

## CHAPTER 141

# ROC Curves

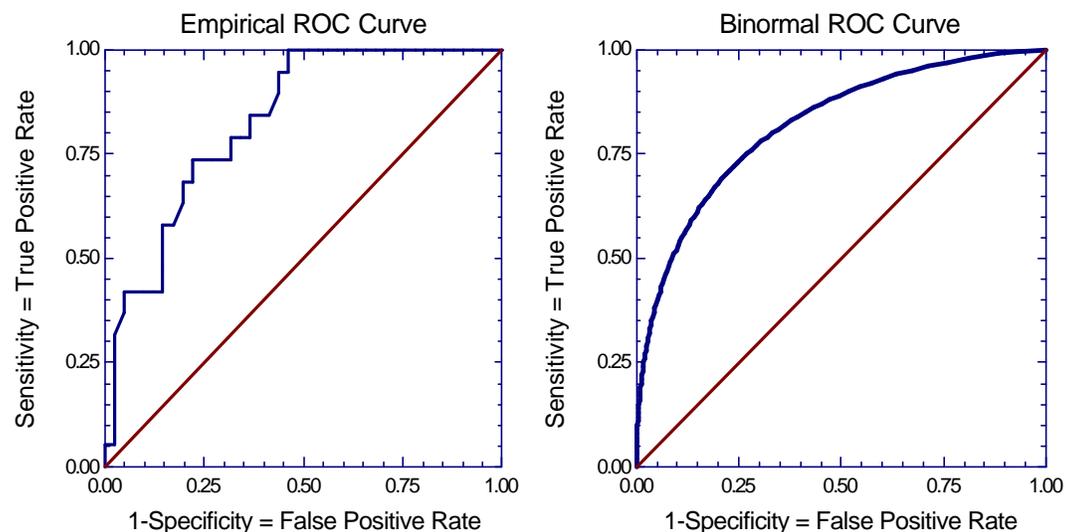
## Introduction

This procedure generates both binormal and empirical (nonparametric) ROC curves. It computes comparative measures such as the whole, and partial, area under the ROC curve. It provides statistical tests comparing the AUCs and partial AUCs for paired and independent sample designs.

## Discussion

A diagnostic test yields a measurement (*criterion* value) that is used to diagnose some condition of interest such as a disease. (In the sequel, we will often call the ‘condition of interest’ the ‘disease.’) The measurement might be a rating along a discrete scale or a value along a continuous scale. A positive or negative diagnosis is made by comparing the measurement to a cutoff value. If the measurement is less (or greater as the case may be) than the cutoff, the test is negative. Otherwise, the test is positive. Thus the cutoff value helps determine the rates of false positives and false negatives.

A receiver operating characteristic (ROC) curve shows the characteristics of a diagnostic test by graphing the false-positive rate (*1-specificity*) on the horizontal axis and the true-positive rate (*sensitivity*) on the vertical axis for various cutoff values. Examples of an empirical ROC curve and a binormal ROC curve are shown below.



Each point on the ROC curve represents a different cutoff value. Cutoff values that result in low false-positive rates tend to result in low true-positive rates as well. As the true-positive rate increases, so does the false positive rate. Obviously, a useful diagnostic test should have a cutoff value at which the true-positive rate is high and the false-positive rate is low. In fact, 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 is useless in determining the disease.

Complete discussions about ROC curves can be found in Altman (1991), Swets (1996), and Zhou et al (2002). Gehlbach (1988) provides an example of its use.

## Methods for Creating ROC Curves

Several methods have been proposed to generate ROC curves. These include the binormal and the empirical (nonparametric) methods.

### Binormal

The most commonly used method to generate smooth ROC curves is the binormal method popularized by a group of researchers including Metz (1978) (who developed the popular ROCFIT software). This method considers two populations: those with, and those without, the disease. It assumes that the criterion variable (or a scale-transformation of it) follows a normal distribution in each population. Using this normality assumption, a smooth ROC curve can be drawn using the sample means and variances of the two populations. Researchers have shown through various simulation studies that this *binormal* assumption is not as limiting as at first thought since non-normal data can often be transformed to a near-normal scale. **So, if you want to use this method, you should make sure that your data has been transformed so that it is nearly normal.**

### Empirical or Nonparametric

An empirical (nonparametric) approach that does not depend on the normality assumptions was developed by DeLong, DeLong, and Clarke-Pearson (1988). These ROC curves are especially useful when the diagnostic test results in a continuous criterion variable.

## Types of ROC Experimental Designs

Either of two experimental designs are usually employed when comparing ROC curves. These designs are *paired* or *independent samples*. Separate methods of analysis are needed to compare ROC curves depending upon which experimental design was used.

### Independent Sample (Non-correlated) Designs

In this design, individuals with, and without, the disease are randomly assigned into two (or more) groups. The first group receives diagnostic test A and the second group receives diagnostic test B. Each individual receives only one diagnostic test.

### Paired (Correlated) Designs

In this design, individuals with, and without, the disease each receive both diagnostic tests. This allows each subject to ‘serve as their own control.’

## An Example Using a Paired Design

ROC curves are explained with an example paraphrased from Gehlbach (1988). Forty-five patients with fever, headache, and a history of tick bite were classified into two groups: those with Rocky Mountain Spotted Fever (RMSF) and those without it. The serum-sodium level of each patient is measured using two techniques. We want to determine if serum-sodium level is useful in detecting RMSF, which technique is most accurate in diagnosing RMSF, and what the diagnostic cutoff value of the selected test should be. The data are presented next.

RMSF=Yes				RMSF=No			
ID	Method1	Method2	Diagnosis	ID	Method1	Method2	Diagnosis
1	124	122	1	22	129	124	0
2	125	124	1	23	131	128	0
3	126	125	1	24	131	130	0
4	126	125	1	25	134	133	0
5	127	126	1	26	134	133	0
6	128	126	1	27	135	133	0
7	128	127	1	28	136	134	0
8	128	128	1	29	136	134	0
9	128	128	1	30	136	134	0
10	129	128	1	31	137	134	0
11	129	130	1	32	137	136	0
12	131	130	1	33	138	136	0
13	132	133	1	34	138	137	0
14	133	133	1	35	139	138	0
15	133	134	1	36	139	138	0
16	135	134	1	37	139	140	0
17	135	134	1	38	139	140	0
18	135	134	1	39	140	141	0
19	136	136	1	40	140	141	0
20	138	138	1	41	141	142	0
21	139	140	1	42	142	142	0
				43	142	142	0
				44	142	142	0
				45	143	144	0

The first step in analyzing these data is to create a two-by-two table showing the diagnostic accuracy of each method at given cutoff value. If the cutoff is set at X, the table would appear as follows:

### Generic Table for Cutoff=X

Method Cutoff=X	RMSF = Yes	RMSF = No
Sodium $\leq$ X, Positive	A	B
Sodium $>$ X, Negative	C	D

The letters A, B, C, and D represent counts of the number of individuals in each of the four possible categories.

For example, if a cutoff of 130 is used to diagnose those with the disease, the tables for each sodium measurement method would be:

**Table for Method 1, Cutoff=130**

Method 1 Cutoff=130	RMSF=Yes	RMSF=No
Sodium $\leq$ 130, Positive	11	1
Sodium $>$ 130, Negative	10	23

**Table for Method 2, Cutoff=130**

Method 2 Cutoff=130	RMSF=Yes	RMSF=No
Sodium $\leq$ 130, Positive	12	3
Sodium $>$ 130, Negative	9	21

If a cutoff of 137 is used to diagnose those with the disease, the tables for each sodium measurement method would be:

**Table for Method 1, Cutoff=137**

Method 1 Cutoff=137	RMSF=Yes	RMSF=No
Sodium $\leq$ 137, Positive	19	11
Sodium $>$ 137, Negative	2	13

**Table for Method 2, Cutoff=137**

Method 2 Cutoff=137	RMSF=Yes	RMSF=No
Sodium $\leq$ 137, Positive	19	13
Sodium $>$ 137, Negative	12	11

As you study these tables, you can see changing the cutoff value changes the table counts. An ROC curve is constructed by creating many of these tables and plotting the sensitivity versus one minus the specificity.

## Definition of Terms

We will now define the indices that are used to create ROC curves.

### Sensitivity

Sensitivity is the proportion of those with the disease that are correctly identified as having the disease by the test. In terms of our two-by-two tables, sensitivity =  $A/(A+C)$ .

### Specificity

Specificity is the proportion of those without the disease that are correctly identified as not having the disease by the test. In terms of our two-by-two tables, specificity =  $D/(B+D)$ .

### Prevalence

Prevalence is the overall proportion of individuals with the disease. In terms of our two-by-two tables, prevalence =  $(A+C)/(A+B+C+D)$ . Notice that since the prevalence is defined in terms of the marginal values, it does not depend on the cutoff value.

### Positive Predictive Value (PPV)

PPV is the proportion of individuals with positive test results who have the disease. In terms of our two-by-two tables, PPV =  $(A)/(A+B)$ .

### Negative Predictive Value (NPV)

NPV is the proportion of individuals with negative test results who do not have the disease. In terms of our two-by-two tables, NPV =  $(D)/(C+D)$ .

## Discussion

A problem with sensitivity and specificity is that they do not assess the probability of making a correct diagnosis. To overcome this, practitioners have developed two other indices: PPV and NPV. Unfortunately, these indices have the disadvantage that they are directly impacted by the prevalence of the disease in the population. For example, if your sampling procedure is constructed to obtain more individuals with the disease than is the case in the whole population of interest, the PPV and NPV need to be adjusted.

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

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

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

Another way of interpreting these terms is as follows. The prevalence of a disease is the prior probability that a subject has the disease before the diagnostic test is run. The values of PPV and 1-NPV are the posterior probabilities of a subject having the disease after the diagnostic test is conducted.

## Likelihood Ratio

The likelihood ratio statistic measures the value of the test for increasing certainty about a positive diagnosis. It is calculated as follows:

$$LR = \frac{\Pr(\text{positive test}|\text{disease})}{\Pr(\text{positive test}|\text{no disease})} = \frac{\text{sensitivity}}{1 - \text{specificity}}$$

## Finding the Optimal Criterion Value

The optimal criterion value is that value that minimizes the average cost. The approach we use was given by Metz (1978) and Zhou et al. (2002). This approach is based on an analysis of the costs (and benefits) of the four possible outcomes of a diagnostic test: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The cost of each of these outcomes must be determined. This is no small task. In fact, a whole field of study has arisen to determine these costs. Once these costs are found, the average overall cost  $C$  of performing a test is given by

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

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. Note that  $P(TP)$  is equal to

$$P(TP) = \text{Sensitivity} [P(\text{Condition} = \text{True})]$$

Metz (1978) showed that the point along the ROC curve where the average cost is minimum is the point where  $\text{sensitivity} - m(1 - \text{specificity})$  is maximized, where

$$m = \frac{P(\text{Condition} = \text{False})}{P(\text{Condition} = \text{True})} \left( \frac{C_{FP} - C_{TN}}{C_{FN} - C_{TP}} \right)$$

$P(\text{Condition} = \text{True})$  is called the *prevalence* of the disease. Depending on the method used to obtain the sample, it may or may not be estimated from the sample. Note that the costs enter this equation as the ratio of the net cost for a test of an individual without the disease to the net cost for a test of an individual with the disease.

Using the above result, the cut optimum cutoff may be found by scanning a report that shows  $C(\text{Cutoff})$  for every value of the cutoff variable.

## The AUC of a Single ROC Curve

The area under an ROC curve (AUC) is a popular measure of the accuracy of a diagnostic test. Other things being equal, the larger the AUC, the better the test is at predicting the existence of the disease. 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 with the disease is larger than the criterion value of another individual drawn at random from the population without the disease.

A statistical test of usefulness of a diagnostic test is to compare it to the value 0.5. Such a statistical test can be made if we are willing to assume that the sample is large enough so that the estimated AUC follows the normal distribution. The statistical test is

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

where  $\tilde{A}$  is the estimated AUC and  $V(\tilde{A})$  is the estimated variance of  $\tilde{A}$ .

Two methods are commonly used to estimate the AUC. The first is the *binormal* method presented by Metz (1978) and McClish (1989). This method results in a smooth ROC curve from which both the complete and partial AUC may be calculated. The second 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 above  $z$  test may be used for both methods, as long as an appropriate estimate of  $V(\tilde{A})$  is used.

### The AUC of a Single 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 disease and the other made up of individuals without the disease. 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 non-diseased population and  $Y$  refer to the value of the criterion variable in the diseased population. The binormal model assumes that both  $X$  and  $Y$  are normally distributed with different means and variances. That is,

$$X \sim N(\mathbf{m}_x, \mathbf{s}_x^2), Y \sim N(\mathbf{m}_y, \mathbf{s}_y^2)$$

The ROC curve is traced out by the function

$$\{FP(c), TP(c)\} = \left\{ F\left(\frac{\mathbf{m}_x - c}{\mathbf{s}_x}\right), F\left(\frac{\mathbf{m}_y - c}{\mathbf{s}_y}\right) \right\}, \quad -\infty < c < \infty$$

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

The area under the whole ROC curve is

$$\begin{aligned} A &= \int_{-\infty}^{\infty} TP(c)FP'(c) dc \\ &= \int_{-\infty}^{\infty} \left[ F\left(\frac{\mathbf{m}_y - c}{\mathbf{s}_y}\right) f\left(\frac{\mathbf{m}_x - c}{\mathbf{s}_x}\right) \right] dc \\ &= F\left[\frac{a}{\sqrt{1 + b^2}}\right] \end{aligned}$$

where

$$a = \frac{\mathbf{m}_y - \mathbf{m}_x}{\mathbf{s}_y} = \frac{D}{\mathbf{s}_y}, \quad b = \frac{\mathbf{s}_x}{\mathbf{s}_y}, \quad D = \mathbf{m}_y - \mathbf{m}_x$$

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

$$\begin{aligned} A &= \int_{c_1}^{c_2} TP(c)FP'(c) dc \\ &= \frac{1}{\mathbf{s}_x} \int_{c_1}^{c_2} \left[ F\left(\frac{\mathbf{m}_y - c}{\mathbf{s}_y}\right) f\left(\frac{\mathbf{m}_x - c}{\mathbf{s}_x}\right) \right] dc \end{aligned}$$

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

$$c_i = \mathbf{m}_x + \mathbf{s}_x F^{-1}(FP_i)$$

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

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

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

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

$$V(\hat{A}) = \left(\frac{\mathcal{J}A}{\mathcal{J}D}\right)^2 V(\hat{D}) + \left(\frac{\mathcal{J}A}{\mathcal{J}\mathbf{s}_x^2}\right)^2 V(\mathbf{s}_x^2) + \left(\frac{\mathcal{J}A}{\mathcal{J}\mathbf{s}_y^2}\right)^2 V(\mathbf{s}_y^2)$$

where

$$\frac{\mathcal{J}A}{\mathcal{J}D} = \frac{E}{\sqrt{2p(1+b^2)\mathbf{s}_y^2}} [F(\tilde{c}_1) - F(\tilde{c}_0)]$$

$$\frac{\mathcal{J}A}{\mathcal{J}\mathbf{s}_x^2} = \frac{E}{4p(1+b^2)\mathbf{s}_x\mathbf{s}_y} [e^{-k_0} - e^{-k_1}] - \frac{abE}{2\mathbf{s}_x\mathbf{s}_y\sqrt{2p(1+b^2)}^{3/2}} [F(\tilde{c}_1) - F(\tilde{c}_0)]$$

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

$$\frac{\mathcal{J}A}{\mathcal{J}\mathbf{s}_y^2} = -\frac{a}{2\mathbf{s}_y} \left(\frac{\mathcal{J}A}{\mathcal{J}D}\right) - b^2 \left(\frac{\mathcal{J}A}{\mathcal{J}\mathbf{s}_x^2}\right)$$

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

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

$$V(\hat{D}) = \frac{s_x^2}{n_x} + \frac{s_y^2}{n_y}$$

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

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

Once estimates of  $\hat{A}$  and  $V(\hat{A})$  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 outside the zero-one range. The transformation is

$$\hat{y} = \frac{1}{2} \ln \left( \frac{1+A}{1-A} \right)$$

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

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

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

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

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

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

## The AUC of a Single 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 formula for computing this estimate of the AUC and its variance are given later in the section on comparing two empirical ROC curves.

## Comparing the AUC of Two ROC Curves

Occasionally, it is of interest to compare the areas under the ROC curve (AUC) of two diagnostic tests using a hypothesis test. This may be done using either the binormal model results shown in McClish (1989) or the empirical (nonparametric) results of DeLong (1988).

### Comparing the AUC of Two Empirical ROC Curves

A statistical test may be constructed that uses empirical estimates of the AUCs, their variances, and covariance. The variance and covariance formulas used depend on whether the design is paired or independent samples. Following Zhou et al. (2002) page 185, the formula to compare two AUCs is the following  $z$  test (which asymptotically follows the standard normal distribution) is given by

$$z = \frac{A_1 - A_2}{\sqrt{V(A_1 - A_2)}}$$

where

$$V(A_1 - A_2) = V(A_1) + V(A_2) - 2\text{Cov}(A_1, A_2)$$

### Independent Samples

For independent samples in which each subject receives only one of the two diagnostic tests, the covariance is zero and the two variances are

$$V(A_k) = \frac{S_{T_{k1}}}{n_{k1}} + \frac{S_{T_{k0}}}{n_{k0}}$$

where

$$S_{T_{ki}} = \frac{1}{n_{ki} - 1} \sum_{j=1}^{n_{ki}} [V(T_{kij}) - A_k]^2, \quad k = 1, 2 \quad i = 0, 1$$

$$V(T_{k1i}) = \frac{1}{n_{k0} - 1} \sum_{j=1}^{n_{k0}} y(T_{k1i}, T_{k0j}), \quad k = 1, 2$$

$$V(T_{k0j}) = \frac{1}{n_{k1} - 1} \sum_{i=1}^{n_{k1}} y(T_{k1i}, T_{k0j}), \quad k = 1, 2$$

$$A_k = \frac{\sum_{i=1}^{n_{k1}} V(T_{k1i})}{n_{k1}} = \frac{\sum_{j=1}^{n_{k0}} V(T_{k0j})}{n_{k0}}, \quad k = 1, 2$$

$$y(X, Y) = \begin{cases} 0 & \text{if } Y > X \\ \frac{1}{2} & \text{if } Y = X \\ 1 & \text{if } Y < X \end{cases}$$

Here  $T_{k0j}$  represents the observed diagnostic test result for the  $j$ th subject in group  $k$  without the disease and  $T_{k1j}$  represents the observed diagnostic test result for the  $j$ th subject in group  $k$  with the disease.

## Paired Samples

For paired samples in which each subject receives both of the two diagnostic tests, the variances are given as above and the covariance is given by

$$\text{Cov}(A_1, A_2) = \frac{S_{T_{11}T_{21}}}{n_1} + \frac{S_{T_{10}T_{20}}}{n_0}$$

where

$$S_{T_{11}T_{21}} = \frac{1}{n_1 - 1} \sum_{j=1}^{n_1} [V(T_{11j}) - A_1][V(T_{21j}) - A_2]$$

$$S_{T_{10}T_{20}} = \frac{1}{n_0 - 1} \sum_{j=1}^{n_0} [V(T_{10j}) - A_1][V(T_{20j}) - A_2]$$

## Comparing Two Binormal AUCs

When the binormal assumption is viable, the hypothesis that the areas under the two ROC curves are equal may be tested using

$$z = \frac{A_1 - A_2}{\sqrt{V(A_1 - A_2)}}$$

## Independent Samples Design

When an independent sample design is used, the variance of the difference in AUC's is the sum of the variances since the covariance is zero. That is,

$$V(A_1 - A_2) = V(A_1) + V(A_2)$$

where  $V(A_1)$  and  $V(A_2)$  are calculated using the formula (with obvious substitution) for  $V(A)$  given above in the section on a single binormal ROC curve.

## Paired Design

When a paired design is used, the variance of the difference in AUC's is

$$V(A_1 - A_2) = V(A_1) + V(A_2) - 2\text{Cov}(A_1, A_2)$$

where  $V(A_1)$  and  $V(A_2)$  are calculated using the formula for  $V(A)$  given above in the section on a single binormal ROC curve. Since the data are paired, a covariance term must also be calculated. This is done using the differential method as follows

$$\begin{aligned} \text{Cov}(A_1, A_2) &= \left( \frac{fA_1}{fD_1} \right) \left( \frac{fA_2}{fD_2} \right) \text{Cov}(\hat{D}_1, \hat{D}_2) \\ &+ \left( \frac{fA_1}{fs_{x_1}^2} \right) \left( \frac{fA_2}{fs_{x_2}^2} \right) \text{Cov}(s_{x_1}^2, s_{x_2}^2) \\ &+ \left( \frac{fA_1}{fs_{y_1}^2} \right) \left( \frac{fA_2}{fs_{y_2}^2} \right) \text{Cov}(s_{y_1}^2, s_{y_2}^2) \end{aligned}$$

where

$$\text{Cov}(\hat{D}_1, \hat{D}_2) = \frac{r_x s_{x_1} s_{x_2}}{n_x} + \frac{r_y s_{y_1} s_{y_2}}{n_y}$$

$$\text{Cov}(s_{x_1}^2, s_{x_2}^2) = \frac{2r_x s_{x_1}^2 s_{x_2}^2}{n_x - 1}$$

$$\text{Cov}(s_{y_1}^2, s_{y_2}^2) = \frac{2r_y s_{y_1}^2 s_{y_2}^2}{n_y - 1}$$

and  $r_y$  ( $r_x$ ) is the correlation between the two sets of criterion values in the diseased (non-diseased) population.

## Transformation Achieve Normality

McClish (1989) ran simulations to study the accuracy of the normality approximation of the above  $z$  statistic for various portions of the AUC curve. She found that a logistic-type transformation resulted in a  $z$  statistic that was closer to normality. This transformation is

$$q(A) = \ln \left( \frac{FP_2 - FP_1 + A}{FP_2 - FP_1 - A} \right)$$

which has the inverse version

$$A = (FP_2 - FP_1) \frac{e^q - 1}{e^q + 1}$$

The variance of this quantity is given by

$$V(q) = \left( \frac{2(FP_2 - FP_1)}{(FP_2 - FP_1)^2 - A^2} \right)^2 V(A)$$

and the covariance is given by

$$\text{Cov}(\mathbf{q}_1, \mathbf{q}_2) = \frac{4(FP_2 - FP_1)^2}{\left[ (FP_2 - FP_1)^2 - A_1^2 \right] \left[ (FP_2 - FP_1)^2 - A_2^2 \right]} \text{Cov}(A_1, A_2)$$

The adjusted  $z$  statistic is

$$\begin{aligned} z &= \frac{\mathbf{q}_1 - \mathbf{q}_2}{\sqrt{V(\mathbf{q}_1 - \mathbf{q}_2)}} \\ &= \frac{\mathbf{q}_1 - \mathbf{q}_2}{\sqrt{V(\mathbf{q}_1) + V(\mathbf{q}_2) - 2\text{Cov}(\mathbf{q}_1, \mathbf{q}_2)}} \end{aligned}$$

## Data Structure

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

## Procedure Options

This section describes the options available in this procedure.

### Variables Tab

This panel specifies which variables are used in the analysis.

#### Actual Condition Variable

A binary response variable which represents whether or not the individual actually has the condition of interest. The value representing a yes is specified in the Positive Condition Value box. The values may be text or numeric.

#### Positive Condition Value

This is the value of the Actual Condition Variable that indicates that the individual has the condition of interest. All other values are considered as not having the condition of interest. Often, the positive value is set to '1' and the negative value is set to '0.' However, any numbering scheme may be used.

#### Criterion Variable(s)

A list of one or more criterion (test, score, discriminant, etc.) variables. If more than one variable is listed, a separate curve is drawn for each.

Note that for a paired design, both criterion variables would be specified here and the Group Variable option would be left blank. However, for an independent sample design, a single criterion variable would be specified here and a Group Variable would be specified.

## Test Direction

This option specifies whether low or high values of the criterion variable indicate that the test is positive for the disease.

### Low X = Positive

A low value of the criterion variable indicates a positive test result. That is, a low value will indicate a positive test.

### High X = Positive

A high value of the criterion variable indicates a positive test result. That is, a high value will indicate a positive test.

## Group Variable

This optional variable may be used to divide the subjects into groups. It is only used when you have an independent samples design and there is just one Criterion Variable specified. If more than one Criterion Variables are specified, this variable is ignored.

When specified and used, a separate ROC curve is generated for each unique value of this variable.

## Frequency Variable

An optional variable containing a set of counts (frequencies). Normally, each row represents one individual. On occasion, however, each row of data may represent more than one individual. This variable contains the number of individuals that a row represents.

## Max Equivalence Difference

This value is used by the equivalence and noninferiority tests. This is the largest value of the difference in AUCs that will still result in the conclusion of equivalence of the two diagnostic tests. That is, if the true difference in AUCs is less than this amount, the two tests are assumed to be equivalent. Care must be used to be certain a reasonable value is selected.

Note that the range of equivalence is from  $-D$  to  $D$ , where 'D' is the value specified here.

We recommend a value of 0.05 as a reasonable choice. The value is usually between 0 and 0.2.

## Filter Active

This option indicates whether the currently defined filter (if any) should be used when running this procedure.

## Reports Tab

The following options control the reports that are displayed.

### Actual Condition Prevalence

This option specifies the prevalence of the disease which is the proportion of individuals in the population that have the disease. As a proportion, this number varies between zero and one. Often an accurate estimate of this value cannot be calculated from the data, so it must be entered.

Using this value, adjusted values of PPV and NPV are calculated.

### Criterion List

Specify the specific values of the criterion variable to be shown on the reports. Enter 'Data' when you want the unique criterion values from the database to be used.

You can enter a list using numbers separated by blanks such as '1 2 3 4 5' or you can use the 'xx TO yy BY inc' syntax or the 'xx:yy(inc)' syntax.

For example, entering '1 TO 10 BY 3' or '1:10(3)' is the same as entering '1 4 7 10'.

## Cost Benefit Ratios

This is the ratio of the net cost when the condition is absent to the net cost when the condition is present. In symbols, this is

$$[\text{Cost}(\text{FP})-\text{Benefit}(\text{TN})] / [(\text{Cost}(\text{FN})-\text{Benefit}(\text{TP}))]$$

This value is used to compute the optimum criterion value. Since it is difficult to calculate this value exactly, you can enter a set of up to 4 values. These values will be used in the Cost-Benefit Report.

You can enter a list of values such as '0.5 0.8 0.9 1.0' or use the special list format: '0.5:0.8(0.1)'.

## Lower and Upper AUC Limits

Note that these options are used with binormal reports only. They are not used with the empirical (nonparametric) reports.

The horizontal axis of the ROC curve is the proportion of false-positives (FP). Usually, the AUC is computed for full range of false-positive, i.e. from  $\text{FP} = 0$  to  $\text{FP} = 1$ . These options let you compute the area for only the portion of FP values between these two limits. This is useful for situations in which only a portion of the ROC curve is of interest.

Note the these values must be between zero and one and that the Lower Limit must be less than the Upper Limit.

## Alpha - C.I.

This option specifies the value of alpha to be used in all confidence intervals. The quantity (1-Alpha) is the confidence coefficient (or confidence level) of all confidence intervals. Sets of  $100 \times (1 - \alpha)\%$  confidence limits are calculated. This must be a value between 0.0 and 0.5. The most common value is 0.05.

## Alpha - H. Tests

This option specifies the value of alpha to be used in all hypothesis tests including tests of noninferiority and equivalence. Alpha is the probability of rejecting the null hypothesis when it is true. This must be a value between 0.0 and 0.5. The most common value is 0.05.

## ROC Plots - Predictive Value Report

Check to display the corresponding report or plot.

### AUC: One Curve

Check to display all reports about a single AUC.

### AUC: Two Curves

Check to display all reports comparing two AUCs.

### AUC: Equivalence

Check to display all reports concerning the testing of equivalence and noninferiority.

## Show Notes

Check to display the notes at the end of each report.

## Format Tab

The following options control the format of the reports that are displayed.

### Variable Names

Specify whether to use variable names or (the longer) variable labels in report headings.

### Precision

Specify the precision of numbers in the report. Single precision will display seven-place accuracy, while the double precision will display thirteen-place accuracy. Note that all reports are formatted for single precision only.

### Skip Line After

When writing a row of information to a report, some variable names/labels may be too long to fit in the space allocated. If the name(or label) contains more characters than this, the rest of the output for that line is moved down to the next line. Most reports are designed to hold a label of up to 15 characters.

Hint:

Enter '1' when you always want each row's output to be printed on two lines. Enter '100' when you want each row printed on only one line. This may cause some columns to be miss-aligned.

### Criterion Decimals - Z-Value Decimals

Specifies the number of decimal places used.

### Report Page Title

Specify a page title to be displayed in report headings.

## ROC Curve Tab

The options on this panel control the appearance of the ROC Curve.

### Plot Style File

Designate a scatter plot style file. This file sets all scatter plot options that are not set directly on this panel. Unless you choose otherwise, the ROC style file is used. These style files are created in the Scatter Plot procedure.

### Plot Title

This is the text of the title. The characters  $\{Y\}$  are replaced by the response variable name. Press the button on the right of the field to specify the font of the text.

### Label (Y and X)

This is the text of the label. Press the button on the right of the field to specify the font of the text.

### Tick Marks - Ref. Numbers (Y and X)

Pressing these buttons brings up a window that sets the font, rotation, and number of decimal places displayed in the reference numbers along the vertical and horizontal axes.

### Major Ticks - Minor Ticks (Y and X)

These options set the number of major and minor tickmarks displayed on each axis.

## Grid Lines (Y and X)

These check boxes indicate whether the grid lines should be displayed.

## Number Binormal Intervals

The range of a criterion variable is divided into this many intervals and a two-by-two table is calculated. Note that each interval ends with a cutoff point.

## Lines Tab

These options set the color, width, and pattern of the up to fifteen lines representing the criterion variables. Note that the color of the 45 degree line is specified in the group immediately after the criterion variables. For example, if you had three criterion variables, the color of the Group 4 option would be the color of the 45 degree line.

Double-clicking the line, or clicking the button to the right of the symbol, brings up a line specification window. This window lets you specify the characteristics of each line in detail.

### Color

The color of the line.

### Width

The width of the line.

### Pattern

The line pattern (solid, dot, dash, etc.).

## Legend Tab

These options control the legend.

### Show Legend

Specifies whether to display the legend.

### Legend Text

Specifies the title of the legend. Click the button on the right to specify the font size, color, and style of the legend text.

## Storage Tab

Various proportions may be stored on the current database for further analysis. These options let you designate which statistics (if any) should be stored and which variables should receive these statistics. The selected statistics are automatically stored to the current database each time you run the procedure.

Note that the variables you specify must already have been named on the current database.

Note that existing data is replaced. Be careful that you do not specify variables that contain important data.

## Criterion List

Specify the specific values of the criterion variable to be used for storing the data back on the spreadsheet. Enter 'Data' when you want the values in the database to be used. You can enter a list using numbers separated by blanks such as '1 2 3 4 5' or you can use the 'xx TO yy BY inc' syntax or you can use the 'xx:yy(inc)' syntax.

For example, entering '1 TO 10 BY 3' or '1:10(3)' is the same as entering '1 4 7 10'.

## Variable Name to NPV 2

Specify the variable to receive these values.

## Template Tab

The options on this panel allow various sets of options to be loaded (File menu: Load Template) or stored (File menu: Save Template). A template file contains all the settings for this procedure.

## File Name

Designate the name of the template file either to be loaded or stored.

## Template Files

A list of previously stored template files for this procedure.

## Template Id's

A list of the Template Id's of the corresponding files. This id value is loaded in the box at the bottom of the panel.

# Tutorial - Example 1 - Paired Design

This section presents an example of how to generate an ROC curve for the RMSF data contained in the **ROC** database. This is an example of data from a paired designed.

Note that you can either enter the options as instructed below or you can go to the Template tab, click on **Example 1**, and press the Load Template button.

## 1 Open the ROC dataset.

- From the File menu of the NCSS Data window, select Open.
- Select the Data subdirectory of the NCSS97 directory.
- Click on the file **ROC.s0**.
- Click **Open**.

## 2 Open the ROC Curves window.

- On the menus, select **Analysis**, then **Diagnostic Tests**, then **ROC Curves**. The ROC Curves procedure will be displayed.
- On the menus, select **File**, then **New Template**. This will fill the procedure with the default template.

## 3 Specify the variables.

- On the ROC Curves window, select the **Variables tab**.
- Set the Actual Condition Variable to **Fever**.
- Set the Criterion Variable(s) to **Sodium1, Sodium2**.
- Set the Positive Condition Value to **1**.
- Set the Test Direction to **Low X = Positive**.
- Set the Max Equivalence Difference to **0.05**.

## 4 Specify the reports.

- On the ROC Curves window, select the **Reports tab**.
- Set the Actual Condition(Disease) Prevalence to **0.10**.
- Set the Criterion List to **120 to 140 by 5**.
- Set the Cost Benefit Ratios to **1.1 1.3 1.5 1.7**.
- Check all reports.

## 5 Specify the format.

- On the ROC Curves window, select the **Format tab**.
- Set the Skip Line After option to **20**.

## 6 Specify the Lines.

- On the ROC Curves window, select the **Lines tab**.
- Click on the Line 1 arrow. Set the width to 60.
- Click on the Line 2 arrow. Set the width to 60.
- Click on the Line 3 arrow. Set the width to 60.

## 7 Run the procedure.

- From the Run menu, select Run Procedure. Alternatively, just click the Run button (the left-most button on the button bar at the top).

# ROC Data using the Empirical ROC Curve

ROC Data for Condition = Fever using the Empirical ROC Curve

Sodium1	Count	Count	Count	Count	Sensitivity		False+	Specificity
Cutoff	+ P	+ A	- P	- A	A/(A+C)	C/(A+C)	B/(B+D)	D/(B+D)
Value	A	B	C	D				
120.00	0	0	21	24	0.00000	1.00000	0.00000	1.00000
125.00	2	0	19	24	0.09524	0.90476	0.00000	1.00000
130.00	11	1	10	23	0.52381	0.47619	0.04167	0.95833
135.00	18	6	3	18	0.85714	0.14286	0.25000	0.75000
140.00	21	19	0	5	1.00000	0.00000	0.79167	0.20833

ROC Data for Condition = Fever using the Empirical ROC Curve

Sodium2	Count	Count	Count	Count	Sensitivity		False+	Specificity
Cutoff	+ P	+ A	- P	- A	A/(A+C)	C/(A+C)	B/(B+D)	D/(B+D)
Value	A	B	C	D				
120.00	0	0	21	24	0.00000	1.00000	0.00000	1.00000
125.00	4	1	17	23	0.19048	0.80952	0.04167	0.95833
130.00	12	3	9	21	0.57143	0.42857	0.12500	0.87500
135.00	18	10	3	14	0.85714	0.14286	0.41667	0.58333
140.00	21	17	0	7	1.00000	0.00000	0.70833	0.29167

Notes:

A is the number of subjects with a POSITIVE test when the condition was PRESENT.  
 B is the number of subjects with a POSITIVE test when the condition was ABSENT.  
 C is the number of subjects with a NEGATIVE test when the condition was PRESENT.  
 D is the number of subjects with a NEGATIVE test when the condition was ABSENT.  
 Sensitivity is the  $\Pr(\text{Positive Test}|\text{Condition Present})$ .  
 False+ is the  $\Pr(\text{Positive Test}|\text{Condition Absent})$ .  
 Specificity is the  $\Pr(\text{Negative Test}|\text{Condition Absent})$ .

The report displays the numeric information used to generate the empirical ROC curve.

## Cutoff

The cutoff values of the criterion variable as set in the Criterion List option of the Reports panel.

## A B C D

These four columns give the counts of the two-by-two tables that are formed at each of the corresponding cutoff points.

## Sensitivity $A/(A+C)$

This is the proportion of those that had the disease that were correctly diagnosed by the test.

## $C/(A+C)$

This is the proportion of those that had the disease that were incorrectly diagnosed.

## False + $B/(B+D)$

The proportion of those who did not have the disease who were incorrectly diagnosed by the test as having it.

## Specificity $D/(B+D)$

This is the proportion of those who did not have the disease who were correctly diagnosed as such.

## ROC Data using the Binormal ROC Curve

ROC Data for Condition = Fever using the Binormal ROC Curve

Sodium1	Count	Count	Count	Count	Sensitivity		False+	Specificity
Cutoff	+ P	+ A	- P	- A	A/(A+C)	C/(A+C)	B/(B+D)	D/(B+D)
Value	A	B	C	D				
120.00	0	0	21	24	0.00751	1.00000	0.00000	1.00000
125.00	2	0	19	24	0.09734	0.90476	0.00000	0.99957
130.00	11	1	10	23	0.43561	0.47619	0.04167	0.97664
135.00	18	6	3	18	0.83464	0.14286	0.25000	0.74153
140.00	21	19	0	5	0.98246	0.00000	0.79167	0.24423

ROC Data for Condition = Fever using the Binormal ROC Curve

Sodium2	Count	Count	Count	Count	Sensitivity		False+	Specificity
Cutoff	+ P	+ A	- P	- A	A/(A+C)	C/(A+C)	B/(B+D)	D/(B+D)
Value	A	B	C	D				
120.00	0	0	21	24	0.01869	1.00000	0.00000	0.99949
125.00	4	1	17	23	0.14344	0.80952	0.04167	0.98899
130.00	12	3	9	21	0.48070	0.42857	0.12500	0.90223
135.00	18	10	3	14	0.83352	0.14286	0.41667	0.61742
140.00	21	17	0	7	0.97642	0.00000	0.70833	0.24291

The report displays the numeric information used to generate the binormal ROC curve.

### Cutoff

The cutoff values of the criterion variable as set in the Criterion List option of the Reports panel.

### A B C D

These four columns give the counts of the two-by-two tables that are formed at each of the corresponding cutoff points.

### Sensitivity $A/(A+C)$

This is the proportion of those that had the disease that were correctly diagnosed by the test. Note that these values are based on the binormal model.

### $C/(A+C)$

This is the proportion of those that had the disease that were incorrectly diagnosed. Note that these values are based on the binormal model.

### False + $B/(B+D)$

The proportion of those who did not have the disease who were incorrectly diagnosed by the test as having it. Note that these values are based on the binormal model.

### Specificity $D/(B+D)$

This is the proportion of those who did not have the disease who were correctly diagnosed as such. Note that these values are based on the binormal model.

## Cost-Benefit Analysis - Empirical Curve

Cost - Benefit Analysis for Condition = Fever with Prevalence = 0.1 using Empirical Curve

Sodium1 Cutoff Value	Sensitivity	Specificity	Cost - Benefit When Ratio = 1.1000	Cost - Benefit When Ratio = 1.3000	Cost - Benefit When Ratio = 1.5000	Cost - Benefit When Ratio = 1.7000
120.00	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
125.00	0.0952	1.0000	0.0952	0.0952	0.0952	0.0952
130.00	0.5238	0.9583	0.1113	0.0363	-0.0387	-0.1137
135.00	0.8571	0.7500	-1.6179	-2.0679	-2.5179	-2.9679
140.00	1.0000	0.2083	-6.8375	-8.2625	-9.6875	-11.1125

Cost - Benefit Analysis for Condition = Fever with Prevalence = 0.1 using Empirical Curve

Sodium2 Cutoff Value	Sensitivity	Specificity	Cost - Benefit When Ratio = 1.1000	Cost - Benefit When Ratio = 1.3000	Cost - Benefit When Ratio = 1.5000	Cost - Benefit When Ratio = 1.7000
120.00	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
125.00	0.1905	0.9583	-0.2220	-0.2970	-0.3720	-0.4470
130.00	0.5714	0.8750	-0.6661	-0.8911	-1.1161	-1.3411
135.00	0.8571	0.5833	-3.2679	-4.0179	-4.7679	-5.5179
140.00	1.0000	0.2917	-6.0125	-7.2875	-8.5625	-9.8375

Notes:

The cost-benefit ratio is the ratio of the net cost when the condition is absent to the net cost when it is present.  
Select the cutoff value for which the computed cost value is maximized (or minimized).  
Prevalence is the actual probability of the condition in the population.

The report displays the numeric information used to generate the ROC curve.

### Cutoff

The cutoff values of the criterion variable as set in the Criterion List option on the Reports tab.

### Sensitivity

This is the proportion of those that had the disease that were correctly diagnosed by the test.

### Specificity

This is the proportion of those who did not have the disease who were correctly diagnosed as such.

### Cost-Benefit When Ratio = 1.1

The cost-benefit ratio is the ratio of the net cost when the condition is absent to the net cost when it is present. The optimum cutoff value is that one at which the computed cost value is maximized (or minimized).

## Cost-Benefit Analysis - Binormal Curve

Cost - Benefit Analysis for Condition = Fever with Prevalence = 0.1 using Binormal Curve

Sodium1 Cutoff Value	Sensitivity	Specificity	Cost - Benefit When Ratio = 1.1000	Cost - Benefit When Ratio = 1.3000	Cost - Benefit When Ratio = 1.5000	Cost - Benefit When Ratio = 1.7000
120.00	0.0075	1.0000	0.0075	0.0075	0.0075	0.0075
125.00	0.0973	0.9996	0.0930	0.0922	0.0915	0.0907
130.00	0.4356	0.9766	0.2044	0.1623	0.1203	0.0783
135.00	0.8346	0.7415	-1.7242	-2.1895	-2.6547	-3.1200
140.00	0.9825	0.2442	-6.4997	-7.8600	-9.2204	-10.5808

Cost - Benefit Analysis for Condition = Fever with Prevalence = 0.1 using Binormal Curve

Sodium2 Cutoff Value	Sensitivity	Specificity	Cost - Benefit When Ratio = 1.1000	Cost - Benefit When Ratio = 1.3000	Cost - Benefit When Ratio = 1.5000	Cost - Benefit When Ratio = 1.7000
120.00	0.0187	0.9995	0.0137	0.0127	0.0118	0.0109
125.00	0.1434	0.9890	0.0345	0.0146	-0.0052	-0.0250
130.00	0.4807	0.9022	-0.4872	-0.6632	-0.8392	-1.0151
135.00	0.8335	0.6174	-2.9540	-3.6427	-4.3313	-5.0200
140.00	0.9764	0.2429	-6.5188	-7.8816	-9.2443	-10.6071

The report displays the numeric information used to generate the ROC curve.

### Cutoff

The cutoff values of the criterion variable as set in the Criterion List option on the Reports tab.

### Sensitivity

This is the proportion of those that had the disease that were correctly diagnosed by the test.

### Specificity

This is the proportion of those who did not have the disease who were correctly diagnosed as such.

### Cost-Benefit When Ratio = 1.1

The cost-benefit ratio is the ratio of the net cost when the condition is absent to the net cost when it is present. The optimum cutoff value is that one at which the computed cost value is maximized (or minimized).

## Predicted Value Section - Empirical Method

### Predictive Value Section for Fever using the Empirical ROC Curve

Sodium1							
Cutoff Value	Sensitivity	Specificity	Likelihood Ratio	Prev. PPV = 0.47	NPV	Prev. PPV = 0.10	NPV
120.00	0.00000	1.00000		0.00000	0.53333	0.00000	0.90000
125.00	0.09524	1.00000		1.00000	0.55814	1.00000	0.90865
130.00	0.52381	0.95833	12.57143	0.91667	0.69697	0.58278	0.94768
135.00	0.85714	0.75000	3.42857	0.75000	0.85714	0.27586	0.97927
140.00	1.00000	0.20833	1.26316	0.52500	1.00000	0.12308	1.00000

### Predictive Value Section for Fever using the Empirical ROC Curve

Sodium2							
Cutoff Value	Sensitivity	Specificity	Likelihood Ratio	Prev. PPV = 0.47	NPV	Prev. PPV = 0.10	NPV
120.00	0.00000	1.00000		0.00000	0.53333	0.00000	0.90000
125.00	0.19048	0.95833	4.57143	0.80000	0.57500	0.33684	0.91420
130.00	0.57143	0.87500	4.57143	0.80000	0.70000	0.33684	0.94839
135.00	0.85714	0.58333	2.05714	0.64286	0.82353	0.18605	0.97351
140.00	1.00000	0.29167	1.41176	0.55263	1.00000	0.13559	1.00000

#### Notes:

Sensitivity is the Pr(Positive Test|Condition Present).

Specificity is the Pr(Negative Test|Condition Absent).

Likelihood Ratio is the ratio Pr(Positive Test|Condition Present)/Pr(Positive Test|Condition Absent).

Prev stands for the prevalence of the disease. The first value is from the data. The other was input.

PPV or Positive Predictive Value is the Pr(Condition Present|Positive Test).

NPV or Negative Predictive Value is the Pr(Condition Absent|Negative Test).

The report displays the information to assess the predicted value of the diagnostic test.

## Cutoff

The cutoff values of the criterion variable as set in the Criterion List option on the Reports tab.

## Sensitivity

This is the proportion of those that had the disease that were correctly diagnosed by the test.

## Specificity

This is the proportion of those who did not have the disease who were correctly diagnosed as such.

## Likelihood Ratio

The likelihood ratio statistic measures the value of the test for increasing certainty about a positive diagnosis. It is calculated as follows:

$$LR = \frac{\Pr(\text{positive test}|\text{disease})}{\Pr(\text{positive test}|\text{no disease})} = \frac{\text{sensitivity}}{1 - \text{specificity}}$$

## Prev = x.xxxx PPV

The values of PPV for the two prevalence values. The first prevalence value is the one that was calculated from the data. The second prevalence value was set by the user.

## Prev = x.xxxx NPV

The values of NPV for the two prevalence values. The first prevalence value is the one that was calculated from the data. The second prevalence value was set by the user.

## Predicted Value Section - Binormal Method

### Predictive Value Section for Fever using the Empirical ROC Curve

Sodium1							
Cutoff			Likelihood	Prev.	= 0.47	Prev.	= 0.10
Value	Sensitivity	Specificity	Ratio	PPV	NPV	PPV	NPV
120.00	0.00751	1.00000	5003.14160	0.99977	0.53521	0.99820	0.90068
125.00	0.09734	0.99957	223.92737	0.99492	0.55860	0.96136	0.90881
130.00	0.43561	0.97664	18.65033	0.94226	0.66416	0.67451	0.93966
135.00	0.83464	0.74153	3.22914	0.73860	0.83673	0.26405	0.97582
140.00	0.98246	0.24423	1.29995	0.53215	0.94088	0.12621	0.99208

### Predictive Value Section for Fever using the Empirical ROC Curve

Sodium2							
Cutoff			Likelihood	Prev.	= 0.47	Prev.	= 0.10
Value	Sensitivity	Specificity	Ratio	PPV	NPV	PPV	NPV
120.00	0.01869	0.99949	36.74964	0.96984	0.53790	0.80328	0.90164
125.00	0.14344	0.98899	13.02933	0.91936	0.56888	0.59145	0.91221
130.00	0.48070	0.90223	4.91677	0.81140	0.66506	0.35330	0.93989
135.00	0.83352	0.61742	2.17868	0.65592	0.80911	0.19490	0.97091
140.00	0.97642	0.24291	1.28969	0.53018	0.92170	0.12534	0.98933

The report displays the information to assess the predicted value of the diagnostic test.

### Cutoff

The cutoff values of the criterion variable as set in the Criterion List option on the Reports tab.

### Sensitivity

This is the proportion of those that had the disease that were correctly diagnosed by the test.

### Specificity

This is the proportion of those who did not have the disease who were correctly diagnosed as such.

### Likelihood Ratio

The likelihood ratio statistic measures the value of the test for increasing certainty about a positive diagnosis. It is calculated as follows:

$$LR = \frac{\Pr(\text{positive test}|\text{disease})}{\Pr(\text{positive test}|\text{no disease})} = \frac{\text{sensitivity}}{1 - \text{specificity}}$$

### Prev = x.xxxx PPV

The values of PPV for the two prevalence values. The first prevalence value is the one that was calculated from the data. The second prevalence value was set by the user.

### Prev = x.xxxx NPV

The values of NPV for the two prevalence values. The first prevalence value is the one that was calculated from the data. The second prevalence value was set by the user.

## Area Under Curve Hypothesis Tests

### Empirical Area Under Curve Analysis for Condition = Fever

Criterion	Empirical Estimate of AUC	AUC's Standard Error	Z-Value to Test AUC > 0.5	1-Sided Prob Level	2-Sided Prob Level	Prevalence of Fever	Count
Sodium1	0.87500	0.05052	7.42	0.0000	0.0000	0.46667	45
Sodium2	0.80754	0.06431	4.78	0.0000	0.0000	0.46667	45

#### Notes:

1. This approach underestimates AUC when there are only a few (3 to 7) unique criterion values.
2. The AUCs, SEs, and hypothesis tests above use the empirical approach for correlated (paired) samples developed by DeLong, DeLong, and Clarke-Pearson.
3. The Z-Value compares the AUC to 0.5, since the AUC of a 'useless' criterion is 0.5. The one-sided test is usually used here since your only interest is that the criterion is better than 'useless'.
4. The Z test used here is only accurate for larger samples with at least 30 subjects with, and another 30 subjects without, the condition of interest.

### Binormal Area Under Curve Analysis for Condition = Fever

Criterion	Binormal Estimate of AUC	AUC's Standard Error	Z-Value to Test AUC > 0.5	1-Sided Prob Level	2-Sided Prob Level	Prevalence of Fever	Count
Sodium1	0.87720	0.03995	4.70	0.0000	0.0000	0.46667	45
Sodium2	0.81350	0.06379	3.12	0.0009	0.0018	0.46667	45

#### Notes:

1. The AUCs, SEs, and hypothesis tests above use the binormal approach given by McClish (1989).
2. The Z-Value compares the AUC to 0.5, since the AUC of a 'useless' criterion is 0.5. The one-sided test is usually used here since your only interest is that the criterion is better than 'useless'.
3. The Z tests used here are only accurate for larger samples with at least 30 subjects with, and another 30 subjects without, the condition of interest.
4. The Z tests use a logistic-type transformation to achieve better normality.

These reports display areas under the ROC curve and associated standard errors and hypotheses tests for each of the criterion variables. The first report is based on the empirical ROC method and the second report is based on the binormal ROC method.

The one-sided and two-sided hypothesis tests test the hypothesis that the diagnostic test is better than flipping a coin to make the diagnosis. The actual formulas used were presented earlier in this chapter.

## Area Under Curve Confidence Intervals

### Empirical Confidence Interval of AUC for Condition = Fever

Criterion	Empirical Estimate of AUC	AUC's Standard Error	Lower 95.0% Confidence Limit	Upper 95.0% Confidence Limit	Prevalence of Fever	Count
Sodium1	0.87500	0.05052	0.73131	0.94432	0.46667	45
Sodium2	0.80754	0.06431	0.63966	0.90188	0.46667	45

#### Notes:

1. This approach underestimates AUC when there are only a few (3 to 7) unique criterion values.
2. The AUCs, SEs, and hypothesis tests above use the nonparametric approach developed by DeLong, DeLong, and Clarke-Pearson.
3. The confidence interval is based on the transformed AUC as given by Zhou et al (2002).
4. This method is only accurate for larger samples with at least 30 subjects with, and another 30 subjects without, the condition of interest.

### Binormal Confidence Interval of AUC for Condition = Fever

Criterion	Binormal Estimate of AUC	AUC's Standard Error	Lower 95.0% Confidence Limit	Upper 95.0% Confidence Limit	Prevalence of Fever	Count
Sodium1	0.87720	0.03995	0.77143	0.93580	0.46667	45
Sodium2	0.81350	0.06379	0.64553	0.90640	0.46667	45

#### Notes:

1. The AUCs, SEs, and hypothesis tests above use the binormal approach given by McClish (1989).
2. The confidence intervals given here are only accurate for larger samples with at least 30 subjects with, and another 30 subjects without, the condition of interest.
3. The confidence interval use a logistic-type transformation to achieve better normality.

These reports display areas under the ROC curve and associated standard errors and confidence intervals for each of the criterion variables. The first report is based on the empirical ROC method and the second report is based on the binormal ROC method. The actual formulas used were presented earlier in this chapter.

## Tests of (AUC1-AUC2) = 0

### Empirical Test of (AUC1 - AUC2) = 0 for Condition = Fever

Criteria 1,2	AUC1	AUC2	Difference Value	Difference Std Error	Difference Percent	Z-Value	Prob Level
Sodium1, Sodium2	0.87500	0.80754	0.06746	0.02130	-7.71	3.17	0.0015
Sodium2, Sodium1	0.80754	0.87500	-0.06746	0.02130	8.35	-3.17	0.0015

Notes:

1. This approach underestimates AUC when there are only a few (3 to 7) unique criterion values.
2. The AUCs, SEs, and hypothesis tests above use the nonparametric approach developed by DeLong, DeLong, and Clarke-Pearson.
3. This method is only accurate for larger samples with at least 30 subjects with, and another 30 subjects without, the condition of interest.

### Binormal Test of (AUC1 - AUC2) = 0 for Condition = Fever

Criteria 1,2	AUC1	AUC2	Difference Value	Difference Std Error	Difference Percent	Z-Value	Prob Level
Sodium1, Sodium2	0.87720	0.81350	0.06371	0.02717	-7.26	4.61	0.0000
Sodium2, Sodium1	0.81350	0.87720	-0.06371	0.02717	7.83	-4.61	0.0000

Notes:

1. The AUCs, SEs, and hypothesis tests above use the binormal approach.
2. The z-test is based on a logistic-type transformation of the areas.

These reports display the results of hypothesis tests concerning the equality of two AUCs. The first report is based on the empirical ROC method and the second report is based on the binormal ROC method. The actual formulas used were presented earlier in this chapter.

## Variances and Covariances of (AUC1-AUC2) = 0

### Empirical Test Variances and Covariances for Condition = Fever

Criteria 1,2	AUC1	AUC2	AUC1 Variance	AUC2 Variance	AUC1,AUC2 Covariance	Difference Variance
Sodium1, Sodium2	0.87500	0.80754	0.00255	0.00414	0.00312	0.00045
Sodium2, Sodium1	0.80754	0.87500	0.00414	0.00255	0.00312	0.00045

Notes:

1. These AUCs, variances, and covariances use the nonparametric approach developed by DeLong, DeLong, and Clarke-Pearson.
2. This method is only accurate for larger samples with at least 30 subjects with, and another 30 subjects without, the condition of interest.

### Binormal Test Variances and Covariances for Condition = Fever

Criteria 1,2	AUC1	AUC2	AUC1 Variance	AUC2 Variance	AUC1,AUC2 Covariance	Difference Variance
Sodium1, Sodium2	0.87720	0.81350	0.00160	0.00407	0.00246	0.00074
Sodium2, Sodium1	0.81350	0.87720	0.00407	0.00160	0.00246	0.00074

Notes:

1. The AUCs, SEs, and hypothesis tests above use the binormal approach.
2. The z-test is based on a logistic-type transformation of the areas.

These reports display the variances and covariances associated with the hypothesis tests given in the last set of reports. The first report is based on the empirical ROC method and the second report is based on the binormal ROC method. The actual formulas used were presented earlier in this chapter.

## Confidence Intervals of (AUC1-AUC2) = 0

### Empirical Confidence Intervals of Differences in AUCs for Condition = Fever

Criteria 1,2	AUC1	AUC2	Difference Value	Difference Std Error	Lower 95.0% Confidence Limit	Upper 95.0% Confidence Limit
Sodium1, Sodium2	0.87500	0.80754	0.06746	0.02130	0.02571	0.10921
Sodium2, Sodium1	0.80754	0.87500	-0.06746	0.02130	-0.10921	-0.02571

Notes:

1. This approach underestimates AUC when there are only a few (3 to 7) unique criterion values.
2. The AUCs, SEs, and confidence limits above use the nonparametric approach developed by DeLong, DeLong, and Clarke-Pearson.
3. This method is only accurate for larger samples with at least 30 subjects with, and another 30 subjects without, the condition of interest.

### Binormal Confidence Interval of Difference in AUCs for Condition = Fever

Criteria 1,2	AUC1	AUC2	Difference Value	Difference Std Error	Lower 95.0% Confidence Limit	Upper 95.0% Confidence Limit
Sodium1, Sodium2	0.87720	0.81350	0.06371	0.02717	0.01046	0.11696
Sodium2, Sodium1	0.81350	0.87720	-0.06371	0.02717	-0.11696	-0.01046

Notes:

1. The AUCs, SEs, and hypothesis tests above use the binormal approach.
2. The z-test is based on a logistic-type transformation of the areas.

These reports display the confidence intervals for difference between a pair of AUCs. The first report is based on the empirical ROC method and the second report is based on the binormal ROC method. The actual formulas used were presented earlier in this chapter.

## Equivalence Tests Comparing AUC1 and AUC2

### Empirical Equivalence Test of the AUCs for Condition = Fever

Criterion Variable1, Variable2	Prob Level	Lower 90.0% Conf. Limit	Upper 90.0% Conf. Limit	Lower Equiv. Bound	Upper Equiv. Bound	Reject H0 and Conclude Equivalence at the 5.0% Significance Level
Sodium1, Sodium2	0.7938	0.03242	0.10250	-0.05000	0.05000	Cannot reject H0
Sodium2, Sodium1	0.7938	-0.10250	-0.03242	-0.05000	0.05000	Cannot reject H0

#### Notes:

1. This approach underestimates AUC when there are only a few (3 to 7) unique criterion values.
2. The AUCs, SEs, and confidence limits above use the empirical approach developed by DeLong, DeLong, and Clarke-Pearson.
3. This method is only accurate for larger samples with at least 30 subjects with, and another 30 subjects without, the condition of interest.
4. Equivalence means that Test2 does not differ from Test1 except for a small, negligible amount which we call the 'Equivalence Bound'.

### Binormal Equivalence Test of the AUCs for Condition = Fever

Criterion Variable1, Variable2	Prob Level	Lower 90.0% Conf. Limit	Upper 90.0% Conf. Limit	Lower Equiv. Bound	Upper Equiv. Bound	Reject H0 and Conclude Equivalence at the 5.0% Significance Level
Sodium1, Sodium2	0.0000	0.01902	0.10839	-0.05000	0.05000	Yes: (AUC1-AUC2)<0.05
Sodium2, Sodium1	0.6930	-0.10839	-0.01902	-0.05000	0.05000	Cannot reject H0

#### Notes:

1. The AUCs, SEs, and confidence limits above use the binormal approach.
2. Equivalence means that Test2 does not differ from Test1 except for a small, negligible amount which we call the 'Equivalence Bound'.
3. The logistic-type transformation is not used in these calculations.

These reports display the results of an equivalence test. This hypothesis test tests whether the two diagnostics are equivalence in the sense that their AUC's are no more different than the maximum amount specified. The first report is based on the empirical ROC method and the second report is based on the binormal ROC method.

Often, you want to show that one diagnostic test is equivalent to another. In this case, you would use a test of equivalence.

## Noninferiority Tests Comparing AUC1 and AUC2

### Empirical Noninferiority Test of the AUCs for Condition = Fever

Criterion Variable1, Variable2	Prob Level	1-Sided 95.0% Conf. Limit	Noninferiority Bound	Reject H0 and Conclude Noninferiority at the 5.0% Significance Level
Sodium1, Sodium2	0.0000	0.03242	0.05000	Yes: (AUC1-AUC2)<0.05
Sodium2, Sodium1	0.7938	-0.10250	0.05000	Cannot reject H0

Notes:

1. This approach underestimates AUC when there are only a few (3 to 7) unique criterion values.
2. The AUCs, SEs, and confidence limits above use the empirical approach developed by DeLong, DeLong, and Clarke-Pearson.
3. This method is only accurate for larger samples with at least 30 subjects with, and another 30 subjects without, the condition of interest.
4. Noninferiority means that Test2 is no worse than Test1 except for a small, negligible amount which we call the 'Noninferiority Bound'.

### Binormal Noninferiority Test of the AUCs for Condition = Fever

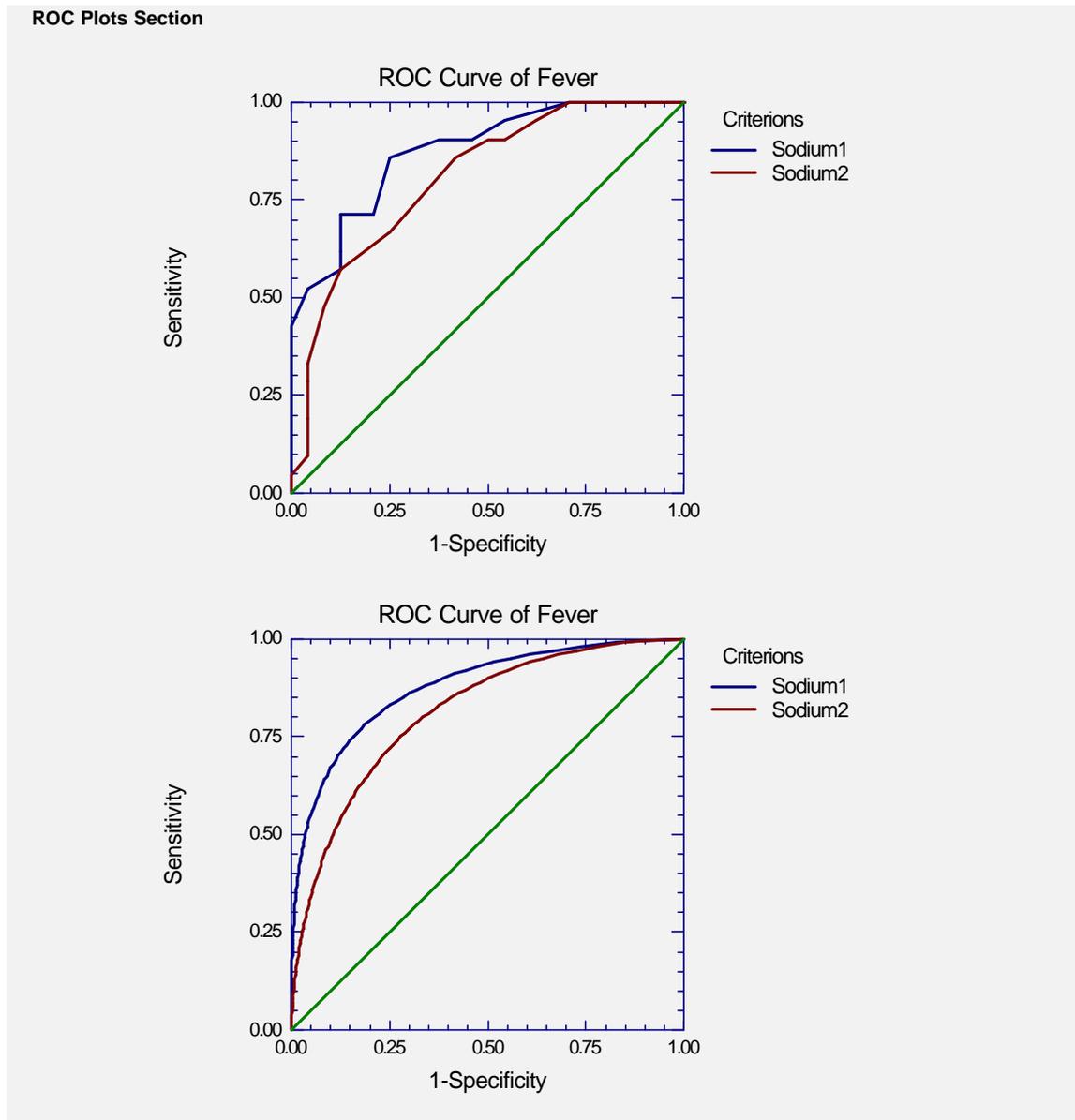
Criterion Variable1, Variable2	Prob Level	1-Sided 95.0% Conf. Limit	Noninferiority Bound	Reject H0 and Conclude Noninferiority at the 5.0% Significance Level
Sodium1, Sodium2	0.0000	0.01902	0.05000	Yes: (AUC1-AUC2)<0.05
Sodium2, Sodium1	0.6930	-0.10839	0.05000	Cannot reject H0

Notes:

1. The AUCs, SEs, and confidence limits above use the binormal approach.
2. Noninferiority means that Test2 is no worse than Test1 except for a small, negligible amount which we call the 'Noninferiority Bound'.
3. The logistic-type transformation is not used in these calculations.

These reports display the results of a noninferiority test. This hypothesis test tests whether diagnostic test 2 is no worse than diagnostic test 1 in the sense that AUC2 is not less than AUC1 by more than a small amount. The first report is based on the empirical ROC method and the second report is based on the binormal ROC method.

## ROC Plot Section



Both the empirical and binormal ROC curves are displayed here. The empirical curve is shown first. It always has a 'zig-zag' pattern. The smooth, binormal ROC curve is shown second.

The ROC curves plot the proportion of those who actually had the disease who were correctly diagnosed on the vertical axis versus the proportion of those who did not have the disease who were falsely diagnosed as having it on the horizontal axis. Hence, an optimum test procedure is one whose ROC curve proceeds from the lower-left corner vertically until it reaches the top and then horizontally across the top to the right side. The 45 degree line represents what you would expect from a chance (flip of the coin) classification procedure.

When you are comparing two curves as in this example, you would generally take the outside curve (the one furthest from the middle line). However, it is possible for the curves to cross so that one test is optimum in a certain range but not in another.

## Tutorial - Example 2 - Validation

Zhou et al. (2002) page 175 presents an example comparing the results of two mammography tests: plain film and digitized film. In this example, both tests were administered to 58 people, so this is a paired design. The results given in Zhou (2002) contain a few typos. We have obtained the corrected results from the authors, which are as follows:

<u>Test</u>	<u>AUC</u>	<u>SE</u>
Plain	0.83504	0.06581
Digitized	0.84701	0.05987

The data for this example is contained in the dataset ZHOU 175.S0. Open this dataset before running this example. Note that you can either enter the options as instructed below or you can go to the Template tab, click on Example 2, and press the Load Template button.

### 1 Open the ZHOU 175 dataset.

- From the File menu of the NCSS Data window, select Open.
- Select the Data subdirectory of the NCSS97 directory.
- Click on the file **ZHOU 175.S0**.
- Click **Open**.

### 2 Open the ROC Curves window.

- On the menus, select **Analysis**, then **Diagnostic Tests**, then **ROC Curves**. The ROC Curves procedure will be displayed.
- On the menus, select **File**, then **New Template**. This will fill the procedure with the default template.

### 3 Specify the variables.

- On the ROC Curves window, select the **Variables tab**.
- Set the Actual Condition Variable to **CANCER**.
- Set the Criterion Variable(s) to **Plainfilm-Digifilm**.
- Set the Frequency Variable to **Count**.
- Set the Positive Condition Value to **1**.
- Set the Test Direction to **High X = Positive**.
- Set the Max Equivalence Difference to **0.05**.

### 4 Specify the reports.

- On the ROC Curves window, select the **Reports tab**.
- Set the Actual Condition(Disease) Prevalence to **0.10**.
- Set the Criterion List to **1 2 3 4**.
- Set the Cost Benefit Ratios to **1**.
- Check on the AUC: One Curve reports.

### 5 Specify the format.

- On the ROC Curves window, select the **Format tab**.
- Set the Skip Line After option to **20**.

### 6 Run the procedure.

- From the Run menu, select Run Procedure. Alternatively, just click the Run button (the left-most button on the button bar at the top).

**Empirical Area Under Curve Analysis for Condition = Cancer**

<b>Criterion</b>	<b>Empirical Estimate of AUC</b>	<b>AUC's Standard Error</b>	<b>Z-Value to Test AUC &gt; 0.5</b>	<b>1-Sided Prob Level</b>	<b>2-Sided Prob Level</b>	<b>Prevalence of Fever</b>	<b>Count</b>
PlainFilm	0.83504	0.06581	5.09	0.0000	0.0000	0.22414	58
DigiFilm	0.84701	0.05987	5.80	0.0000	0.0000	0.22414	58

Note that the estimated AUC's and standard errors match those given by Zhou (2002) exactly.