A demonstration of the nproc package

Yang Feng, Jessica Li and Xin Tong

2017-03-02

We provide a detailed demo of the usage for `nproc` package.

Introduction

Let (X, Y) be random variables where $X \in \mathcal{X}$ is a vector of d features and $Y \in \{0, 1\}$ represents a binary class label. A data set that contains independent observations $\{(x_i, y_i)\}_{i=1}^{n+m}$ sampled from the joint distribution of (X, Y) are often divided into training data $\{(x_i, y_i)\}_{i=1}^{n}$ and test data $\{(x_i, y_i)\}_{i=n+1}^{n+m}$.

Based on training data, a *classifier* $\phi(\cdot)$ is a mapping $\phi : \mathcal{X} \to \{0, 1\}$ that returns the predicted class label given X. Classification error occurs when $\phi(X) \neq Y$, and the binary loss is defined as $1(\phi(X) \neq Y)$, where $1(\cdot)$ denotes the indicator function. The risk is defined as $R(\phi) = E[1(\phi(X) \neq Y)] = P(\phi(X) \neq Y)$, which can be expressed as a weighted sum of type I and II errors: $R(\phi) = P(Y = 0)R_0(\phi) + P(Y = 1)R_1(\phi)$, where $R_0(\phi) = P(\phi(X) \neq Y|Y = 0)$ denotes the type I error, and $R_1(\phi) = P(\phi(X) \neq Y|Y = 1)$ denotes the type II error.

The classical classification paradigm aims to find an oracle classifier ϕ^* by minimizing the risk, $\phi^* = \arg\min_\phi R(\phi)$.

In contrast, the NP classification paradigm aims to mimic the NP oracle classifier ϕ^*_α with respect to a pre-specified type I error upper bound α, $\phi^*_\alpha = \arg\min_{\phi:\ R_0(\phi)\leq\alpha} R_1(\phi)$, where α reflects users' conservative attitude (priority) towards the type I error.

Back to Top

Installation and Package Load

Like many other R packages, the simplest way to obtain `nproc` is to install it directly from CRAN. Type the following command in R console:

```r
install.packages("nproc", repos = "http://cran.us.r-project.org")
```

Users may change the `repos` options depending on their locations and preferences. Other options such as the directories where to install the packages can be altered in the command. For more details, see `help(install.packages)`.

Here the R package has been downloaded and installed to the default directories.

Alternatively, users can download the package source at http://cran.r-project.org/web/packages/nproc/index.html and type Unix commands to install it to the desired location.

Then we can load the `nproc` package:

```r
library(nproc)
```

Back to Top

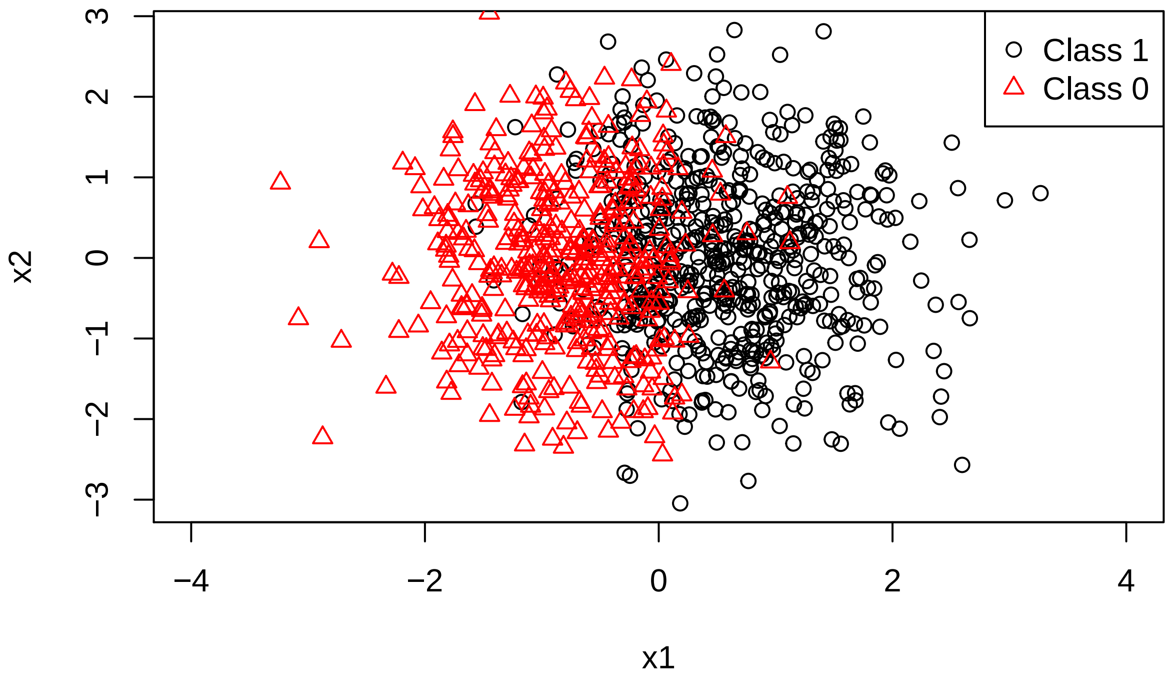
Neyman-Pearson Classification

Here, we provide a demonstration of Neyman-Pearson Classification with a type-I error control. In the first step, we create a dataset (x,y) from a logistic regression model with 2 features and sample size 1000.

```
n = 1000
set.seed(0)
x = matrix(rnorm(n*2),n,2)
c = 1+3*x[,1]
y = rbinom(n,1,1/(1+exp(-c)))
```

A visualization of the two classes.

```
plot(x[y==1,],col=1,xlim=c(-4,4),xlab='x1',ylab='x2')
points(x[y==0,],col=2,pch=2)
legend("topright",legend=c('Class 1','Class 0'),col=1:2,pch=c(1,2))
```



Then, the `npc` function can be called to perform the Neyman-Pearson Classification (npc). If one would like to use Linear Discriminant Analysis as the classifier, we can set `method` = "lda". The default type I error control is `alpha=0.05`. The `alpha` value can be changed to any desirable type I error upper bound in $(0, 1)$.

```
fit = npc(x, y, method = "lda", alpha = 0.05)
```

We can now evaluate the prediction performance of the NP classifier on a test set (xtest, ytest) generated as follows.

```
xtest = matrix(rnorm(n*2),n,2)
ctest = 1+3*xtest[,1]
ytest = rbinom(n,1,1/(1+exp(-ctest)))
```

We calculate the overall accuracy of the classifier as well as the realized Type I error. It is shown that the Type I error is smaller than `alpha`.

```
pred = predict(fit,xtest)
fit.score = predict(fit,x)
accuracy = mean(pred$pred.label==ytest)
cat("Overall Accuracy: ",  accuracy,'\n')
```

```
## Overall Accuracy:  0.708
```

```
ind0 = which(ytest==0)
typeI = mean(pred$pred.label[ind0]!=ytest[ind0]) #type I error on test set
cat('Type I error: ', typeI, '\n')
```

```
## Type I error:  0.02216749
```

The classification method implemented in the npc function includes the following options.

- logistic: Logistic regression. `glm` function with family = 'binomial'
- penlog: Penalized logistic regression with LASSO penalty. `glmnet` in `glmnet` package
- svm: Support Vector Machines. `svm` in `e1071` package
- randomforest: Random Forest. `randomForest` in `randomForest` package
- lda: Linear Discriminant Analysis. `lda` in `MASS` package
- nb: Naive Bayes. `naiveBayes` in `e1071` package
- ada: Ada-Boost. `ada` in `ada` package
- custom: a custom classifier

Now, we can try the change the method to logistic regression and change `alpha` to 0.1.

```
fit = npc(x, y, method = "logistic", alpha = 0.1)
pred = predict(fit,xtest)
accuracy = mean(pred$pred.label==ytest)
cat("Overall Accuracy: ",  accuracy,'\n')
```

```
## Overall Accuracy:  0.798
```

```
ind0 = which(ytest==0)
typeI = mean(pred$pred.label[ind0]!=ytest[ind0]) #type I error on test set
cat('Type I error: ', typeI, '\n')
```

```
## Type I error:  0.08866995
```

The package also provides implementation of the ensembled classifier. One can set the value `split` to the number of splits. Here, we try to change the number to 11.

```
fit = npc(x, y, method = "logistic", alpha = 0.1, split = 11)
pred = predict(fit,xtest)
accuracy = mean(pred$pred.label==ytest)
cat("Overall Accuracy: ",  accuracy,'\n')
```

```
## Overall Accuracy:  0.802
```

```
ind0 = which(ytest==0)
typeI = mean(pred$pred.label[ind0]!=ytest[ind0]) #type I error on test set
cat('Type I error: ', typeI, '\n')
```

```
## Type I error:  0.091133
```

Let's see the performance of this dataset using all implemented methods as a comparison.

```
methodlist = c("logistic", "penlog", "svm", "randomforest",
                                        "lda", "nb", "ada")
for(method in methodlist){
```

```
fit = npc(x, y, method = method, alpha = 0.05)
pred = predict(fit,xtest)
accuracy = mean(pred$pred.label==ytest)
cat(method, ': Overall Accuracy: ',  accuracy,'\n')
ind0 = which(ytest==0)
typeI = mean(pred$pred.label[ind0]!=ytest[ind0]) #type I error on test set
cat(method, ': Type I error: ', typeI, '\n')
}
```

```
## logistic : Overall Accuracy:  0.708
## logistic : Type I error:  0.02216749
## penlog : Overall Accuracy:  0.709
## penlog : Type I error:  0.02216749
## svm : Overall Accuracy:  0.52
## svm : Type I error:  0.05665025
## randomforest : Overall Accuracy:  0.613
## randomforest : Type I error:  0.01477833
## lda : Overall Accuracy:  0.708
## lda : Type I error:  0.02216749
## nb : Overall Accuracy:  0.713
## nb : Type I error:  0.02216749
## ada : Overall Accuracy:  0.731
## ada : Type I error:  0.03448276
```

The package also implmented a generic classifier with the scores on each observation needed. An example is follows.

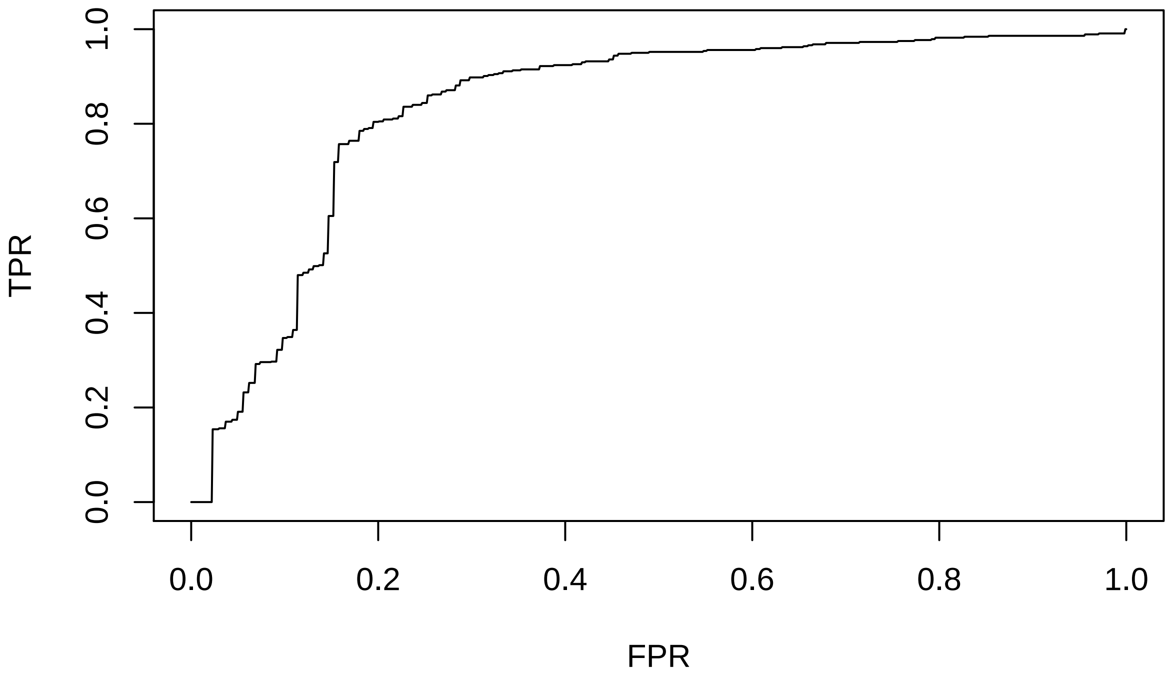
```
fit2 = npc(y = y, score = pred$pred.score, method = 'custom')
```

Back to Top

Neyman-Pearson Receiver Operator Curve

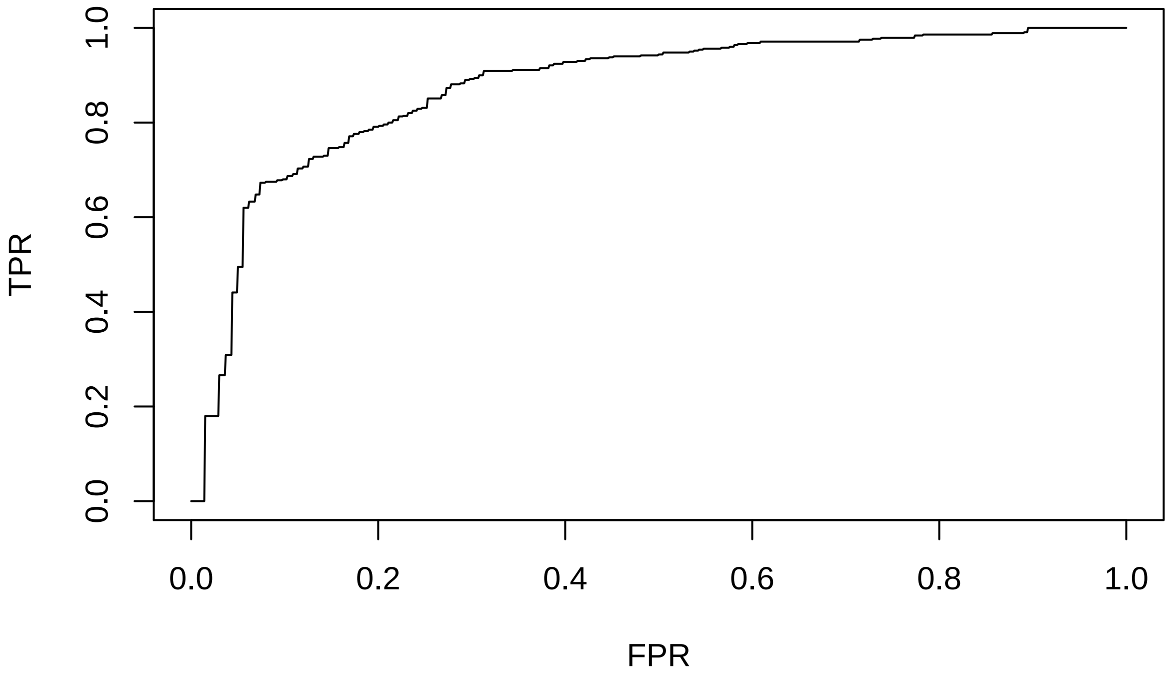
The package provides an implmentation of Neyman-Pearson Receiver Operator Curve (nproc) via the function `nproc`. Here is a brief demo. We use the same data in the NP classifier, i.e., a dataset (x,y) from a logistic regression model with 2 features and sample size 1000. Then, we can call the `nproc` function with a specificed classifier.

```
fit = nproc(x, y, method = "svm")
plot(fit)
```



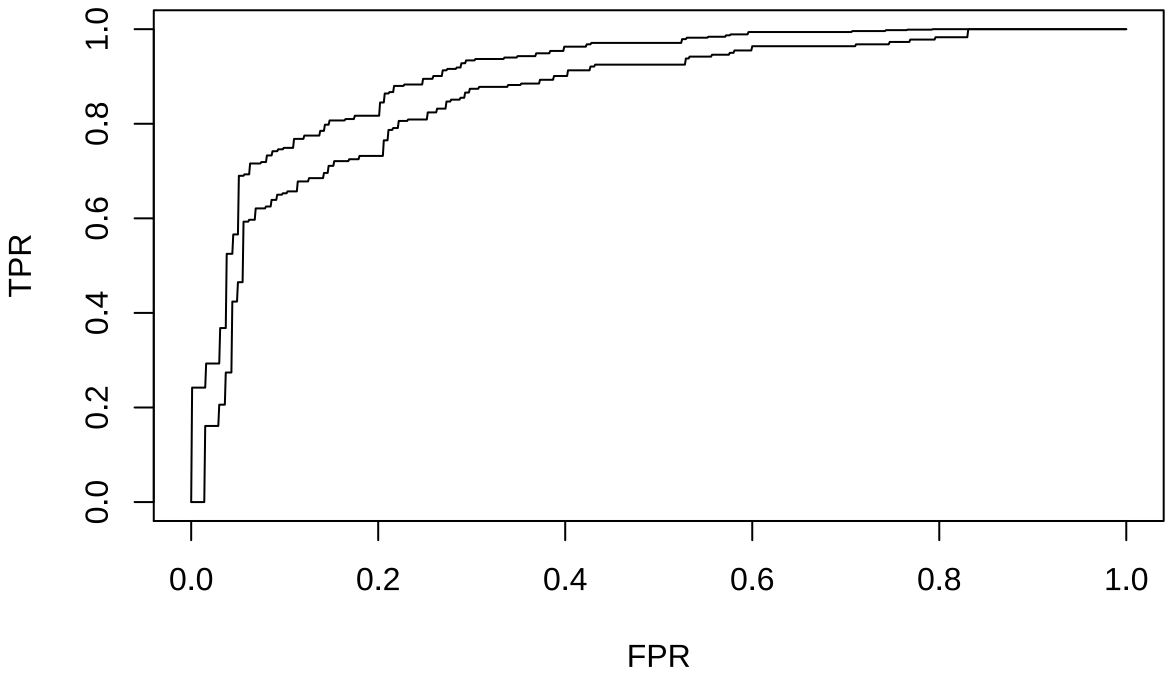
The implementation with linear discriminant analysis is as follows.

```r
fit = nproc(x, y, method = "lda")
plot(fit)
```



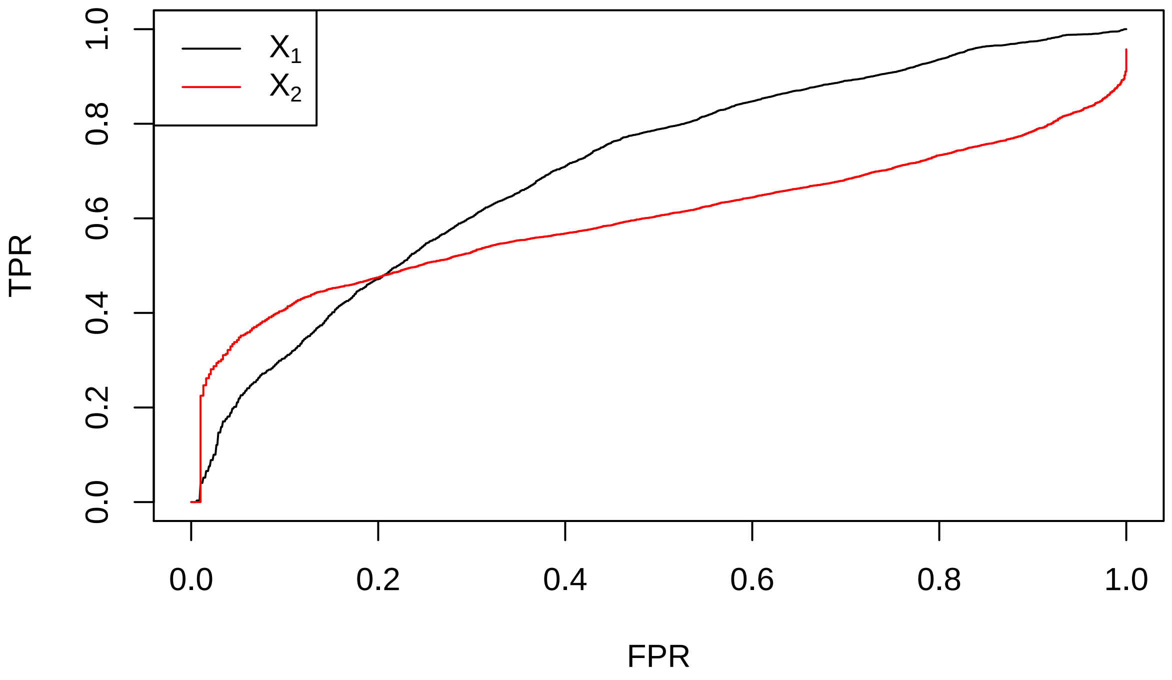
Another important usage of the package is to create a point-wise confidence interval of NP-ROC curves with a given tolerance probability `delta`. The default `delta = 0.05` corresponds to the 95% point-wise confidence interval. Here is one example.

```r
fit = nproc(x, y, method = "logistic", band = TRUE)
plot(fit)
```



The package provides comparison ability between two different NP-ROC curves. The following compares the NP-ROC curves generated by logistic regression with the two predictors. The graph shows the regions of the alpha values where one NP-ROC curve is significantly better than the other one.

```
n = 1000
set.seed(0)
x1 = c(rnorm(n), rnorm(n) + 1)
x2 = c(rnorm(n), rnorm(n)*sqrt(6) + 1)
y = c(rep(0,n), rep(1,n))
fit1 = nproc(x1, y, split = 11, method = 'lda')
fit2 = nproc(x2, y, split = 11, method = 'lda')
v = compare(fit1, fit2)
legend('topleft',legend = c(expression(X[1]),expression(X[2])),col = 1:2,lty = c(1,1))
```



Back to Top