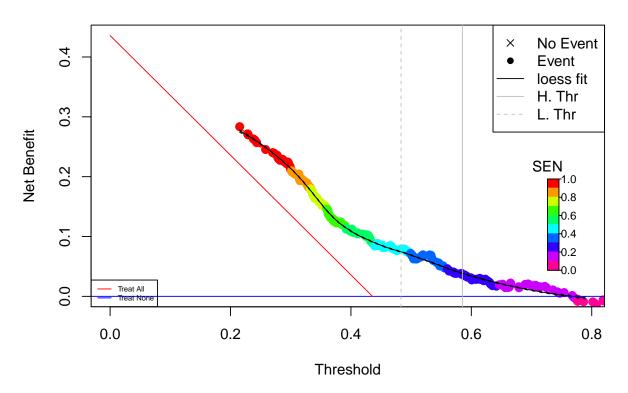
1.5.2 Calibrating the index on the test data

h0	Gain	DeltaTime
0.535	0.925	4.87

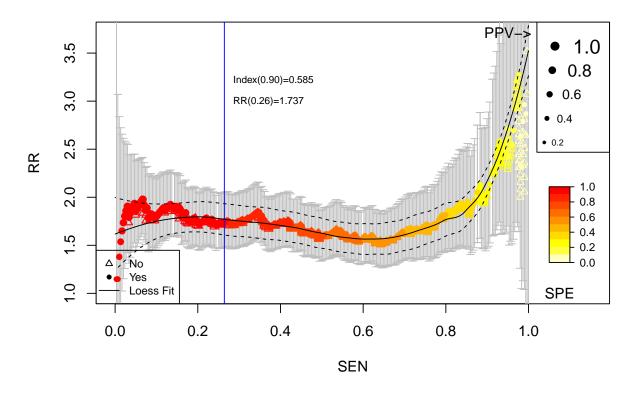
Cumulative vs. Observed: Cal. Test: Breast Cancer



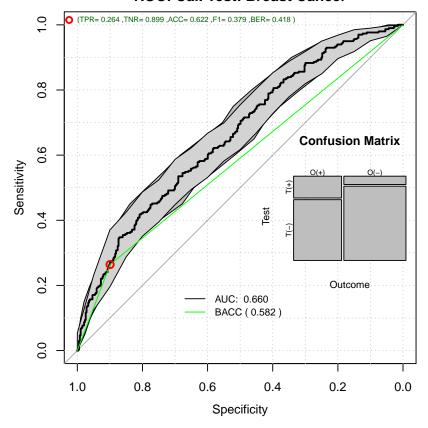
Decision Curve Analysis: Cal. Test: Breast Cancer



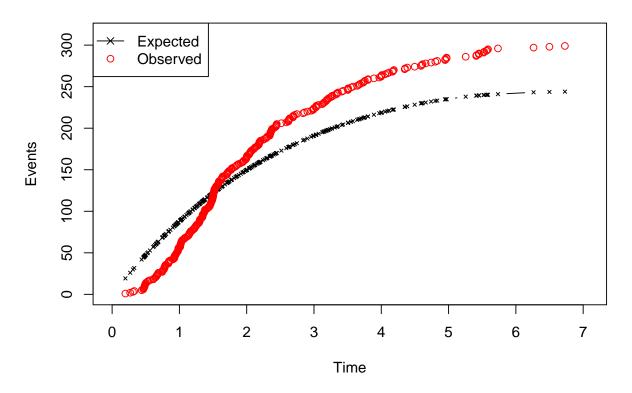
Relative Risk: Cal. Test: Breast Cancer



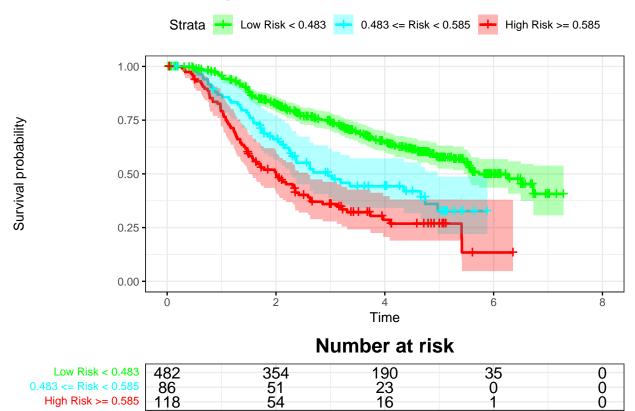
ROC: Cal. Test: Breast Cancer



Time vs. Events: Cal. Test: Breast Cancer



Kaplan-Meier: Cal. Test: Breast Cancer



1.5.3 After Calibration Report

pander::pander(t(rrAnalysis\$keyPoints),caption="Threshold values")

Table 37: Threshold values

	@:0.9	@:0.8	@MAX_BACC	C @MAX_RR	@SPE100	p(0.5)
Thr	0.5843	0.483	0.489	0.270	2.15e-01	0.4991
$\mathbf{R}\mathbf{R}$	1.7405	1.732	1.758	3.279	2.64e + 01	1.7385
RR_LCI	1.4790	1.475	1.498	1.641	5.65 e-02	1.4816
RR_UCI	2.0483	2.035	2.063	6.552	1.23e + 04	2.0399
\mathbf{SEN}	0.2676	0.425	0.418	0.977	1.00e+00	0.3980
\mathbf{SPE}	0.8992	0.798	0.809	0.111	1.55e-02	0.8191
\mathbf{BACC}	0.5834	0.612	0.613	0.544	5.08e-01	0.6086
NetBenefit	0.0367	0.079	0.079	0.240	2.84e-01	0.0718

pander::pander(t(rrAnalysis\$OERatio\$estimate),caption="0/E Ratio")

Table 38: O/E Ratio

O/E	Low	Upper	p.value
1.23	1.09	1.37	0.00061

pander::pander(rrAnalysis\$c.index,caption="C. Index")

• C Index: 0.664

Dxy: 0.328S.D.: 0.0311

• n: 686

• missing: θ

• uncensored: 299

Relevant Pairs: 266144
 Concordant: 176737
 Uncertain: 203702

• cstatCI:

mean.C Index	median	lower	upper
0.664	0.663	0.634	0.694

pander::pander(t(rrAnalysis\$ROCAnalysis\$aucs),caption="ROC AUC")

Table 40: ROC AUC

est	lower	upper
0.66	0.619	0.7

pander::pander((rrAnalysis\$ROCAnalysis\$sensitivity), caption="Sensitivity")

Table 41: Sensitivity

est	lower	upper
0.264	0.215	0.318

pander::pander((rrAnalysis\$ROCAnalysis\$specificity), caption="Specificity")

Table 42: Specificity

est	lower	upper
0.899	0.865	0.927

pander::pander(t(rrAnalysis\$thr_atP),caption="Probability Thresholds")

Table 43: Probability Thresholds

90%	80%
0.585	0.483

pander::pander(rrAnalysis\$surdif,caption="Logrank test")

Table 44: Logrank test Chisq = 80.835092 on 2 degrees of freedom, p = 0.000000

	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	482	173	232.4	15.20	69.5
class=1	86	47	32.0	7.02	7.9
class=2	118	79	34.6	57.14	65.4

1.6 Logistic Model

Here we train a logistic model on the same data set

```
## Only label subjects that present event withing five years

dataBrestCancerR <- subset(dataBrestCancerTrain, time>=5 | status==1)

dataBrestCancerR$status <- dataBrestCancerR$status * (dataBrestCancerR$time < 5)

dataBrestCancerR$time <- NULL

#ml <- BSWiMS.model(status~1, data=dataBrestCancerR, loops=20, NumberofRepeats = 5)

mlog <- BSWiMS.model(status~1, data=dataBrestCancerR, loops=1, NumberofRepeats = 5)</pre>
```

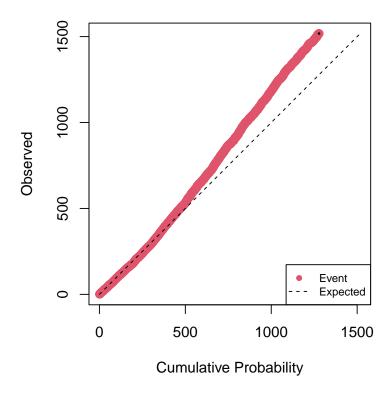
```
sm <- summary(mlog)
pander::pander(sm$coefficients)</pre>
```

Fatim	otomor OP	upporu Aggi	ım Aracıı	rfunkt Acc	ura&yCAUGull.A	IMONI NIDI	a IDI a NDI	Dolto MWGuoney
ESUIII	allewer OII	upperu.Acci	шавусси	randy.Acc	unady CAO Unit.A		Z.1D1 Z.1VIU	Dena. A wed uency
	1.001 1.001	1.001 0.669	0.571	0.668	0.6270.5000.628	0.1123 6 .636	547.86 18.870	0.1284901
03 nodes 4.33e-	1.040 1.044	1.048 0.676	0.634	0.690	0.639 0.621 0.662	0.07110.5710	064.1316.179	0.0404941
02	1 01/1 015	(1.016.0.682	0.627	0.686	0.6490.6240.655	0.06590.5494	342 66 15 650	m 03109 7 1
02	1.0141.016	1.010 0.002	0.031	0.000	0.049 0.024 0.055	0.00000.0400	043.00 13.030	0.0310071
age_nodle \$6e-	1.001 1.001	1.001 0.678	0.653	0.686	0.6420.6210.657	0.0334 6 .213	1 2 9.39 5.710	0.0358961
size_grad@5e-	1.001 1.002	21.0020.632	0.682	0.686	0.6260.6460.655	0.01780.294	16.74 7.728	0.0086481
03 age_size8.73e-	1.000 1.000	1.000 0.608	0.682	0.686	0.577 0.649 0.657	0.01534.291	5 8 .41 7.652	0.0076001
05 grade 2.27e-	1 168 1 254	1.347 0.571	0.683	0 690	0.500 0.653 0.662	0.01340.1903	3 6 20 4 983	0 0084611
01								
age_meno 6.04e-		0.996 0.571	0.676	0.686	0.500 0.645 0.657	0.00780.080	54.76 2.337	0.0120651
03								

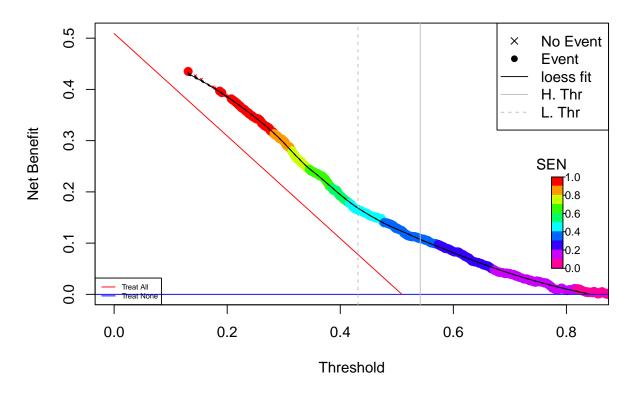
Estim	atower OR.	upperu. Accı	ma. A vccu	rack. Acc	ura&VCAUGull.A	UKDI NRI z.ID	I z.NRIDelta. AFr@ uency
-			-	-			
age_pgr - 5.42e-	1.000 1.00	01.0000.571	0.080	0.686	0.5000.6560.657	0.00514.00744.11	0.194 0.0004171
0.42e-							
age_grade	0 0070 00	8 0.999 0.574	0.690	0.690	0.507 0.661 0.662	0 00450 11379 60	2 960 0 0003151
1.65e-	0.551 0.55	00.5550.514	0.030	0.030	0.507 0.001 0.002	0.00404.11072.00	2.300 0.0003131
03							
meno_grade-	1.045 1.10	71.1730.571	0.683	0.686	0.5000.6520.657	0.00426.20428.47	5.343 0.0044411
01							
nodes_hormo	on 10.979 0.98	60.9940.587	0.688	0.686	0.5260.6580.655	0.0028 0 .4552 2 .44	12.150 - 1
1.38e-							0.002853
02							
	1.0021.00	41.0060.611	0.693	0.690	0.6180.6630.662	0.0050 0 .2105 3 .42	
03							0.001075
meno_p&19e-	1.0001.00	01.0010.571	0.687	0.686	0.5000.6570.657	0.0031 6 .0597 7 .35	
04	1 000 1 00	01 000 0 551	0.000	0.000	0 500 0 050 0 055	0.0005510550.04	0.000429
pgr -	1.000 1.00	01.0000.571	0.689	0.686	0.500 0.659 0.655	0.0025 0 .1975 2 .64	
1.07e- 04							0.004123
meno nodes	0.055.0.07	40 0040 640	0.686	0.686	0.595 0.656 0.657	0.00264 - 2.59	- 0.0006311
2.60e-	0.5050.51	40.3340.040	0.000	0.000	0.000 0.001	0.00204 - 2.53	1.645
02						0.00023	1.040
grade_pgr	1.000 1.00	01.0000.571	0.669	0.668	0.500 0.627 0.628	0.00240.17472.55	5.058 0.0012521
3.51e-							
05							
meno_s iz &4e-	1.0001.00	21.0040.604	0.691	0.690	0.5780.6630.662	0.00186.10222.43	2.662 - 1
03							0.001378

1.7 Logistic Model Performance

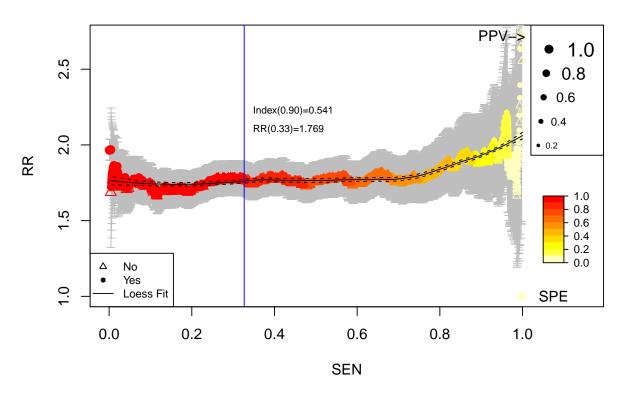
Cumulative vs. Observed: Logistic Train: Breast Cancer



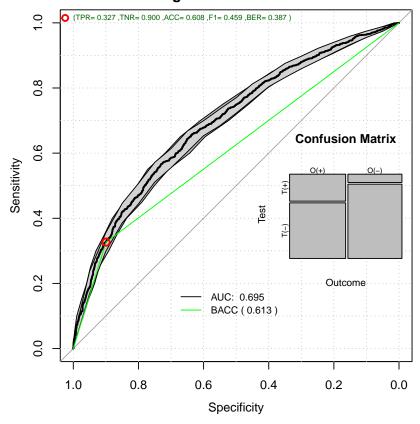
Decision Curve Analysis: Logistic Train: Breast Cancer



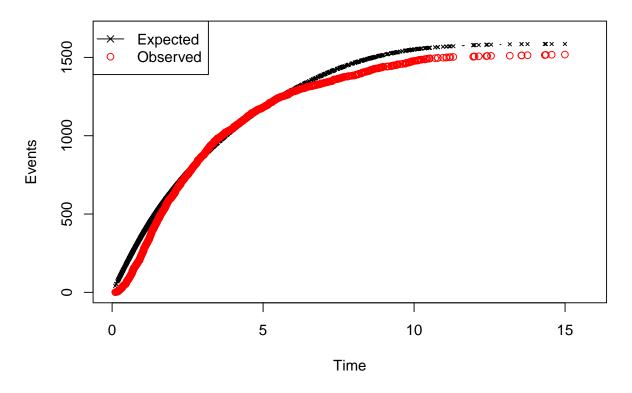
Relative Risk: Logistic Train: Breast Cancer



ROC: Logistic Train: Breast Cancer

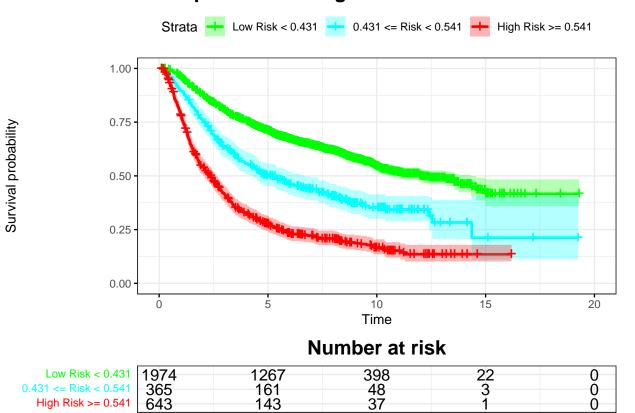


Time vs. Events: Logistic Train: Breast Cancer



Kaplan-Meier: Logistic Train: Breast Cancer

0



par(op)

1.7.1 Training Report

0.431 <= Risk < 0.541

High Risk >= 0.541

365 643

pander::pander(t(rrAnalysisTrain\$keyPoints),caption="Threshold values")

Table 46: Threshold values

	@:0.9	@:0.8	@MAX_BACC @M	MAX_RR	@SPE100	p(0.5)
Thr	0.542	0.431	0.394	0.255	0.130969	0.500
$\mathbf{R}\mathbf{R}$	1.765	1.739	1.799	2.213	1.000000	1.773
RR_LCI	1.659	1.627	1.676	1.764	0.000000	1.665
RR_UCI	1.879	1.858	1.931	2.777	0.000000	1.888
\mathbf{SEN}	0.327	0.470	0.566	0.962	1.000000	0.374
\mathbf{SPE}	0.900	0.799	0.731	0.125	0.000683	0.874
\mathbf{BACC}	0.613	0.635	0.648	0.543	0.500342	0.624
NetBenefit	0.108	0.165	0.202	0.342	0.435125	0.129

pander::pander(t(rrAnalysisTrain\$0ERatio\$estimate),caption="0/E Ratio")

Table 47: O/E Ratio

O/E	Low	Upper	p.value
0.957	0.91	1.01	0.0901

pander::pander(rrAnalysisTrain\$c.index, caption="C. Index")

• C Index: 0.68

Dxy: 0.36S.D.: 0.014

• n: 2982

• missing: θ

• uncensored: 1518

• Relevant Pairs: 6184528

Concordant: 4206584Uncertain: 2703838

• cstatCI:

mean.C Index	median	lower	upper
0.68	0.681	0.667	0.695

pander::pander(t(rrAnalysisTrain\$ROCAnalysis\$aucs),caption="ROC AUC")

Table 49: ROC AUC

est	lower	upper
0.695	0.677	0.714

pander::pander((rrAnalysisTrain\$ROCAnalysis\$sensitivity),caption="Sensitivity")

Table 50: Sensitivity

est	lower	upper
0.327	0.303	0.351

pander::pander((rrAnalysisTrain\$ROCAnalysis\$specificity), caption="Specificity")

Table 51: Specificity

est	lower	upper
0.9	0.883	0.915

pander::pander(t(rrAnalysisTrain\$thr_atP),caption="Probability Thresholds")

Table 52: Probability Thresholds

90%	80%
0.541	0.431

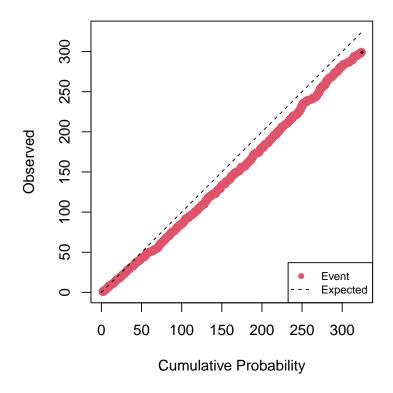
pander::pander(rrAnalysisTrain\$surdif,caption="Logrank test")

Table 53: Logrank test Chisq = 541.976716 on 2 degrees of freedom, p = 0.000000

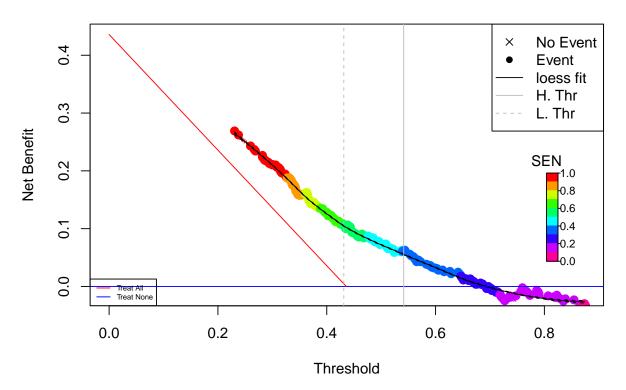
	N	Observed	Expected	$(O-E)^2/E$	$(O-E)^2/V$
class=0	1974	804	1144	100.9	415.3
class=1	365	218	170	13.4	15.1
class=2	643	496	204	418.2	490.7

1.7.2 Results on the validation set using Logistic model

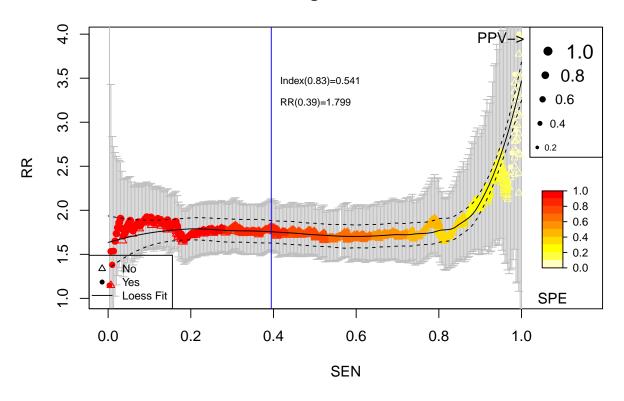
Cumulative vs. Observed: Logistic Test: Breast Cancer



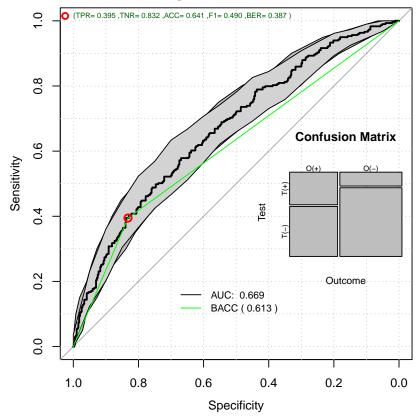
Decision Curve Analysis: Logistic Test: Breast Cancer



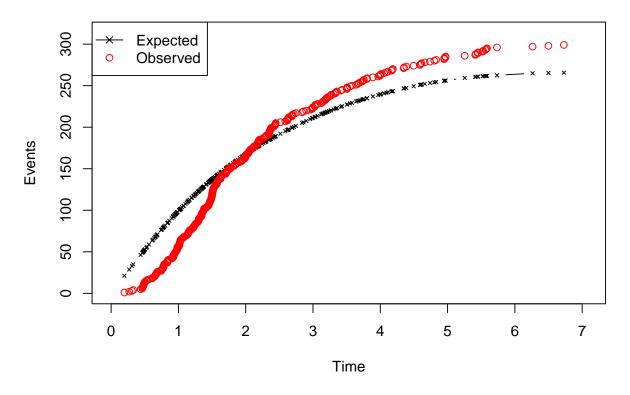
Relative Risk: Logistic Test: Breast Cancer



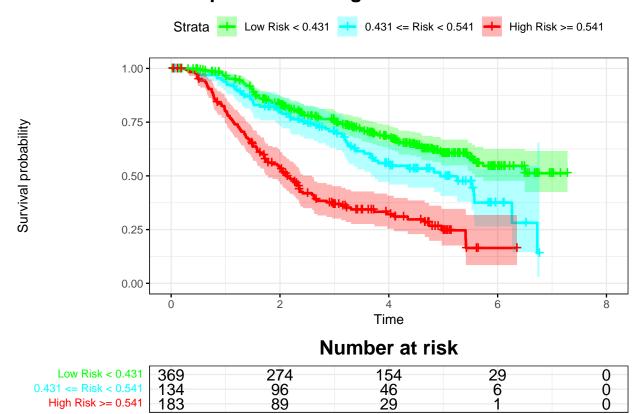
ROC: Logistic Test: Breast Cancer



Time vs. Events: Logistic Test: Breast Cancer



Kaplan-Meier: Logistic Test: Breast Cancer



par(op)

1.7.3 Validation Report

pander::pander(t(rrAnalysis\$keyPoints),caption="Threshold values")

Table 54: Threshold values

	@:0.541	@:0.431	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.542	0.431	0.439	0.306	2.31e-01	0.4996
$\mathbf{R}\mathbf{R}$	1.792	1.702	1.756	2.678	2.20e+01	1.7318
RR_LCI	1.529	1.428	1.477	1.679	4.75e-02	1.4731
RR_UCI	2.100	2.029	2.088	4.271	1.02e+04	2.0360
\mathbf{SEN}	0.395	0.595	0.579	0.950	1.00e+00	0.4482
\mathbf{SPE}	0.832	0.638	0.669	0.181	1.29e-02	0.7804
\mathbf{BACC}	0.613	0.617	0.624	0.565	5.06e-01	0.6143
NetBenefit	0.060	0.105	0.106	0.210	2.69e-01	0.0717

pander::pander(t(rrAnalysis\$OERatio\$estimate),caption="0/E Ratio")

Table 55: O/E Ratio

O/E	Low	Upper	p.value
1.13	1	1.26	0.0428

pander::pander(rrAnalysis\$c.index,caption="C. Index")

• C Index: 0.669

Dxy: 0.338S.D.: 0.0309

• **n**: 686

• missing: θ

• uncensored: 299

• Relevant Pairs: 266144

• Concordant: 178115

• Uncertain: 203702

• cstatCI:

mean.C Index	median	lower	upper
0.669	0.67	0.64	0.7

pander::pander(t(rrAnalysis\$ROCAnalysis\$aucs),caption="ROC AUC")

Table 57: ROC AUC

est	lower	upper
0.669	0.628	0.709

pander::pander((rrAnalysis\$ROCAnalysis\$sensitivity),caption="Sensitivity")

Table 58: Sensitivity

est	lower	upper
0.395	0.339	0.453

pander::pander((rrAnalysis\$ROCAnalysis\$specificity),caption="Specificity")

Table 59: Specificity

est	lower	upper
0.832	0.791	0.868

```
pander::pander(t(rrAnalysis$thr_atP),caption="Probability Thresholds")
```

Table 60: Probability Thresholds

90%	80%
0.541	0.431

pander::pander(rrAnalysis\$surdif,caption="Logrank test")

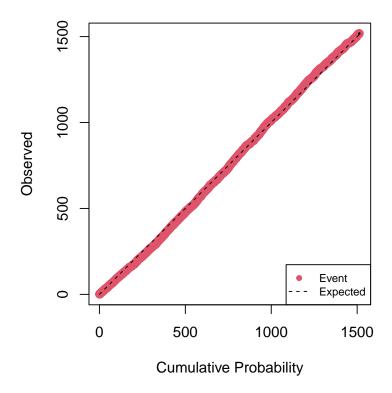
Table 61: Logrank test Chisq = 92.507991 on 2 degrees of freedom, p = 0.000000

	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	369	121	181.7	20.2997	52.3868
class=1	134	60	61.7	0.0479	0.0604
class=2	183	118	55.5	70.2342	88.0195

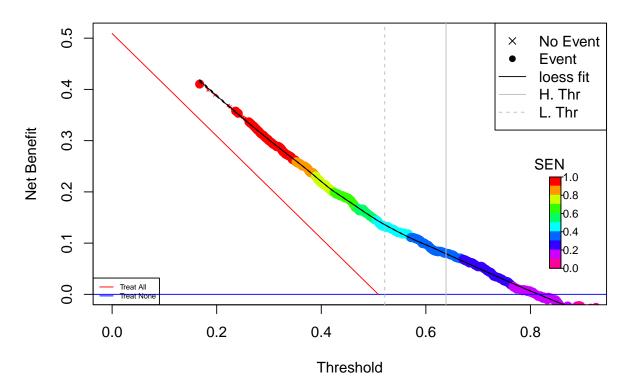
1.8 Logistic Model Poisson Calibration

h0	Gain	DeltaTime
0.676	1.31	7.14

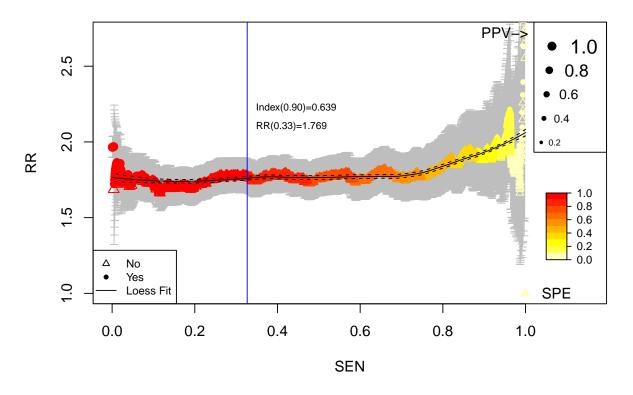
Cumulative vs. Observed: Cal. Logistic Train: Breast Cancer



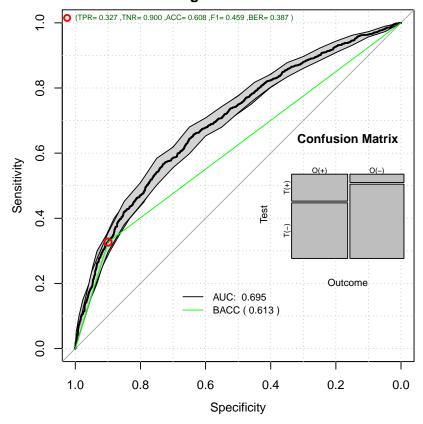
Decision Curve Analysis: Cal. Logistic Train: Breast Cancer



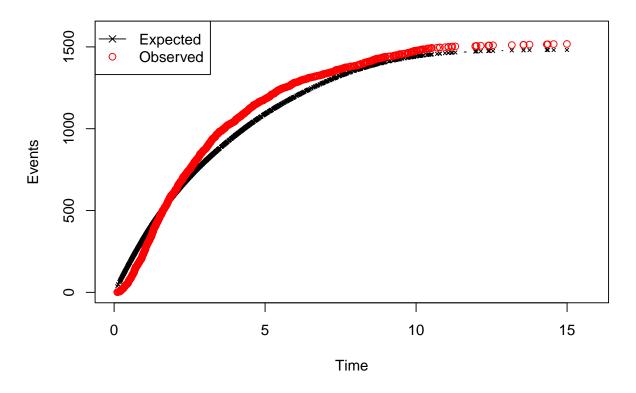
Relative Risk: Cal. Logistic Train: Breast Cancer



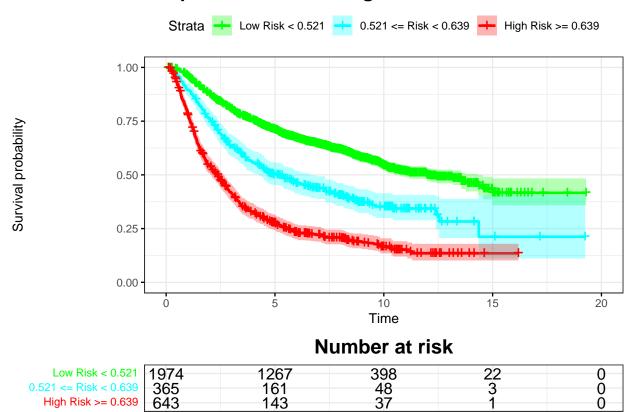
ROC: Cal. Logistic Train: Breast Cancer



Time vs. Events: Cal. Logistic Train: Breast Cancer



Kaplan-Meier: Cal. Logistic Train: Breast Cancer



par(op)

High Risk >= 0.639

1.8.1 Report of the calibrated logistic: training

pander::pander(t(rrAnalysisTrain\$keyPoints),caption="Threshold values")

Table 63: Threshold values

	@:0.9	@:0.8	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.6395	0.521	0.480	0.319	0.167426	0.500
$\mathbf{R}\mathbf{R}$	1.7654	1.739	1.799	2.213	1.000000	1.759
RR_LCI	1.6587	1.627	1.676	1.764	0.000000	1.643
RR_UCI	1.8790	1.858	1.931	2.777	0.000000	1.882
\mathbf{SEN}	0.3267	0.470	0.566	0.962	1.000000	0.507
\mathbf{SPE}	0.8996	0.799	0.731	0.125	0.000683	0.774
\mathbf{BACC}	0.6132	0.635	0.648	0.543	0.500342	0.641
NetBenefit	0.0789	0.132	0.166	0.288	0.410407	0.147

pander::pander(t(rrAnalysisTrain\$0ERatio\$estimate),caption="0/E Ratio")

Table 64: O/E Ratio

O/E	Low	Upper	p.value
1.02	0.974	1.08	0.343

pander::pander(rrAnalysisTrain\$c.index,caption="C. Index")

• **C** Index: 0.68

Dxy: 0.36S.D.: 0.014

n: 2982missing: 0

• uncensored: 1518

• Relevant Pairs: 6184528

Concordant: 4206590Uncertain: 2703838

• cstatCI:

mean.C Index	median	lower	upper
0.68	0.68	0.667	0.693

pander::pander(t(rrAnalysisTrain\$ROCAnalysis\$aucs),caption="ROC AUC")

Table 66: ROC AUC

est	lower	upper
0.695	0.677	0.714

pander::pander((rrAnalysisTrain\$ROCAnalysis\$sensitivity), caption="Sensitivity")

Table 67: Sensitivity

est	lower	upper
0.327	0.303	0.351

pander::pander((rrAnalysisTrain\$ROCAnalysis\$specificity), caption="Specificity")

Table 68: Specificity

est	lower	upper
0.9	0.883	0.915

pander::pander(t(rrAnalysisTrain\$thr_atP),caption="Probability Thresholds")

Table 69: Probability Thresholds

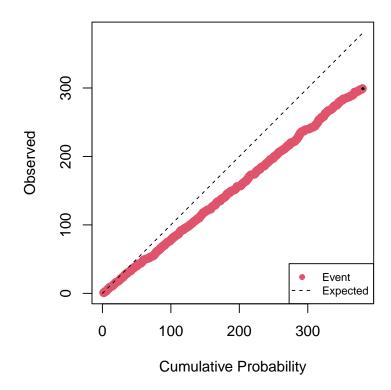
90%	80%
0.639	0.521

pander::pander(rrAnalysisTrain\$surdif,caption="Logrank test")

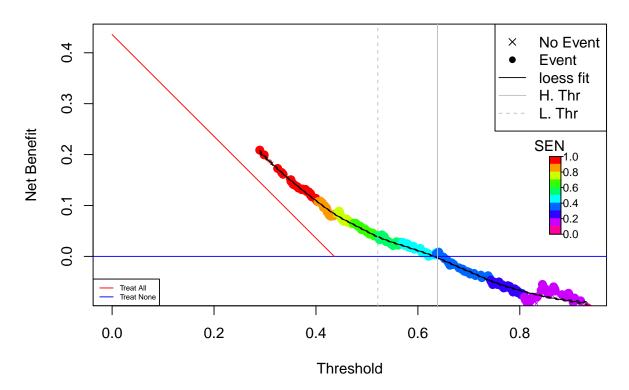
Table 70: Logrank test Chisq = 541.976716 on 2 degrees of freedom, p = 0.000000

	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	1974	804	1144	100.9	415.3
class=1	365	218	170	13.4	15.1
class=2	643	496	204	418.2	490.7

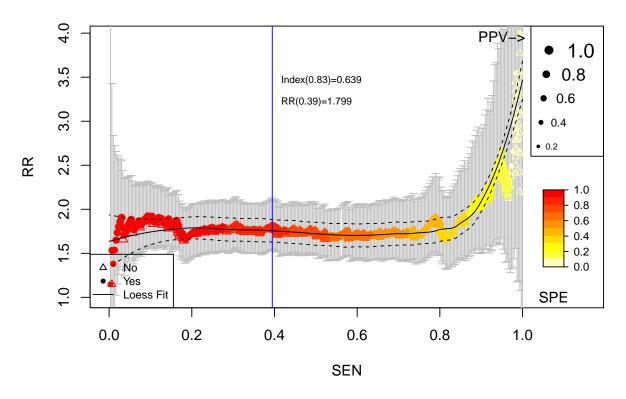
Cumulative vs. Observed: Cal. Logistic Test: Breast Cancer



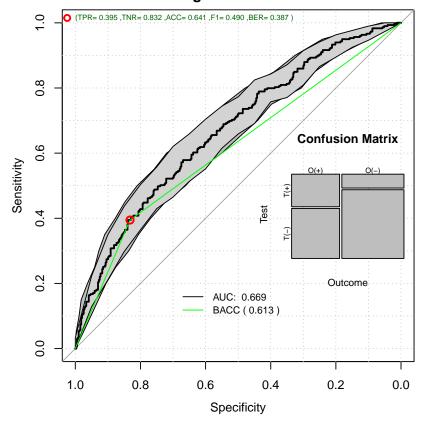
Decision Curve Analysis: Cal. Logistic Test: Breast Cancer



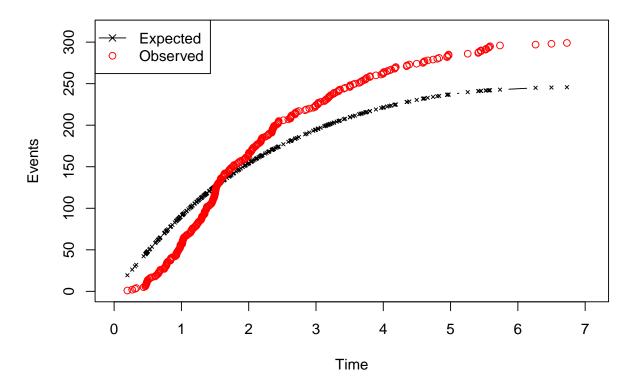
Relative Risk: Cal. Logistic Test: Breast Cancer



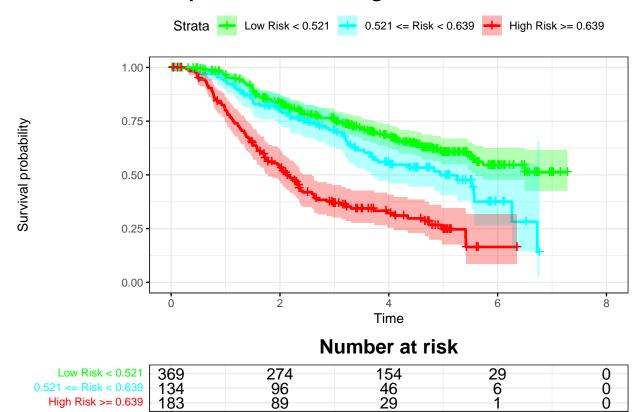
ROC: Cal. Logistic Test: Breast Cancer



Time vs. Events: Cal. Logistic Test: Breast Cancer



Kaplan-Meier: Cal. Logistic Test: Breast Cancer



par(op)

1.8.2 Report of the calibrated validation

pander::pander(t(rrAnalysisTestLogistic\$keyPoints),caption="Threshold values")

Table 71: Threshold values

	@:0.639	@:0.521	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.63882	0.5212	0.5294	0.379	2.90e-01	0.5001
RR	1.79193	1.7024	1.7562	2.678	2.20e+01	1.7026
RR_LCI	1.52914	1.4283	1.4771	1.679	4.75e-02	1.4179
RR_UCI	2.09988	2.0290	2.0880	4.271	1.02e+04	2.0446
\mathbf{SEN}	0.39465	0.5953	0.5786	0.950	1.00e+00	0.6421
\mathbf{SPE}	0.83204	0.6382	0.6693	0.181	1.29e-02	0.5866
\mathbf{BACC}	0.61335	0.6168	0.6239	0.565	5.06e-01	0.6144
NetBenefit	0.00447	0.0374	0.0423	0.132	2.09e-01	0.0466

pander::pander(t(rrAnalysisTestLogistic\$0ERatio\$estimate),caption="0/E Ratio")

Table 72: O/E Ratio

O/E	Low	Upper	p.value
1.22	1.08	1.36	0.00101

pander::pander(rrAnalysisTestLogistic\$c.index,caption="C. Index")

C Index: 0.669Dxy: 0.338

• **S.D.**: 0.0309

• n: 686

• missing: θ

• uncensored: 299

• Relevant Pairs: 266144

• Concordant: 178115

• Uncertain: 203702

• cstatCI:

mean.C Index	median	lower	upper
0.669	0.67	0.638	0.699

pander::pander(t(rrAnalysisTestLogistic\$ROCAnalysis\$aucs),caption="ROC AUC")

Table 74: ROC AUC

est	lower	upper
0.669	0.628	0.709

pander::pander((rrAnalysisTestLogistic\$ROCAnalysis\$sensitivity),caption="Sensitivity")

Table 75: Sensitivity

est	lower	upper
0.395	0.339	0.453

pander::pander((rrAnalysisTestLogistic\$ROCAnalysis\$specificity), caption="Specificity")

Table 76: Specificity

est	lower	upper
0.832	0.791	0.868

pander::pander(t(rrAnalysisTestLogistic\$thr_atP),caption="Probability Thresholds")

Table 77: Probability Thresholds

90%	80%
0.639	0.521

pander::pander(rrAnalysisTestLogistic\$surdif,caption="Logrank test")

Table 78: Logrank test Chisq = 92.507991 on 2 degrees of freedom, p = 0.000000

	N	Observed	Expected	$(O-E)^2/E$	(O-E)^2/V
class=0	369	121	181.7	20.2997	52.3868
class=1	134	60	61.7	0.0479	0.0604
class=2	183	118	55.5	70.2342	88.0195

1.9 Comparing the COX and Logistic Models on the Independent Data

pander::pander(t(rrCoxTestAnalysis\$OAcum95ci))

mean	50%	2.5%	97.5%
0.841	0.841	0.84	0.843

pander::pander(t(rrAnalysisTestLogistic\$OAcum95ci))

mean	50%	2.5%	97.5%
0.791	0.791	0.791	0.792

pander::pander(t(rrCoxTestAnalysis\$0E95ci))

mean	50%	2.5%	97.5%
1.11	1.11	1.08	1.13

pander::pander(t(rrAnalysisTestLogistic\$0E95ci))

mean	50%	2.5%	97.5%
0.989	0.989	0.962	1.01

maxobs <- sum(dataBrestCancerTest\$status)</pre>

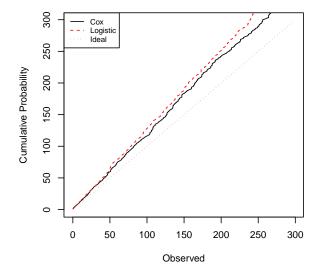
par(mfrow=c(1,2),cex=0.75)

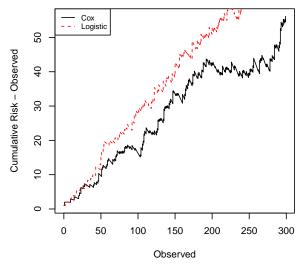
plot(rrCoxTestAnalysis\$CumulativeOvs[,1:2],type="l",lty=1,

```
main="Cumulative Probability",
     xlab="Observed",
     vlab="Cumulative Probability",
     ylim=c(0,maxobs),
     xlim=c(0,maxobs))
lines(rrAnalysisTestLogistic$CumulativeOvs[,1:2],lty=2,col="red")
lines(x=c(0,maxobs),y=c(0,maxobs),lty=3,col="gray")
legend("topleft",legend = c("Cox","Logistic","Ideal"),
       col=c("black","red","gray"),
       lty=c(1,2,3),
       cex=0.75
)
plot(rrCoxTestAnalysis$CumulativeOvs$Observed,
     rrCoxTestAnalysis$CumulativeOvs$Cumulative-
       rrCoxTestAnalysis$CumulativeOvs$Observed,
     main="Cumulative Risk Difference",
     xlab="Observed",
     ylab="Cumulative Risk - Observed",
     type="1",
     lty=1)
lines(rrAnalysisTestLogistic$CumulativeOvs$Observed,
     rrAnalysisTestLogistic$CumulativeOvs$Cumulative-
       rrAnalysisTestLogistic$CumulativeOvs$Observed,
     lty=2,
     col="red")
legend("topleft",legend = c("Cox","Logistic"),
       col=c("black","red"),
       lty=c(1,2),
       cex=0.75
)
```

Cumulative Probability

Cumulative Risk Difference

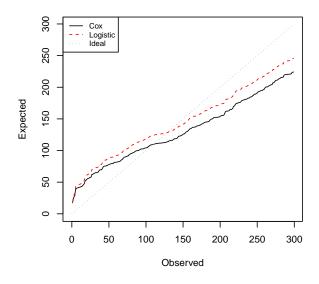


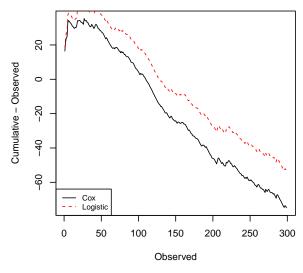


```
plot(rrCoxTestAnalysis$0EData[,2:3],type="1",lty=1,
     main="Expected over Time",
     xlab="Observed",
     ylab="Expected",
     ylim=c(0,maxobs),
     xlim=c(0,maxobs))
lines(rrAnalysisTestLogistic$0EData[,2:3],lty=2,col="red")
lines(x=c(0,maxobs),y=c(0,maxobs),lty=3,col="gray")
legend("topleft",legend = c("Cox","Logistic","Ideal"),
       col=c("black","red","gray"),
       lty=c(1,2,3),
       cex=0.75
)
plot(rrCoxTestAnalysis$0EData$0bserved,
     rrCoxTestAnalysis$0EData$Expected-
       rrCoxTestAnalysis$OEData$Observed,
     main="Expected vs Observed Difference",
     xlab="Observed",
     ylab="Cumulative - Observed",
     type="1",
     lty=1)
lines(rrAnalysisTestLogistic$0EData$0bserved,
     rrAnalysisTestLogistic$OEData$Expected-
       rrAnalysisTestLogistic$0EData$0bserved,
     lty=2,col="red")
legend("bottomleft",legend = c("Cox","Logistic"),
       col=c("black","red"),
       lty=c(1,2),
       cex=0.75
)
```

Expected over Time

Expected vs Observed Difference





par(op)