Risk-Evaluation: Breast Cancer Royston-Altman

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Contents

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: miscTools
```

```
## Loading required package: Hmisc
```

```
##
## 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$pid
gbsgdata$pid <- NULL

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)]

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))

data$`(Intercept)` <- NULL

dataBrestCancerTrain <- cbind(time=odata[rownames(data),"rfstime"],status=odata[rownames(data),"status"]

colnames(dataBrestCancerTrain) <-str_replace_all(colnames(dataBrestCancerTrain),":","_")
colnames(dataBrestCancerTrain) <-str_replace_all(colnames(dataBrestCancerTrain)," ","")
colnames(dataBrestCancerTrain) <-str_replace_all(colnames(dataBrestCancerTrain),"\\.","_")
colnames(dataBrestCancerTrain) <-str_replace_all(colnames(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),"sta

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")
```

Table 2: gbsg

0	1
499	183

1.3 Cox Modeling

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

——.

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

	Estimate	lower HR	upper	u. Accuracy	cv Accuracy	full. Accuracy	cv AUC	C.AUC	full. AUC	IDI	NRI	z.IDI	z.NRI	Delta. AUC	Frequency
age__nodes	0.000716	1.001	1.001	1.001	0.626	0.600	0.632	0.630	0.601	0.634	0.03040	0.4594	12.81	14.37	0.0330561
size__grade	0.005641	1.005	1.006	1.006	0.598	0.623	0.632	0.599	0.626	0.634	0.01868	0.3914	9.82	11.29	0.0079471
nodes	0.086582	2.082	1.090	1.099	0.637	0.642	0.643	0.640	0.643	0.644	0.00745	0.0564	8.33	1.66	0.0001481
size	0.006888	1.005	1.007	1.009	0.595	0.641	0.643	0.595	0.642	0.644	0.01447	0.3587	8.05	9.97	0.0013221
size__nodes	1.000	1.000	1.000	1.000	0.624	0.643	0.643	0.629	0.644	0.644	0.00340	0.3430	7.25	9.57	- 1
	0.000378														0.000377
age__size	- 1.000	1.000	1.000	1.000	0.567	0.627	0.632	0.568	0.630	0.634	0.00635	0.1935	5.95	5.36	0.0040781
	0.000149														
grade	0.204934	1.227	1.314	0.565	0.637	0.643	0.561	0.638	0.644	0.00926	0.2069	5.88	6.31	0.0053441	

	Estimate	lower HR	upper	u. Accuracy	r. Accuracy	full. Accuracy	r. AUC	f. AUC	full. AUC	IDI	NRI	z.IDI	z.NRI	Delta.AUC	Frequency
age	-0.003113	0.996	0.997	0.998	0.513	0.628	0.643	0.513	0.628	0.644	0.00410	0.0917	5.27	2.51	0.0154651
grade_nodes	0.013784	0.981	0.986	0.992	0.635	0.645	0.643	0.639	0.646	0.644	0.00207	-0.0910	5.03	-2.55	-0.002609	1

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()

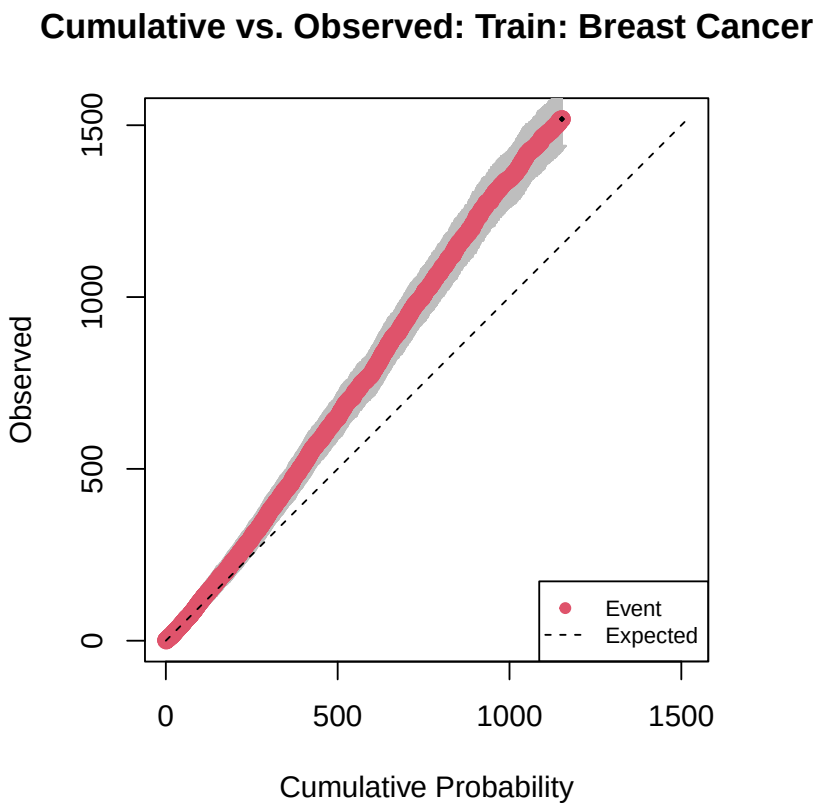
Here we will use the predicted event probability assuming a baseline hazard for events withing 5 years

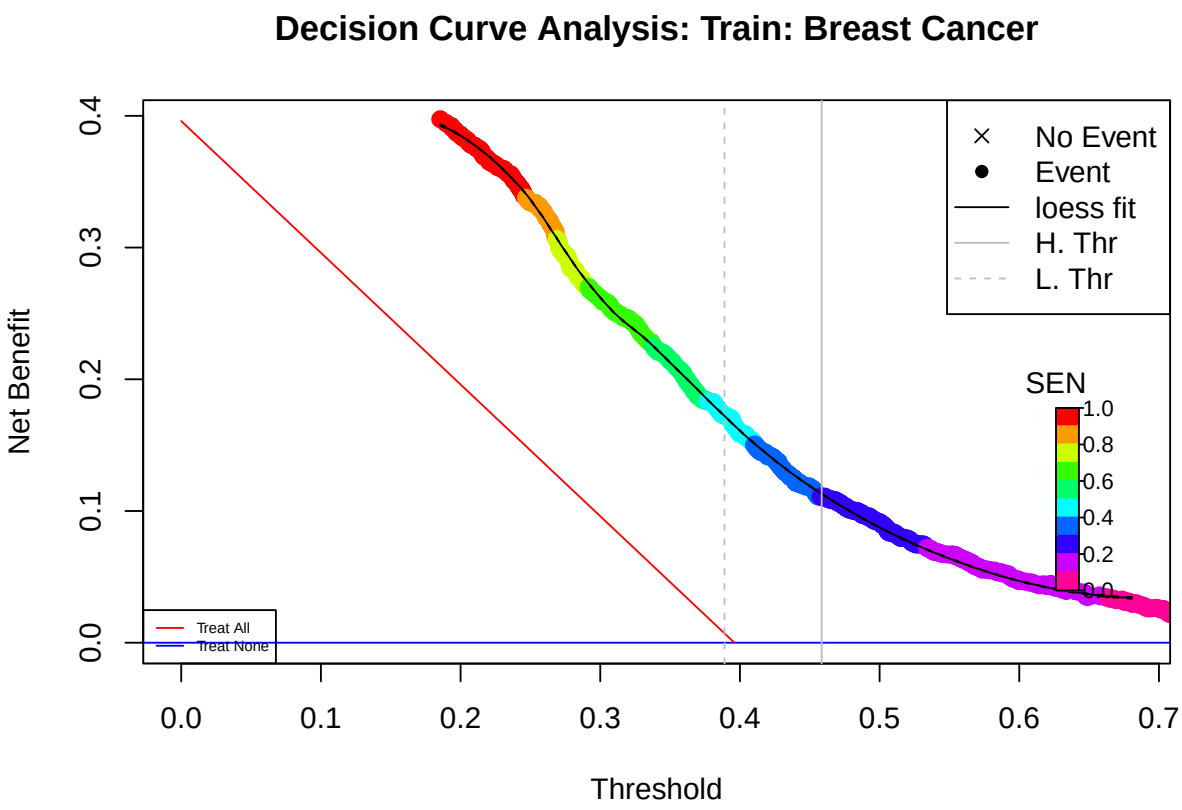
```
timeinterval <- 5 # Five years

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")
```

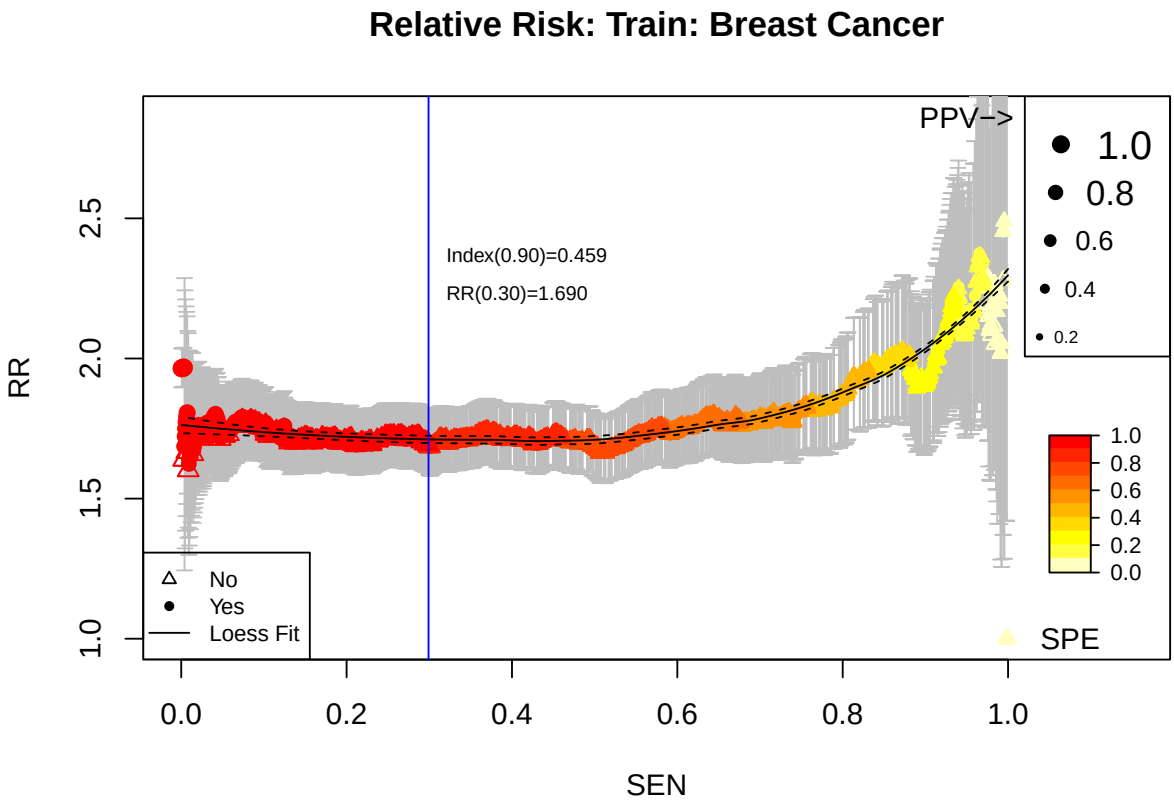
Table 4: Initial Parameters

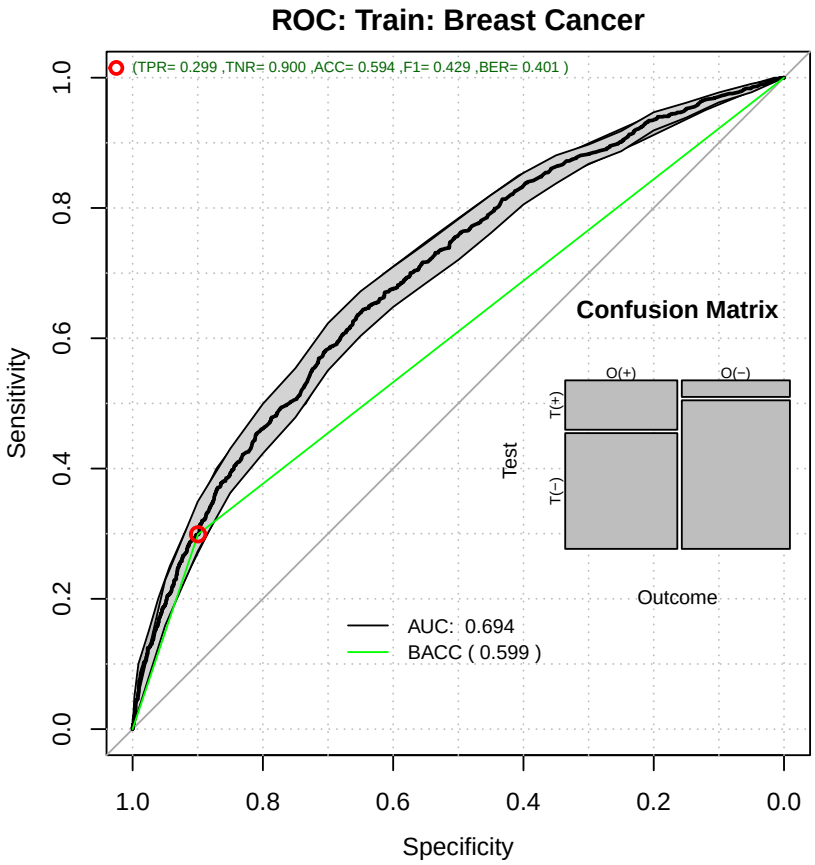
h0	timeinterval
0.429	5

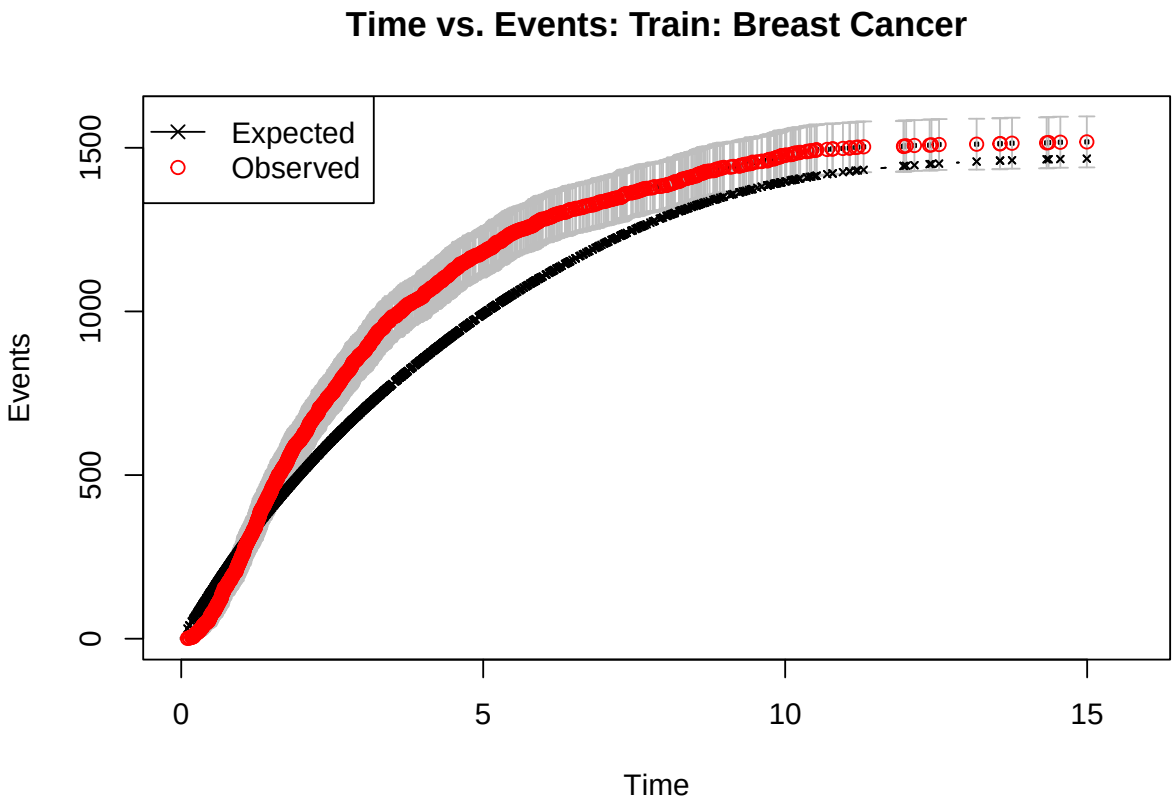
```
index <- predict(ml,dataBrestCancerTrain)
rdata <- cbind(dataBrestCancerTrain$status,ppoisGzero(index,h0))

rrAnalysisTrain <- RRPlot(rdata,atRate=c(0.90,0.80),
                      timetoEvent=dataBrestCancerTrain$time,
                      title="Train: Breast Cancer",
                      ysurvlim=c(0.00,1.0),
                      riskTimeInterval=timeinterval)
```

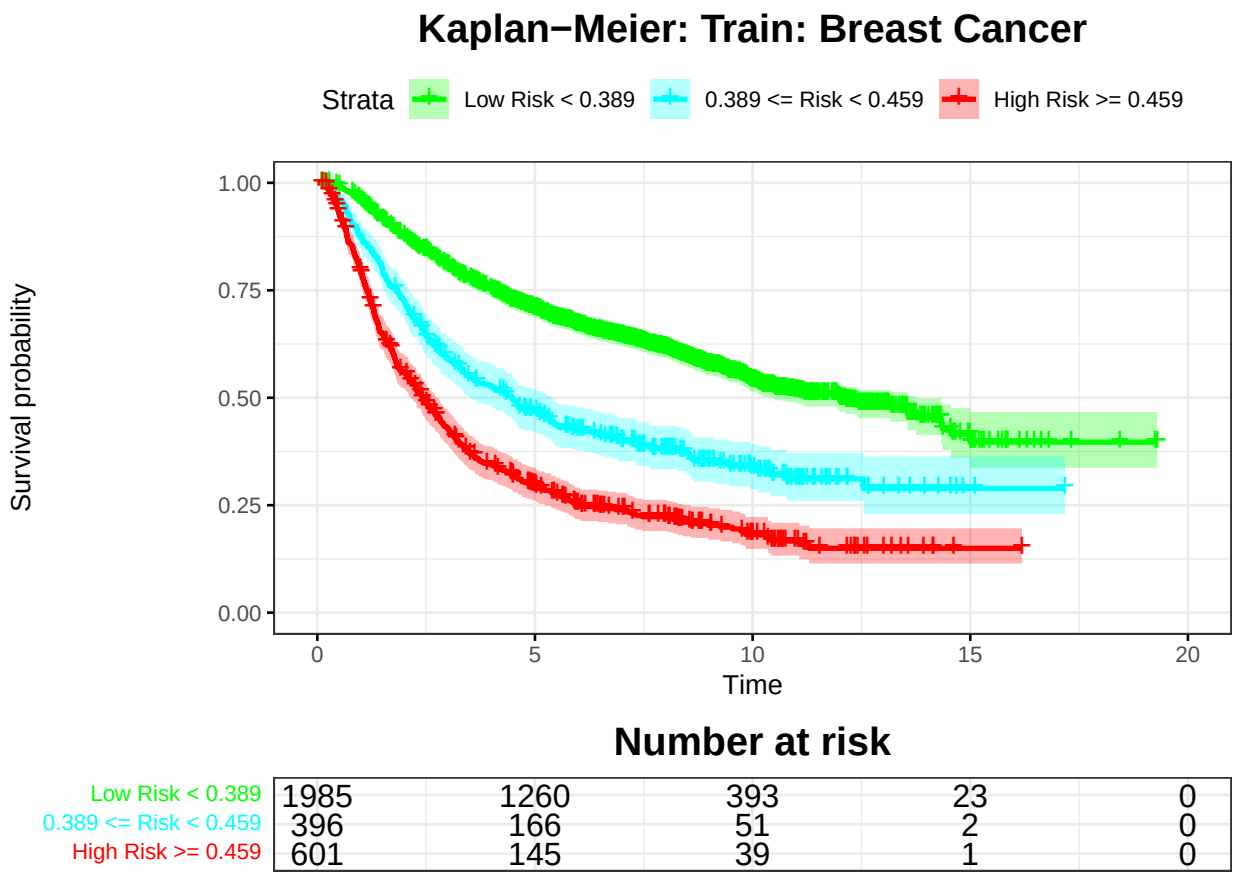

Cumulative vs. Observed: Train: Breast Cancer
Observed
0
500
1000
1500
Cumulative Probability
0
500
1000
1500
Event
Expected


Decision Curve Analysis: Train: Breast Cancer
Net Benefit
0.0
0.1
0.2
0.3
0.4
Threshold
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None


Relative Risk: Train: Breast Cancer
PPV–>
1.0
0.8
0.6
0.4
0.2
Index(0.90)=0.459
RR(0.30)=1.690
1.0
0.8
0.6
0.4
0.2
0.0
No
Yes
Loess Fit
SPE
RR
2.5
2.0
1.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
SEN


ROC: Train: Breast Cancer
(TPR= 0.299 ,TNR= 0.900 ,ACC= 0.594 ,F1= 0.429 ,BER= 0.401)
Sensitivity
Specificity
1.0
0.8
0.6
0.4
0.2
0.0
Confusion Matrix
O(+)
O(−)
T(+)
T(−)
Test
Outcome
AUC: 0.694
BACC (0.599)


Time vs. Events: Train: Breast Cancer
Expected
Observed
Events
0
500
1000
1500
0
5
10
15
Time



1.4.2 Time to event

```
toinclude <- rdata[,1]==1
obstiemToEvent <- dataBrestCancerTrain[,"time"]
tmin<-min(obstiemToEvent)
sum(toinclude)
```

[1] 1518

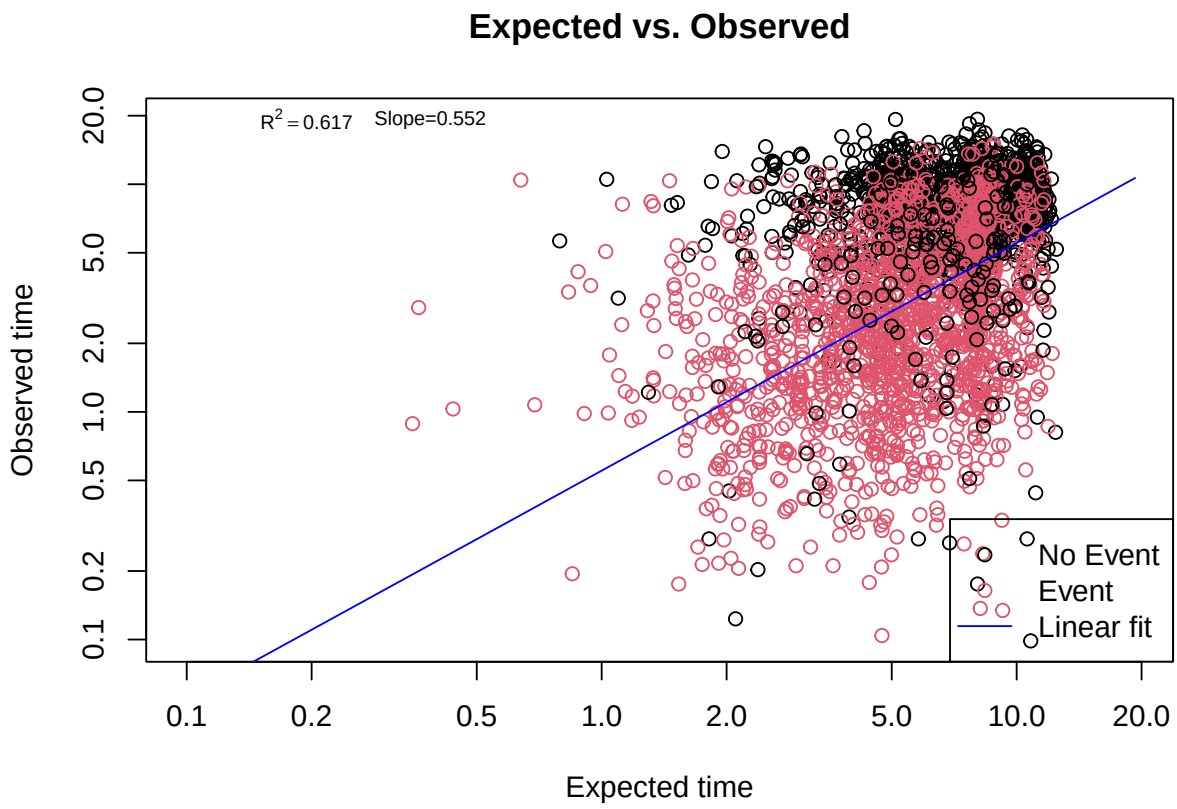
```
timetoEvent <- meanTimeToEvent(rdata[,2],timeinterval)
tmax<-max(c(obstiemToEvent,timetoEvent))
lmfit <- lm(obstiemToEvent[toinclude]~0+timetoEvent[toinclude])
sm <- summary(lmfit)
pander::pander(sm)
```

	Estimate	Std. Error	t value	Pr(>|t|)
timetoEvent[toinclude]	0.552	0.0112	49.4	3.39e-318

Table 6: Fitting linear model: obstiemToEvent[toinclude] ~ 0 + timetoEvent[toinclude]

Observations	Residual Std. Error	R^2	Adjusted R^2
1518	2.67	0.617	0.616

```
plot(timetoEvent,obstiemToEvent,
     col=1+rdata[,1],
     xlab="Expected time",
     ylab="Observed time",
     main="Expected vs. Observed",
     xlim=c(tmin,tmax),
     ylim=c(tmin,tmax),
     log="xy")
lines(x=c(tmin,tmax),y=lmfit$coefficients*c(tmin,tmax),lty=1,col="blue")
txt <- bquote(paste(R^2 == .(round(sm$r.squared,3))))
text(tmin+0.005*(tmax-tmin),tmax,txt,cex=0.7)
text(tmin+0.015*(tmax-tmin),tmax,sprintf("Slope=%4.3f",sm$coefficients[1]),cex=0.7)
legend("bottomright",legend=c("No Event","Event","Linear fit"),
              pch=c(1,1,-1),
              col=c(1,2,"blue"),
              lty=c(-1,-1,1)
              )
```



```
MADerror2 <- mean(abs(timetoEvent[toinclude]-obstiemToEvent[toinclude]))
pander::pander(MADerror2)
```

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 7: Threshold values

	@:0.9	@:0.8	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.459	0.389	0.320	0.214	0.18549	0.4996
RR	1.690	1.713	1.799	2.376	1.00000	1.7255
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
SEN	0.299	0.462	0.644	0.965	1.00000	0.2464
SPE	0.900	0.798	0.646	0.125	0.00137	0.9310
BACC	0.599	0.630	0.645	0.545	0.50068	0.5887
NetBenefit	0.110	0.172	0.246	0.374	0.39742	0.0916

```
pander::pander(t(rrAnalysisTrain$OERatio$estimate),caption="O/E Ratio")
```

Table 8: O/E Ratio

O/E	Low	Upper	p.value
1.03	0.984	1.09	0.183

```
pander::pander(t(rrAnalysisTrain$OE95ci),caption="O/E Mean")
```

Table 9: O/E Mean

mean	50%	2.5%	97.5%
1.14	1.14	1.13	1.15

```
pander::pander(t(rrAnalysisTrain$OAcum95ci),caption="O/Acum Mean")
```

Table 10: O/Acum Mean

mean	50%	2.5%	97.5%
1.31	1.31	1.31	1.32

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

mean.C Index	median	lower	upper
0.676	0.677	0.663	0.691

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

Table 12: ROC AUC

est	lower	upper
0.694	0.675	0.713

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

Table 13: Sensitivity

est	lower	upper
0.299	0.276	0.323

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

Table 14: Specificity

est	lower	upper
0.9	0.883	0.915

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

Table 15: Probability Thresholds

90%	80%
0.459	0.389

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

Table 16: 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

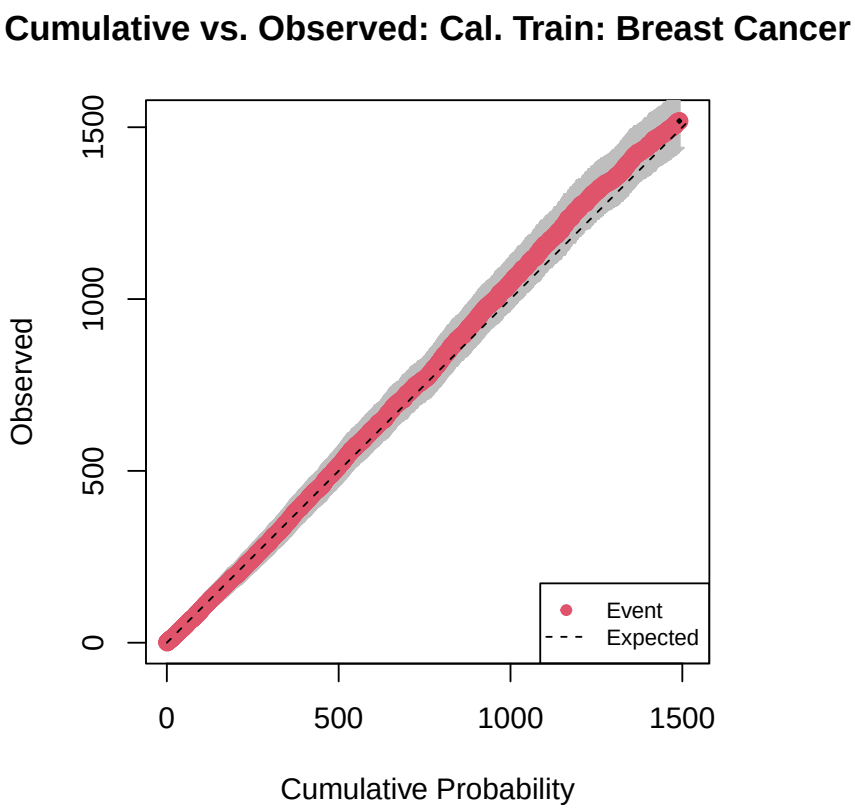
1.4.4 Cox Calibration

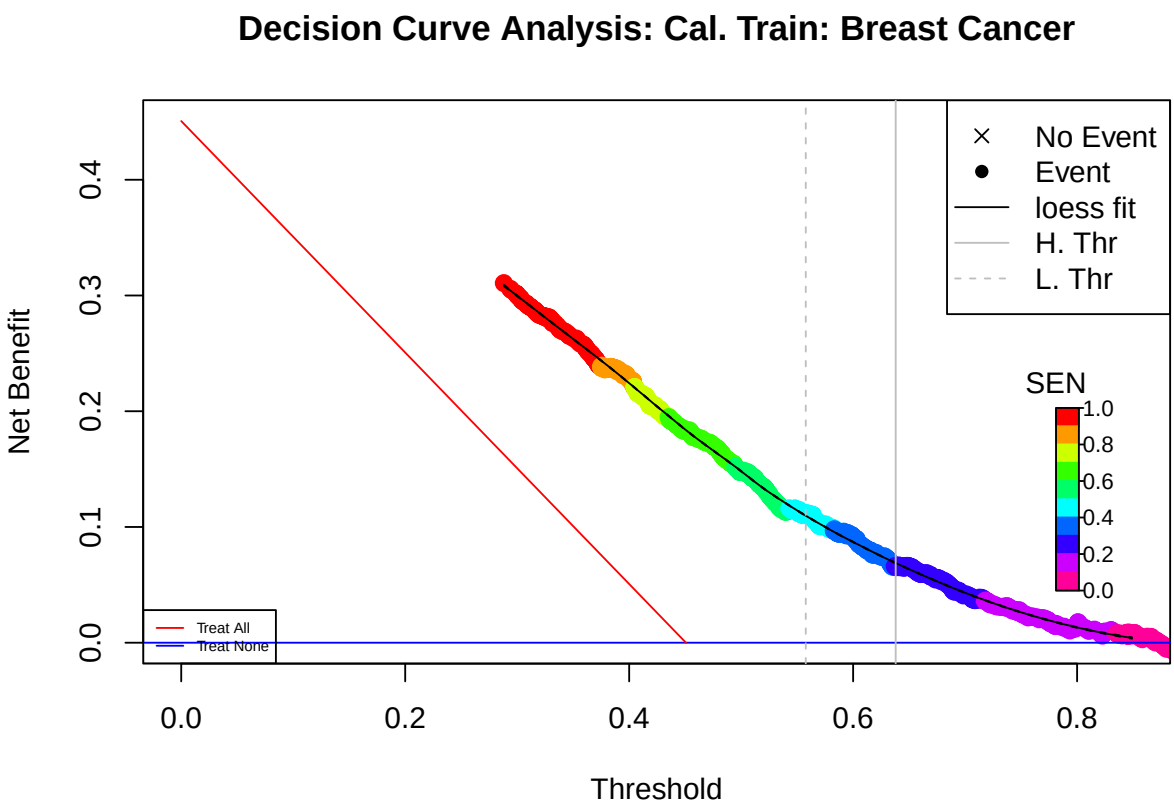
```
op <- par(no.readonly = TRUE)


calprob <- CoxRiskCalibration(ml,dataBrestCancerTrain,"status","time")


pander::pander(c(h0=calprob$h0,
                 Gain=calprob$hazardGain,
                 DeltaTime=calprob$timeInterval),
               caption="Cox Calibration Parameters")
```

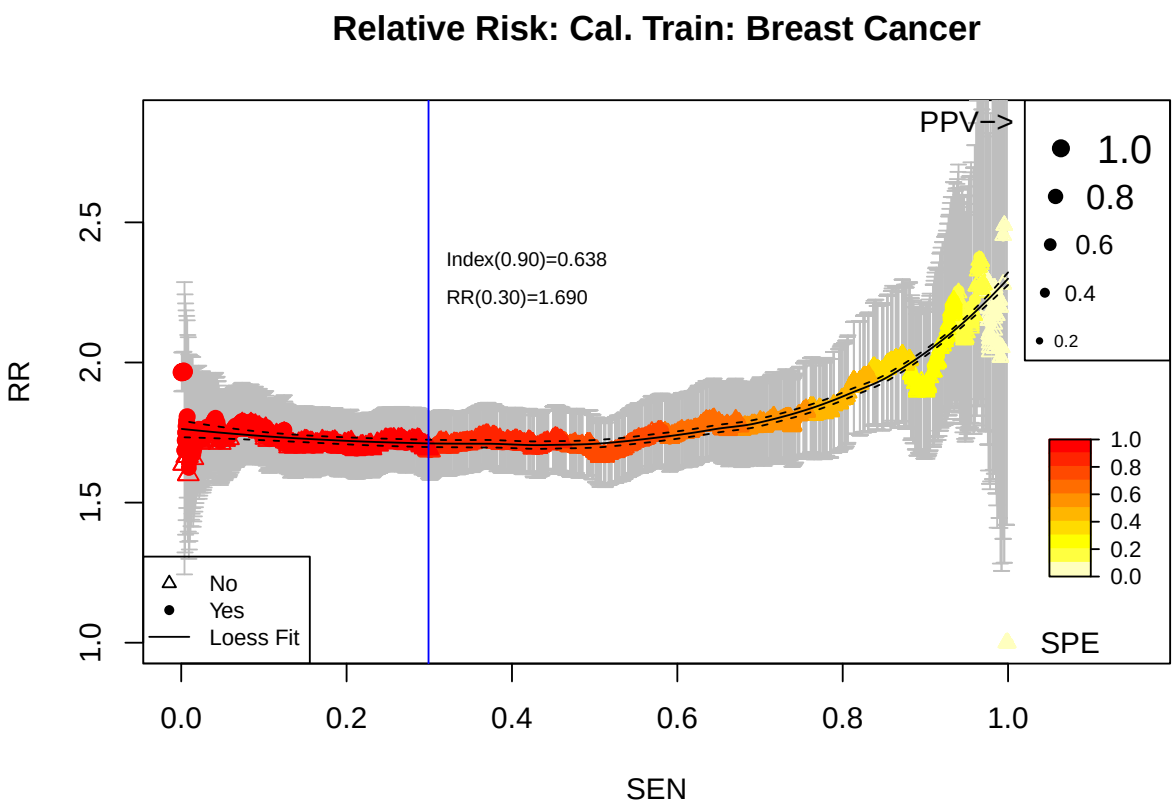
h0	Gain	DeltaTime
0.711	1.37	7.17

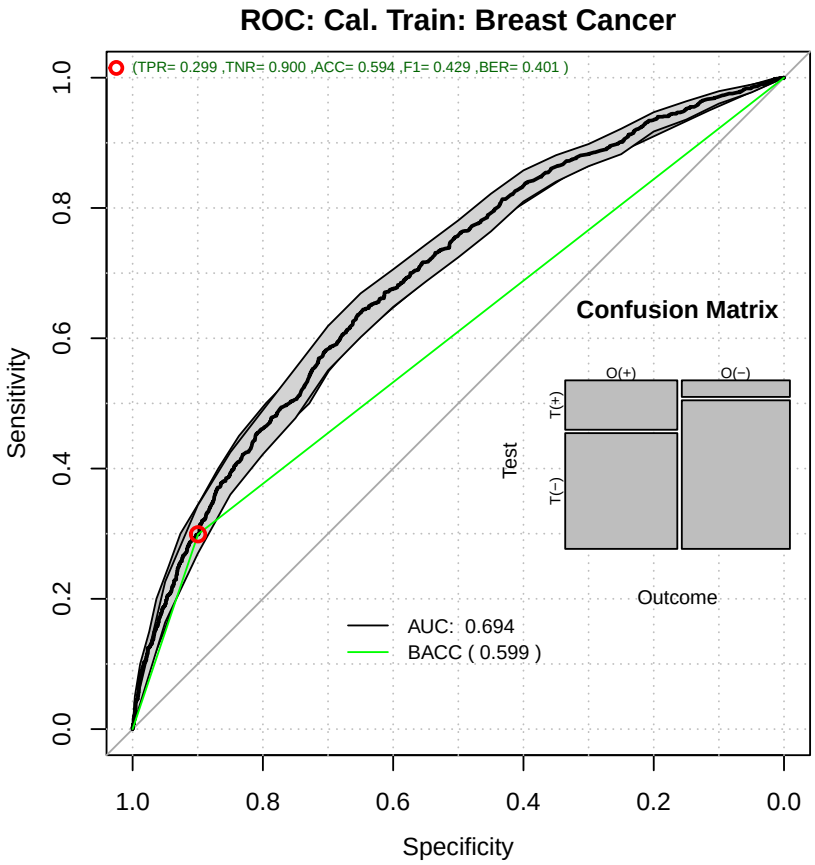
1.4.5 The RRplot() of the calibrated model

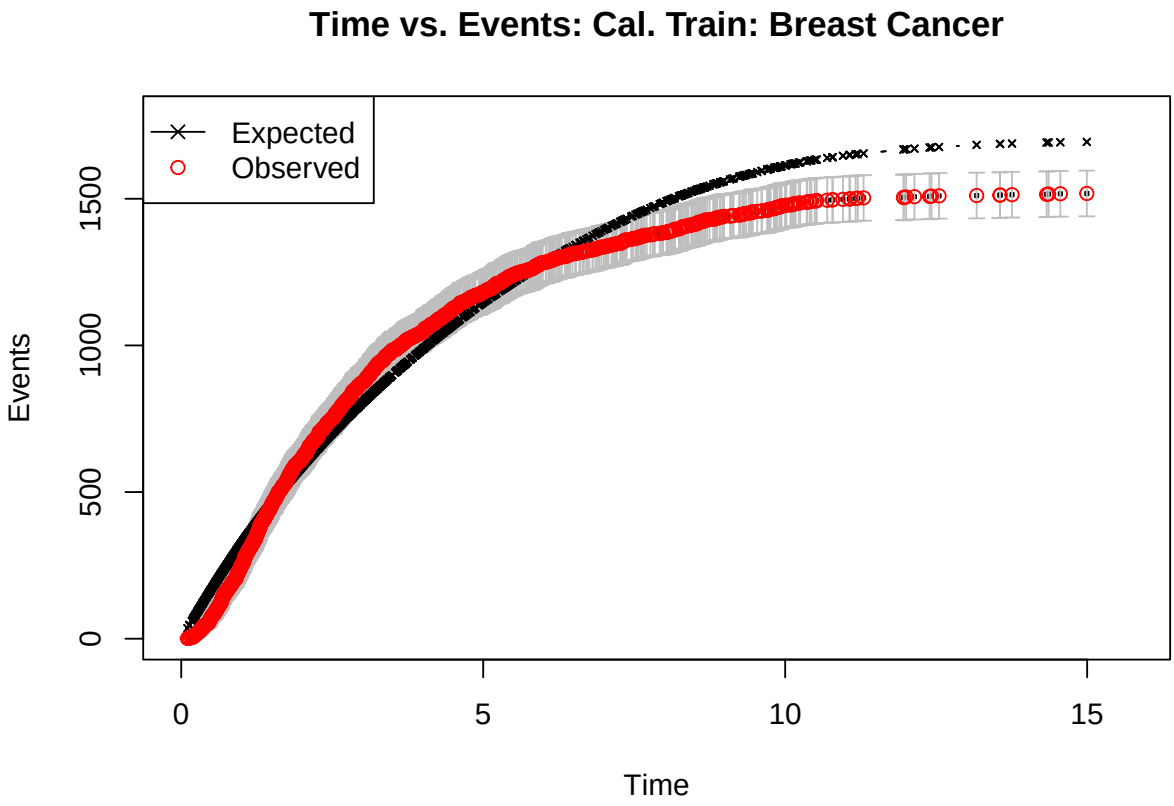
```
h0 <- calprob$h0
timeinterval <- calprob$timeInterval;

rdata <- cbind(dataBrestCancerTrain$status,calprob$prob)


rrAnalysisTrain <- RRPlot(rdata,atRate=c(0.90,0.80),
                      timetoEvent=dataBrestCancerTrain$time,
                      title="Cal. Train: Breast Cancer",
                      ysurvlim=c(0.00,1.0),
                      riskTimeInterval=timeinterval)
```

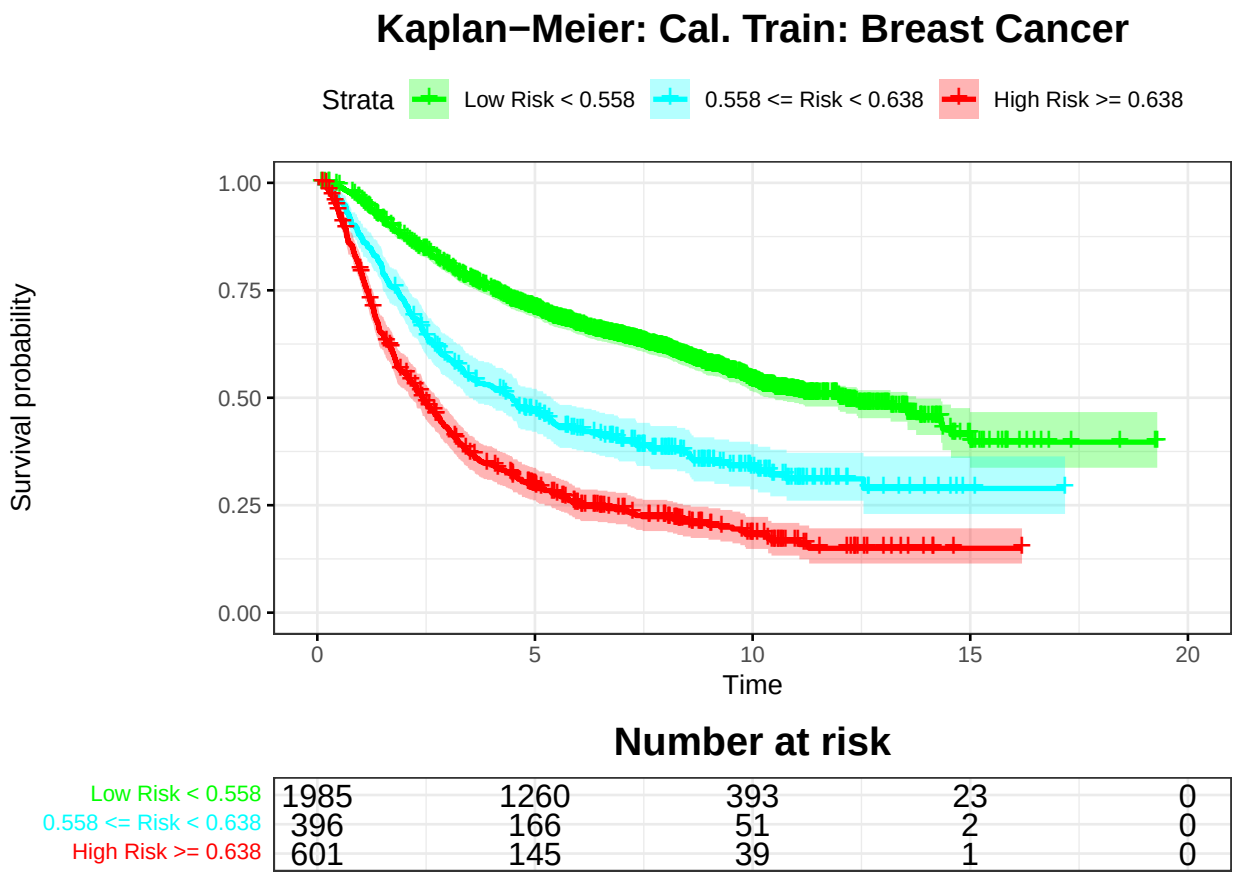

Cumulative vs. Observed: Cal. Train: Breast Cancer
Observed
0
500
1000
1500
0
500
1000
1500
Cumulative Probability
Event
Expected


Decision Curve Analysis: Cal. Train: Breast Cancer
Net Benefit
0.0
0.1
0.2
0.3
0.4
Threshold
0.0
0.2
0.4
0.6
0.8
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None


Relative Risk: Cal. Train: Breast Cancer
PPV–>
1.0
0.8
0.6
0.4
0.2
Index(0.90)=0.638
RR(0.30)=1.690
1.0
0.8
0.6
0.4
0.2
0.0
SPE
No
Yes
Loess Fit
RR
1.0
1.5
2.0
2.5
0.0
0.2
0.4
0.6
0.8
1.0
SEN


ROC: Cal. Train: Breast Cancer
(TPR= 0.299 ,TNR= 0.900 ,ACC= 0.594 ,F1= 0.429 ,BER= 0.401)
Sensitivity
Specificity
1.0
0.8
0.6
0.4
0.2
0.0
Confusion Matrix
O(+)
O(−)
T(+)
T(−)
Test
Outcome
AUC: 0.694
BACC (0.599)


Time vs. Events: Cal. Train: Breast Cancer
Expected
Observed
Events
0
500
1000
1500
0
5
10
15
Time



1.4.6 Time to event after calibration

```
timetoEvent <- meanTimeToEvent(rdata[,2],timeinterval)
tmax<-max(c(obstiemToEvent,timetoEvent))
lmfit <- lm(obstiemToEvent[toinclude]~0+timetoEvent[toinclude])
sm <- summary(lmfit)
pander::pander(sm)
```

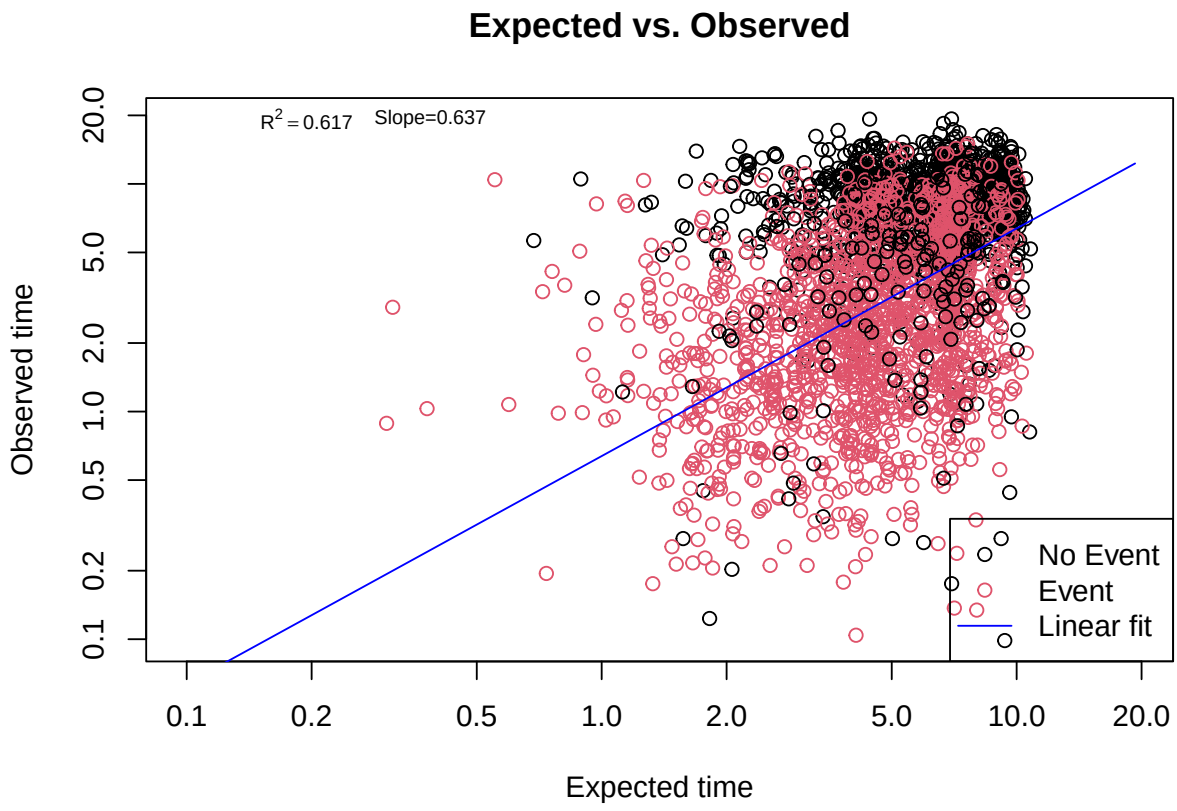
	Estimate	Std. Error	t value	Pr(>|t|)
timetoEvent[toinclude]	0.637	0.0129	49.4	3.39e-318

Table 19: Fitting linear model: obstiemToEvent[toinclude] ~ 0 + timetoEvent[toinclude]

Observations	Residual Std. Error	R^2	Adjusted R^2
1518	2.67	0.617	0.616

```
plot(timetoEvent,obstiemToEvent,
     col=1+rdata[,1],
     xlab="Expected time",
     ylab="Observed time",
```

```
     main="Expected vs. Observed",
     xlim=c(tmin,tmax),
     ylim=c(tmin,tmax),
     log="xy")
lines(x=c(tmin,tmax),y=lmfit$coefficients*c(tmin,tmax),lty=1,col="blue")
txt <- bquote(paste(R^2 == .(round(sm$r.squared,3))))
text(tmin+0.005*(tmax-tmin),tmax,txt,cex=0.7)
text(tmin+0.015*(tmax-tmin),tmax,sprintf("Slope=%4.3f",sm$coefficients[1]),cex=0.7)
legend("bottomright",legend=c("No Event","Event","Linear fit"),
             pch=c(1,1,-1),
             col=c(1,2,"blue"),
             lty=c(-1,-1,1)
             )
```




```
MADerror2 <- c(MADerror2,mean(abs(timetoEvent[toinclude]-obstiemToEvent[toinclude])))
pander::pander(MADerror2)
```

3.12 and *2.65*

1.4.7 Calibrated Train Performance

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

Table 20: Threshold values

	@:0.9	@:0.8	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.6383	0.558	0.472	0.329	0.28808	0.499
RR	1.6904	1.713	1.799	2.376	1.00000	1.741
RR_LCI	1.5860	1.603	1.666	1.869	0.00000	1.620
RR_UCI	1.8018	1.830	1.942	3.019	0.00000	1.872
SEN	0.2991	0.462	0.644	0.965	1.00000	0.589
SPE	0.8996	0.798	0.646	0.125	0.00137	0.691
BACC	0.5993	0.630	0.645	0.545	0.50068	0.640
NetBenefit	0.0653	0.111	0.173	0.281	0.31069	0.149

```
pander::pander(t(rrAnalysisTrain$OERatio$estimate),caption="O/E Ratio")
```

Table 21: O/E Ratio

O/E	Low	Upper	p.value
0.896	0.852	0.942	1.44e-05

```
pander::pander(t(rrAnalysisTrain$OE95ci),caption="O/E Mean")
```

Table 22: O/E Mean

mean	50%	2.5%	97.5%
0.988	0.988	0.982	0.995

```
pander::pander(t(rrAnalysisTrain$OAcum95ci),caption="O/Acum Mean")
```

Table 23: O/Acum Mean

mean	50%	2.5%	97.5%
1.03	1.03	1.03	1.03

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

mean.C Index	median	lower	upper
0.676	0.676	0.664	0.689

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

Table 25: ROC AUC

est	lower	upper
0.694	0.675	0.713

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

Table 26: Sensitivity

est	lower	upper
0.299	0.276	0.323

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

Table 27: Specificity

est	lower	upper
0.9	0.883	0.915

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

Table 28: Probability Thresholds

90%	80%
0.638	0.558

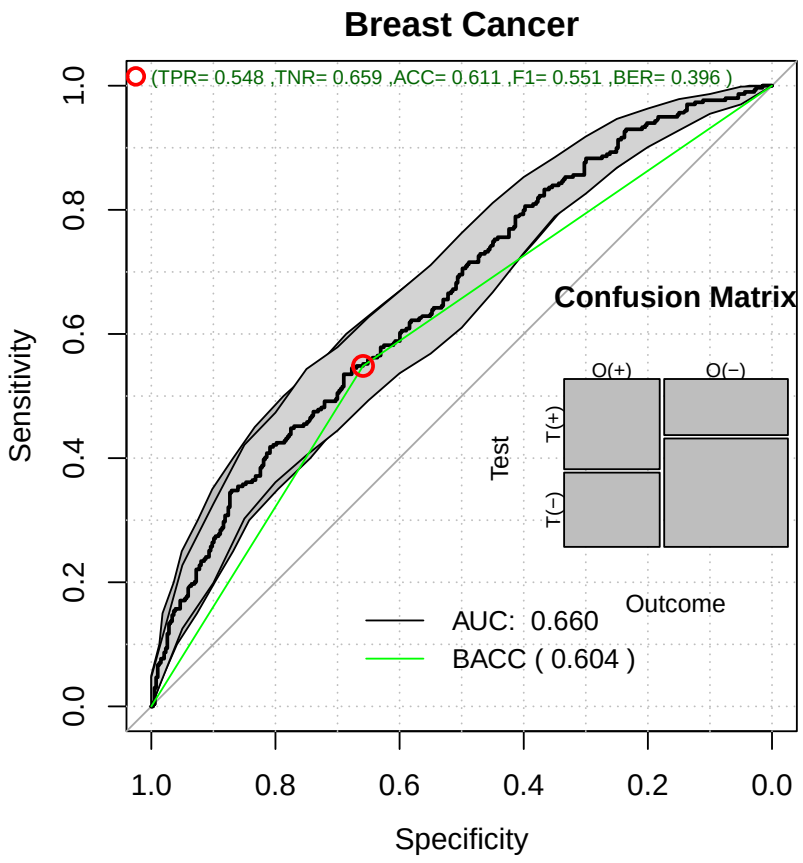
```
pander::pander(rrAnalysisTrain$surdif,caption="Logrank test")
```

Table 29: Logrank test Chisq = 465.079317 on 2 degrees of freedom, p = 0.000000

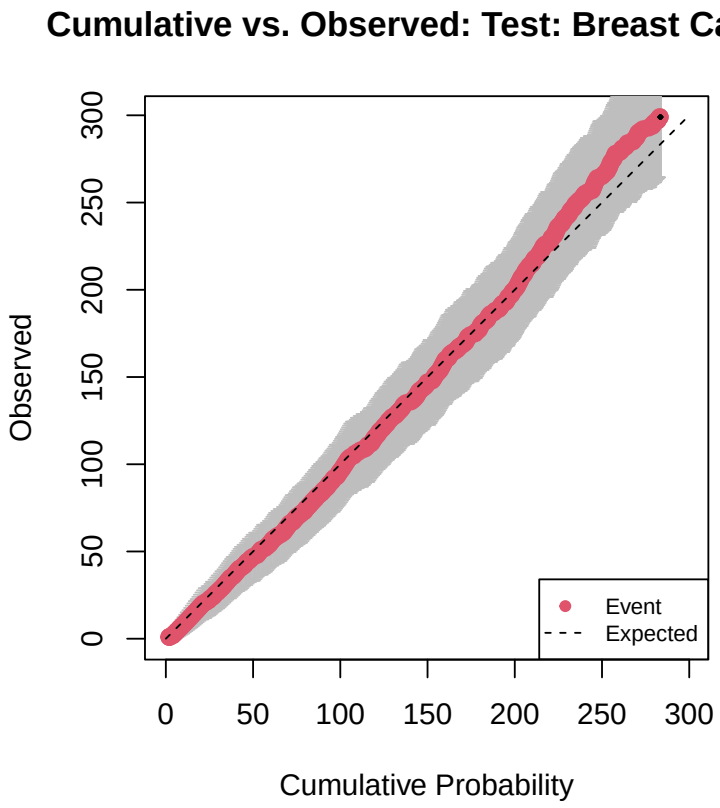
	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	1985	816	1144	93.9	385.7
class=1	396	248	177	28.0	31.8
class=2	601	454	197	336.3	391.3

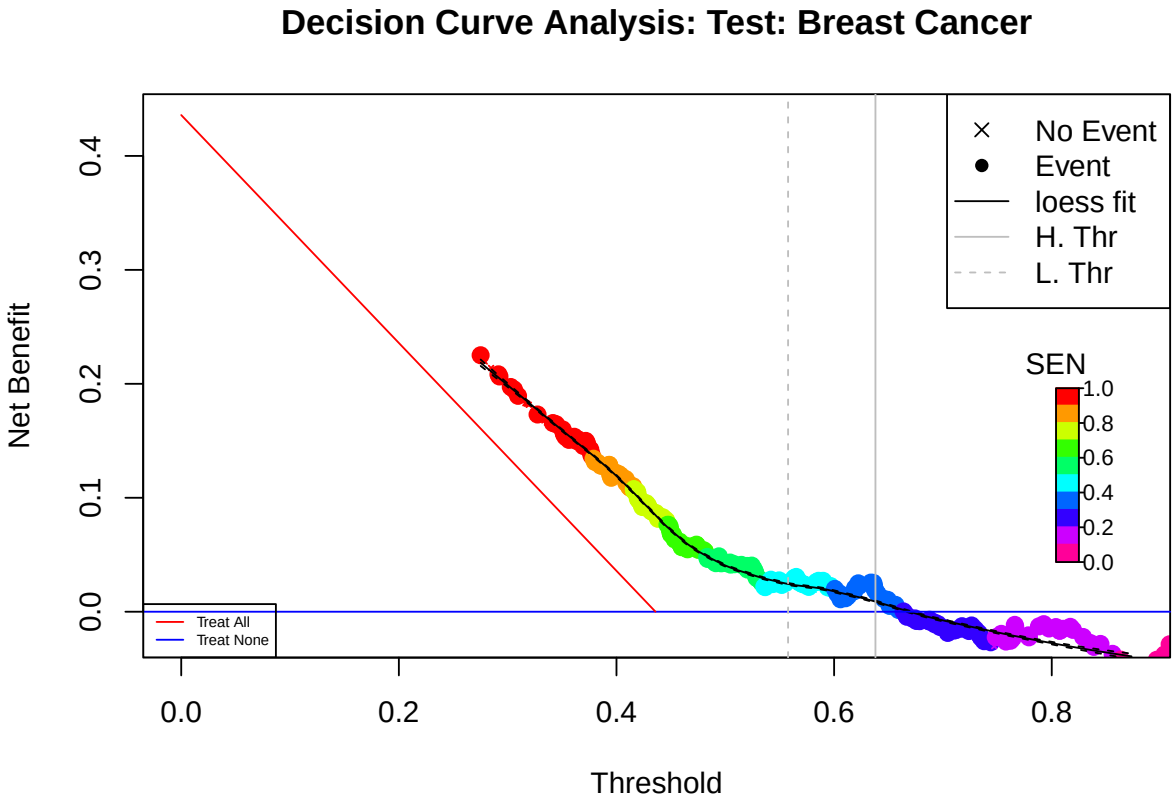
1.5 Performance on the external data set

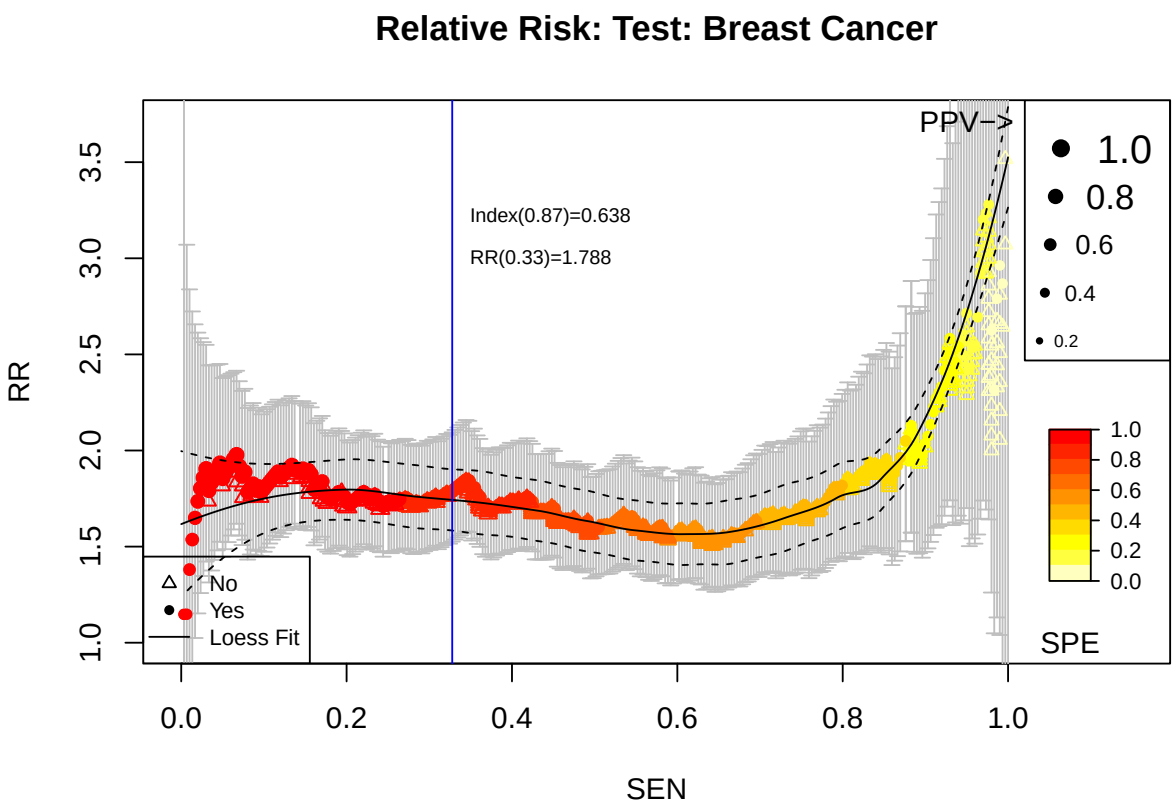
```
index <- predict(ml,dataBrestCancerTest)
pp <- predictionStats_binary(cbind(dataBrestCancerTest$status,index),plotname="Breast Cancer")
```

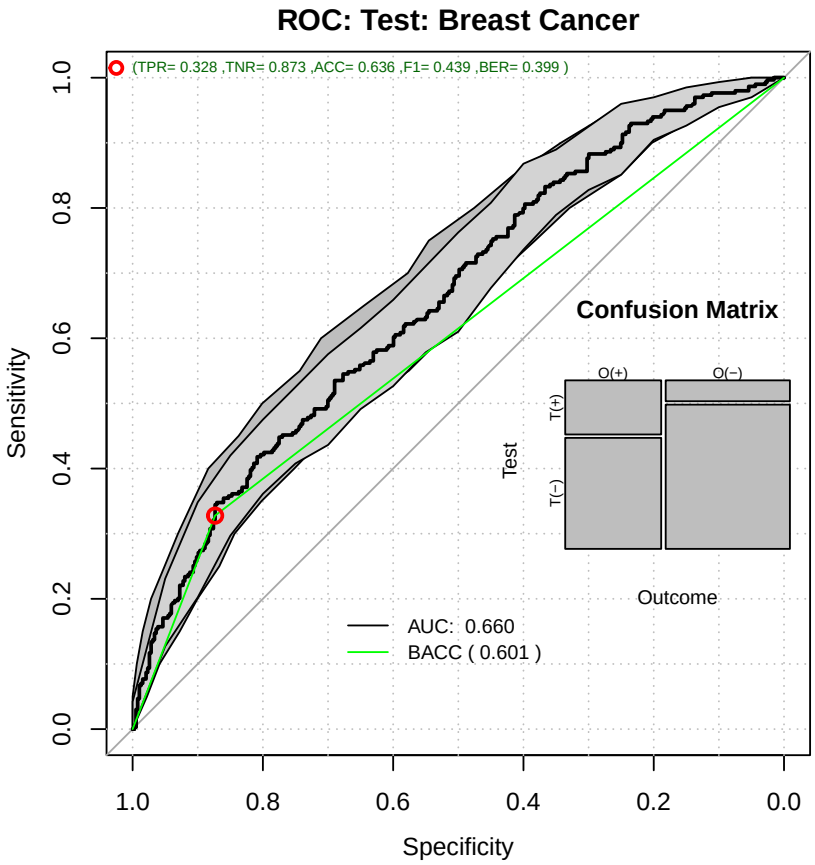


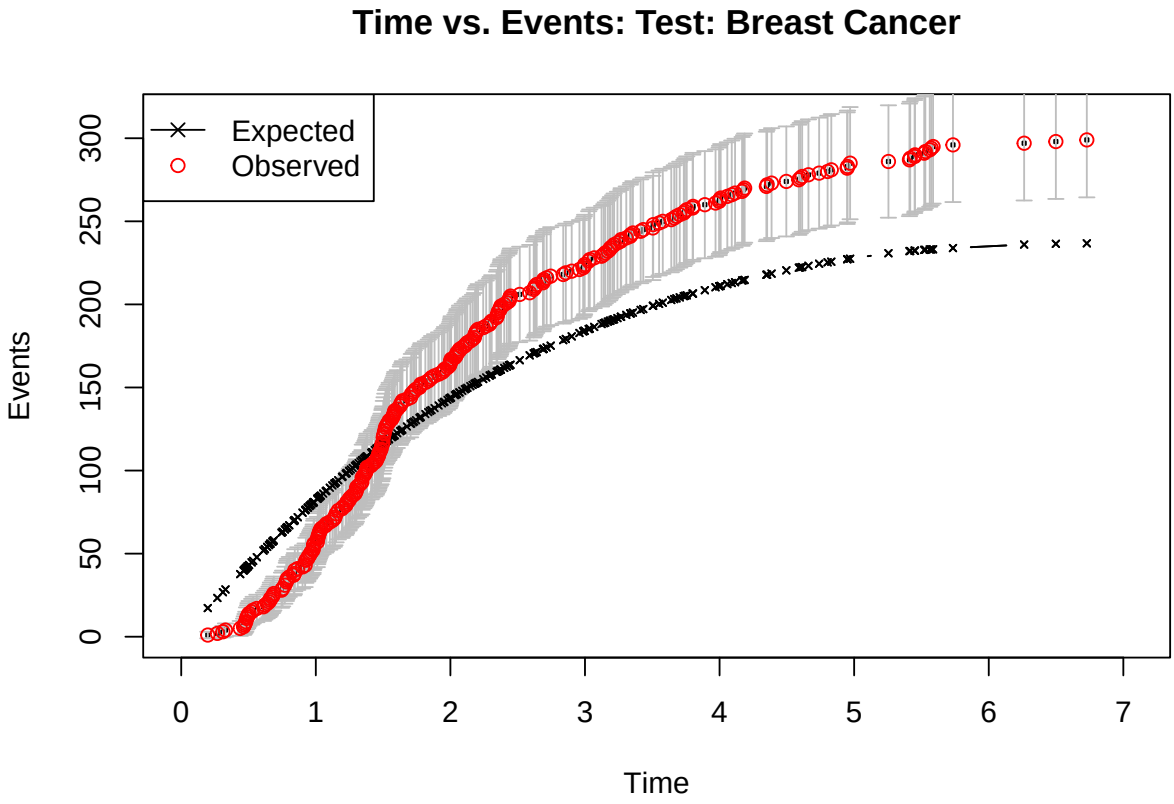

```
par(op)


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

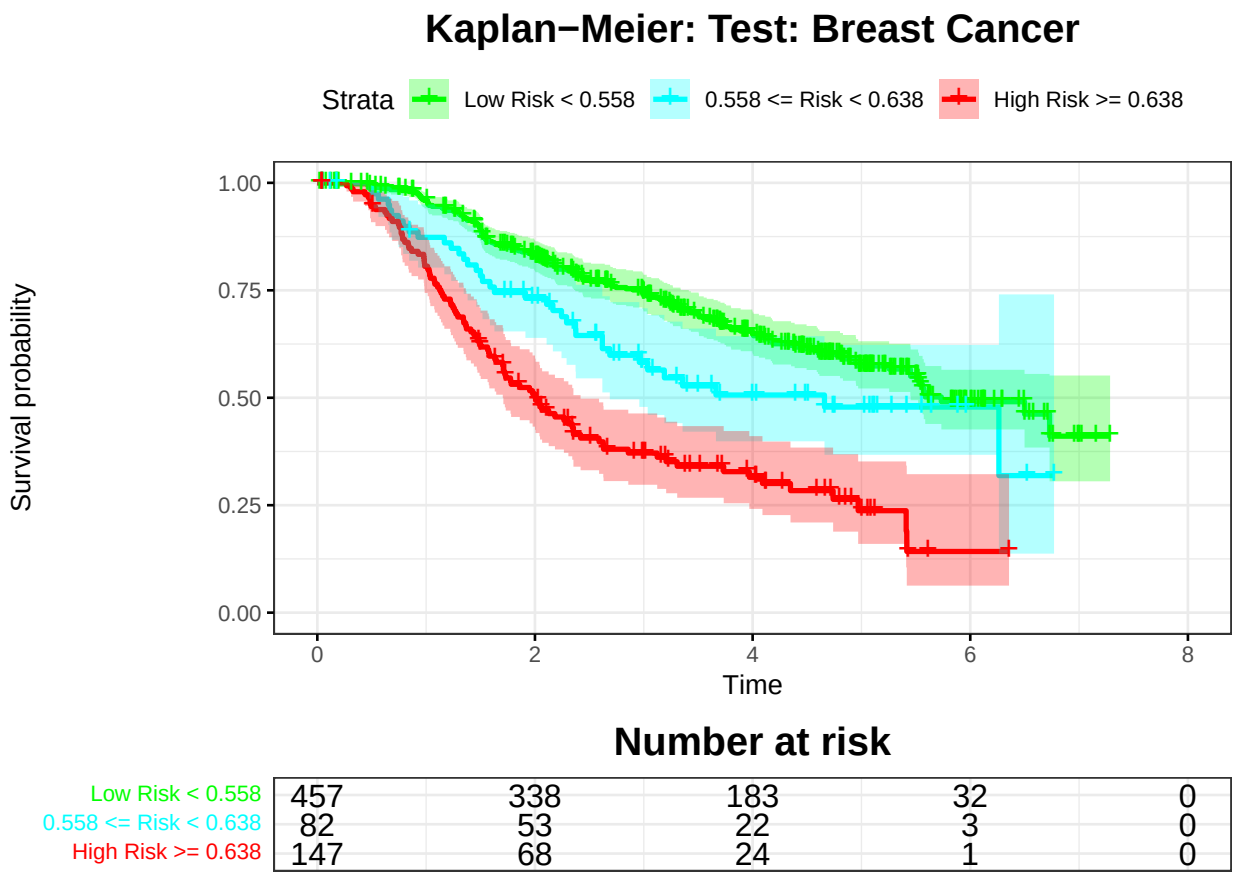

Cumulative vs. Observed: Test: Breast Cancer
Observed
0
50
100
150
200
250
300
Event
Expected
Cumulative Probability


Decision Curve Analysis: Test: Breast Cancer
Net Benefit
0.0
0.1
0.2
0.3
0.4
Threshold
0.0
0.2
0.4
0.6
0.8
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None


Relative Risk: Test: Breast Cancer
PPV–>
Index(0.87)=0.638
RR(0.33)=1.788
1.0
0.8
0.6
0.4
0.2
1.0
0.8
0.6
0.4
0.2
0.0
SPE
No
Yes
Loess Fit
RR
1.0
1.5
2.0
2.5
3.0
3.5
0.0
0.2
0.4
0.6
0.8
1.0
SEN


ROC: Test: Breast Cancer
(TPR= 0.328 ,TNR= 0.873 ,ACC= 0.636 ,F1= 0.439 ,BER= 0.399)
Sensitivity
Specificity
1.0
0.8
0.6
0.4
0.2
0.0
Confusion Matrix
O(+)
O(−)
T(+)
T(−)
Test
Outcome
AUC: 0.660
BACC (0.601)


Time vs. Events: Test: Breast Cancer
Expected
Observed
Events
0
50
100
150
200
250
300
0
1
2
3
4
5
6
7
Time




```
par(op)
```

1.5.1 External Data Report

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

Table 30: Threshold values

	@:0.638	@:0.558	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.6378	0.5580	0.5899	0.342	2.75e-01	0.4992
RR	1.7994	1.6427	1.7581	3.279	2.64e+01	1.5739
RR_LCI	1.5366	1.3951	1.4980	1.641	5.65e-02	1.3253
RR_UCI	2.1071	1.9343	2.0632	6.552	1.23e+04	1.8691
SEN	0.3311	0.4515	0.4181	0.977	1.00e+00	0.5619
SPE	0.8734	0.7571	0.8088	0.111	1.55e-02	0.6382
BACC	0.6022	0.6043	0.6134	0.544	5.08e-01	0.6001
NetBenefit	0.0186	0.0238	0.0271	0.166	2.25e-01	0.0415

```
pander::pander(t(rrCoxTestAnalysis$OERatio$estimate),caption="O/E Ratio")
```

Table 31: O/E Ratio

O/E	Low	Upper	p.value
1.26	1.12	1.41	9.48e-05

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

- **C Index**: *0.664*
- **Dxy**: *0.328*
- **S.D.**: *0.0311*
- **n**: *686*
- **missing**: *0*
- **uncensored**: *299*
- **Relevant Pairs**: *266144*
- **Concordant**: *176738*
- **Uncertain**: *203702*
- **cstatCI**:

mean.C Index	median	lower	upper
0.664	0.664	0.633	0.695

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

Table 33: ROC AUC

est	lower	upper
0.66	0.619	0.7

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

Table 34: Sensitivity

est	lower	upper
0.328	0.275	0.384

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

Table 35: Specificity

est	lower	upper
0.873	0.836	0.905

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

Table 36: Probability Thresholds

90%	80%
0.638	0.558

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

Table 37: Logrank test Chisq = 81.471750 on 2 degrees of freedom, p = 0.000000

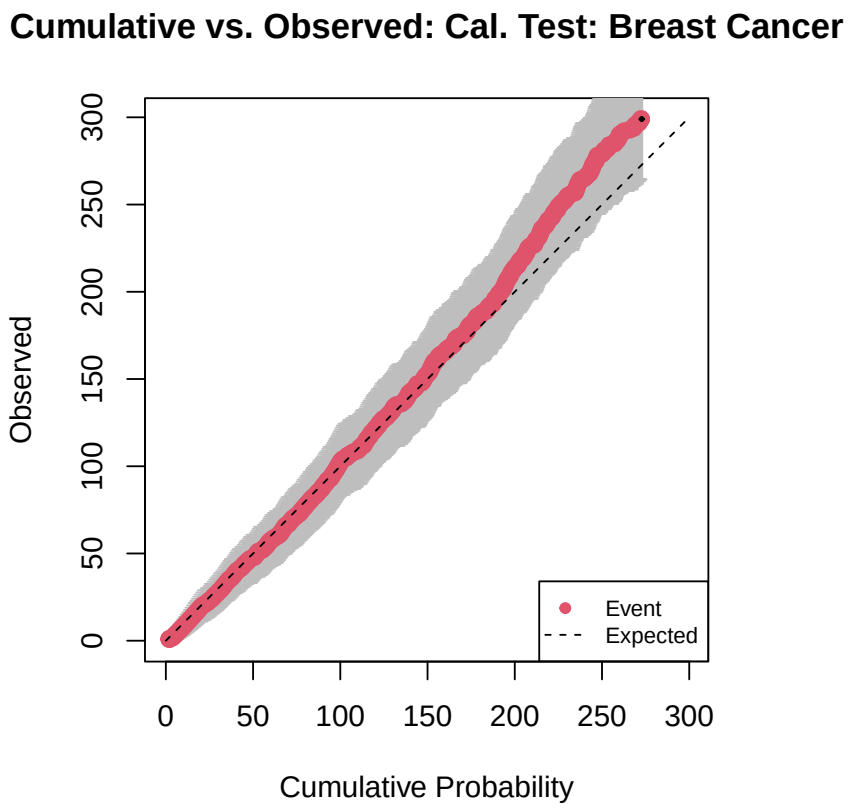
	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	457	164	221.4	14.888	58.181
class=1	82	37	33.2	0.438	0.494
class=2	147	98	44.4	64.710	77.254

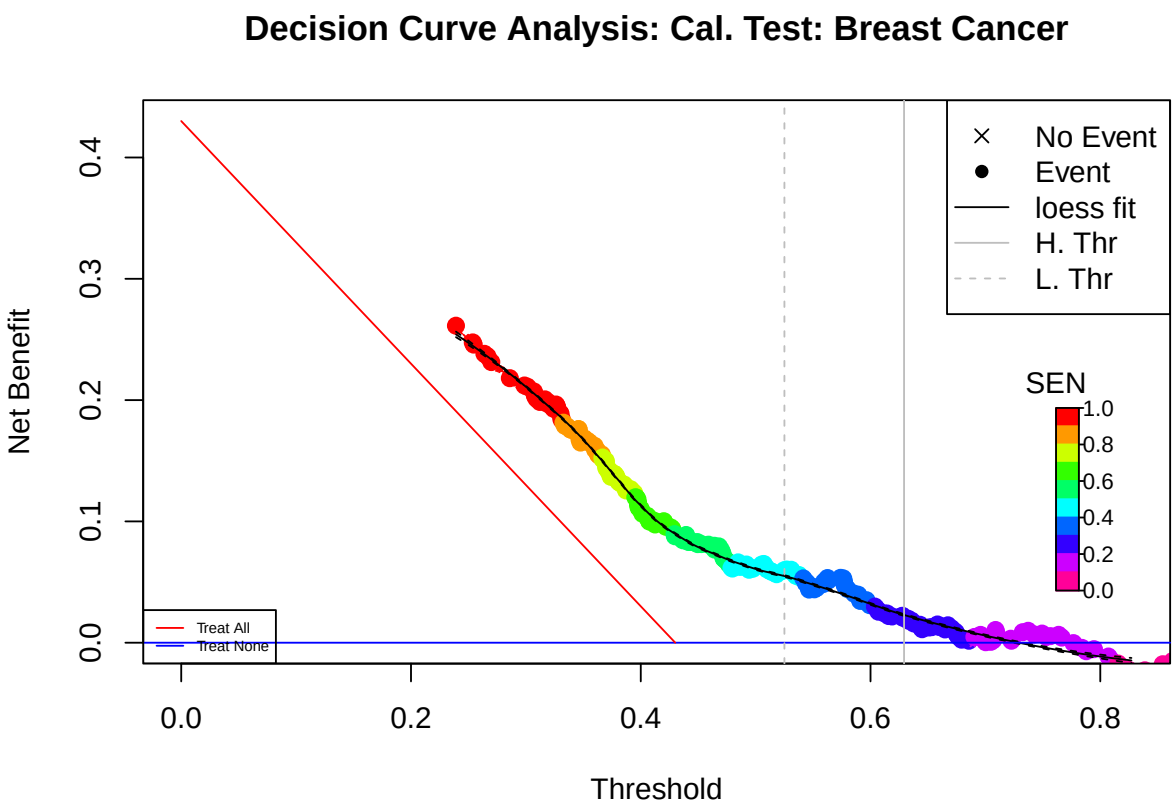
1.5.2 Calibrating the index on the test data

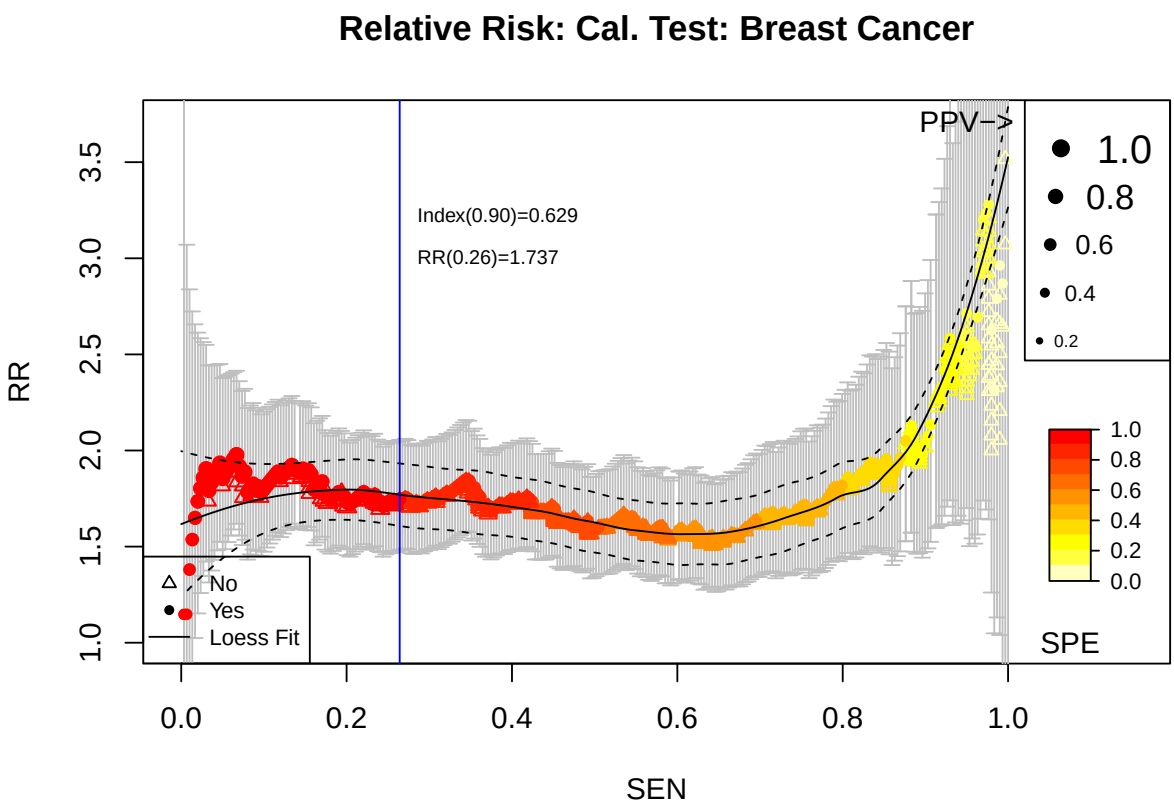
```
calprob <- CoxRiskCalibration(ml,dataBrestCancerTest,"status","time")

pander::pander(c(h0=calprob$h0,
                 Gain=calprob$hazardGain,
                 DeltaTime=calprob$timeInterval),
               caption="Cox Calibration Parameters")
```

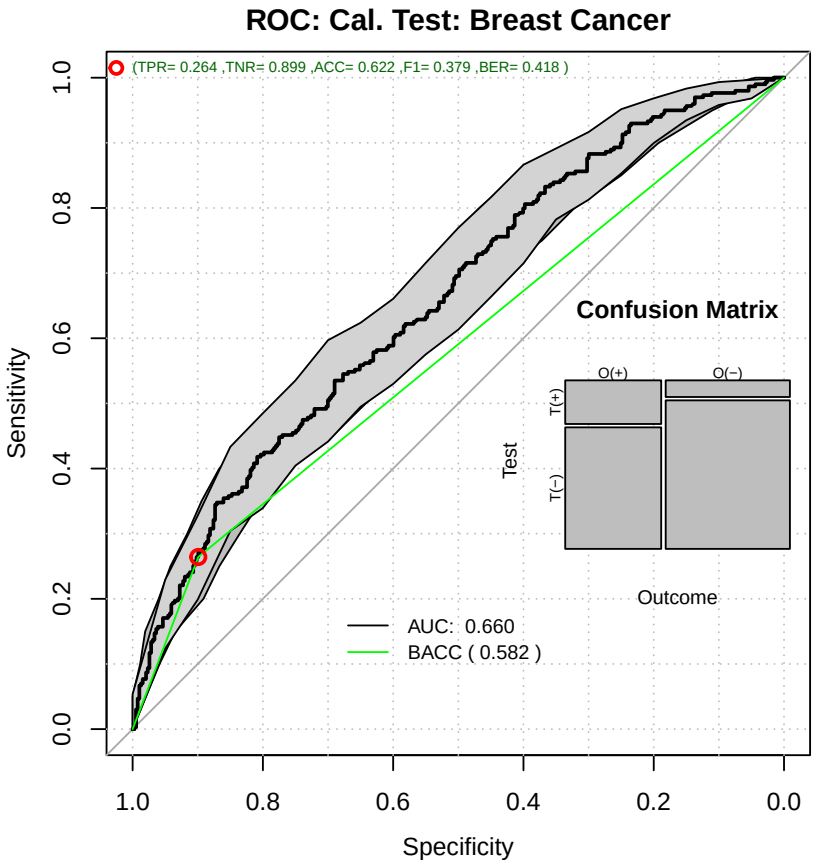
h0	Gain	DeltaTime
0.604	1.04	5.73

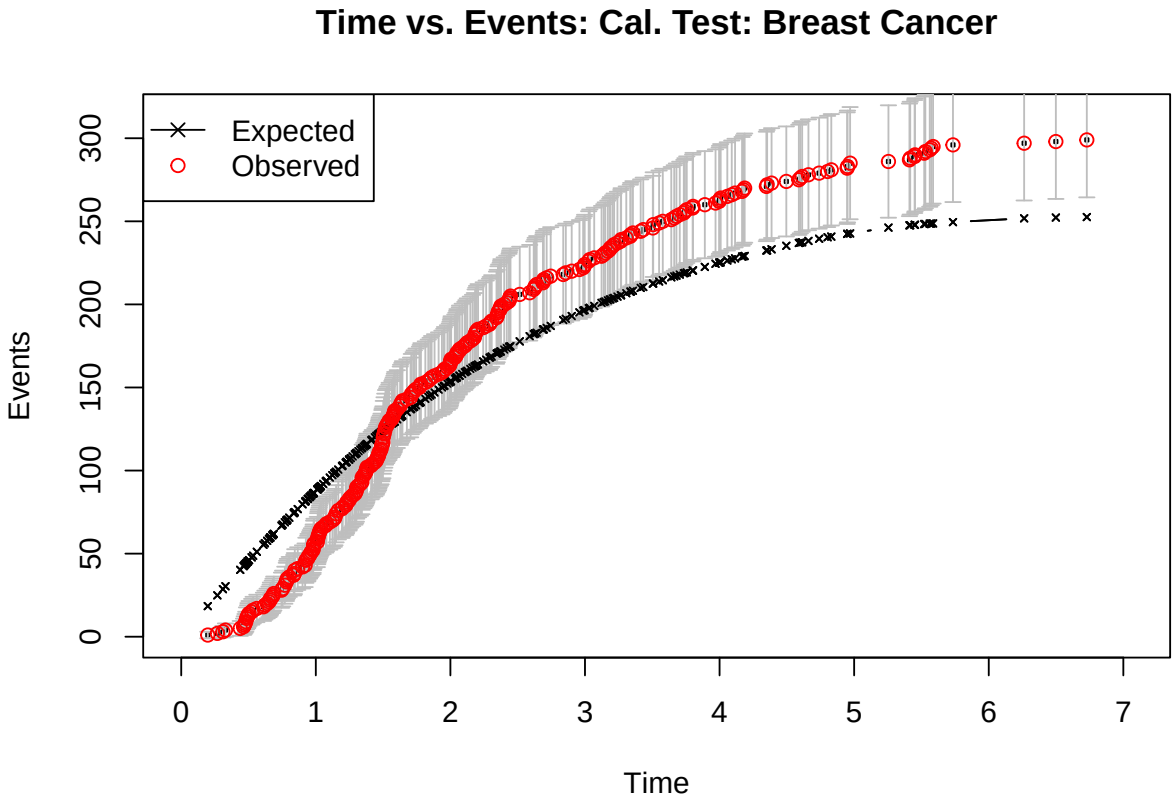
```
rdata <- cbind(dataBrestCancerTest$status,calprob$prob)

rrAnalysis <- RRPlot(rdata,atRate=c(0.90,0.80),
                     timetoEvent=dataBrestCancerTest$time,
                     title="Cal. Test: Breast Cancer",
                     ysurvlim=c(0.00,1.0),
                     riskTimeInterval=calprob$timeInterval)
```

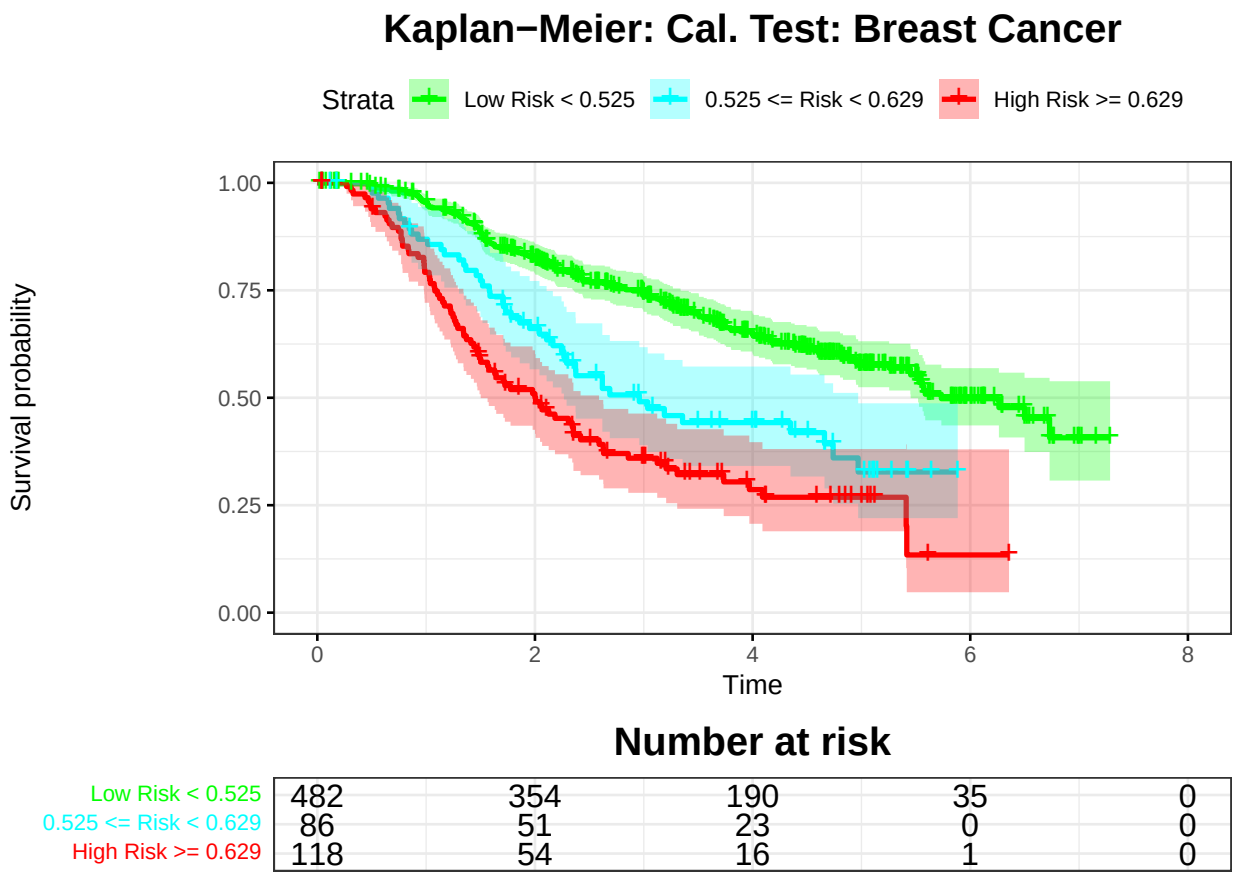

Cumulative vs. Observed: Cal. Test: Breast Cancer
Observed
0
50
100
150
200
250
300
Cumulative Probability
Event
Expected


Decision Curve Analysis: Cal. Test: Breast Cancer
Net Benefit
0.0
0.1
0.2
0.3
0.4
Threshold
0.0
0.2
0.4
0.6
0.8
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None


Relative Risk: Cal. Test: Breast Cancer
PPV–>
Index(0.90)=0.629
RR(0.26)=1.737
1.0
0.8
0.6
0.4
0.2
1.0
0.8
0.6
0.4
0.2
0.0
SPE
No
Yes
Loess Fit
RR
SEN
1.0
1.5
2.0
2.5
3.0
3.5
0.0
0.2
0.4
0.6
0.8
1.0


ROC: Cal. Test: Breast Cancer
(TPR= 0.264 ,TNR= 0.899 ,ACC= 0.622 ,F1= 0.379 ,BER= 0.418)
Sensitivity
1.0
0.8
0.6
0.4
0.2
0.0
Specificity
1.0
0.8
0.6
0.4
0.2
0.0
Confusion Matrix
O(+)
O(−)
T(+)
T(−)
Test
Outcome
AUC: 0.660
BACC (0.582)


Time vs. Events: Cal. Test: Breast Cancer
Expected
Observed
Events
0
50
100
150
200
250
300
0
1
2
3
4
5
6
7
Time



1.5.3 After Calibration Report

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

Table 39: Threshold values

	@:0.9	@:0.8	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.6284	0.5247	0.5310	0.299	2.39e-01	0.5002
RR	1.7405	1.7325	1.7581	3.279	2.64e+01	1.6427
RR_LCI	1.4790	1.4751	1.4980	1.641	5.65e-02	1.3951
RR_UCI	2.0483	2.0347	2.0632	6.552	1.23e+04	1.9343
SEN	0.2676	0.4247	0.4181	0.977	1.00e+00	0.4515
SPE	0.8992	0.7984	0.8088	0.111	1.55e-02	0.7571
BACC	0.5834	0.6116	0.6134	0.544	5.08e-01	0.6043
NetBenefit	0.0205	0.0596	0.0601	0.212	2.61e-01	0.0597

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

Table 40: O/E Ratio

O/E	Low	Upper	p.value
1.18	1.05	1.33	0.00418

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

- **C Index**: *0.664*
- **Dxy**: *0.328*
- **S.D.**: *0.0311*
- **n**: *686*
- **missing**: *0*
- **uncensored**: *299*
- **Relevant Pairs**: *266144*
- **Concordant**: *176736*
- **Uncertain**: *203702*
- **cstatCI**:

mean.C Index	median	lower	upper
0.664	0.664	0.634	0.696

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

Table 42: ROC AUC

est	lower	upper
0.66	0.619	0.7

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

Table 43: Sensitivity

est	lower	upper
0.264	0.215	0.318

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

Table 44: Specificity

est	lower	upper
0.899	0.865	0.927

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

Table 45: Probability Thresholds

90%	80%
0.629	0.525

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

Table 46: 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)
```

——..

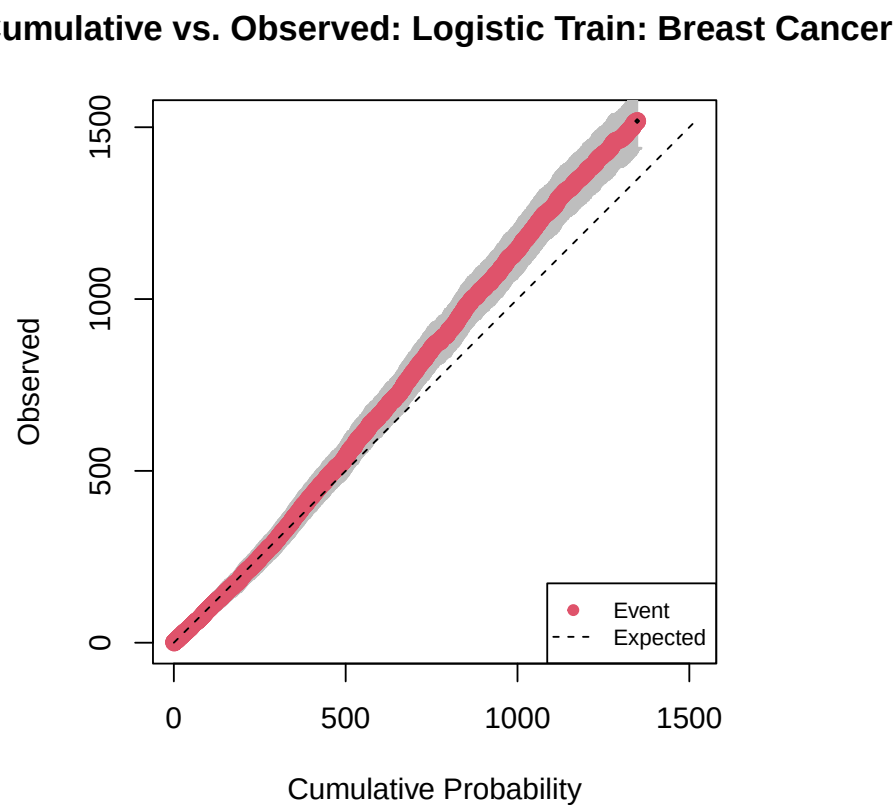
```
sm <- summary(mlog)
pander::pander(sm$coefficients)
```

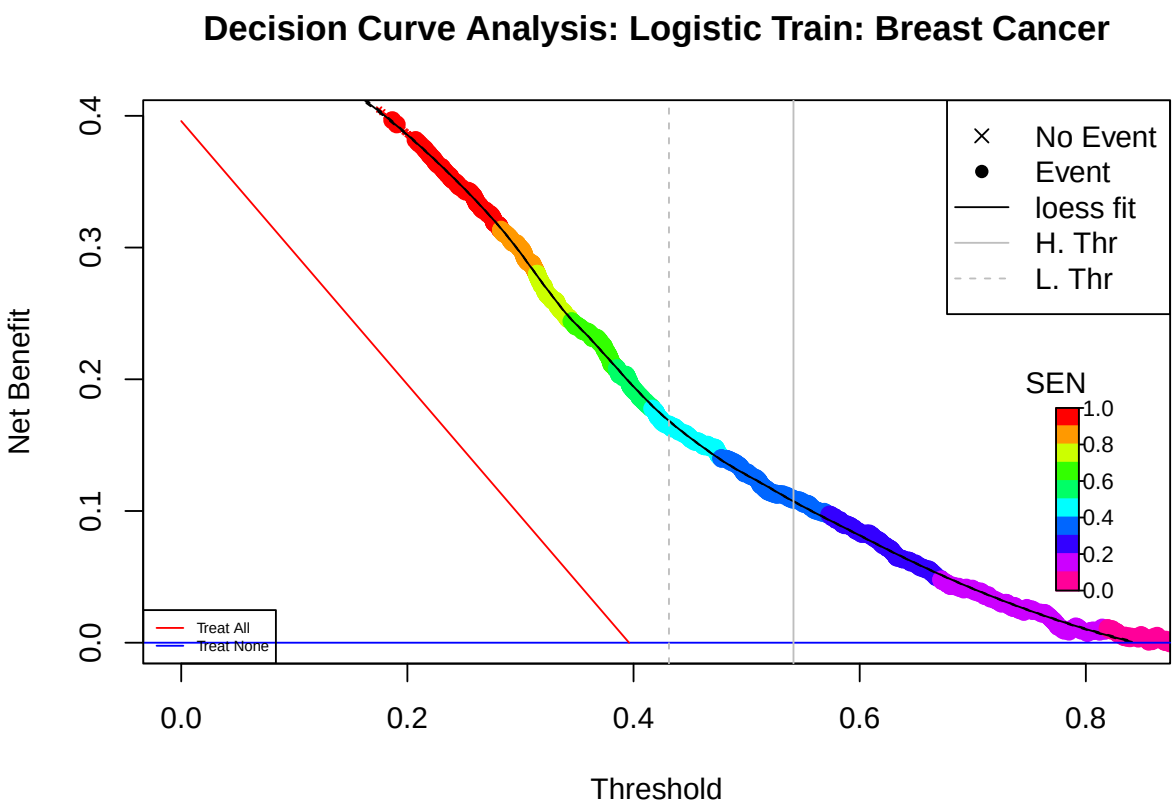
	Estimate	lower OR	upper	u.Accuracy	z.Accuracy	fdr.Accuracy	u.AUC	z.AUC	full.AUC	IDI	NRI	z.IDI	z.NRI	Delta.AUC	Frequency
size__nodes	1.05e-03	1.001	1.001	1.001	0.669	0.571	0.668	0.627	0.500	0.628	0.11230	0.636547	17.86	18.870	0.1284901
nodes	4.33e-02	1.040	1.044	1.048	0.676	0.634	0.690	0.639	0.621	0.662	0.07110	0.571061	14.13	16.179	0.0404941
grade__nodes	1.70e-02	1.014	1.015	1.016	0.682	0.637	0.686	0.649	0.624	0.655	0.06580	0.548661	13.66	15.650	0.0310871
age__nodes	1.06e-03	1.001	1.001	1.001	0.678	0.653	0.686	0.642	0.621	0.657	0.03340	0.213121	9.39	5.710	0.0358961
size__grade	1.75e-03	1.001	1.002	1.002	0.632	0.682	0.686	0.626	0.646	0.655	0.01787	0.294116	6.74	7.728	0.0086481
age__size	8.73e-05	1.000	1.000	1.000	0.608	0.682	0.686	0.577	0.649	0.657	0.01530	0.291528	6.41	7.652	0.0076001
grade	2.27e-01	1.168	1.254	1.347	0.571	0.683	0.690	0.500	0.653	0.662	0.01340	0.190366	6.20	4.983	0.0084611
age__meno	6.04e-03	0.992	0.994	0.996	0.571	0.676	0.686	0.500	0.645	0.657	0.00782	0.080574	4.76	2.337	0.0120651

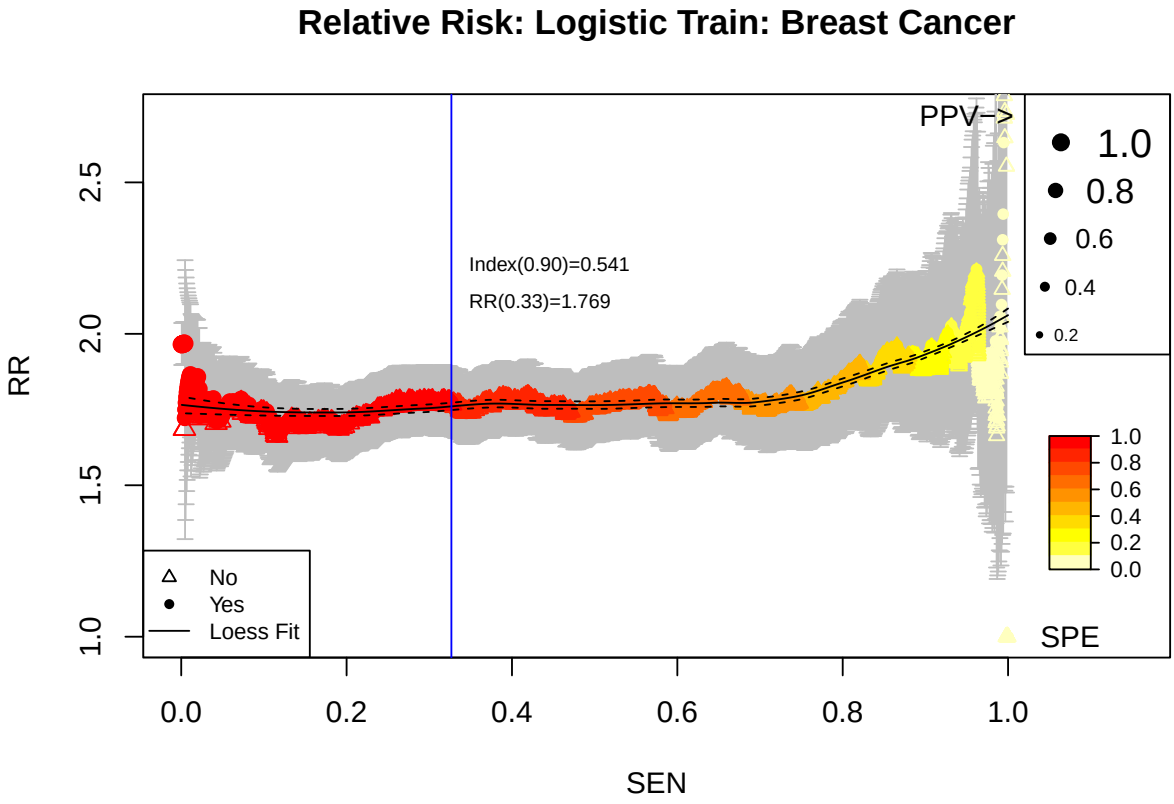
	Estimate	lower OR	upper	u. Accuracy	Accuracy	full. Accuracy	u. AUC	AUC	full. AUC	IDI	NRI	z.IDI	z.NRI	Delta. AUC	Frequency
age_pgr	-5.42e-06	1.000	1.000	1.000	0.571	0.686	0.686	0.500	0.656	0.657	0.00512	0.00745	1.11	0.194	0.000417	1
age_grade	1.65e-03	0.997	0.998	0.999	0.574	0.690	0.690	0.507	0.661	0.662	0.00454	0.11373	2.60	2.960	0.000315	1
meno_grade	1.02e-01	1.045	1.107	1.173	0.571	0.683	0.686	0.500	0.652	0.657	0.00426	0.20428	3.47	5.343	0.004411	1
nodes_hormon	1.38e-02	0.979	0.986	0.994	0.587	0.688	0.686	0.526	0.658	0.655	0.00280	0.45522	3.44	12.150	-0.002853	1
size	3.94e-03	1.002	1.004	1.006	0.611	0.693	0.690	0.618	0.663	0.662	0.00507	0.21056	3.42	5.600	-0.001075	1
meno_pgr	3.19e-04	1.000	1.000	1.001	0.571	0.687	0.686	0.500	0.657	0.657	0.00316	0.05977	3.35	1.558	-0.000429	1
pgr	-1.07e-04	1.000	1.000	1.000	0.571	0.689	0.686	0.500	0.659	0.655	0.00257	0.19759	2.64	5.745	-0.004123	1
meno_nodes	2.60e-02	0.955	0.974	0.994	0.640	0.686	0.686	0.595	0.656	0.657	0.00264	-0.06329	2.59	-1.645	0.000631	1
grade_pgr	3.51e-05	1.000	1.000	1.000	0.571	0.669	0.668	0.500	0.627	0.628	0.00240	0.17471	2.55	5.058	0.001252	1
meno_size	2.34e-03	1.000	1.002	1.004	0.604	0.691	0.690	0.578	0.663	0.662	0.00185	0.10227	2.43	2.662	-0.001378	1

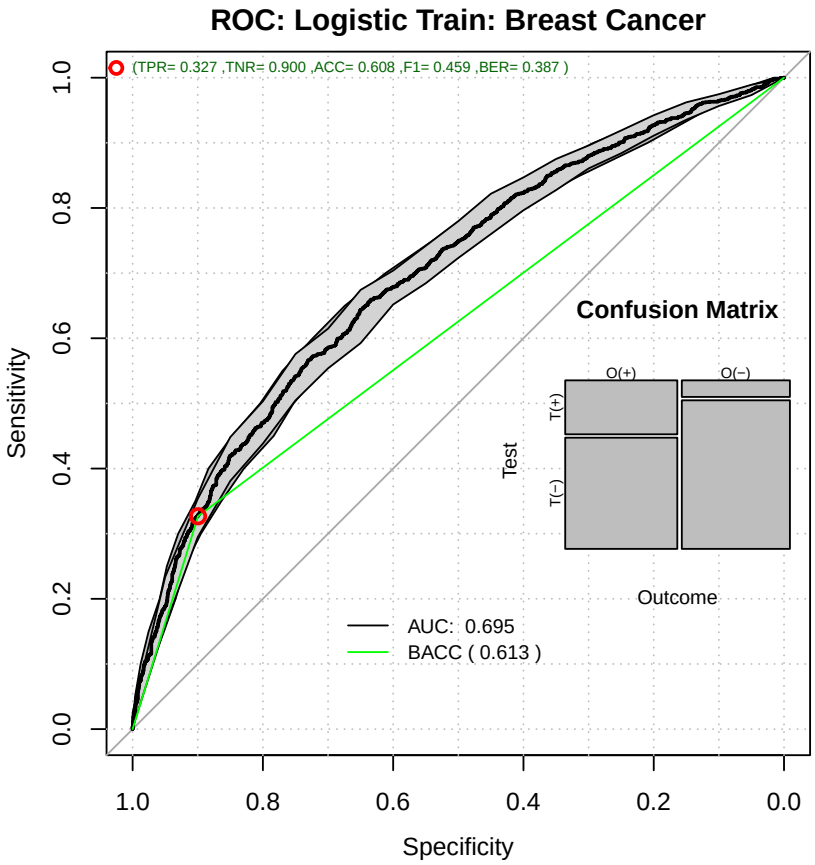
1.7 Logistic Model Performance

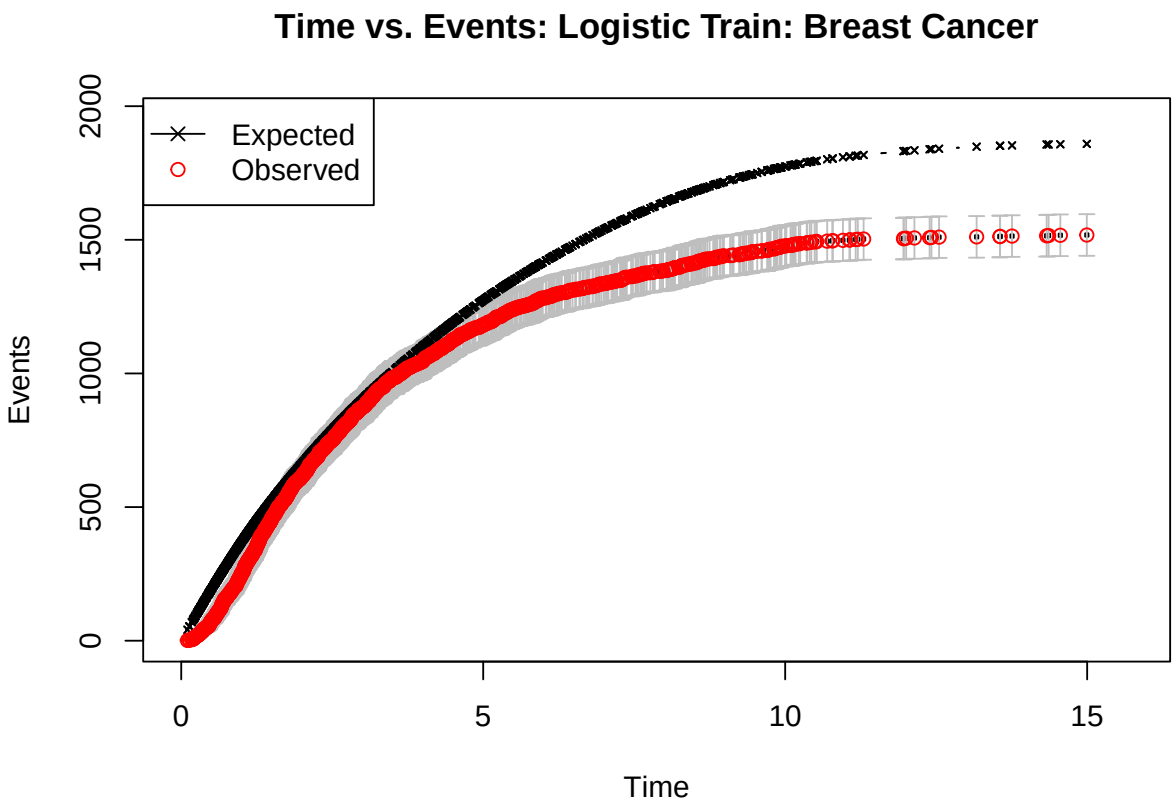
```
op <- par(no.readonly = TRUE)


cprob <- predict(mlog,dataBrestCancerTrain)

rdata <- cbind(dataBrestCancerTrain$status,cprob)
rrAnalysisTrain <- RRPlot(rdata,atRate=c(0.90,0.80),
                      timetoEvent=dataBrestCancerTrain$time,
                      title="Logistic Train: Breast Cancer",
                      ysurvlim=c(0.00,1.0),
                      riskTimeInterval=5.0)
```

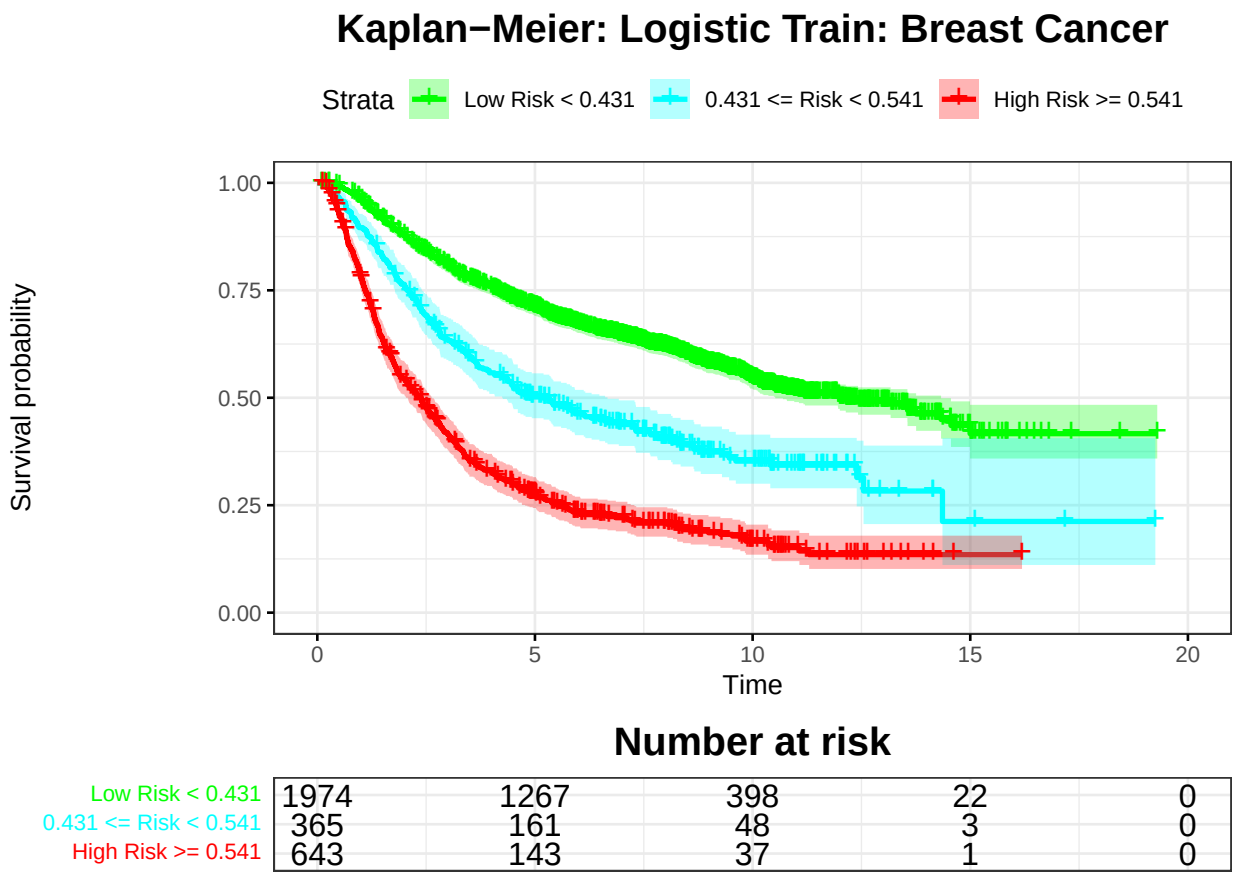

Cumulative vs. Observed: Logistic Train: Breast Cancer
Observed
0
500
1000
1500
Cumulative Probability
0
500
1000
1500
Event
Expected


Decision Curve Analysis: Logistic Train: Breast Cancer
Net Benefit
0.0
0.1
0.2
0.3
0.4
Threshold
0.0
0.2
0.4
0.6
0.8
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None


Relative Risk: Logistic Train: Breast Cancer
PPV–>
1.0
0.8
0.6
0.4
0.2
Index(0.90)=0.541
RR(0.33)=1.769
1.0
0.8
0.6
0.4
0.2
0.0
No
Yes
Loess Fit
SPE
RR
2.5
2.0
1.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
SEN


ROC: Logistic Train: Breast Cancer
(TPR= 0.327 ,TNR= 0.900 ,ACC= 0.608 ,F1= 0.459 ,BER= 0.387)
Sensitivity
Specificity
1.0
0.8
0.6
0.4
0.2
0.0
Confusion Matrix
O(+)
O(−)
T(+)
T(−)
Test
Outcome
AUC: 0.695
BACC (0.613)


Time vs. Events: Logistic Train: Breast Cancer
Expected
Observed
Events
0
500
1000
1500
2000
0
5
10
15
Time




```
par(op)
```

1.7.1 Training Report

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

Table 48: Threshold values

	@:0.9	@:0.8	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.542	0.431	0.394	0.255	0.130969	0.500
RR	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
SEN	0.327	0.470	0.566	0.962	1.000000	0.374
SPE	0.900	0.799	0.731	0.125	0.000683	0.874
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$OERatio$estimate),caption="O/E Ratio")
```

Table 49: O/E Ratio

O/E	Low	Upper	p.value
0.817	0.776	0.859	3.78e-16

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

- **C Index**: *0.68*
- **Dxy**: *0.36*
- **S.D.**: *0.014*
- **n**: *2982*
- **missing**: *0*
- **uncensored**: *1518*
- **Relevant Pairs**: *6184528*
- **Concordant**: *4206598*
- **Uncertain**: *2703838*
- **cstatCI**:

mean.C Index	median	lower	upper
0.68	0.68	0.667	0.694

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

Table 51: ROC AUC

est	lower	upper
0.695	0.677	0.714

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

Table 52: Sensitivity

est	lower	upper
0.327	0.303	0.351

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

Table 53: Specificity

est	lower	upper
0.9	0.883	0.915

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

Table 54: Probability Thresholds

90%	80%
0.541	0.431

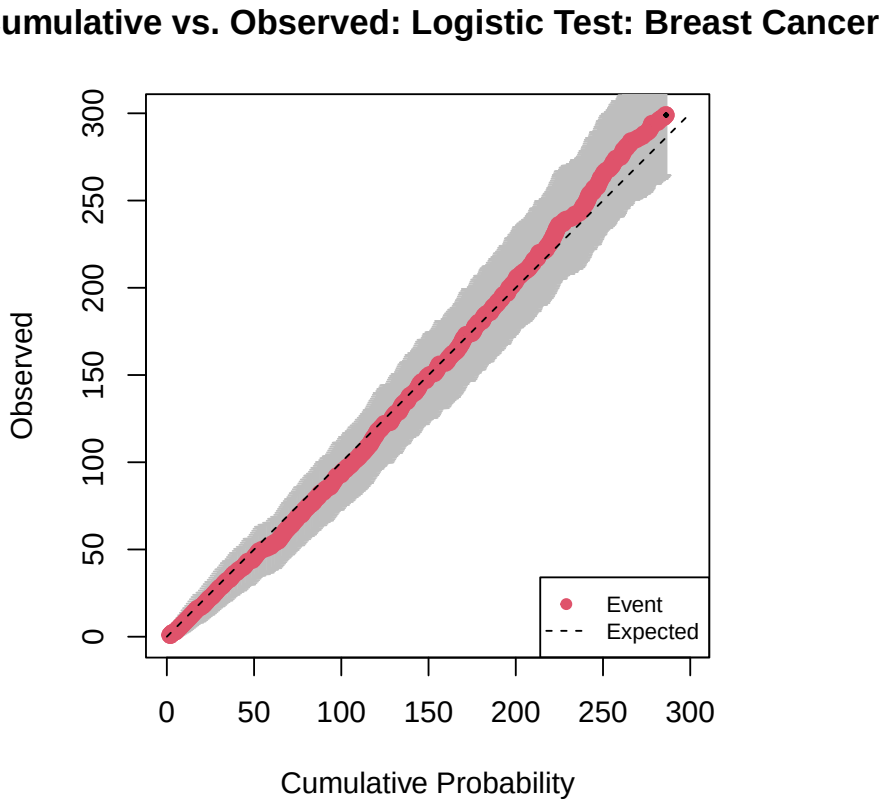
```
pander::pander(rrAnalysisTrain$surdif,caption="Logrank test")
```

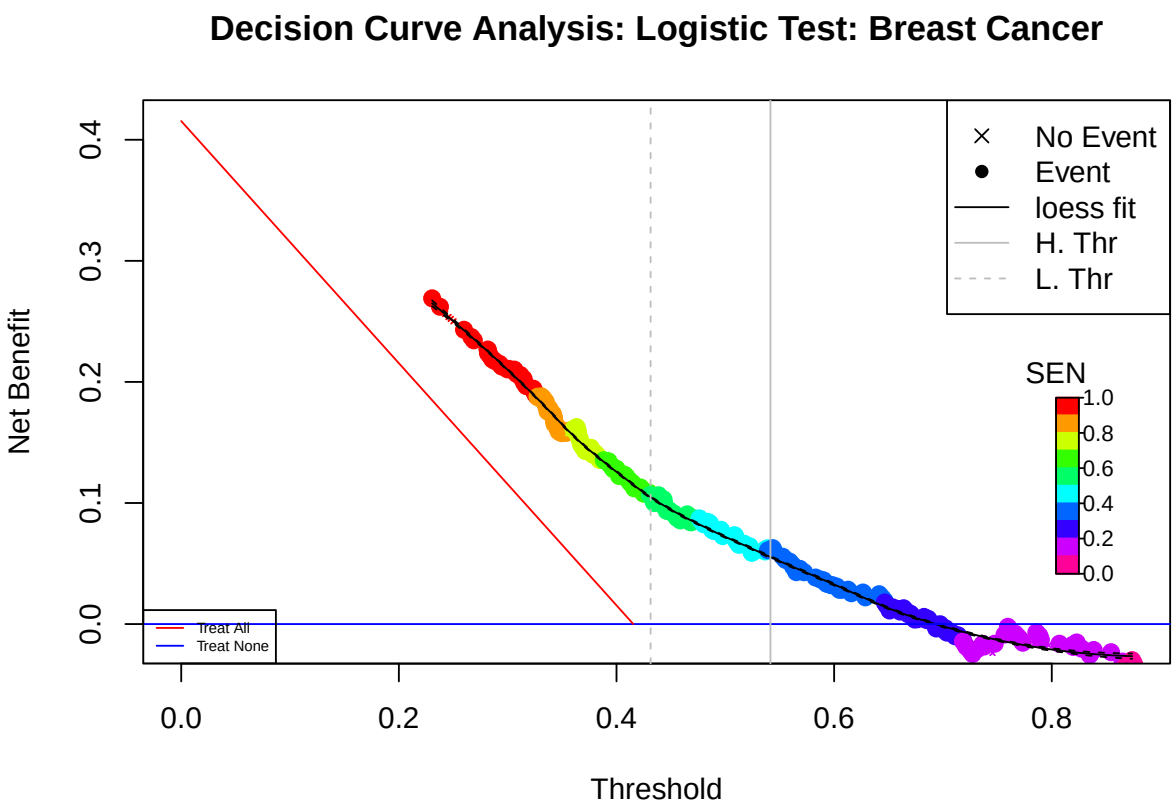
Table 55: Logrank test Chisq = 541.976716 on 2 degrees of freedom, p = 0.000000

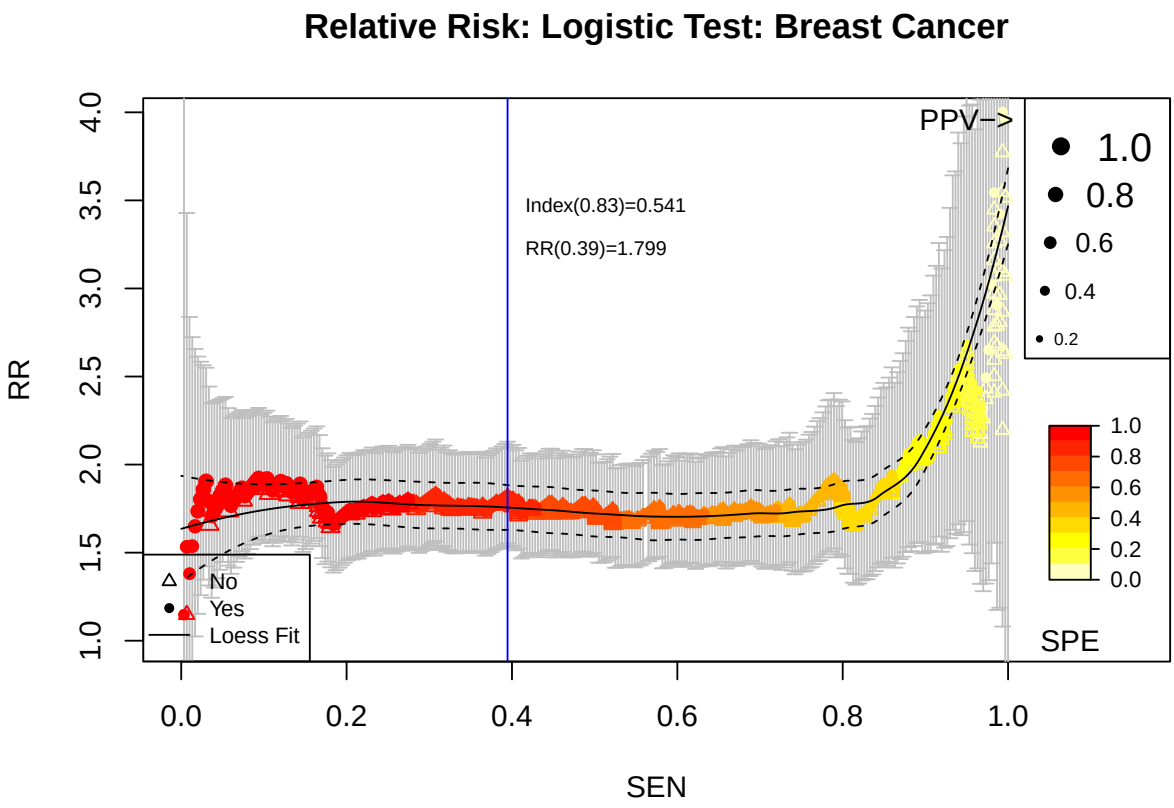
	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	1974	804	1144	100.9	415.3
class=1	365	218	170	13.4	15.1
class=2	643	496	204	418.2	490.7

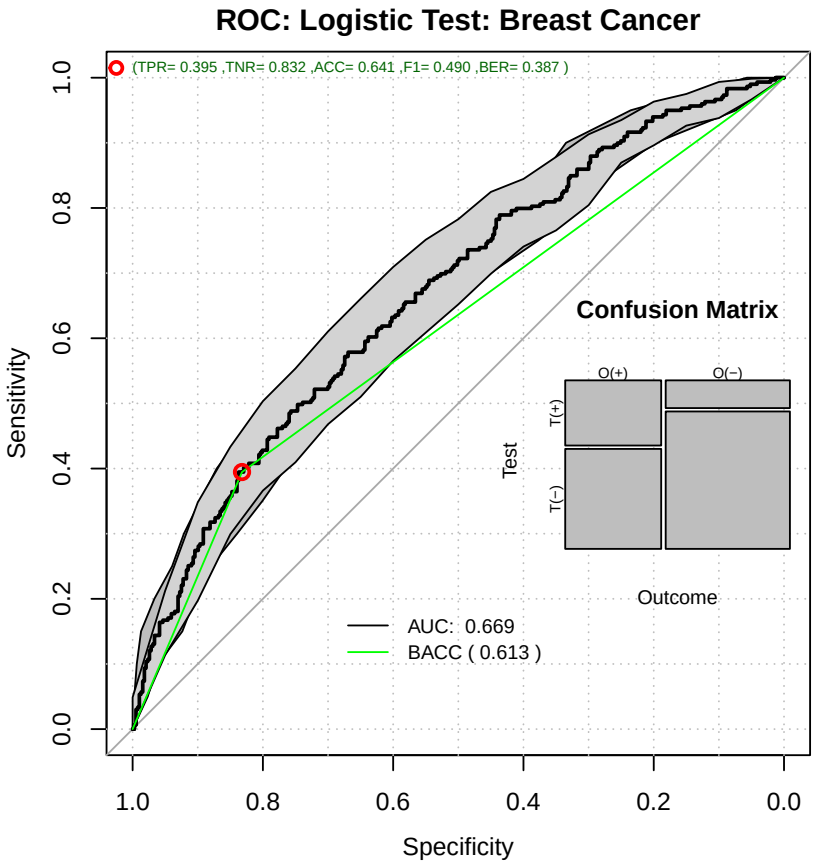
1.7.2 Results on the validation set using Logistic model

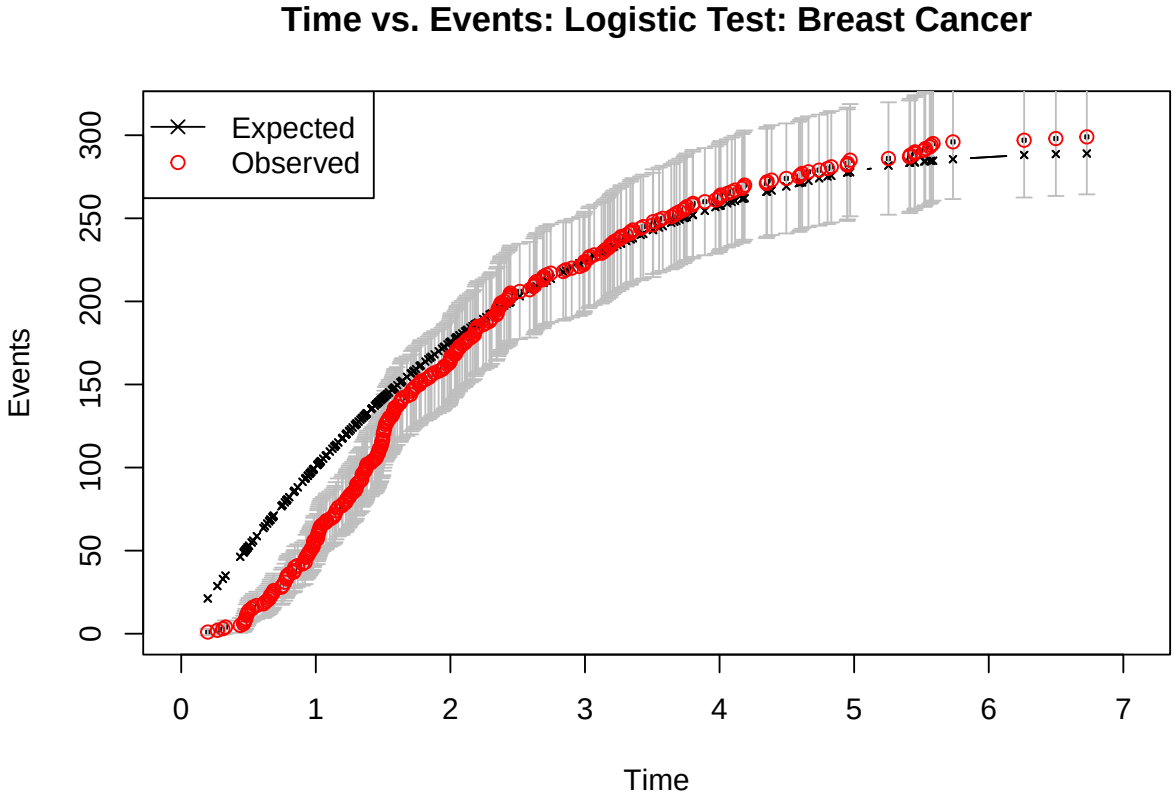
```
pre <- predict(mlog,dataBrestCancerTest)
rdata <- cbind(dataBrestCancerTest$status,pre)

rrAnalysis <- RRPlot(rdata,atThr=rrAnalysisTrain$thr_atP,
                     timetoEvent=dataBrestCancerTest$time,
                     title="Logistic Test: Breast Cancer",
                     ysurvlim=c(0.00,1.0),
                     riskTimeInterval=5)
```

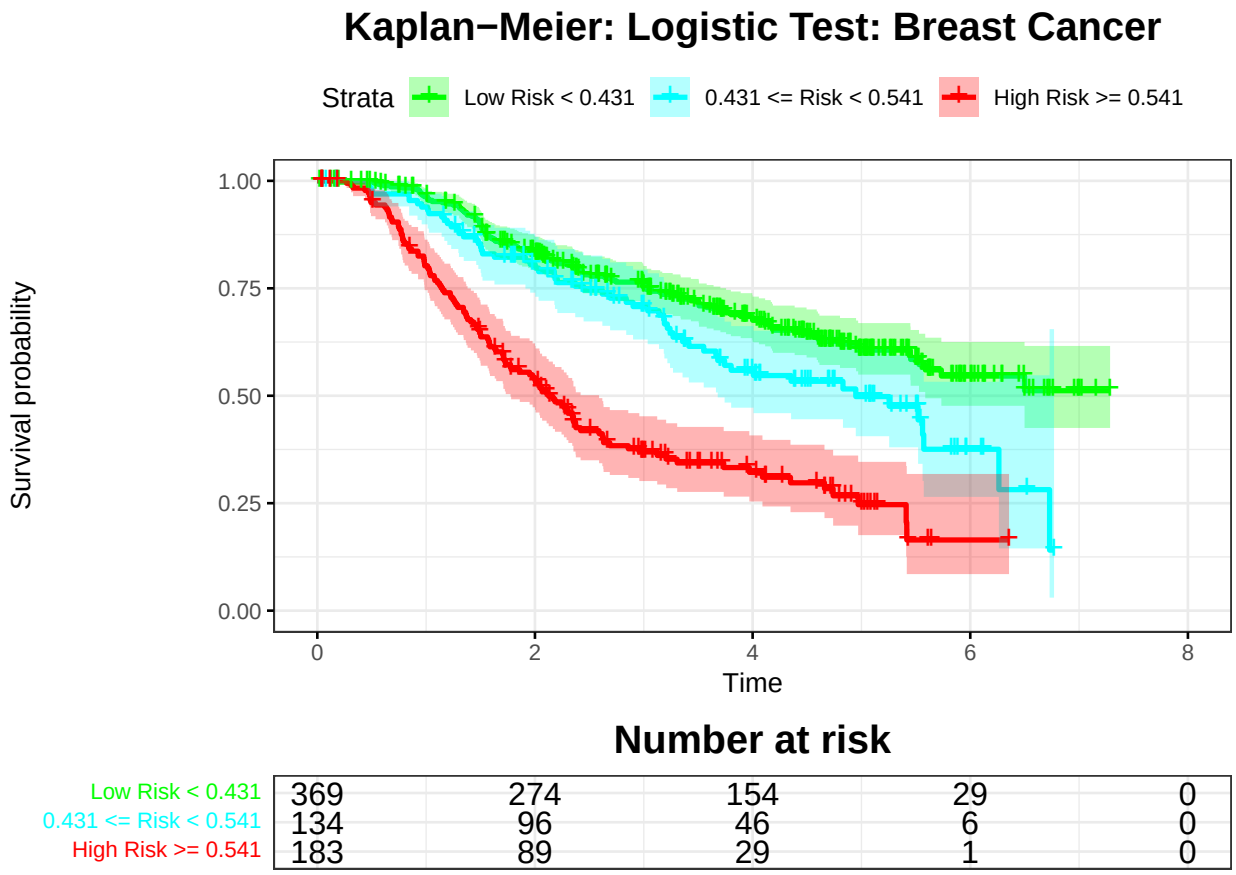

Cumulative vs. Observed: Logistic Test: Breast Cancer
Observed
0
50
100
150
200
250
300
Cumulative Probability
Event
Expected


Decision Curve Analysis: Logistic Test: Breast Cancer
Net Benefit
0.0
0.1
0.2
0.3
0.4
Threshold
0.0
0.2
0.4
0.6
0.8
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None


Relative Risk: Logistic Test: Breast Cancer
RR
SEN
PPV–>
SPE
Index(0.83)=0.541
RR(0.39)=1.799
No
Yes
Loess Fit
1.0
0.8
0.6
0.4
0.2
0.0
1.0
2.0
2.5
3.0
3.5
4.0
0.0
0.2
0.4
0.6
0.8
1.0


ROC: Logistic Test: Breast Cancer
(TPR= 0.395 ,TNR= 0.832 ,ACC= 0.641 ,F1= 0.490 ,BER= 0.387)
Sensitivity
Specificity
1.0
0.8
0.6
0.4
0.2
0.0
Confusion Matrix
O(+)
O(−)
T(+)
T(−)
Test
Outcome
AUC: 0.669
BACC (0.613)


Time vs. Events: Logistic Test: Breast Cancer
Expected
Observed
Events
0
50
100
150
200
250
300
0
1
2
3
4
5
6
7
Time




```
par(op)
```

1.7.3 Validation Report

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

Table 56: 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
RR	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
SEN	0.395	0.595	0.579	0.950	1.00e+00	0.4482
SPE	0.832	0.638	0.669	0.181	1.29e-02	0.7804
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="O/E Ratio")
```

Table 57: O/E Ratio

O/E	Low	Upper	p.value
1.03	0.921	1.16	0.556

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

- **C Index**: *0.669*
- **Dxy**: *0.338*
- **S.D.**: *0.0309*
- **n**: *686*
- **missing**: *0*
- **uncensored**: *299*
- **Relevant Pairs**: *266144*
- **Concordant**: *178115*
- **Uncertain**: *203702*
- **cstatCI**:

mean.C Index	median	lower	upper
0.669	0.67	0.643	0.698

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

Table 59: ROC AUC

est	lower	upper
0.669	0.628	0.709

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

Table 60: Sensitivity

est	lower	upper
0.395	0.339	0.453

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

Table 61: Specificity

est	lower	upper
0.832	0.791	0.868

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

Table 62: Probability Thresholds

90%	80%
0.541	0.431

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

Table 63: Logrank test Chisq = 92.507991 on 2 degrees of freedom, p = 0.000000

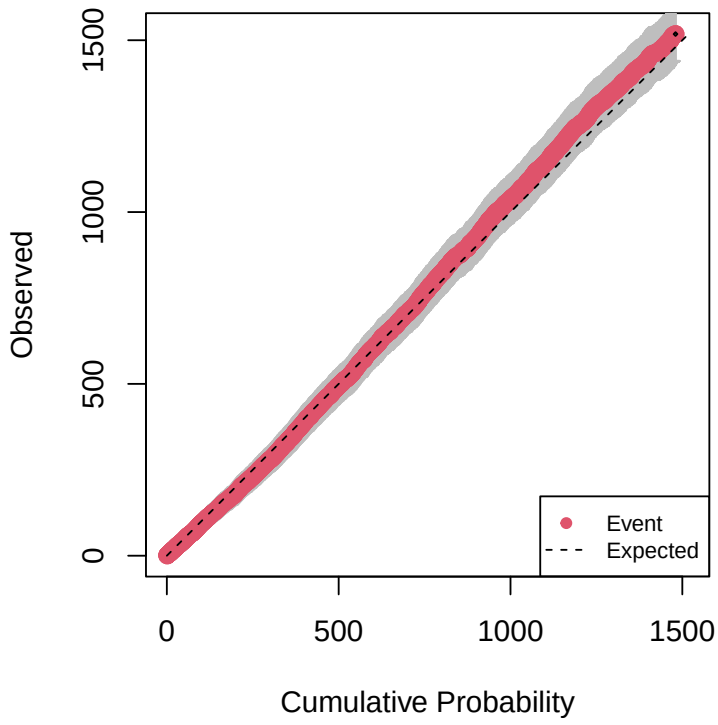
	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	369	121	181.7	20.2997	52.3868
class=1	134	60	61.7	0.0479	0.0604
class=2	183	118	55.5	70.2342	88.0195

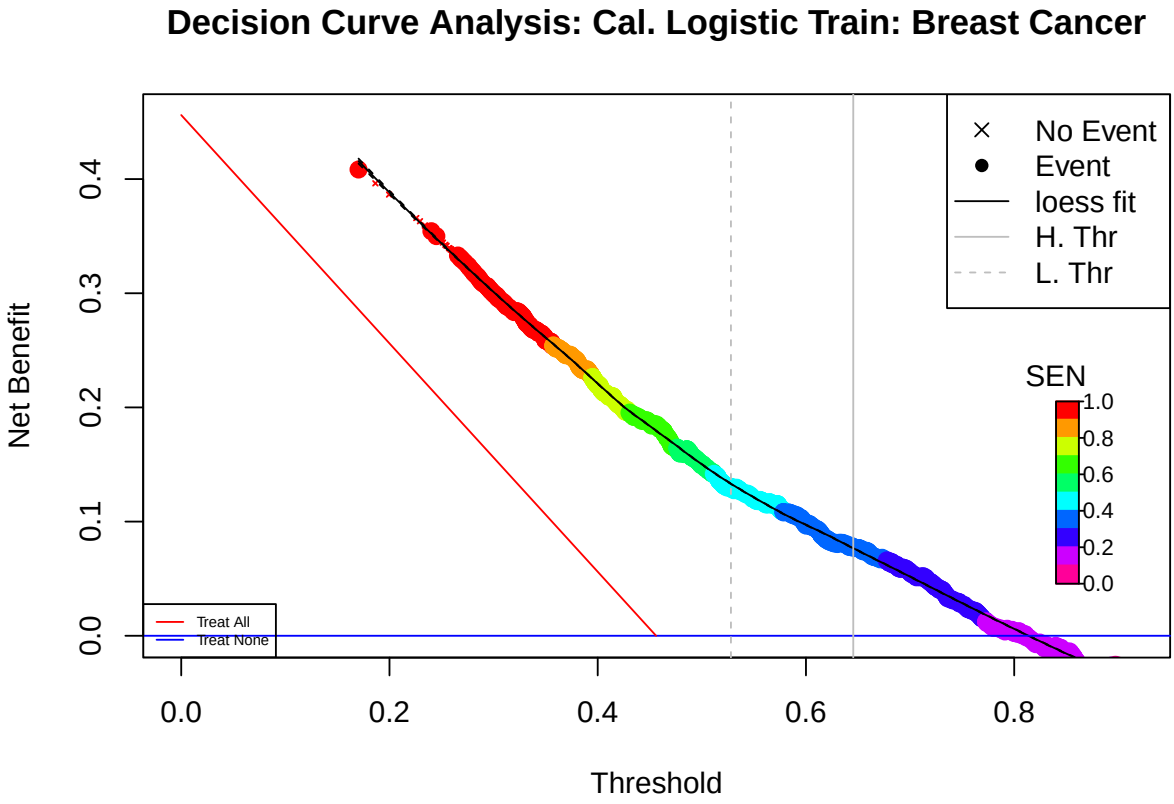
1.8 Logistic Model Poisson Calibration

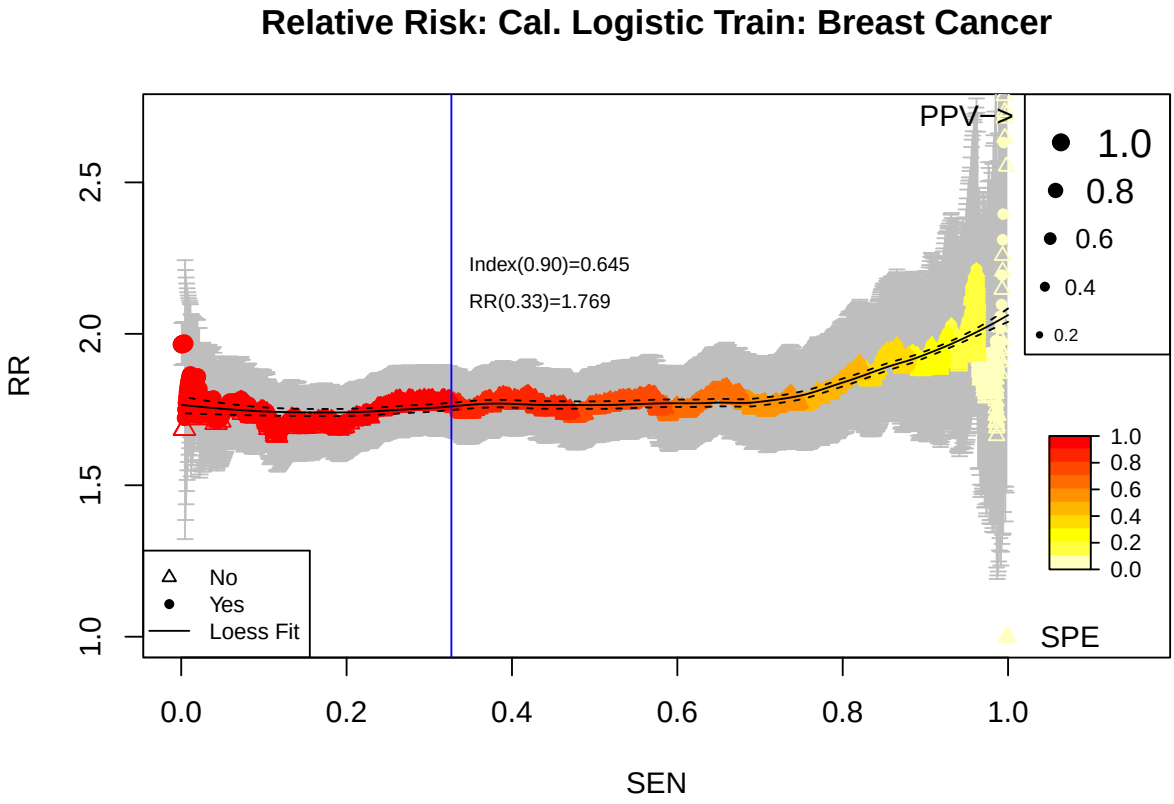
```
riskdata <- cbind(dataBrestCancerTrain$status,predict(mlog,dataBrestCancerTrain,type="prob"),dataBrestCa
calprob <- CalibrationProbPoissonRisk(riskdata)

pander::pander(c(h0=calprob$h0,
                 Gain=calprob$hazardGain,
                 DeltaTime=calprob$timeInterval),
               caption="Logistic Calibration Parameters")
```

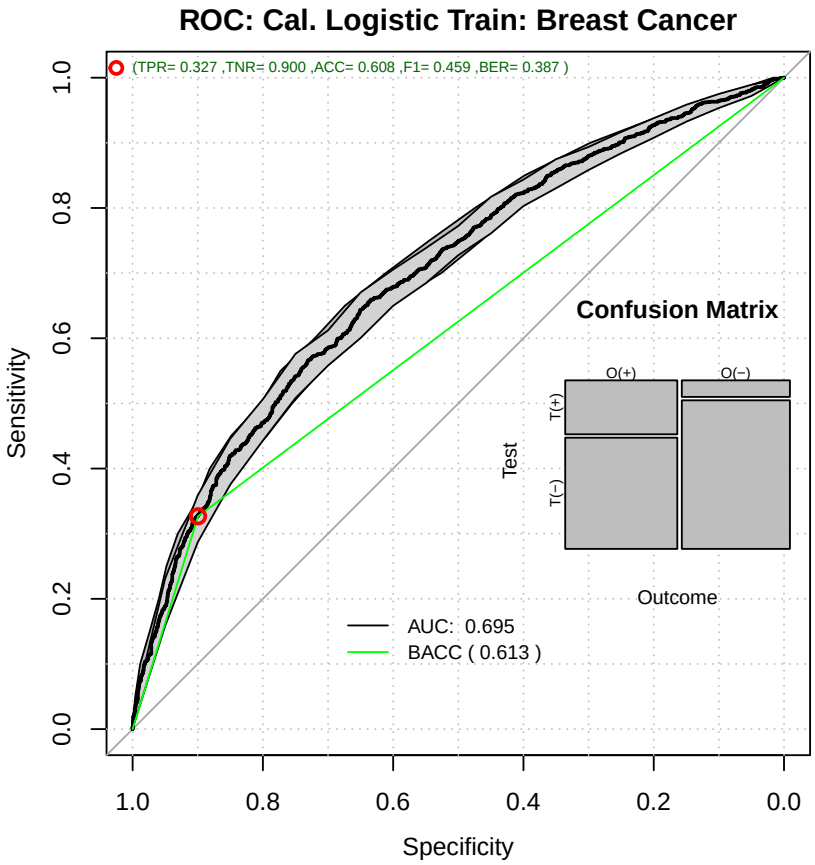
h0	Gain	DeltaTime
0.689	1.33	7.44

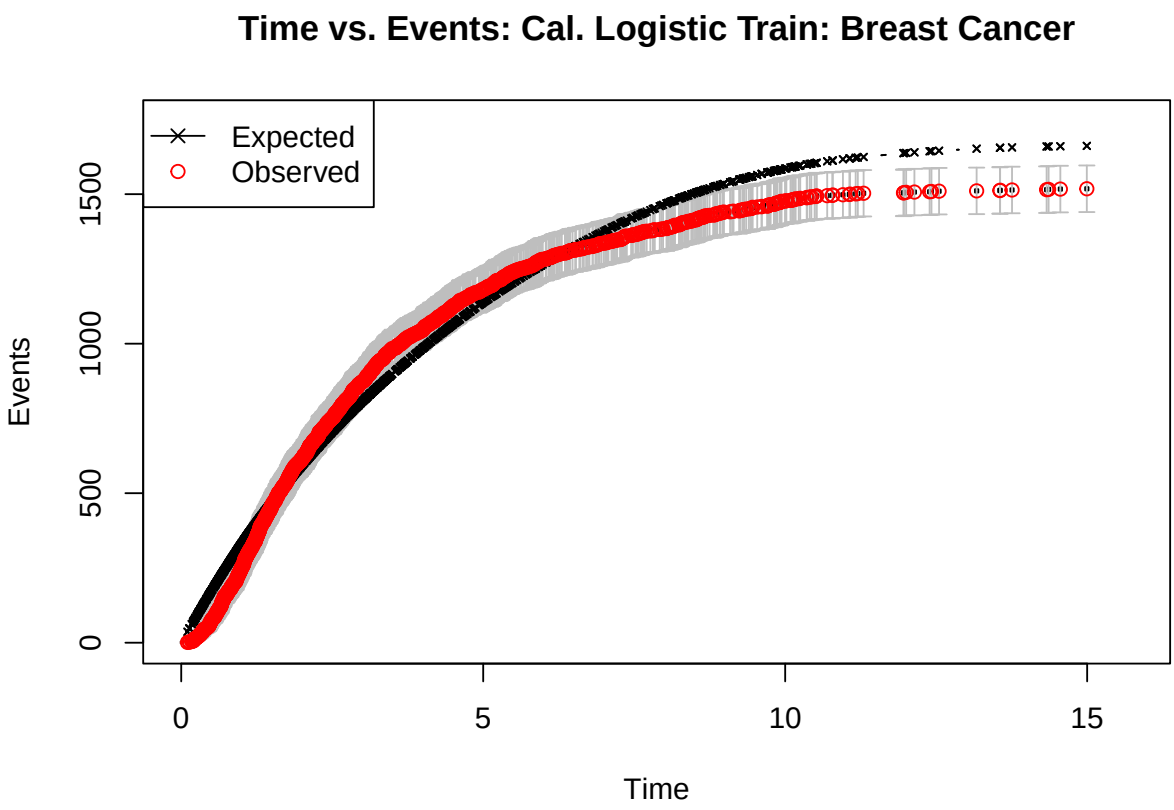
```
timeinterval <- calprob$timeInterval;
gain <- calprob$hazardGain

rdata <- cbind(dataBrestCancerTrain$status,calprob$prob)


rrAnalysisTrain <- RRPlot(rdata,atRate=c(0.90,0.80),
                      timetoEvent=dataBrestCancerTrain$time,
                      title="Cal. Logistic Train: Breast Cancer",
                      ysurvlim=c(0.00,1.0),
                      riskTimeInterval=timeinterval)
```

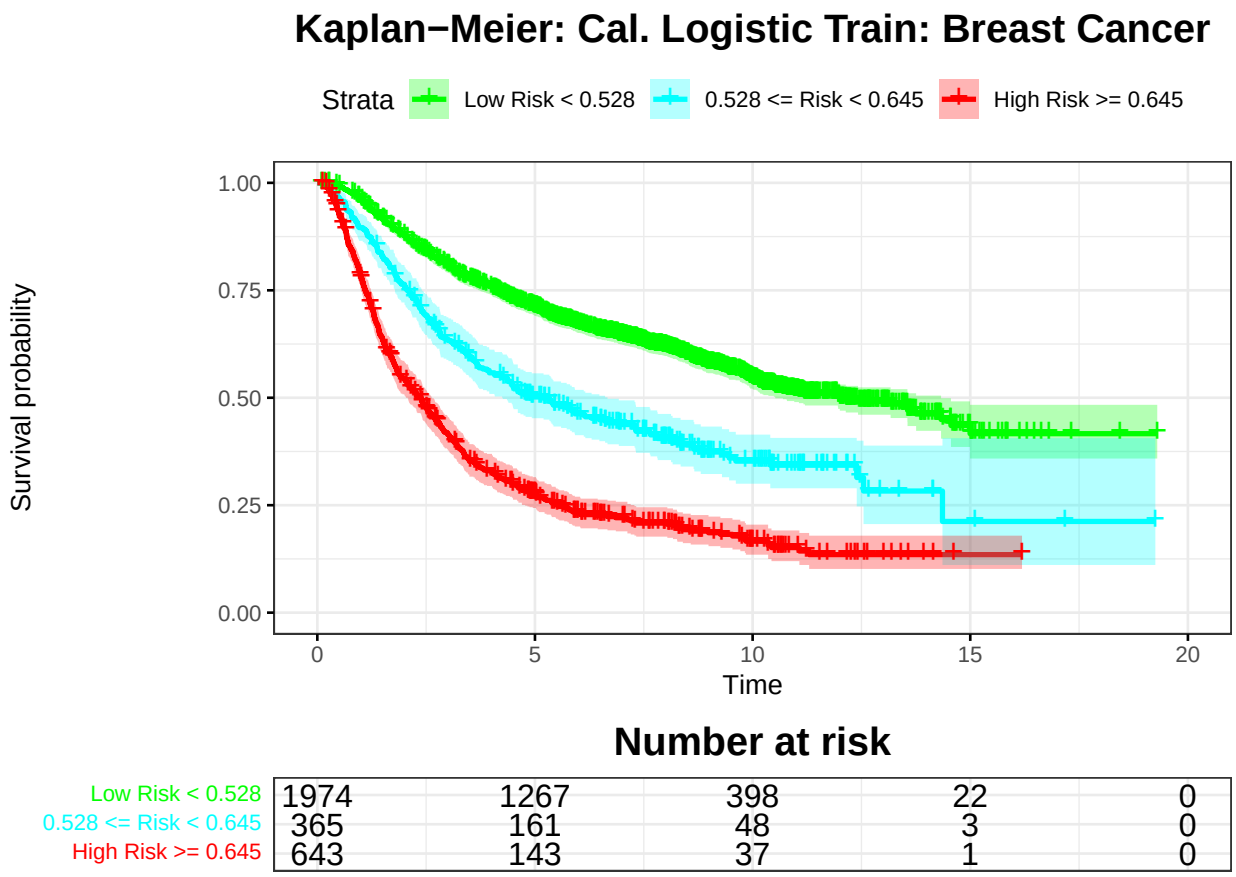

Cumulative vs. Observed: Cal. Logistic Train: Breast Cancer
Observed
0
500
1000
1500
Cumulative Probability
0
500
1000
1500
Event
Expected


Decision Curve Analysis: Cal. Logistic Train: Breast Cancer
Net Benefit
0.0
0.1
0.2
0.3
0.4
0.0
0.2
0.4
0.6
0.8
Threshold
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None


Relative Risk: Cal. Logistic Train: Breast Cancer
PPV–>
1.0
0.8
0.6
0.4
0.2
Index(0.90)=0.645
RR(0.33)=1.769
1.0
0.8
0.6
0.4
0.2
0.0
No
Yes
Loess Fit
SPE
RR
2.5
2.0
1.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
SEN


ROC: Cal. Logistic Train: Breast Cancer
(TPR= 0.327 ,TNR= 0.900 ,ACC= 0.608 ,F1= 0.459 ,BER= 0.387)
Sensitivity
Specificity
1.0
0.8
0.6
0.4
0.2
0.0
Confusion Matrix
O(+)
O(−)
T(+)
T(−)
Test
Outcome
AUC: 0.695
BACC (0.613)


Time vs. Events: Cal. Logistic Train: Breast Cancer
Expected
Observed
Events
0
500
1000
1500
0
5
10
15
Time




```
par(op)
```

1.8.1 Report of the calibrated logistic: training

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

Table 65: Threshold values

	@:0.9	@:0.8	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.6463	0.528	0.486	0.324	0.170289	0.500
RR	1.7654	1.739	1.799	2.213	1.000000	1.764
RR_LCI	1.6587	1.627	1.676	1.764	0.000000	1.648
RR_UCI	1.8790	1.858	1.931	2.777	0.000000	1.889
SEN	0.3267	0.470	0.566	0.962	1.000000	0.519
SPE	0.8996	0.799	0.731	0.125	0.000683	0.765
BACC	0.6132	0.635	0.648	0.543	0.500342	0.642
NetBenefit	0.0763	0.129	0.163	0.284	0.408374	0.149

```
pander::pander(t(rrAnalysisTrain$OERatio$estimate),caption="O/E Ratio")
```

Table 66: O/E Ratio

O/E	Low	Upper	p.value
0.914	0.868	0.961	0.000392

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

- **C Index**: *0.68*
- **Dxy**: *0.36*
- **S.D.**: *0.014*
- **n**: *2982*
- **missing**: *0*
- **uncensored**: *1518*
- **Relevant Pairs**: *6184528*
- **Concordant**: *4206587*
- **Uncertain**: *2703838*
- **cstatCI**:

mean.C Index	median	lower	upper
0.68	0.68	0.666	0.693

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

Table 68: ROC AUC

est	lower	upper
0.695	0.677	0.714

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

Table 69: Sensitivity

est	lower	upper
0.327	0.303	0.351

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

Table 70: Specificity

est	lower	upper
0.9	0.883	0.915

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

Table 71: Probability Thresholds

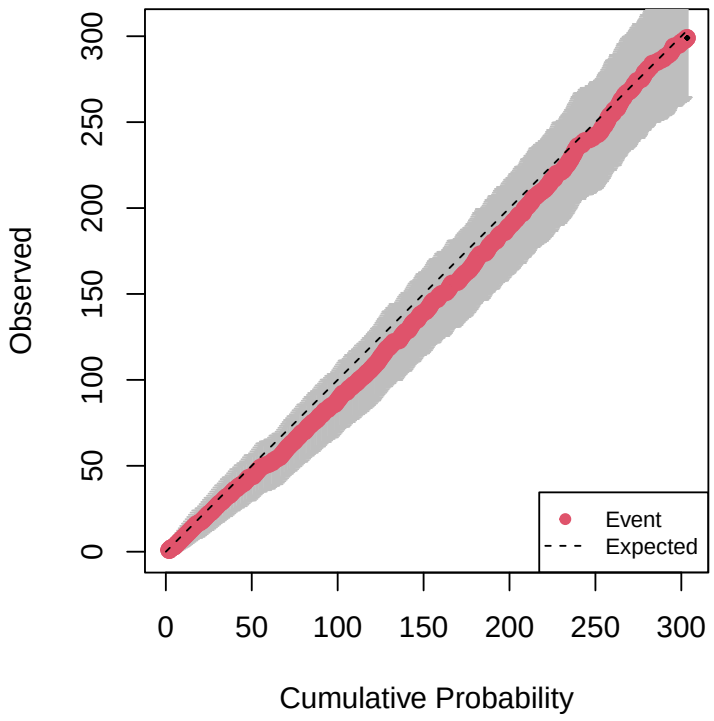
90%	80%
0.645	0.528

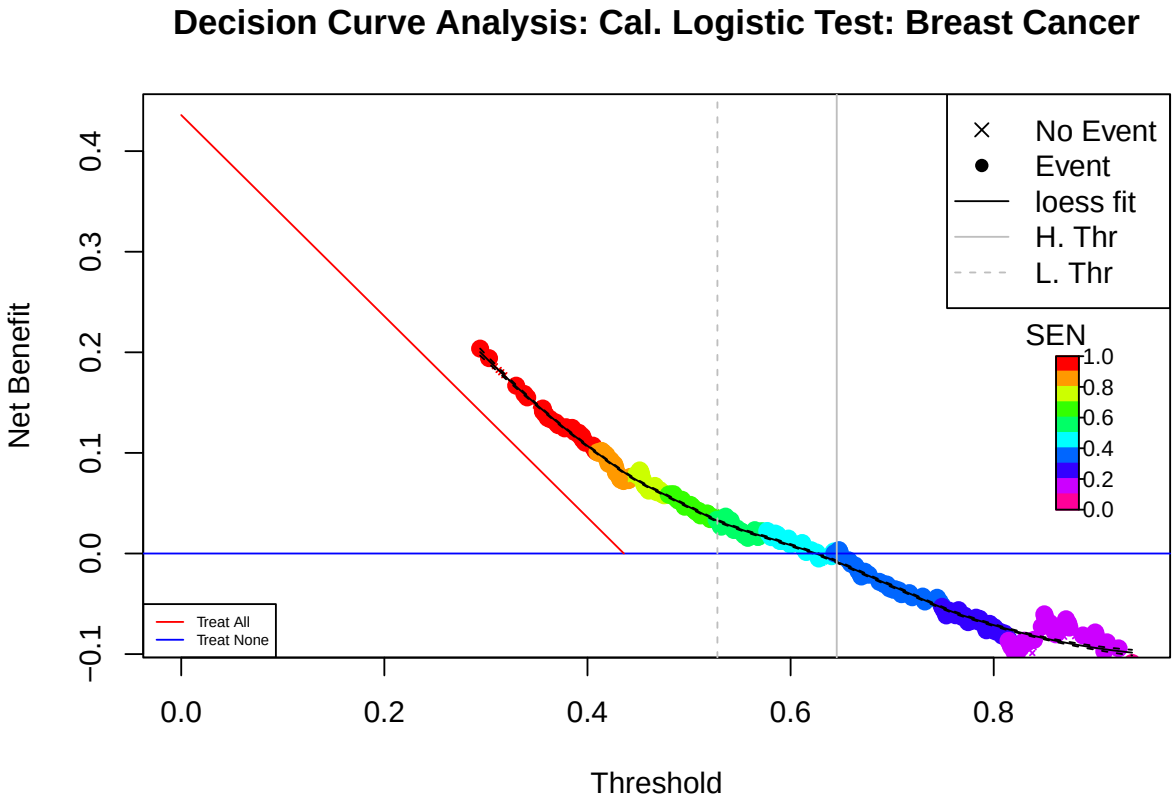
```
pander::pander(rrAnalysisTrain$surdif,caption="Logrank test")
```

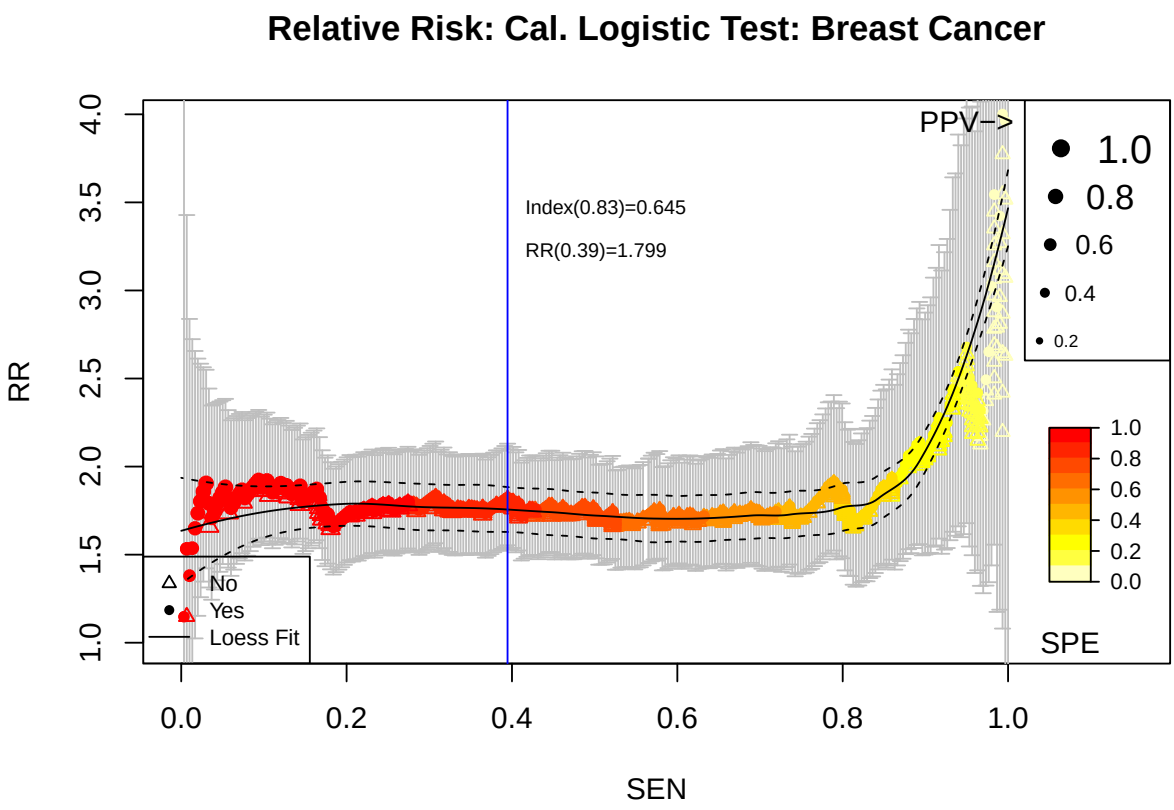
Table 72: Logrank test Chisq = 541.976716 on 2 degrees of freedom, p = 0.000000

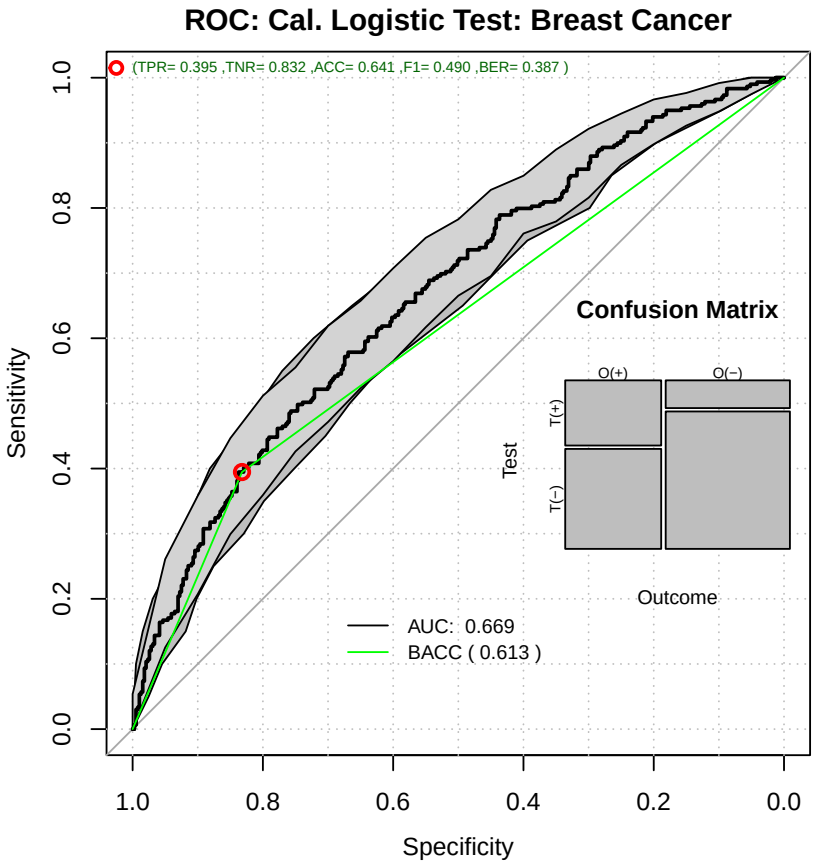
	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	1974	804	1144	100.9	415.3
class=1	365	218	170	13.4	15.1
class=2	643	496	204	418.2	490.7

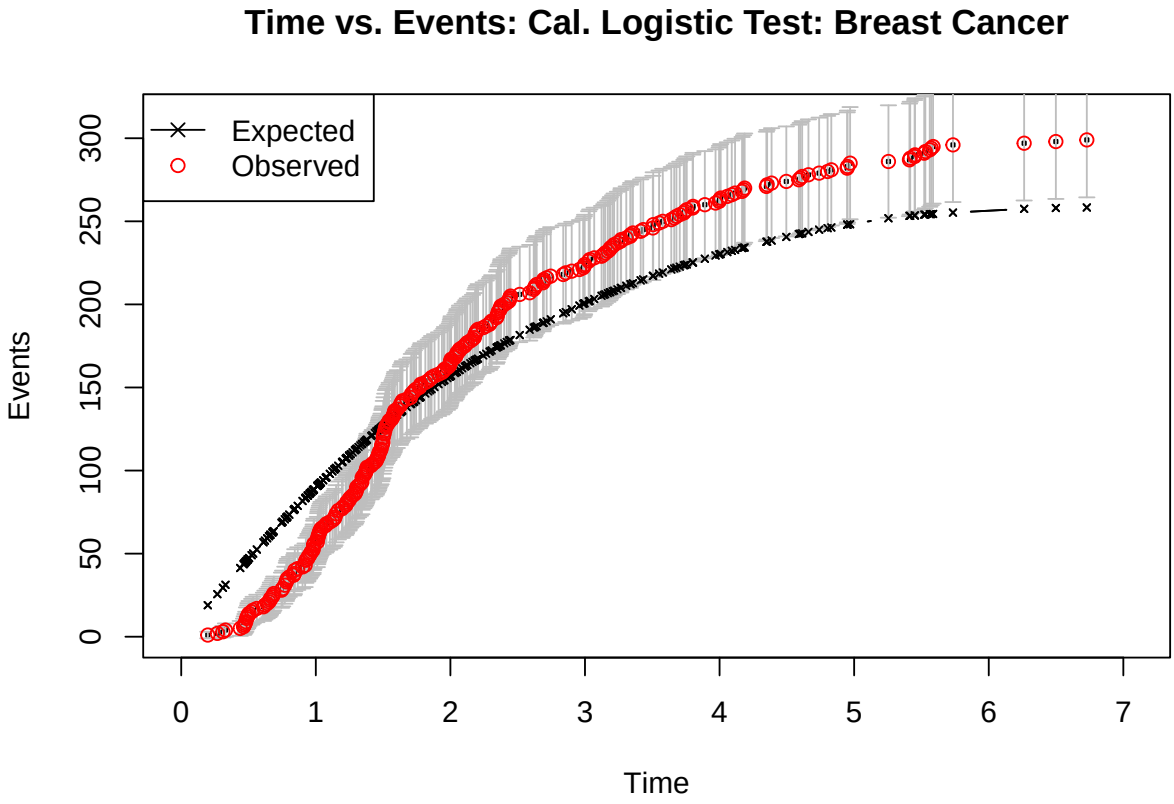
```
probLog <- predict(mlog,dataBrestCancerTest)
aprob <- adjustProb(probLog,gain)

rdata <- cbind(dataBrestCancerTest$status,aprob)
rrAnalysisTestLogistic <- RRPlot(rdata,atThr=rrAnalysisTrain$thr_atP,
                      timetoEvent=dataBrestCancerTest$time,
                      title="Cal. Logistic Test: Breast Cancer",
                      ysurvlim=c(0.00,1.0),
                      riskTimeInterval=timeinterval)
```

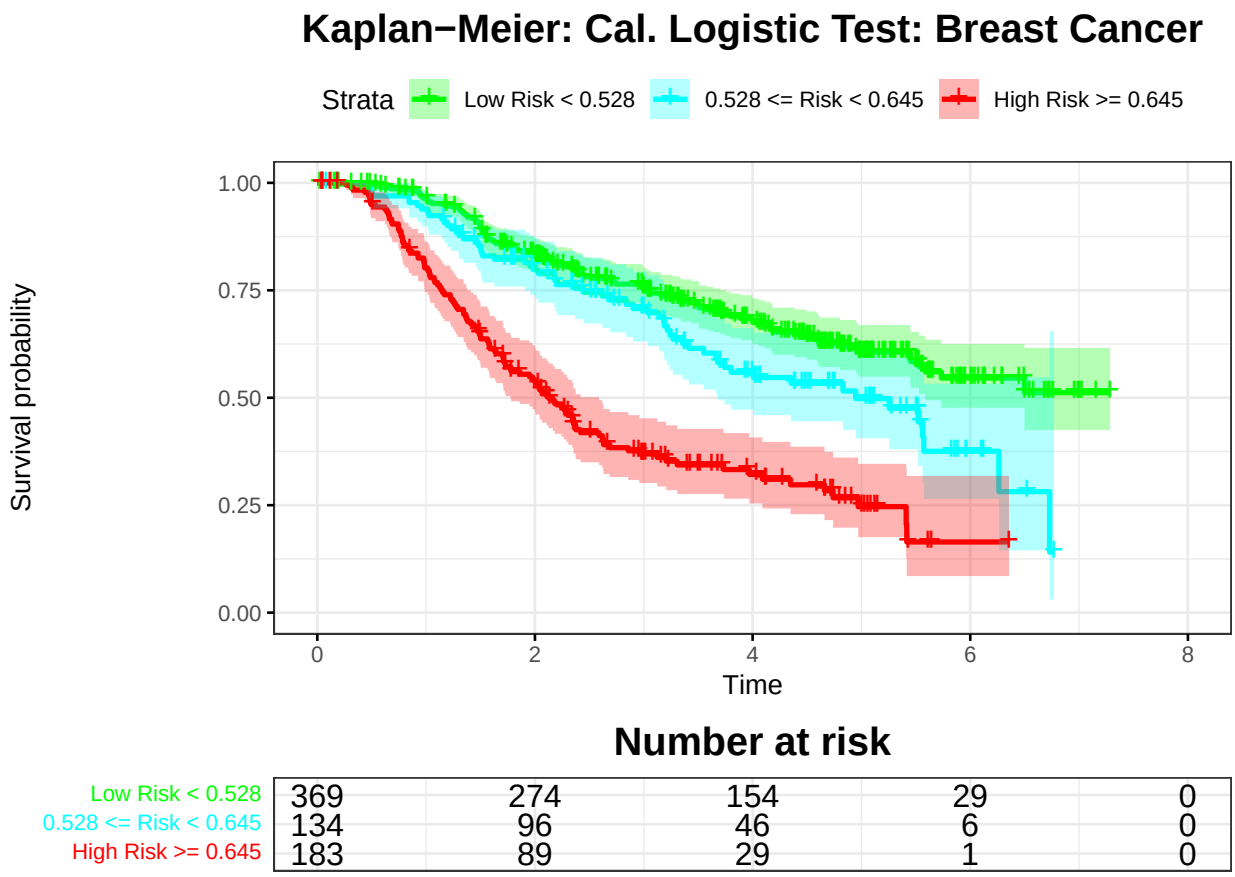

Cumulative vs. Observed: Cal. Logistic Test: Breast Cancer
Observed
0
50
100
150
200
250
300
Cumulative Probability
Event
Expected


Decision Curve Analysis: Cal. Logistic Test: Breast Cancer
Net Benefit
−0.1
0.0
0.1
0.2
0.3
0.4
0.0
0.2
0.4
0.6
0.8
Threshold
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None


Relative Risk: Cal. Logistic Test: Breast Cancer
RR
SEN
PPV–>
Index(0.83)=0.645
RR(0.39)=1.799
No
Yes
Loess Fit
SPE
1.0
0.8
0.6
0.4
0.2
0.0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
0.0
0.2
0.4
0.6
0.8
1.0


ROC: Cal. Logistic Test: Breast Cancer
(TPR= 0.395 ,TNR= 0.832 ,ACC= 0.641 ,F1= 0.490 ,BER= 0.387)
Sensitivity
Specificity
1.0
0.8
0.6
0.4
0.2
0.0
Confusion Matrix
O(+)
O(−)
T(+)
T(−)
Test
Outcome
AUC: 0.669
BACC (0.613)


Time vs. Events: Cal. Logistic Test: Breast Cancer
Expected
Observed
Events
0
50
100
150
200
250
300
0
1
2
3
4
5
6
7
Time




```
par(op)
```

1.8.2 Report of the calibrated validation

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

Table 73: Threshold values

	@:0.645	@:0.528	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.645672	0.5277	0.5360	0.385	2.94e-01	0.5001
RR	1.791927	1.7024	1.7562	2.678	2.20e+01	1.7232
RR_LCI	1.529135	1.4283	1.4771	1.679	4.75e-02	1.4313
RR_UCI	2.099881	2.0290	2.0880	4.271	1.02e+04	2.0746
SEN	0.394649	0.5953	0.5786	0.950	1.00e+00	0.6555
SPE	0.832041	0.6382	0.6693	0.181	1.29e-02	0.5762
BACC	0.613345	0.6168	0.6239	0.565	5.06e-01	0.6159
NetBenefit	-0.000601	0.0315	0.0367	0.125	2.04e-01	0.0466

```
pander::pander(t(rrAnalysisTestLogistic$OERatio$estimate),caption="O/E Ratio")
```

Table 74: O/E Ratio

O/E	Low	Upper	p.value
1.16	1.03	1.3	0.0128

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

- **C Index**: *0.669*
- **Dxy**: *0.338*
- **S.D.**: *0.0309*
- **n**: *686*
- **missing**: *0*
- **uncensored**: *299*
- **Relevant Pairs**: *266144*
- **Concordant**: *178115*
- **Uncertain**: *203702*
- **cstatCI**:

mean.C Index	median	lower	upper
0.669	0.669	0.639	0.7

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

Table 76: ROC AUC

est	lower	upper
0.669	0.628	0.709

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

Table 77: Sensitivity

est	lower	upper
0.395	0.339	0.453

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

Table 78: Specificity

est	lower	upper
0.832	0.791	0.868

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

Table 79: Probability Thresholds

90%	80%
0.645	0.528

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

Table 80: 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%
1.01	1.01	1	1.01

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

mean	50%	2.5%	97.5%
0.944	0.944	0.94	0.947

```
pander::pander(t(rrCoxTestAnalysis$OE95ci))
```

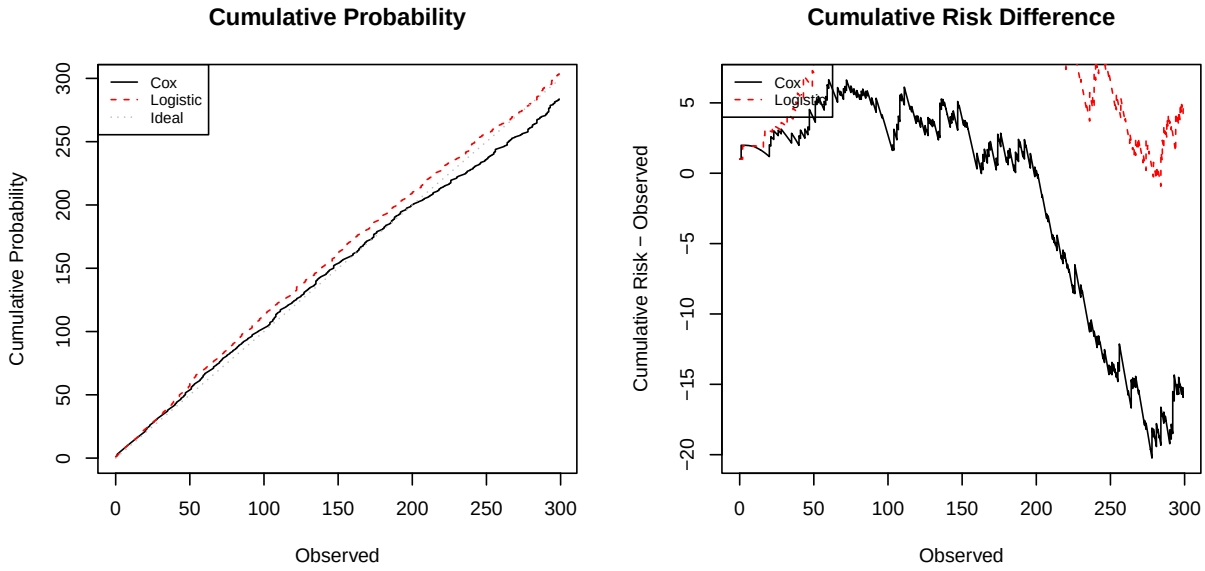
mean	50%	2.5%	97.5%
1.07	1.07	1.04	1.1

```
pander::pander(t(rrAnalysisTestLogistic$OE95ci))
```

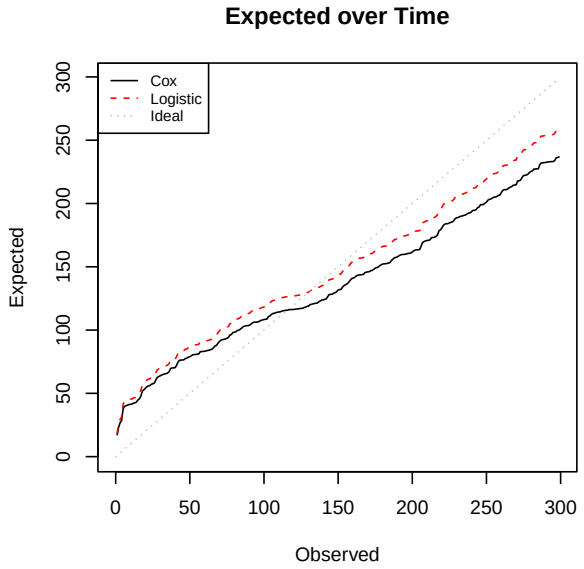
mean	50%	2.5%	97.5%
0.981	0.982	0.956	1.01

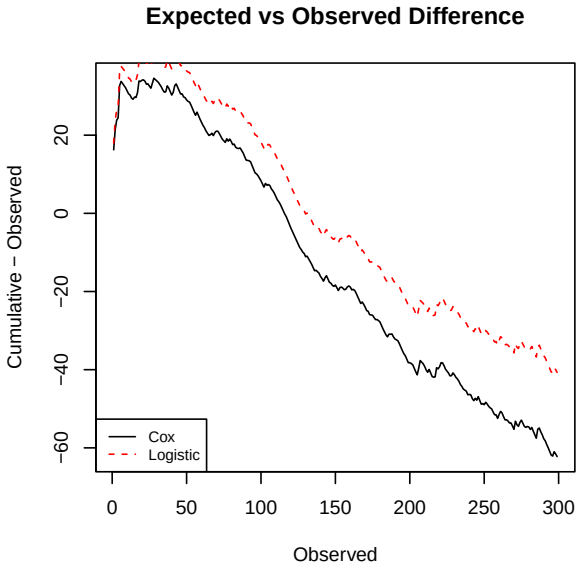
```
maxobs <- sum(dataBrestCancerTest$status)

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

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

```
     main="Cumulative Probability",
     xlab="Observed",
     ylab="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="l",
     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
)
```



```
plot(rrCoxTestAnalysis$OEData[,2:3],type="l",lty=1,
     main="Expected over Time",
     xlab="Observed",
     ylab="Expected",
     ylim=c(0,maxobs),
     xlim=c(0,maxobs))
lines(rrAnalysisTestLogistic$OEData[,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$OEData$Observed,
     rrCoxTestAnalysis$OEData$Expected-
       rrCoxTestAnalysis$OEData$Observed,
     main="Expected vs Observed Difference",
     xlab="Observed",
     ylab="Cumulative - Observed",
     type="l",
     lty=1)
lines(rrAnalysisTestLogistic$OEData$Observed,
     rrAnalysisTestLogistic$OEData$Expected-
       rrAnalysisTestLogistic$OEData$Observed,
     lty=2,col="red")

legend("bottomleft",legend = c("Cox","Logistic"),
       col=c("black","red"),
       lty=c(1,2),
       cex=0.75
)
```





```
par(op)
```