With1.6

```
library(gdata)
library(MASS)
library(ggplot2)
library("ggthemes")
library("GGally")
library("extracat")
library(hdrcde)
library(KernSmooth)
library("ggplot2")
library("gridExtra")
library("vcd")
library(class)
library(sqldf)
```

```
## Warning in doTryCatch(return(expr), name, parentenv, handler):      '/Library/Frameworks/R.framework/Re
##  dlopen(/Library/Frameworks/R.framework/Resources/modules//R_X11.so, 6): Library not loaded: /opt/X11/
##   Referenced from: /Library/Frameworks/R.framework/Resources/modules//R_X11.so
##   Reason: image not found
```

```
library(cccrm)
```

First, read the data and modify into categories

```
set.seed(40001)
df = read.xls ("data1.xlsx", sheet = 1, header = TRUE,na.strings=c("NA","<NA>","","*","unclear"))
#head(df)
#df[,6]
df[,6]<-as.numeric(as.character(df[,6]))
```

```
## Warning:       NA
```

```
data_2<-df
data_2<-df[complete.cases(df), ]
df<-df[complete.cases(df), ]
colnames(data_2)<-c('C1','C2','C3','C4','EC1','EC2','EC3')
##
head(data_2)
```

```
##   C1 C2 C3   C4   EC1   EC2  EC3
## 1 60  0 30 1.50 -1.02 -6.10 1.57
## 3 80  0 40 1.33  0.71  4.12 1.66
## 4 60  0 60 1.00  3.20  5.60 2.26
## 5 60  0 20 1.50 -2.50 -2.30 1.40
## 6 40  0 30 1.00  0.16 -1.29 1.53
## 7 90  1 40 1.50  0.15  0.50 1.50
```

```
data_2[,1][df[,1]<100]<-0
data_2[,2][df[,2]==0]<-0
data_2[,3][df[,3]<40]<-0
data_2[,4][df[,4]<1.6]<-0
data_2[,5][df[,5]<2.0]<-0
data_2[,6][df[,6]<2.0]<-0
data_2[,7][df[,7]<1.8]<-0
##
```

```
data_2[,1][df[,1]>=100]<-1
data_2[,2][df[,2]!=0]<-1
data_2[,3][df[,3]>=40]<-1
data_2[,4][df[,4]>=1.6]<-1
data_2[,5][df[,5]>=2.0]<-1
data_2[,6][df[,6]>=2.0]<-1
data_2[,7][df[,7]>=1.6]<-1
##
C1<-data_2[,1]
C2<-data_2[,2]
C3<-data_2[,3]
C4<-data_2[,4]
EC1<-data_2[,5]
EC2<-data_2[,6]
EC3<-data_2[,7]
##
head(data_2)
```

```
##   C1 C2 C3 C4 EC1 EC2 EC3
## 1  0  0  0  0   0   0   0
## 3  0  0  1  0   0   1   1
## 4  0  0  1  0   1   1   1
## 5  0  0  0  0   0   0   0
## 6  0  0  0  0   0   0   0
## 7  0  1  1  0   0   0   0
```

Therefore, the datas are divided into binary format.

```
library(fmsb)
```

```
##
## Attaching package: 'fmsb'

## The following object is masked from 'package:vcd':
##
##     oddsratio
```

```
CEC11<-Kappa.test(C1,EC1,conf.level = 0.90)
CEC21<-Kappa.test(C2,EC1,conf.level = 0.90)
CEC31<-Kappa.test(C3,EC1,conf.level = 0.90)
CEC41<-Kappa.test(C4,EC1,conf.level = 0.90)
CEC12<-Kappa.test(C1,EC2,conf.level = 0.90)
CEC22<-Kappa.test(C2,EC2,conf.level = 0.90)
CEC32<-Kappa.test(C3,EC2,conf.level = 0.90)
CEC42<-Kappa.test(C4,EC2,conf.level = 0.90)
CEC13<-Kappa.test(C1,EC3,conf.level = 0.90)
CEC23<-Kappa.test(C2,EC3,conf.level = 0.90)
CEC33<-Kappa.test(C3,EC3,conf.level = 0.90)
CEC43<-Kappa.test(C4,EC3,conf.level = 0.90)
Kappa_values<-c(CEC11$Result$estimate,CEC21$Result$estimate,CEC31$Result$estimate,CEC41$Result$estimate
                CEC12$Result$estimate,CEC22$Result$estimate,CEC32$Result$estimate,CEC42$Result$estimate
                CEC13$Result$estimate,CEC23$Result$estimate,CEC33$Result$estimate,CEC43$Result$estimate)
pvalues<-c(CEC11$Result$p.value,CEC21$Result$p.value,CEC31$Result$p.value,CEC41$Result$p.value,
           CEC12$Result$p.value,CEC22$Result$p.value,CEC32$Result$p.value,CEC42$Result$p.value,
           CEC13$Result$p.value,CEC23$Result$p.value,CEC33$Result$p.value,CEC43$Result$p.value)
Judgements<-c(CEC11$Judgement,CEC21$Judgement,CEC31$Judgement,CEC41$Judgement,
```

```r
              CEC12$Judgement,CEC22$Judgement,CEC32$Judgement,CEC42$Judgement,
              CEC13$Judgement,CEC23$Judgement,CEC33$Judgement,CEC43$Judgement)
results_cp<-cbind(Kappa_values,pvalues,Judgements)
rownames(results_cp)<-c('C1&EC1','C2&EC1','C3&EC1','C4&EC1',
                        'C1&EC2','C2&EC2','C3&EC2','C4&EC2',
                        'C1&EC3','C2&EC3','C3&EC3','C4&EC3')
C1_C2_EC1<-Kappa.test(C1*C2,EC1,conf.level = 0.90)
C1_C3_EC1<-Kappa.test(C1*C3,EC1,conf.level = 0.90)
C1_C4_EC1<-Kappa.test(C1*C4,EC1,conf.level = 0.90)
C2_C3_EC1<-Kappa.test(C2*C3,EC1,conf.level = 0.90)
C2_C4_EC1<-Kappa.test(C2*C4,EC1,conf.level = 0.90)
C3_C4_EC1<-Kappa.test(C3*C4,EC1,conf.level = 0.90)
#
C1_C2_EC2<-Kappa.test(C1*C2,EC2,conf.level = 0.90)
C1_C3_EC2<-Kappa.test(C1*C3,EC2,conf.level = 0.90)
C1_C4_EC2<-Kappa.test(C1*C4,EC2,conf.level = 0.90)
C2_C3_EC2<-Kappa.test(C2*C3,EC2,conf.level = 0.90)
C2_C4_EC2<-Kappa.test(C2*C4,EC2,conf.level = 0.90)
C3_C4_EC2<-Kappa.test(C3*C4,EC2,conf.level = 0.90)
#
C1_C2_EC3<-Kappa.test(C1*C2,EC3,conf.level = 0.90)
C1_C3_EC3<-Kappa.test(C1*C3,EC3,conf.level = 0.90)
C1_C4_EC3<-Kappa.test(C1*C4,EC3,conf.level = 0.90)
C2_C3_EC3<-Kappa.test(C2*C3,EC3,conf.level = 0.90)
C2_C4_EC3<-Kappa.test(C2*C4,EC3,conf.level = 0.90)
C3_C4_EC3<-Kappa.test(C3*C4,EC3,conf.level = 0.90)

#
Kappa_values.2<-c(C1_C2_EC1$Result$estimate,C1_C3_EC1$Result$estimate,C1_C4_EC1$Result$estimate,C2_C3_E
                  C1_C2_EC2$Result$estimate,C1_C3_EC2$Result$estimate,C1_C4_EC2$Result$estimate,C2_C3_E
                  C1_C2_EC3$Result$estimate,C1_C3_EC3$Result$estimate,C1_C4_EC3$Result$estimate,C2_C3_E
pvalues.2<-c(C1_C2_EC1$Result$p.value,C1_C3_EC1$Result$p.value,C1_C4_EC1$Result$p.value,C2_C3_EC1$Resul
             C1_C2_EC2$Result$p.value,C1_C3_EC2$Result$p.value,C1_C4_EC2$Result$p.value,C2_C3_EC2$Resul
             C1_C2_EC3$Result$p.value,C1_C3_EC3$Result$p.value,C1_C4_EC3$Result$p.value,C2_C3_EC3$Resul
Judgements.2<-c(C1_C2_EC1$Judgement,C1_C3_EC1$Judgement,C1_C4_EC1$Judgement,C2_C3_EC1$Judgement,C2_C4_E
                C1_C2_EC2$Judgement,C1_C3_EC2$Judgement,C1_C4_EC2$Judgement,C2_C3_EC2$Judgement,C2_C4_E
                C1_C2_EC3$Judgement,C1_C3_EC3$Judgement,C1_C4_EC3$Judgement,C2_C3_EC3$Judgement,C2_C4_E
results_cp.2<-cbind(Kappa_values.2,pvalues.2,Judgements.2)
rownames(results_cp.2)<-c('C1_C2&EC1','C1_C3&EC1','C1_C4&EC1','C2_C3&EC1','C2_C4&EC1','C3_C4&EC1',
                          'C1_C2&EC2','C1_C3&EC2','C1_C4&EC2','C2_C3&EC2','C2_C4&EC2','C3_C4&EC2',
                          'C1_C2&EC3','C1_C3&EC3','C1_C4&EC3','C2_C3&EC3','C2_C4&EC3','C3_C4&EC3')
#write.table(results_cp.2, "/Users/hemu/Desktop/re_2_results18.txt", sep="\t")
##3 combinations

C1_C2_C3_EC1<-Kappa.test(C1*C2*C3,EC1,conf.level = 0.90)
C1_C2_C4_EC1<-Kappa.test(C1*C2*C4,EC1,conf.level = 0.90)
C1_C3_C4_EC1<-Kappa.test(C1*C3*C4,EC1,conf.level = 0.90)
C2_C3_C4_EC1<-Kappa.test(C2*C3*C4,EC1,conf.level = 0.90)
C1_C2_C3_EC2<-Kappa.test(C1*C2*C3,EC2,conf.level = 0.90)
C1_C2_C4_EC2<-Kappa.test(C1*C2*C4,EC2,conf.level = 0.90)
C1_C3_C4_EC2<-Kappa.test(C1*C3*C4,EC2,conf.level = 0.90)
C2_C3_C4_EC2<-Kappa.test(C2*C3*C4,EC2,conf.level = 0.90)
C1_C2_C3_EC3<-Kappa.test(C1*C2*C3,EC3,conf.level = 0.90)
```

```
C1_C2_C4_EC3<-Kappa.test(C1*C2*C4,EC3,conf.level = 0.90)
C1_C3_C4_EC3<-Kappa.test(C1*C3*C4,EC3,conf.level = 0.90)
C2_C3_C4_EC3<-Kappa.test(C2*C3*C4,EC3,conf.level = 0.90)
Kappa_values.3<-c(C1_C2_C3_EC1$Result$estimate,C1_C2_C4_EC1$Result$estimate,C1_C3_C4_EC1$Result$estimate
                  C1_C2_C3_EC2$Result$estimate,C1_C2_C4_EC2$Result$estimate,C1_C3_C4_EC2$Result$estimate
                  C1_C2_C3_EC3$Result$estimate,C1_C2_C4_EC3$Result$estimate,C1_C3_C4_EC3$Result$estimate
pvalues.3<-c(C1_C2_C3_EC1$Result$p.value,C1_C2_C4_EC1$Result$p.value,C1_C3_C4_EC1$Result$p.value,C2_C3_C
             C1_C2_C3_EC2$Result$p.value,C1_C2_C4_EC2$Result$p.value,C1_C3_C4_EC2$Result$p.value,C2_C3_C
             C1_C2_C3_EC3$Result$p.value,C1_C2_C4_EC3$Result$p.value,C1_C3_C4_EC3$Result$p.value,C2_C3_C
Judgements.3<-c(C1_C2_C3_EC1$Judgement,C1_C2_C4_EC1$Judgement,C1_C3_C4_EC1$Judgement,C2_C3_C4_EC1$Judgem
                C1_C2_C3_EC2$Judgement,C1_C2_C4_EC2$Judgement,C1_C3_C4_EC2$Judgement,C2_C3_C4_EC2$Judgem
                C1_C2_C3_EC3$Judgement,C1_C2_C4_EC3$Judgement,C1_C3_C4_EC3$Judgement,C2_C3_C4_EC3$Judgem
results_cp.3<-cbind(Kappa_values.3,pvalues.3,Judgements.3)
rownames(results_cp.3)<-c('C1_C2_C3&EC1','C1_C2_C4&EC1','C1_C3_C4&EC1','C2_C3_C4&EC1','C1_C2_C3&EC2','C
##

C1_EC1_EC2<-Kappa.test(C1,EC1*EC2,conf.level = 0.90)
C1_EC1_EC3<-Kappa.test(C1,EC1*EC3,conf.level = 0.90)
C1_EC2_EC3<-Kappa.test(C1,EC2*EC3,conf.level = 0.90)
C2_EC1_EC2<-Kappa.test(C2,EC1*EC2,conf.level = 0.90)
C2_EC1_EC3<-Kappa.test(C2,EC1*EC3,conf.level = 0.90)
C2_EC2_EC3<-Kappa.test(C2,EC2*EC3,conf.level = 0.90)
C3_EC1_EC2<-Kappa.test(C3,EC1*EC2,conf.level = 0.90)
C3_EC1_EC3<-Kappa.test(C3,EC1*EC3,conf.level = 0.90)
C3_EC2_EC3<-Kappa.test(C3,EC2*EC3,conf.level = 0.90)
C4_EC1_EC2<-Kappa.test(C4,EC1*EC2,conf.level = 0.90)
C4_EC1_EC3<-Kappa.test(C4,EC1*EC3,conf.level = 0.90)
C4_EC2_EC3<-Kappa.test(C4,EC2*EC3,conf.level = 0.90)
Kappa_values.4<-c(C1_EC1_EC2$Result$estimate,C1_EC1_EC3$Result$estimate,C1_EC2_EC3$Result$estimate,
                  C2_EC1_EC2$Result$estimate,C2_EC1_EC3$Result$estimate,C2_EC2_EC3$Result$estimate,
                  C3_EC1_EC2$Result$estimate,C3_EC1_EC3$Result$estimate,C3_EC2_EC3$Result$estimate,
                  C4_EC1_EC2$Result$estimate,C4_EC1_EC3$Result$estimate,C4_EC2_EC3$Result$estimate)
pvalues.4<-c(C1_EC1_EC2$Result$p.value,C1_EC1_EC3$Result$p.value,C1_EC2_EC3$Result$p.value,
             C2_EC1_EC2$Result$p.value,C2_EC1_EC3$Result$p.value,C2_EC2_EC3$Result$p.value,
             C3_EC1_EC2$Result$p.value,C3_EC1_EC3$Result$p.value,C3_EC2_EC3$Result$p.value,
             C4_EC1_EC2$Result$p.value,C4_EC1_EC3$Result$p.value,C4_EC2_EC3$Result$p.value)
Judgements.4<-c(C1_EC1_EC2$Judgement,C1_EC1_EC3$Judgement,C1_EC2_EC3$Judgement,
                C2_EC1_EC2$Judgement,C2_EC1_EC3$Judgement,C2_EC2_EC3$Judgement,
                C3_EC1_EC2$Judgement,C3_EC1_EC3$Judgement,C3_EC2_EC3$Judgement,
                C4_EC1_EC2$Judgement,C4_EC1_EC3$Judgement,C4_EC2_EC3$Judgement)
results_cp.4<-cbind(Kappa_values.4,pvalues.4,Judgements.4)
rownames(results_cp.4)<-c('C1&EC1_EC2','C1&EC1_EC3','C1&EC2_EC3',
                          'C2&EC1_EC2','C2&EC1_EC3','C2&EC2_EC3',
                          'C3&EC1_EC2','C3&EC1_EC3','C3&EC2_EC3',
                          'C4&EC1_EC2','C4&EC1_EC3','C4&EC2_EC3')
C1_EC1_EC2_EC3<-Kappa.test(C1,EC1*EC2*EC3,conf.level = 0.90)
C2_EC1_EC2_EC3<-Kappa.test(C2,EC1*EC2*EC3,conf.level = 0.90)
C3_EC1_EC2_EC3<-Kappa.test(C3,EC1*EC2*EC3,conf.level = 0.90)
C4_EC1_EC2_EC3<-Kappa.test(C4,EC1*EC2*EC3,conf.level = 0.90)
Kappa_values.5<-c(C1_EC1_EC2_EC3$Result$estimate,C2_EC1_EC2_EC3$Result$estimate,
                  C3_EC1_EC2_EC3$Result$estimate,C4_EC1_EC2_EC3$Result$estimate)
pvalues.5<-c(C1_EC1_EC2_EC3$Result$p.value,C2_EC1_EC2_EC3$Result$p.value,
             C3_EC1_EC2_EC3$Result$p.value,C4_EC1_EC2_EC3$Result$p.value)
```

```r
Judgements.5<-c(C1_EC1_EC2_EC3$Judgement,C2_EC1_EC2_EC3$Judgement,
                C3_EC1_EC2_EC3$Judgement,C4_EC1_EC2_EC3$Judgement)
results_cp.5<-cbind(Kappa_values.5,pvalues.5,Judgements.5)
rownames(results_cp.5)<-c('C1&EC1_EC2_EC3','C2&EC1_EC2_EC3','C3&EC1_EC2_EC3','C4&EC1_EC2_EC3')
##
C1_C2_C3_C4_EC1_EC2_EC3<-Kappa.test(C1*C2*C3*C4,EC1*EC2*EC3,conf.level = 0.90)
Kappa_values.6<-c(C1_C2_C3_C4_EC1_EC2_EC3$Result$estimate)
pvalues.6<-c(C1_C2_C3_C4_EC1_EC2_EC3$Result$p.value)
Judgements.6<-c(C1_C2_C3_C4_EC1_EC2_EC3$Judgement)
results_cp.6<-cbind(Kappa_values.6,pvalues.6,Judgements.6)
rownames(results_cp.6)<-c('C1_C2_C3_C4&EC1_EC2_EC3')
##
cbresults<-rbind(results_cp,results_cp.2,results_cp.3,results_cp.4,results_cp.5,results_cp.6)
colnames(cbresults)<-c('Kappa_values','pvalues','Judgements')
cbresults
```

```
##                          Kappa_values           pvalues
## C1&EC1                   "0.0915515409139215"   "0.086236116907047"
## C2&EC1                   "0.0927958833619214"   "0.0947056182528914"
## C3&EC1                   "0.106129164952694"    "0.0382428027248299"
## C4&EC1                   "0.0971671163307415"   "0.0343144250518543"
## C1&EC2                   "0.0481964416280767"   "0.257156180729936"
## C2&EC2                   "-0.0220916092419942"  "0.609813831354921"
## C3&EC2                   "0.137807606263982"    "0.0155087236200574"
## C4&EC2                   "0.047183098591549"    "0.196948834313463"
## C1&EC3                   "0.0247499073731013"   "0.31115872844219"
## C2&EC3                   "0.0662908680947013"   "0.0963508933009044"
## C3&EC3                   "-0.0152885443583117"  "0.622961330793225"
## C4&EC3                   "-0.0159644617199973"  "0.63216558099716"
## C1_C2&EC1                "0.0670348314980542"   "0.196358420725198"
## C1_C3&EC1                "0.00643116786280171"  "0.465788440834035"
## C1_C4&EC1                "0.0717759517021637"   "0.15118497211517"
## C2_C3&EC1                "0.0592734225621409"   "0.220920380164853"
## C2_C4&EC1                "0.0388732024427087"   "0.308532762122575"
## C3_C4&EC1                "0.0614111376069574"   "0.189401963187765"
## C1_C2&EC2                "-0.0403010952763562"  "0.670210833731205"
## C1_C3&EC2                "0.0994165427296654"   "0.123078984158666"
## C1_C4&EC2                "0.0745829244357211"   "0.168101846661537"
## C2_C3&EC2                "-0.019461260309593"   "0.586324168862563"
## C2_C4&EC2                "-0.00928305014504686" "0.540919653451397"
## C3_C4&EC2                "0.126311289420895"    "0.0522994750783627"
## C1_C2&EC3                "0.0362064306944069"   "0.243579047135683"
## C1_C3&EC3                "0.00984319560489894"  "0.424323349874286"
## C1_C4&EC3                "0.0242478670857656"   "0.316218545465158"
## C2_C3&EC3                "0.0498827869797469"   "0.168279538434992"
## C2_C4&EC3                "0.0430596210137115"   "0.203850569801143"
## C3_C4&EC3                "0.000524246395806047" "0.495877244084578"
## C1_C2_C3&EC1             "0.0327987584066219"   "0.341512604159997"
## C1_C2_C4&EC1             "0.0247770069375625"   "0.378155150511409"
## C1_C3_C4&EC1             "0.000447914000511487" "0.497661317097694"
## C2_C3_C4&EC1             "0.0118786047789069"   "0.441040211660881"
## C1_C2_C3&EC2             "-0.0122098483832015"  "0.551289471331964"
## C1_C2_C4&EC2             "-0.0195317666769537"  "0.582404675177318"
## C1_C3_C4&EC2             "0.107985336308575"    "0.110275549519501"
```

```
## C2_C3_C4&EC2            "0.00595026642983958"  "0.474841746229216"
## C1_C2_C3&EC3            "0.0305183459522423"   "0.280055237841078"
## C1_C2_C4&EC3            "0.0224091807854846"   "0.334179467458987"
## C1_C3_C4&EC3            "0.00950993174323173"  "0.427179309034931"
## C2_C3_C4&EC3            "0.0360052766353689"   "0.245764413010168"
## C1&EC1_EC2              "0.00439407955596707"  "0.479698479251195"
## C1&EC1_EC3              "0.115339348764221"    "0.0684013022795533"
## C1&EC2_EC3              "0.0185212298682278"   "0.412228114841814"
## C2&EC1_EC2              "0.00136836343732865"  "0.494305116178753"
## C2&EC1_EC3              "0.0562195661797258"   "0.251450684204202"
## C2&EC2_EC3              "-0.0171355498721229"  "0.573923699745733"
## C3&EC1_EC2              "0.0702472293265129"   "0.159228306425296"
## C3&EC1_EC3              "0.145833333333334"    "0.0134422208384067"
## C3&EC2_EC3              "0.0961379081717217"   "0.0818179369330275"
## C4&EC1_EC2              "0.0701591511936338"   "0.114621704449421"
## C4&EC1_EC3              "0.0948997716315657"   "0.0459231686424771"
## C4&EC2_EC3              "0.00737218635491197"  "0.449194888780799"
## C1&EC1_EC2_EC3          "0.0347533632286994"   "0.353714921953989"
## C2&EC1_EC2_EC3          "-0.0308720560152771"  "0.615671893105962"
## C3&EC1_EC2_EC3          "0.102731054440224"    "0.0807255174147591"
## C4&EC1_EC2_EC3          "0.0668271851717245"   "0.131195058526265"
## C1_C2_C3_C4&EC1_EC2_EC3 "-0.0234600716514504"  "0.557405783302795"
##                         Judgements
## C1&EC1                  "Slight agreement"
## C2&EC1                  "Slight agreement"
## C3&EC1                  "Slight agreement"
## C4&EC1                  "Slight agreement"
## C1&EC2                  "Slight agreement"
## C2&EC2                  "No agreement"
## C3&EC2                  "Slight agreement"
## C4&EC2                  "Slight agreement"
## C1&EC3                  "Slight agreement"
## C2&EC3                  "Slight agreement"
## C3&EC3                  "No agreement"
## C4&EC3                  "No agreement"
## C1_C2&EC1               "Slight agreement"
## C1_C3&EC1               "Slight agreement"
## C1_C4&EC1               "Slight agreement"
## C2_C3&EC1               "Slight agreement"
## C2_C4&EC1               "Slight agreement"
## C3_C4&EC1               "Slight agreement"
## C1_C2&EC2               "No agreement"
## C1_C3&EC2               "Slight agreement"
## C1_C4&EC2               "Slight agreement"
## C2_C3&EC2               "No agreement"
## C2_C4&EC2               "No agreement"
## C3_C4&EC2               "Slight agreement"
## C1_C2&EC3               "Slight agreement"
## C1_C3&EC3               "Slight agreement"
## C1_C4&EC3               "Slight agreement"
## C2_C3&EC3               "Slight agreement"
## C2_C4&EC3               "Slight agreement"
## C3_C4&EC3               "Slight agreement"
## C1_C2_C3&EC1            "Slight agreement"
```

```
## C1_C2_C4&EC1            "Slight agreement"
## C1_C3_C4&EC1            "Slight agreement"
## C2_C3_C4&EC1            "Slight agreement"
## C1_C2_C3&EC2            "No agreement"
## C1_C2_C4&EC2            "No agreement"
## C1_C3_C4&EC2            "Slight agreement"
## C2_C3_C4&EC2            "Slight agreement"
## C1_C2_C3&EC3            "Slight agreement"
## C1_C2_C4&EC3            "Slight agreement"
## C1_C3_C4&EC3            "Slight agreement"
## C2_C3_C4&EC3            "Slight agreement"
## C1&EC1_EC2              "Slight agreement"
## C1&EC1_EC3              "Slight agreement"
## C1&EC2_EC3              "Slight agreement"
## C2&EC1_EC2              "Slight agreement"
## C2&EC1_EC3              "Slight agreement"
## C2&EC2_EC3              "No agreement"
## C3&EC1_EC2              "Slight agreement"
## C3&EC1_EC3              "Slight agreement"
## C3&EC2_EC3              "Slight agreement"
## C4&EC1_EC2              "Slight agreement"
## C4&EC1_EC3              "Slight agreement"
## C4&EC2_EC3              "Slight agreement"
## C1&EC1_EC2_EC3          "Slight agreement"
## C2&EC1_EC2_EC3          "No agreement"
## C3&EC1_EC2_EC3          "Slight agreement"
## C4&EC1_EC2_EC3          "Slight agreement"
## C1_C2_C3_C4&EC1_EC2_EC3 "No agreement"
```

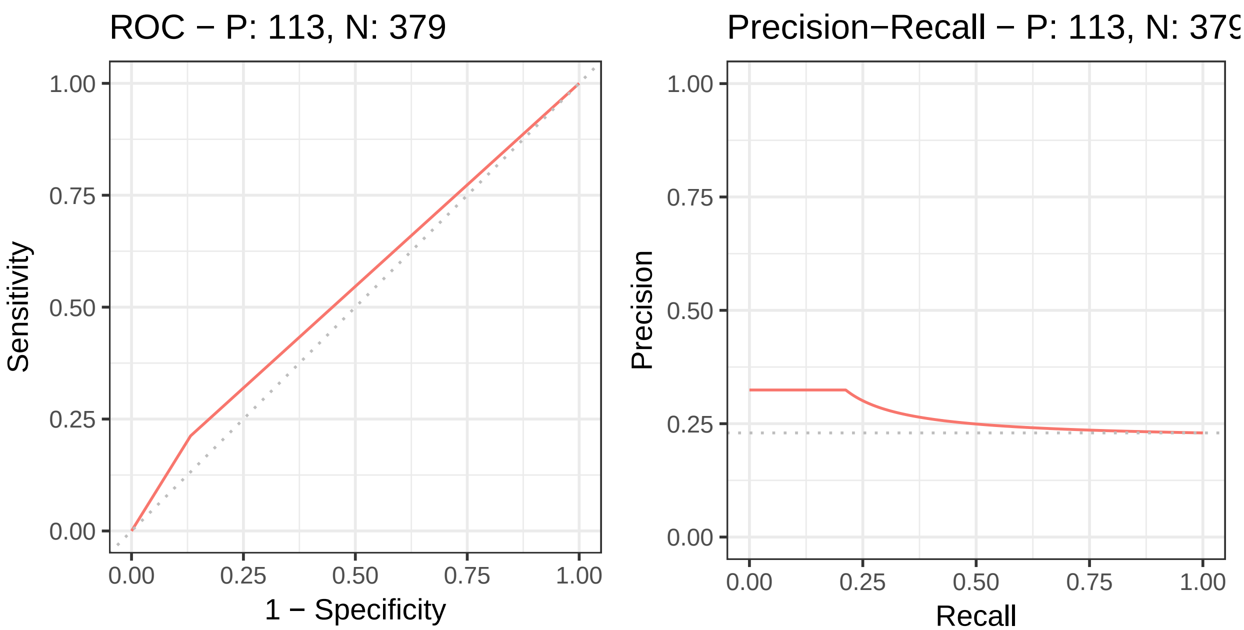
```r
library(caret)
library(precrec)
```

```r
###C1
t_C1_EC1<-table(C1,EC1)
confusionMatrix(t_C1_EC1)
```

```
## Confusion Matrix and Statistics
##
##    EC1
## C1    0   1
##   0 329  89
##   1  50  24
##
##                Accuracy : 0.7175
##                  95% CI : (0.6755, 0.7569)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.997279
##
##                   Kappa : 0.0916
##  Mcnemar's Test P-Value : 0.001268
##
##             Sensitivity : 0.8681
##             Specificity : 0.2124
##          Pos Pred Value : 0.7871
##          Neg Pred Value : 0.3243
```

```
##               Prevalence : 0.7703
##           Detection Rate : 0.6687
##     Detection Prevalence : 0.8496
##        Balanced Accuracy : 0.5402
##
##         'Positive' Class : 0
##
```

```r
sscurves11<- evalmod(scores = C1, labels = EC1)
autoplot(sscurves11)
```

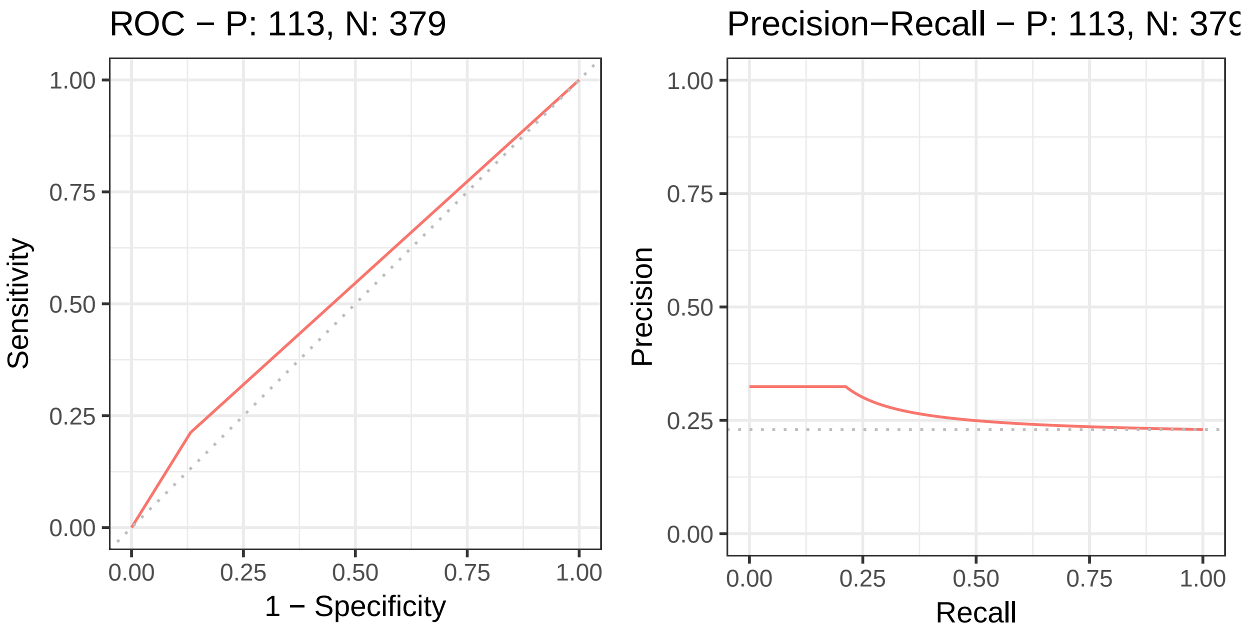



```r
########
t_C1_EC2<-table(C1,EC2)
confusionMatrix(t_C1_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
## C1    0   1
##   0 349  69
##   1  58  16
##
##                Accuracy : 0.7419
##                  95% CI : (0.7008, 0.78)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 1.0000
##
##                   Kappa : 0.0482
##  Mcnemar's Test P-Value : 0.3749
##
##             Sensitivity : 0.8575
##             Specificity : 0.1882
##          Pos Pred Value : 0.8349
##          Neg Pred Value : 0.2162
##              Prevalence : 0.8272
```

```
##          Detection Rate : 0.7093
##    Detection Prevalence : 0.8496
##       Balanced Accuracy : 0.5229
##
##        'Positive' Class : 0
##
```

```r
sscurves12<- evalmod(scores = C1, labels = c(EC1))
autoplot(sscurves12)
```

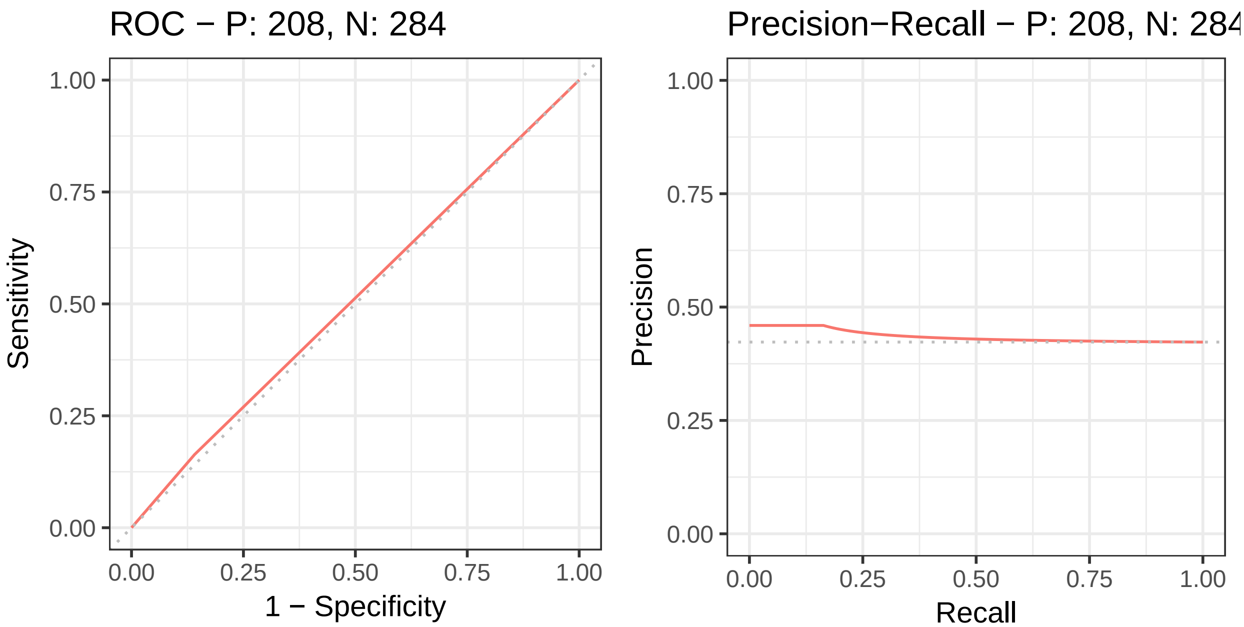



```r
#######
t_C1_EC3<-table(C1,EC3)
confusionMatrix(t_C1_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
## C1    0   1
##   0 244 174
##   1  40  34
##
##                Accuracy : 0.565
##                  95% CI : (0.5199, 0.6094)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.724
##
##                   Kappa : 0.0247
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.8592
##             Specificity : 0.1635
##          Pos Pred Value : 0.5837
##          Neg Pred Value : 0.4595
##              Prevalence : 0.5772
##          Detection Rate : 0.4959
```

```
##    Detection Prevalence : 0.8496
##       Balanced Accuracy : 0.5113
##
##        'Positive' Class : 0
##
```

```r
sscurves13<- evalmod(scores = C1, labels = EC3)
autoplot(sscurves13)
```

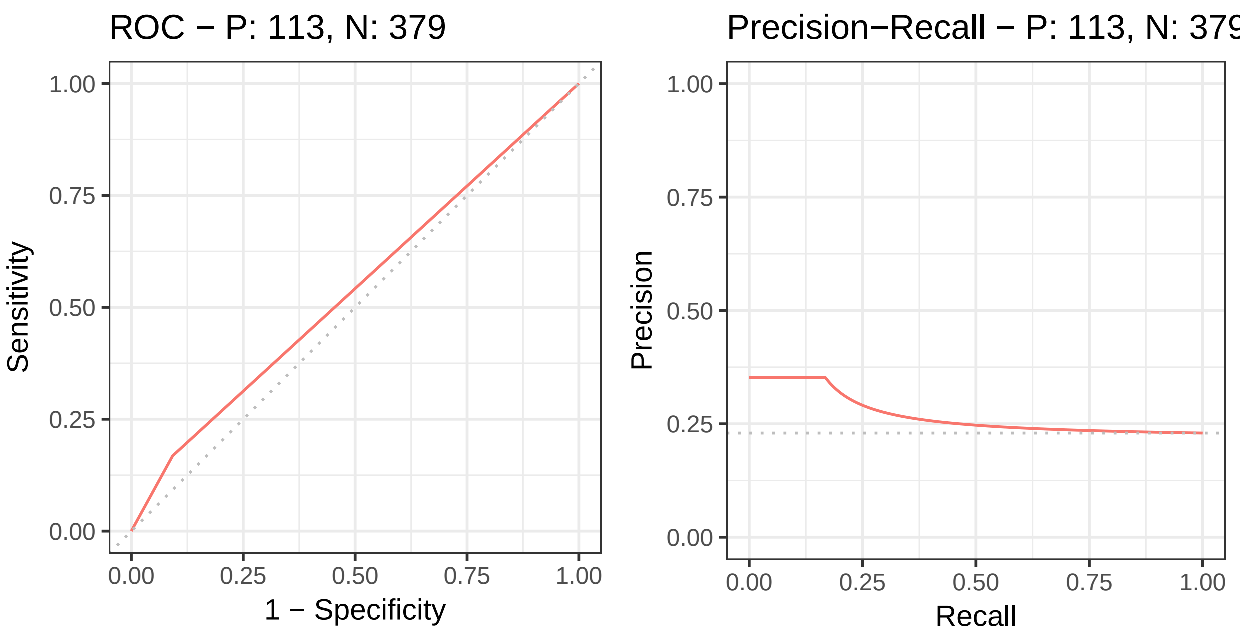



```r
###C2
t_C2_EC1<-table(C2,EC1)
confusionMatrix(t_C2_EC1)
```

```
## Confusion Matrix and Statistics
##
##      EC1
## C2     0   1
##    0 344  94
##    1  35  19
##
##                Accuracy : 0.7378
##                  95% CI : (0.6966, 0.7762)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.9599
##
##                   Kappa : 0.0928
##  Mcnemar's Test P-Value : 3.28e-07
##
##             Sensitivity : 0.9077
##             Specificity : 0.1681
##          Pos Pred Value : 0.7854
##          Neg Pred Value : 0.3519
##              Prevalence : 0.7703
##          Detection Rate : 0.6992
##    Detection Prevalence : 0.8902
```

```
##         Balanced Accuracy : 0.5379
##
##          'Positive' Class : 0
##
```

```r
sscurves21<- evalmod(scores = C2, labels = EC1)
autoplot(sscurves21)
```

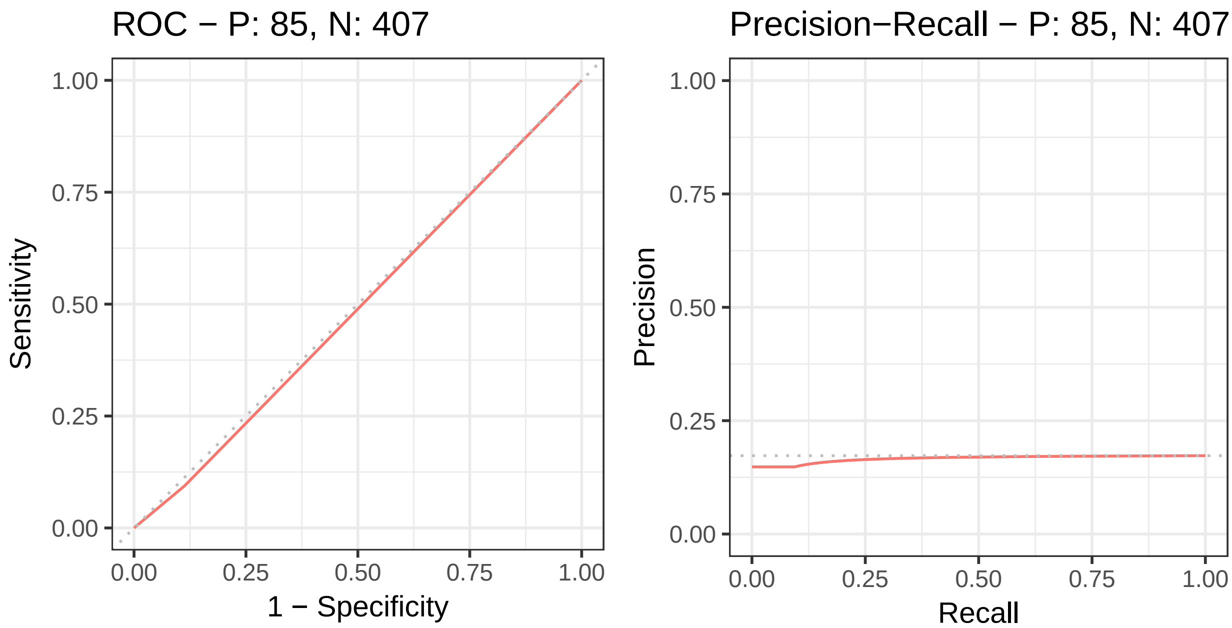



```r
#
t_C2_EC2<-table(C2,EC2)
confusionMatrix(t_C2_EC2)
```

```
## Confusion Matrix and Statistics
##
##     EC2
## C2     0   1
##    0 361  77
##    1  46   8
##
##                Accuracy : 0.75
##                  95% CI : (0.7093, 0.7877)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 0.99999
##
##                   Kappa : -0.0221
##  Mcnemar's Test P-Value : 0.00683
##
##             Sensitivity : 0.88698
##             Specificity : 0.09412
##          Pos Pred Value : 0.82420
##          Neg Pred Value : 0.14815
##              Prevalence : 0.82724
##          Detection Rate : 0.73374
##    Detection Prevalence : 0.89024
##       Balanced Accuracy : 0.49055
```

```
##
##        'Positive' Class : 0
##
```

```r
sscurves22<- evalmod(scores = C2, labels = EC2)
autoplot(sscurves22)
```

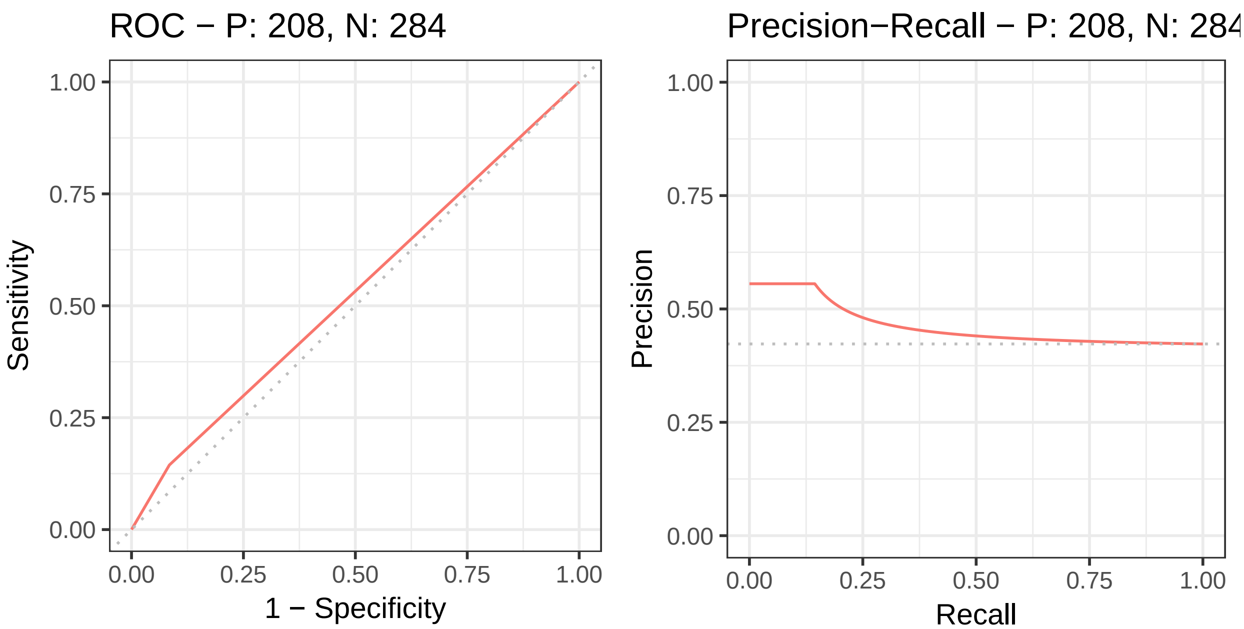



```r
#
t_C2_EC3<-table(C2,EC3)
confusionMatrix(t_C2_EC3)
```

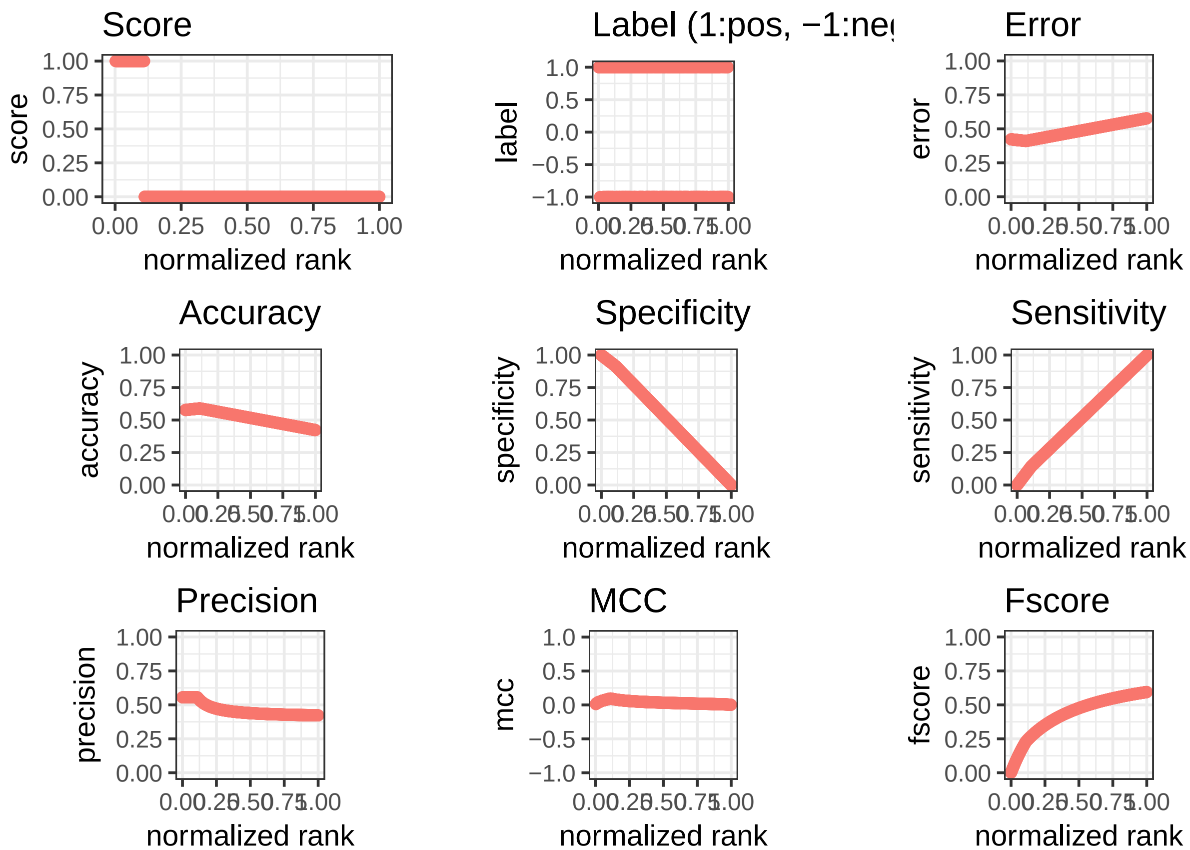
```
## Confusion Matrix and Statistics
##
##     EC3
## C2     0   1
##    0 260 178
##    1  24  30
##
##                Accuracy : 0.5894
##                  95% CI : (0.5445, 0.6333)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.3085
##
##                   Kappa : 0.0663
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9155
##             Specificity : 0.1442
##          Pos Pred Value : 0.5936
##          Neg Pred Value : 0.5556
##              Prevalence : 0.5772
##          Detection Rate : 0.5285
##    Detection Prevalence : 0.8902
##       Balanced Accuracy : 0.5299
##
```

```
##        'Positive' Class : 0
##
```

```r
sscurves23<- evalmod(scores = C2, labels = EC3)
autoplot(sscurves23)
```




```r
sspoints23 <- evalmod(mode = "basic", scores = C2,labels = EC3)
## Normalized ranks vs. basic evaluation measures
autoplot(sspoints23)
```

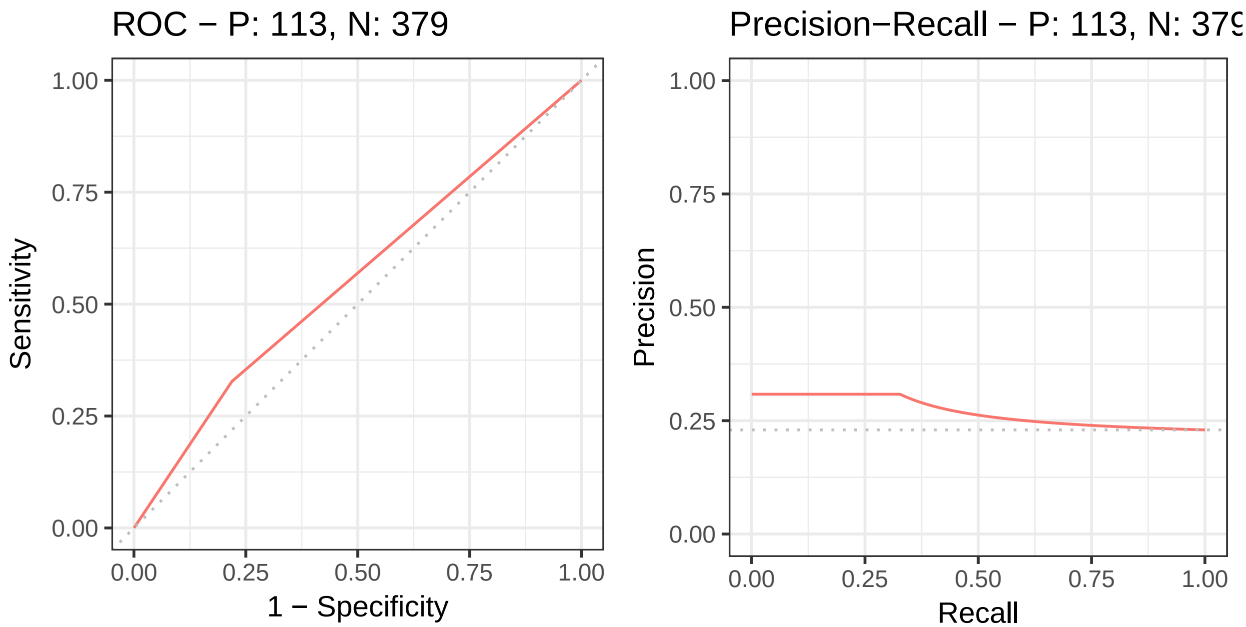



```
###C3
t_C3_EC1<-table(C3,EC1)
confusionMatrix(t_C3_EC1)
```

```
## Confusion Matrix and Statistics
##
##    EC1
## C3    0   1
##   0 296  76
##   1  83  37
##
##                Accuracy : 0.6768
##                  95% CI : (0.6335, 0.718)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 1.0000
##
##                   Kappa : 0.1061
##  Mcnemar's Test P-Value : 0.6342
##
##             Sensitivity : 0.7810
##             Specificity : 0.3274
##          Pos Pred Value : 0.7957
##          Neg Pred Value : 0.3083
##              Prevalence : 0.7703
##          Detection Rate : 0.6016
##    Detection Prevalence : 0.7561
##       Balanced Accuracy : 0.5542
```

```
##
##        'Positive' Class : 0
##
```

```
sscurves31<- evalmod(scores = C3, labels = EC1)
autoplot(sscurves31)
```

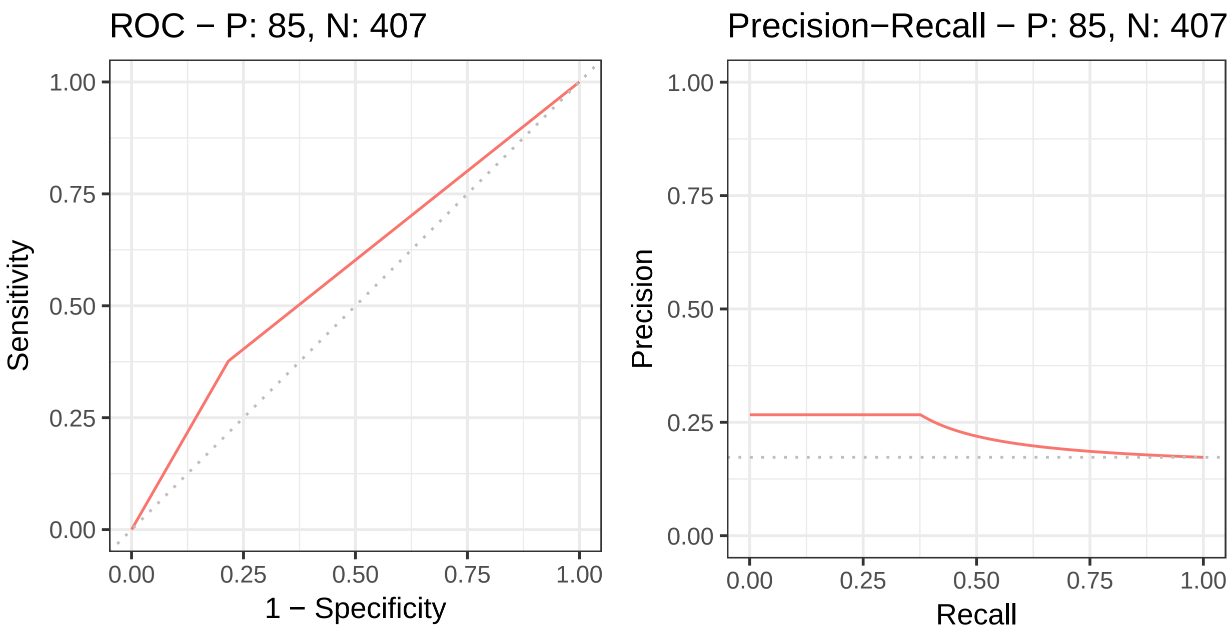



```
#
t_C3_EC2<-table(C3,EC2)
confusionMatrix(t_C3_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
## C3    0   1
##   0 319  53
##   1  88  32
##
##                Accuracy : 0.7134
##                  95% CI : (0.6712, 0.753)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 1.000000
##
##                   Kappa : 0.1378
##  Mcnemar's Test P-Value : 0.004192
##
##             Sensitivity : 0.7838
##             Specificity : 0.3765
##          Pos Pred Value : 0.8575
##          Neg Pred Value : 0.2667
##              Prevalence : 0.8272
##          Detection Rate : 0.6484
##    Detection Prevalence : 0.7561
##       Balanced Accuracy : 0.5801
##
```

```
##        'Positive' Class : 0
##
```

```r
sscurves32<- evalmod(scores = C3, labels = EC2)
autoplot(sscurves32)
```

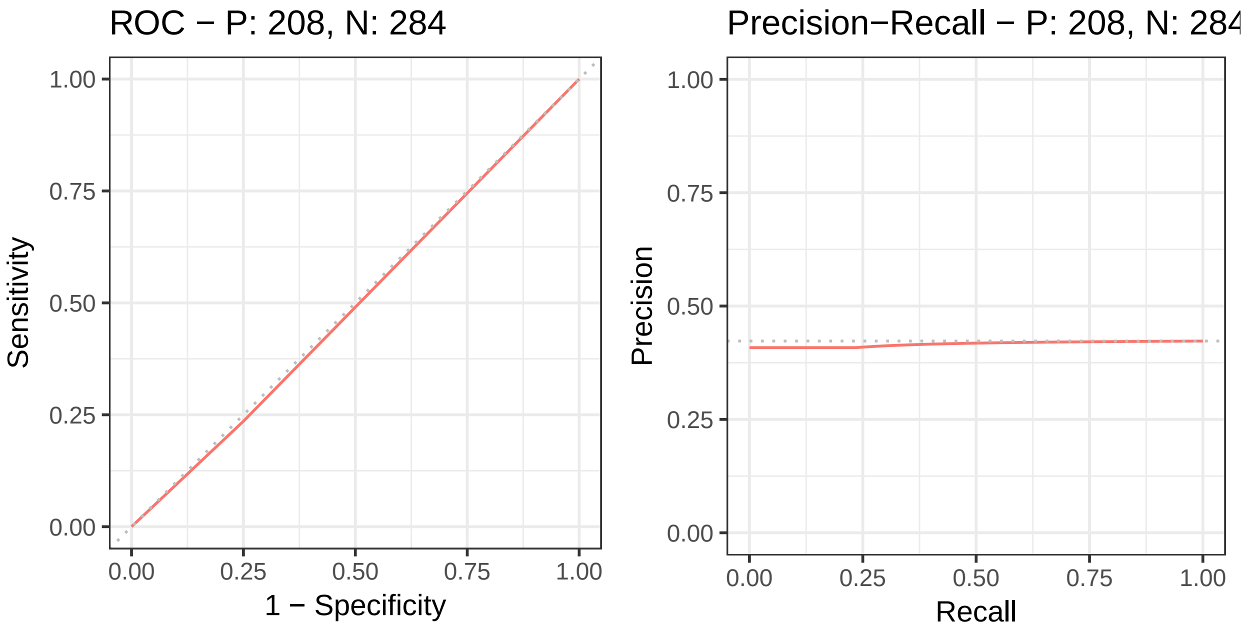



```r
#
t_C3_EC3<-table(C3,EC3)
confusionMatrix(t_C3_EC3)
```

```
## Confusion Matrix and Statistics
##
##     EC3
## C3    0   1
##    0 213 159
##    1  71  49
##
##                Accuracy : 0.5325
##                  95% CI : (0.4873, 0.5773)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.9797
##
##                   Kappa : -0.0153
##  Mcnemar's Test P-Value : 9.659e-09
##
##             Sensitivity : 0.7500
##             Specificity : 0.2356
##          Pos Pred Value : 0.5726
##          Neg Pred Value : 0.4083
##              Prevalence : 0.5772
##          Detection Rate : 0.4329
##    Detection Prevalence : 0.7561
##       Balanced Accuracy : 0.4928
##
##        'Positive' Class : 0
```

```
##
```

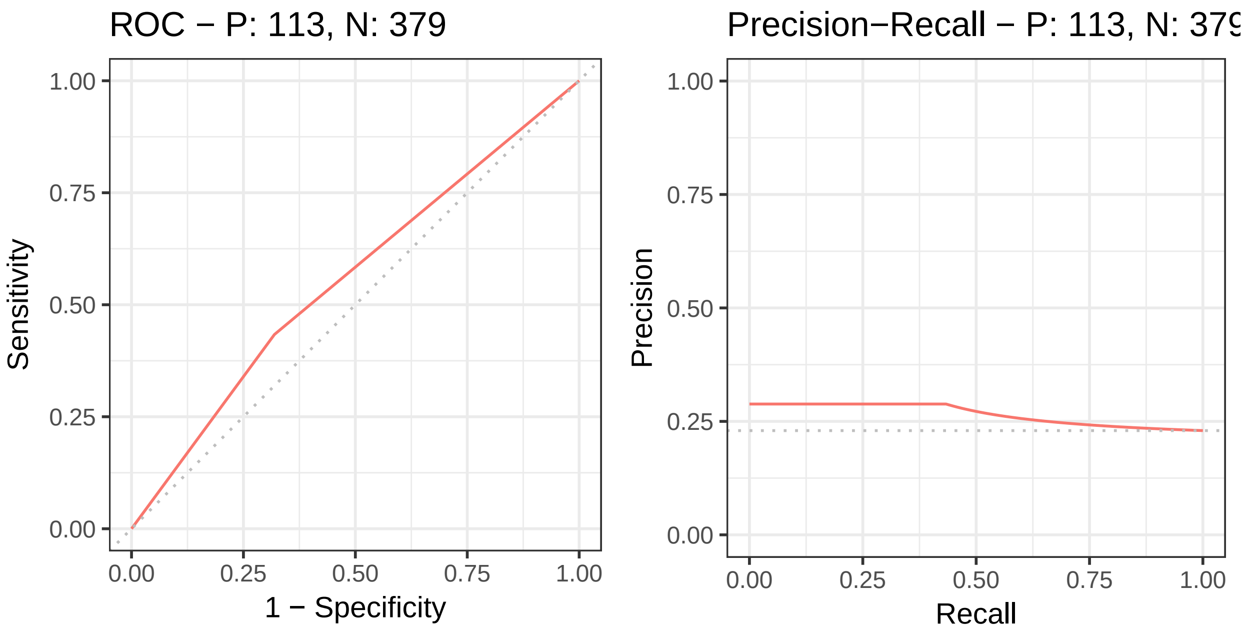
```r
sscurves33<- evalmod(scores = C3, labels = EC3)
autoplot(sscurves33)
```




```r
###C4
t_C4_EC1<-table(C4,EC1)
confusionMatrix(t_C4_EC1)
```

```
## Confusion Matrix and Statistics
##
##     EC1
## C4     0   1
##    0 258  64
##    1 121  49
##
##                Accuracy : 0.624
##                  95% CI : (0.5795, 0.6669)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.0972
##  Mcnemar's Test P-Value : 3.835e-05
##
##             Sensitivity : 0.6807
##             Specificity : 0.4336
##          Pos Pred Value : 0.8012
##          Neg Pred Value : 0.2882
##              Prevalence : 0.7703
##          Detection Rate : 0.5244
##    Detection Prevalence : 0.6545
##       Balanced Accuracy : 0.5572
##
##        'Positive' Class : 0
##
```

```
sscurves41<- evalmod(scores = C4, labels = EC1)
autoplot(sscurves41)
```

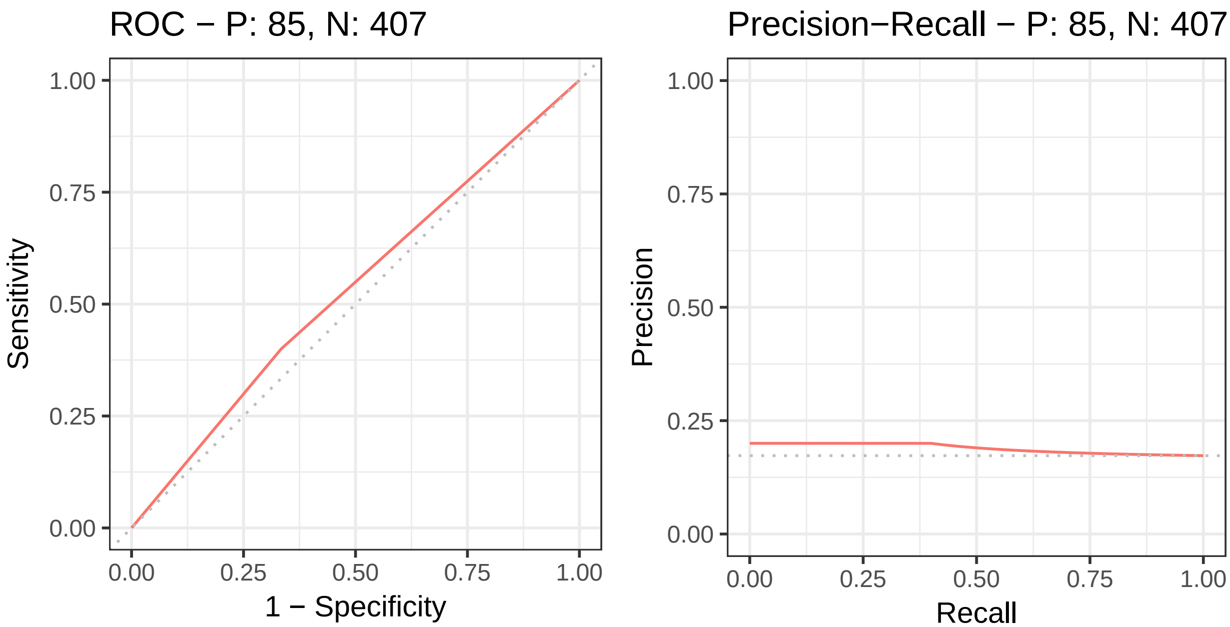



```
t_C4_EC2<-table(C4,EC2)
confusionMatrix(t_C4_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
## C4    0   1
##   0 271  51
##   1 136  34
##
##                Accuracy : 0.6199
##                  95% CI : (0.5754, 0.663)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.0472
##  Mcnemar's Test P-Value : 8.114e-10
##
##             Sensitivity : 0.6658
##             Specificity : 0.4000
##          Pos Pred Value : 0.8416
##          Neg Pred Value : 0.2000
##              Prevalence : 0.8272
##          Detection Rate : 0.5508
##    Detection Prevalence : 0.6545
##       Balanced Accuracy : 0.5329
##
##        'Positive' Class : 0
##
```

```
sscurves42<- evalmod(scores = C4, labels = EC2)
```

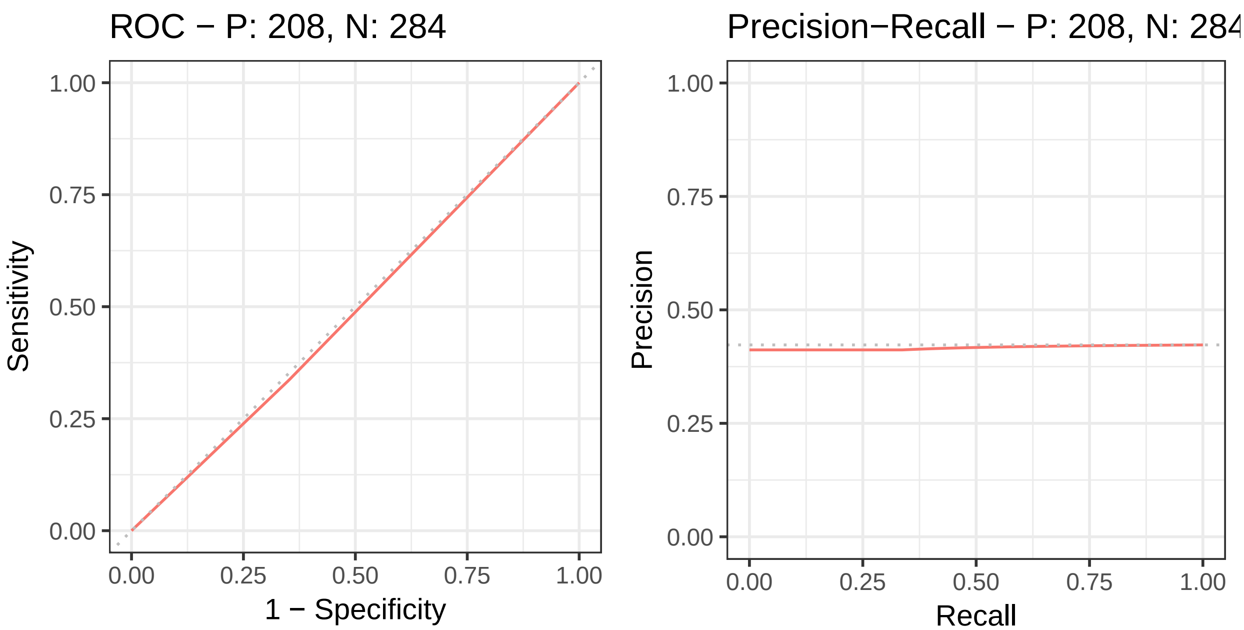
```r
autoplot(sscurves42)
```




```r
t_C4_EC3<-table(C4,EC3)
confusionMatrix(t_C4_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
## C4    0   1
##   0 184 138
##   1 100  70
##
##                Accuracy : 0.5163
##                  95% CI : (0.4711, 0.5612)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.99721
##
##                   Kappa : -0.016
##  Mcnemar's Test P-Value : 0.01647
##
##             Sensitivity : 0.6479
##             Specificity : 0.3365
##          Pos Pred Value : 0.5714
##          Neg Pred Value : 0.4118
##              Prevalence : 0.5772
##          Detection Rate : 0.3740
##    Detection Prevalence : 0.6545
##       Balanced Accuracy : 0.4922
##
##        'Positive' Class : 0
##
```

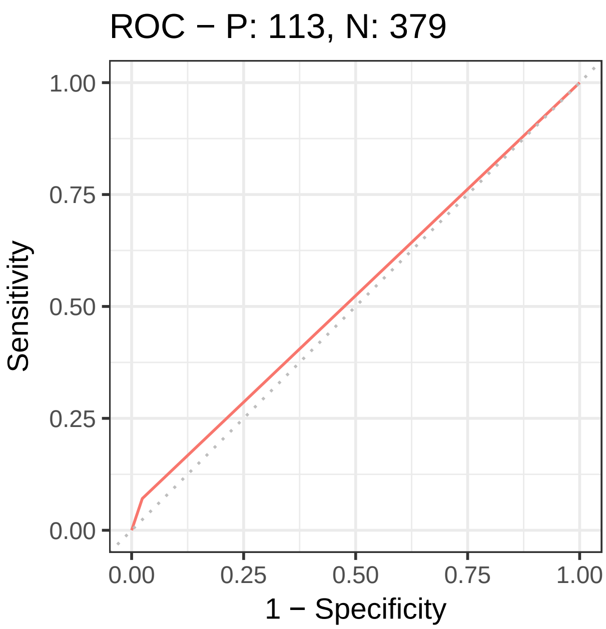
```r
sscurves43<- evalmod(scores = C4, labels = EC3)
autoplot(sscurves43)
```

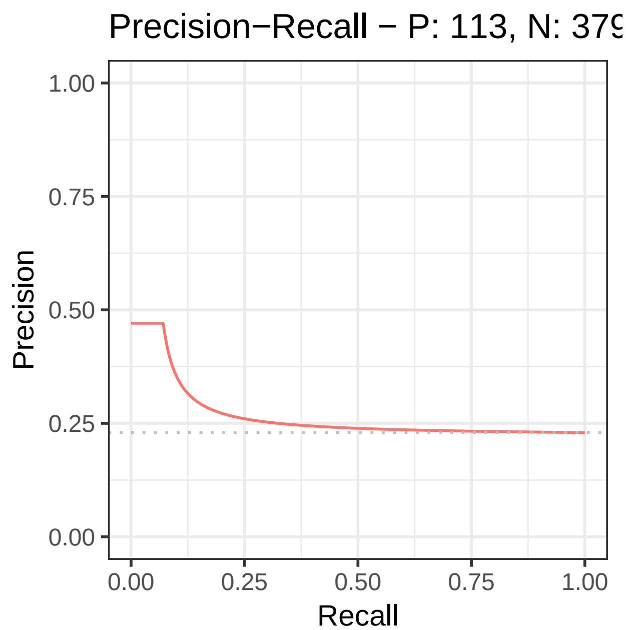



```
###C1_C2 and EC1
#1
t_C1_C2_EC1<-table(C1*C2,EC1)
confusionMatrix(t_C1_C2_EC1)
```

```
## Confusion Matrix and Statistics
##
##     EC1
##        0   1
##   0 370 105
##   1   9   8
##
##                Accuracy : 0.7683
##                  95% CI : (0.7284, 0.8049)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.5676
##
##                   Kappa : 0.067
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9763
##             Specificity : 0.0708
##          Pos Pred Value : 0.7789
##          Neg Pred Value : 0.4706
##              Prevalence : 0.7703
##          Detection Rate : 0.7520
##    Detection Prevalence : 0.9654
##       Balanced Accuracy : 0.5235
##
##        'Positive' Class : 0
##
```

```
sscurves12_1<- evalmod(scores = C1*C2, labels = EC1)
autoplot(sscurves12_1)
```

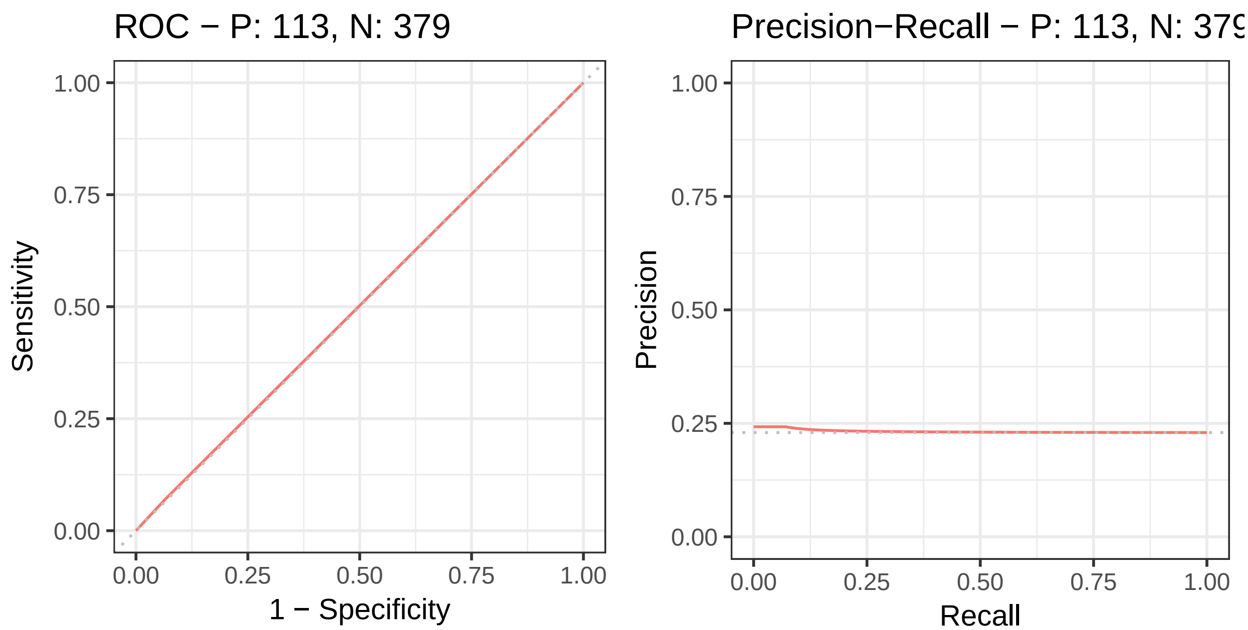





```r
#2
t_C1_C3_EC1<-table(C1*C3,EC1)
confusionMatrix(t_C1_C3_EC1)
```

```
## Confusion Matrix and Statistics
##
##    EC1
##       0   1
##   0 354 105
##   1  25   8
##
##                Accuracy : 0.7358
##                  95% CI : (0.6945, 0.7742)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.9681
##
##                   Kappa : 0.0064
##  Mcnemar's Test P-Value : 4.246e-12
##
##             Sensitivity : 0.9340
##             Specificity : 0.0708
##          Pos Pred Value : 0.7712
##          Neg Pred Value : 0.2424
##              Prevalence : 0.7703
##          Detection Rate : 0.7195
##    Detection Prevalence : 0.9329
##       Balanced Accuracy : 0.5024
##
##        'Positive' Class : 0
##
```

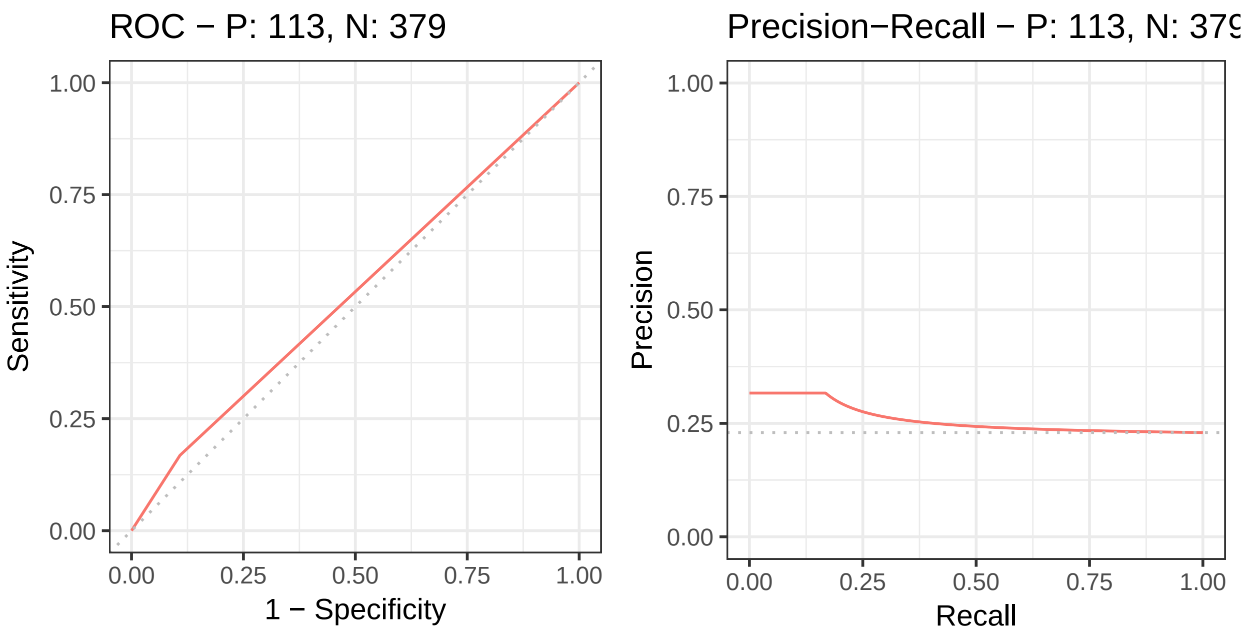
```r
sscurves13_1<- evalmod(scores = C1*C3, labels = EC1)
autoplot(sscurves13_1)
```




```r
#3
t_C1_C4_EC1<-table(C1*C4,EC1)
confusionMatrix(t_C1_C4_EC1)
```

```
## Confusion Matrix and Statistics
##
##    EC1
##       0   1
##   0 338  94
##   1  41  19
##
##                Accuracy : 0.7256
##                  95% CI : (0.6839, 0.7646)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.9911
##
##                   Kappa : 0.0718
##  Mcnemar's Test P-Value : 7.625e-06
##
##             Sensitivity : 0.8918
##             Specificity : 0.1681
##          Pos Pred Value : 0.7824
##          Neg Pred Value : 0.3167
##              Prevalence : 0.7703
##          Detection Rate : 0.6870
##    Detection Prevalence : 0.8780
##       Balanced Accuracy : 0.5300
##
##        'Positive' Class : 0
##
```

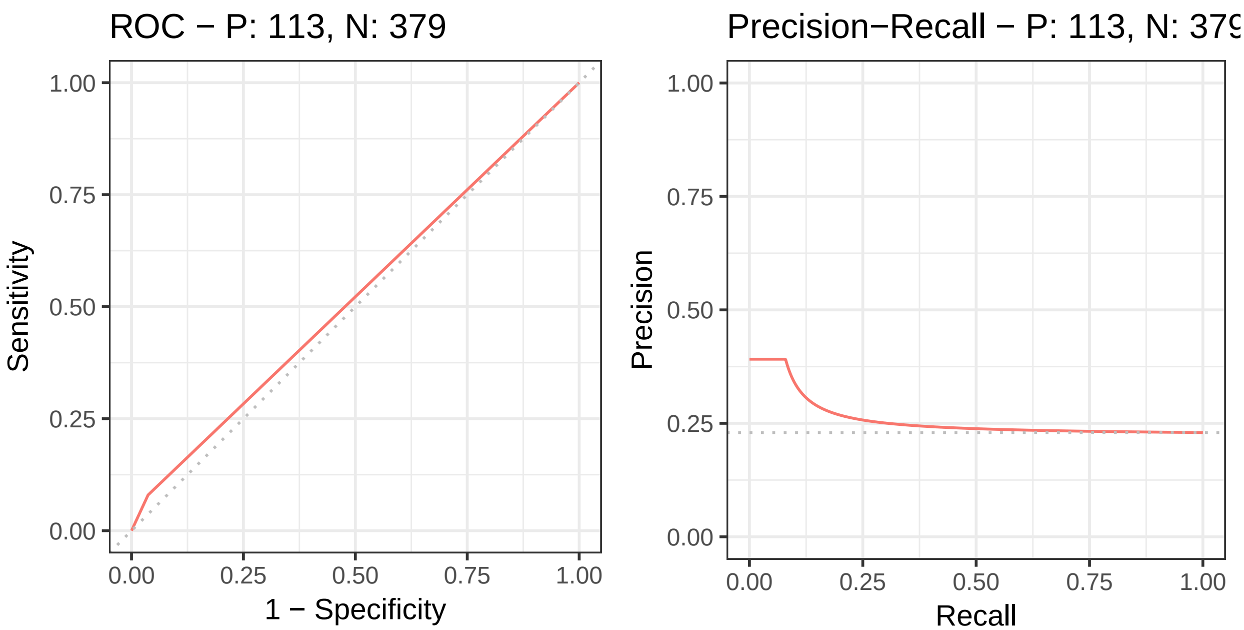
```r
sscurves14_1<- evalmod(scores = C1*C4, labels = EC1)
autoplot(sscurves14_1)
```




```r
#4
t_C2_C3_EC1<-table(C2*C3,EC1)
confusionMatrix(t_C2_C3_EC1)
```

```
## Confusion Matrix and Statistics
##
##    EC1
##       0   1
##   0 365 104
##   1  14   9
##
##                Accuracy : 0.7602
##                  95% CI : (0.7199, 0.7972)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.7243
##
##                   Kappa : 0.0593
##  Mcnemar's Test P-Value : 2.546e-16
##
##             Sensitivity : 0.96306
##             Specificity : 0.07965
##          Pos Pred Value : 0.77825
##          Neg Pred Value : 0.39130
##              Prevalence : 0.77033
##          Detection Rate : 0.74187
##    Detection Prevalence : 0.95325
##       Balanced Accuracy : 0.52135
##
##        'Positive' Class : 0
##
```

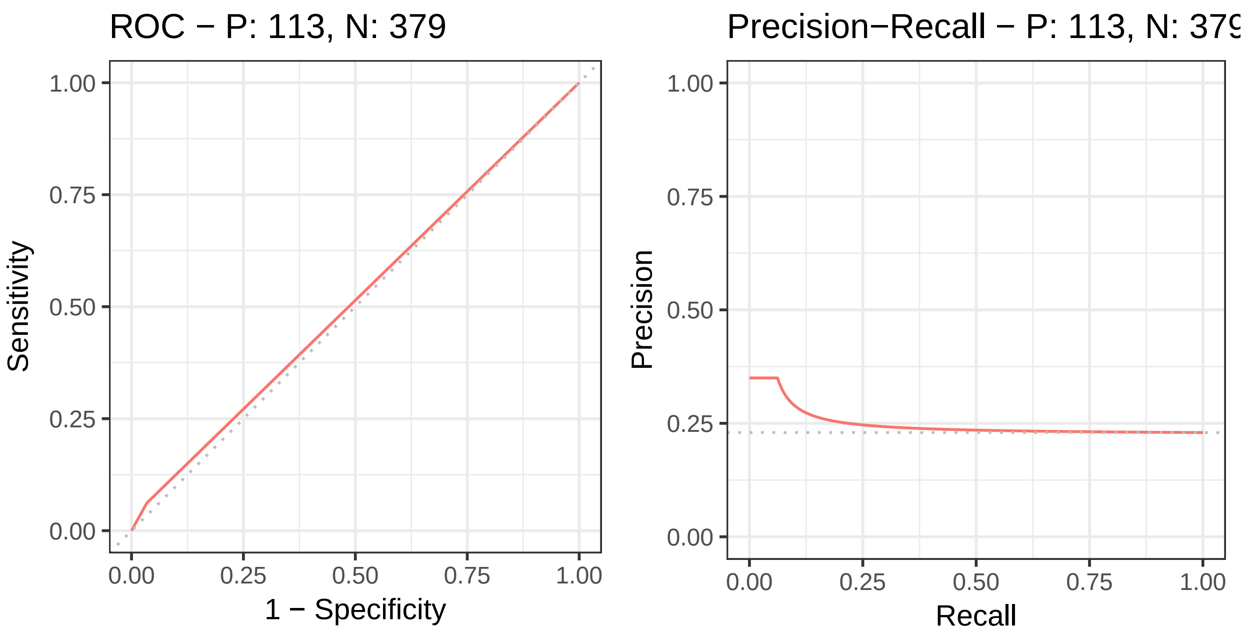
```r
sscurves23_1<- evalmod(scores = C2*C3, labels = EC1)
autoplot(sscurves23_1)
```




```
#5
t_C2_C4_EC1<-table(C2*C4,EC1)
confusionMatrix(t_C2_C4_EC1)
```

```
## Confusion Matrix and Statistics
##
##    EC1
##       0   1
##   0 366 106
##   1  13   7
##
##                Accuracy : 0.7581
##                  95% CI : (0.7178, 0.7953)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.7585
##
##                   Kappa : 0.0389
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.96570
##             Specificity : 0.06195
##          Pos Pred Value : 0.77542
##          Neg Pred Value : 0.35000
##              Prevalence : 0.77033
##          Detection Rate : 0.74390
##    Detection Prevalence : 0.95935
##       Balanced Accuracy : 0.51382
##
##        'Positive' Class : 0
##
```

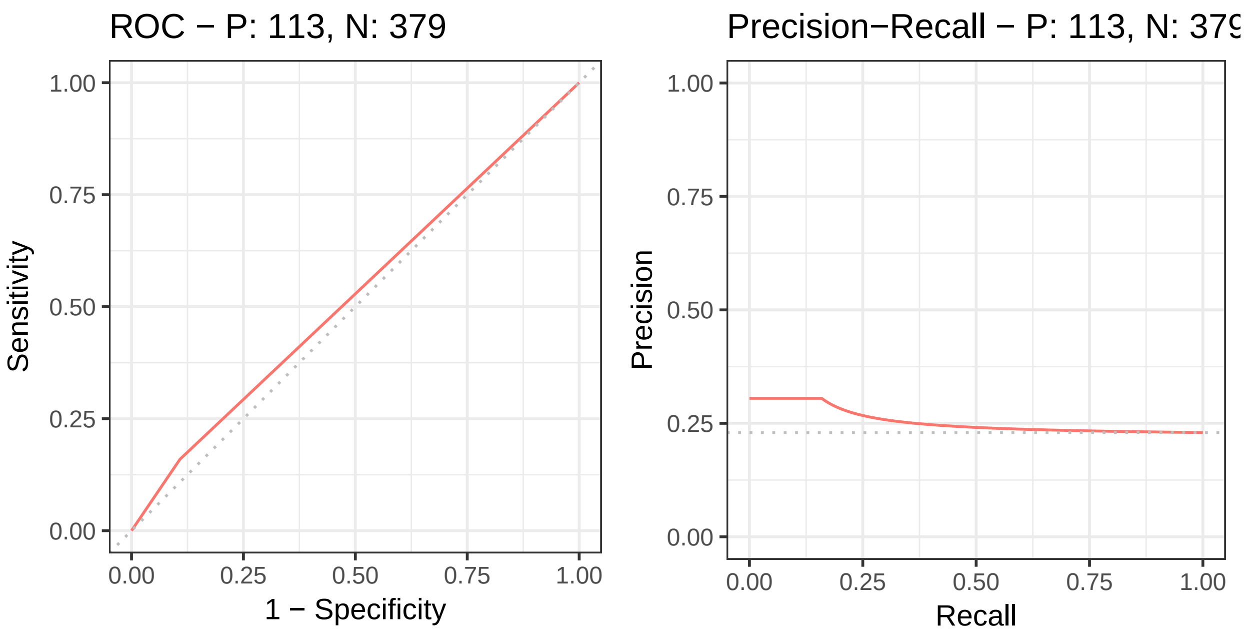
```
sscurves24_1<- evalmod(scores = C2*C4, labels = EC1)
autoplot(sscurves24_1)
```




```r
#6
t_C3_C4_EC1<-table(C3*C4,EC1)
confusionMatrix(t_C3_C4_EC1)
```

```
## Confusion Matrix and Statistics
##
##    EC1
##       0   1
##   0 338  95
##   1  41  18
##
##                Accuracy : 0.7236
##                  95% CI : (0.6818, 0.7627)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.9933
##
##                   Kappa : 0.0614
##  Mcnemar's Test P-Value : 5.501e-06
##
##             Sensitivity : 0.8918
##             Specificity : 0.1593
##          Pos Pred Value : 0.7806
##          Neg Pred Value : 0.3051
##              Prevalence : 0.7703
##          Detection Rate : 0.6870
##    Detection Prevalence : 0.8801
##       Balanced Accuracy : 0.5256
##
##        'Positive' Class : 0
##
```

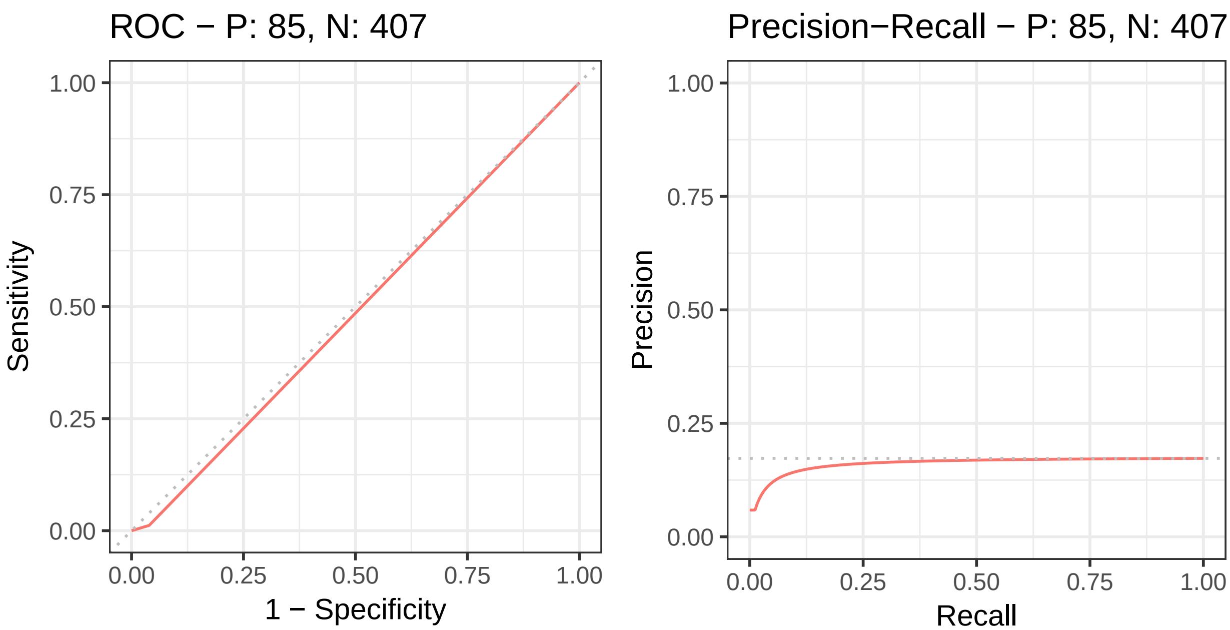
```r
sscurves34_1<- evalmod(scores = C3*C4, labels = EC1)
autoplot(sscurves34_1)
```




```
###C1_C2 and EC2
#1
t_C1_C2_EC2<-table(C1*C2,EC2)
confusionMatrix(t_C1_C2_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
##       0   1
##   0 391  84
##   1  16   1
##
##                Accuracy : 0.7967
##                  95% CI : (0.7584, 0.8314)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 0.9656
##
##                   Kappa : -0.0403
##  Mcnemar's Test P-Value : 2.084e-11
##
##             Sensitivity : 0.96069
##             Specificity : 0.01176
##          Pos Pred Value : 0.82316
##          Neg Pred Value : 0.05882
##              Prevalence : 0.82724
##          Detection Rate : 0.79472
##    Detection Prevalence : 0.96545
##       Balanced Accuracy : 0.48623
##
##        'Positive' Class : 0
##
```

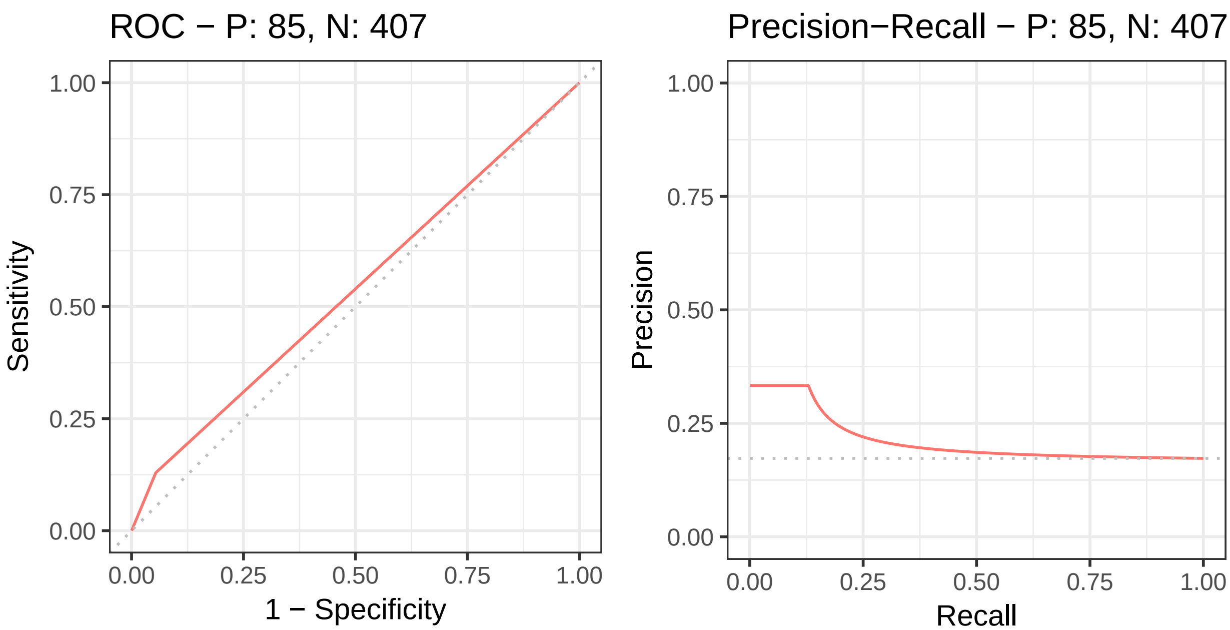
```
sscurves12_2<- evalmod(scores = C1*C2, labels = EC2)
autoplot(sscurves12_2)
```




```r
#2
t_C1_C3_EC2<-table(C1*C3,EC2)
confusionMatrix(t_C1_C3_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
##       0   1
##   0 385  74
##   1  22  11
##
##                Accuracy : 0.8049
##                  95% CI : (0.7671, 0.839)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 0.9132
##
##                   Kappa : 0.0994
##  Mcnemar's Test P-Value : 1.938e-07
##
##             Sensitivity : 0.9459
##             Specificity : 0.1294
##          Pos Pred Value : 0.8388
##          Neg Pred Value : 0.3333
##              Prevalence : 0.8272
##          Detection Rate : 0.7825
##    Detection Prevalence : 0.9329
##       Balanced Accuracy : 0.5377
##
##        'Positive' Class : 0
##
```

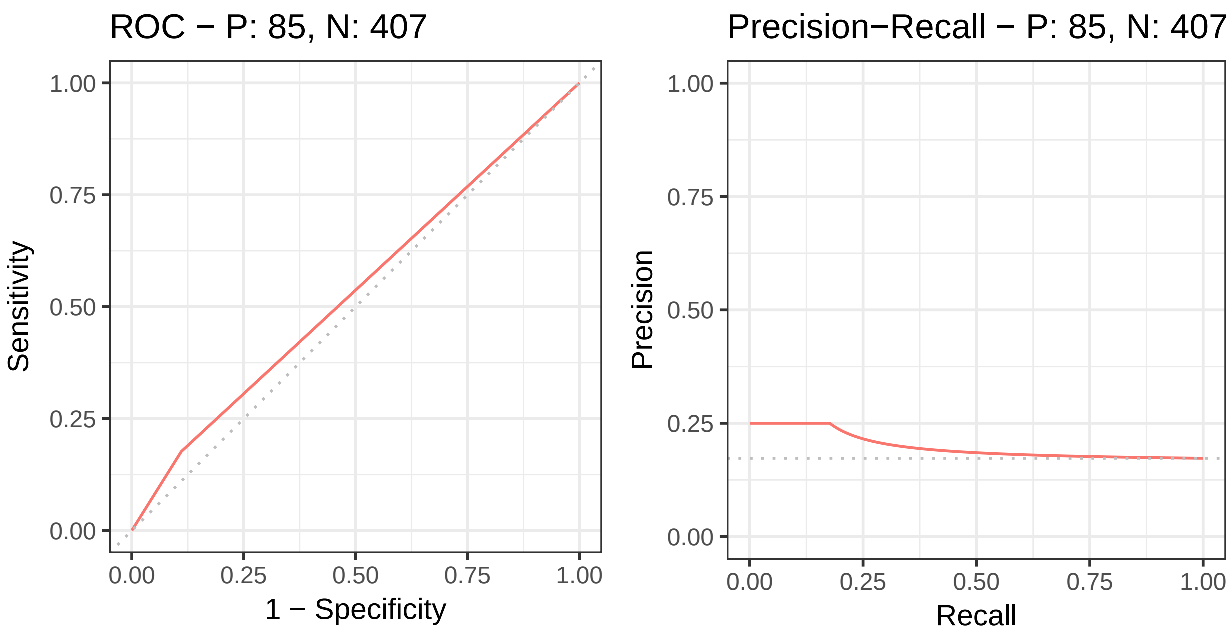
```r
sscurves13_2<- evalmod(scores = C1*C3, labels = EC2)
autoplot(sscurves13_2)
```




```r
#3
t_C1_C4_EC2<-table(C1*C4,EC2)
confusionMatrix(t_C1_C4_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
##       0   1
##   0 362  70
##   1  45  15
##
##                Accuracy : 0.7663
##                  95% CI : (0.7263, 0.803)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 0.99977
##
##                   Kappa : 0.0746
##  Mcnemar's Test P-Value : 0.02522
##
##             Sensitivity : 0.8894
##             Specificity : 0.1765
##          Pos Pred Value : 0.8380
##          Neg Pred Value : 0.2500
##              Prevalence : 0.8272
##          Detection Rate : 0.7358
##    Detection Prevalence : 0.8780
##       Balanced Accuracy : 0.5330
##
##        'Positive' Class : 0
##
```

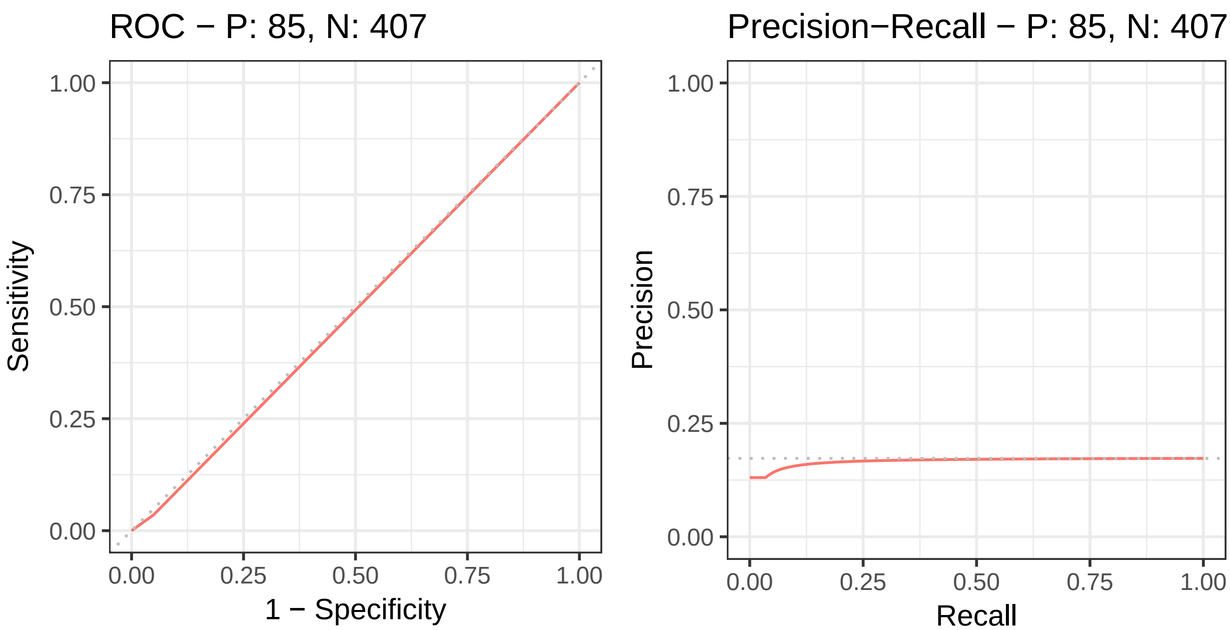
```r
sscurves14_2<- evalmod(scores = C1*C4, labels = EC2)
autoplot(sscurves14_2)
```




```
#4
t_C2_C3_EC2<-table(C2*C3,EC2)
confusionMatrix(t_C2_C3_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
##       0   1
##   0 387  82
##   1  20   3
##
##                Accuracy : 0.7927
##                  95% CI : (0.7541, 0.8277)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 0.9797
##
##                   Kappa : -0.0195
##  Mcnemar's Test P-Value : 1.542e-09
##
##             Sensitivity : 0.95086
##             Specificity : 0.03529
##          Pos Pred Value : 0.82516
##          Neg Pred Value : 0.13043
##              Prevalence : 0.82724
##          Detection Rate : 0.78659
##    Detection Prevalence : 0.95325
##       Balanced Accuracy : 0.49308
##
##        'Positive' Class : 0
##
```

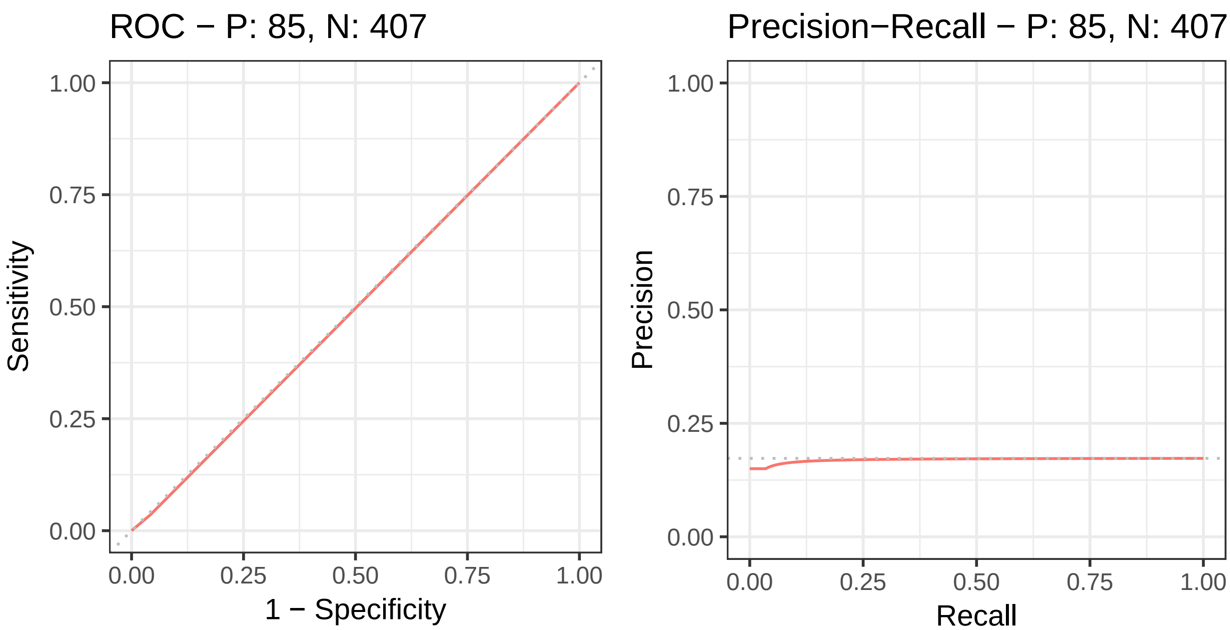
```
sscurves23_2<- evalmod(scores = C2*C3, labels = EC2)
autoplot(sscurves23_2)
```




```r
#5
t_C2_C4_EC2<-table(C2*C4,EC2)
confusionMatrix(t_C2_C4_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
##       0   1
##   0 390  82
##   1  17   3
##
##                Accuracy : 0.7988
##                  95% CI : (0.7606, 0.8333)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 0.956
##
##                   Kappa : -0.0093
##  Mcnemar's Test P-Value : 1.257e-10
##
##             Sensitivity : 0.95823
##             Specificity : 0.03529
##          Pos Pred Value : 0.82627
##          Neg Pred Value : 0.15000
##              Prevalence : 0.82724
##          Detection Rate : 0.79268
##    Detection Prevalence : 0.95935
##       Balanced Accuracy : 0.49676
##
##        'Positive' Class : 0
##
```

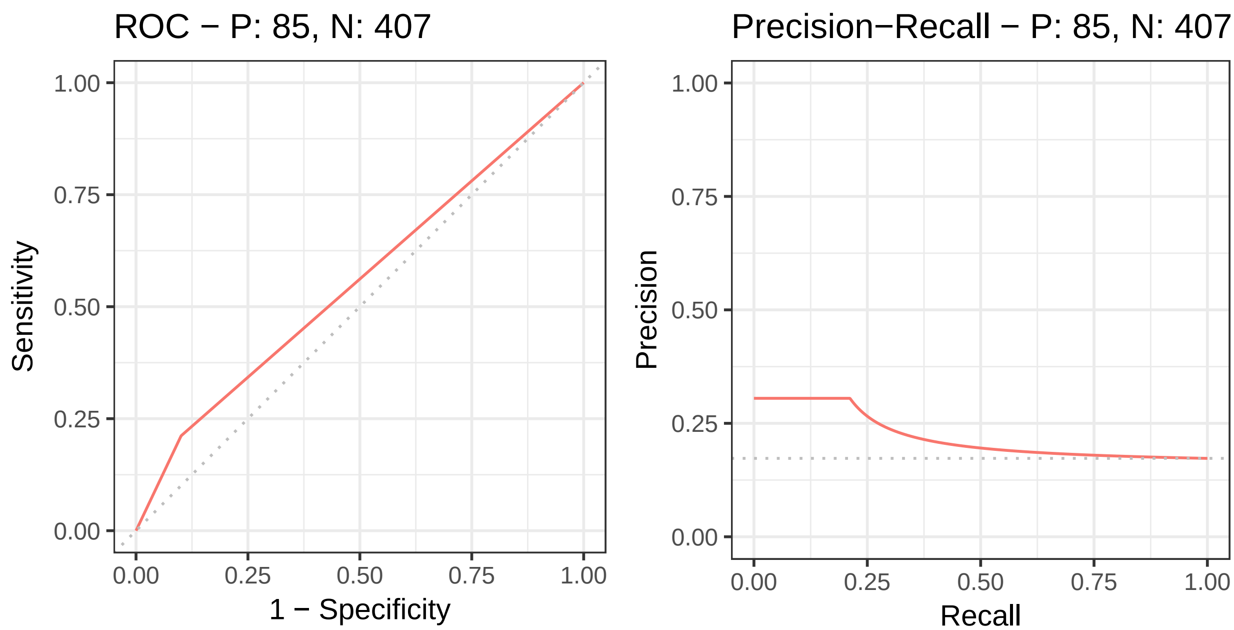
```r
sscurves24_2<- evalmod(scores = C2*C4, labels = EC2)
autoplot(sscurves24_2)
```




```r
#6
t_C3_C4_EC2<-table(C3*C4,EC2)
confusionMatrix(t_C3_C4_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
##       0   1
##   0 366  67
##   1  41  18
##
##                Accuracy : 0.7805
##                  95% CI : (0.7413, 0.8163)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 0.99677
##
##                   Kappa : 0.1263
##  Mcnemar's Test P-Value : 0.01614
##
##             Sensitivity : 0.8993
##             Specificity : 0.2118
##          Pos Pred Value : 0.8453
##          Neg Pred Value : 0.3051
##              Prevalence : 0.8272
##          Detection Rate : 0.7439
##    Detection Prevalence : 0.8801
##       Balanced Accuracy : 0.5555
##
##        'Positive' Class : 0
##
```

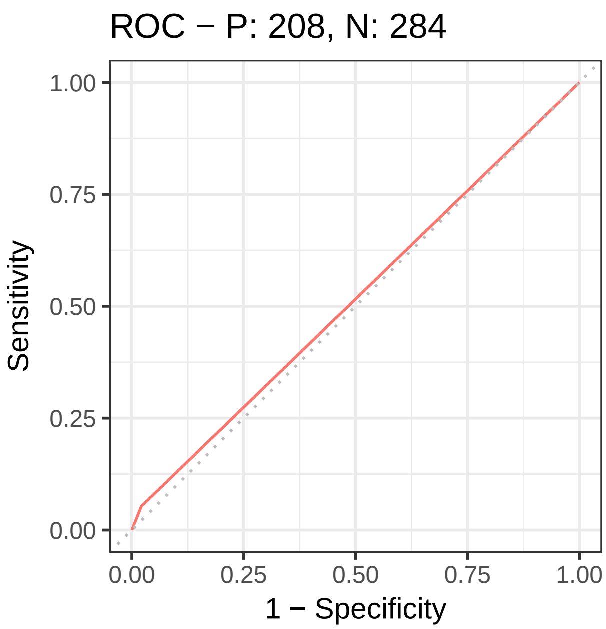
```r
sscurves34_2<- evalmod(scores = C3*C4, labels = EC2)
autoplot(sscurves34_2)
```

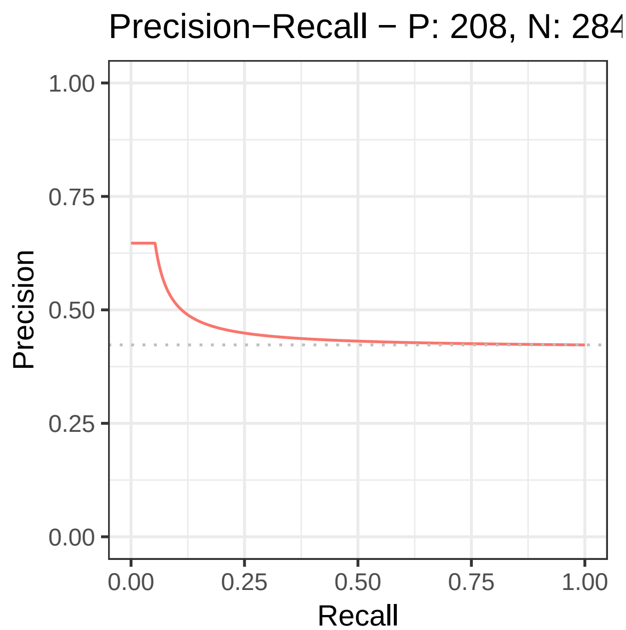



```r
###C1_C2 and EC3
#1
t_C1_C2_EC3<-table(C1*C2,EC3)
confusionMatrix(t_C1_C2_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
##       0   1
##   0 278 197
##   1   6  11
##
##                Accuracy : 0.5874
##                  95% CI : (0.5425, 0.6313)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.3414
##
##                   Kappa : 0.0362
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.97887
##             Specificity : 0.05288
##          Pos Pred Value : 0.58526
##          Neg Pred Value : 0.64706
##              Prevalence : 0.57724
##          Detection Rate : 0.56504
##    Detection Prevalence : 0.96545
##       Balanced Accuracy : 0.51588
##
##        'Positive' Class : 0
##
```

```r
sscurves12_3<- evalmod(scores = C1*C2, labels = EC3)
autoplot(sscurves12_3)
```

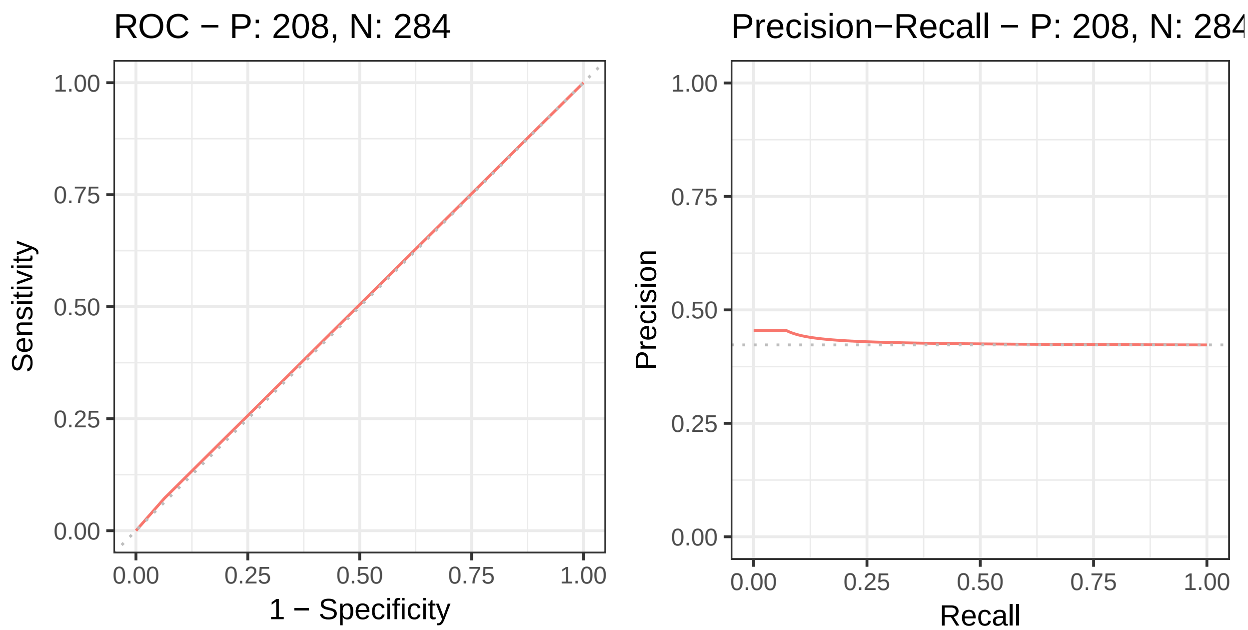





```r
#2
t_C1_C3_EC3<-table(C1*C3,EC3)
confusionMatrix(t_C1_C3_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
##       0   1
##   0 266 193
##   1  18  15
##
##                Accuracy : 0.5711
##                  95% CI : (0.5261, 0.6153)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.6261
##
##                   Kappa : 0.0098
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.93662
##             Specificity : 0.07212
##          Pos Pred Value : 0.57952
##          Neg Pred Value : 0.45455
##              Prevalence : 0.57724
##          Detection Rate : 0.54065
##    Detection Prevalence : 0.93293
##       Balanced Accuracy : 0.50437
##
##        'Positive' Class : 0
##
```

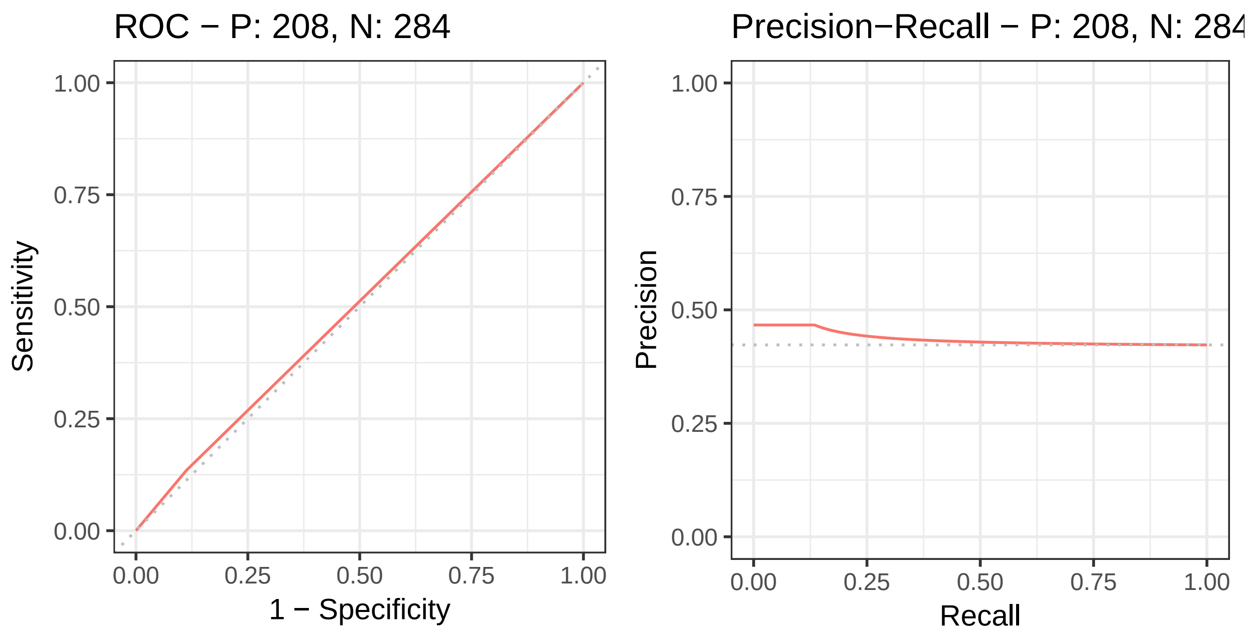
```r
sscurves13_3<- evalmod(scores = C1*C3, labels = EC3)
autoplot(sscurves13_3)
```




```
#3
t_C1_C4_EC3<-table(C1*C4,EC3)
confusionMatrix(t_C1_C4_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
##       0   1
##   0 252 180
##   1  32  28
##
##                Accuracy : 0.5691
##                  95% CI : (0.524, 0.6133)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.66
##
##                   Kappa : 0.0242
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.8873
##             Specificity : 0.1346
##          Pos Pred Value : 0.5833
##          Neg Pred Value : 0.4667
##              Prevalence : 0.5772
##          Detection Rate : 0.5122
##    Detection Prevalence : 0.8780
##       Balanced Accuracy : 0.5110
##
##        'Positive' Class : 0
##
```

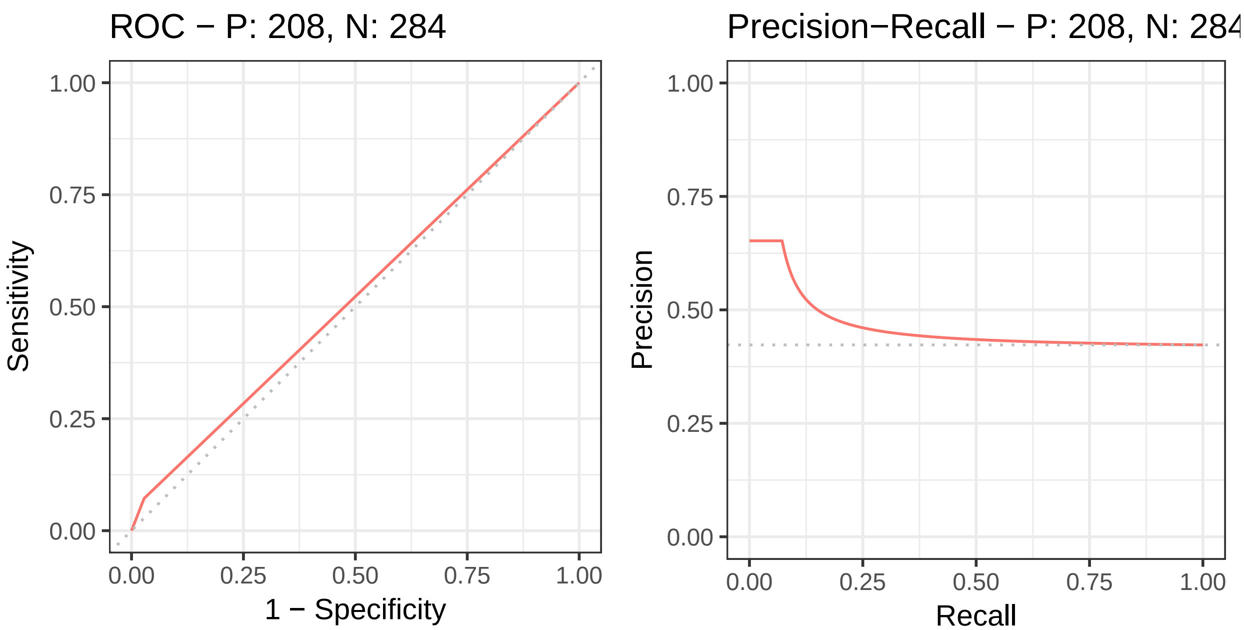
```
sscurves14_3<- evalmod(scores = C1*C4, labels = EC3)
autoplot(sscurves14_3)
```




```r
#4
t_C2_C3_EC3<-table(C2*C3,EC3)
confusionMatrix(t_C2_C3_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
##       0   1
##   0 276 193
##   1   8  15
##
##                Accuracy : 0.5915
##                  95% CI : (0.5466, 0.6353)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.2771
##
##                   Kappa : 0.0499
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.97183
##             Specificity : 0.07212
##          Pos Pred Value : 0.58849
##          Neg Pred Value : 0.65217
##              Prevalence : 0.57724
##          Detection Rate : 0.56098
##    Detection Prevalence : 0.95325
##       Balanced Accuracy : 0.52197
##
##        'Positive' Class : 0
##
```

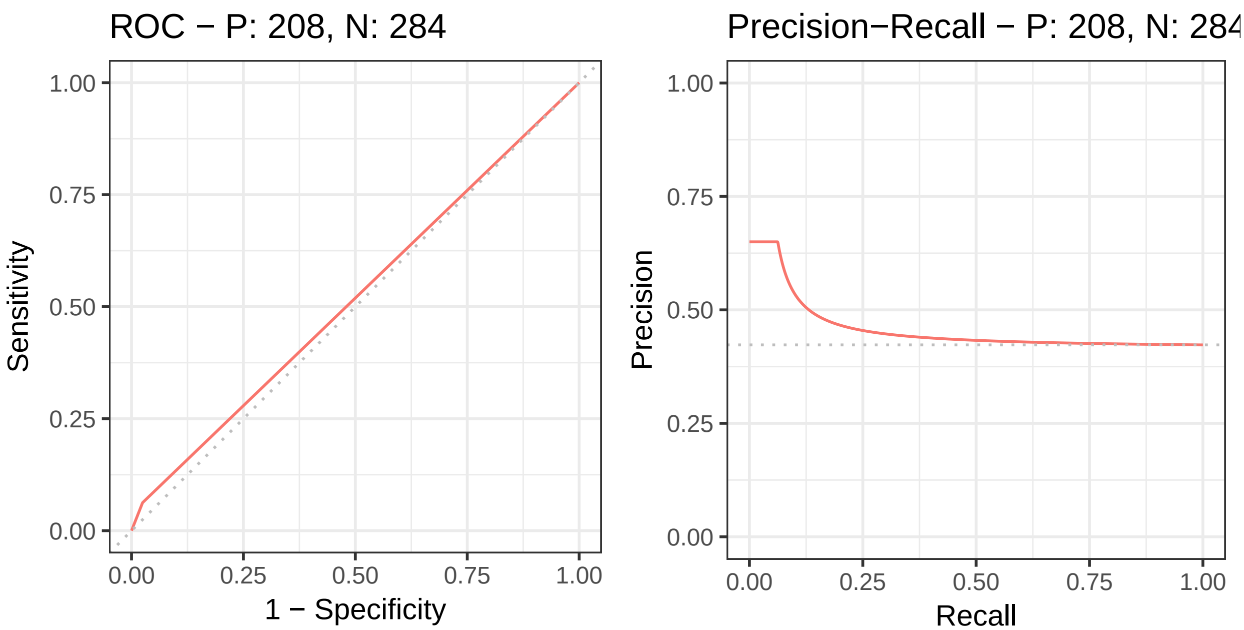
```r
sscurves23_3<- evalmod(scores = C2*C3, labels = EC3)
autoplot(sscurves23_3)
```




```
#5
t_C2_C4_EC3<-table(C2*C4,EC3)
confusionMatrix(t_C2_C4_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
##       0   1
##   0 277 195
##   1   7  13
##
##                Accuracy : 0.5894
##                  95% CI : (0.5445, 0.6333)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.3085
##
##                   Kappa : 0.0431
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9754
##             Specificity : 0.0625
##          Pos Pred Value : 0.5869
##          Neg Pred Value : 0.6500
##              Prevalence : 0.5772
##          Detection Rate : 0.5630
##    Detection Prevalence : 0.9593
##       Balanced Accuracy : 0.5189
##
##        'Positive' Class : 0
##
```

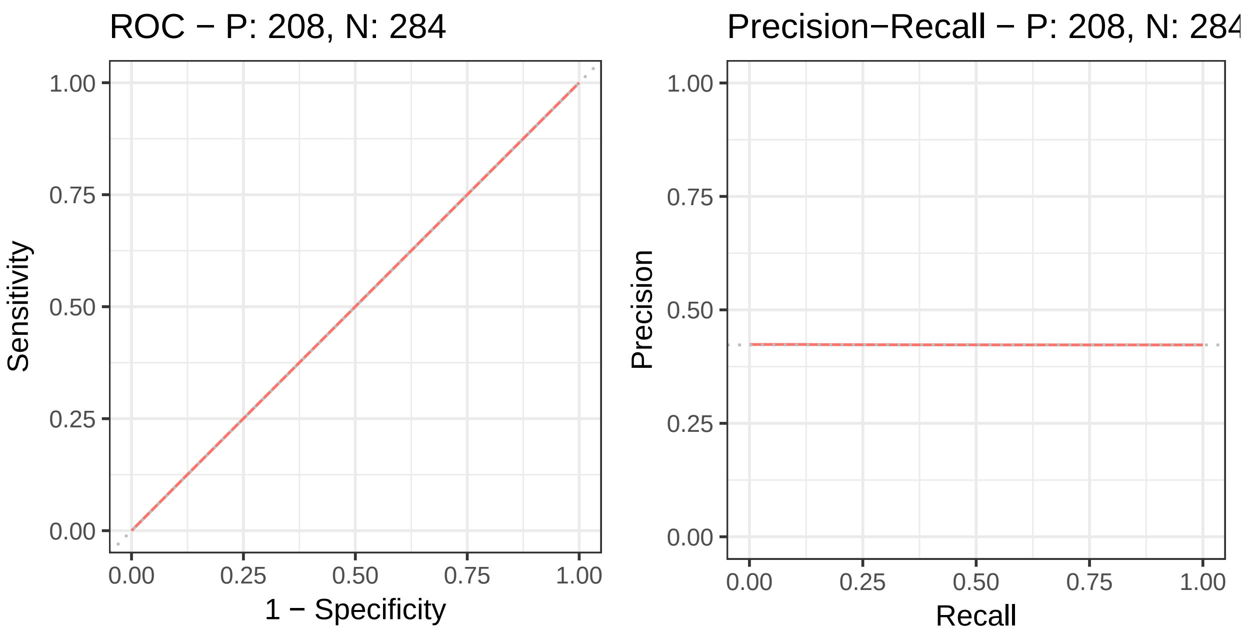
```
sscurves24_3<- evalmod(scores = C2*C4, labels = EC3)
autoplot(sscurves24_3)
```




```
#6
t_C3_C4_EC3<-table(C3*C4,EC3)
confusionMatrix(t_C3_C4_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
##       0   1
##   0 250 183
##   1  34  25
##
##                Accuracy : 0.5589
##                  95% CI : (0.5138, 0.6034)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.8072
##
##                   Kappa : 5e-04
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.8803
##             Specificity : 0.1202
##          Pos Pred Value : 0.5774
##          Neg Pred Value : 0.4237
##              Prevalence : 0.5772
##          Detection Rate : 0.5081
##    Detection Prevalence : 0.8801
##       Balanced Accuracy : 0.5002
##
##        'Positive' Class : 0
##
```

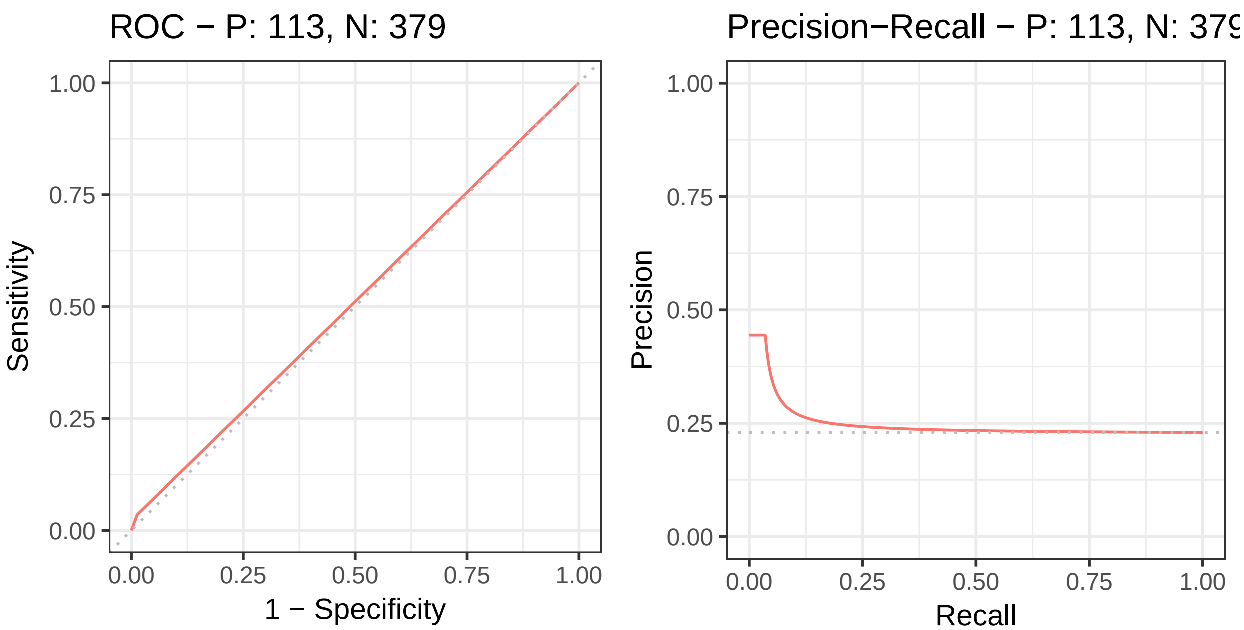
```
sscurves34_3<- evalmod(scores = C3*C4, labels = EC3)
autoplot(sscurves34_3)
```




```
####C1_C2_C3 and EC1
#1
t_C1_C2_C3_EC1<-table(C1*C2*C3,EC1)
confusionMatrix(t_C1_C2_C3_EC1)
```

```
## Confusion Matrix and Statistics
##
##    EC1
##       0   1
##   0 374 109
##   1   5   4
##
##                Accuracy : 0.7683
##                  95% CI : (0.7284, 0.8049)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.5676
##
##                   Kappa : 0.0328
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9868
##             Specificity : 0.0354
##          Pos Pred Value : 0.7743
##          Neg Pred Value : 0.4444
##              Prevalence : 0.7703
##          Detection Rate : 0.7602
##    Detection Prevalence : 0.9817
##       Balanced Accuracy : 0.5111
##
##        'Positive' Class : 0
##
```

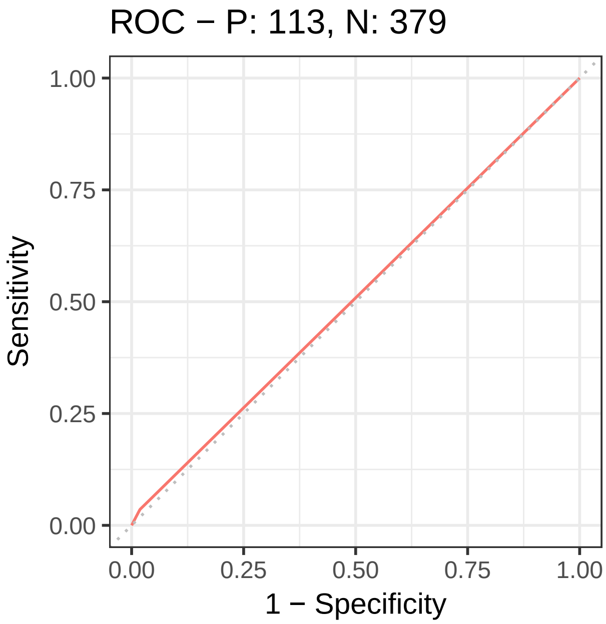
```
sscurves123_1<- evalmod(scores = C1*C2*C3, labels = EC1)
autoplot(sscurves123_1)
```

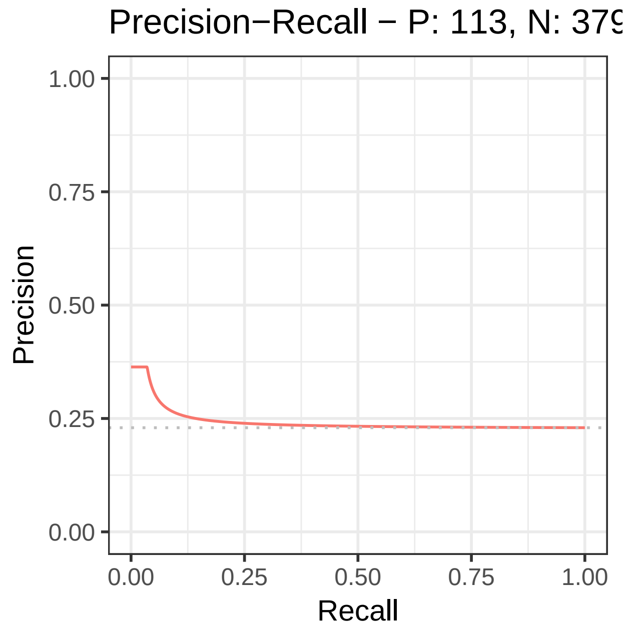



```
#2
t_C1_C2_C4_EC1<-table(C1*C2*C4,EC1)
confusionMatrix(t_C1_C2_C4_EC1)
```

```
## Confusion Matrix and Statistics
##
##    EC1
##       0   1
##   0 372 109
##   1   7   4
##
##                Accuracy : 0.7642
##                  95% CI : (0.7242, 0.8011)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.6493
##
##                   Kappa : 0.0248
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9815
##             Specificity : 0.0354
##          Pos Pred Value : 0.7734
##          Neg Pred Value : 0.3636
##              Prevalence : 0.7703
##          Detection Rate : 0.7561
##    Detection Prevalence : 0.9776
##       Balanced Accuracy : 0.5085
##
##        'Positive' Class : 0
##
```

```
sscurves124_1<- evalmod(scores = C1*C2*C4, labels = EC1)
autoplot(sscurves124_1)
```

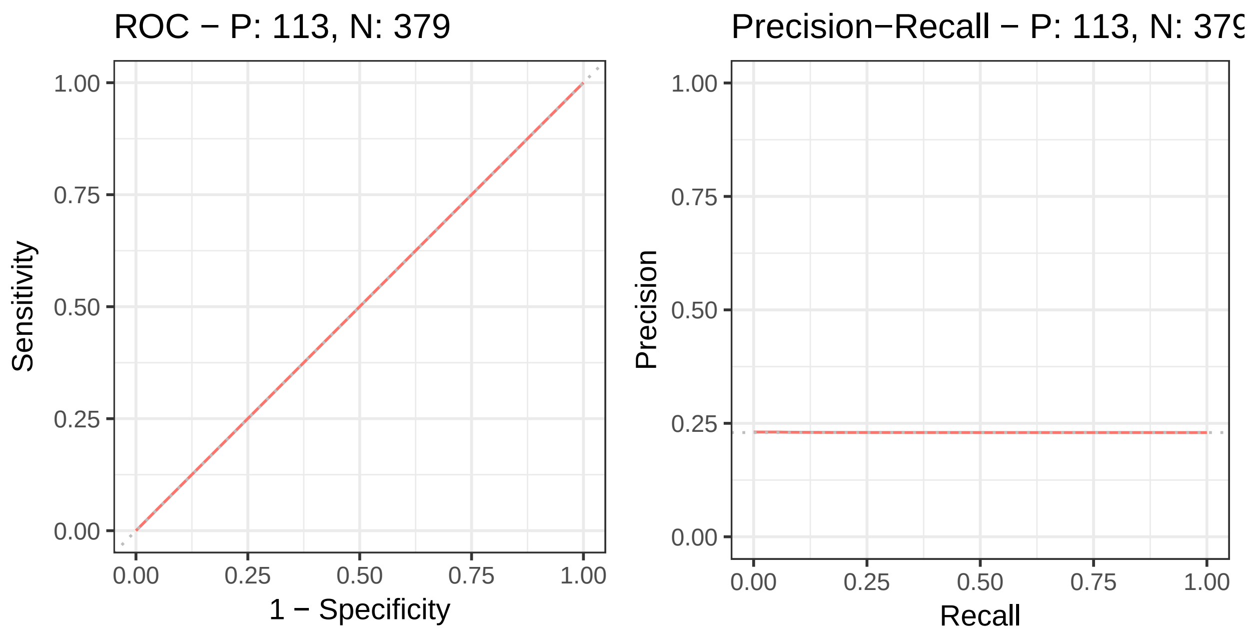





```r
#3
t_C1_C3_C4_EC1<-table(C1*C3*C4,EC1)
confusionMatrix(t_C1_C3_C4_EC1)
```

```
## Confusion Matrix and Statistics
##
##    EC1
##       0   1
##   0 359 107
##   1  20   6
##
##                Accuracy : 0.7419
##                  95% CI : (0.7008, 0.78)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.9384
##
##                   Kappa : 4e-04
##  Mcnemar's Test P-Value : 2.325e-14
##
##             Sensitivity : 0.9472
##             Specificity : 0.0531
##          Pos Pred Value : 0.7704
##          Neg Pred Value : 0.2308
##              Prevalence : 0.7703
##          Detection Rate : 0.7297
##    Detection Prevalence : 0.9472
##       Balanced Accuracy : 0.5002
##
##        'Positive' Class : 0
##
```

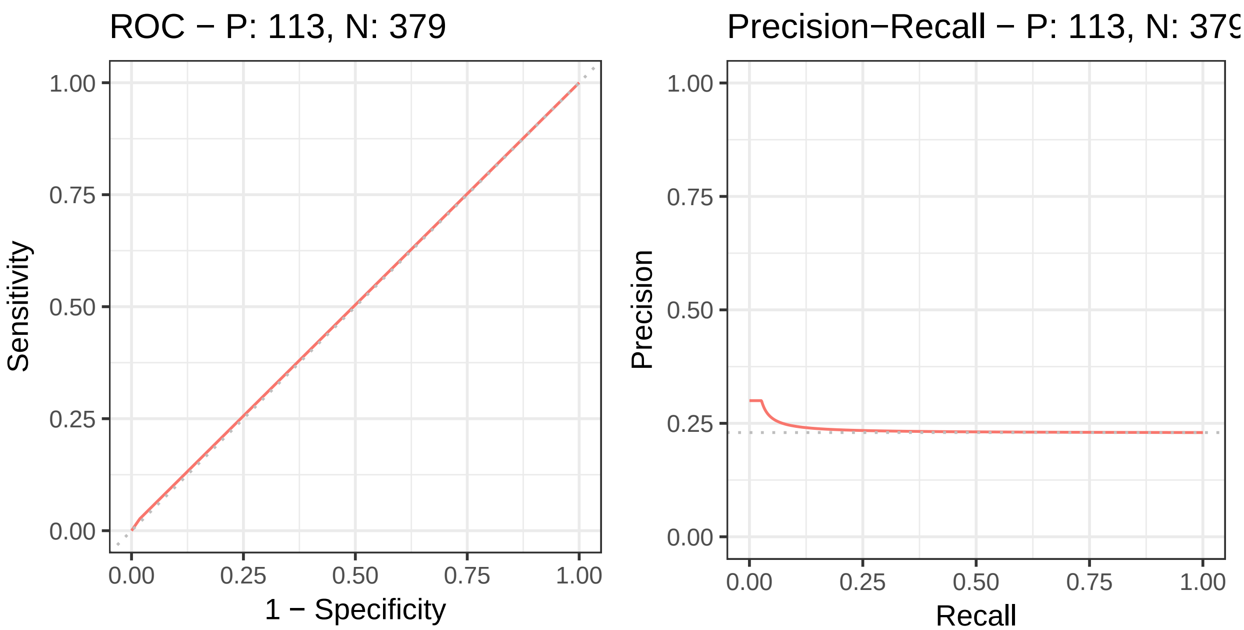
```r
sscurves134_1<- evalmod(scores = C1*C3*C4, labels = EC1)
autoplot(sscurves134_1)
```




```
#4
t_C2_C3_C4_EC1<-table(C2*C3*C4,EC1)
confusionMatrix(t_C2_C3_C4_EC1)
```

```
## Confusion Matrix and Statistics
##
##    EC1
##       0   1
##   0 372 110
##   1   7   3
##
##                Accuracy : 0.7622
##                  95% CI : (0.722, 0.7992)
##     No Information Rate : 0.7703
##     P-Value [Acc > NIR] : 0.6878
##
##                   Kappa : 0.0119
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.98153
##             Specificity : 0.02655
##          Pos Pred Value : 0.77178
##          Neg Pred Value : 0.30000
##              Prevalence : 0.77033
##          Detection Rate : 0.75610
##    Detection Prevalence : 0.97967
##       Balanced Accuracy : 0.50404
##
##        'Positive' Class : 0
##
```

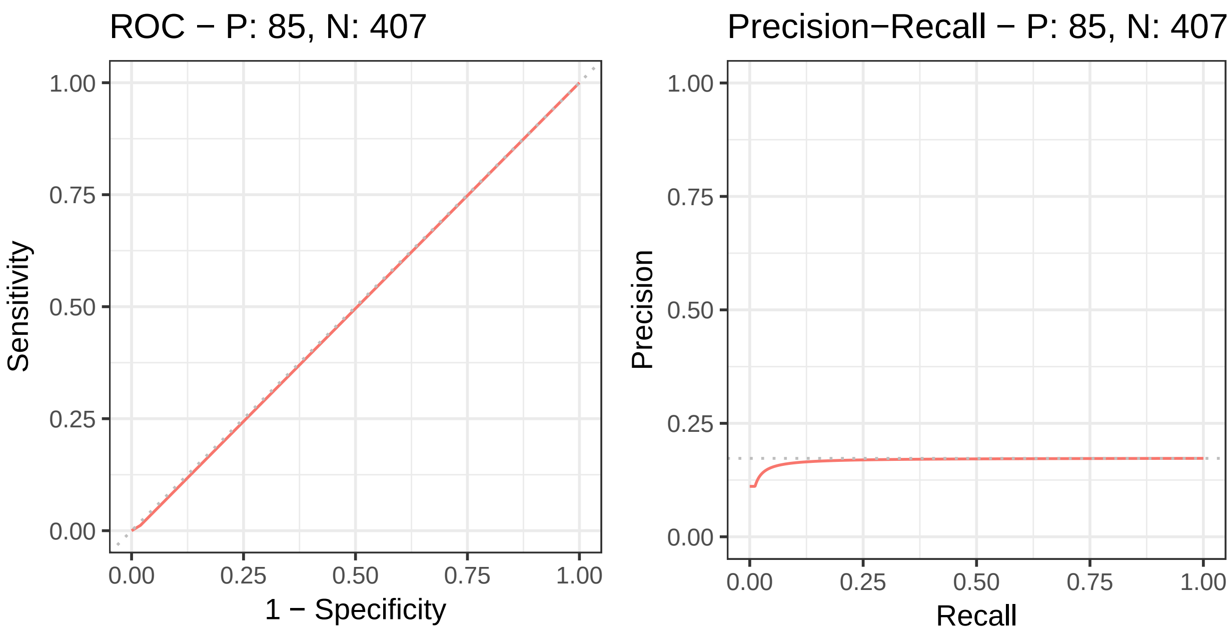
```
sscurves234_1<- evalmod(scores = C2*C3*C4, labels = EC1)
autoplot(sscurves234_1)
```




```
####C1_C2_C3 and EC2
#1
t_C1_C2_C3_EC2<-table(C1*C2*C3,EC2)
confusionMatrix(t_C1_C2_C3_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
##       0   1
##   0 399  84
##   1   8   1
##
##                Accuracy : 0.813
##                  95% CI : (0.7757, 0.8465)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 0.8152
##
##                   Kappa : -0.0122
##  Mcnemar's Test P-Value : 5.312e-15
##
##             Sensitivity : 0.98034
##             Specificity : 0.01176
##          Pos Pred Value : 0.82609
##          Neg Pred Value : 0.11111
##              Prevalence : 0.82724
##          Detection Rate : 0.81098
##    Detection Prevalence : 0.98171
##       Balanced Accuracy : 0.49605
##
##        'Positive' Class : 0
##
```

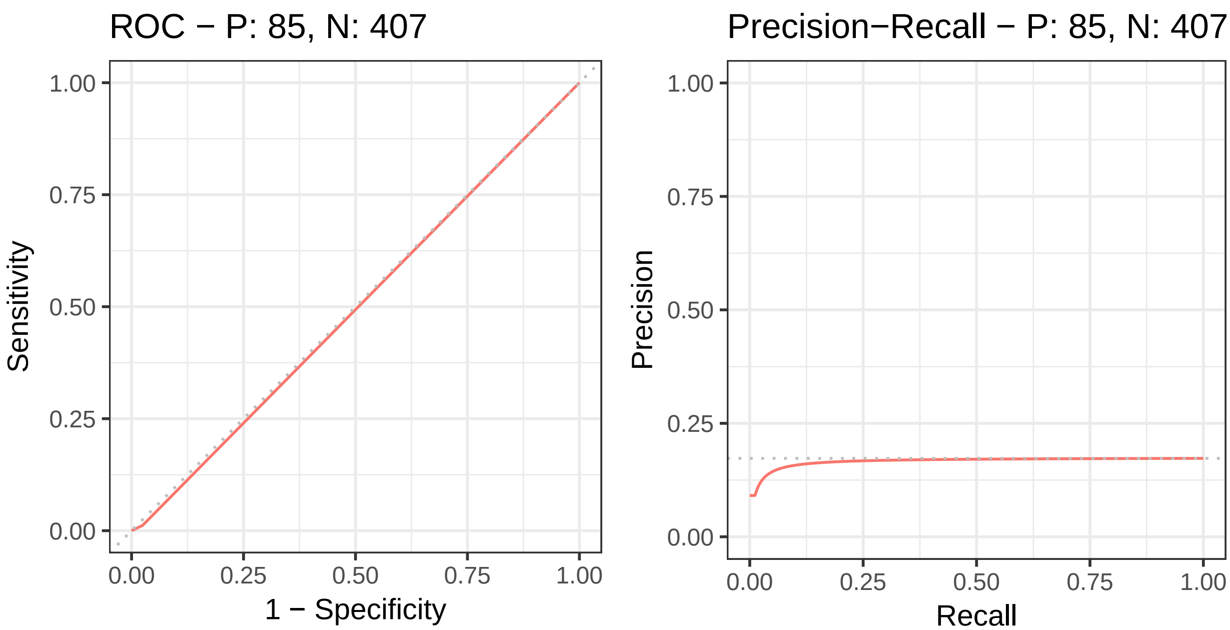
```
sscurves123_2<- evalmod(scores = C1*C2*C3, labels = EC2)
autoplot(sscurves123_2)
```




```r
#2
t_C1_C2_C4_EC2<-table(C1*C2*C4,EC2)
confusionMatrix(t_C1_C2_C4_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
##       0   1
##   0 397  84
##   1  10   1
##
##                Accuracy : 0.8089
##                  95% CI : (0.7714, 0.8428)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 0.8707
##
##                   Kappa : -0.0195
##  Mcnemar's Test P-Value : 5.098e-14
##
##             Sensitivity : 0.97543
##             Specificity : 0.01176
##          Pos Pred Value : 0.82536
##          Neg Pred Value : 0.09091
##              Prevalence : 0.82724
##          Detection Rate : 0.80691
##    Detection Prevalence : 0.97764
##       Balanced Accuracy : 0.49360
##
##        'Positive' Class : 0
##
```

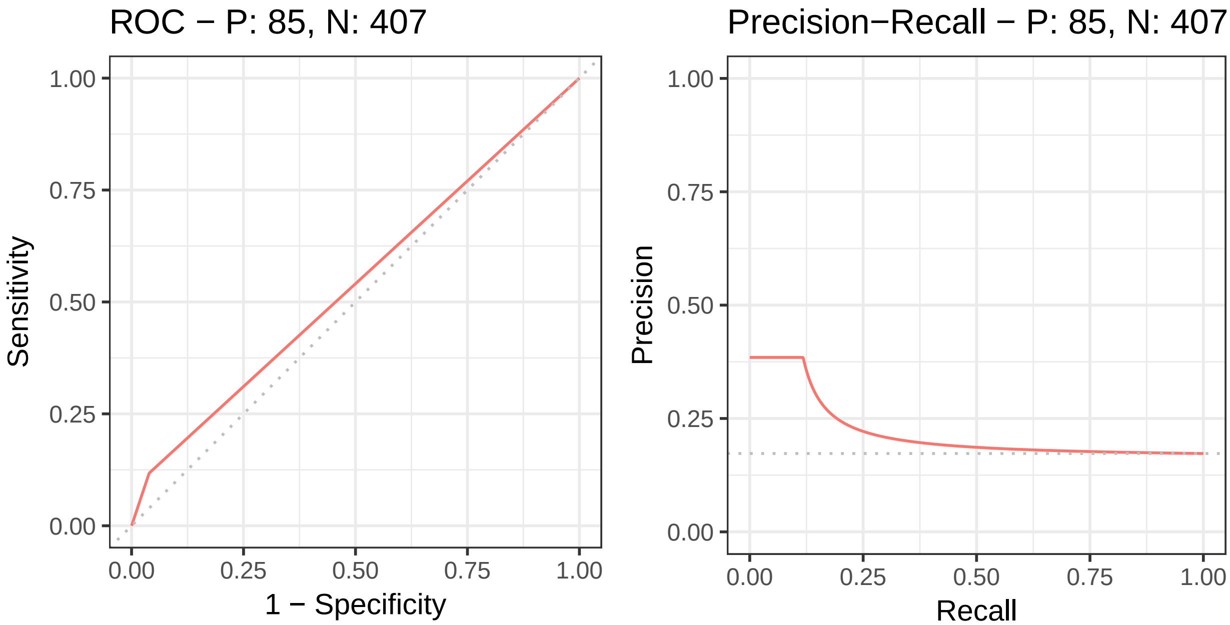
```r
sscurves124_2<- evalmod(scores = C1*C2*C4, labels = EC2)
autoplot(sscurves124_2)
```




```r
#3
t_C1_C3_C4_EC2<-table(C1*C3*C4,EC2)
confusionMatrix(t_C1_C3_C4_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
##       0   1
##   0 391  75
##   1  16  10
##
##                Accuracy : 0.815
##                  95% CI : (0.7779, 0.8484)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 0.7824
##
##                   Kappa : 0.108
##  Mcnemar's Test P-Value : 1.201e-09
##
##             Sensitivity : 0.9607
##             Specificity : 0.1176
##          Pos Pred Value : 0.8391
##          Neg Pred Value : 0.3846
##              Prevalence : 0.8272
##          Detection Rate : 0.7947
##    Detection Prevalence : 0.9472
##       Balanced Accuracy : 0.5392
##
##        'Positive' Class : 0
##
```

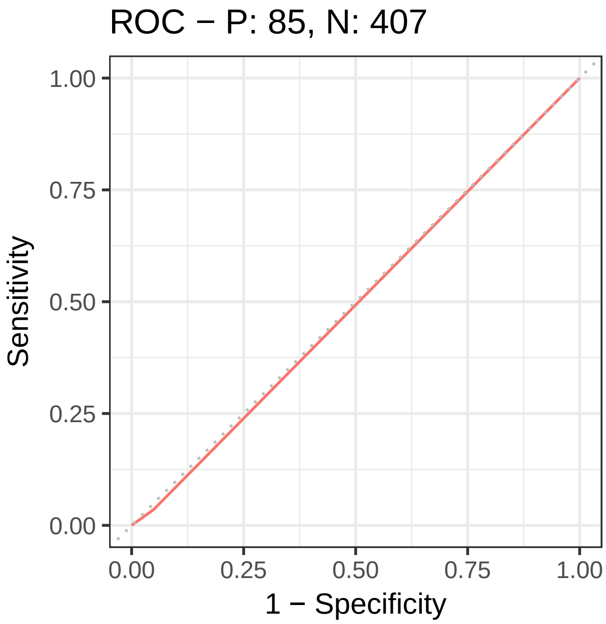
```r
sscurves134_2<- evalmod(scores = C1*C3*C4, labels = EC2)
autoplot(sscurves134_2)
```

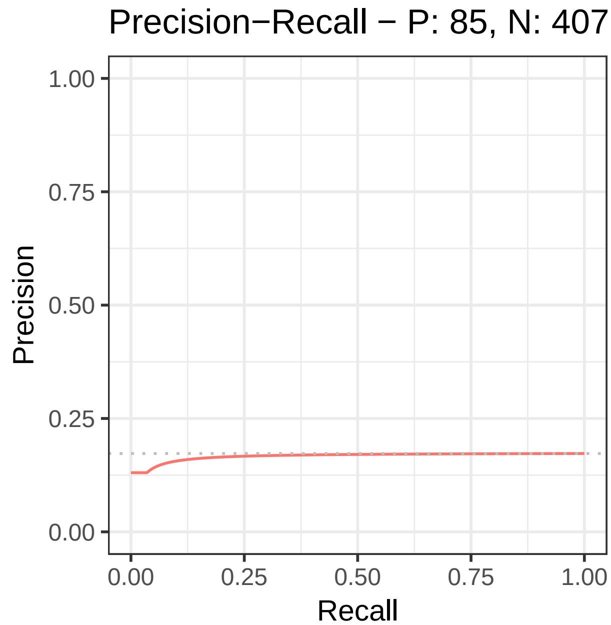



```r
#4
t_C2_C3_C4_EC2<-table(C2*C3*C4,EC2)
confusionMatrix(t_C2_C3_C4_EC2)
```

```
## Confusion Matrix and Statistics
##
##    EC2
##       0   1
##   0 399  83
##   1   8   2
##
##                Accuracy : 0.815
##                  95% CI : (0.7779, 0.8484)
##     No Information Rate : 0.8272
##     P-Value [Acc > NIR] : 0.7824
##
##                   Kappa : 0.006
##  Mcnemar's Test P-Value : 8.675e-15
##
##             Sensitivity : 0.98034
##             Specificity : 0.02353
##          Pos Pred Value : 0.82780
##          Neg Pred Value : 0.20000
##              Prevalence : 0.82724
##          Detection Rate : 0.81098
##    Detection Prevalence : 0.97967
##       Balanced Accuracy : 0.50194
##
##        'Positive' Class : 0
##
```

```r
sscurves234_2<- evalmod(scores = C2*C3*C2, labels = EC2)
autoplot(sscurves234_2)
```

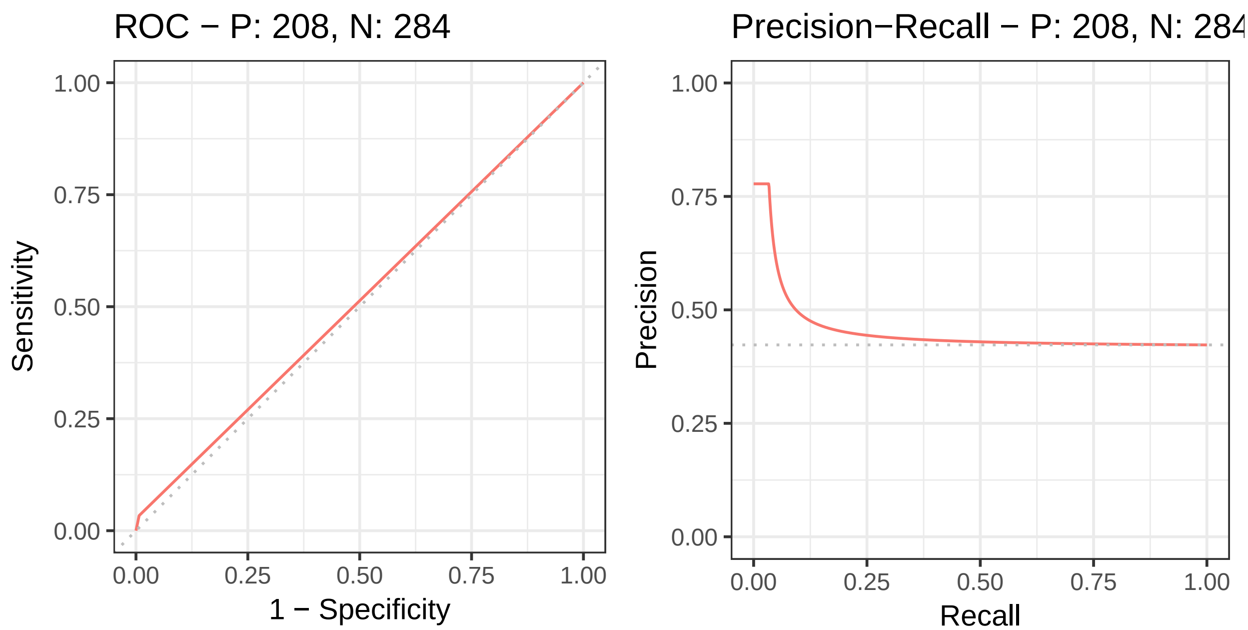





```r
####C1_C2_C3 and EC3
#1
t_C1_C2_C3_EC3<-table(C1*C2*C3,EC3)
confusionMatrix(t_C1_C2_C3_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
##       0   1
##   0 282 201
##   1   2   7
##
##                Accuracy : 0.5874
##                  95% CI : (0.5425, 0.6313)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.3414
##
##                   Kappa : 0.0305
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.99296
##             Specificity : 0.03365
##          Pos Pred Value : 0.58385
##          Neg Pred Value : 0.77778
##              Prevalence : 0.57724
##          Detection Rate : 0.57317
##    Detection Prevalence : 0.98171
##       Balanced Accuracy : 0.51331
##
##        'Positive' Class : 0
##
```

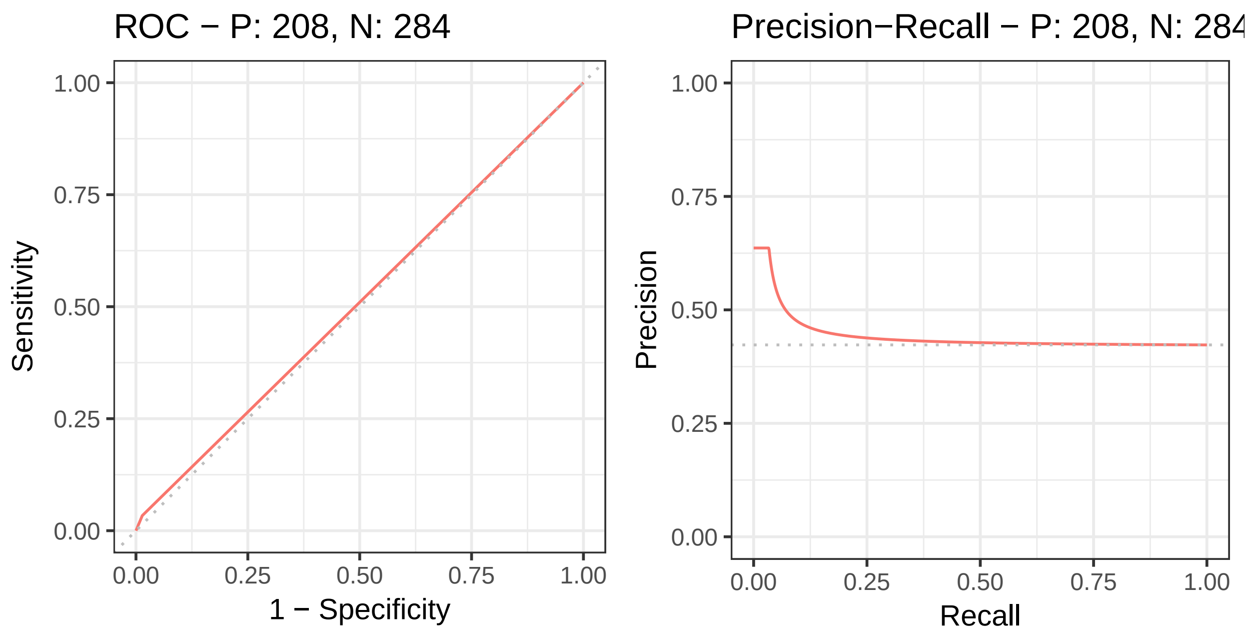
```r
sscurves123_3<- evalmod(scores = C1*C2*C3, labels = EC3)
autoplot(sscurves123_3)
```




```
#2
t_C1_C2_C4_EC3<-table(C1*C2*C4,EC3)
confusionMatrix(t_C1_C2_C4_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
##       0   1
##   0 280 201
##   1   4   7
##
##                Accuracy : 0.5833
##                  95% CI : (0.5384, 0.6273)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.4106
##
##                   Kappa : 0.0224
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.98592
##             Specificity : 0.03365
##          Pos Pred Value : 0.58212
##          Neg Pred Value : 0.63636
##              Prevalence : 0.57724
##          Detection Rate : 0.56911
##    Detection Prevalence : 0.97764
##       Balanced Accuracy : 0.50978
##
##        'Positive' Class : 0
##
```

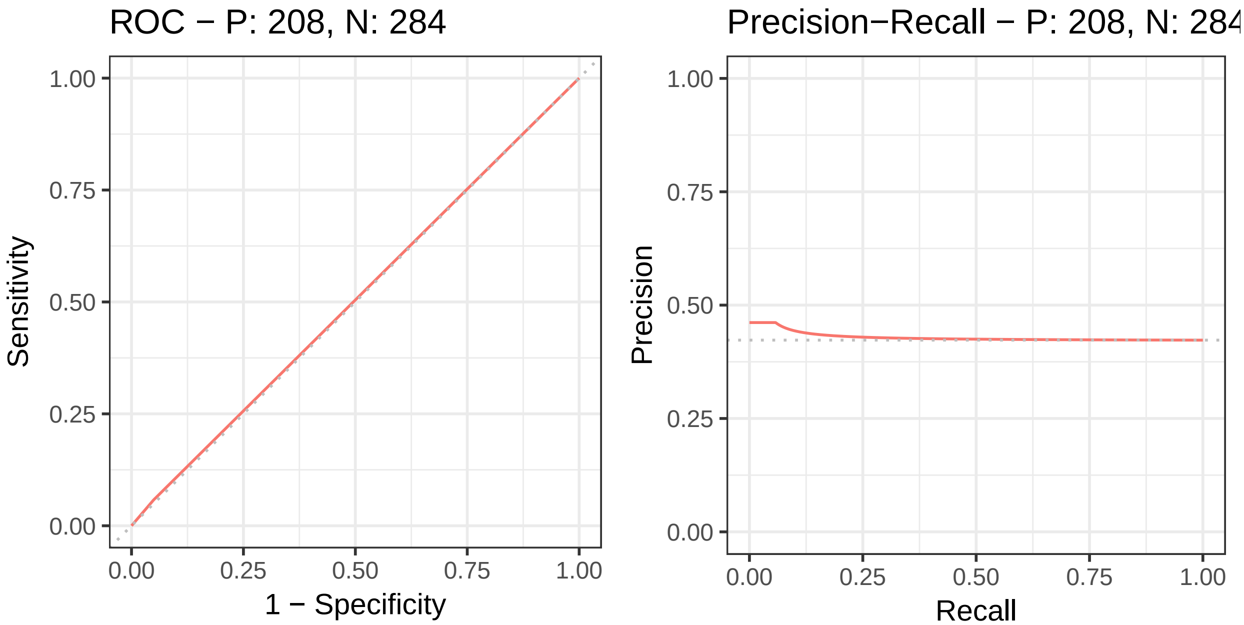
```
sscurves124_3<- evalmod(scores = C1*C2*C4, labels = EC3)
autoplot(sscurves124_3)
```




```r
#3
t_C1_C3_C4_EC3<-table(C1*C3*C4,EC3)
confusionMatrix(t_C1_C3_C4_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
##       0   1
##   0 270 196
##   1  14  12
##
##                Accuracy : 0.5732
##                  95% CI : (0.5281, 0.6173)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.5911
##
##                   Kappa : 0.0095
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.95070
##             Specificity : 0.05769
##          Pos Pred Value : 0.57940
##          Neg Pred Value : 0.46154
##              Prevalence : 0.57724
##          Detection Rate : 0.54878
##    Detection Prevalence : 0.94715
##       Balanced Accuracy : 0.50420
##
##        'Positive' Class : 0
##
```

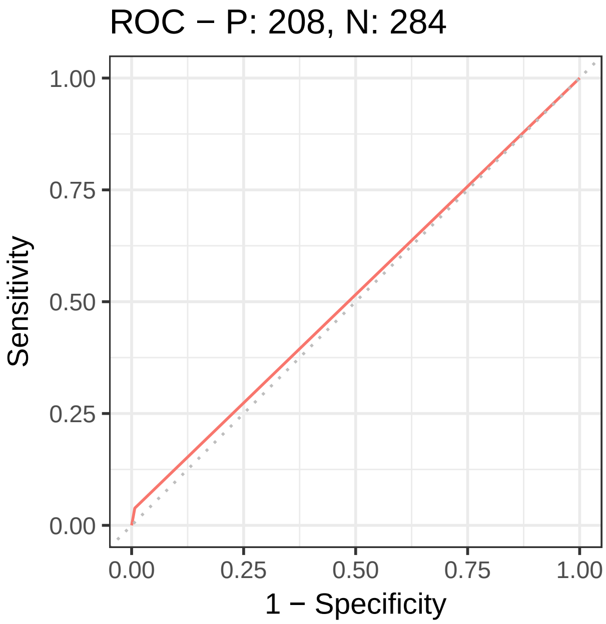
```r
sscurves134_3<- evalmod(scores = C1*C3*C4, labels = EC3)
autoplot(sscurves134_3)
```

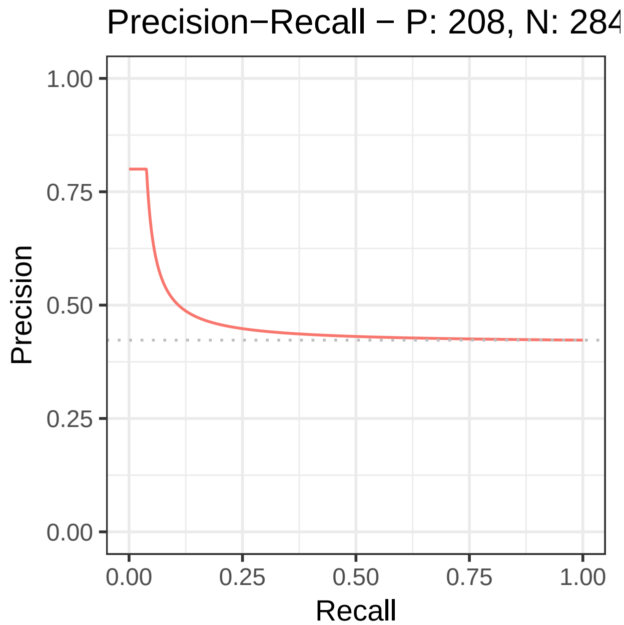



```r
#4
t_C2_C3_C4_EC3<-table(C2*C3*C4,EC3)
confusionMatrix(t_C2_C3_C4_EC3)
```

```
## Confusion Matrix and Statistics
##
##    EC3
##       0   1
##   0 282 200
##   1   2   8
##
##                Accuracy : 0.5894
##                  95% CI : (0.5445, 0.6333)
##     No Information Rate : 0.5772
##     P-Value [Acc > NIR] : 0.3085
##
##                   Kappa : 0.036
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.99296
##             Specificity : 0.03846
##          Pos Pred Value : 0.58506
##          Neg Pred Value : 0.80000
##              Prevalence : 0.57724
##          Detection Rate : 0.57317
##    Detection Prevalence : 0.97967
##       Balanced Accuracy : 0.51571
##
##        'Positive' Class : 0
##
```

```r
sscurves234_3<- evalmod(scores = C2*C3*C4, labels = EC3)
autoplot(sscurves234_3)
```


ROC − P: 208, N: 284
Sensitivity
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
1 − Specificity


Precision−Recall − P: 208, N: 284
Precision
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
Recall