

Chapter 546

One ROC Curve and Cutoff Analysis

Introduction

This procedure generates empirical (nonparametric) and Binormal ROC curves. It also gives the area under the ROC curve (AUC), the corresponding confidence interval of AUC, and a statistical test to determine if AUC is greater than a specified value. Summary measures for a desired (user-specified) list of cutoff values are also available. Some of these measures include sensitivity, specificity, proportion correctly specified, table counts, positive predictive value, cost analysis, likelihood ratios, and the Youden index. These measures are often used to determine the optimal cutoff value (optimal decision threshold).

Discussion and Technical Details

Although ROC curve analysis can be used for a variety of applications across a number of research fields, we will examine ROC curves through the lens of diagnostic testing. In a typical diagnostic test, each unit (e.g., individual or patient) is measured on some scale or given a score with the intent that the measurement or score will be useful in classifying the unit into one of two conditions (e.g., Positive / Negative, Yes / No, Diseased / Non-diseased). Based on a (hopefully large) number of individuals for which the score and condition is known, researchers may use ROC curve analysis to determine the ability of the score to classify or predict the condition. The analysis may also be used to determine the optimal cutoff value (optimal decision threshold).

For a given cutoff value, a positive or negative diagnosis is made for each unit by comparing the measurement to the cutoff value. If the measurement is less (or greater, as the case may be) than the cutoff, the predicted condition is negative. Otherwise, the predicted condition is positive. However, the predicted condition doesn't necessarily match the true condition of the experimental unit (patient). There are four possible outcomes: true positive, true negative, false positive, false negative.

Classification Table

		Predicted Condition	
		Positive	Negative
True Condition	Positive	True Positive	False Negative
	Negative	False Positive	True Negative

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Each unit falls into only one of the four outcomes. When all of the units are assigned to the four outcomes for a given cutoff, a count for each outcome is produced. The four counts are labeled A, B, C, and D in the table below.

Classification Table (Counts)

		Predicted Condition		
		Positive	Negative	Total
True Condition	Positive	True Positive (A)	False Negative (C)	A + C
	Negative	False Positive (B)	True Negative (D)	B + D
Total		A + B	C + D	A + B + C + D

Various rates (proportions) can be used to describe a classification table. Some rates are based on the true condition, some rates are based on the predicted condition, and some rates are based on the whole table. These rates will be described in the following sections.

Rates Assuming a True Condition

The following rates assume one of the two true conditions.

True Positive Rate (TPR) or Sensitivity = $A / (A + C)$

The true positive rate is the proportion of the units with a known positive condition for which the predicted condition is positive. This rate is often called the sensitivity and constitutes the Y axis on the ROC curve.

		Predicted Condition		
		Positive	Negative	
True Condition	Positive	True Positive (A)	False Negative (C)	$TPR = A / (A + C)$ (Y Axis on ROC Curve)
	Negative	False Positive (B)	True Negative (D)	

True Negative Rate (TNR) or Specificity = $D / (B + D)$

The true negative rate is the proportion of the units with a known negative condition for which the predicted condition is negative. This rate is often called the specificity. One minus this value constitutes the X axis on the ROC curve.

		Predicted Condition		
		Positive	Negative	
True Condition	Positive	True Positive (A)	False Negative (C)	$TNR = D / (B + D)$
	Negative	False Positive (B)	True Negative (D)	

False Negative Rate (FNR) or Miss Rate = $C / (A + C)$

The false negative rate is the proportion of the units with a known positive condition for which the predicted condition is negative. This rate is sometimes called the miss rate.

		Predicted Condition		
		Positive	Negative	
True Condition	Positive	True Positive (A)	False Negative (C)	$FNR = C / (A + C)$
	Negative	False Positive (B)	True Negative (D)	

False Positive Rate (FPR) or Fall-out = $B / (B + D)$

The false positive rate is the proportion of the units with a known negative condition for which the predicted condition is positive. This rate is sometimes called the fall-out and constitutes the X axis on the ROC curve.

		Predicted Condition		
		Positive	Negative	
True Condition	Positive	True Positive (A)	False Negative (C)	$FPR = B / (B + D)$ (X Axis on ROC Curve)
	Negative	False Positive (B)	True Negative (D)	

Rates Assuming a Predicted Condition

The following rates assume one of the two predicted conditions.

Positive Predictive Value (PPV) or Precision = $A / (A + B)$

The positive predictive value is the proportion of the units with a predicted positive condition for which the true condition is positive. This rate is sometimes called the precision.

		Predicted Condition	
		Positive	Negative
True Condition	Positive	True Positive (A)	False Negative (C)
	Negative	False Positive (B)	True Negative (D)

$$PPV = A / (A + B)$$

Positive Predictive Value Adjusted for Known Prevalence

When the prevalence (or pre-test probability of a positive condition) is known for the experimental units, an adjusted formula for positive predictive value, based on the known prevalence value, can be used.

Using Bayes theorem, adjusted values of PPV are calculated based on known prevalence values as follows:

$$Adjusted\ PPV = \frac{sensitivity \times known\ prevalence}{sensitivity \times known\ prevalence + (1 - specificity) \times (1 - known\ prevalence)}$$

Negative Predictive Value (NPV) = $D / (C + D)$

The negative predictive value is the proportion of the units with a predicted negative condition for which the true condition is negative.

		Predicted Condition	
		Positive	Negative
True Condition	Positive	True Positive (A)	False Negative (C)
	Negative	False Positive (B)	True Negative (D)

$$NPV = D / (C + D)$$

Negative Predictive Value Adjusted for Known Prevalence

When the prevalence (or pre-test probability of a positive condition) is known for the experimental units, an adjusted formula for negative predictive value, based on the known prevalence value, can be used.

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Using Bayes theorem, adjusted values of NPV are calculated based on known prevalence values as follows:

$$\text{Adjusted NPV} = \frac{\text{specificity} \times (1 - \text{known prevalence})}{(1 - \text{sensitivity}) \times \text{known prevalence} + \text{specificity} \times (1 - \text{known prevalence})}$$

False Omission Rate (FOR) = C / (C + D)

The false omission rate is the proportion of the units with a predicted negative condition for which the true condition is positive.

		Predicted Condition	
		Positive	Negative
True Condition	Positive	True Positive (A)	False Negative (C)
	Negative	False Positive (B)	True Negative (D)

$$\text{FOR} = C / (C + D)$$

False Discovery Rate (FDR) = B / (A + B)

The false discovery rate is the proportion of the units with a predicted positive condition for which the true condition is negative.

		Predicted Condition	
		Positive	Negative
True Condition	Positive	True Positive (A)	False Negative (C)
	Negative	False Positive (B)	True Negative (D)

$$\text{FDR} = B / (A + B)$$

Whole Table Rates

The following rates are proportions based on all the units.

$$\text{Prevalence} = (A + C) / (A + B + C + D)$$

The prevalence may be estimated from the table if all the units are randomly sampled from the population.

		Predicted Condition		
		Positive	Negative	
True Condition	Positive	True Positive (A)	False Negative (C)	Prevalence = $(A + C) / (A + B + C + D)$
	Negative	False Positive (B)	True Negative (D)	

$$\text{Accuracy or Proportion Correctly Classified} = (A + D) / (A + B + C + D)$$

The accuracy reflects the total proportion of units that are correctly predicted or classified.

		Predicted Condition		
		Positive	Negative	
True Condition	Positive	True Positive (A)	False Negative (C)	Accuracy = $(A + D) / (A + B + C + D)$
	Negative	False Positive (B)	True Negative (D)	

$$\text{Proportion Incorrectly Classified} = (B + C) / (A + B + C + D)$$

The proportion incorrectly classified reflects the total proportion of units that are incorrectly predicted or classified.

		Predicted Condition		
		Positive	Negative	
True Condition	Positive	True Positive (A)	False Negative (C)	PIC = $(B + C) / (A + B + C + D)$
	Negative	False Positive (B)	True Negative (D)	

Confidence Intervals for Rates (Proportions)

Confidence limits for the above rates are calculated using the exact (Binomial distribution) methods described in the One Proportion chapter of the documentation.

Other Diagnostic Accuracy Indices

Over the past several decades, a number of table summary indices have been considered, above those described above. Those available in **NCSS** are described below.

Youden Index

Conceptually, the Youden index is the vertical distance between the 45 degree line and the point on the ROC curve. The formula for the Youden index is

$$\text{Youden Index} = \text{sensitivity} + \text{specificity} - 1$$

Higher values of the Youden index are better than lower values.

Sensitivity + Specificity

The addition of the sensitivity and the specificity gives essentially the same information as the Youden index but may be slightly more intuitive for interpretation.

Higher values of sensitivity plus specificity are better than lower values.

Distance to Corner

The distance to the top-left corner of the ROC curve for each cutoff value is given by

$$d = \sqrt{(1 - \text{sensitivity})^2 + (1 - \text{specificity})^2}$$

Lower distances to the corner are better than higher distances.

Positive Likelihood Ratio (LR+) = TPR / FPR

The positive likelihood ratio is the ratio of the true positive rate (sensitivity) to the false positive rate (1 - specificity). This likelihood ratio statistic measures the value of the test for increasing certainty about a positive diagnosis.

$$LR+ = \frac{TPR}{FPR}$$

Negative Likelihood Ratio (LR-) = FNR / TNR

The negative likelihood ratio is the ratio of the false negative rate to the true negative rate (specificity).

$$LR- = \frac{FNR}{TNR}$$

Diagnostic Odds Ratio (DOR) = LR+ / LR-

The diagnostic odds ratio is the ratio of the positive likelihood ratio to the negative likelihood ratio.

$$DOR = \frac{LR+}{LR-}$$

Cost

A cost approach is sometimes used when seeking to determine the optimal cutoff value. This approach is based on an analysis of the costs of the four possible outcomes of a diagnostic test: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). If the cost of each of these outcomes is known. The average overall cost C of performing a test at a given cutoff is given by

$$Cost = C_0 + C_{TP}P(TP) + C_{TN}P(TN) + C_{FP}P(FP) + C_{FN}P(FN)$$

Here, C_0 is the fixed cost of performing the test, C_{TP} is the cost associated with a true positive, $P(TP)$ is the proportion of TP 's in the population, and so on.

Metz (1978) showed that the slope of the ROC curve at the optimal cutoff value is

$$m = \frac{1 - Prevalence}{Prevalence} \times \frac{C_{FP} - C_{TN}}{C_{FN} - C_{TP}}$$

Zweig and Campbell (1993) showed that the point along the ROC curve where the average cost is minimum corresponds to the cutoff value where

$$f_m = sensitivity - m(1 - specificity)$$

is maximized. We refer to f_m as the Cost Index.

In order to make these cost calculations, known prevalence and cost values (or cost ratio) must be supplied.

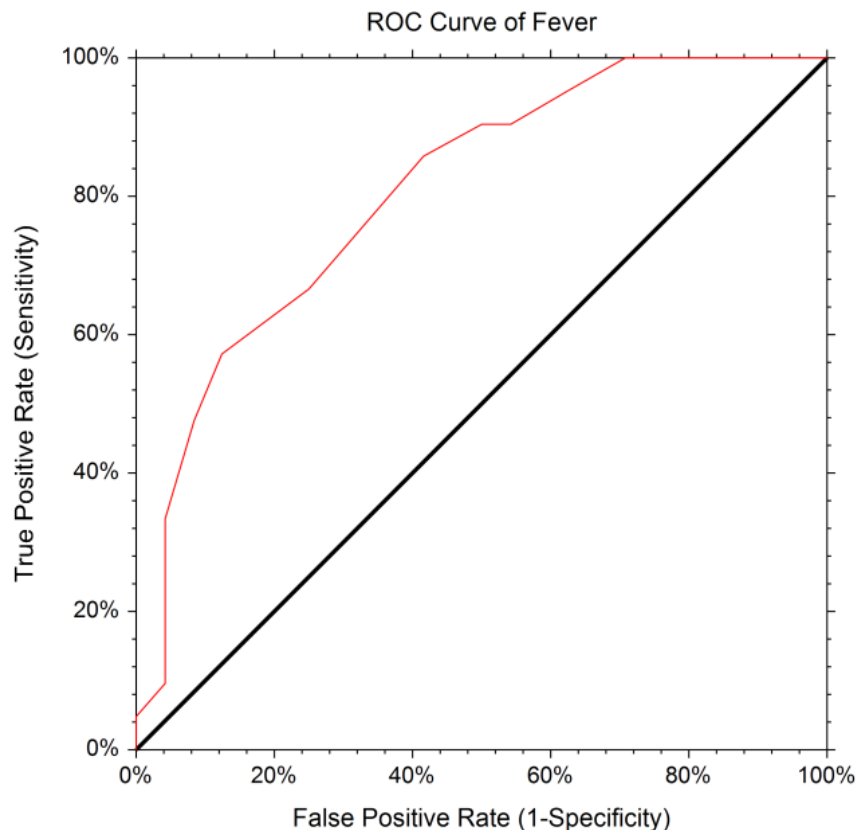
ROC Curves

Each of the rates above are calculated for a given table, based on a single cutoff value. A receiver operating characteristic (ROC) curve plots the true positive rate (sensitivity) against the false positive rate ($1 - \text{specificity}$) for *all possible* cutoff values. General discussions of ROC curves can be found in Altman (1991), Swets (1996), Zhou et al (2002), and Krzanowski and Hand (2009). Gehlbach (1988) provides an example of its use.

Two types of ROC curves can be generated in **NCSS**: the empirical ROC curve and the binormal ROC curve.

Empirical ROC Curve

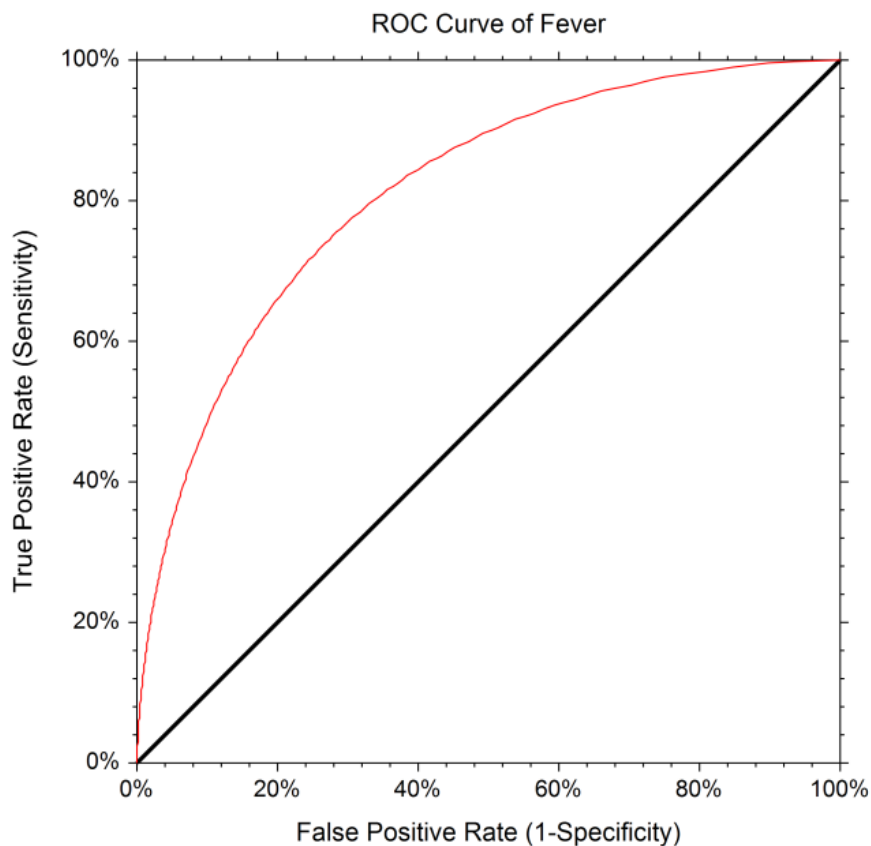
The empirical ROC curve is the more common version of the ROC curve. The empirical ROC curve is a plot of the true positive rate versus the false positive rate for all possible cut-off values.



That is, each point on the ROC curve represents a different cutoff value. The points are connected to form the curve. Cutoff values that result in low false-positive rates tend to result low true-positive rates as well. As the true-positive rate increases, the false positive rate increases. The better the diagnostic test, the more quickly the true positive rate nears 1 (or 100%). A near-perfect diagnostic test would have an ROC curve that is almost vertical from (0,0) to (0,1) and then horizontal to (1,1). The diagonal line serves as a reference line since it is the ROC curve of a diagnostic test that randomly classifies the condition.

Binormal ROC Curve

The Binormal ROC curve is based on the assumption that the diagnostic test scores corresponding to the positive condition and the scores corresponding to the negative condition can each be represented by a Normal distribution. To estimate the Binormal ROC curve, the sample mean and sample standard deviation are estimated from the known positive group, and again for the known negative group. These sample means and sample standard deviations are used to specify two Normal distributions. The Binormal ROC curve is then generated from the two Normal distributions. When the two Normal distributions closely overlap, the Binormal ROC curve is closer to the 45-degree diagonal line. When the two Normal distributions overlap only in the tails, the Binormal ROC curve has a much greater distance from the 45-degree diagonal line.



It is recommended that researchers identify whether the scores for the positive and negative groups need to be transformed to follow the Normal distribution more closely before using the Binormal ROC Curve methods.

Area under the ROC Curve (AUC)

The area under an ROC curve (AUC) is a popular measure of the accuracy of a diagnostic test. In general, higher AUC values indicate better test performance. The possible values of AUC range from 0.5 (no diagnostic ability) to 1.0 (perfect diagnostic ability).

The AUC has a physical interpretation. The AUC is the probability that the criterion value of an individual drawn at random from the population of those with a positive condition is larger than the criterion value of another individual drawn at random from the population of those where the condition is negative.

Another interpretation of AUC is the average true positive rate (average sensitivity) across all possible false positive rates.

Two methods are commonly used to estimate the AUC. One method is the empirical (nonparametric) method by DeLong et al. (1988). This method has become popular because it does not make the strong normality assumptions that the Binormal method makes. The other method is the Binormal method presented by Metz (1978) and McClish (1989). This method results in a smooth ROC curve from which the complete (and partial) AUC may be calculated.

AUC of an Empirical ROC Curve

The empirical (nonparametric) method by DeLong et al. (1988) is a popular method for computing the AUC. This method has become popular because it does not make the strong Normality assumptions that the Binormal method makes.

The value of AUC using the empirical method is calculated by summing the area of the trapezoids that are formed below the connected points making up the ROC curve. From DeLong et al. (1988), define the T_1 component of the i^{th} subject, $V(T_{1i})$ as

$$V(T_{1i}) = \frac{1}{n_0} \sum_{j=1}^{n_0} \Psi(T_{1i}, T_{0j})$$

and define the T_0 component of the j^{th} subject, $V(T_{0j})$ as

$$V(T_{0j}) = \frac{1}{n_1} \sum_{i=1}^{n_1} \Psi(T_{1i}, T_{0j})$$

where

$$\Psi(X, Y) = 0 \text{ if } Y > X,$$

$$\Psi(X, Y) = 1/2 \text{ if } Y = X,$$

$$\Psi(X, Y) = 1 \text{ if } Y < X$$

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The empirical AUC is estimated as

$$A_{Emp} = \sum_{i=1}^{n_1} V(T_{1i})/n_1 = \sum_{j=1}^{n_0} V(T_{0j})/n_0$$

The variance of the estimated AUC is estimated as

$$V(A_{Emp}) = \frac{1}{n_1} S_{T_1}^2 + \frac{1}{n_0} S_{T_0}^2$$

where $S_{T_1}^2$ and $S_{T_0}^2$ are the variances

$$S_{T_i}^2 = \frac{1}{n_i - 1} \sum_{i=1}^{n_i} [V(T_{1i}) - A_{Emp}]^2, \quad i = 0, 1$$

AUC of a Binormal ROC Curve

The formulas that we use here come from McClish (1989). Suppose there are two populations, one made up of individuals with the condition being positive and the other made up of individuals with the negative condition. Further, suppose that the value of a criterion variable is available for all individuals. Let X refer to the value of the criterion variable in the negative population and Y refer to the value of the criterion variable in the positive population. The binormal model assumes that both X and Y are normally distributed with different means and variances. That is,

$$X \sim N(\mu_x, \sigma_x^2), \quad Y \sim N(\mu_y, \sigma_y^2)$$

The ROC curve is traced out by the function

$$\{FP(c), TP(c)\} = \left\{ \Phi\left(\frac{\mu_x - c}{\sigma_x}\right), \Phi\left(\frac{\mu_y - c}{\sigma_y}\right) \right\}, \quad -\infty < c < \infty$$

where $\Phi(z)$ is the cumulative normal distribution function.

The area under the whole ROC curve is

$$\begin{aligned} A &= \int_{-\infty}^{\infty} TP(c) FP'(c) \, dc \\ &= \int_{-\infty}^{\infty} \left[\Phi\left(\frac{\mu_y - c}{\sigma_y}\right) \Phi\left(\frac{\mu_x - c}{\sigma_x}\right) \right] \, dc \\ &= \Phi\left[\frac{a}{\sqrt{1 + b^2}}\right] \end{aligned}$$

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where

$$a = \frac{\mu_y - \mu_x}{\sigma_y} = \frac{\Delta}{\sigma_y}$$

$$b = \frac{\sigma_x}{\sigma_y}$$

$$\Delta = \mu_y - \mu_x$$

The area under a portion of the AUC curve is given by

$$\begin{aligned} A &= \int_{c_1}^{c_2} TP(c)FP'(c) dc \\ &= \frac{1}{\sigma_x} \int_{c_2}^{c_1} \left[\Phi\left(\frac{\mu_y - c}{\sigma_y}\right) \Phi\left(\frac{\mu_x - c}{\sigma_x}\right) \right] dc \end{aligned}$$

The partial area under an ROC curve is usually defined in terms of a range of false-positive rates rather than the criterion limits c_1 and c_2 . However, the one-to-one relationship between these two quantities, given by

$$c_i = \mu_x + \sigma_x \Phi^{-1}(FP_i)$$

allows the criterion limits to be calculated from desired false-positive rates.

The MLE of A is found by substituting the MLE's of the means and variances into the above expression and using numerical integration. When the area under the whole curve is desired, these formulas reduce to

$$\hat{A} = \Phi \left[\frac{\hat{a}}{\sqrt{1 + \hat{b}^2}} \right]$$

Note that for ease of reading we will often omit the use of the *hat* to indicate an MLE in the following.

The variance of \hat{A} is derived using the method of differentials as

$$V(\hat{A}) = \left(\frac{\partial A}{\partial \Delta} \right)^2 V(\hat{\Delta}) + \left(\frac{\partial A}{\partial \sigma_x^2} \right)^2 V(s_x^2) + \left(\frac{\partial A}{\partial \sigma_y^2} \right)^2 V(s_y^2)$$

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where

$$\frac{\partial A}{\partial \Delta} = \frac{E}{\sqrt{2\pi(1+b^2)\sigma_y^2}} [\Phi(\tilde{c}_1) - \Phi(\tilde{c}_0)]$$

$$\frac{\partial A}{\partial \sigma_x^2} = \frac{E}{4\pi(1+b^2)\sigma_x\sigma_y} [e^{-k_0} - e^{-k_1}] - \frac{abE}{2\sigma_x\sigma_y\sqrt{2\pi(1+b^2)^{3/2}}} [\Phi(\tilde{c}_1) - \Phi(\tilde{c}_0)]$$

$$E = \exp\left(-\frac{a^2}{2(1+b^2)}\right)$$

$$\frac{\partial A}{\partial \sigma_y^2} = -\frac{a}{2\sigma_y} \left(\frac{\partial A}{\partial \Delta}\right) - b^2 \left(\frac{\partial A}{\partial \sigma_x^2}\right)$$

$$\tilde{c}_i = \left[\Phi^{-1}(FP_i) + \frac{ab}{(1+b^2)} \right] \sqrt{(1+b^2)}$$

$$k_i = \frac{\tilde{c}_i^2}{2}$$

$$V(\hat{\Delta}) = \frac{\sigma_x^2}{n_x} + \frac{\sigma_y^2}{n_y}$$

$$V(s_x^2) = \frac{2\sigma_x^4}{n_x - 1}$$

$$V(s_y^2) = \frac{2\sigma_y^4}{n_y - 1}$$

AUC Confidence Limits

Once estimates of AUC and the variance of AUC are calculated, hypothesis tests and confidence intervals can be calculated using standard methods. However, following the advice of Zhou et al. (2002) page 125, we use the following transformation which results in statistics that are closer to normality and ensures confidence limits that are inside the zero-one range. The transformation is

$$\hat{\Psi} = \ln\left(\frac{1 + \hat{A}}{1 - \hat{A}}\right)$$

The variance of $\hat{\Psi}$ is estimated using

$$V(\hat{\Psi}) = \frac{4}{(1 - \hat{A}^2)^2} V(\hat{A})$$

An $100(1 - \alpha)\%$ confidence interval for Ψ may then be constructed as

$$L, U = \hat{\Psi} \mp z_{1-\alpha/2} \sqrt{V(\hat{\Psi})}$$

Using the inverse transformation, the confidence interval for AUC is given by the two limits

$$\frac{1 - e^{-L}}{1 + e^{-L}} \quad \text{and} \quad \frac{1 - e^{-U}}{1 + e^{-U}}$$

AUC Hypothesis Tests

A statistical test to determine whether the test has any classification utility is to test the AUC against the value 0.5, which corresponds to the AUC of the 45-degree diagonal line and represents random classification. For larger sample sizes, the estimated AUC can be assumed to follow the Normal distribution. The test statistic is

$$Z = \frac{A - 0.5}{\sqrt{V(A)}}$$

where A is the AUC estimate. More generally, the AUC estimate may be compared to any value using

$$Z = \frac{A - A_0}{\sqrt{V(A)}}$$

This general form may be used for both the empirical and Binormal methods for estimating AUC.

Finding the Optimal Cutoff Value (Optimal Decision Threshold)

While the ROC curve and corresponding AUC give an overall picture of the behavior of a diagnostic test across all cutoff values, there remains a practical need to determine the specific cutoff value that should be used for individuals requiring diagnosis. If the cost of each diagnostic decision is known, as well as the positive condition prevalence, the optimal cutoff value is the one that minimizes cost, as described under Cost in the Other Diagnostic Accuracy Indices section. However, cost and prevalence values are typically unknown and unattainable. In this case, a recommended approach is to find the cutoff with highest Youden Index, or equivalently, the highest Sensitivity + Specificity (see Krzanowski and Hand, 2009). These indices are also described in the Other Diagnostic Accuracy Indices section.

Data Structure

The data are entered in two or more columns. One column specifies the true condition of the individual. The other column(s) contain the criterion value(s) for the tests being examined.

Criterion dataset

Condition	Score
0	1
0	3
0	4
1	7
0	4
0	5
1	9
1	4
.	.
.	.
.	.

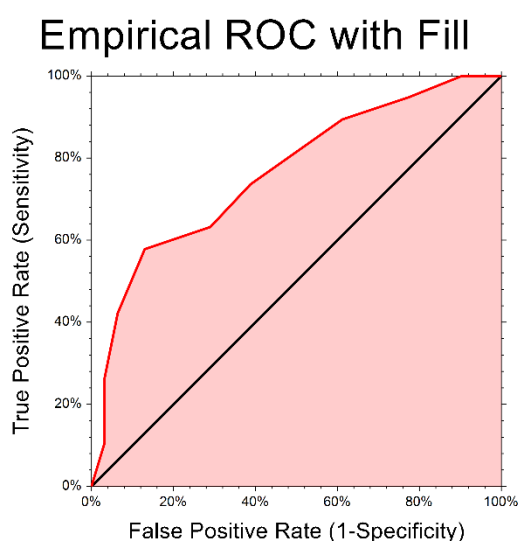
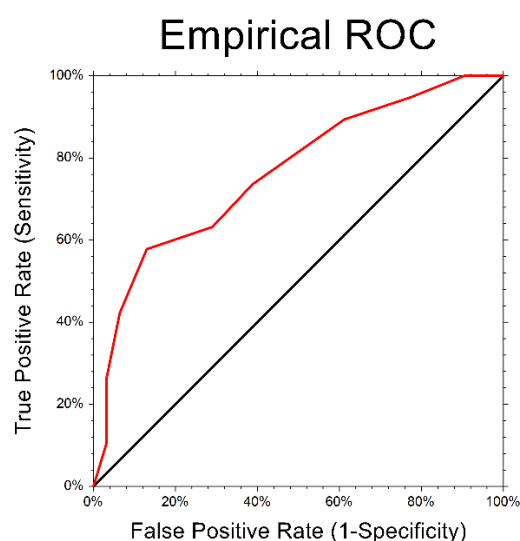
ROC Plot Format Window Options

This section describes some of the options available on the ROC Plot Format window, which is displayed when the ROC Plot Chart Format button is clicked. Common options, such as axes, labels, legends, and titles are documented in the Graphics Components chapter.

ROC Plot Tab

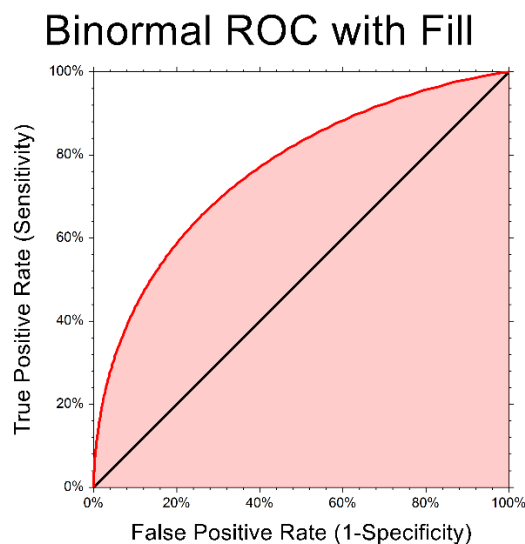
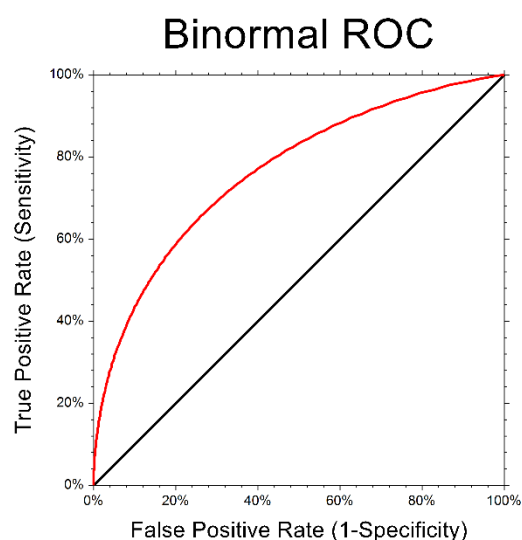
Empirical ROC Line Section

You can specify the format of the empirical ROC curve lines using the options in this section.



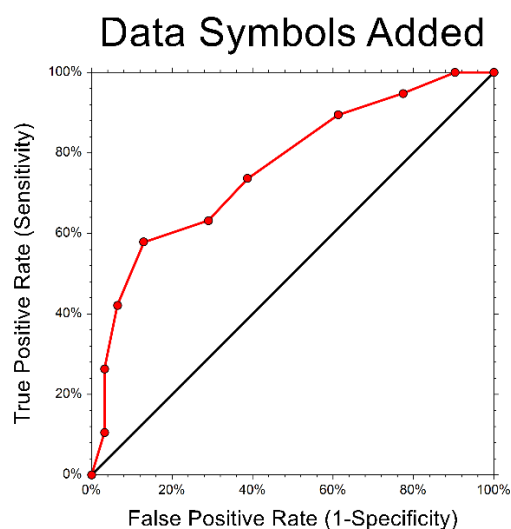
Binormal ROC Line Section

You can specify the format of the binormal ROC curves lines using the options in this section.



Symbols Section

You can modify the attributes of the symbols using the options in this section.



Reference Line Section

You can modify the attributes of the 45° reference line using the options in this section.

Titles, Legend, Numeric Axis, Group Axis, Grid Lines, and Background Tabs

Details on setting the options in these tabs are given in the Graphics Components chapter.

Example 1 – ROC Curve and General Cutoff Analysis

This section presents an example of producing a general cutoff analysis, AUC analysis, and ROC curve, based on the Criterion dataset. In this dataset, a 1 for Condition indicates the condition is present, while a 0 indicates the condition is absent. It is anticipated that higher Score values are associated with the condition being present.

Setup

To run this example, complete the following steps:

1 Open the Criterion example dataset

- From the File menu of the NCSS Data window, select **Open Example Data**.
- Select **Criterion** and click **OK**.

2 Specify the One ROC Curve and Cutoff Analysis procedure options

- Find and open the **One ROC Curve and Cutoff Analysis** procedure using the menus or the Procedure Navigator.
- The settings for this example are listed below and are stored in the **Example 1** settings file. To load these settings to the procedure window, click **Open Example Settings File** in the Help Center or File menu.

Variables Tab

Condition Variable **Condition**

Positive Condition Value **1**

Criterion Variable(s) **Score**

Criterion Direction **Higher values indicate a Positive Condition**

Cutoff Reports Tab

Cutoff Value List **Data**

3 Run the procedure

- Click the **Run** button to perform the calculations and generate the output.

Common Rates and Indices for Each Cutoff Value

Common Rates and Indices for Each Cutoff Value

Criterion Variable: Score

Estimated Prevalence = $19 / 50 = 0.38$

Estimated Prevalence is the proportion of the sample with a positive condition of 1, or $(A + C) / (A + B + C + D)$ for all cutoff values. The estimated prevalence should only be used as a valid estimate of the population prevalence when the entire sample is a random sample of the population.

Table Counts									
Cutoff Value	TPs A	FPs B	FNs C	TNs D	TPR (Sensitivity)	TNR (Specificity)	PPV	Accuracy	TPR + TNR
≥ 1	19	31	0	0	1.0000	0.0000	0.3800	0.38	1.0000
≥ 2	19	28	0	3	1.0000	0.0968	0.4043	0.44	1.0968
≥ 3	18	24	1	7	0.9474	0.2258	0.4286	0.50	1.1732
≥ 4	17	19	2	12	0.8947	0.3871	0.4722	0.58	1.2818
≥ 5	14	12	5	19	0.7368	0.6129	0.5385	0.66	1.3497
≥ 6	12	9	7	22	0.6316	0.7097	0.5714	0.68	1.3413
≥ 7	11	4	8	27	0.5789	0.8710	0.7333	0.76	1.4499
≥ 8	8	2	11	29	0.4211	0.9355	0.8000	0.74	1.3565
≥ 9	5	1	14	30	0.2632	0.9677	0.8333	0.70	1.2309
≥ 10	2	1	17	30	0.1053	0.9677	0.6667	0.64	1.0730

Definitions:

Cutoff Value	Indicates the criterion value range that predicts a positive condition.
A	The number of True Positives.
B	The number of False Positives.
C	The number of False Negatives.
D	The number of True Negatives.
TPR	The True Positive Rate or Sensitivity = $A / (A + C)$.
TNR	The True Negative Rate or Specificity = $D / (B + D)$.
PPV	The Positive Predictive Value or Precision = $A / (A + B)$.
Accuracy	The Proportion Correctly Classified = $(A + D) / (A + B + C + D)$.
TPR + TNR	The Sensitivity + Specificity.

The report displays some of the more commonly used rates for each cutoff value.

One ROC Curve and Cutoff Analysis

Counts, TPR, TNR, FNR, FPR

Counts, TPR, TNR, FNR, FPR

Criterion Variable: Score

Table Counts								
Cutoff Value	TPs A	FPs B	FNs C	TNs D	TPR (Sensitivity)	TNR (Specificity)	FNR (Miss Rate)	FPR (Fall-out)
≥ 1	19	31	0	0	1.0000	0.0000	0.0000	1.0000
≥ 2	19	28	0	3	1.0000	0.0968	0.0000	0.9032
≥ 3	18	24	1	7	0.9474	0.2258	0.0526	0.7742
≥ 4	17	19	2	12	0.8947	0.3871	0.1053	0.6129
≥ 5	14	12	5	19	0.7368	0.6129	0.2632	0.3871
≥ 6	12	9	7	22	0.6316	0.7097	0.3684	0.2903
≥ 7	11	4	8	27	0.5789	0.8710	0.4211	0.1290
≥ 8	8	2	11	29	0.4211	0.9355	0.5789	0.0645
≥ 9	5	1	14	30	0.2632	0.9677	0.7368	0.0323
≥ 10	2	1	17	30	0.1053	0.9677	0.8947	0.0323

Definitions:

Cutoff Value Indicates the criterion value range that predicts a positive condition.

A The number of True Positives.

B The number of False Positives.

C The number of False Negatives.

D The number of True Negatives.

TPR The True Positive Rate or Sensitivity = $A / (A + C)$.TNR The True Negative Rate or Specificity = $D / (B + D)$.FNR The False Negative Rate or Miss Rate = $C / (A + C)$.FPR The False Positive Rate or Fall-out = $B / (B + D)$.

The report displays for each cutoff value the counts and rates assuming a true condition.

TPR (Sensitivity) and TNR (Specificity) Confidence Intervals

TPR (Sensitivity) and TNR (Specificity) Confidence Intervals

Criterion Variable: Score

Cutoff Value	TPR (Sensitivity)	95% Confidence Interval Limits		TNR (Specificity)	95% Confidence Interval Limits	
		Lower	Upper		Lower	Upper
≥ 1	1.0000	0.8235	1.0000	0.0000	0.0000	0.1122
≥ 2	1.0000	0.8235	1.0000	0.0968	0.0204	0.2575
≥ 3	0.9474	0.7397	0.9987	0.2258	0.0959	0.4110
≥ 4	0.8947	0.6686	0.9870	0.3871	0.2185	0.5781
≥ 5	0.7368	0.4880	0.9085	0.6129	0.4219	0.7815
≥ 6	0.6316	0.3836	0.8371	0.7097	0.5196	0.8578
≥ 7	0.5789	0.3350	0.7975	0.8710	0.7017	0.9637
≥ 8	0.4211	0.2025	0.6650	0.9355	0.7858	0.9921
≥ 9	0.2632	0.0915	0.5120	0.9677	0.8330	0.9992
≥ 10	0.1053	0.0130	0.3314	0.9677	0.8330	0.9992

Definitions:

Cutoff Value	Indicates the criterion value range that predicts a positive condition.
TPR	The True Positive Rate or Sensitivity = $A / (A + C)$.
Confidence Interval Limits	Form the confidence interval for TPR.
TNR	The True Negative Rate or Specificity = $D / (B + D)$.
Confidence Interval Limits	Form the confidence interval for TNR.

The report displays confidence intervals for the sensitivity (true positive rate) and specificity (true negative rate) for each cutoff value.

Counts, PPV, NPV, FOR, FDR

Counts, PPV, NPV, FOR, FDR

Criterion Variable: Score

Cutoff Value	Table Counts				PPV (Precision)	NPV	FOR	FDR
	TPs A	FPs B	FNs C	TNs D				
≥ 1	19	31	0	0	0.3800			0.6200
≥ 2	19	28	0	3	0.4043	1.0000	0.0000	0.5957
≥ 3	18	24	1	7	0.4286	0.8750	0.1250	0.5714
≥ 4	17	19	2	12	0.4722	0.8571	0.1429	0.5278
≥ 5	14	12	5	19	0.5385	0.7917	0.2083	0.4615
≥ 6	12	9	7	22	0.5714	0.7586	0.2414	0.4286
≥ 7	11	4	8	27	0.7333	0.7714	0.2286	0.2667
≥ 8	8	2	11	29	0.8000	0.7250	0.2750	0.2000
≥ 9	5	1	14	30	0.8333	0.6818	0.3182	0.1667
≥ 10	2	1	17	30	0.6667	0.6383	0.3617	0.3333

Definitions:

Cutoff Value Indicates the criterion value range that predicts a positive condition.

A The number of True Positives.

B The number of False Positives.

C The number of False Negatives.

D The number of True Negatives.

PPV The Positive Predictive Value or Precision = $A / (A + B)$.

NPV The Negative Predictive Value = $D / (C + D)$.

FOR The False Omission Rate = $C / (C + D)$.

FDR The False Discovery Rate = $B / (A + B)$.

The report displays for each cutoff value the counts and rates assuming a predicted condition.

Counts, Proportion Correctly Classified, Proportion Incorrectly Classified, Estimated Prevalence

Counts, Proportion Correctly Classified, Proportion Incorrectly Classified, Estimated Prevalence

Criterion Variable: Score

Estimated Prevalence = $19 / 50 = 0.38$

Estimated Prevalence is the proportion of the sample with a positive condition of 1, or $(A + C) / (A + B + C + D)$ for all cutoff values. The estimated prevalence should only be used as a valid estimate of the population prevalence when the entire sample is a random sample of the population.

Cutoff Value	Table Counts				Proportion Classified	
	TPs	FPs	FNs	TNs	Correctly	Incorrectly
	A	B	C	D		
≥ 1	19	31	0	0	0.38	0.62
≥ 2	19	28	0	3	0.44	0.56
≥ 3	18	24	1	7	0.50	0.50
≥ 4	17	19	2	12	0.58	0.42
≥ 5	14	12	5	19	0.66	0.34
≥ 6	12	9	7	22	0.68	0.32
≥ 7	11	4	8	27	0.76	0.24
≥ 8	8	2	11	29	0.74	0.26
≥ 9	5	1	14	30	0.70	0.30
≥ 10	2	1	17	30	0.64	0.36

Definitions:

Cutoff Value	Indicates the criterion value range that predicts a positive condition.
A	The number of True Positives.
B	The number of False Positives.
C	The number of False Negatives.
D	The number of True Negatives.
Proportion Correctly Classified	Accuracy = $(A + D) / (A + B + C + D)$.
Proportion Incorrectly Classified	Inaccuracy = $(B + C) / (A + B + C + D)$.

The report displays the estimated prevalence, the counts, and the proportions correctly and incorrectly classified, for each cutoff value.

One ROC Curve and Cutoff Analysis

Counts, Youden Index, Sensitivity + Specificity, Distance to Corner, LR+, LR-, DOR

Counts, Youden Index, Sensitivity + Specificity, Distance to Corner, LR+, LR-, DOR

Criterion Variable: Score

Table Counts										
Cutoff Value	TPs A	FPs B	FNs C	TNs D	Youden Index	Sensitivity + Specificity	Distance to Corner	LR+	LR-	DOR (LR+ / LR-)
≥ 1	19	31	0	0	0.0000	1.0000	1.0000	1.0000		
≥ 2	19	28	0	3	0.0968	1.0968	0.9032	1.1071	0.0000	
≥ 3	18	24	1	7	0.1732	1.1732	0.7760	1.2237	0.2331	5.2500
≥ 4	17	19	2	12	0.2818	1.2818	0.6219	1.4598	0.2719	5.3684
≥ 5	14	12	5	19	0.3497	1.3497	0.4681	1.9035	0.4294	4.4333
≥ 6	12	9	7	22	0.3413	1.3413	0.4691	2.1754	0.5191	4.1905
≥ 7	11	4	8	27	0.4499	1.4499	0.4404	4.4868	0.4834	9.2813
≥ 8	8	2	11	29	0.3565	1.3565	0.5825	6.5263	0.6189	10.5455
≥ 9	5	1	14	30	0.2309	1.2309	0.7375	8.1579	0.7614	10.7143
≥ 10	2	1	17	30	0.0730	1.0730	0.8953	3.2632	0.9246	3.5294

Definitions:

Cutoff Value	Indicates the criterion value range that predicts a positive condition.
A	The number of True Positives.
B	The number of False Positives.
C	The number of False Negatives.
D	The number of True Negatives.
Youden Index	The Sensitivity + Specificity - 1.
Sensitivity + Specificity	The True Positive Rate plus the True Negative Rate.
Distance to Corner	The distance from the top left corner of the ROC curve to the point on the ROC curve.
LR+	The Positive Likelihood Ratio, or the ratio of TPR (Sensitivity) to FPR (1 - Specificity).
LR-	The Negative Likelihood Ratio, or the ratio of FNR to TNR.
DOR	The Diagnostic Odds Ratio, or the ratio of LR+ to LR-.

The report displays other useful diagnostic accuracy indices for each cutoff value.

Area Under Curve Analysis (Empirical Estimation)

Area Under Curve Analysis (Empirical Estimation)

Estimated Prevalence = $19 / 50 = 0.38$

Estimated Prevalence is the proportion of the sample with a positive condition of 1. The estimated prevalence should only be used as a valid estimate of the population prevalence when the entire sample is a random sample of the population.

Criterion	Count	AUC	Standard Error	Upper One-Sided Test of H0: AUC ≤ 0.5 vs. H1: AUC > 0.5		95% Confidence Interval Limits	
				Z-Value	P-Value	Lower	Upper
Score	50	0.764	0.071	3.72	0.0001	0.586	0.8717

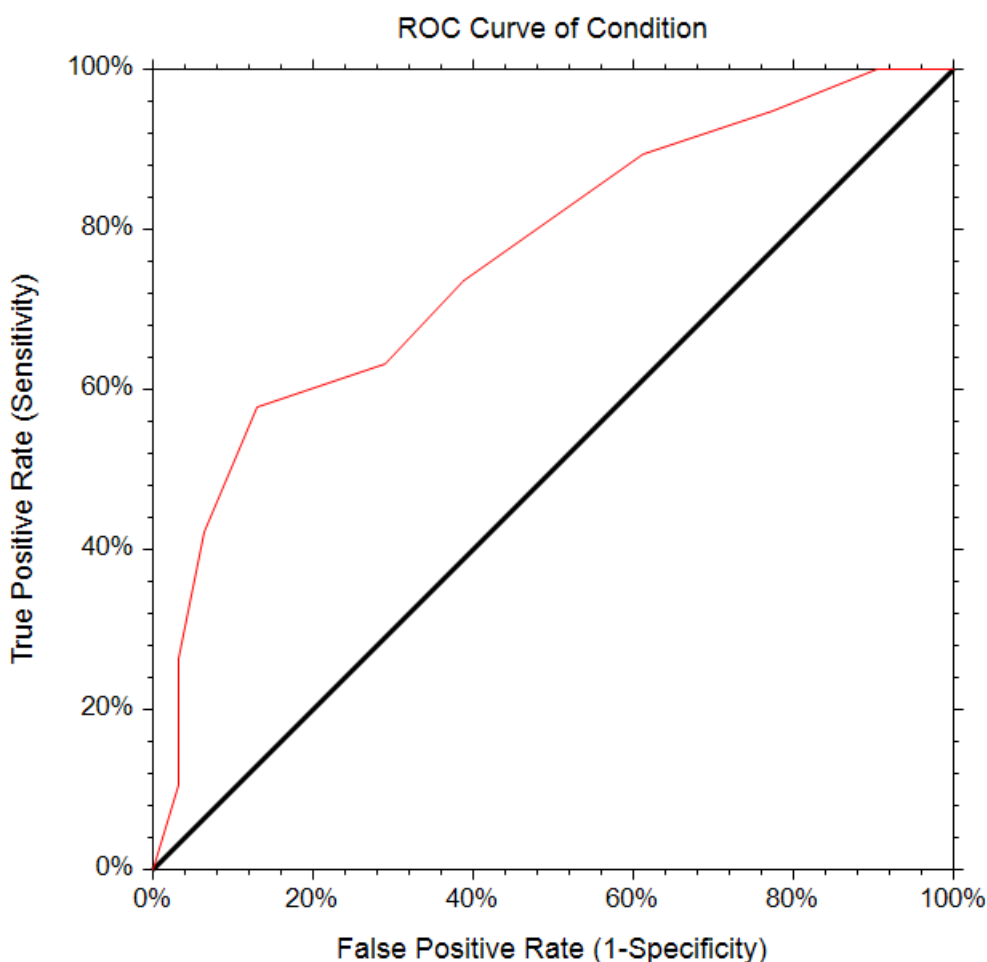
Definitions:

Criterion	The Criterion Variable containing the scores of the individuals.
Count	The number of the individuals used in the analysis.
AUC	The area under the ROC curve using the empirical (trapezoidal) approach.
Standard Error	The standard error of the AUC estimate.
Z-Value	The Z-score for testing the designated hypothesis test.
P-Value	The p-value associated with the Z-Value.
Confidence Interval Limits	Form the confidence interval for AUC.

This report gives a statistical test comparing the area under the curve to the value 0.5. The small P-value indicates a significant difference from 0.5. The report also gives the 95% confidence interval for the estimated AUC.

ROC Plot

ROC Plot



The plot can be made to contain the empirical ROC curve, the Binormal ROC curve, or both, by making the proper selection after clicking the ROC Plot Format button.

The coordinates of the points of this ROC curve are the TPR and FPR for each of the unique Score values. The diagonal (45 degree) line is an ROC curve of random classification and serves as a baseline. The ROC curve shows the overall ability of using the score to classify the condition. This curve shows a moderate classification ability of the score to classify the condition. The ROC curve for an ideal test would go up to 100% quickly on the left side and then stay level at 100% across the top.

Example 2 – Choosing the Optimal Cutoff Value

This section presents an example of choosing the optimal cutoff value, based on the Criterion dataset.

Setup

To run this example, complete the following steps:

1 Open the Criterion example dataset

- From the File menu of the NCSS Data window, select **Open Example Data**.
- Select **Criterion** and click **OK**.

2 Specify the One ROC Curve and Cutoff Analysis procedure options

- Find and open the **One ROC Curve and Cutoff Analysis** procedure using the menus or the Procedure Navigator.
- The settings for this example are listed below and are stored in the **Example 2** settings file. To load these settings to the procedure window, click **Open Example Settings File** in the Help Center or File menu.

Variables Tab

Condition Variable **Condition**
 Positive Condition Value **1**
 Criterion Variable(s) **Score**
 Criterion Direction **Higher values indicate a Positive Condition**

Cutoff Reports Tab

Cutoff Value List **Data**
 Counts, TPR (Sensitivity), TNR **Checked**
 (Specificity), PPV, Accuracy,
 TPR + TNR, Prevalence
 Counts, Youden Index, Sensitivity + **Checked**
 Sensitivity + Specificity, Distance to
 Corner, LR+, LR-, DOR

3 Run the procedure

- Click the **Run** button to perform the calculations and generate the output.

Common Rates and Indices for each Cutoff Value

Common Rates and Indices for each Cutoff Value

Criterion Variable: Score

Estimated Prevalence = $19 / 50 = 0.38$

Estimated Prevalence is the proportion of the sample with a positive condition of 1, or $(A + C) / (A + B + C + D)$ for all cutoff values. The estimated prevalence should only be used as a valid estimate of the population prevalence when the entire sample is a random sample of the population.

Table Counts									
Cutoff Value	TPs A	FPs B	FNs C	TNs D	TPR (Sensitivity)	TNR (Specificity)	PPV	Accuracy	TPR + TNR
≥ 1	19	31	0	0	1.0000	0.0000	0.3800	0.38	1.0000
≥ 2	19	28	0	3	1.0000	0.0968	0.4043	0.44	1.0968
≥ 3	18	24	1	7	0.9474	0.2258	0.4286	0.50	1.1732
≥ 4	17	19	2	12	0.8947	0.3871	0.4722	0.58	1.2818
≥ 5	14	12	5	19	0.7368	0.6129	0.5385	0.66	1.3497
≥ 6	12	9	7	22	0.6316	0.7097	0.5714	0.68	1.3413
≥ 7	11	4	8	27	0.5789	0.8710	0.7333	0.76	1.4499
≥ 8	8	2	11	29	0.4211	0.9355	0.8000	0.74	1.3565
≥ 9	5	1	14	30	0.2632	0.9677	0.8333	0.70	1.2309
≥ 10	2	1	17	30	0.1053	0.9677	0.6667	0.64	1.0730

Definitions:

Cutoff Value	Indicates the criterion value range that predicts a positive condition.
A	The number of True Positives.
B	The number of False Positives.
C	The number of False Negatives.
D	The number of True Negatives.
TPR	The True Positive Rate or Sensitivity = $A / (A + C)$.
TNR	The True Negative Rate or Specificity = $D / (B + D)$.
PPV	The Positive Predictive Value or Precision = $A / (A + B)$.
Accuracy	The Proportion Correctly Classified = $(A + D) / (A + B + C + D)$.
TPR + TNR	The Sensitivity + Specificity.

The cutoff value giving the highest accuracy (proportion correctly classified) and the highest TPR + TNR (Sensitivity + Specificity) is 7.

One ROC Curve and Cutoff Analysis

Counts, Youden Index, Sensitivity + Specificity, Distance to Corner, LR+, LR-, DOR

Counts, Youden Index, Sensitivity + Specificity, Distance to Corner, LR+, LR-, DOR

Criterion Variable: Score

Table Counts										
Cutoff Value	TPs A	FPs B	FNs C	TNs D	Youden Index	Sensitivity + Specificity	Distance to Corner	LR+	LR-	DOR (LR+ / LR-)
≥ 1	19	31	0	0	0.0000	1.0000	1.0000	1.0000		
≥ 2	19	28	0	3	0.0968	1.0968	0.9032	1.1071	0.0000	
≥ 3	18	24	1	7	0.1732	1.1732	0.7760	1.2237	0.2331	5.2500
≥ 4	17	19	2	12	0.2818	1.2818	0.6219	1.4598	0.2719	5.3684
≥ 5	14	12	5	19	0.3497	1.3497	0.4681	1.9035	0.4294	4.4333
≥ 6	12	9	7	22	0.3413	1.3413	0.4691	2.1754	0.5191	4.1905
≥ 7	11	4	8	27	0.4499	1.4499	0.4404	4.4868	0.4834	9.2813
≥ 8	8	2	11	29	0.3565	1.3565	0.5825	6.5263	0.6189	10.5455
≥ 9	5	1	14	30	0.2309	1.2309	0.7375	8.1579	0.7614	10.7143
≥ 10	2	1	17	30	0.0730	1.0730	0.8953	3.2632	0.9246	3.5294

Definitions:

Cutoff Value	Indicates the criterion value range that predicts a positive condition.
A	The number of True Positives.
B	The number of False Positives.
C	The number of False Negatives.
D	The number of True Negatives.
Youden Index	The Sensitivity + Specificity - 1.
Sensitivity + Specificity	The True Positive Rate plus the True Negative Rate.
Distance to Corner	The distance from the top left corner of the ROC curve to the point on the ROC curve.
LR+	The Positive Likelihood Ratio, or the ratio of TPR (Sensitivity) to FPR (1 - Specificity).
LR-	The Negative Likelihood Ratio, or the ratio of FNR to TNR.
DOR	The Diagnostic Odds Ratio, or the ratio of LR+ to LR-.

The cutoff value corresponding to the point with the lowest distance to the upper-left corner of the ROC curve is also 7. Based on these criteria, the optimal cutoff value is 7. If the condition prevalence is known, as well as the relative cost of false positives, true negatives, false negatives, and true positives, a cost approach may then be used to determine the optimal cutoff value.

Example 3 – Choosing the Optimal Cutoff Value using the Cost Approach

When the condition prevalence is known, as well as the relative cost of false positives, true negatives, false negatives, and true positives, a cost approach may then be used to determine the optimal cutoff value. For details, see the Cost section under Other Diagnostic Accuracy Details of this chapter. In this example, suppose that condition prevalence is known to be 0.16. The relative cost of false positives, true negatives, false negatives, and true positives is estimated to be 4.2, 1, 7.7, and 1, respectively. The dataset used is the Criterion dataset.

Setup

To run this example, complete the following steps:

1 Open the Criterion example dataset

- From the File menu of the NCSS Data window, select **Open Example Data**.
- Select **Criterion** and click **OK**.

2 Specify the One ROC Curve and Cutoff Analysis procedure options

- Find and open the **One ROC Curve and Cutoff Analysis** procedure using the menus or the Procedure Navigator.
- The settings for this example are listed below and are stored in the **Example 3** settings file. To load these settings to the procedure window, click **Open Example Settings File** in the Help Center or File menu.

Variables Tab

Condition Variable	Condition
Positive Condition Value.....	1
Criterion Variable(s).....	Score
Criterion Direction	Higher values indicate a Positive Condition

Cutoff Reports Tab

Cutoff Value List	Data
Cost Analysis	Checked
Known Prevalence for Cost	0.16
Cost of False Positive, C(FP).....	4.2
Cost of True Negative, C(TN)	1
Cost of False Negative, C(FN).....	7.7
Cost of True Positive, C(TP)	1

3 Run the procedure

- Click the **Run** button to perform the calculations and generate the output.

Cost Analysis

Cost Analysis

Criterion Variable:	Score
Known Prevalence for Cost:	0.16
Cost of False Positive, C(FP):	4.2
Cost of True Negative, C(TN):	1
Cost of False Negative, C(FN):	7.7
Cost of True Positive, C(TP):	1
Cost Ratio = $(C(FP) - C(TN)) / (C(FN) - C(TP)) = 0.4776$	

Value	Sensitivity	Specificity	Cost Index
≥ 1	1.0000	0.0000	-1.5075
≥ 2	1.0000	0.0968	-1.2648
≥ 3	0.9474	0.2258	-0.9939
≥ 4	0.8947	0.3871	-0.6421
≥ 5	0.7368	0.6129	-0.2338
≥ 6	0.6316	0.7097	-0.0964
≥ 7	0.5789	0.8710	0.2554
≥ 8	0.4211	0.9355	0.2593
≥ 9	0.2632	0.9677	0.1823
≥ 10	0.1053	0.9677	0.0244

Definitions:

Cutoff Value	Indicates the criterion value range that predicts a positive condition.
Sensitivity	The True Positive Rate = $A / (A + C)$.
Specificity	The True Negative Rate = $D / (B + D)$.
Cost Index	Derived from the Known Prevalence, Sensitivity, Specificity, and the user-input costs. The optimal cutoff value is the one with the highest Cost Index.

For this scenario, the Cost Index associated with the cutoff value of 8 is slightly higher than the Cost Index associated with the cutoff value of 7. Using the cost approach, given the prevalence value of 0.16 and the four specified relative costs, the optimal cutoff value is 8.

Example 4 – ROC Curve and Cutoff Analysis using Binormal Estimation

This section presents an example of producing a general cutoff analysis, AUC analysis, and ROC curve, using the Binormal estimation methods. The dataset used in this example is the Criterion dataset. In this dataset, a 1 for Condition indicates the condition is present, while a 0 indicates the condition is absent. It is anticipated that higher Score values are associated with the condition being present.

Setup

To run this example, complete the following steps:

1 Open the Criterion example dataset

- From the File menu of the NCSS Data window, select **Open Example Data**.
- Select **Criterion** and click **OK**.

2 Specify the One ROC Curve and Cutoff Analysis procedure options

- Find and open the **One ROC Curve and Cutoff Analysis** procedure using the menus or the Procedure Navigator.
- The settings for this example are listed below and are stored in the **Example 4** settings file. To load these settings to the procedure window, click **Open Example Settings File** in the Help Center or File menu.

Variables Tab

Condition Variable **Condition**
 Positive Condition Value **1**
 Criterion Variable(s) **Score**
 Criterion Direction **Higher values indicate a Positive Condition**

Cutoff Reports Tab

Cutoff Value List **Data**
 Rates from Binormal Estimation **Checked**
 Known Prevalence for PPV and NPV **0.16**

AUC Reports Tab

Area Under Curve (AUC) Analysis **Unchecked**
 (Empirical Estimation)
 Area Under Curve (AUC) Analysis **Checked**
 (Binormal Estimation)

One ROC Curve and Cutoff Analysis

Plots Tab

ROC Plot**Checked**ROC Plot Format (*Click the Button*)Empirical ROC Line**Unchecked**Binormal ROC Line.....**Checked****3 Run the procedure**

- Click the **Run** button to perform the calculations and generate the output.

Rates from Binormal Estimation**Rates from Binormal Estimation**

Criterion Variable: Score

Known Prevalence for Adjustment: 0.16

Cutoff Value	TPR (Sensitivity)	TNR (Specificity)	FNR (Miss Rate)	FPR (Fall-out)	Known Prevalence Adjusted		LR+	Sensitivity + Specificity
					PPV	NPV		
≥ 1	0.9891	0.0673	0.0000	1.0000	0.1680	0.9699	1.0604	1.0563
≥ 2	0.9700	0.1509	0.0000	0.9032	0.1787	0.9636	1.1425	1.1210
≥ 3	0.9293	0.2848	0.0526	0.7742	0.1984	0.9548	1.2993	1.2141
≥ 4	0.8553	0.4583	0.1053	0.6129	0.2312	0.9433	1.5789	1.3136
≥ 5	0.7417	0.6403	0.2632	0.3871	0.2820	0.9286	2.0618	1.3820
≥ 6	0.5940	0.7947	0.3684	0.2903	0.3554	0.9113	2.8940	1.3888
≥ 7	0.4313	0.9009	0.4211	0.1290	0.4533	0.8927	4.3538	1.3323
≥ 8	0.2797	0.9600	0.5789	0.0645	0.5712	0.8749	6.9924	1.2397
≥ 9	0.1599	0.9866	0.7368	0.0323	0.6946	0.8604	11.9418	1.1465
≥ 10	0.0799	0.9963	0.8947	0.0323	0.8046	0.8504	21.6148	1.0762

Definitions:

Cutoff Value	Indicates the criterion value range that predicts a positive condition.
TPR	The Binormal-estimated True Positive Rate or Sensitivity.
TNR	The Binormal-estimated True Negative Rate or Specificity.
FNR	The Binormal-estimated False Negative Rate or Miss Rate.
FPR	The Binormal-estimated False Positive Rate or Fall-out.
Adjusted PPV	The Positive Predictive Value based on the Sensitivity, Specificity, and Known Prevalence (see documentation for formula).
Adjusted NPV	The Negative Predictive Value based on the Sensitivity, Specificity, and Known Prevalence (see documentation for formula).
LR+	The Positive Likelihood Ratio, or the ratio of TPR (Sensitivity) to FPR (1 - Specificity).
Sensitivity + Specificity	The True Positive Rate plus the True Negative Rate.

The report displays a variety of rates for each cutoff value. The highest Sensitivity + Specificity corresponds to a cutoff value of 6.

Area Under Curve Analysis (Binormal Estimation)

Area Under Curve Analysis (Binormal Estimation)

Estimated Prevalence = $19 / 50 = 0.38$

Estimated Prevalence is the proportion of the sample with a positive condition of 1. The estimated prevalence should only be used as a valid estimate of the population prevalence when the entire sample is a random sample of the population.

Criterion	Count	AUC	Standard Error	Upper One-Sided Test of H0: AUC \leq 0.5 vs. H1: AUC > 0.5		95% Confidence Interval Limits	
				Z-Value	P-Value	Lower	Upper
Score	50	0.7654	0.0686	3.868	0.0001	0.5944	0.8702

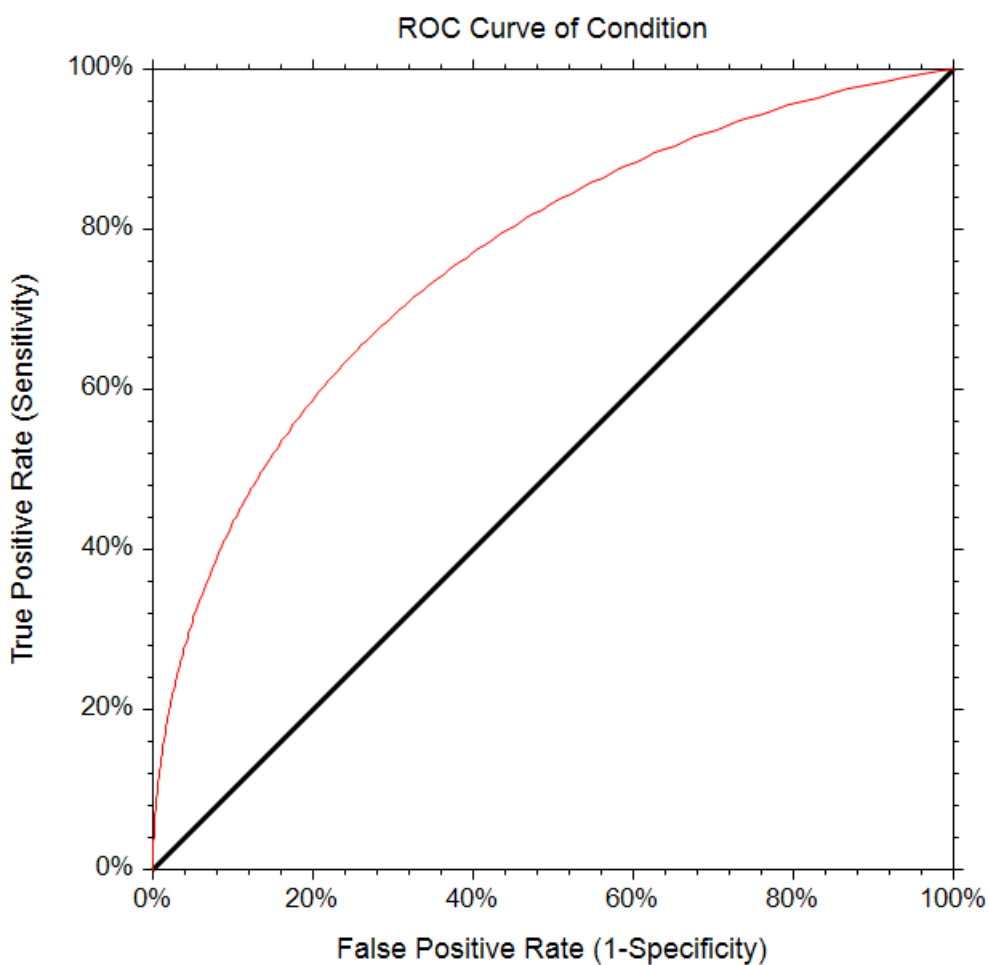
Definitions:

Criterion	The Criterion Variable containing the scores of the individuals.
Count	The number of the individuals used in the analysis.
AUC	The area under the ROC curve using the Binormal estimation approach.
Standard Error	The standard error of the AUC estimate.
Z-Value	The Z-score for testing the designated hypothesis test.
P-Value	The p-value associated with the Z-Value.
Confidence Interval Limits	Form the confidence interval for AUC.

This report gives a statistical test comparing the area under the curve to the value 0.5. The small P-value indicates a significant difference from 0.5. The report also gives the 95% confidence interval for the estimated AUC. These values are very close to those obtained when using empirical estimation.

ROC Plot

ROC Plot



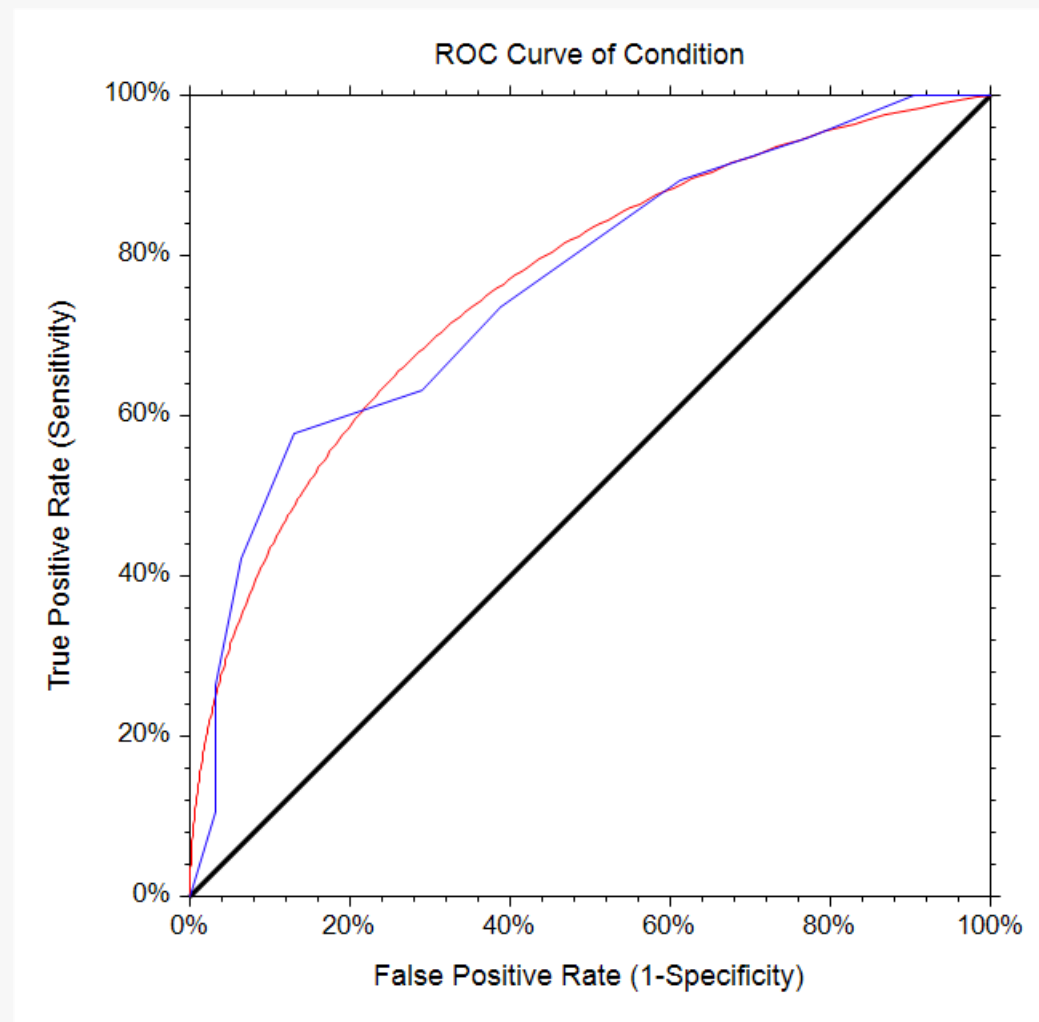
The plot can be made to contain the empirical ROC curve, the Binormal ROC curve, or both, by making the proper selection after clicking the ROC Plot Format button.

The Binormal estimation ROC plot is a smooth curve estimation of the true ROC curve. The diagonal (45 degree) line is an ROC curve of random classification and serves as a baseline.

One ROC Curve and Cutoff Analysis

The Binormal estimation ROC plot and the empirical estimation ROC plot can be superimposed in one plot using the plot format button (**Example 4b**):

ROC Plot



The plot can be made to contain the empirical ROC curve, the Binormal ROC curve, or both, by making the proper selection after clicking the ROC Plot Format button.