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
```

```r
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

```r
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

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

—.

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

	Estimate	lower	HR	upper	u.Accuracy	r.Accuracy	full.Accuracy	u.AUC	r.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	0.0304	0.4594	12.81	14.37	0.033056	1
size_grade	0.005649	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	0.007947	1
nodes	0.086582	1.082	1.090	1.099	0.637	0.642	0.643	0.640	0.643	0.644	0.00746	0.0564	8.33	1.66	0.000148	1
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	0.001322	1
size_nodes	-0.000378	1.000	1.000	1.000	0.624	0.643	0.643	0.629	0.644	0.644	0.00346	0.3430	7.25	9.57	-0.000377	1
age_size	-0.000149	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	0.004078	1
grade	0.204934	1.146	1.227	1.314	0.565	0.637	0.643	0.561	0.638	0.644	0.00926	0.2069	5.88	6.31	0.005344	1

	Estimate	lower	HR	upper	u.Accuracy	r.Accuracy	full.Accuracy	u.AUC	r.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	0.00416	0.0917	5.27	2.51	0.015465	1
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()

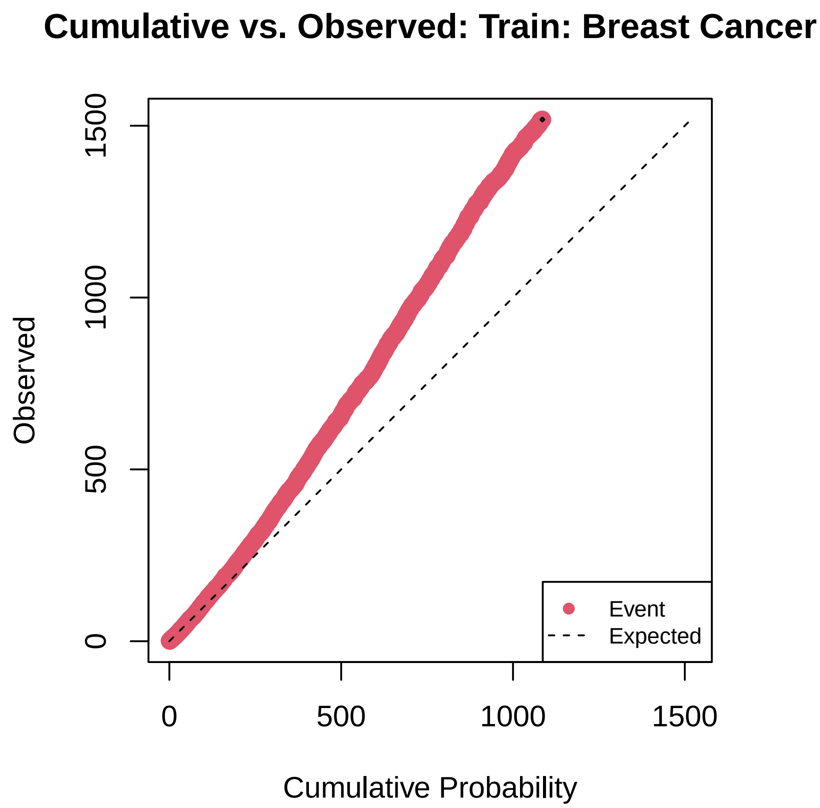
Here we will use the predicted event probability assuming a baseline hazard for events withing 5 years

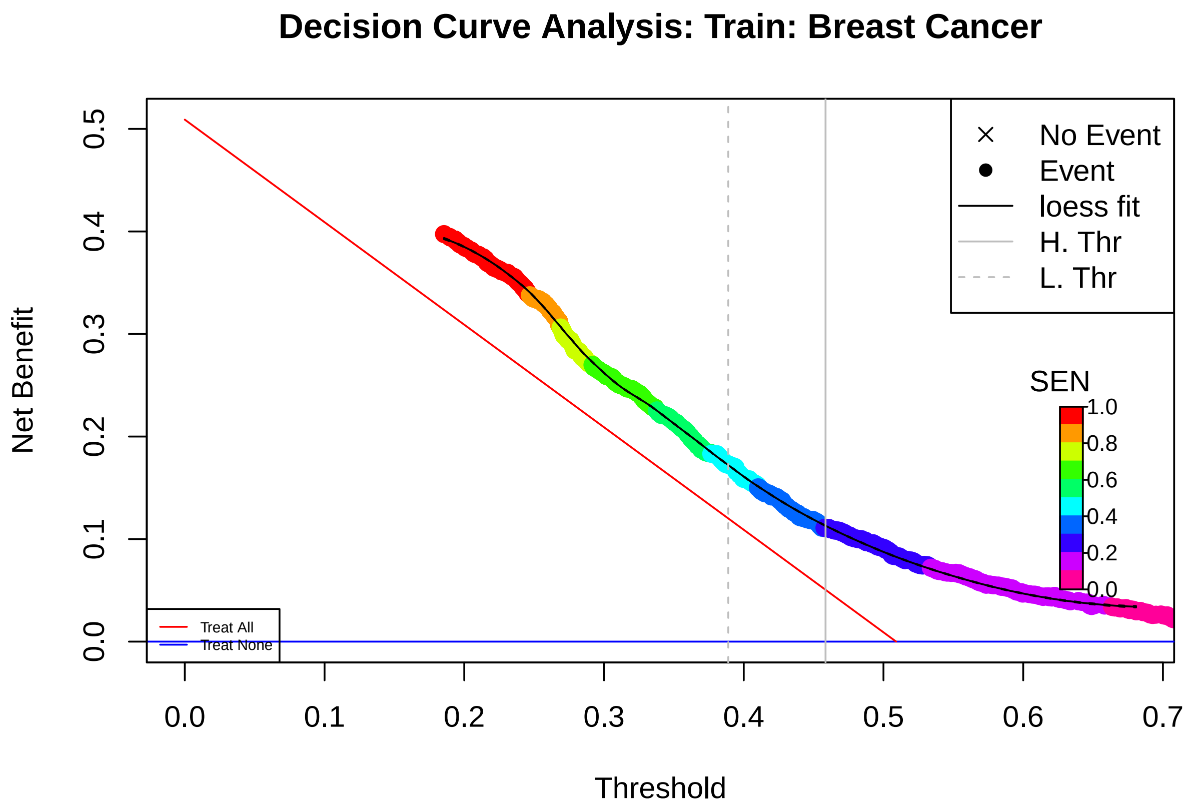
```
timeinterval <- 5 # Five years

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

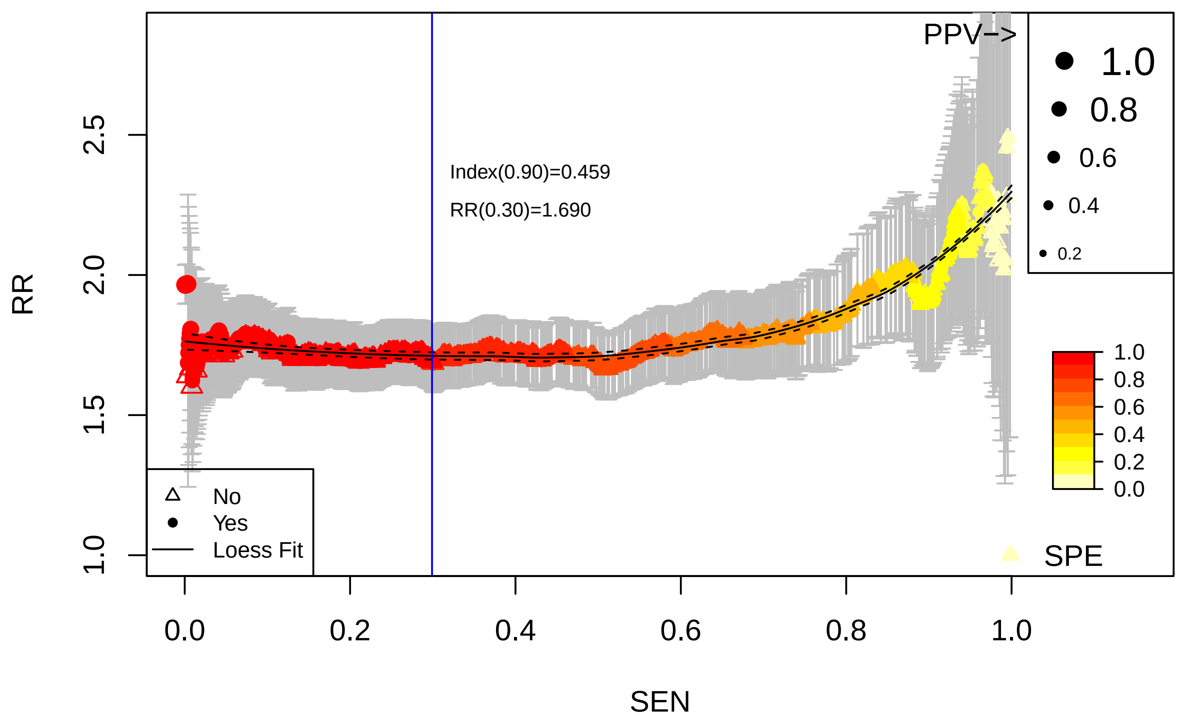
h0	timeinterval
0.429	5

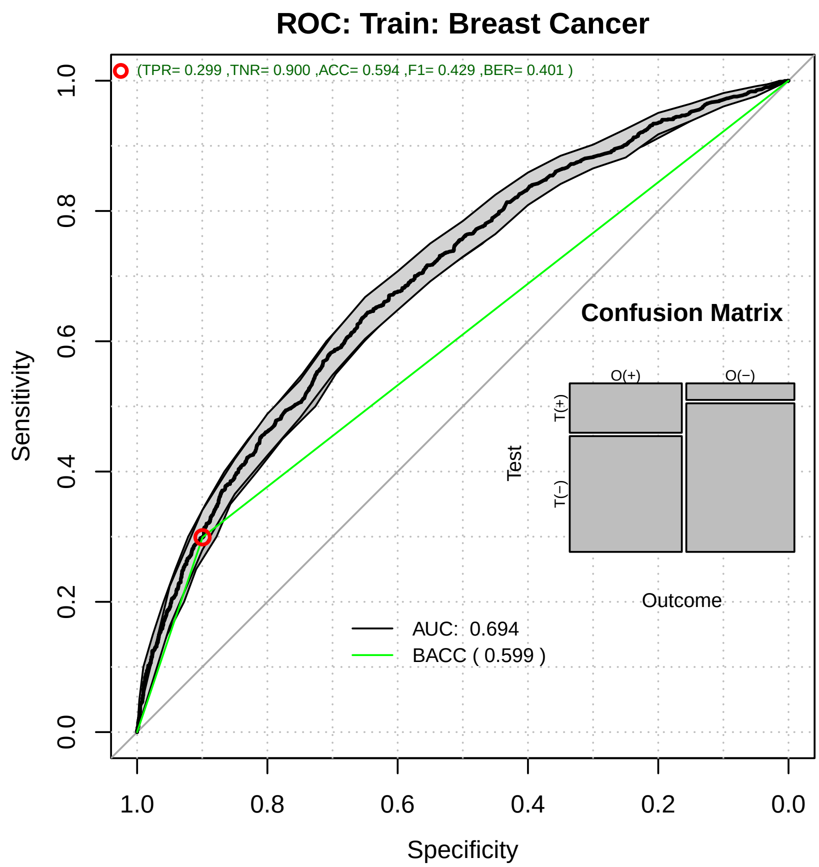
```
index <- predict(ml,dataBrestCancerTrain)
rdata <- cbind(dataBrestCancerTrain$status,ppoisGzero(index,h0))

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
Event
Expected
Cumulative Probability

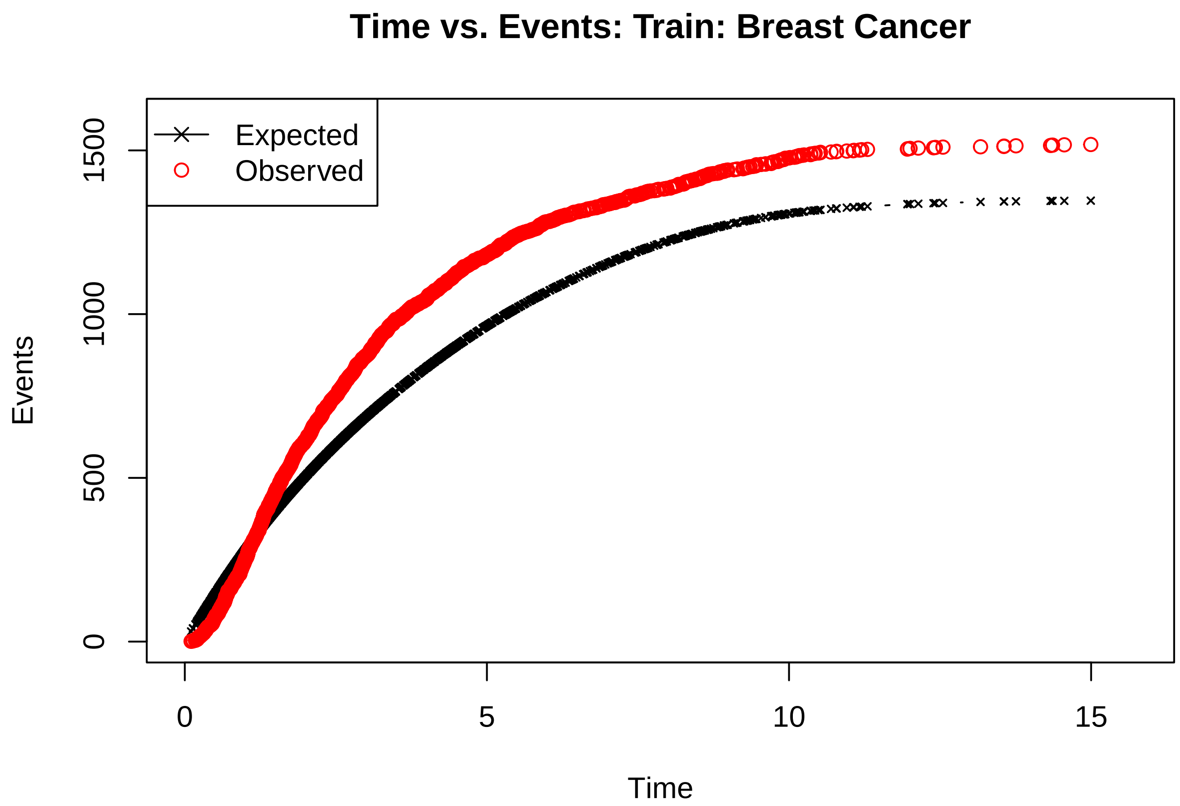

Decision Curve Analysis: Train: Breast Cancer
Net Benefit
Threshold
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None

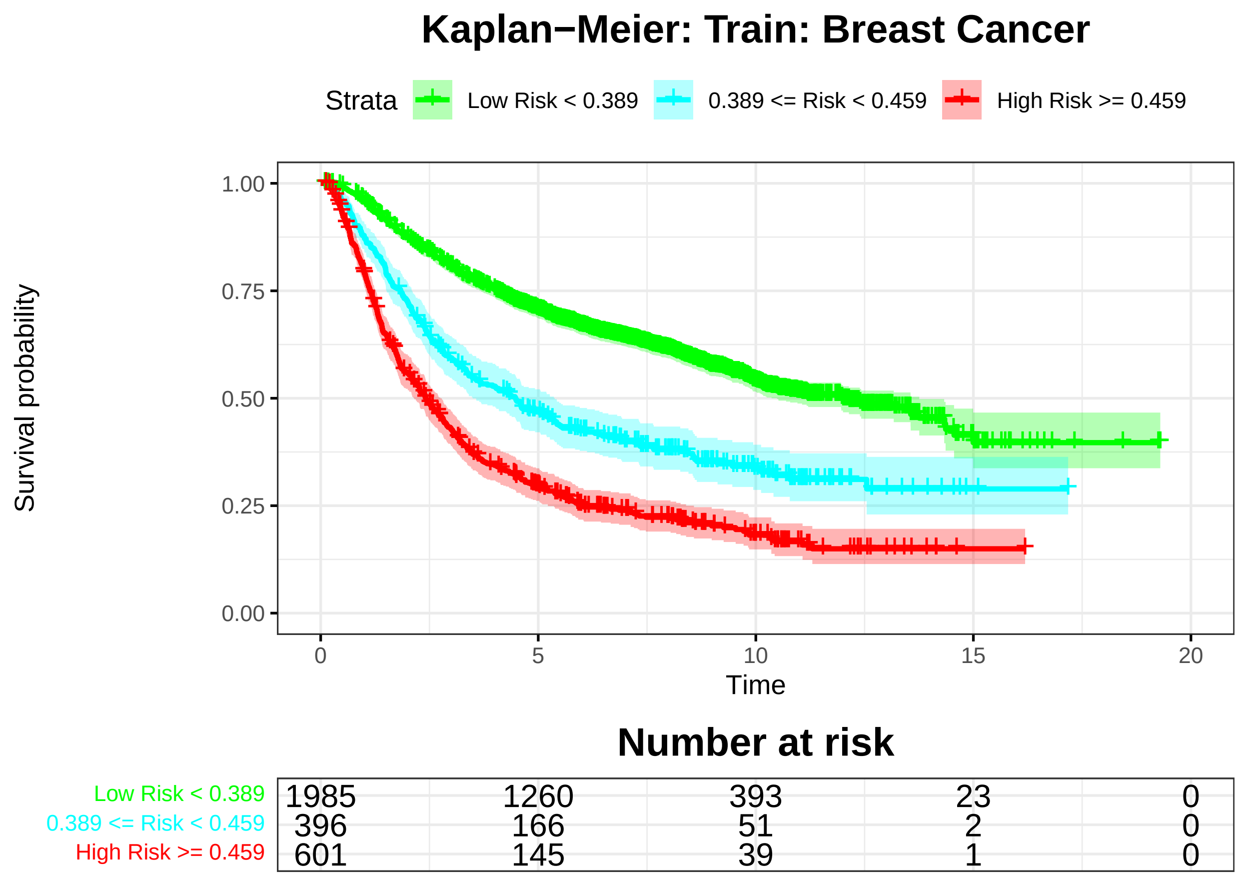
Relative Risk: Train: Breast Cancer





ROC: Train: Breast Cancer
(TPR= 0.299 ,TNR= 0.900 ,ACC= 0.594 ,F1= 0.429 ,BER= 0.401)
Sensitivity
Specificity
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
Time
0
5
10
15



1.4.2 Time to event

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

[1] 1518

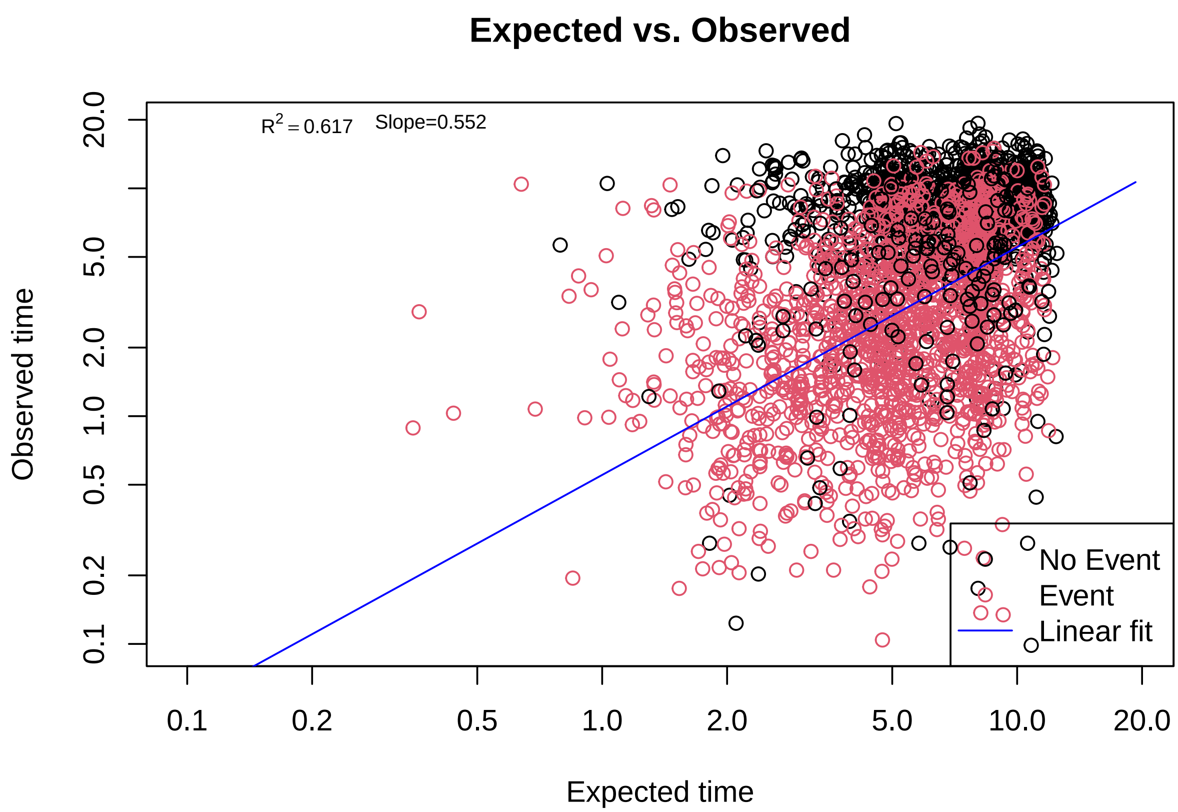
```
timetoEvent <- meanTimeToEvent(rdata[,2],timeinterval)
tmax<-max(c(obstiemToEvent,timetoEvent))
lmfit <- lm(obstiemToEvent[toinclude]~0+timetoEvent[toinclude])
sm <- summary(lmfit)
pander::pander(sm)
```

	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)
            )
```



```r
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

```r
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

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

Table 8: O/E Ratio

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

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

Table 9: O/E Mean

mean	50%	2.5%	97.5%
1.16	1.16	1.15	1.17

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

Table 10: O/Acum Mean

mean	50%	2.5%	97.5%
1.35	1.35	1.35	1.35

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

mean.C Index	median	lower	upper
0.676	0.676	0.663	0.69

```
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

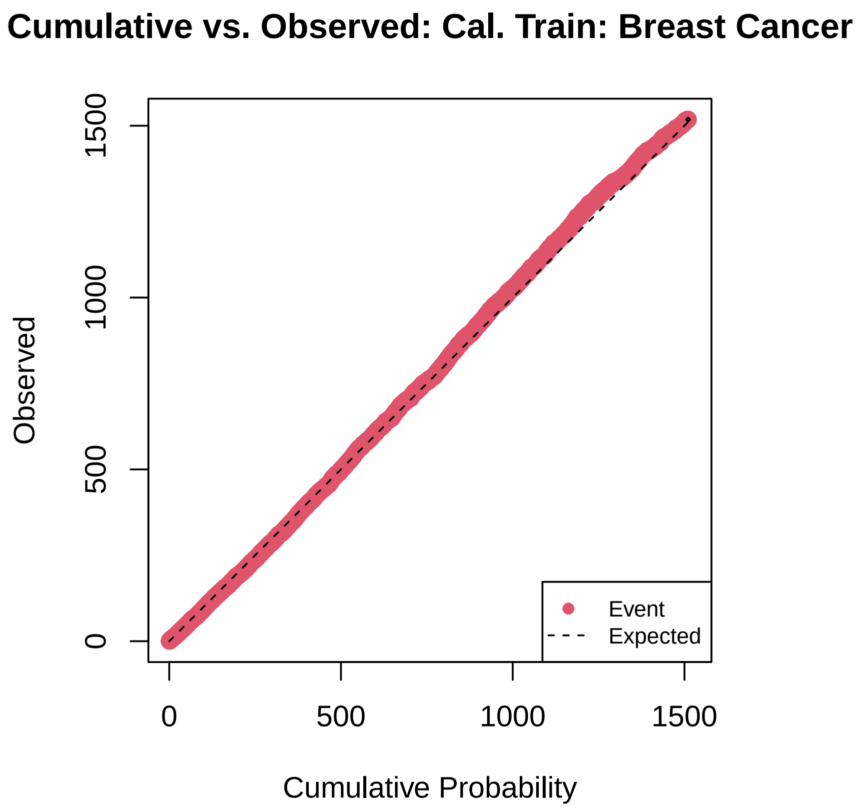
1.4.4 Cox Calibration

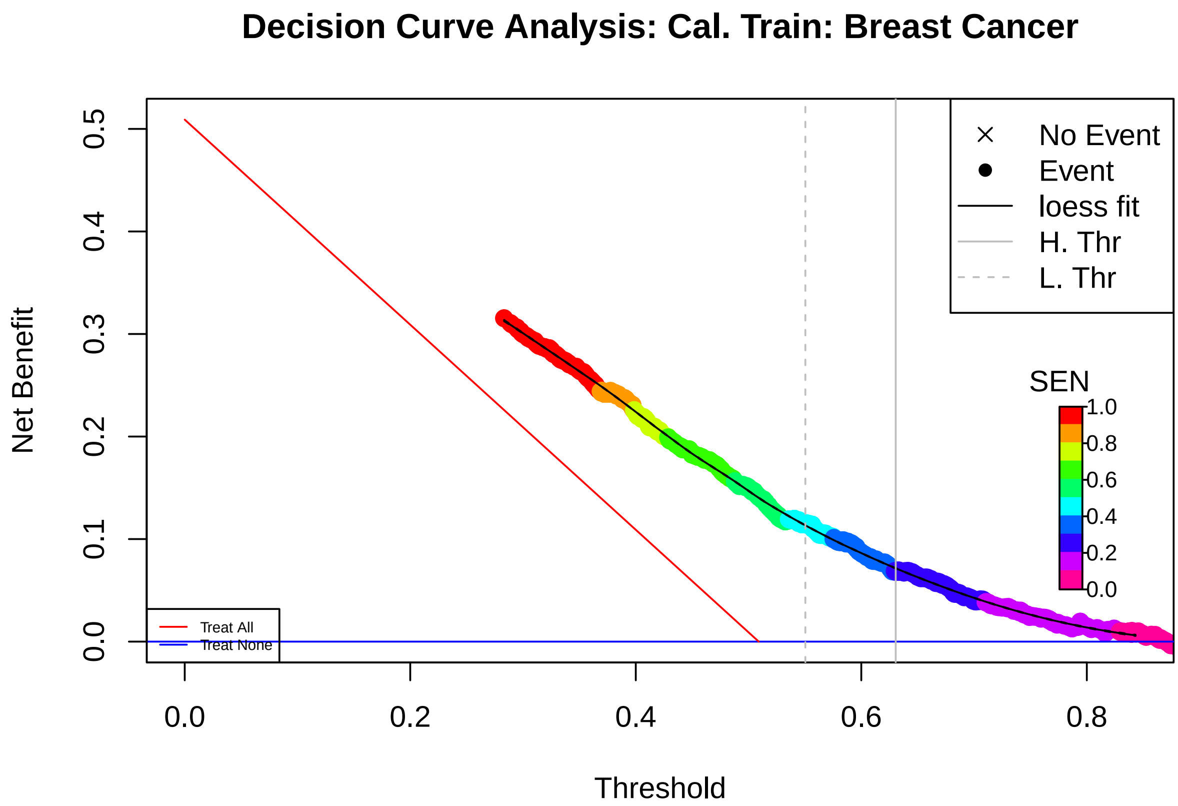
```r
op <- par(no.readonly = TRUE)


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


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

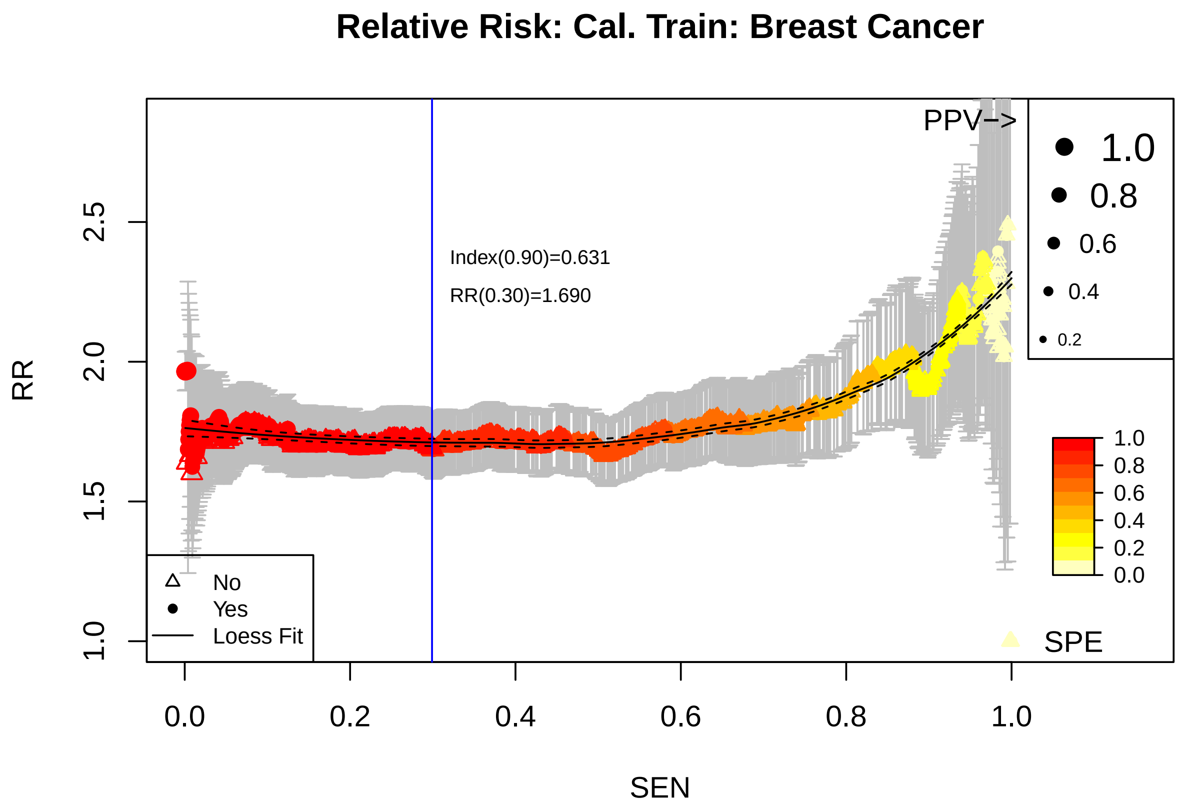
h0	Gain	DeltaTime
0.696	1.62	6.95

1.4.5 The RRplot() of the calibrated model

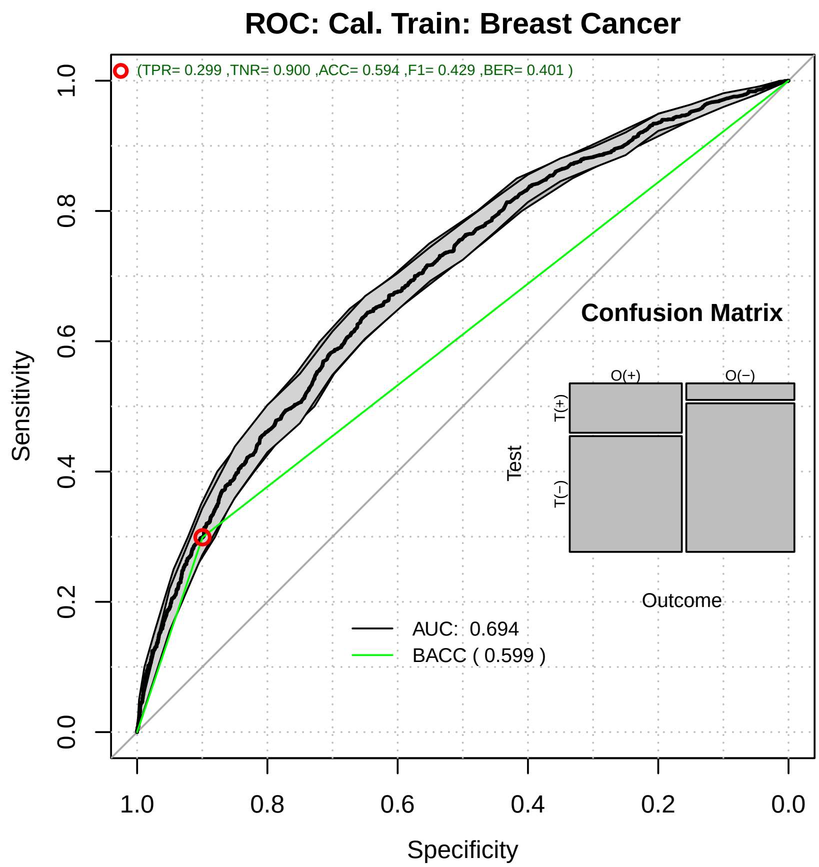
```r
h0 <- calprob$h0
timeinterval <- calprob$timeInterval;

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)
```

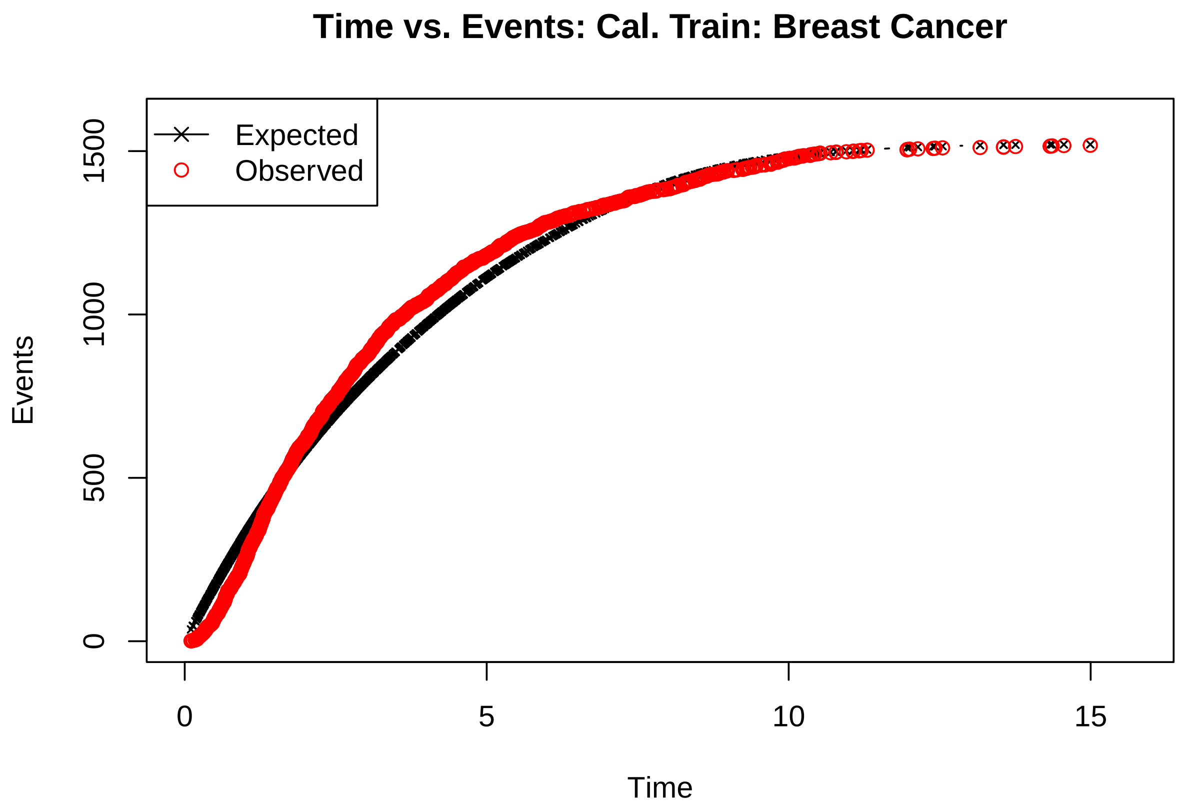

Cumulative vs. Observed: Cal. Train: Breast Cancer
Observed
0
500
1000
1500
Cumulative Probability
0
500
1000
1500
Event
Expected

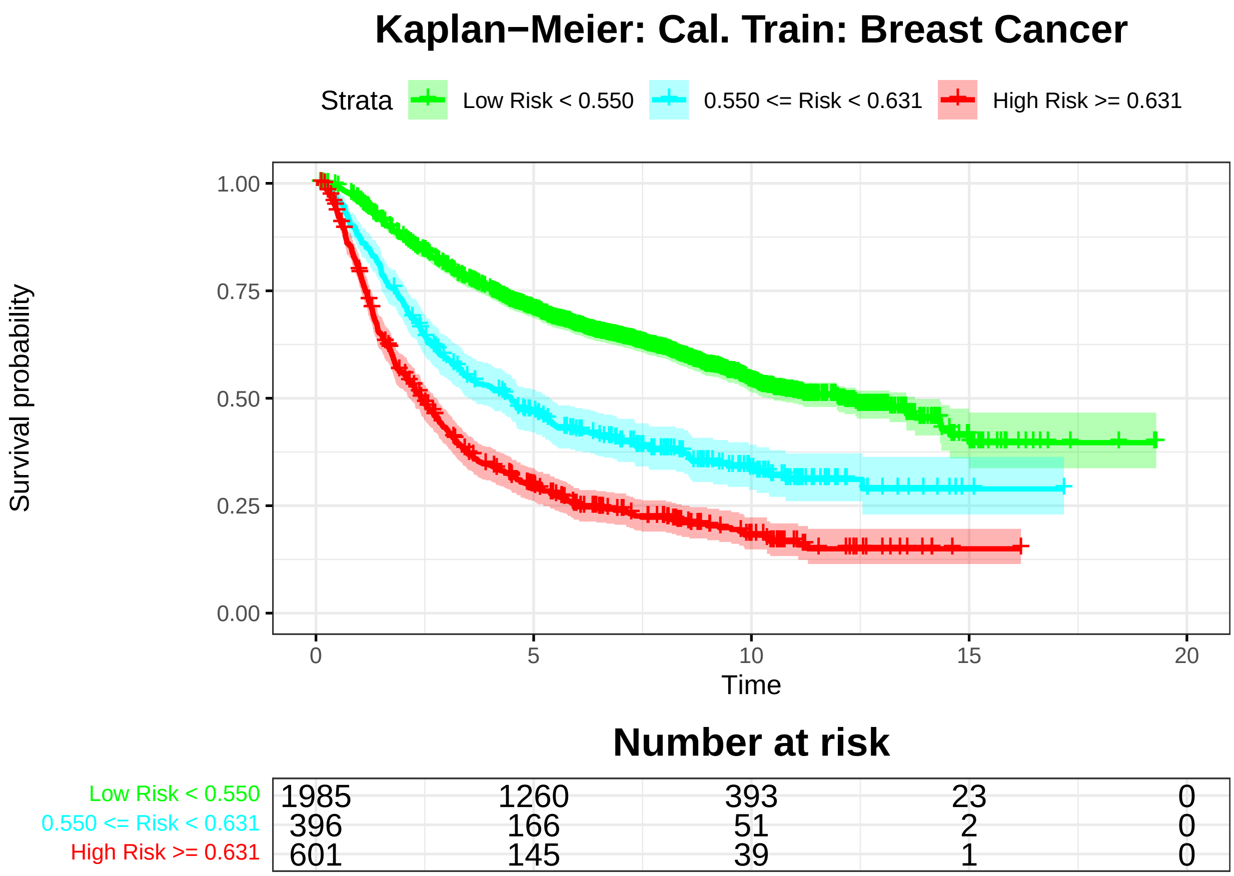

Decision Curve Analysis: Cal. Train: Breast Cancer
Net Benefit
Threshold
0.0
0.1
0.2
0.3
0.4
0.5
0.0
0.2
0.4
0.6
0.8
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None



Relative Risk: Cal. Train: Breast Cancer
PPV->
1.0
0.8
0.6
0.4
0.2
Index(0.90)=0.631
RR(0.30)=1.690
No
Yes
Loess Fit
SPE
RR
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
Time
0
5
10
15



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)
```

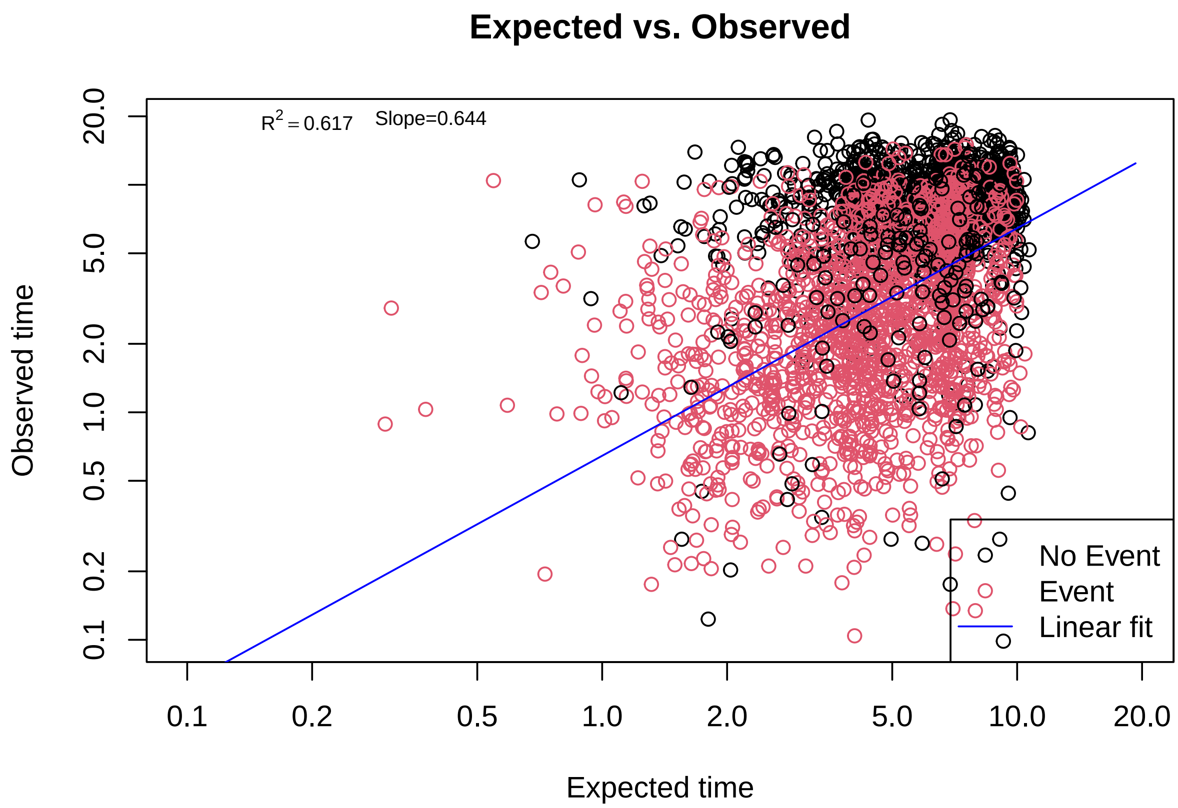
	Estimate	Std. Error	t value	Pr(>|t|)
timetoEvent[toinclude]	0.644	0.013	49.4	3.39e-318

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 *2.63*

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	0.631	0.550	0.465	0.323	0.28321	0.500
RR	1.690	1.713	1.799	2.376	1.00000	1.751
RR_LCI	1.586	1.603	1.666	1.869	0.00000	1.630
RR_UCI	1.802	1.830	1.942	3.019	0.00000	1.881
SEN	0.299	0.462	0.644	0.965	1.00000	0.578
SPE	0.900	0.798	0.646	0.125	0.00137	0.706
BACC	0.599	0.630	0.645	0.545	0.50068	0.642
NetBenefit	0.068	0.114	0.177	0.286	0.31537	0.150

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

Table 21: O/E Ratio

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

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

Table 22: O/E Mean

mean	50%	2.5%	97.5%
1	1	0.995	1.01

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

Table 23: 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	0.689

```
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%
0.631	0.55

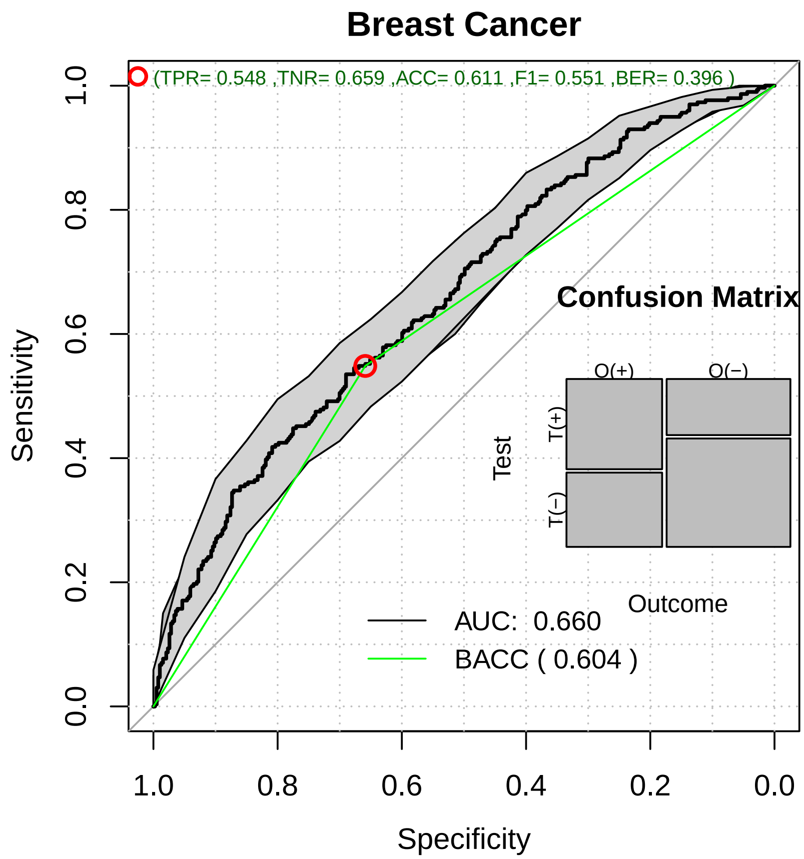
```
pander::pander(rrAnalysisTrain$surdif,caption="Logrank test")
```

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

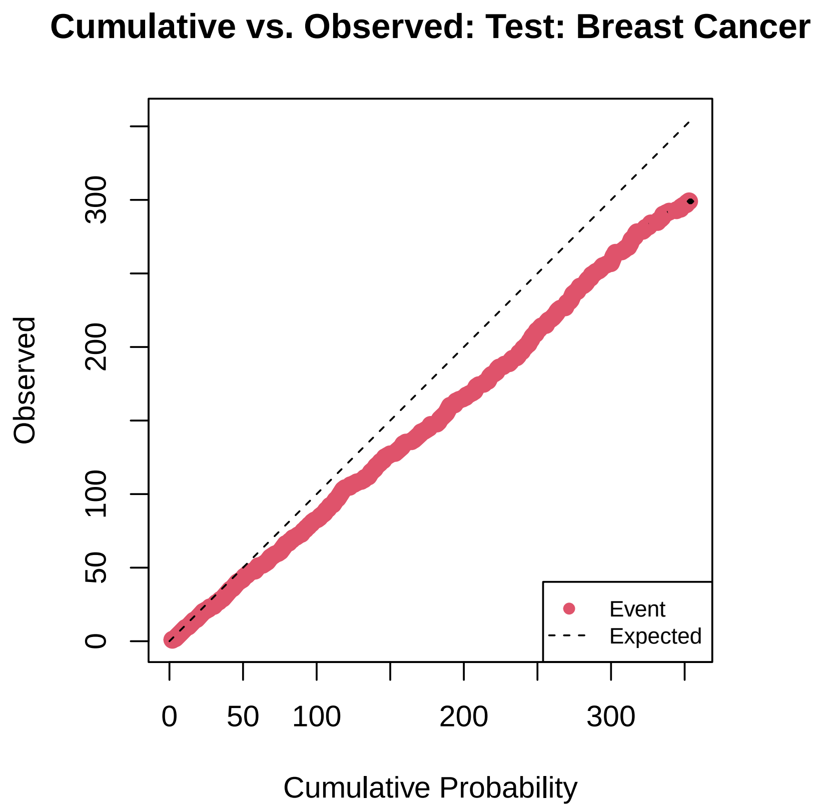
	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	1985	816	1144	93.9	385.7
class=1	396	248	177	28.0	31.8
class=2	601	454	197	336.3	391.3

1.5 Performance on the external data set

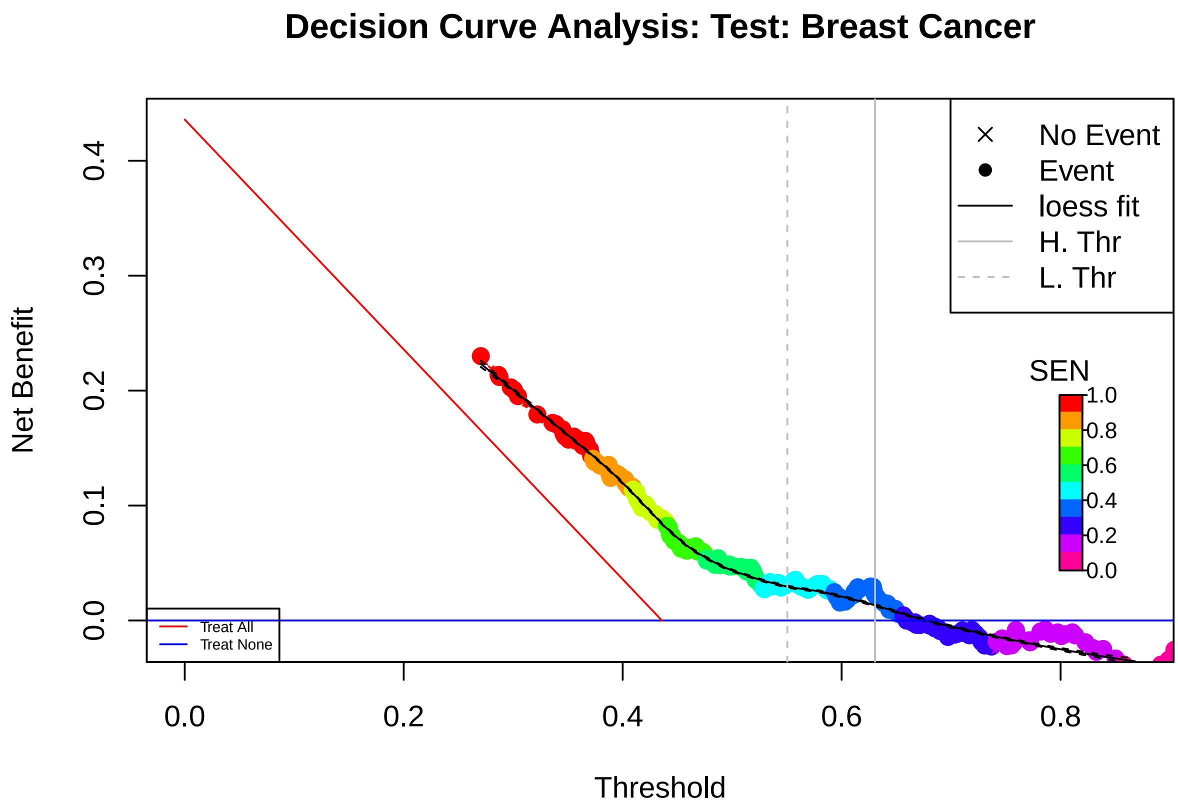
```
index <- predict(ml,dataBrestCancerTest)
pp <- predictionStats_binary(cbind(dataBrestCancerTest$status,index),plotname="Breast Cancer")
```



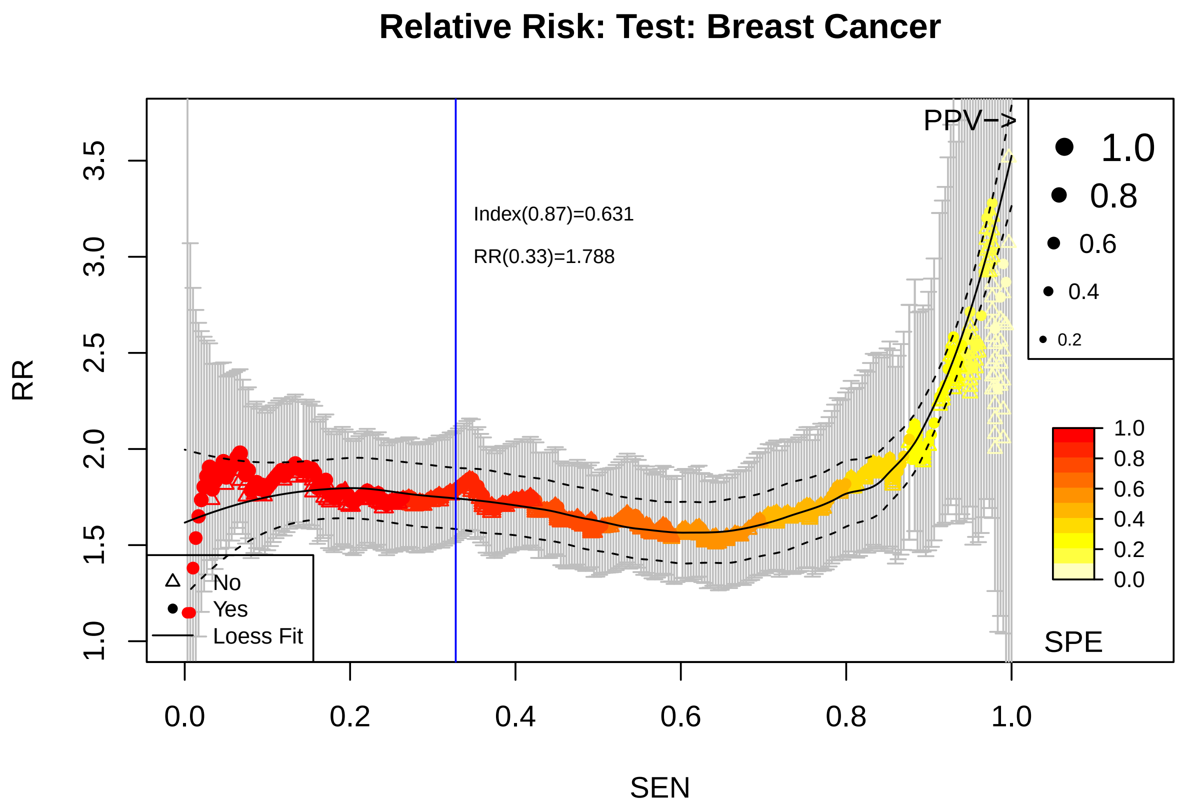

```
par(op)


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)
```



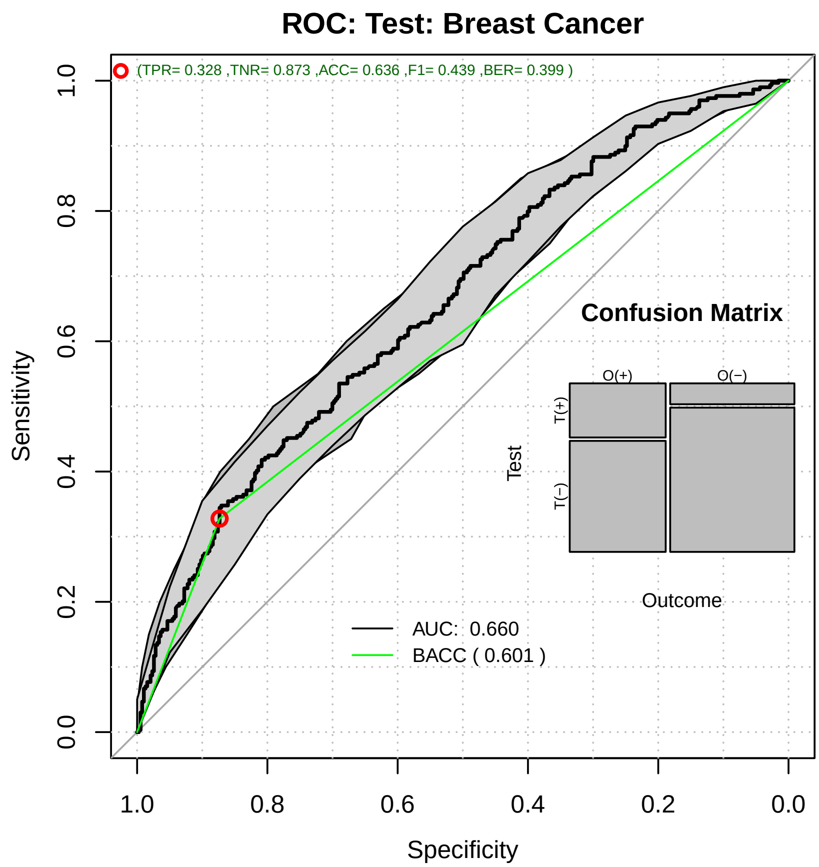
Cumulative vs. Observed: Test: Breast Cancer
Observed
0
50
100
200
300
Event
Expected
0
50
100
200
300
Cumulative Probability

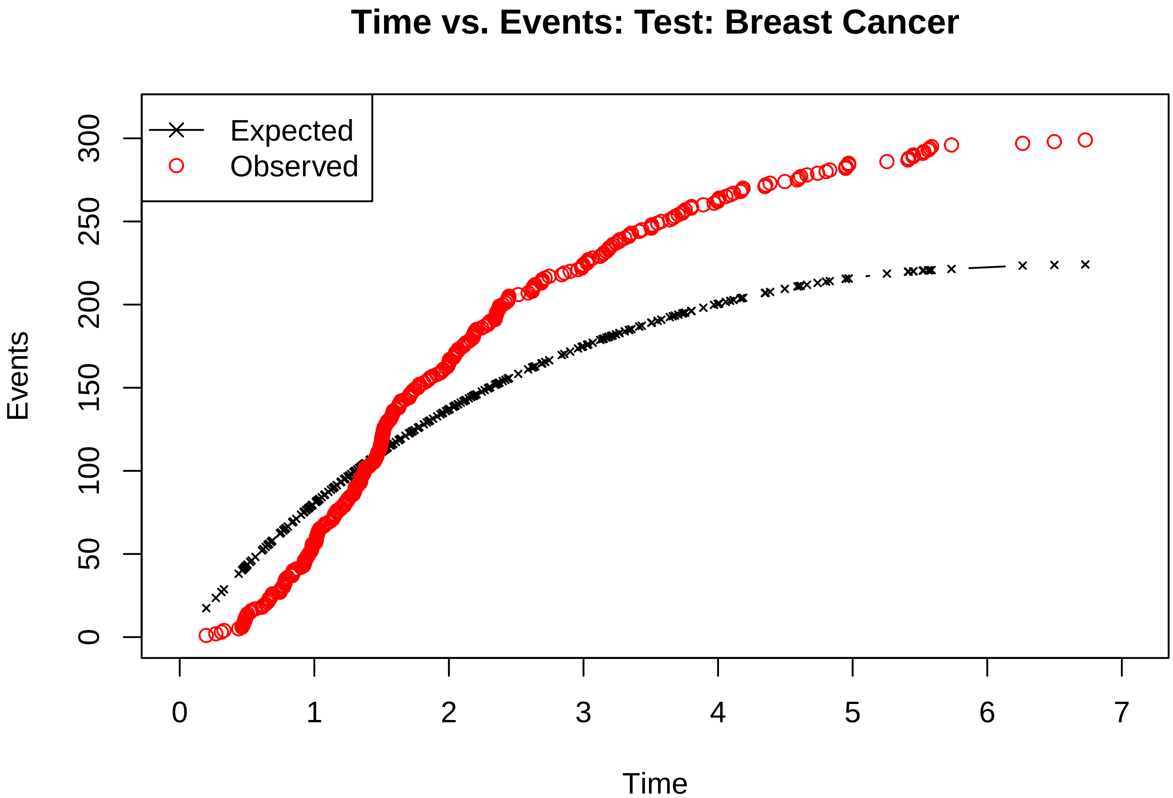


Decision Curve Analysis: Test: Breast Cancer
Net Benefit
Threshold
0.0
0.1
0.2
0.3
0.4
0.0
0.2
0.4
0.6
0.8
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None

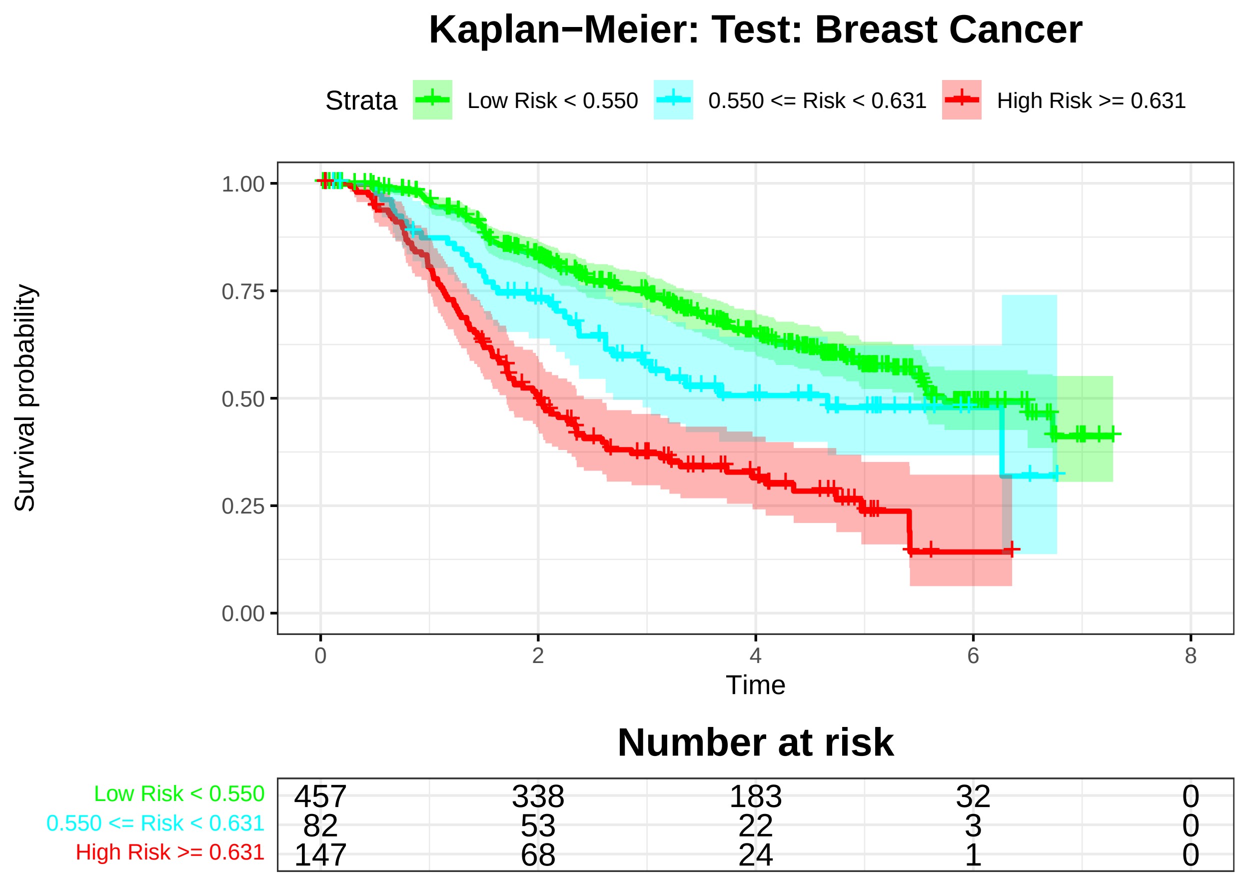


Relative Risk: Test: Breast Cancer
RR
SEN
Index(0.87)=0.631
RR(0.33)=1.788
PPV−>
1.0
0.8
0.6
0.4
0.2
No
Yes
Loess Fit
SPE
0.0
0.2
0.4
0.6
0.8
1.0
1.0
1.5
2.0
2.5
3.0
3.5


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
Time
0
50
100
150
200
250
300
0
1
2
3
4
5
6
7




```
par(op)
```

1.5.1 External Data Report

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

Table 30: Threshold values

	@:0.631	@:0.55	@MAX_BACC	@MAX_RR	@SPE100	p(0.5)
Thr	0.6303	0.5507	0.5825	0.336	2.70e-01	0.500
RR	1.7994	1.6427	1.7581	3.279	2.64e+01	1.603
RR_LCI	1.5366	1.3951	1.4980	1.641	5.65e-02	1.352
RR_UCI	2.1071	1.9343	2.0632	6.552	1.23e+04	1.902
SEN	0.3311	0.4515	0.4181	0.977	1.00e+00	0.552
SPE	0.8734	0.7571	0.8088	0.111	1.55e-02	0.656
BACC	0.6022	0.6043	0.6134	0.544	5.08e-01	0.604
NetBenefit	0.0226	0.0289	0.0318	0.172	2.30e-01	0.047

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

Table 31: O/E Ratio

O/E	Low	Upper	p.value
1.33	1.19	1.49	1.73e-06

```
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	0.694

```
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%
0.631	0.55

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

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

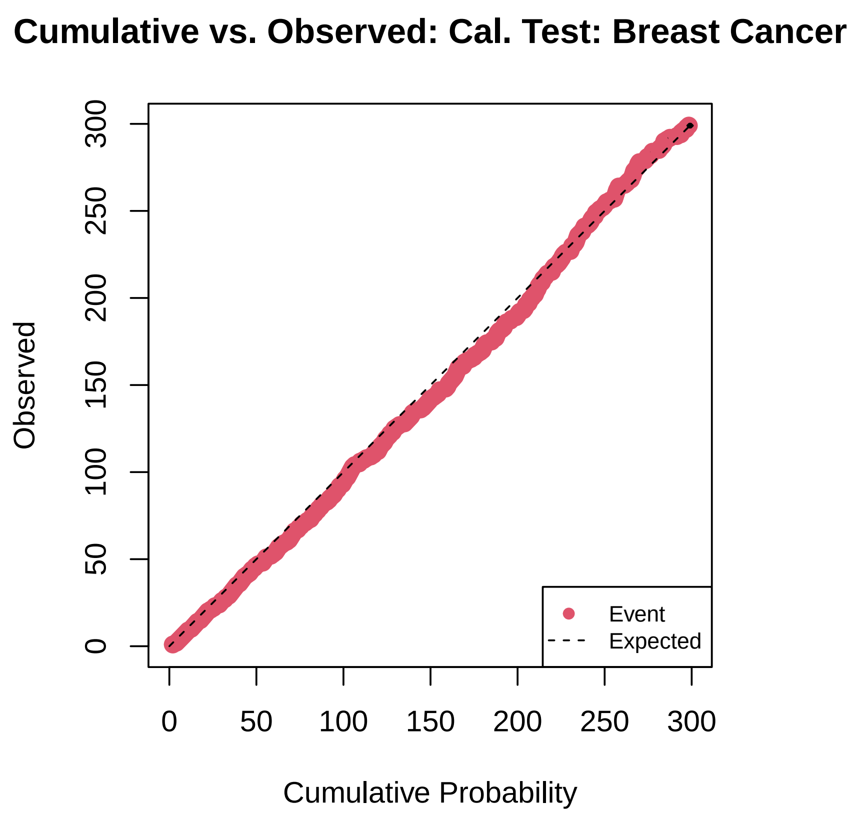
	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	457	164	221.4	14.888	58.181
class=1	82	37	33.2	0.438	0.494
class=2	147	98	44.4	64.710	77.254

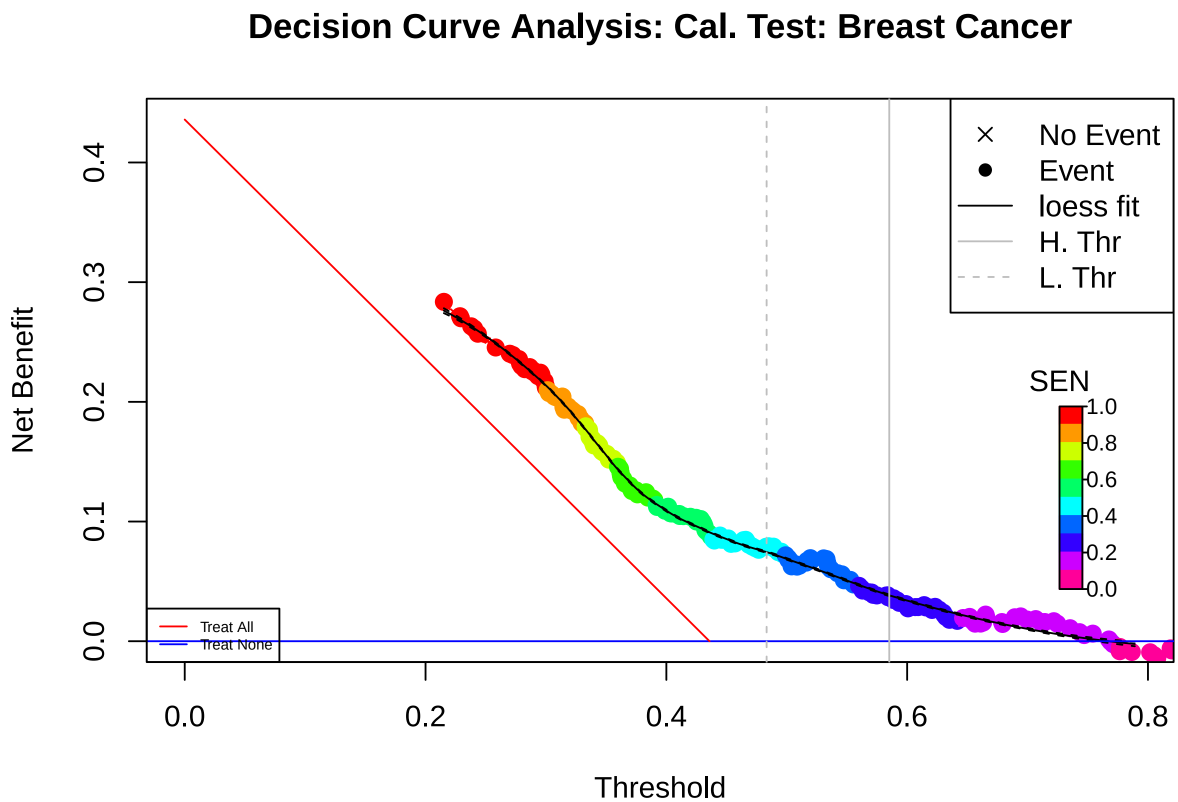
1.5.2 Calibrating the index on the test data

```
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
0.535	0.925	4.87

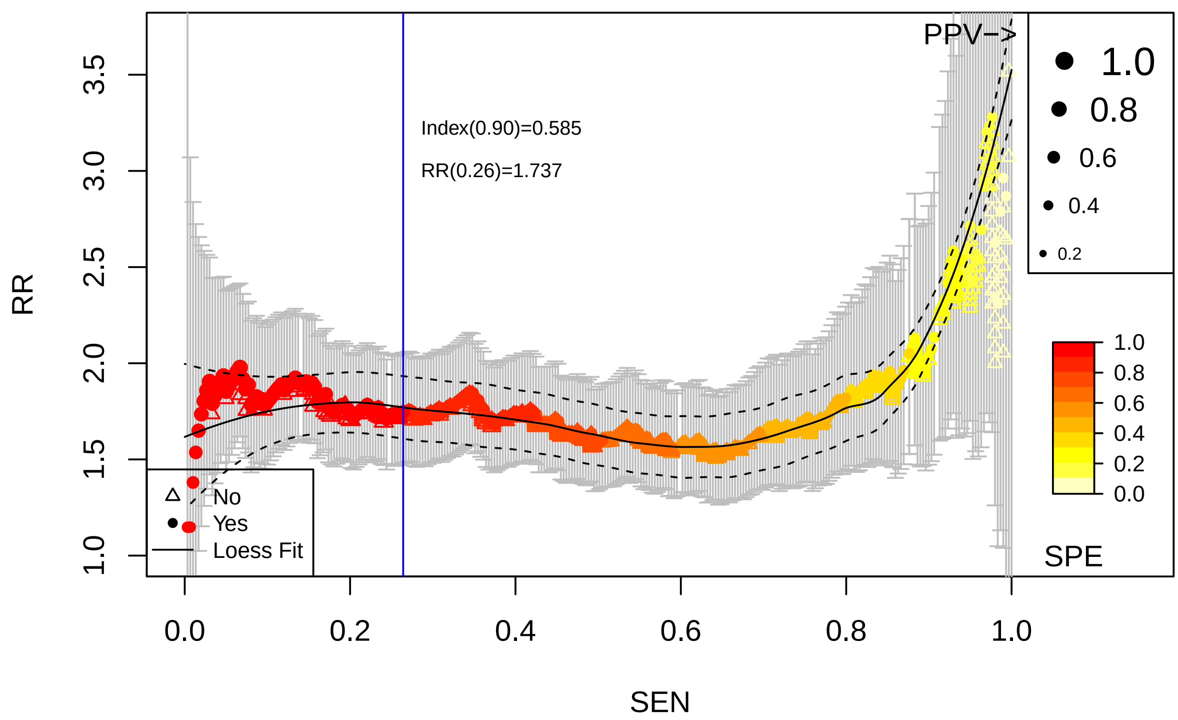
```
rdata <- cbind(dataBrestCancerTest$status,calprob$prob)

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)
```

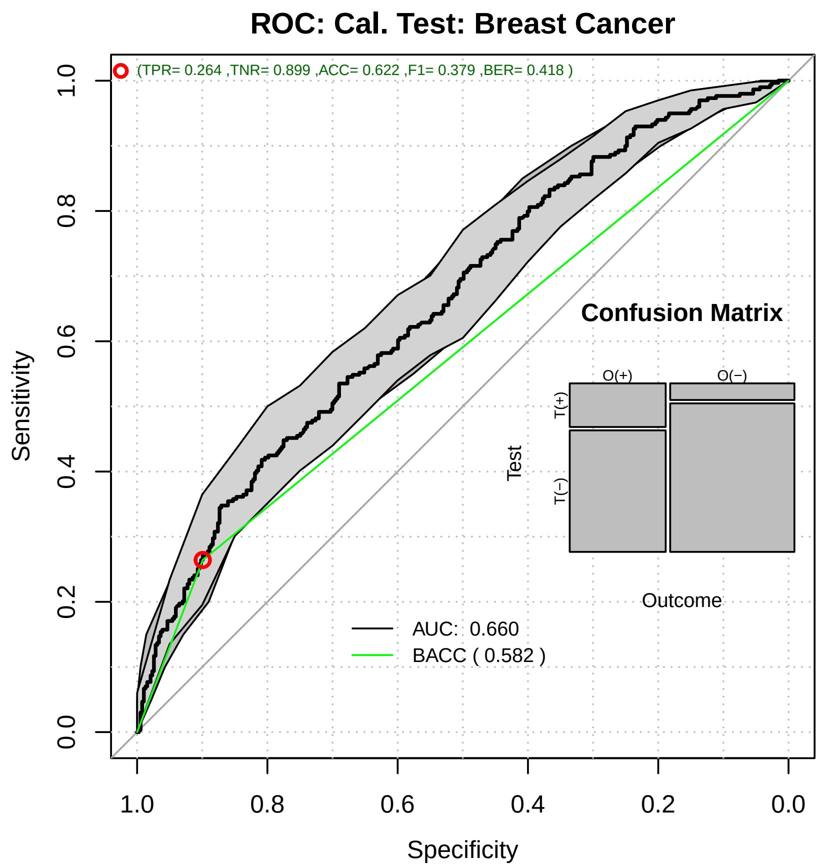

Cumulative vs. Observed: Cal. Test: Breast Cancer
Observed
0
50
100
150
200
250
300
Event
Expected
0
50
100
150
200
250
300
Cumulative Probability

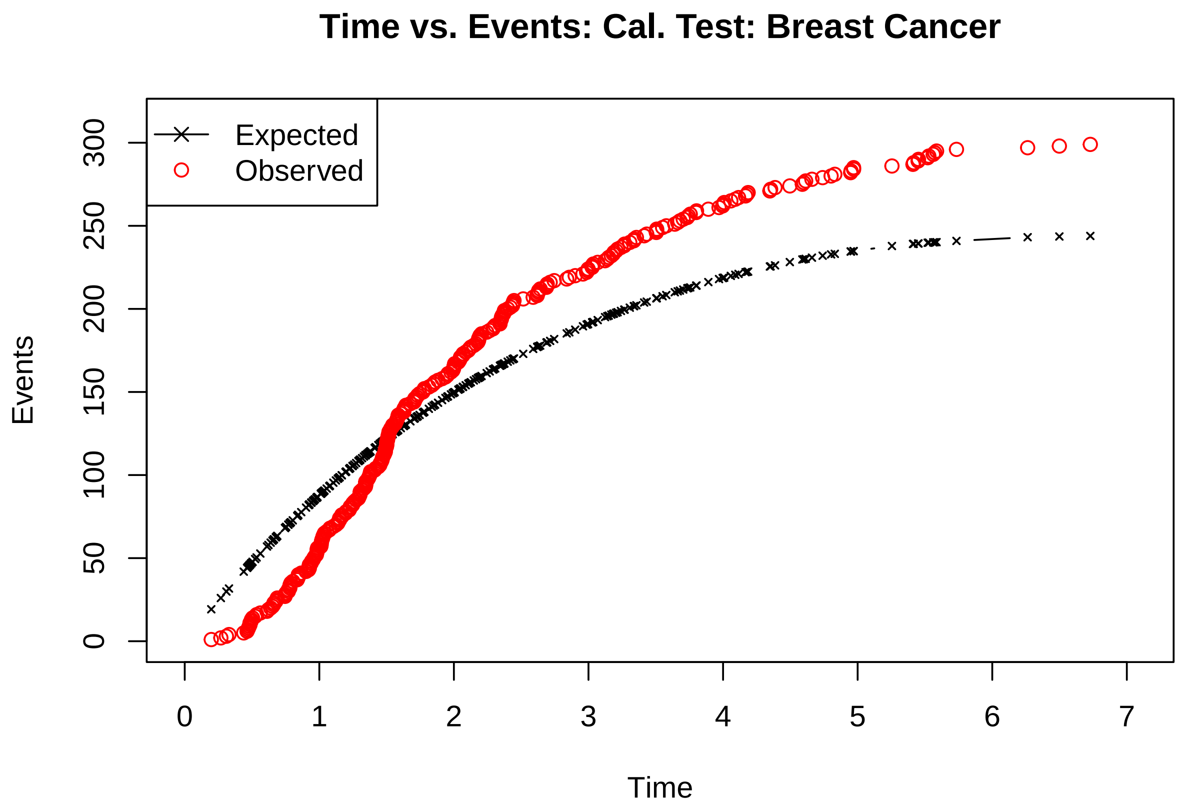


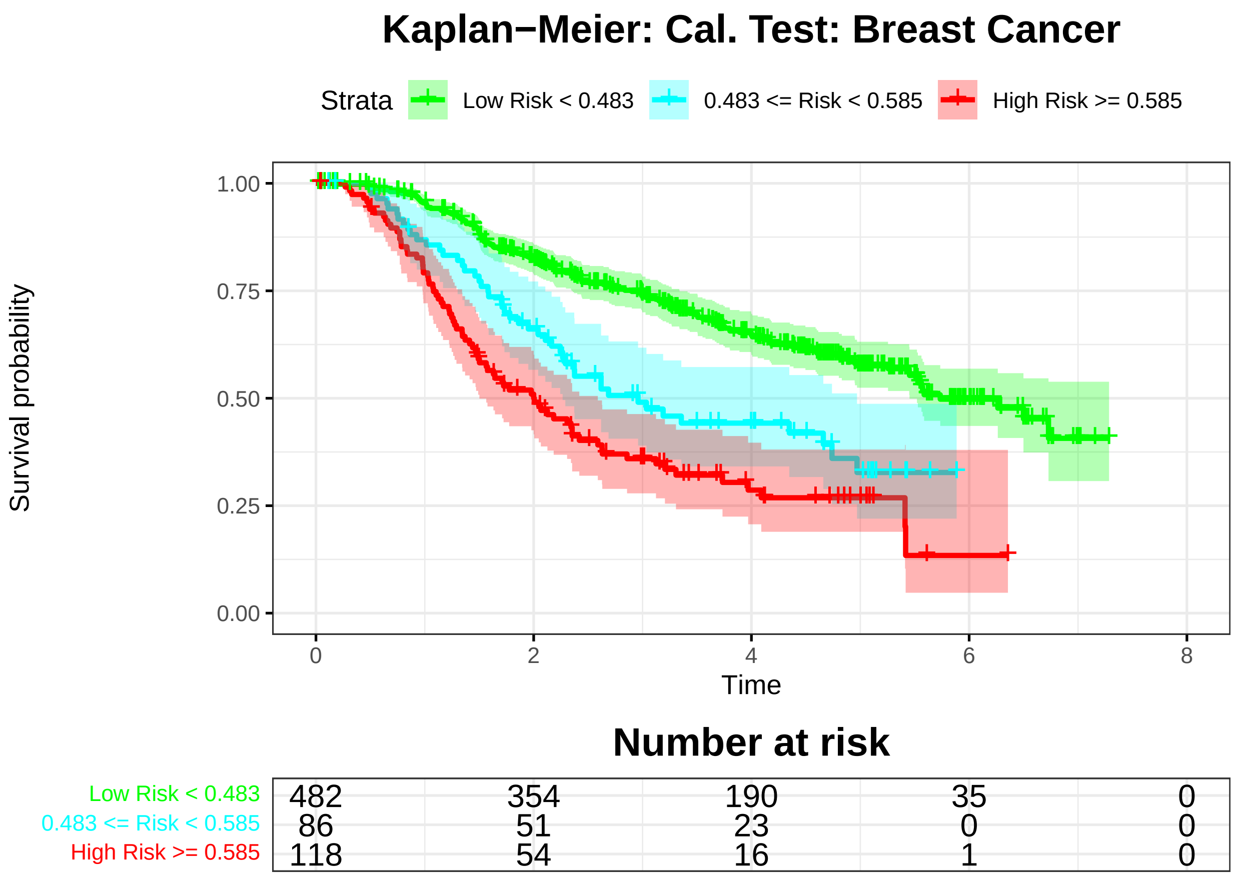
Decision Curve Analysis: Cal. Test: Breast Cancer
Net Benefit
Threshold
0.0
0.1
0.2
0.3
0.4
0.0
0.2
0.4
0.6
0.8
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None

Relative Risk: Cal. Test: Breast Cancer




ROC: Cal. Test: Breast Cancer
(TPR= 0.264 ,TNR= 0.899 ,ACC= 0.622 ,F1= 0.379 ,BER= 0.418)
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 (0.582)


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	0.5843	0.483	0.489	0.270	2.15e-01	0.4991
RR	1.7405	1.732	1.758	3.279	2.64e+01	1.7385
RR_LCI	1.4790	1.475	1.498	1.641	5.65e-02	1.4816
RR_UCI	2.0483	2.035	2.063	6.552	1.23e+04	2.0399
SEN	0.2676	0.425	0.418	0.977	1.00e+00	0.3980
SPE	0.8992	0.798	0.809	0.111	1.55e-02	0.8191
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="O/E Ratio")
```

Table 40: O/E Ratio

O/E	Low	Upper	p.value
1.23	1.09	1.37	0.000607

```r
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**: *176737*
- **Uncertain**: *203702*
- **cstatCI**:

mean.C Index	median	lower	upper
0.664	0.664	0.632	0.693

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

Table 42: ROC AUC

est	lower	upper
0.66	0.619	0.7

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

Table 43: Sensitivity

est	lower	upper
0.264	0.215	0.318

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

Table 44: Specificity

est	lower	upper
0.899	0.865	0.927

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

Table 45: Probability Thresholds

90%	80%
0.585	0.483

```
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)
```

—..

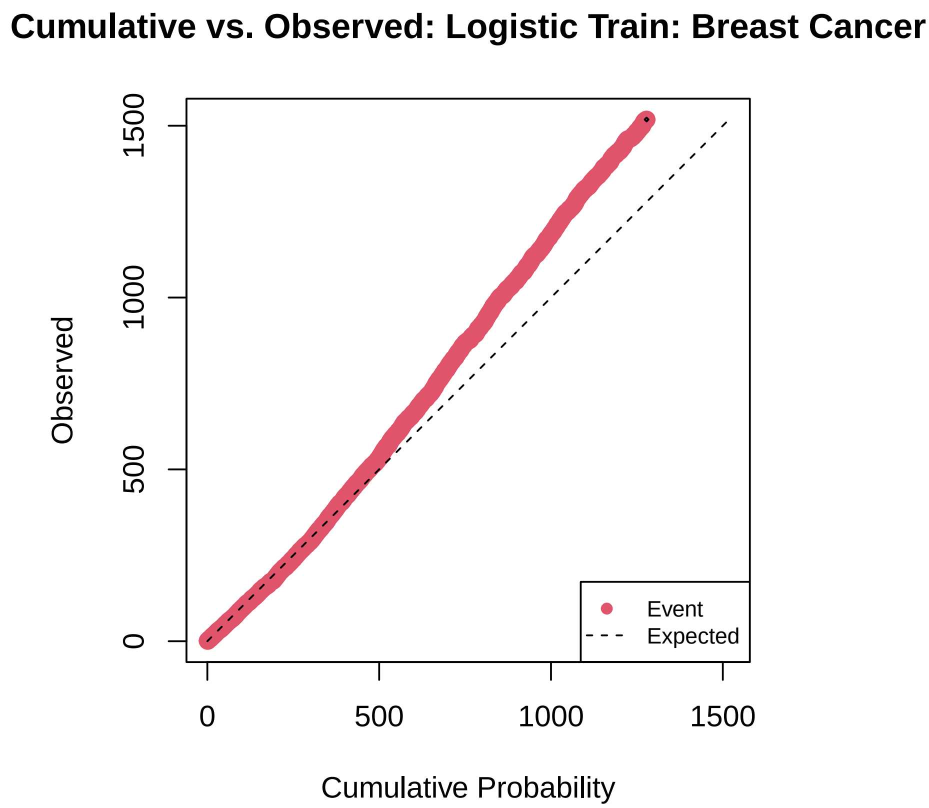
```
sm <- summary(mlog)
pander::pander(sm$coefficients)
```

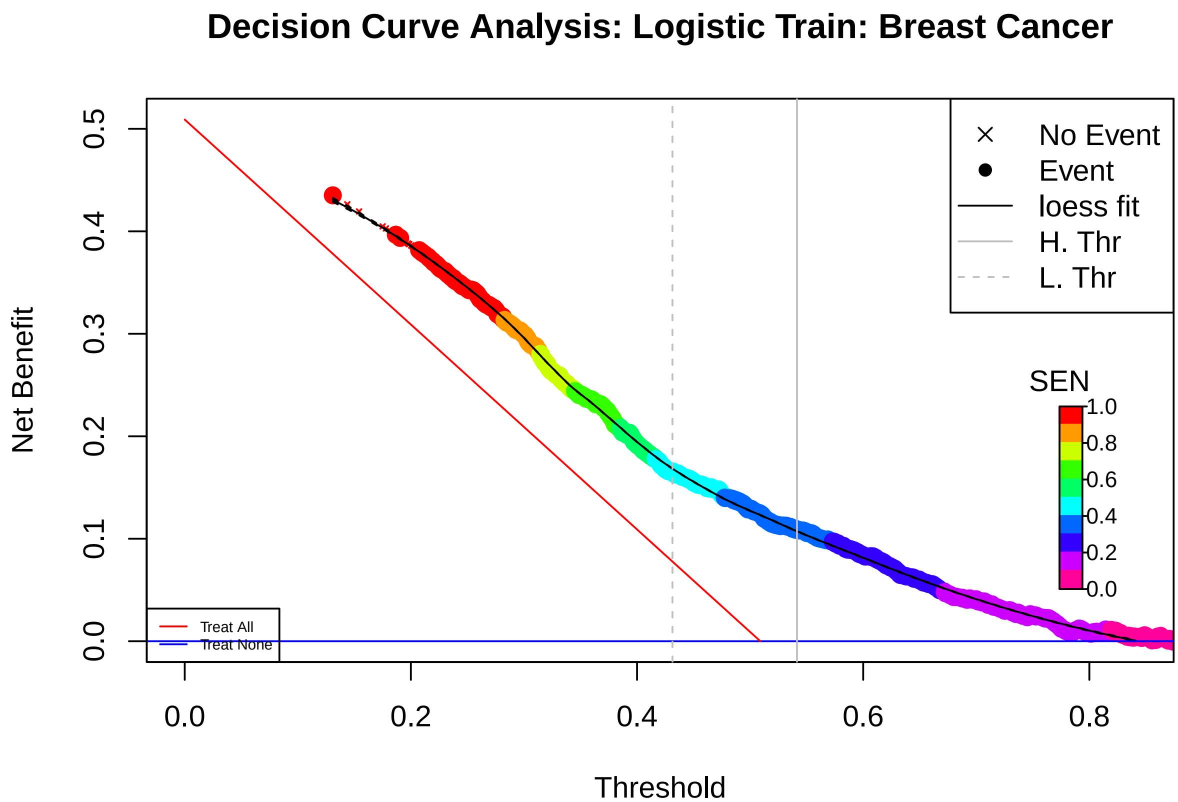
	Estimate	lower	OR	upper	u.Accuracy	r.Accuracy	full.Accuracy	u.AUC	r.AUC	full.AUC	IDI	NRI	z.IDI	z.NRI	Delta.AUC	Frequency
size_nodes	1.05e-03	1.001	1.001	1.001	0.669	0.571	0.668	0.627	0.500	0.628	0.11230	0.63654	17.86	18.870	0.128490	1
nodes	4.33e-02	1.040	1.044	1.048	0.676	0.634	0.690	0.639	0.621	0.662	0.07110	0.57106	14.13	16.179	0.040494	1
grade_nodes	1.50e-02	1.014	1.015	1.016	0.682	0.637	0.686	0.649	0.624	0.655	0.06580	0.54866	13.66	15.650	0.031087	1
age_nodes	1.06e-03	1.001	1.001	1.001	0.678	0.653	0.686	0.642	0.621	0.657	0.03346	0.21319	9.39	5.710	0.035896	1
size_grade	1.75e-03	1.001	1.002	1.002	0.632	0.682	0.686	0.626	0.646	0.655	0.01780	0.29411	6.74	7.728	0.008648	1
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	0.29152	6.41	7.652	0.007600	1
grade	2.27e-01	1.168	1.254	1.347	0.571	0.683	0.690	0.500	0.653	0.662	0.01340	0.19036	6.20	4.983	0.008461	1
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	0.08057	4.76	2.337	0.012065	1

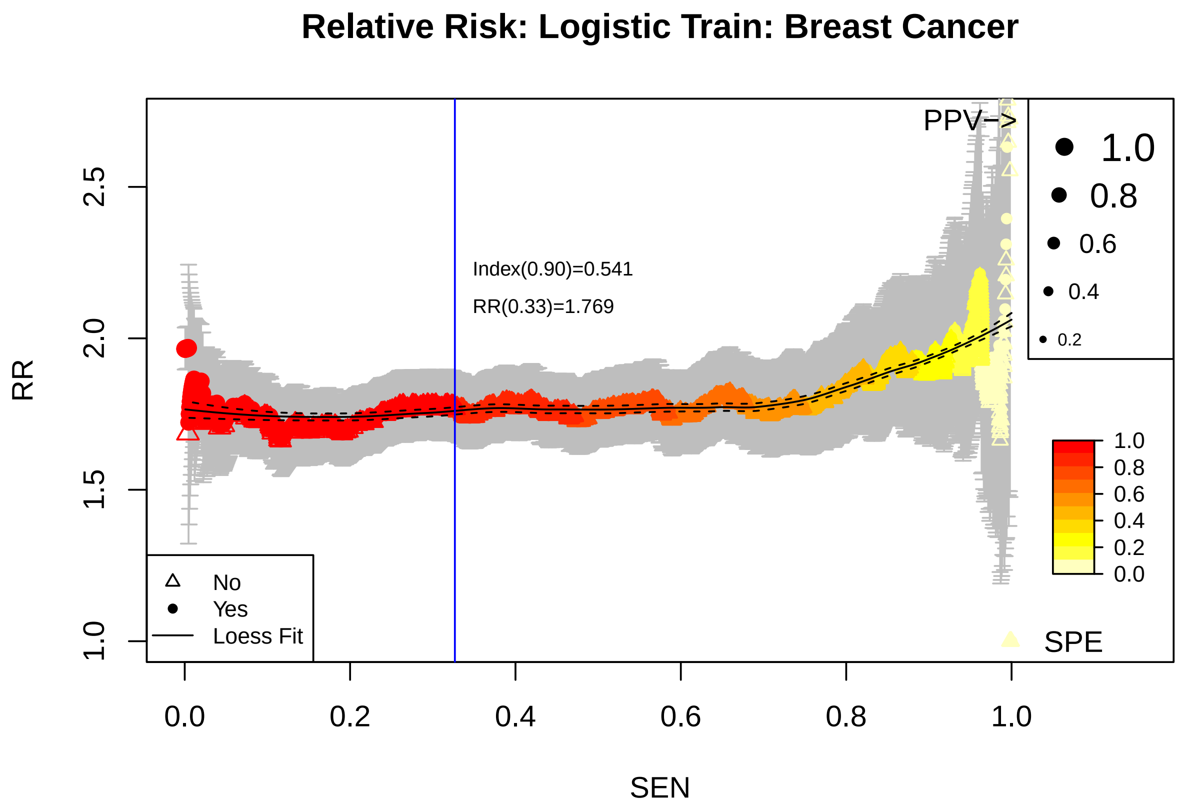
	Estimate	lower	OR	upper	u.Accuracy	r.Accuracy	full.Accuracy	u.AUC	r.AUC	full.AUC	IDI	NRI	z.IDI	z.NRI	Delta.AUC	Frequency
age__pgr	-5.42e-06	1.000	1.000	1.000	0.571	0.686	0.686	0.500	0.656	0.657	0.00512	0.00745	4.11	0.194	0.000417	1
age__grade	1.65e-03	0.997	0.998	0.999	0.574	0.690	0.690	0.507	0.661	0.662	0.00450	0.11372	3.60	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	0.004441	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	0.21050	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	0.00241	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	0.00186	0.10227	2.43	2.662	-0.001378	1

1.7 Logistic Model Performance

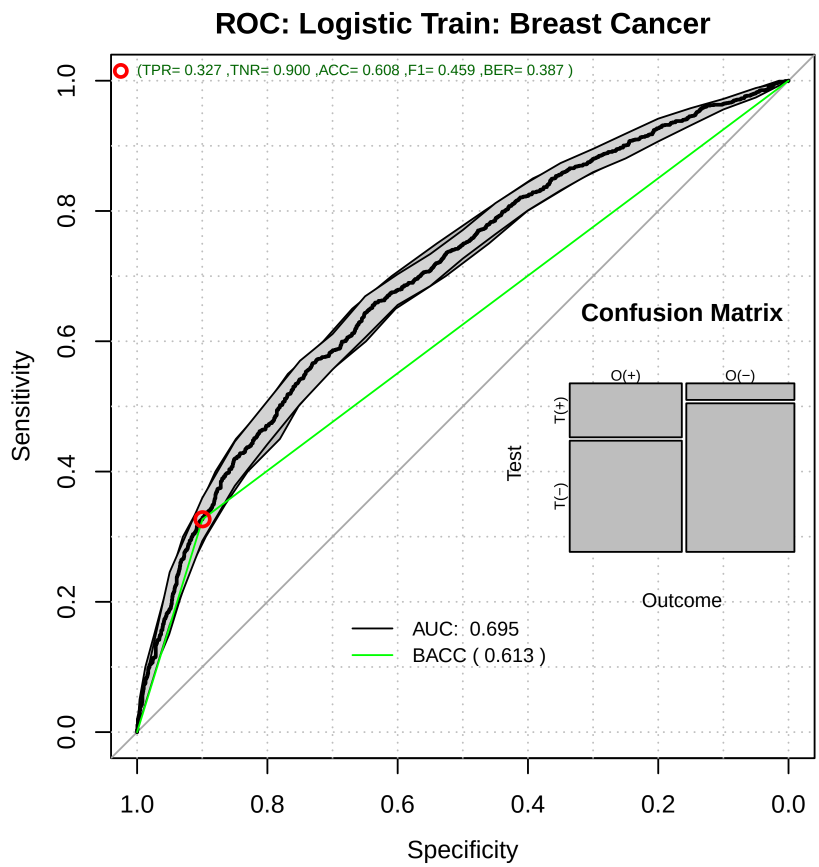
```
op <- par(no.readonly = TRUE)


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)
```

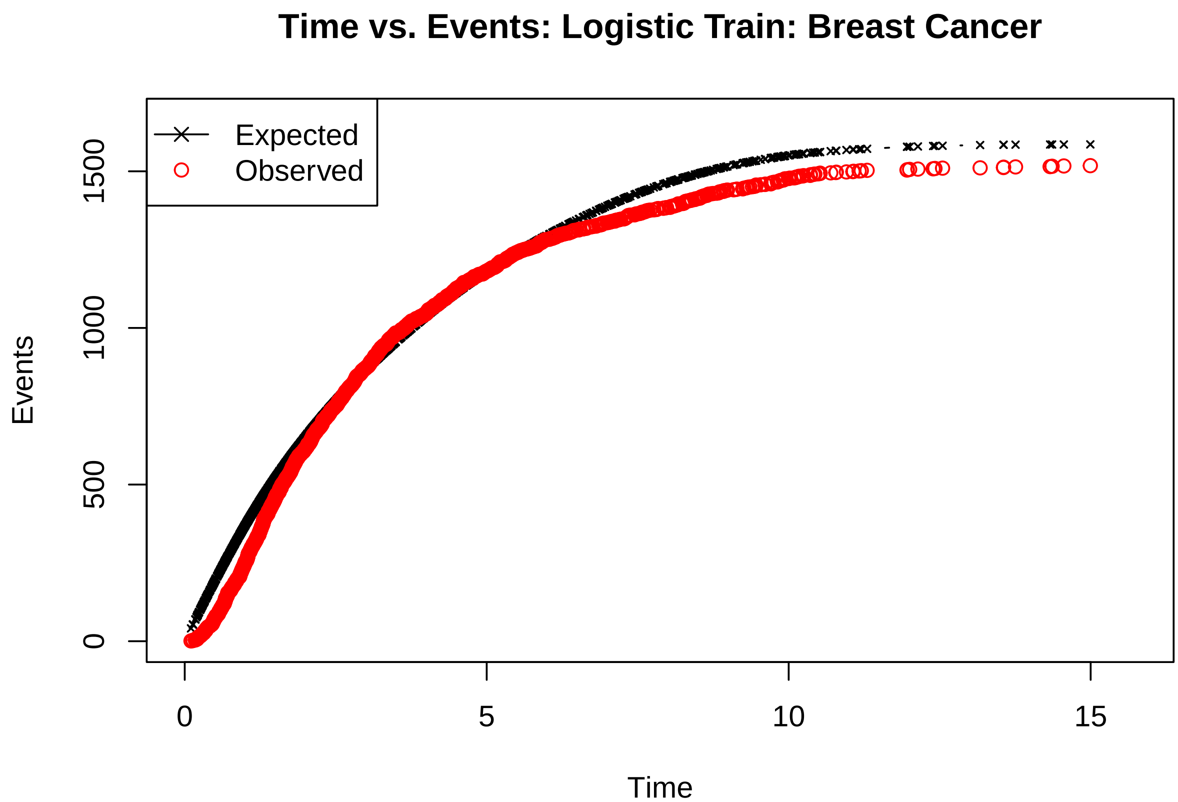

Cumulative vs. Observed: Logistic Train: Breast Cancer
Observed
Cumulative Probability
0
500
1000
1500
0
500
1000
1500
Event
Expected

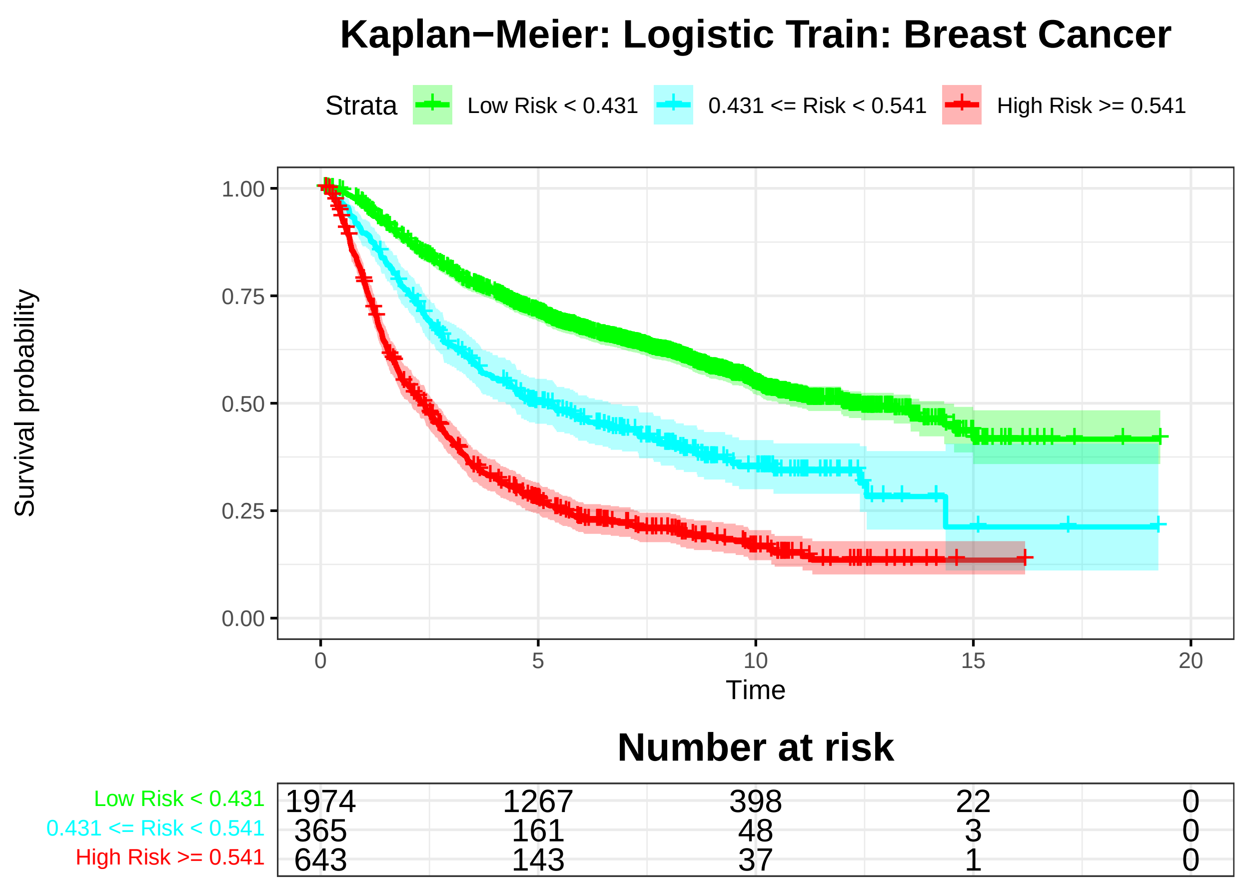

Decision Curve Analysis: Logistic Train: Breast Cancer
Net Benefit
Threshold
0.0
0.1
0.2
0.3
0.4
0.5
0.0
0.2
0.4
0.6
0.8
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None



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
RR
2.5
2.0
1.5
1.0
No
Yes
Loess Fit
SPE
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
Confusion Matrix
O(+)
O(−)
T(+)
T(−)
Test
Outcome
AUC: 0.695
BACC (0.613)
0.0
0.2
0.4
0.6
0.8
1.0


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




```
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
0.957	0.91	1.01	0.0901

```
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**: *4206594*
- **Uncertain**: *2703838*
- **cstatCI**:

mean.C Index	median	lower	upper
0.68	0.68	0.666	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")
```

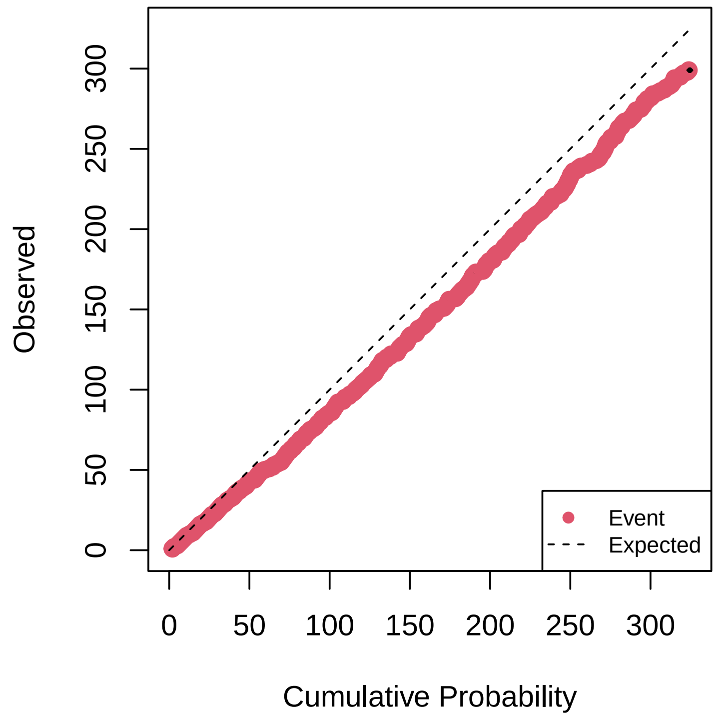
Table 55: Logrank test Chisq = 541.976716 on 2 degrees of freedom, p = 0.000000

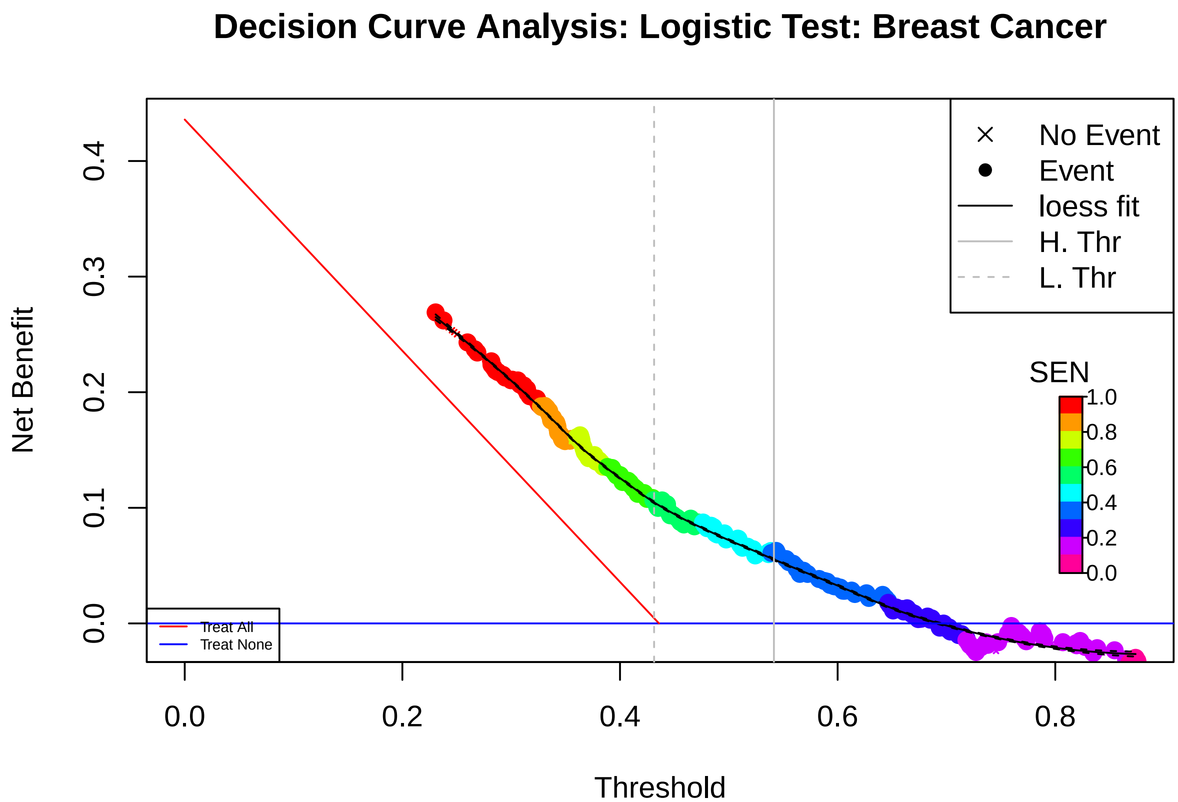
	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	1974	804	1144	100.9	415.3
class=1	365	218	170	13.4	15.1
class=2	643	496	204	418.2	490.7

1.7.2 Results on the validation set using Logistic model

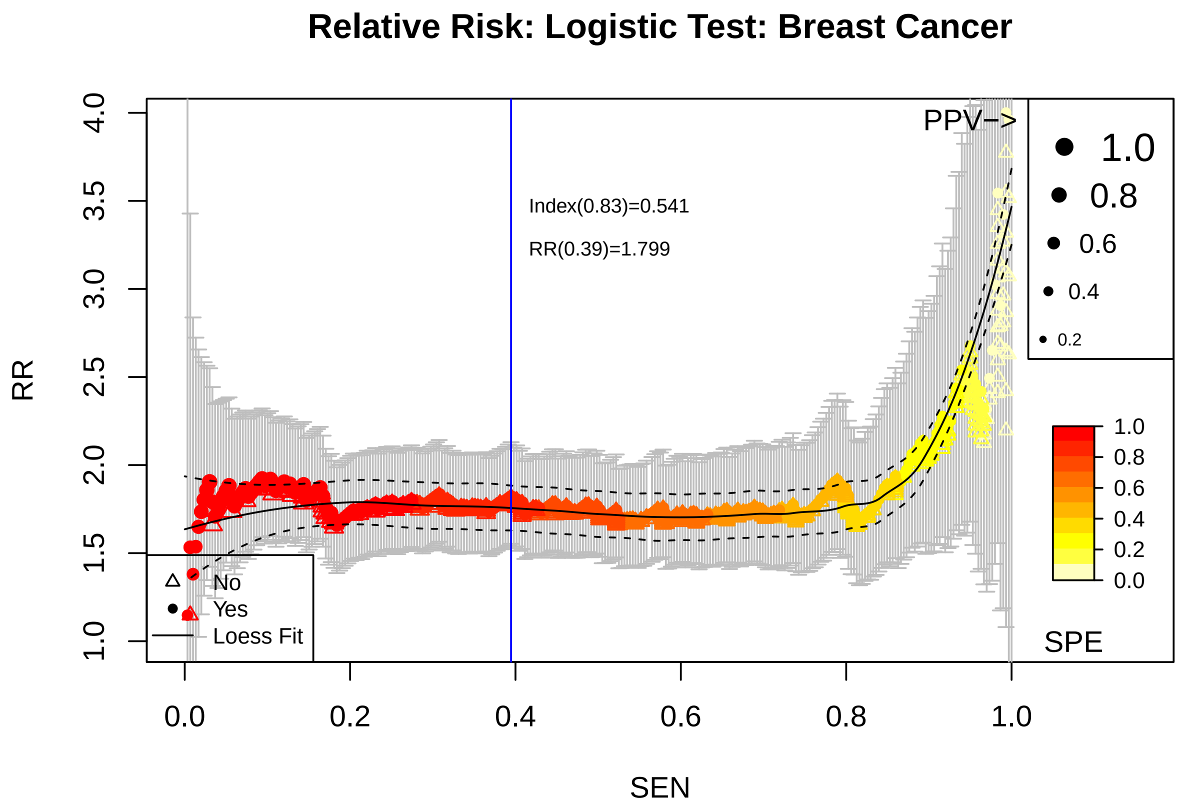
```
pre <- predict(mlog,dataBrestCancerTest)
rdata <- cbind(dataBrestCancerTest$status,pre)

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

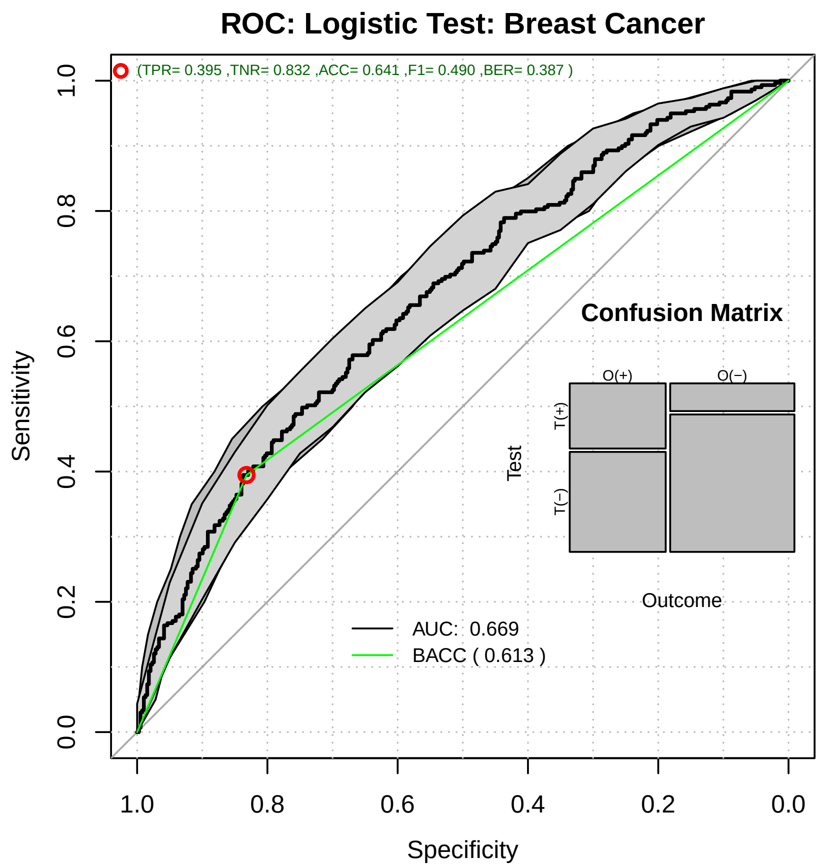


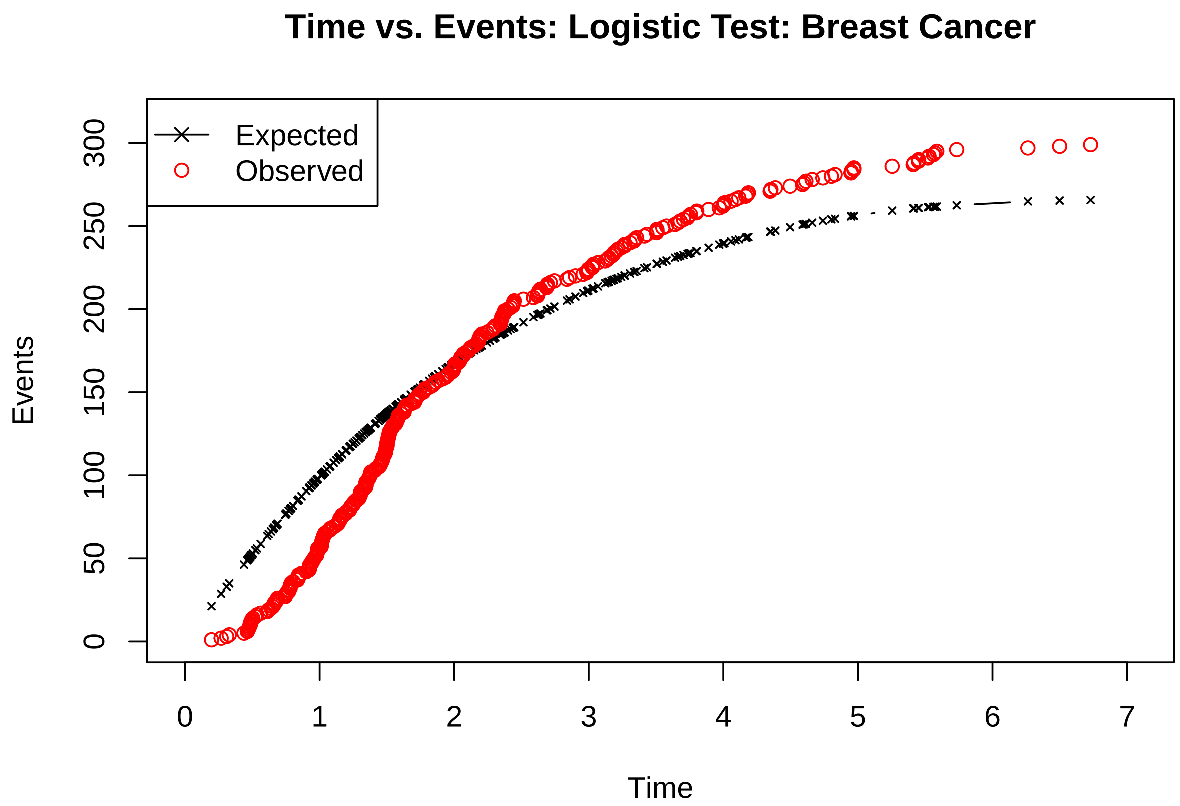


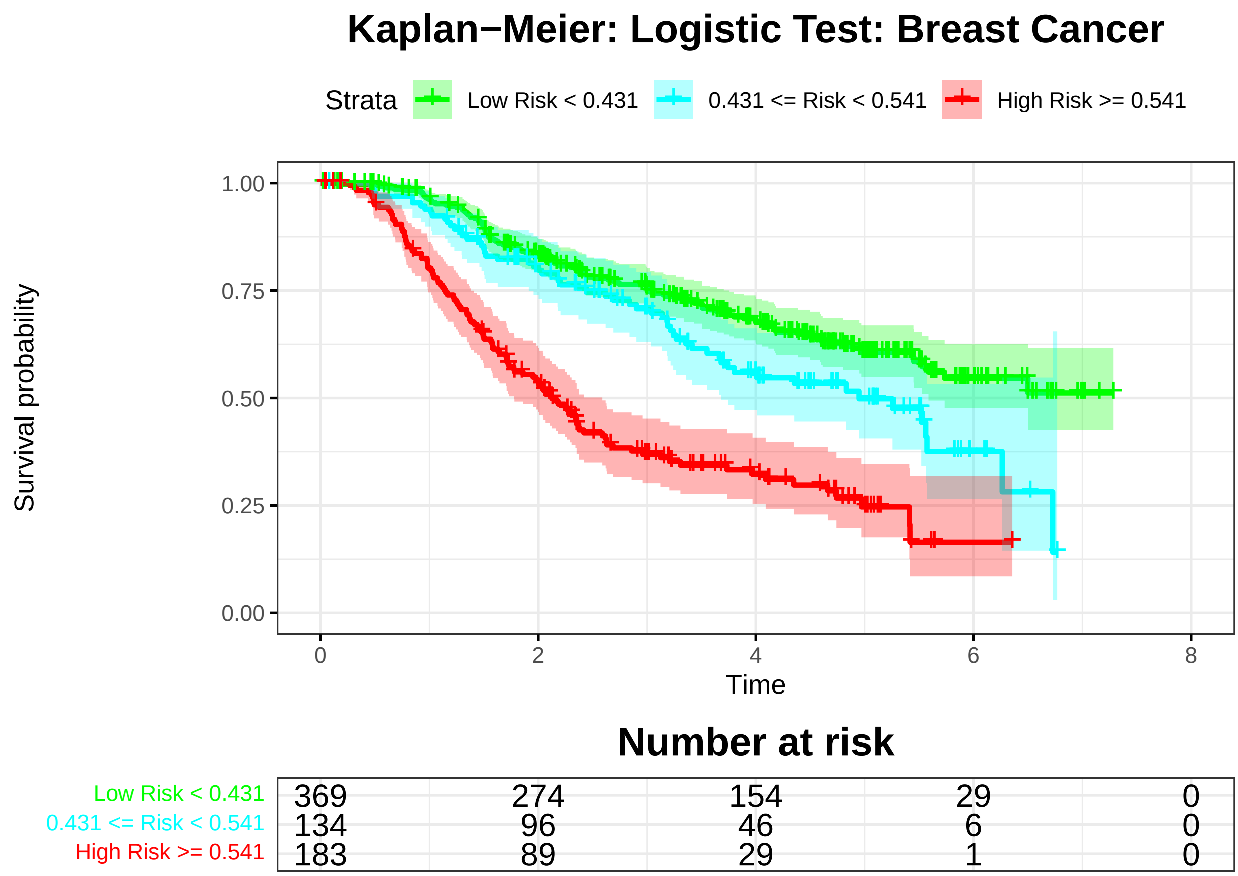
Decision Curve Analysis: Logistic Test: Breast Cancer
Net Benefit
0.0
0.1
0.2
0.3
0.4
Threshold
0.0
0.2
0.4
0.6
0.8
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None



Relative Risk: Logistic Test: Breast Cancer
RR
SEN
0.0
0.2
0.4
0.6
0.8
1.0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Index(0.83)=0.541
RR(0.39)=1.799
PPV−>
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


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


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




```
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
1.13	1	1.26	0.0428

```
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	0.669	0.638	0.699

```
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

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

Table 62: Probability Thresholds

90%	80%
0.541	0.431

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

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

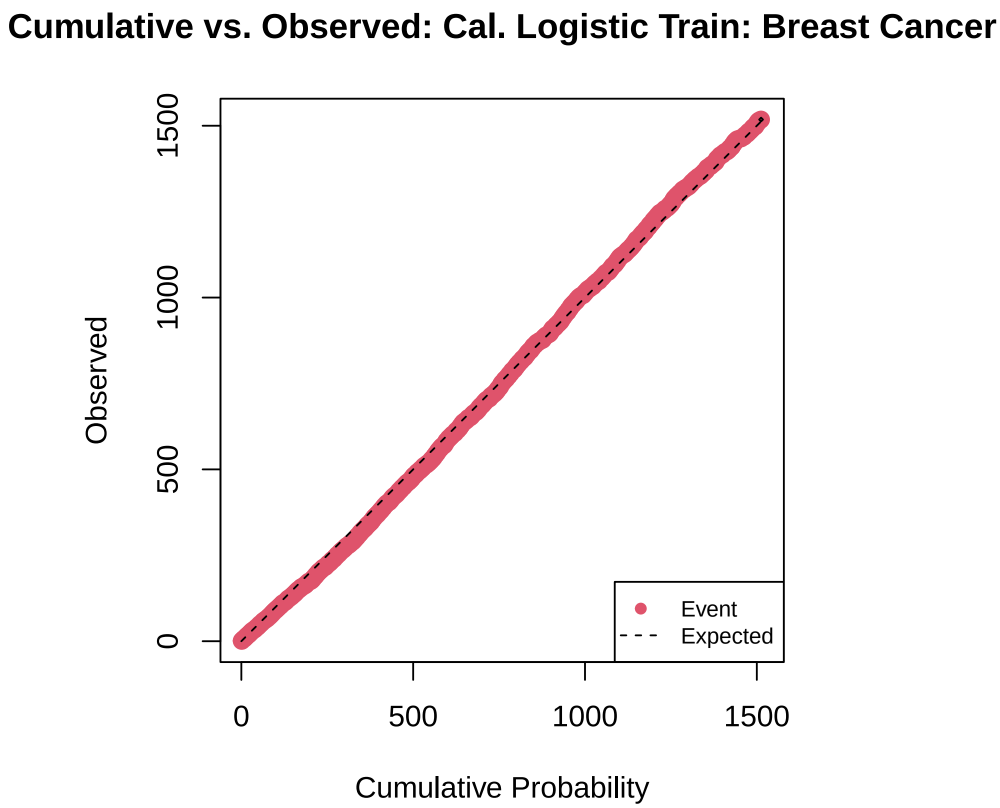
	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	369	121	181.7	20.2997	52.3868
class=1	134	60	61.7	0.0479	0.0604
class=2	183	118	55.5	70.2342	88.0195

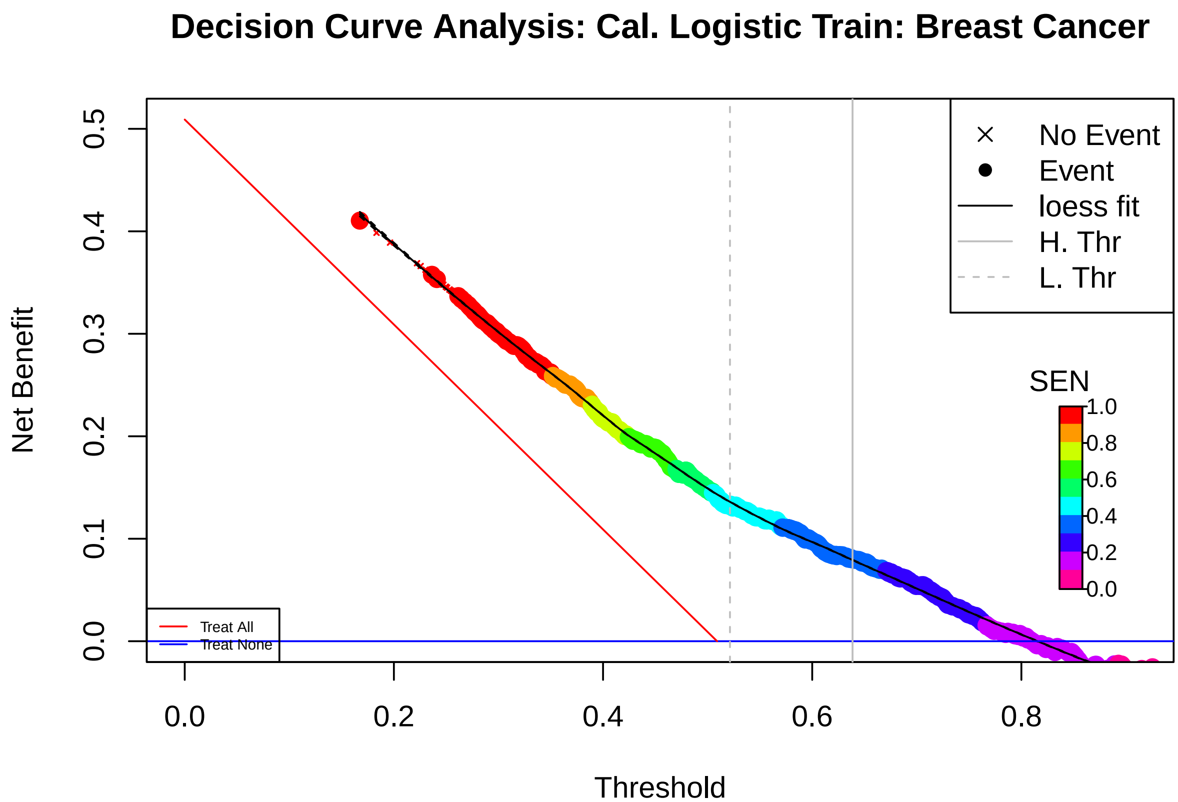
1.8 Logistic Model Poisson Calibration

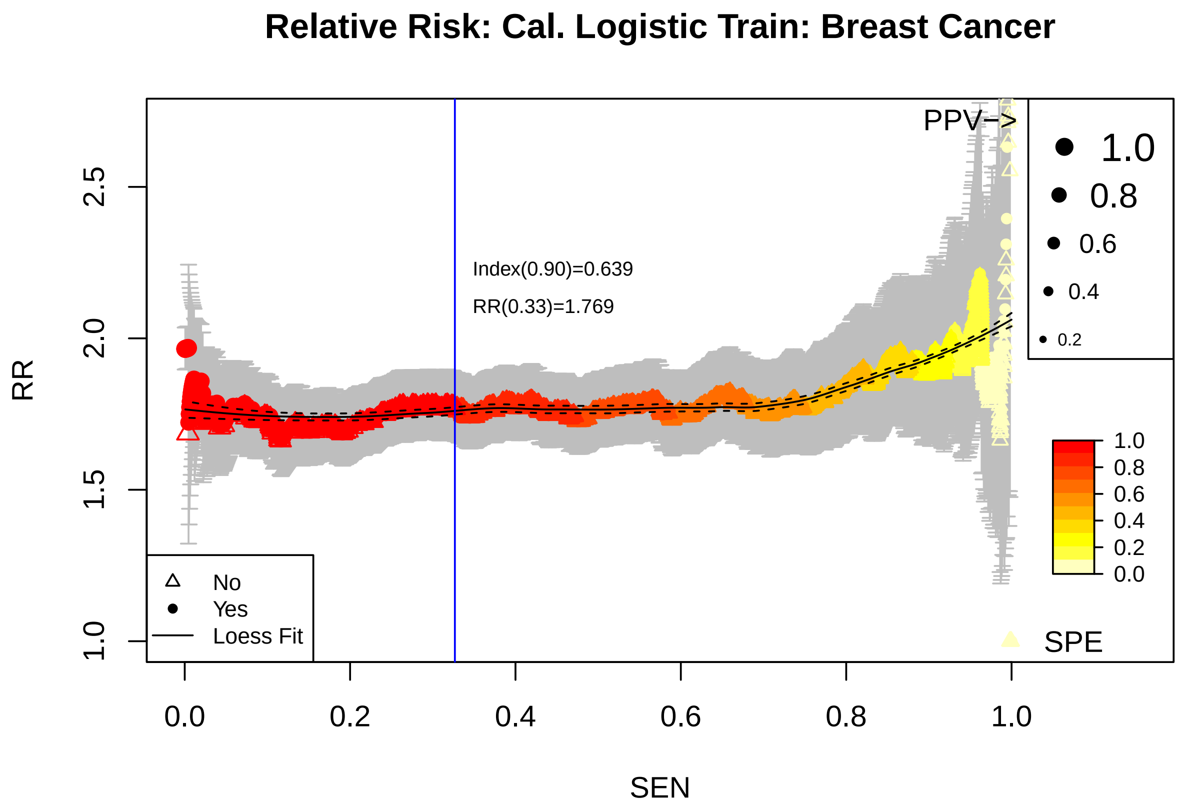
```r
riskdata <- cbind(dataBrestCancerTrain$status,predict(mlog,dataBrestCancerTrain,type="prob"),dataBrestCa
calprob <- CalibrationProbPoissonRisk(riskdata)

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

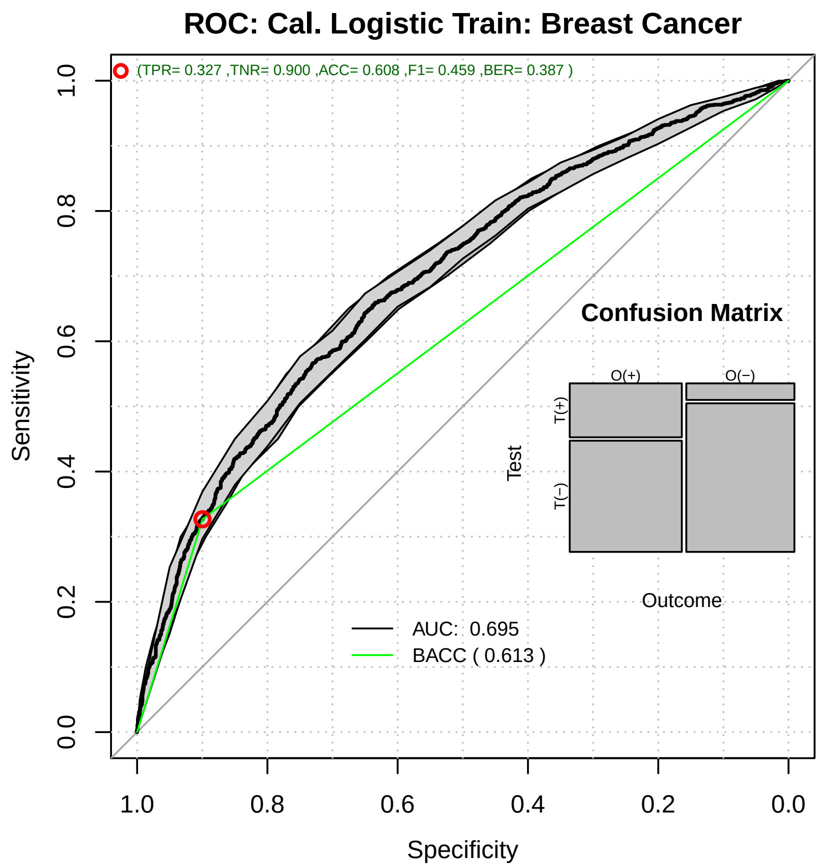
h0	Gain	DeltaTime
0.676	1.31	7.14

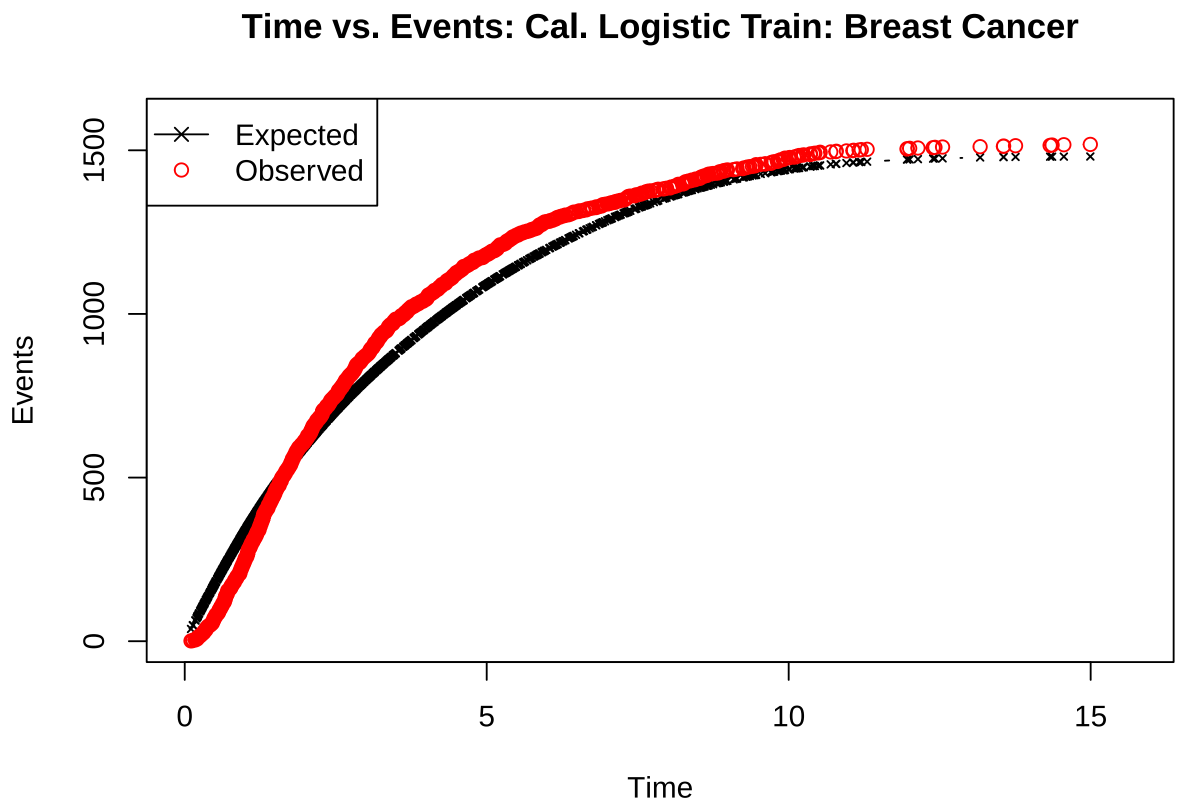
```r
timeinterval <- calprob$timeInterval;
gain <- calprob$hazardGain

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
0
500
1000
1500
Cumulative Probability
Event
Expected

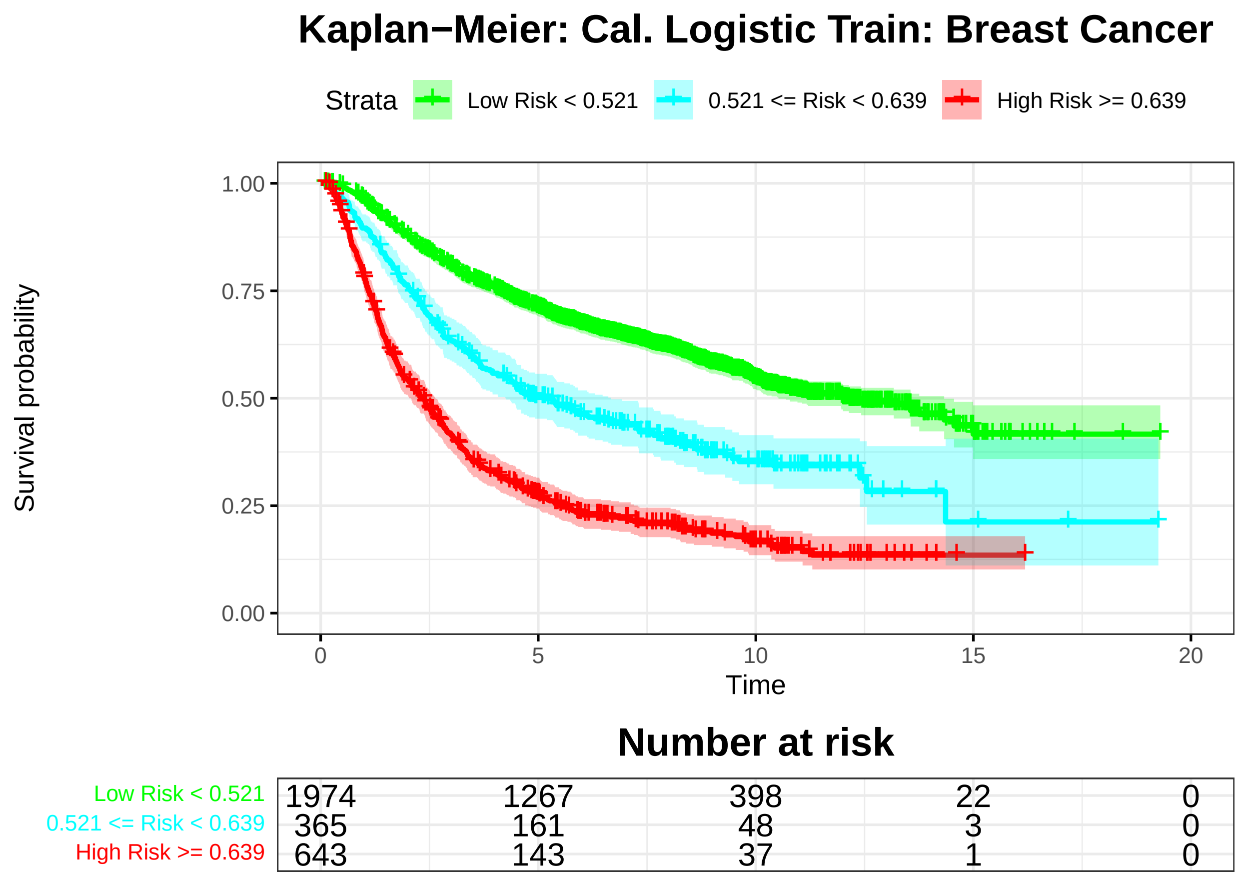

Decision Curve Analysis: Cal. Logistic Train: Breast Cancer
Net Benefit
0.0
0.1
0.2
0.3
0.4
0.5
0.0
0.2
0.4
0.6
0.8
Threshold
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None


Relative Risk: Cal. Logistic Train: Breast Cancer
PPV->
1.0
0.8
0.6
0.4
0.2
Index(0.90)=0.639
RR(0.33)=1.769
RR
2.5
2.0
1.5
1.0
1.0
0.8
0.6
0.4
0.2
0.0
No
Yes
Loess Fit
SPE
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
Time
0
5
10
15




```
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	0.6395	0.521	0.480	0.319	0.167426	0.500
RR	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
SEN	0.3267	0.470	0.566	0.962	1.000000	0.507
SPE	0.8996	0.799	0.731	0.125	0.000683	0.774
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$OERatio$estimate),caption="O/E Ratio")
```

Table 66: O/E Ratio

O/E	Low	Upper	p.value
1.02	0.974	1.08	0.336

```
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**: *4206588*
- **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

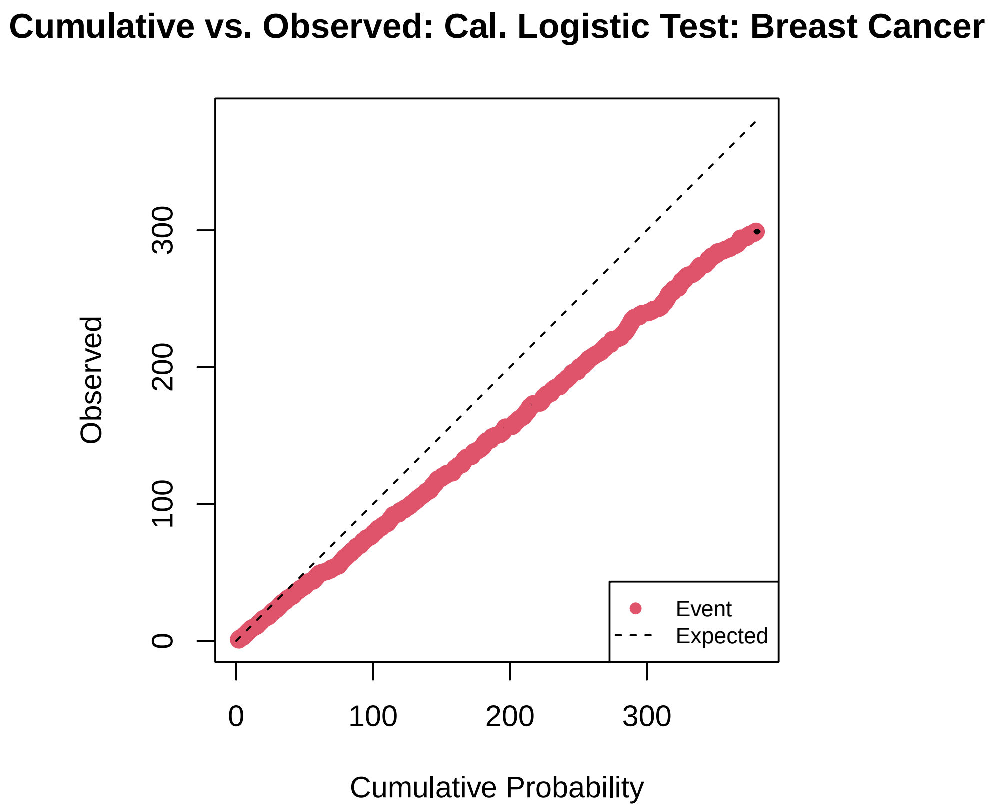
90%	80%
0.639	0.521

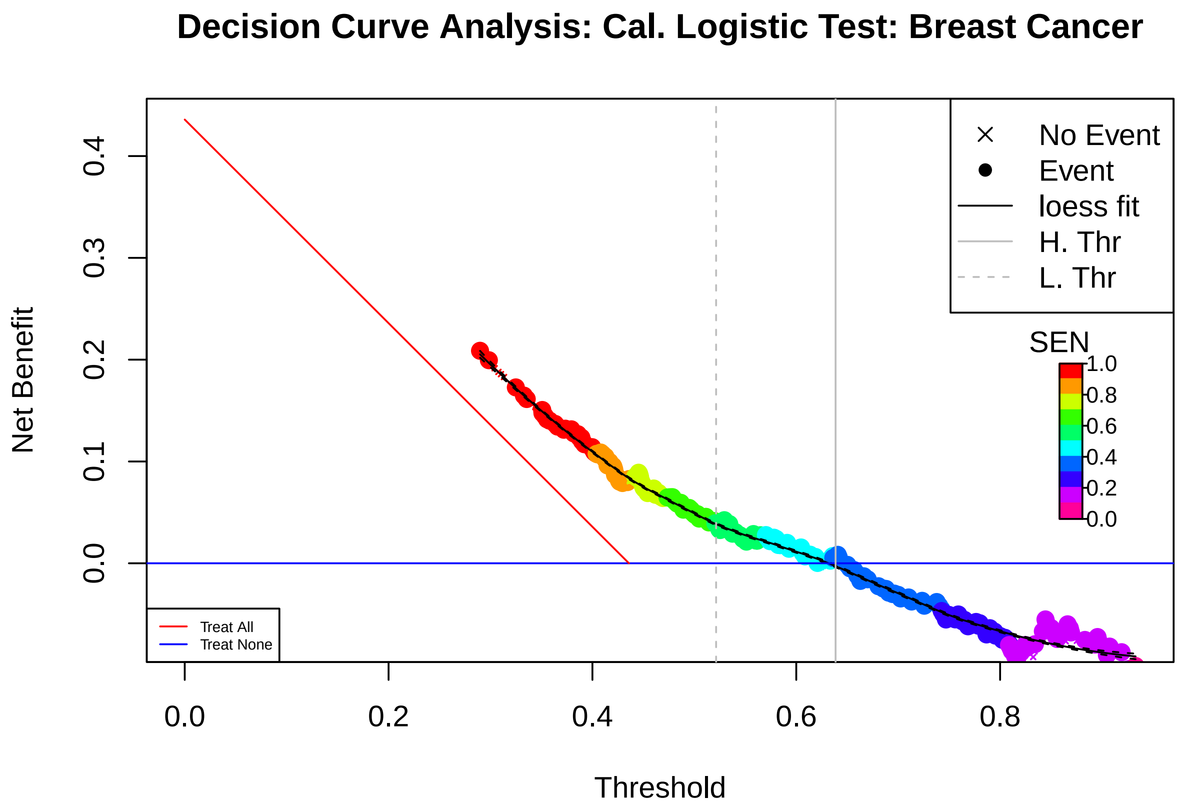
```
pander::pander(rrAnalysisTrain$surdif,caption="Logrank test")
```

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

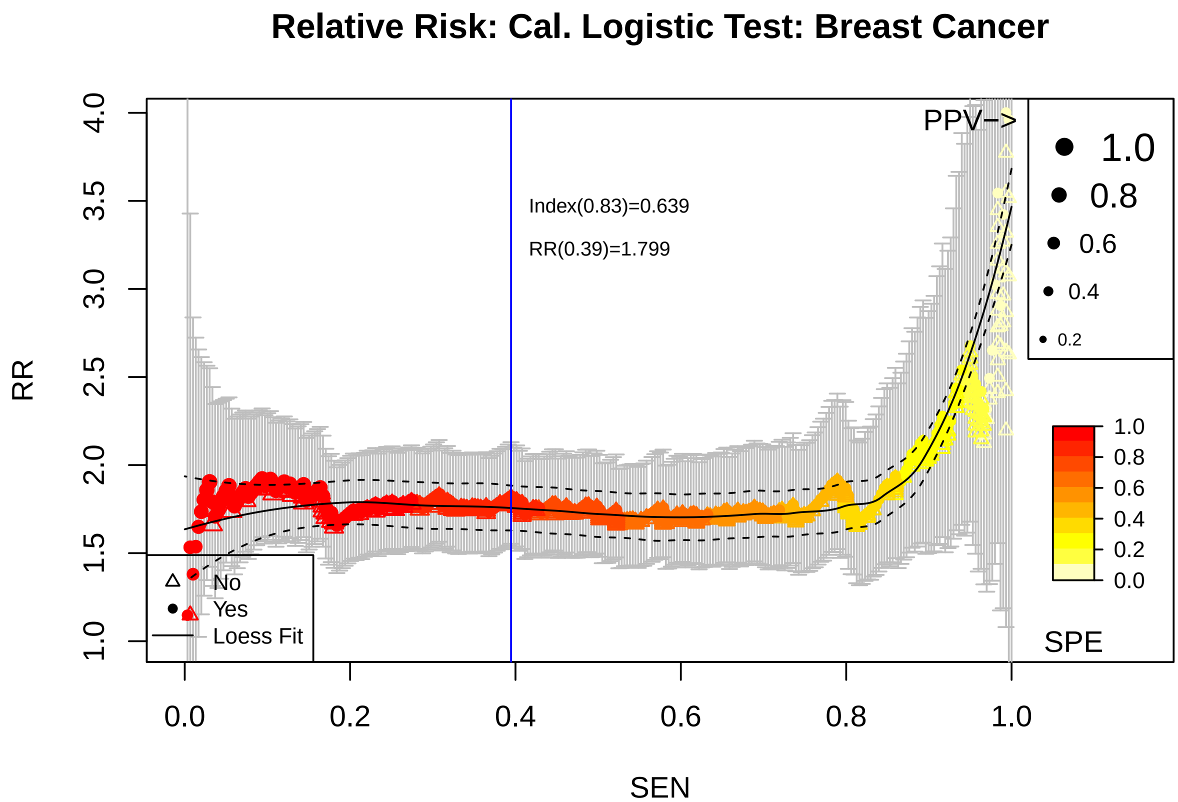
	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
class=0	1974	804	1144	100.9	415.3
class=1	365	218	170	13.4	15.1
class=2	643	496	204	418.2	490.7

```
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)
```

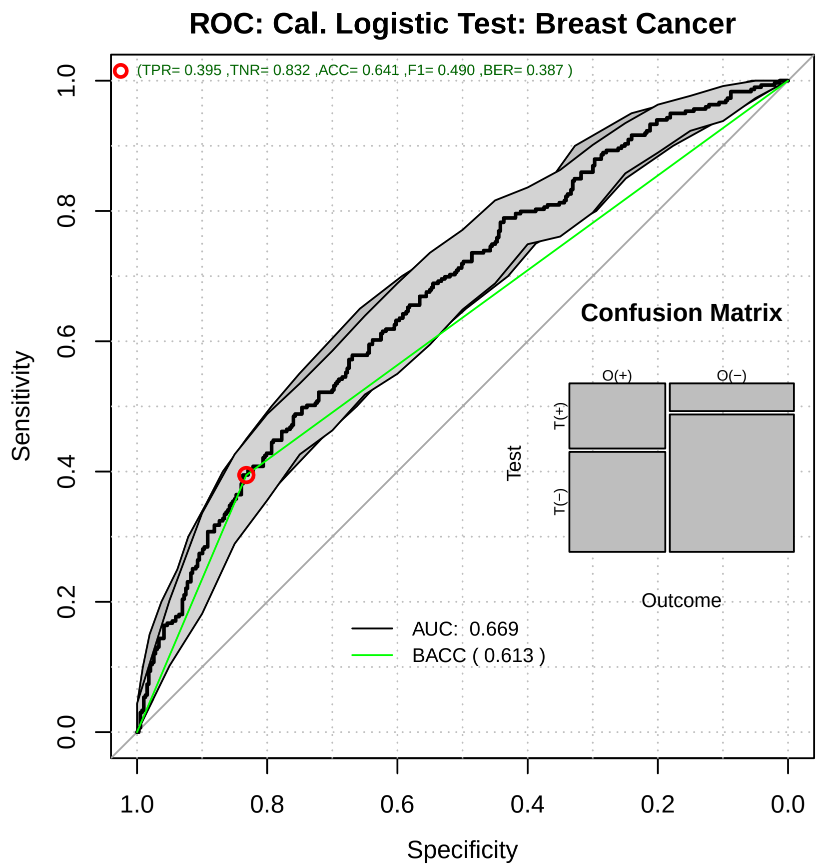

Cumulative vs. Observed: Cal. Logistic Test: Breast Cancer
Observed
0
100
200
300
Cumulative Probability
Event
Expected

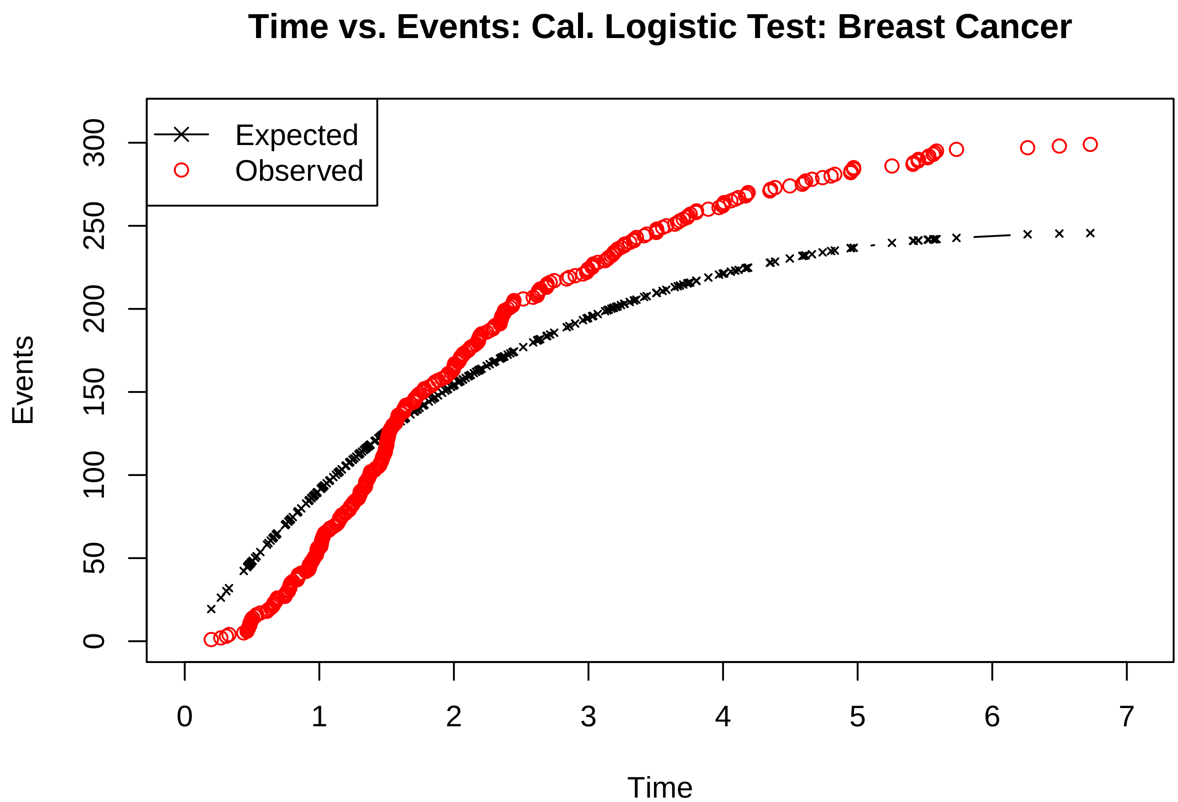


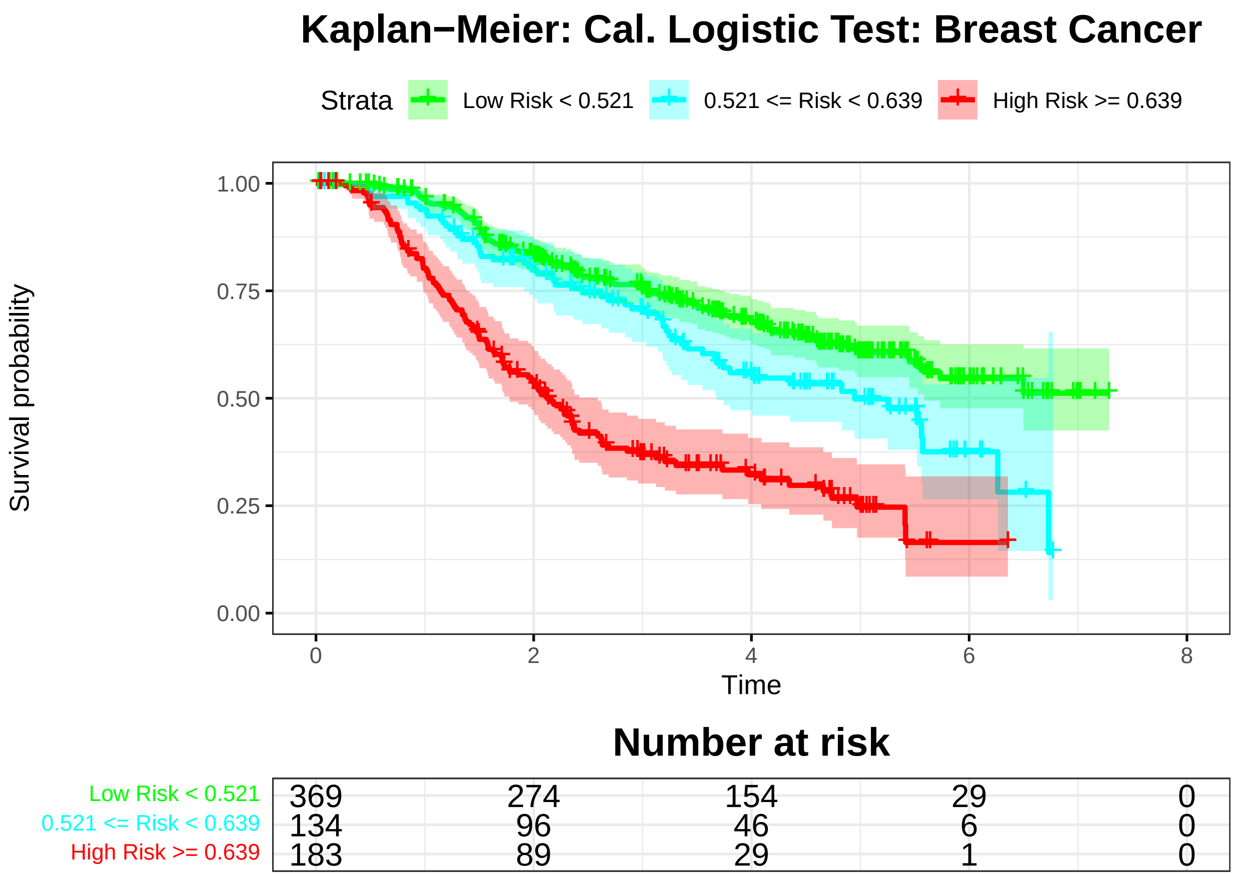
Decision Curve Analysis: Cal. Logistic Test: Breast Cancer
Net Benefit
0.0
0.1
0.2
0.3
0.4
0.0
0.2
0.4
0.6
0.8
Threshold
No Event
Event
loess fit
H. Thr
L. Thr
SEN
1.0
0.8
0.6
0.4
0.2
0.0
Treat All
Treat None



Relative Risk: Cal. Logistic Test: Breast Cancer
RR
SEN
Index(0.83)=0.639
RR(0.39)=1.799
PPV−>
1.0
0.8
0.6
0.4
0.2
SPE
No
Yes
Loess Fit


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
Time
0
50
100
150
200
250
300
0
1
2
3
4
5
6
7




```
par(op)
```

1.8.2 Report of the calibrated validation

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

Table 73: 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
SEN	0.39465	0.5953	0.5786	0.950	1.00e+00	0.6421
SPE	0.83204	0.6382	0.6693	0.181	1.29e-02	0.5866
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$OERatio$estimate),caption="O/E Ratio")
```

Table 74: O/E Ratio

O/E	Low	Upper	p.value
1.22	1.08	1.36	0.000902

```
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	0.67	0.639	0.701

```
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%
0.639	0.521

```
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%
0.842	0.842	0.841	0.844

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

mean	50%	2.5%	97.5%
0.791	0.791	0.791	0.792

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

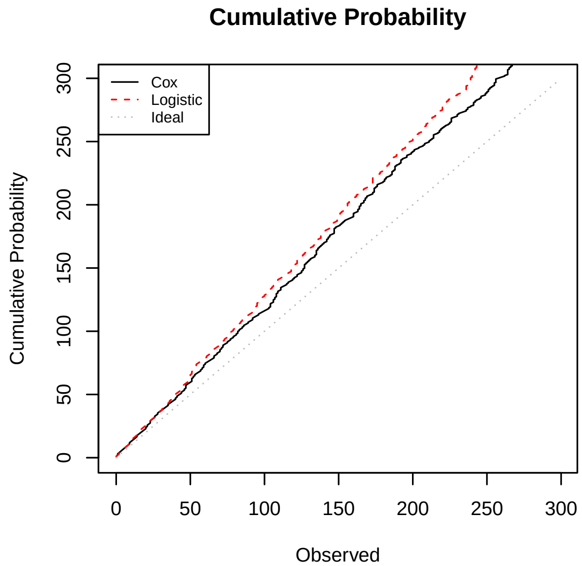
mean	50%	2.5%	97.5%
1.11	1.11	1.08	1.13

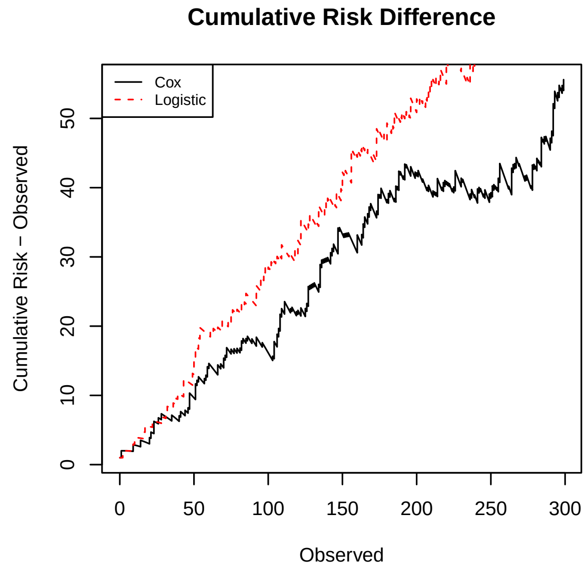
```
pander::pander(t(rrAnalysisTestLogistic$OE95ci))
```

mean	50%	2.5%	97.5%
0.989	0.989	0.961	1.02

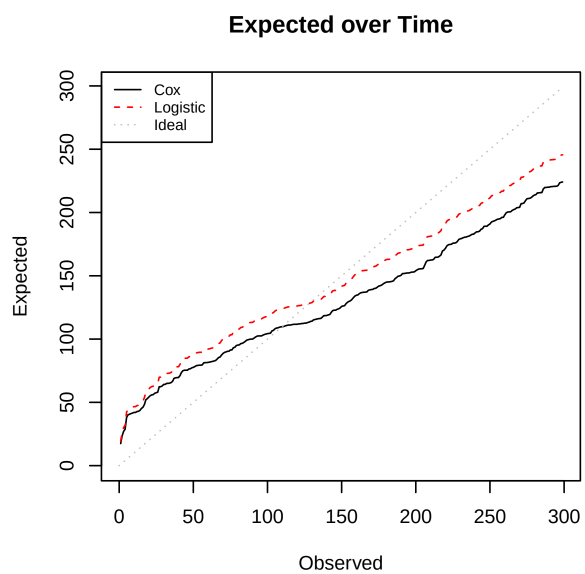
```
maxobs <- sum(dataBrestCancerTest$status)

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

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

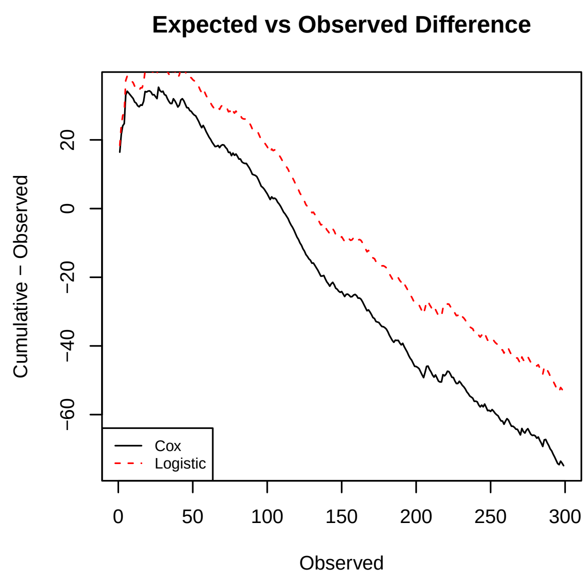
```
      main="Cumulative Probability",
      xlab="Observed",
      ylab="Cumulative Probability",
      ylim=c(0,maxobs),
      xlim=c(0,maxobs))
lines(rrAnalysisTestLogistic$CumulativeOvs[,1:2],lty=2,col="red")
lines(x=c(0,maxobs),y=c(0,maxobs),lty=3,col="gray")
legend("topleft",legend = c("Cox","Logistic","Ideal"),
        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
)
```





```r
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)
```