

# Package: caROC (via r-universe)

September 7, 2024

**Type** Package

**Title** Continuous Biomarker Evaluation with Adjustment of Covariates

**Version** 0.1.5

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**Description** Compute covariate-adjusted specificity at controlled sensitivity level, or covariate-adjusted sensitivity at controlled specificity level, or covariate-adjust receiver operating characteristic curve, or covariate-adjusted thresholds at controlled sensitivity/specificity level. All statistics could also be computed for specific sub-populations given their covariate values. Methods are described in Ziyi Li, Yijian Huang, Datta Patil, Martin G. Sanda (2021+) ``Covariate adjustment in continuous biomarker assessment''.

**License** GPL-2

**Encoding** UTF-8

**Depends** R (>= 4.0), quantreg, RColorBrewer

**Suggests** knitr, rmarkdown

**VignetteBuilder** knitr

**NeedsCompilation** no

**Date/Publication** 2021-04-02 08:20:03 UTC

**Repository** <https://ziyili20.r-universe.dev>

**RemoteUrl** <https://github.com/cran/caROC>

**RemoteRef** HEAD

**RemoteSha** 6c243aa38c14806fac04fefb5fb164e189fc920a

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caROC	<i>Covariate-adjusted ROC</i>
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## Description

Compute covariate-adjusted specificity at controlled sensitivity level, or covariate-adjusted sensitivity at controlled specificity level, or covariate-adjust receiver operating characteristic curve.

## Usage

```
caROC(diseaseData, controlData, userFormula, control_sensitivity = NULL,
      control_specificity = NULL, mono_resp_method = "ROC",
      whichSE = "sample", global_ROC_controlled_by = "sensitivity",
      nbootstrap = 100, CI_alpha = 0.95, logit_CI = TRUE,
      verbose = TRUE)
```

## Arguments

diseaseData	Data from patients including dependent (biomarker) and independent (covariates) variables.
controlData	Data from controls including dependent (biomarker) and independent (covariates) variables.
userFormula	A character string to represent the function for covariate adjustment. For example, let Y denote biomarker, Z1 and Z2 denote two covariates. Then userFormula = "Y ~ Z1 + Z2".
control_sensitivity	The level(s) of sensitivity to be controlled at. Could be a scalar (e.g. 0.7) or a numeric vector (e.g. c(0.7, 0.8, 0.9)).
control_specificity	The level(s) of specificity to be controlled at. Could be a scalar (e.g. 0.7) or a numeric vector (e.g. c(0.7, 0.8, 0.9)).
mono_resp_method	The method used to restore monotonicity of the ROC curve or computed sensitivity/specificity value. It should one from the following: "none", "ROC". "none" is not applying any monotonicity respecting method. "ROC" is to apply ROC-based monotonicity respecting approach. Default value is "ROC".

whichSE	The method used to compute standard error. It should be one from the following: "sample", "bootstrap", meaning to calculate the standard error using sample-based approach or bootstrap. Default is "sample".
global_ROC_controlled_by	Whether sensitivity/specificity is used to control when computing global ROC. It should one from the following: "sensitivity", "specificity". Default is "sensitivity".
nbootstrap	Number of bootstrap iterations. Default is 100.
CI_alpha	Percentage of confidence interval. Default is 0.95.
logit_CI	Whether to apply logit-based confidence interval. Logit-transformed CI has been identified to be more robust near border area.
verbose	Whether to print out messages. Default value is true.

### Value

If control\_sensitivity or control\_specificity is provided, compute covariate-adjusted specificity (sensitivity) at controlled sensitivity (specificity) level.

Estimate	Covariate-adjusted sensitivity/specificity.
SE	Estimated standard error.
CI	Estimated confidence intervals.

If both control\_sensitivity and control\_specificity are null, compute covariate-adjusted ROC curve.

sensitivity	Estimated sensitivity.
specificity	Estimated specificity.
mono_adj	Monotonicity adjustment method.

### Author(s)

Ziyi.li <ziyi.li@emory.edu>

### Examples

```
n1 = n0 = 500

## generate data
Z_D <- rbinom(n1, size = 1, prob = 0.3)
Z_C <- rbinom(n0, size = 1, prob = 0.7)

Y_C_Z0 <- rnorm(n0, 0.1, 1)
Y_D_Z0 <- rnorm(n1, 1.1, 1)
Y_C_Z1 <- rnorm(n0, 0.2, 1)
Y_D_Z1 <- rnorm(n1, 0.9, 1)

M0 <- Y_C_Z0 * (Z_C == 0) + Y_C_Z1 * (Z_C == 1)
M1 <- Y_D_Z0 * (Z_D == 0) + Y_D_Z1 * (Z_D == 1)

diseaseData <- data.frame(M = M1, Z = Z_D)
```

```

controlData <- data.frame(M = M0, Z = Z_C)
userFormula = "M~Z"

## calculate covariate-adjusted specificity at
## controlled sensitivity levels (0.2, 0.8, 0.9)
caROC(diseaseData,controlData,userFormula,
      control_sensitivity = c(0.2,0.8, 0.9),
      control_specificity = NULL,mono_resp_method = "ROC",
      whichSE = "bootstrap",nbootstrap = 100,
      CI_alpha = 0.95, logit_CI = TRUE)

## calculate covariate-adjusted sensitivity at
## controlled specificity levels (0.2, 0.8, 0.9)
caROC(diseaseData,controlData,userFormula,
      control_sensitivity = NULL,
      control_specificity = c(0.7,0.8, 0.9),mono_resp_method = "none",
      whichSE = "sample",nbootstrap = 100,
      CI_alpha = 0.95, logit_CI = TRUE)

## calculate the whole covariate-adjusted ROC curve
ROC1 <- caROC(diseaseData,controlData,userFormula = "M~Z",
              mono_resp_method = "none")
ROC2 <- caROC(diseaseData,controlData,userFormula = "M~Z",
              mono_resp_method = "ROC")

```

---

caROC\_CB

*Get confidence band for covariate-adjusted ROC curve.*


---

## Description

Use this function to compute the confidence band for covariate-adjusted ROC curve, with or without monotonicity respecting methods.

## Usage

```

caROC_CB(diseaseData, controlData, userFormula,
          mono_resp_method, global_ROC_controlled_by = "sensitivity",
          CB_alpha = 0.95, logit_CB = FALSE, nbootstrap = 100,
          nbin = 100, verbose = FALSE)

```

## Arguments

diseaseData	Data from patients including dependent (biomarker) and independent (covariates) variables.
controlData	Data from controls including dependent (biomarker) and independent (covariates) variables.
userFormula	A character string to represent the function for covariate adjustment. For example, let Y denote biomarker, Z1 and Z2 denote two covariates. Then userFormula = "Y ~ Z1 + Z2".

mono_resp_method	The method used to restore monotonicity of the ROC curve or computed sensitivity/specificity value. It should one from the following: "none", "ROC". "none" is not applying any monotonicity respecting method. "ROC" is to apply ROC-based monotonicity respecting approach. Default value is "ROC".
global_ROC_controlled_by	Whether sensitivity/specificity is used to control when computing global ROC. It should one from the following: "sensitivity", "specificity". Default is "sensitivity".
CB_alpha	Percentage of confidence band. Default is 0.95.
logit_CB	Whether to use logit-transformed (then transform back) confidence band. Default is FALSE.
nbootstrap	Number of bootstrap iterations. Default is 100.
nbin	Number of bins used for constructing confidence band. Default is 100.
verbose	Whether to print out messages during bootstrap. Default value is FALSE.

**Value**

If global ROC is controlled by sensitivity, a list will be output including the following

```
Sensitivity      Vector of sensitivities;
Specificity_upper
                  Upper confidence band for specificity estimations;
Specificity_lower
                  Lower confidence band for specificity estimations;
global_ROC_controlled_by
                  "sensitivity".
```

If global ROC is controlled by Specificity, a list will be output including the following

```
Specificity      Vector of specificity;
Sensitivity_upper
                  Upper confidence band for sensitivity estimations;
Sensitivity_lower
                  Lower confidence band for sensitivity estimations;
global_ROC_controlled_by
                  "specificity".
```

**Author(s)**

Ziyi.li <ziyi.li@emory.edu>

**Examples**

```
n1 = n0 = 500

## generate data
Z_D <- rbinom(n1, size = 1, prob = 0.3)
```

```

Z_C <- rbinom(n0, size = 1, prob = 0.7)

Y_C_Z0 <- rnorm(n0, 0.1, 1)
Y_D_Z0 <- rnorm(n1, 1.1, 1)
Y_C_Z1 <- rnorm(n0, 0.2, 1)
Y_D_Z1 <- rnorm(n1, 0.9, 1)

M0 <- Y_C_Z0 * (Z_C == 0) + Y_C_Z1 * (Z_C == 1)
M1 <- Y_D_Z0 * (Z_D == 0) + Y_D_Z1 * (Z_D == 1)

diseaseData <- data.frame(M = M1, Z = Z_D)
controlData <- data.frame(M = M0, Z = Z_C)
userFormula = "M~Z"

### calculate confidence band by controlling sensitivity
### using different monotonicity respecting methods

ROC_CB1 <- caROC_CB(diseaseData,controlData,userFormula,
                    mono_resp_method = "none",
                    CB_alpha = 0.95,
                    nbin = 100,verbose = FALSE)
ROC_CB2 <- caROC_CB(diseaseData,controlData,userFormula,
                    mono_resp_method = "ROC",
                    CB_alpha = 0.95,
                    nbin = 100,verbose = FALSE)

```

---

caThreshold

*Calculate covariate-adjusted threshold.*


---

### Description

This function is used to calculate covariate-adjusted threshold(s) at controlled sensitivity levels or specificity levels.

### Usage

```

caThreshold(userFormula, new_covariates, diseaseData = NULL,
            controlData = NULL, control_sensitivity = NULL,
            control_specificity = NULL)

```

### Arguments

**userFormula** A character string to represent the function for covariate adjustment. For example, let Y denote biomarker, Z1 and Z2 denote two covariates. Then userFormula = "Y ~ Z1 + Z2".

**new\_covariates** A data frame containing covariates for new data. For example, if my userFormula is "Y ~ Z1 + Z2", new\_covariates could be data.frame(Z1 = rnorm(100), Z2 = rnorm(100)).

diseaseData      Data from patients including dependent (biomarker) and independent (covariates) variables.

controlData      Data from controls including dependent (biomarker) and independent (covariates) variables.

control\_sensitivity  
                     The level(s) of sensitivity to be controlled at. Could be a scalar (e.g. 0.7) or a numeric vector (e.g. c(0.7, 0.8, 0.9)).

control\_specificity  
                     The level(s) of specificity to be controlled at. Could be a scalar (e.g. 0.7) or a numeric vector (e.g. c(0.7, 0.8, 0.9)).

### Value

A vector of covariate-adjusted threshold for all subjects if a scalar sensitivity/specificity is given. A data matrix of covariate-adjusted thresholds for all subjects if a vector of sensitivity/specificity is given.

### Author(s)

Ziyi Li <ziyi.li@emory.edu>

### Examples

```
n1 = n0 = 500

## generate data
Z_D <- rbinom(n1, size = 1, prob = 0.3)
Z_C <- rbinom(n0, size = 1, prob = 0.7)

Y_C_Z0 <- rnorm(n0, 0.1, 1)
Y_D_Z0 <- rnorm(n1, 1.1, 1)
Y_C_Z1 <- rnorm(n0, 0.2, 1)
Y_D_Z1 <- rnorm(n1, 0.9, 1)

M0 <- Y_C_Z0 * (Z_C == 0) + Y_C_Z1 * (Z_C == 1)
M1 <- Y_D_Z0 * (Z_D == 0) + Y_D_Z1 * (Z_D == 1)

diseaseData <- data.frame(M = M1, Z = Z_D)
controlData <- data.frame(M = M0, Z = Z_C)
userFormula = "M~Z"

### generate new covariates
new_covariates <- data.frame(Z = rbinom(20, size = 1, prob = 0.5))

### calculate covariate-adjusted thresholds at controlled
### sensitivity level 0.7, 0.8, 0.9
caThreshold(userFormula, new_covariates,
            diseaseData = diseaseData,
            controlData = NULL,
            control_sensitivity = c(0.7,0.8,0.9),
            control_specificity = NULL)
```

```

### calculate covariate-adjusted thresholds at controlled
### sensitivity level 0.7
caThreshold(userFormula,new_covariates,
            diseaseData = diseaseData,
            controlData = NULL,
            control_sensitivity = 0.7,
            control_specificity = NULL)

### calculate covariate-adjusted thresholds at controlled
### specificity level 0.7, 0.8, 0.9
caThreshold(userFormula,new_covariates,
            diseaseData = NULL,
            controlData = controlData,
            control_sensitivity = NULL,
            control_specificity = c(0.7,0.8,0.9))

### calculate covariate-adjusted thresholds at controlled
### specificity level 0.7
caThreshold(userFormula,new_covariates,
            diseaseData = NULL,
            controlData = controlData,
            control_sensitivity = NULL,
            control_specificity = 0.7)

```

---

plot\_caROC

*Plot covariate-adjusted ROC.*


---

### Description

Function to plot the ROC curve generated from caROC().

### Usage

```
plot_caROC(myROC, ...)
```

### Arguments

myROC	ROC output from caROC() function.
...	Arguments to tune generated plots.

### Details

This function can be used to plot other ROC curve, as long as the input contains two components "sensitivity" and "specificity".

### Value

Plot the ROC curve.



**Author(s)**

Ziyi Li <zli16@mdanderson.org>

**Examples**

```
n1 = n0 = 500

## generate data
Z_D <- rbinom(n1, size = 1, prob = 0.3)
Z_C <- rbinom(n0, size = 1, prob = 0.7)

Y_C_Z0 <- rnorm(n0, 0.1, 1)
Y_D_Z0 <- rnorm(n1, 1.1, 1)
Y_C_Z1 <- rnorm(n0, 0.2, 1)
Y_D_Z1 <- rnorm(n1, 0.9, 1)

M0 <- Y_C_Z0 * (Z_C == 0) + Y_C_Z1 * (Z_C == 1)
M1 <- Y_D_Z0 * (Z_D == 0) + Y_D_Z1 * (Z_D == 1)

diseaseData <- data.frame(M = M1, Z = Z_D)
controlData <- data.frame(M = M0, Z = Z_C)
userFormula = "M~Z"

ROC1 <- caROC(diseaseData,controlData,userFormula,
              mono_resp_method = "none")
ROC2 <- caROC(diseaseData,controlData,userFormula,
              mono_resp_method = "ROC")

plot_caROC(ROC1)
plot_caROC(ROC2, col = "blue")
```

---

plot\_caROC\_CB

*Plot confidence band of covariate-adjusted ROC.*


---

**Description**

A function to plot the confidence band of covariate-adjusted ROC.

**Usage**

```
plot_caROC_CB(myROC_CB, add = TRUE, ...)
```

**Arguments**

myROC_CB	Output from caROC_CB() function.
add	Whether to add confidence band to existing plot (TRUE) or draw a new one (FALSE). Default is TRUE.
...	Any parameters related with the plot.

**Value**

No values will be return. This function is for plotting only.

**Author(s)**

Ziyi Li<ziyi.li@emory.edu>

**Examples**

```
library(caROC)
n1 = n0 = 100

## generate data
Z_D <- rbinom(n1, size = 1, prob = 0.3)
Z_C <- rbinom(n0, size = 1, prob = 0.7)

Y_C_Z0 <- rnorm(n0, 0.1, 1)
Y_D_Z0 <- rnorm(n1, 1.1, 1)
Y_C_Z1 <- rnorm(n0, 0.2, 1)
Y_D_Z1 <- rnorm(n1, 0.9, 1)

M0 <- Y_C_Z0 * (Z_C == 0) + Y_C_Z1 * (Z_C == 1)
M1 <- Y_D_Z0 * (Z_D == 0) + Y_D_Z1 * (Z_D == 1)

diseaseData <- data.frame(M = M1, Z = Z_D)
controlData <- data.frame(M = M0, Z = Z_C)
formula = "M~Z"

ROC_CB1 <- caROC_CB(diseaseData,controlData,formula,
                    mono_resp_method = "none",
                    CB_alpha = 0.95,
                    nbin = 100,verbose = FALSE)
### plot confidence band individually
plot_caROC_CB(ROC_CB1, add = FALSE, lty = 2, col = "blue")

### plot confidence band together with the ROC curve
ROC1 <- caROC(diseaseData,controlData,formula,
              mono_resp_method = "none", verbose = FALSE)
plot_caROC(ROC1)
plot_caROC_CB(ROC_CB1, add = TRUE, lty = 2, col = "blue")
```

---

plot\_sscarOC

*Plot covariate-adjusted ROC for specific subpopulations.*

---

**Description**

Function to plot the ROC curve generated from sscarOC().

**Usage**

```
plot_sccaROC(myROC, ...)
```

**Arguments**

```
myROC          ROC output from sccaROC() function.  
...           Arguments to tune generated plots.
```

**Details**

This function can be used to plot other ROC curve, as long as the input contains two components "sensitivity" and "specificity".

**Value**

Plot the ROC curve.

**Author(s)**

Ziyi Li <zli16@mdanderson.org>

**Examples**

```
n1 = n0 = 1000  
  
## generate data  
Z_D1 <- rbinom(n1, size = 1, prob = 0.3)  
Z_D2 <- rnorm(n1, 0.8, 1)  
  
Z_C1 <- rbinom(n0, size = 1, prob = 0.7)  
Z_C2 <- rnorm(n0, 0.8, 1)  
  
Y_C_Z0 <- rnorm(n0, 0.1, 1)  
Y_D_Z0 <- rnorm(n1, 1.1, 1)  
Y_C_Z1 <- rnorm(n0, 0.2, 1)  
Y_D_Z1 <- rnorm(n1, 0.9, 1)  
  
M0 <- Y_C_Z0 * (Z_C1 == 0) + Y_C_Z1 * (Z_C1 == 1) + Z_C2  
M1 <- Y_D_Z0 * (Z_D1 == 0) + Y_D_Z1 * (Z_D1 == 1) + 1.5 * Z_D2  
  
diseaseData <- data.frame(M = M1, Z1 = Z_D1, Z2 = Z_D2)  
controlData <- data.frame(M = M0, Z1 = Z_C1, Z2 = Z_C2)  
userFormula = "M~Z1+Z2"  
  
target_covariates = c(1, 0.7, 0.9)  
  
myROC <- sccaROC(diseaseData,  
                 controlData,  
                 userFormula,  
                 target_covariates,
```

```

      global_ROC_controlled_by = "sensitivity",
      mono_resp_method = "none")
plot_sscaroc(myROC, lwd = 1.6)

```

---

plot_sscaroc_CB	<i>Plot confidence band of covariate-adjusted ROC in specific subpopulations.</i>
-----------------	---

---

### Description

A function to plot the confidence band of covariate-adjusted ROC in specific subpopulations.

### Usage

```
plot_sscaroc_CB(myROC_CB, add = TRUE, ...)
```

### Arguments

myROC_CB	Output from sscaroc_CB() function.
add	Whether to add confidence band to existing plot (TRUE) or draw a new one (FALSE). Default is TRUE.
...	Any parameters related with the plot.

### Value

No values will be return. This function is for plotting only.

### Author(s)

Ziyi Li<zli16@mdanderson.org>

### Examples

```

n1 = n0 = 500

## generate data
Z_D1 <- rbinom(n1, size = 1, prob = 0.3)
Z_D2 <- rnorm(n1, 0.8, 1)
Z_C1 <- rbinom(n0, size = 1, prob = 0.7)
Z_C2 <- rnorm(n0, 0.8, 1)
Y_C_Z0 <- rnorm(n0, 0.1, 1)
Y_D_Z0 <- rnorm(n1, 1.1, 1)
Y_C_Z1 <- rnorm(n0, 0.2, 1)
Y_D_Z1 <- rnorm(n1, 0.9, 1)

M0 <- Y_C_Z0 * (Z_C1 == 0) + Y_C_Z1 * (Z_C1 == 1) + Z_C2
M1 <- Y_D_Z0 * (Z_D1 == 0) + Y_D_Z1 * (Z_D1 == 1) + 1.5 * Z_D2

```

```

diseaseData <- data.frame(M = M1, Z1 = Z_D1, Z2 = Z_D2)
controlData <- data.frame(M = M0, Z1 = Z_C1, Z2 = Z_C2)

userFormula = "M~Z1+Z2"
target_covariates = c(1, 0.7, 0.9)

# example that takes more than a minute to run
myROC <- sscaROC(diseaseData,
                 controlData,
                 userFormula,
                 target_covariates,
                 global_ROC_controlled_by = "sensitivity",
                 mono_resp_method = "none")

# default nbootstrap is 100
# set nbootstrap as 10 here to improve example speed
myROCband <- sscaROC_CB(diseaseData,
                       controlData,
                       userFormula,
                       mono_resp_method = "none",
                       target_covariates,
                       global_ROC_controlled_by = "sensitivity",
                       CB_alpha = 0.95,
                       logit_CB = FALSE,
                       nbootstrap = 10,
                       nbin = 100,
                       verbose = FALSE)

plot_sscaROC(myROC, lwd = 1.6)
plot_sscaROC_CB(myROCband, col = "purple", lty = 2)

```

---

sscaROC	<i>Covariate-adjusted continuous biomarker evaluations for specific population.</i>
---------	---

---

## Description

Provides evaluation for continuous biomarkers at controlled sensitivity/specificity level, or ROC curve in specified sub-population.

## Usage

```

sscaROC(diseaseData, controlData, userFormula, target_covariates,
        control_sensitivity = NULL, control_specificity = NULL, mono_resp_method = "ROC",
        whichSE = "sample", global_ROC_controlled_by = "sensitivity", nbootstrap = 100,
        CI_alpha = 0.95, logit_CI = TRUE, verbose = TRUE)

```

**Arguments**

diseaseData	Data from patients including dependent (biomarker) and independent (covariates) variables.
controlData	Data from controls including dependent (biomarker) and independent (covariates) variables.
userFormula	A character string to represent the function for covariate adjustment. For example, let Y denote biomarker, Z1 and Z2 denote two covariates. Then userFormula = "Y ~ Z1 + Z2".
target_covariates	Covariates of the interested sub-population. It could be a vector, e.g. c(1, 0.5, 0.8), or a matrix, e.g. target_covariates = matrix(c(1, 0.7, 0.9, 1, 0.8, 0.8), 2, 3, byrow = TRUE)
control_sensitivity	The level(s) of sensitivity to be controlled at. Could be a scalar (e.g. 0.7) or a numeric vector (e.g. c(0.7, 0.8, 0.9)).
control_specificity	The level(s) of specificity to be controlled at. Could be a scalar (e.g. 0.7) or a numeric vector (e.g. c(0.7, 0.8, 0.9)).
mono_resp_method	The method used to restore monotonicity of the ROC curve or computed sensitivity/specificity value. It should one from the following: "none", "ROC". "none" is not applying any monotonicity respecting method. "ROC" is to apply ROC-based monotonicity respecting approach. Default value is "ROC".
whichSE	The method used to compute standard error. It should be one from the following: "sample", "bootstrap", meaning to calculate the standard error using sample-based approach or bootstrap. Default is "sample".
global_ROC_controlled_by	Whether sensitivity/specificity is used to control when computing global ROC. It should one from the following: "sensitivity", "specificity". Default is "sensitivity".
nbootstrap	Number of bootstrap iterations. Default is 100.
CI_alpha	Percentage of confidence interval. Default is 0.95.
logit_CI	Whether to apply logit-based confidence interval. Logit-transformed CI has been identified to be more robust near border area.
verbose	Whether to print out messages. Default value is true.

**Value**

If control\_sensitivity or control\_specificity is provided, compute covariate-adjusted specificity (sensitivity) at controlled sensitivity (specificity) level.

Estimate	Covariate-adjusted sensitivity/specificity.
SE	Estimated standard error.
CI	Estimated confidence intervals.

If both control\_sensitivity and control\_specificity are null, compute covariate-adjusted ROC curve.

sensitivity	Estimated sensitivity.
specificity	Estimated specificity.
mono_adj	Monotonicity adjustment method.

### Author(s)

Ziyi.li <zli16@mdanderson.org>

### Examples

```
n1 = n0 = 1000
## generate data
Z_D1 <- rbinom(n1, size = 1, prob = 0.3)
Z_D2 <- rnorm(n1, 0.8, 1)
Z_C1 <- rbinom(n0, size = 1, prob = 0.7)
Z_C2 <- rnorm(n0, 0.8, 1)
Y_C_Z0 <- rnorm(n0, 0.1, 1)
Y_D_Z0 <- rnorm(n1, 1.1, 1)
Y_C_Z1 <- rnorm(n0, 0.2, 1)
Y_D_Z1 <- rnorm(n1, 0.9, 1)
M0 <- Y_C_Z0 * (Z_C1 == 0) + Y_C_Z1 * (Z_C1 == 1) + Z_C2
M1 <- Y_D_Z0 * (Z_D1 == 0) + Y_D_Z1 * (Z_D1 == 1) + 1.5 * Z_D2
diseaseData <- data.frame(M = M1, Z1 = Z_D1, Z2 = Z_D2)
controlData <- data.frame(M = M0, Z1 = Z_C1, Z2 = Z_C2)
userFormula = "M~Z1+Z2"
target_covariates = c(1, 0.7, 0.9)
res <- sscaROC(diseaseData,controlData,
               userFormula = userFormula,
               control_sensitivity = c(0.2,0.8, 0.9),
               target_covariates = target_covariates,
               control_specificity = NULL,
               mono_resp_method = "none",
               whichSE = "sample",nbootstrap = 100,
               CI_alpha = 0.95, logit_CI = TRUE)

## bootstrap-based variance estimation
res <- sscaROC(diseaseData,controlData,
               userFormula = userFormula,
               control_sensitivity = c(0.2,0.8, 0.9),
               target_covariates = target_covariates,
               control_specificity = NULL,
               mono_resp_method = "none",
               whichSE = "bootstrap",nbootstrap = 100,
               CI_alpha = 0.95, logit_CI = TRUE)

## monotonization by ROC-based
res <- sscaROC(diseaseData,controlData,
               userFormula = userFormula,
               control_sensitivity = c(0.2,0.8, 0.9),
               target_covariates = target_covariates,
```

```

        control_specificity = NULL,
        mono_resp_method = "ROC",
        whichSE = "bootstrap", nbootstrap = 100,
        CI_alpha = 0.95, logit_CI = TRUE)
## control specificity
res <- sscaROC(diseaseData, controlData,
               userFormula = userFormula,
               control_sensitivity = NULL,
               target_covariates = target_covariates,
               control_specificity = c(0.2, 0.8, 0.9),
               mono_resp_method = "ROC",
               whichSE = "bootstrap", nbootstrap = 100,
               CI_alpha = 0.95, logit_CI = TRUE)
### get ROC curves
myROC <- sscaROC(diseaseData,
                 controlData,
                 userFormula,
                 target_covariates,
                 global_ROC_controlled_by = "sensitivity",
                 mono_resp_method = "none")

```

---

sscaROC\_CB

*Get confidence band for covariate-adjusted ROC curve for specified sub-population.*

---

### Description

Use this function to compute the confidence band for covariate-adjusted ROC curve, with or without monotonicity respecting methods for sub-population.

### Usage

```

sscaROC_CB(diseaseData, controlData, userFormula, mono_resp_method = "none",
            target_covariates, global_ROC_controlled_by = "sensitivity", CB_alpha = 0.95,
            logit_CB = FALSE, nbootstrap = 100, nbin = 100, verbose = FALSE)

```

### Arguments

diseaseData	Data from patients including dependent (biomarker) and independent (covariates) variables.
controlData	Data from controls including dependent (biomarker) and independent (covariates) variables.
userFormula	A character string to represent the function for covariate adjustment. For example, let Y denote biomarker, Z1 and Z2 denote two covariates. Then userFormula = "Y ~ Z1 + Z2".



mono_resp_method	The method used to restore monotonicity of the ROC curve or computed sensitivity/specificity value. It should one from the following: "none", "ROC". "none" is not applying any monotonicity respecting method. "ROC" is to apply ROC-based monotonicity respecting approach. Default value is "ROC".
target_covariates	Covariates of the interested sub-population. It could be a vector, e.g. c(1, 0.5, 0.8), or a matrix, e.g. target_covariates = matrix(c(1, 0.7, 0.9, 1, 0.8, 0.8), 2, 3, byrow = TRUE)
global_ROC_controlled_by	Whether sensitivity/specificity is used to control when computing global ROC. It should one from the following: "sensitivity", "specificity". Default is "sensitivity".
CB_alpha	Percentage of confidence band. Default is 0.95.
logit_CB	Whether to use logit-transformed (then transform back) confidence band. Default is FALSE.
nbootstrap	Number of bootstrap iterations. Default is 100.
nbin	Number of bins used for constructing confidence band. Default is 100.
verbose	Whether to print out messages during bootstrap. Default value is FALSE.

### Value

If global ROC is controlled by sensitivity, a list will be output including the following

Sensitivity	Vector of sensitivities;
Specificity_upper	Upper confidence band for specificity estimations;
Specificity_lower	Lower confidence band for specificity estimations;
global_ROC_controlled_by	"sensitivity".

If global ROC is controlled by Specificity, a list will be output including the following

Specificity	Vector of specificity;
Sensitivity_upper	Upper confidence band for sensitivity estimations;
Sensitivity_lower	Lower confidence band for sensitivity estimations;
global_ROC_controlled_by	"specificity".

### Author(s)

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**Examples**

```
n1 = n0 = 500

## generate data
Z_D1 <- rbinom(n1, size = 1, prob = 0.3)
Z_D2 <- rnorm(n1, 0.8, 1)
Z_C1 <- rbinom(n0, size = 1, prob = 0.7)
Z_C2 <- rnorm(n0, 0.8, 1)
Y_C_Z0 <- rnorm(n0, 0.1, 1)
Y_D_Z0 <- rnorm(n1, 1.1, 1)
Y_C_Z1 <- rnorm(n0, 0.2, 1)
Y_D_Z1 <- rnorm(n1, 0.9, 1)

M0 <- Y_C_Z0 * (Z_C1 == 0) + Y_C_Z1 * (Z_C1 == 1) + Z_C2
M1 <- Y_D_Z0 * (Z_D1 == 0) + Y_D_Z1 * (Z_D1 == 1) + 1.5 * Z_D2

diseaseData <- data.frame(M = M1, Z1 = Z_D1, Z2 = Z_D2)
controlData <- data.frame(M = M0, Z1 = Z_C1, Z2 = Z_C2)

userFormula = "M~Z1+Z2"
target_covariates = c(1, 0.7, 0.9)

# default nbootstrap is 100
# set nbootstrap as 10 here to improve example speed

myROCband <- sscaROC_CB(diseaseData,
                        controlData,
                        userFormula,
                        mono_resp_method = "none",
                        target_covariates,
                        global_ROC_controlled_by = "sensitivity",
                        CB_alpha = 0.95,
                        logit_CB = FALSE,
                        nbootstrap = 10,
                        nbin = 100,
                        verbose = FALSE)
```

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