

# CHAPTER 12

## The CORR Procedure

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### Overview

The CORR procedure is a statistical procedure for numeric random variables that computes Pearson correlation coefficients, three nonparametric measures of association, and the probabilities associated with these statistics. The correlation statistics include

- Pearson product-moment and weighted product-moment correlation
- Spearman rank-order correlation
- Kendall's tau-b

- Hoeffding's measure of dependence, D
- Pearson, Spearman, and Kendall partial correlation.

PROC CORR also computes Cronbach's coefficient alpha for estimating reliability.

The default correlation analysis includes descriptive statistics, Pearson correlation statistics, and probabilities for each analysis variable. You can save the correlation statistics in a SAS data set for use with other statistical and reporting procedures.

Output 12.1 on page 274 is the simplest form of PROC CORR output. Pearson correlation statistics are computed for all numeric variables from a study investigating the effect of exercise on physical fitness. The statements that produce the output follow:

```
options pagesize=60;
proc corr data=fitness;
run;
```

**Output 12.1** Simple Correlation Analysis for a Fitness Study Using PROC CORR

The SAS System							1
The CORR Procedure							
4 Variables: Age Weight Runtime Oxygen							
Simple Statistics							
Variable	N	Mean	Std Dev	Sum	Minimum	Maximum	
Age	30	47.56667	5.26330	1427	38.00000	57.00000	
Weight	30	77.70500	8.34152	2331	59.08000	91.63000	
Runtime	29	10.61448	1.41655	307.82000	8.17000	14.03000	
Oxygen	29	47.06445	5.32129	1365	37.38800	60.05500	
Pearson Correlation Coefficients							
Prob >  r  under H0: Rho=0							
Number of Observations							
	Age	Weight	Runtime	Oxygen			
Age	1.00000	-0.21777	0.19528	-0.32899			
		0.2477	0.3100	0.0814			
	30	30	29	29			
Weight	-0.21777	1.00000	0.15155	-0.19900			
	0.2477		0.4326	0.3007			
	30	30	29	29			
Runtime	0.19528	0.15155	1.00000	-0.78346			
	0.3100	0.4326		<.0001			
	29	29	29	28			
Oxygen	-0.32899	-0.19900	-0.78346	1.00000			
	0.0814	0.3007	<.0001				
	29	29	28	29			

Output 12.2 on page 275 and Output 12.3 on page 276 illustrate the use of PROC CORR to calculate partial correlation statistics for the fitness study and to store the results in an output data set. The statements that produce the analysis also

- suppress the descriptive statistics
- select and label analysis variables

- exclude all observations with missing values
- calculate the partial covariance matrix
- calculate three types of partial correlation coefficients
- generate an output data set that contains Pearson correlation statistics and print the output data set.

For an explanation of the program that produces the following output, see Example 4 on page 309.

## Output 12.2 Customized Correlation Analysis with Partial Covariances and Correlation Statistics

Partial Correlations for a Fitness and Exercise Study					1
The CORR Procedure					
1 Partial Variables: Age					
3 Variables: Weight Oxygen Runtime					
Partial Covariance Matrix, DF = 26					
		Weight	Oxygen	Runtime	
Weight	Wt in kg	72.43742055	-12.75113194	2.06766763	
Oxygen	O2 use	-12.75113194	27.01654904	-5.59370556	
Runtime	1.5 mi in minutes	2.06766763	-5.59370556	1.94512451	
Pearson Partial Correlation Coefficients, N = 28					
Prob >  r  under H0: Partial Rho=0					
		Weight	Oxygen	Runtime	
Weight		1.00000	-0.28824	0.17419	
Wt in kg			0.1448	0.3849	
Oxygen		-0.28824	1.00000	-0.77163	
O2 use		0.1448		<.0001	
Runtime		0.17419	-0.77163	1.00000	
1.5 mi in minutes		0.3849	<.0001		
Spearman Partial Correlation Coefficients, N = 28					
Prob >  r  under H0: Partial Rho=0					
		Weight	Oxygen	Runtime	
Weight		1.00000	-0.16407	0.08708	
Wt in kg			0.4135	0.6658	
Oxygen		-0.16407	1.00000	-0.67112	
O2 use		0.4135		0.0001	
Runtime		0.08708	-0.67112	1.00000	
1.5 mi in minutes		0.6658	0.0001		
Kendall Partial Tau b Correlation Coefficients, N = 28					
		Weight	Oxygen	Runtime	
Weight		1.00000	-0.09021	0.02854	
Wt in kg					
Oxygen		-0.09021	1.00000	-0.52158	
O2 use					
Runtime		0.02854	-0.52158	1.00000	
1.5 mi in minutes					

**Output 12.3** Output Data Set with Pearson Partial Correlation Statistics

Pearson Correlation Statistics Using the PARTIAL Statement					2
Output Data Set from PROC CORR					
<u>_TYPE_</u>	<u>_NAME_</u>	Weight	Oxygen	Runtime	
COV	Weight	72.4374	-12.7511	2.0677	
COV	Oxygen	-12.7511	27.0165	-5.5937	
COV	Runtime	2.0677	-5.5937	1.9451	
MEAN		0.0000	0.0000	0.0000	
STD		8.5110	5.1977	1.3947	
N		28.0000	28.0000	28.0000	
CORR	Weight	1.0000	-0.2882	0.1742	
CORR	Oxygen	-0.2882	1.0000	-0.7716	
CORR	Runtime	0.1742	-0.7716	1.0000	

---

## Procedure Syntax

**Tip:** Supports the Output Delivery System, see “Output Delivery System” on page 19

**Reminder:** You can use the ATTRIB, FORMAT, LABEL, and WHERE statements. See Chapter 3, "Statements with the Same Function in Multiple Procedures," for details. You can also use any global statements as well. See Chapter 2, "Fundamental Concepts for Using Base SAS Procedures," for a list.

---

```

PROC CORR <option(s)>;
  BY <DESCENDING> variable-1<...<DESCENDING> variable-n>
    <NOTSORTED>;
  FREQ frequency-variable;
  PARTIAL variable(s);
  VAR variable(s);
  WEIGHT weight-variable;
  WITH variable(s);

```

To do this	Use this statement
Produce separate correlation analyses for each BY group	BY
Identify a variable whose values represent the frequency of each observation	FREQ
Identify controlling variables to compute Pearson, Spearman, or Kendall partial correlation coefficients	PARTIAL
Identify variables to correlate and their order in the correlation matrix	VAR

To do this	Use this statement
Identify a variable whose values weight each observation to compute Pearson weight product-moment correlation	WEIGHT
Compute correlations for specific combinations of variables	WITH

## PROC CORR Statement

**PROC CORR** *<option(s)>*;

To do this	Use this option
Specify the input data set	DATA=
Create output data sets	
Specify an output data set to contain Hoeffding's D statistics	OUTH=
Specify an output data set to contain Kendall correlations	OUTK=
Specify an output data set to contain Pearson correlations	OUTP=
Specify an output data set to contain Spearman correlations	OUTS=
Control statistical analysis	
Exclude observations with nonpositive weight values from the analysis	EXCLNPWGT
Request Hoeffding's measure of dependence, D	HOEFFDING
Request Kendall's tau-b	KENDALL
Request Pearson product-moment correlation	PEARSON
Request Spearman rank-order correlation	SPEARMAN
Control Pearson correlation statistics	
Compute Cronbach's coefficient alpha	ALPHA
Compute covariances	COV
Compute corrected sums of squares and crossproducts	CSSCP
Exclude missing values	NOMISS
Specify singularity criterion	SINGULAR=
Compute sums of squares and crossproducts	SSCP
Specify the divisor for variance calculations	VARDEF=
Control printed output	
Specify the number and order of correlation coefficients	BEST=
Suppress Pearson correlations	NOCORR
Suppress all printed output	NOPRINT
Suppress significance probabilities	NOPROB

To do this	Use this option
Suppress descriptive statistics	NOSIMPLE
Change the order of correlation coefficients	RANK

## Options

### ALPHA

calculates and prints Cronbach's coefficient alpha. PROC CORR computes separate coefficients using raw and standardized values (scaling the variables to a unit variance of 1). For each VAR statement variable, PROC CORR computes the correlation between the variable and the total of the remaining variables. It also computes Cronbach's coefficient alpha using only the remaining variables.

**Main discussion:** "Cronbach's Coefficient Alpha" on page 293

**Restriction:** If you use a WITH statement, ALPHA is invalid.

**Interaction:** ALPHA invokes PEARSON.

**Interaction:** If you specify OUTF=, the output data set also contains six observations with Cronbach's coefficient alpha.

**Interaction:** When you use the PARTIAL statement, PROC CORR calculates Cronbach's coefficient alpha for partialled variables.

**See also:** OUTF= option

**Featured in:** Example 3 on page 306

### BEST=*n*

prints *n* correlation coefficients for each variable. Correlations are ordered from highest to lowest in absolute value. Otherwise, PROC CORR prints correlations in a rectangular table using the variable names as row and column labels.

**Interaction:** When you specify Hoeffding, PROC CORR prints the D statistics in order from highest to lowest.

**Range:** 1 to the maximum number of variables

### COV

calculates and prints covariances.

**Interaction:** COV invokes PEARSON.

**Interaction:** If you specify OUTF=, the output data set contains the covariance matrix and the \_TYPE\_ variable value is COV.

**Interaction:** When you use the PARTIAL statement, PROC CORR computes a partial covariance matrix.

**See also:** OUTF= option

**Featured in:** Example 2 on page 303 and Example 4 on page 309

### CSSCP

prints the corrected sums of squares and crossproducts.

**Interaction:** CSSCP invokes PEARSON.

**Interaction:** If you specify OUTF=, the output data set contains a CSSCP matrix and the \_TYPE\_ variable value is CSSCP. If you use a PARTIAL statement, the output data set contains a partial CSSCP matrix.

**Interaction:** When you use a PARTIAL statement, PROC CORR prints both an unpartial and a partial CSSCP matrix.

**See also:** OUTF= option

**DATA=SAS-data-set**

specifies the input SAS data set.

**Main discussion:** “Input Data Sets” on page 18

**EXCLNPWGT**

excludes observations with nonpositive weight values (zero or negative) from the analysis. By default, PROC CORR treats observations with negative weights like those with zero weights and counts them in the total number of observations.

**Requirement:** You must use a WEIGHT statement.

**See also:** “WEIGHT Statement” on page 285

**HOEFFDING**

calculates and prints Hoeffding’s D statistics. This D statistic is 30 times larger than the usual definition and scales the range between -0.5 and 1 so that only large positive values indicate dependence.

**Main discussion:** “Hoeffding’s Measure of Dependence, D” on page 291

**Restriction:** When you use a WEIGHT or PARTIAL statement, HOEFFDING is invalid.

**Featured in:** Example 1 on page 300

**KENDALL**

calculates and prints Kendall tau-b coefficients based on the number of concordant and discordant pairs of observations. Kendall’s tau-b ranges from -1 to 1.

**Main discussion:** “Kendall’s tau-b” on page 290

**Restriction:** When you use a WEIGHT statement, KENDALL is invalid.

**Interactions:** When you use a PARTIAL statement, probability values for Kendall’s partial tau-b are not available.

**Featured in:** Example 4 on page 309

**NOCORR**

suppresses calculating and printing of Pearson correlations.

**Interaction:** If you specify OUTP=, the data set type remains CORR. To change the data set type to COV, CSSCP, or SSCP, use the TYPE= data set option.

**See also:** “Output Data Sets” on page 298

**Featured in:** Example 3 on page 306

**NOMISS**

excludes observations with missing values from the analysis. Otherwise, PROC CORR computes correlation statistics using all the nonmissing pairs of variables.

**Main discussion:** “Missing Values” on page 297

**Tip:** Using NOMISS is computationally more efficient.

**Featured in:** Example 3 on page 306

**NOPRINT**

suppresses all printed output.

**Tip:** Use NOPRINT when you want to create an output data set only.

**NOPROB**

suppresses printing the probabilities associated with each correlation coefficient.

**NOSIMPLE**

suppresses printing simple descriptive statistics for each variable. However, if you request an output data set, the output data set still contains simple descriptive statistics for the variables.

**Featured in:** Example 2 on page 303



**OUTH=output-data-set**

creates an output data set containing Hoeffding's D statistics. The contents of the output data set are similar to the OUTF= data set.

**Main discussion:** "Output Data Sets" on page 298

**Interaction:** OUTH= invokes Hoeffding.

**OUTK=output-data-set**

creates an output data set containing Kendall correlation statistics. The contents of the output data set are similar to the OUTF= data set.

**Main discussion:** "Output Data Sets" on page 298

**Interaction:** OUTK= option invokes Kendall.

**OUTP=output-data-set**

creates an output data set containing Pearson correlation statistics. This data set also includes means, standard deviations, and the number of observations. The value of the \_TYPE\_ variable is CORR.

**Main discussion:** "Output Data Sets" on page 298

**Interaction:** OUTP= invokes Pearson.

**Interaction:** If you specify ALPHA, the output data set also contains six observations with Cronbach's coefficient alpha.

**Featured in:** Example 4 on page 309

**OUTS=SAS-data-set**

creates an output data set containing Spearman correlation statistics. The contents of the output data set are similar to the OUTF= data set.

**Main discussion:** "Output Data Sets" on page 298

**Interaction:** OUTS= invokes Spearman.

**PEARSON**

calculates and prints Pearson product-moment correlations when you use the Hoeffding, Kendall, or Spearman option. If you omit the correlation type, PROC CORR automatically produces Pearson correlations. The correlations range from -1 to 1.

**Main discussion:** "Pearson Product-Moment Correlation" on page 289

**Featured in:** Example 1 on page 300

**RANK**

prints the correlation coefficients for each variable. Correlations are ordered from highest to lowest in absolute value. Otherwise, PROC CORR prints correlations in a rectangular table using the variable names as row and column labels.

**Interaction:** If you use Hoeffding, PROC CORR prints the D statistics in order from highest to lowest.

**SINGULAR=*p***

specifies the criterion for determining the singularity of a variable when you use a PARTIAL statement. A variable is considered singular if its corresponding diagonal element after Cholesky decomposition has a value less than *p* times the original unpartialled corrected sum of squares of that variable.

**Main discussion:** "Partial Correlation" on page 291

**Default:** 1E-8

**Range:** between 0 and 1

**SPEARMAN**

calculates and prints Spearman correlation coefficients based on the ranks of the variables. The correlations range from -1 to 1.

**Main discussion:** “Spearman Rank-Order Correlation” on page 290

**Restriction:** When you specify a WEIGHT statement, SPEARMAN is invalid.  
Example 1 on page 300

**Featured in:**

### SSCP

prints the sums of squares and crossproducts.

**Interaction:** SSCP invokes PEARSON.

**Interaction:** When you specify OUTP=, the output data set contains a SSCP matrix and the \_TYPE\_ variable value is SSCP. If you use a PARTIAL statement, the output data set does not contain an SSCP matrix.

**Interaction:** When you use a PARTIAL statement, PROC CORR prints the unpartial SSCP matrix.

**Featured in:** Example 2 on page 303

### VARDEF=*divisor*

specifies the divisor to use in the calculation of variances, standard deviations, and covariances.

Table 12.1 on page 282 shows the possible values for *divisor* and associated divisors where  $k$  is the number of PARTIAL statement variables.

**Table 12.1** Possible Values for VARDEF=

Value	Divisor	Formula
DF	degrees of freedom	$n - k - 1$
N	number of observations	$n$
WDF	sum of weights minus one	$(\sum_i w_i) - k - 1$
WEIGHT WGT	sum of weights	$\sum_i w_i$

The procedure computes the variance as  $CSS/divisor$ , where  $CSS$  is the corrected sums of squares and equals  $\sum (x_i - \bar{x})^2$ . When you weight the analysis variables,  $CSS$  equals  $\sum w_i (x_i - \bar{x}_w)^2$ , where  $\bar{x}_w$  is the weighted mean.

**Default:** DF

**Tip:** When you use the WEIGHT statement and VARDEF=DF, the variance is an estimate of  $\sigma^2$ , where the variance of the  $i$ th observation is  $var(x_i) = \sigma^2/w_i$  and  $w_i$  is the weight for the  $i$ th observation. This yields an estimate of the variance of an observation with unit weight.

**Tip:** When you use the WEIGHT statement and VARDEF=WGT, the computed variance is asymptotically (for large  $n$ ) an estimate of  $\sigma^2/\bar{w}$ , where  $\bar{w}$  is the average weight. This yields an asymptotic estimate of the variance of an observation with average weight.

**Main discussion:** Weighted statistics “Example” on page 74.

---

## BY Statement

**Calculates separate correlation statistics for each BY group.**

Main discussion: “BY” on page 68

---

**BY** <DESCENDING> *variable-1* <...<DESCENDING> *variable-n*><NOTSORTED>;

### Required Arguments

#### ***variable***

specifies the variable that the procedure uses to form BY groups. You can specify more than one variable. If you do not use the NOTSORTED option in the BY statement, the observations in the data set must either be sorted by all the variables that you specify, or they must be indexed appropriately. Variables in a BY statement are called *BY variables*.

### Options

#### **DESCENDING**

specifies that the observations are sorted in descending order by the variable that immediately follows the word DESCENDING in the BY statement.

#### **NOTSORTED**

specifies that observations are not necessarily sorted in alphabetic or numeric order. The observations are grouped in another way, for example, chronological order.

The requirement for ordering or indexing observations according to the values of BY variables is suspended for BY-group processing when you use the NOTSORTED option. In fact, the procedure does not use an index if you specify NOTSORTED. The procedure defines a BY group as a set of contiguous observations that have the same values for all BY variables. If observations with the same values for the BY variables are not contiguous, the procedure treats each contiguous set as a separate BY group.

---

## FREQ Statement

**Treats observations as if they appear multiple times in the input data set.**

**Tip:** The effects of the FREQ and WEIGHT statements are similar except when calculating degrees of freedom.

**See also:** For an example that uses the FREQ statement, see “FREQ” on page 70

---

**FREQ** *variable*;

### Required Arguments

***variable***

specifies a numeric variable whose value represents the frequency of the observation. If you use the **FREQ** statement, the procedure assumes that each observation represents  $n$  observations, where  $n$  is the value of *variable*. If  $n$  is not an integer, the SAS System truncates it. If  $n$  is less than 1 or is missing, the procedure does not use that observation to calculate statistics.

The sum of the frequency variable represents the total number of observations.

---

## PARTIAL Statement

**Computes Pearson partial correlation, Spearman partial rank-order correlation, or Kendall's partial tau-b.**

**Restriction:** Not valid with the **HOEFFDING** option.

**Interaction:** Invokes the **NOMISS** option to exclude all observations with missing values.

**Main discussion:** "Partial Correlation" on page 291

**Featured in:** Example 4 on page 309

---

**PARTIAL** *variable(s)*;

### Required Arguments

***variable(s)***

identifies one or more variables to use in the calculation of partial correlation statistics.

### Details

- If you use the **PEARSON** option, **PROC CORR** also prints the partial variance and standard deviation for each **VAR** or **WITH** statement variable.
- If you use the **KENDALL** option, **PROC CORR** cannot compute probability values for Kendall's partial tau-b.

---

## VAR Statement

**Specifies the variables to use to calculate correlation statistics.**

**Default:** If you omit this statement, **PROC CORR** computes correlations for all numeric variables not listed in the other statements.

**Featured in:** Example 1 on page 300 and Example 2 on page 303

---

**VAR** *variable(s)*;

## Required Arguments

### *variable(s)*

identifies one or more variables to use in the calculation of correlation coefficients.

---

## WEIGHT Statement

Specifies weights for the analysis variables in the calculation of Pearson weighted product-moment correlation.

**Restriction:** Not valid with the HOEFFDING, KENDALL, or SPEARMAN option.

**See also:** For information on calculating weighted correlations, see “Pearson Product-Moment Correlation” on page 289.

---

**WEIGHT** *variable*;

## Required Arguments

### *variable*

specifies a numeric variable to use to compute weighted product-moment correlation coefficients. The variable does not have to be an integer. If the value of the weight variable is

Weight value...	PROC CORR...
0	counts the observation in the total number of observations
less than 0	converts the value to zero and counts the observation in the total number of observations
missing	excludes the observation

To exclude observations that contain negative and zero weights from the analysis, use EXCLNPWGT. Note that most SAS/STAT procedures, such as PROC GLM, exclude negative and zero weights by default.

**Tip:** When you use the WEIGHT statement, consider which value of the VARDEF= option is appropriate. See the discussion of the VARDEF= option on page 282 for more information.

*Note:* Prior to Version 8 of the SAS System, the procedure did not exclude the observations with missing weights from the count of observations.  $\Delta$

---

## WITH Statement

Determines the variables to use in conjunction with the VAR statement variables to calculate limited combinations of correlation coefficients.

**Restriction:** Not valid with the ALPHA option.

**Featured in:** Example 2 on page 303

---

**WITH** *variable(s)*;

### Required Argument

***variable(s)***

lists one or more variables to obtain correlations for specific combinations of variables. The WITH statement variables appear down the side of the correlation matrix and the VAR statement variables appear across the top of the correlation matrix. PROC CORR computes the following correlations for the VAR statement variables A and B and the WITH statement variables X, Y, and Z:

X and A	X and B
Y and A	Y and B
Z and A	Z and B

---

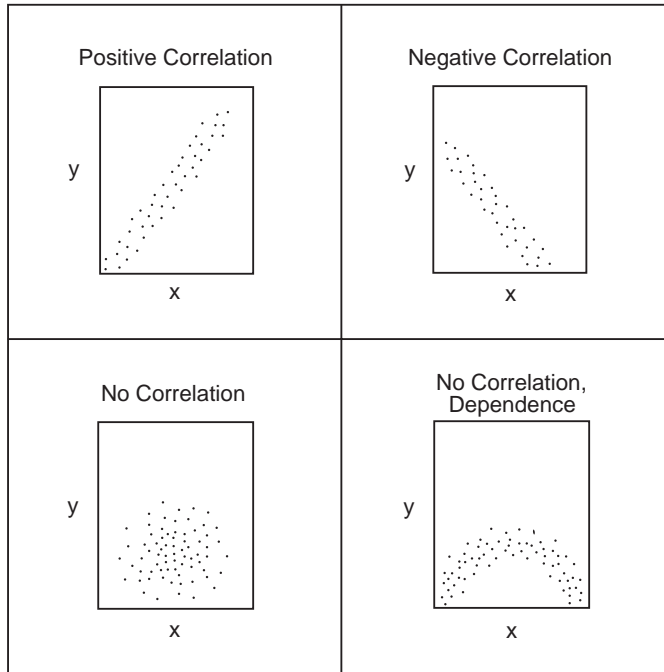
## Concepts

---

### Interpreting Correlation Coefficients

Correlation coefficients contain information on both the strength and direction of a linear relationship between two numeric random variables. If one variable  $x$  is an exact linear function of another variable  $y$ , a positive relationship exists when the correlation is 1 and an inverse relationship exists when the correlation is -1. If there is no linear predictability between the two variables, the correlation is 0. If the variables are normal and correlation is 0, the two variables are independent. However, correlation does not imply causality because, in some cases, an underlying causal relationship may exist.

The scatterplots in Figure 12.1 on page 287 depict the relationship between two numeric random variables.

**Figure 12.1** Examining Correlations Using Scatterplots

When the relationship between two variables is nonlinear or when outliers are present, the correlation coefficient incorrectly estimates the strength of the relationship. Plotting the data before computing a correlation coefficient enables you to verify the linear relationship and to identify the potential outliers.

---

## Determining Computer Resources

The only factor limiting the number of variables that you can analyze is the amount of available memory. The computer resources that PROC CORR requires depend on which statements and options you specify. To determine the computer resources that you need, use

N	number of observations in the data set.
C	number of correlation types (1 to 4).
V	number of VAR statement variables.
W	number of WITH statement variables.
P	number of PARTIAL statement variables.

so that

$$T = V + W + P$$

$$K = V * W \quad \text{when } W > 0$$

$$V * (V + 1) / 2 \quad \text{when } W = 0$$

$$L = K \quad \text{when } P = 0$$

$$T * (T + 1) / 2 \quad \text{when } P > 0$$

For small N and large K, the CPU time varies as K for all types of correlations. For large N, the CPU time depends on the type of correlation. To calculate CPU time use

K*N	with PEARSON (default)
T*N*log N	with SPEARMAN
K*N*log N	with HOEFFDING or KENDALL

You can reduce CPU time by specifying NOMISS. Without NOMISS, processing is much faster when most observations do not contain missing values.

The options and statements you use in the procedure require different amounts of storage to process the data. For Pearson correlations, the amount of temporary storage in bytes (M) is

40T+16L	with NOMISS and NOSIMPLE
40T+16L+56T	with NOMISS
40T+16L+56K	with NOSIMPLE
40T+16L+56K+56T	with no options

Using a PARTIAL statement increases the amount of temporary storage by 12T bytes. Using the ALPHA option increases the amount of temporary storage by 32V+16 bytes.

The following example uses a PARTIAL statement, which invokes NOMISS.

```
proc corr;
  var x1 x2;
  with y1 y2 y3;
  partial z1;
```

Therefore, using 40T+16L+56T+12T, the minimum temporary storage equals 984 bytes ( $T=2+3+1$  and  $L=T(T+1)/2$ ).

Using the SPEARMAN, KENDALL, or HOEFFDING option requires additional temporary storage for each observation. For the most time-efficient processing, the amount of temporary storage in bytes is

$$40T+8K+8L*C+12T*N+28N+QS+QP+QK$$

where

QS=	0	with NOSIMPLE
	68T	otherwise
QP=	56K	with PEARSON and without NOMISS
	0	otherwise
QK =	32N	with KENDALL or HOEFFDING
	0	otherwise.

The following example uses KENDALL:

```
proc corr kendall;
  var x1 x2 x3;
```

Therefore, the minimum temporary storage in bytes is

$$40*3+8*6+8*6*1+12*3N+28N+3*68+32N = 420+96N$$

where N is the number of observations.

If M bytes are not available, PROC CORR must process the data multiple times to compute all the statistics. This reduces the minimum temporary storage you need by



12(T-2)N bytes. When this occurs, PROC CORR prints a note suggesting a larger memory region.

---

## Statistical Computations

PROC CORR computes several parametric and nonparametric correlation statistics as measures of association. The formulas for computing these measures and the associated probabilities follow.

---

### Pearson Product-Moment Correlation

The Pearson product-moment correlation is a parametric measure of association for two continuous random variables. The formula for the true Pearson product-moment correlation, denoted  $\rho_{xy}$ , is

$$\begin{aligned}\rho_{xy} &= \frac{\text{cov}(x, y)}{\sqrt{\text{var}(x) \text{var}(y)}} \\ &= \frac{E((x - Ex)(y - Ey))}{\sqrt{E(x - Ex)^2 E(y - Ey)^2}}\end{aligned}$$

The sample correlation, such as a Pearson product-moment correlation or weighted product-moment correlation, estimates the true correlation. The formula for the Pearson product-moment correlation is

$$r_{xy} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

where  $\bar{x}$  is the sample mean of  $x$  and  $\bar{y}$  is the sample mean of  $y$ .

The formula for a weighted Pearson product-moment correlation is

$$r_{xy} = \frac{\sum w_i (x_i - \bar{x}_w)(y_i - \bar{y}_w)}{\sqrt{\sum w_i (x_i - \bar{x}_w)^2 \sum w_i (y_i - \bar{y}_w)^2}}$$

where

$$\begin{aligned}\bar{x}_w &= \sum w_i x_i / \sum w_i \\ \bar{y}_w &= \sum w_i y_i / \sum w_i\end{aligned}$$

Note that  $\bar{x}_w$  is the weighted mean of  $x$ ,  $\bar{y}_w$  is the weighted mean of  $y$ , and  $w_i$  is the weight.

When one variable is dichotomous (0,1) and the other variable is continuous, a Pearson correlation is equivalent to a point biserial correlation. When both variables are dichotomous, a Pearson correlation coefficient is equivalent to the phi coefficient.

---

## Spearman Rank-Order Correlation

Spearman rank-order correlation is a nonparametric measure of association based on the rank of the data values. The formula is

$$\theta = \frac{\sum (R_i - \bar{R})(S_i - \bar{S})}{\sqrt{\sum (R_i - \bar{R})^2 \sum (S_i - \bar{S})^2}}$$

where  $R_i$  is the rank of the  $i$ th  $x$  value,  $S_i$  is the rank of the  $i$ th  $y$  value,  $\bar{R}$  is the mean of the  $R_i$  values, and  $\bar{S}$  is the mean of the  $S_i$  values.

PROC CORR computes the Spearman's correlation by ranking the data and using the ranks in the Pearson product-moment correlation formula. In case of ties, the averaged ranks are used.

---

## Kendall's tau-b

Kendall's tau-b is a nonparametric measure of association based on the number of concordances and discordances in paired observations. Concordance occurs when paired observations vary together, and discordance occurs when paired observations vary differently. The formula for Kendall's tau-b is

$$\tau = \frac{\sum_{i < j} \text{sgn}(x_i - x_j) \text{sgn}(y_i - y_j)}{\sqrt{(T_0 - T_1)(T_0 - T_2)}}$$

where

$$\begin{aligned} T_0 &= n(n-1)/2 \\ T_1 &= \sum t_i(t_i-1)/2 \\ T_2 &= \sum u_i(u_i-1)/2 \end{aligned}$$

and where  $t_i$  is the number of tied  $x$  values in the  $i$ th group of tied  $x$  values,  $u_i$  is the number of tied  $y$  values in the  $i$ th group of tied  $y$  values,  $f$  is the number of observations, and  $\text{sgn}(z)$  is defined as

$$\text{sgn}(z) = \begin{cases} 1 & \text{if } z > 0 \\ 0 & \text{if } z = 0 \\ -1 & \text{if } z < 0 \end{cases}$$

PROC CORR computes Kendall's correlation by ranking the data and using a method similar to Knight (1966). The data are double sorted by ranking observations according

to values of the first variable and reranking the observations according to values of the second variable. PROC CORR computes Kendall's tau-b from the number of interchanges of the first variable and corrects for tied pairs (pairs of observations with equal values of X or equal values of Y).

---

## Hoeffding's Measure of Dependence, D

Hoeffding's measure of dependence, D, is a nonparametric measure of association that detects more general departures from independence. The statistic approximates a weighted sum over observations of chi-square statistics for two-by-two classification tables (Hoeffding 1948). Each set of  $(x, y)$  values are cut points for the classification. The formula for Hoeffding's D is

$$D = 30 \frac{(n-2)(n-3)D_1 + D_2 - 2(n-2)D_3}{n(n-1)(n-2)(n-3)(n-4)}$$

where

$$D_1 = \sum_i (Q_i - 1)(Q_i - 2)$$

$$D_2 = \sum_i (R_i - 1)(R_i - 2)(S_i - 1)(S_i - 2)$$

$$D_3 = \sum_i (R_i - 2)(S_i - 2)(Q_i - 1)$$

$R_i$  is the rank of  $x_i$ ,  $S_i$  is the rank of  $y_i$ , and  $Q_i$  (also called the bivariate rank) is 1 plus the number of points with both  $x$  and  $y$  values less than the  $i$ th point. A point that is tied on only the  $x$  value or  $y$  value contributes 1/2 to  $Q_i$  if the other value is less than the corresponding value for the  $i$ th point. A point that is tied on both  $x$  and  $y$  contributes 1/4 to  $Q_i$ .

PROC CORR obtains the  $Q_i$  values by first ranking the data. The data are then double sorted by ranking observations according to values of the first variable and reranking the observations according to values of the second variable. Hoeffding's D statistic is computed using the number of interchanges of the first variable.

When no ties occur among data set observations, the D statistic values are between -0.5 and 1, with 1 indicating complete dependence. However, when ties occur, the D statistic may result in a smaller value. That is, for a pair of variables with identical values, the Hoeffding's D statistic may be less than 1. With a large number of ties in a small data set, the D statistic may be less than -0.5. For more information on Hoeffding's D, see Hollander and Wolfe (1973, p. 228).

---

## Partial Correlation

A partial correlation measures the strength of a relationship between two variables, while controlling the effect of one or more additional variables. The Pearson partial correlation for a pair of variables may be defined as the correlation of errors after regression on the controlling variables. Let  $\mathbf{y} = (y_1, y_2, \dots, y_v)$  be the set of variables to correlate. Also let  $\boldsymbol{\alpha}$  and  $\boldsymbol{\beta}$  be sets of regression parameters and  $\mathbf{z}$  be the set of

controlling variables, where  $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \dots, \alpha_v)$ ,  $\boldsymbol{\beta}$  is the slope, and  $\mathbf{z} = (z_1, z_2, \dots, z_p)$ . Suppose

$$E(\mathbf{y}) = \boldsymbol{\alpha} + \mathbf{z}\boldsymbol{\beta}$$

is a regression model for  $\mathbf{y}$  given  $\mathbf{z}$ . The population Pearson partial correlation between the  $i$ th and the  $j$ th variables of  $\mathbf{y}$  given  $\mathbf{z}$  is defined as the correlation between errors  $(y_i - E(y_i))$  and  $(y_j - E(y_j))$ .

If the exact values of  $\boldsymbol{\alpha}$  and  $\boldsymbol{\beta}$  are unknown, you can use a sample Pearson partial correlation to estimate the population Pearson partial correlation. For a given sample of observations, you estimate the sets of unknown parameters  $\boldsymbol{\alpha}$  and  $\boldsymbol{\beta}$  using the least-squares estimators  $\hat{\boldsymbol{\alpha}}$  and  $\hat{\boldsymbol{\beta}}$ . Then the fitted least-squares regression model is

$$\hat{\mathbf{y}} = \hat{\boldsymbol{\alpha}} + \mathbf{z}\hat{\boldsymbol{\beta}}$$

The partial corrected sums of squares and crossproducts (CSSCP) of  $\mathbf{y}$  given  $\mathbf{z}$  are the corrected sums of squares and crossproducts of the residuals  $\mathbf{y} - \hat{\mathbf{y}}$ . Using these partial corrected sums of squares and crossproducts, you can calculate the partial variances, partial covariances, and partial correlations.

PROC CORR derives the partial corrected sums of squares and crossproducts matrix by applying the Cholesky decomposition algorithm to the CSSCP matrix. For Pearson partial correlations, let  $\mathbf{S}$  be the partitioned CSSCP matrix between two sets of variables,  $\mathbf{z}$  and  $\mathbf{y}$ :

$$\mathbf{S} = \begin{bmatrix} \mathbf{S}_{zz} & \mathbf{S}_{zy} \\ \mathbf{S}'_{zy} & \mathbf{S}_{yy} \end{bmatrix}$$

PROC CORR calculates  $\mathbf{S}_{yy \cdot z}$ , the partial CSSCP matrix of  $\mathbf{y}$  after controlling for  $\mathbf{z}$ , by applying the Cholesky decomposition algorithm sequentially on the rows associated with  $\mathbf{z}$ , the variables being partialled out.

After applying the Cholesky decomposition algorithm to each row associated with variables  $\mathbf{z}$ , PROC CORR checks all higher numbered diagonal elements associated with  $\mathbf{z}$  for singularity. After the Cholesky decomposition, a variable is considered singular if the value of the corresponding diagonal element is less than  $p$  times the original unpartialled corrected sum of squares of that variable. You can specify the singularity criterion  $p$  using the SINGULAR= option. For Pearson partial correlations, a controlling variable  $\mathbf{z}$  is considered singular if the  $R^2$  for predicting this variable from the variables that are already partialled out exceeds  $1 - p$ . When this happens, PROC CORR excludes the variable from the analysis. Similarly, a variable is considered singular if the  $R^2$  for predicting this variable from the controlling variables exceeds  $1 - p$ . When this happens, its associated diagonal element and all higher numbered elements in this row or column are set to zero.

After the Cholesky decomposition algorithm is performed on all rows associated with  $\mathbf{z}$ , the resulting matrix has the form

$$\begin{bmatrix} \mathbf{T}_{zz} & \mathbf{T}_{zy} \\ \mathbf{0} & \mathbf{S}_{yy \cdot z} \end{bmatrix}$$

where  $\mathbf{T}_{zz}$  is an upper triangular matrix with

$$\begin{aligned} \mathbf{T}'_{zz} \mathbf{T}_{zz} &= \mathbf{S}_{zz}' \\ \mathbf{T}'_{zz} \mathbf{T}_{zy} &= \mathbf{S}_{zy}' \\ \mathbf{S}_{yy \cdot z} &= \mathbf{S}_{yy} - \mathbf{T}'_{zy} \mathbf{T}_{zy}. \end{aligned}$$

If  $\mathbf{S}_{zz}$  is positive definite, then the partial CSSCP matrix  $\mathbf{S}_{yy \cdot z}$  is identical to the matrix derived from the formula

$$\mathbf{S}_{yy \cdot z} = \mathbf{S}_{yy} - \mathbf{S}'_{zy} \mathbf{S}_{zz}^{-1} \mathbf{S}_{zy}$$

The partial variance-covariance matrix is calculated with the variance divisor (VARDEF= option). PROC CORR can then use the standard Pearson correlation formula on the partial variance-covariance matrix to calculate the Pearson partial correlation matrix. Another way to calculate Pearson partial correlation is by applying the Cholesky decomposition algorithm directly to the correlation matrix and by using the correlation formula on the resulting matrix.

To derive the corresponding Spearman partial rank-order correlations and Kendall partial tau-b correlations, PROC CORR applies the Cholesky decomposition algorithm to the Spearman rank-order correlation matrix and Kendall tau-b correlation matrix and uses the correlation formula. The singularity criterion for nonparametric partial correlations is identical to Pearson partial correlation except that PROC CORR uses a matrix of nonparametric correlations and sets a singular variable's associated correlations to missing. The partial tau-b correlations range from  $-1$  to  $1$ . However, the sampling distribution of this partial tau-b is unknown; therefore, the probability values are not available.

When a correlation matrix (Pearson, Spearman, or Kendall tau-b correlation matrix) is positive definite, the resulting partial correlation between variables  $x$  and  $y$  after adjusting for a single variable  $z$  is identical to that obtained from the first-order partial correlation formula

$$r_{xy \cdot z} = \frac{r_{xy} - r_{xz}r_{yz}}{\sqrt{(1 - r_{xz}^2)(1 - r_{yz}^2)}}$$

where  $r_{xy}$ ,  $r_{xz}$ , and  $r_{yz}$  are the appropriate correlations.

The formula for higher-order partial correlations is a straightforward extension of the above first-order formula. For example, when the correlation matrix is positive definite, the partial correlation between  $x$  and  $y$  controlling for both  $z_1$  and  $z_2$  is identical to the second-order partial correlation formula

$$r_{xy \cdot z_1 z_2} = \frac{r_{xy \cdot z_1} - r_{xz_2 \cdot z_1} r_{yz_2 \cdot z_1}}{\sqrt{(1 - r_{xz_2 \cdot z_1}^2)(1 - r_{yz_2 \cdot z_1}^2)}}$$

where  $r_{xy \cdot z_1}$ ,  $r_{xz_2 \cdot z_1}$ , and  $r_{yz_2 \cdot z_1}$  are first-order partial correlations among variables  $x$ ,  $y$ , and  $z_2$  given  $z_1$ .

---

## Cronbach's Coefficient Alpha

Analyzing latent constructs such as job satisfaction, motor ability, sensory recognition, or customer satisfaction requires instruments to accurately measure the

constructs. Interrelated items may be summed to obtain an overall score for each participant. Cronbach's coefficient alpha estimates the reliability of this type of scale by determining the internal consistency of the test or the average correlation of items within the test (Cronbach 1951).

When a value is recorded, the observed value contains some degree of measurement error. Two sets of measurements on the same variable for the same individual may not have identical values. However, repeated measurements for a series of individuals will show some consistency. Reliability measures internal consistency from one set of measurements to another. The observed value  $Y$  is divided into two components, a true value  $T$  and a measurement error  $E$ . The measurement error is assumed to be independent of the true value, that is,

$$Y = T + E, \quad \text{cov}(T, E) = 0$$

The reliability coefficient of a measurement test is defined as the squared correlation between the observed value  $Y$  and the true value  $T$ , that is,

$$\begin{aligned} \rho^2(Y, T) &= \frac{\text{cov}(Y, T)^2}{\text{var}(Y) \text{var}(T)} \\ &= \frac{\text{var}(T)^2}{\text{var}(Y) \text{var}(T)} \\ &= \frac{\text{var}(T)}{\text{var}(Y)} \end{aligned}$$

which is the proportion of the observed variance due to true differences among individuals in the sample. If  $Y$  is the sum of several observed variables measuring the same feature, you can estimate  $\text{var}(T)$ . Cronbach's coefficient alpha, based on a lower bound for  $\text{var}(T)$ , is an estimate of the reliability coefficient.

Suppose  $p$  variables are used with  $Y_j = T_j + E_j$  for  $j = 1, 2, \dots, p$ , where  $Y_j$  is the observed value,  $T_j$  is the true value, and  $E_j$  is the measurement error. The measurement errors ( $E_j$ ) are independent of the true values ( $T_j$ ) and are also independent of each other. Let  $Y_0 = \sum Y_j$  be the total observed score and  $T_0 = \sum T_j$  be the total true score. Because

$$(p-1) \sum \text{var}(T_j) \geq \sum_{i \neq j} \text{cov}(T_i, T_j),$$

a lower bound for  $\text{var}(T_0)$  is given by

$$\frac{p}{p-1} \sum_{i \neq j} \text{cov}(T_i, T_j)$$

With  $\text{cov}(Y_i, Y_j) = \text{cov}(T_i, T_j)$  for  $i \neq j$ , a lower bound for the reliability coefficient is then given by the Cronbach's coefficient alpha:

$$\begin{aligned}\alpha &= \left(\frac{p}{p-1}\right) \frac{\sum_{i \neq j} \text{cov}(Y_i, Y_j)}{\text{var}(Y_0)} \\ &= \left(\frac{p}{p-1}\right) \left(1 - \frac{\sum_j \text{var}(Y_j)}{\text{var}(Y_0)}\right)\end{aligned}$$

If the variances of the items vary widely, you can standardize the items to a standard deviation of 1 before computing the coefficient alpha. If the variables are dichotomous (0,1), the coefficient alpha is equivalent to the Kuder-Richardson 20 (KR-20) reliability measure.

When the correlation between each pair of variables is 1, the coefficient alpha has a maximum value of 1. With negative correlations between some variables, the coefficient alpha can have a value less than zero. The larger the overall alpha coefficient, the more likely that items contribute to a reliable scale. Nunnally (1978) suggests .70 as an acceptable reliability coefficient; smaller reliability coefficients are seen as inadequate. However, this varies by discipline.

To determine how each item reflects the reliability of the scale, you calculate a coefficient alpha after deleting each variable independently from the scale. The Cronbach's coefficient alpha from all variables except the  $k$ th variable is given by

$$\alpha_k = \left(\frac{p-1}{p-2}\right) \left(1 - \frac{\sum_{i \neq k} \text{var}(Y_i)}{\text{var}\left(\sum_{i \neq k} Y_i\right)}\right)$$

If the reliability coefficient increases after deleting an item from the scale, you can assume that the item is not correlated highly with other items in the scale. Conversely, if the reliability coefficient decreases you can assume that the item is highly correlated with other items in the scale. See *SAS Communications*, 4th Quarter 1994, for more information on how to interpret Cronbach's coefficient alpha.

Listwise deletion of observations with missing values is necessary to correctly calculate Cronbach's coefficient alpha. PROC CORR does not automatically use listwise deletion when you specify ALPHA. Therefore, use the NOMISS option if the data set contains missing values. Otherwise, PROC FREQ prints a warning message in the SAS log indicating the need to use NOMISS with ALPHA.

---

## Probability Values

Probability values for the Pearson and Spearman correlations are computed by treating

$$\frac{(n-2)^{1/2} r}{(1-r^2)^{1/2}}$$

as coming from a  $t$  distribution with  $n - 2$  degrees of freedom, where  $r$  is the appropriate correlation.

Probability values for the Pearson and Spearman partial correlations are computed by treating

$$\frac{(n - k - 2)^{1/2} r}{(1 - r^2)^{1/2}}$$

as coming from a  $t$  distribution with  $n - k - 2$  degrees of freedom, where  $r$  is the appropriate partial correlation and  $k$  is the number of variables being partialled out.

Probability values for Kendall correlations are computed by treating

$$\frac{s}{\sqrt{\text{var}(s)}}$$

as coming from a normal distribution when

$$s = \sum_{i < j} \text{sgn}(x_i - x_j) \text{sgn}(y_i - y_j)$$

and where  $x_i$  are the values of the first variable,  $y_i$  are the values of the second variable, and the function  $\text{sgn}(z)$  is defined as

$$\text{sgn}(z) = \begin{cases} 1 & \text{if } z > 0 \\ 0 & \text{if } z = 0 \\ -1 & \text{if } z < 0 \end{cases}$$

The formula for the variance of  $s$ ,  $\text{var}(s)$ , is computed as

$$\text{var}(s) = \frac{v_0 - v_t - v_u}{18} + \frac{v_1}{2n(n-1)} + \frac{v_2}{9n(n-1)(n-2)}$$

where

$$\begin{aligned} v_0 &= n(n-1)(2n+5) \\ v_t &= \sum t_i(t_i-1)(2t_i+5) \\ v_u &= \sum u_i(u_i-1)(2u_i+5) \\ v_1 &= (\sum t_i(t_i-1))(\sum u_i(u_i-1)) \\ v_2 &= (\sum t_i(t_i-1)(t_i-2))(\sum u_i(u_i-1)(u_i-2)) \end{aligned}$$

The sums are over tied groups of values where  $t_i$  is the number of tied  $x$  values and  $u_i$  is the number of tied  $y$  values (Noether 1967). The sampling distribution of Kendall's partial tau-b is unknown; therefore, the probability values are not available.

The probability values for Hoeffding's  $D$  statistic are computed using the asymptotic distribution computed by Blum, Kiefer, and Rosenblatt (1961). The formula is

$$\frac{(n-1)\pi^4}{60} D + \frac{\pi^4}{72}$$



which comes from the asymptotic distribution. When the sample size is less than 10, see the tables for the distribution of  $D$  in Hollander and Wolfe (1973).

---

## Results

---

### Missing Values

By default, PROC CORR uses *pairwise deletion* when observations contain missing values. PROC CORR includes all nonmissing pairs of values for each pair of variables in the statistical computations. Therefore, the correlations statistics may be based on different numbers of observations.

If you specify the NOMISS option, PROC CORR uses *listwise deletion* when a value of the BY, FREQ, VAR, WEIGHT, or WITH statement variable is missing. PROC CORR excludes all observations with missing values from the analysis. Therefore, the number of observations for each pair of variables is identical. The PARTIAL statement always excludes the observations with missing values by automatically invoking NOMISS. Listwise deletion is needed to correctly calculate Cronbach's coefficient alpha when data are missing. If a data set contains missing values, when you specify ALPHA use the NOMISS option

There are two reasons to specify NOMISS and, thus, to avoid pairwise deletion. First, NOMISS is computationally more efficient, so you use fewer computer resources. Second, if you use the correlations as input to regression or other statistical procedures, a pairwise-missing correlation matrix leads to several statistical difficulties. Pairwise correlation matrices may not be nonnegative definite, and the pattern of missing values may bias the results.

---

### Procedure Output

By default, PROC CORR prints a report that includes descriptive statistics and correlation statistics for each variable. The descriptive statistics include the number of observations with nonmissing values, the mean, the standard deviation, the minimum, and the maximum. PROC CORR reports the following additional descriptive statistics when you request various correlation statistics:

```
sum
  for Pearson correlation only
median
  for nonparametric measures of association
partial variance
  for Pearson partial correlation
partial standard deviation
  for Pearson partial correlation.
```

If variable labels are available, PROC CORR labels the variables.

When you specify the CSSCP, SSCP, or COV option, the appropriate sum-of-squares and crossproducts and covariance matrix appears at the top of the correlation report. If the data set contains missing values, PROC CORR prints additional statistics for each pair of variables. These statistics, calculated from the observations with nonmissing row and column variable values, may include

```
SSCP(W,'V')
  uncorrected sum-of-squares and crossproducts
```

USS(W')	uncorrected sum-of-squares for the row variable
USS(V')	uncorrected sum-of-squares for the column variable
CSSCP(W',V')	corrected sum-of-squares and crossproducts
CSS(W')	corrected sum-of-squares for the row variable
CSS(V')	corrected sum-of-squares for the column variable
COV (W',V')	covariance
VAR (W')	variance for the row variable
VAR (V')	variance for the column variable
DF(W',V')	divisor for calculating covariance and variances.

For each pair of variables, PROC CORR always prints the correlation coefficients, the number of observations used to calculate the coefficient, and the significance probability. When you specify the ALPHA option, PROC CORR prints Cronbach's coefficient alpha, the correlation between the variable and the total of the remaining variables, and Cronbach's coefficient alpha using the remaining variables for the raw variables and the standardized variables.

---

## Output Data Sets

When you specify the OUTP=, OUTS=, OUTK=, or OUTH= option, PROC CORR creates an output data set containing statistics for Pearson correlation, Spearman correlation, Kendall correlation, or Hoeffding's D, respectively. By default, the output data set is a special data set type (TYPE=CORR) that many SAS/STAT procedures recognize, including PROC REG and PROC FACTOR. When you specify the NOCORR option and the COV, CSSCP, or SSCP option, use the TYPE= data set option to change the data set type to COV, CSSCP, or SSCP. For example, the following statement

```
proc corr nocorr cov outp=b(type=cov);
```

specifies the output data set type as COV.

PROC CORR does not print the output data set. Use PROC PRINT, PROC REPORT, or another SAS reporting tool to print the output data set.

The output data set includes the following variables

BY variables

identifies the BY group when using a BY statement.

\_TYPE\_ variable

identifies the type of observation.

\_NAME\_ variable

identifies the variable that corresponds to a given row of the correlation matrix.

INTERCEP variable

identifies variable sums when specifying the SSCP option.

**VAR variables**

identifies the variables listed in the VAR statement.

You can use a combination of the `_TYPE_` and `_NAME_` variables to identify the contents of an observation. The `_NAME_` variable indicates which row of the correlation matrix the observation corresponds to. The values of the `_TYPE_` variable are

**SSCP**

uncorrected sums of squares and crossproducts

**CSSCP**

corrected sums of squares and crossproducts

**COV**

covariances

**MEAN**

mean of each variable

**STD**

standard deviation of each variable

**N**

number of nonmissing observations for each variable

**SUMWGT**

sum of the weights for each variable when using a `WEIGHT` statement

**CORR**

correlation statistics for each variable.

When you specify the `SSCP` option, the `OUTP=` data set includes an additional observation that contains intercept values. When you specify the `ALPHA` option, the `OUTP=` data set also includes observations with the following `_TYPE_` values:

**RAWALPHA**

Cronbach's coefficient alpha for raw variables

**STDALPHA**

Cronbach's coefficient alpha for standardized variables

**RAWALDEL**

Cronbach's coefficient alpha for raw variables after deleting one variable

**STDALDEL**

Cronbach's coefficient alpha for standardized variables after deleting one variable

**RAWCTDEL**

correlation between a raw variable and the total of the remaining raw variables

**STDCTDEL**

correlation between a standardized variable and the total of the remaining standardized variables.

When you use a `PARTIAL` statement, the previous statistics are calculated for the variables after partialling. If `PROC CORR` computes Pearson correlation statistics, `MEAN` equals zero and `STD` equals the partial standard deviation associated with the partial variance for the `OUTP=`, `OUTK=`, or `OUTS=` data set. Otherwise, `PROC CORR` assigns missing values to `MEAN` and `STD`. Output 12.4 on page 299 lists the observations in an `OUTP=` data set when the `COV` option and `PARTIAL` statement are used to compute Pearson partial correlations. The `_TYPE_` variable identifies `COV`, `MEAN`, `STD`, `N`, and `CORR` as the statistical values for the variables `Weight`, `Oxygen`, and `Runtime`. `MEAN` always equals 0, while `STD` is a partial standard deviation.

**Output 12.4** OUTP= Data Set with Pearson Partial Correlations

Pearson Correlation Statistics Using the PARTIAL Statement 1				
Output Data Set from PROC CORR				
<u>_TYPE_</u>	<u>_NAME_</u>	Weight	Oxygen	Runtime
COV	Weight	72.4374	-12.7511	2.0677
COV	Oxygen	-12.7511	27.0165	-5.5937
COV	Runtime	2.0677	-5.5937	1.9451
MEAN		0.0000	0.0000	0.0000
STD		8.5110	5.1977	1.3947
N		28.0000	28.0000	28.0000
CORR	Weight	1.0000	-0.2882	0.1742
CORR	Oxygen	-0.2882	1.0000	-0.7716
CORR	Runtime	0.1742	-0.7716	1.0000

---

## Examples

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### Example 1: Computing Pearson Correlations and Other Measures of Association

**Procedure features:**

PROC CORR statement options:

HOEFFDING

PEARSON

SPEARMAN

VAR statement

This example

- produces a correlation analysis with descriptive statistics, Pearson product-moment correlation, Spearman rank-order correlation, and Hoeffding's measure of dependence, D
- selects the analysis variables.

**Program**

```
options nodate pageno=1 linesize=80 pagesize=60;
```

The data set FITNESS contains measurements from a study of physical fitness for 30 participants between the ages 38 and 57. Each observation represents one person. Two observations contain missing values.

```

data fitness;
  input Age Weight Runtime Oxygen @@;
  datalines;
57 73.37 12.63 39.407 54 79.38 11.17 46.080
52 76.32 9.63 45.441 50 70.87 8.92 .
51 67.25 11.08 45.118 54 91.63 12.88 39.203
51 73.71 10.47 45.790 57 59.08 9.93 50.545
49 76.32 . 48.673 48 61.24 11.5 47.920
52 82.78 10.5 47.467 44 73.03 10.13 50.541
45 87.66 14.03 37.388 45 66.45 11.12 44.754
47 79.15 10.6 47.273 54 83.12 10.33 51.855
49 81.42 8.95 40.836 51 77.91 10.00 46.672
48 91.63 10.25 46.774 49 73.37 10.08 50.388
44 89.47 11.37 44.609 40 75.07 10.07 45.313
44 85.84 8.65 54.297 42 68.15 8.17 59.571
38 89.02 9.22 49.874 47 77.45 11.63 44.811
40 75.98 11.95 45.681 43 81.19 10.85 49.091
44 81.42 13.08 39.442 38 81.87 8.63 60.055
;

```

PEARSON, SPEARMAN, and HOEFFDING compute correlation statistics. When you request nonparametric correlations, specify PEARSON to compute Pearson correlations.

```
proc corr data=fitness pearson spearman hoeffding;
```

The VAR statement specifies the analysis variables and the order to print them.

```
var weight oxygen runtime;
```

The TITLE statement specifies a title for the report.

```
title 'Measures of Association for';
title2 'a Physical Fitness Study';
run;
```

## Output

The correlation report includes descriptive statistics, Pearson's rho, Spearman's rho, and Hoeffding's D. The report uses the median, instead of the sum, as a descriptive measure when PROC CORR computes nonparametric measures of association.

Because missing data are excluded pairwise, the number of observations PROC CORR uses to calculate the correlation coefficients varies.

Measures of Association for a Physical Fitness Study							1
The CORR Procedure							
3 Variables: Weight Oxygen Runtime							
Simple Statistics							
Variable	N	Mean	Std Dev	Median	Minimum	Maximum	
Weight	30	77.70500	8.34152	77.68000	59.08000	91.63000	
Oxygen	29	47.06445	5.32129	46.67200	37.38800	60.05500	
Runtime	29	10.61448	1.41655	10.47000	8.17000	14.03000	
Pearson Correlation Coefficients							
Prob >  r  under H0: Rho=0							
Number of Observations							
	Weight	Oxygen	Runtime				
Weight	1.00000	-0.19900	0.15155				
		0.3007	0.4326				
	30	29	29				
Oxygen	-0.19900	1.00000	-0.78346				
	0.3007		<.0001				
	29	29	28				
Runtime	0.15155	-0.78346	1.00000				
	0.4326	<.0001					
	29	28	29				
Spearman Correlation Coefficients							
Prob >  r  under H0: Rho=0							
Number of Observations							
	Weight	Oxygen	Runtime				
Weight	1.00000	-0.13110	0.10546				
		0.4979	0.5861				
	30	29	29				
Oxygen	-0.13110	1.00000	-0.68363				
	0.4979		<.0001				
	29	29	28				
Runtime	0.10546	-0.68363	1.00000				
	0.5861	<.0001					
	29	28	29				

Measures of Association for a Physical Fitness Study				2
The CORR Procedure				
Hoeffding Dependence Coefficients				
Prob > D under H0: D=0				
Number of Observations				
	Weight	Oxygen	Runtime	
Weight	0.97559 <.0001 30	-0.01789 0.9775 29	-0.02418 1.0000 29	
Oxygen	-0.01789 0.9775 29	1.00000 29	0.16554 <.0001 28	
Runtime	-0.02418 1.0000 29	0.16554 <.0001 28	1.00000 29	

## Example 2: Computing Rectangular Correlation Statistics with Missing Data

### Procedure features:

PROC CORR statement options:

COV  
NOSIMPLE  
SSCP

VAR statement

WITH statement

This example

- suppresses descriptive statistics
- prints uncorrected sum-of-squares and crossproducts
- calculates a rectangular covariance matrix
- calculates a rectangular correlation matrix
- excludes observations with missing values using pairwise deletion (default method).

### Program

```
options nodate pageno=1 linesize=80 pagesize=60;
```

The data set SETOSA contains measurements for four iris parts: sepal length, sepal width, petal length, and petal width based on Fisher's iris data (1936). Fifty iris specimens from the species *Iris setosa* are used. Each observation represents one specimen. Three observations contain missing values. The LABEL statement associates a label with each variable.

```

data setosa;
  input SepalLength SepalWidth PetalLength PetalWidth @@;
  label sepallength='Sepal Length in mm.'
        sepalwidth='Sepal Width in mm.'
        petallength='Petal Length in mm.'
        petalwidth='Petal Width in mm.';
  datalines;
50 33 14 02   46 34 14 03   46 36 . 02
51 33 17 05   55 35 13 02   48 31 16 02
52 34 14 02   49 36 14 01   44 32 13 02
50 35 16 06   44 30 13 02   47 32 16 02
48 30 14 03   51 38 16 02   48 34 19 02
50 30 16 02   50 32 12 02   43 30 11 .
58 40 12 02   51 38 19 04   49 30 14 02
51 35 14 02   50 34 16 04   46 32 14 02
57 44 15 04   50 36 14 02   54 34 15 04
52 41 15 .    55 42 14 02   49 31 15 02
54 39 17 04   50 34 15 02   44 29 14 02
47 32 13 02   46 31 15 02   51 34 15 02
50 35 13 03   49 31 15 01   54 37 15 02
54 39 13 04   51 35 14 03   48 34 16 02
48 30 14 01   45 23 13 03   57 38 17 03
51 38 15 03   54 34 17 02   51 37 15 04
52 35 15 02   53 37 15 02
;

```

SSCP displays the uncorrected sum-of-squares and crossproducts matrix and invokes PEARSON. COV calculates the covariance matrix. NOSIMPLE suppresses descriptive statistics.

```
proc corr data=setosa sscp cov nosimple;
```

The WITH statement together with the VAR statement produces a rectangular correlation matrix. The matrix rows are PetalLength and PetalWidth while the matrix columns are SepalLength and SepalWidth.

```

var sepallength sepalwidth;
with petallength petalwidth;

```

The TITLE statement specifies a title for the report.

```

title 'Fisher (1936) Iris Setosa Data';
run;

```

## Output



The correlation report includes rectangular sum-of-squares and crossproducts, covariances, and the correlation matrix using the two WITH variables and two VAR variables. The descriptive statistics do not appear. PROC CORR uses variable labels to label matrix rows (WITH variables).

PROC CORR calculates sum-of-squares and crossproducts and covariances statistics for each pair of variables by using observations with nonmissing row and column variable values.

Because missing data are excluded pairwise, the number of observations PROC CORR uses to calculate the correlation coefficients changes.

Fisher (1936) Iris Setosa Data			1
The CORR Procedure			
2	With Variables:	PetalLength	PetalWidth
2	Variables:	SepalLength	SepalWidth
Sums of Squares and Crossproducts			
SSCP / Row Var SS / Col Var SS			
		SepalLength	SepalWidth
PetalLength		36214.00000	24756.00000
Petal Length in mm.		10735.00000	10735.00000
		123793.0000	58164.0000
PetalWidth		6113.00000	4191.00000
Petal Width in mm.		355.00000	355.00000
		121356.0000	56879.0000
Variances and Covariances			
Covariance / Row Var Variance / Col Var Variance / DF			
		SepalLength	SepalWidth
PetalLength		1.270833333	1.363095238
Petal Length in mm.		2.625000000	2.625000000
		12.33333333	14.60544218
		48	48
PetalWidth		0.911347518	1.048315603
Petal Width in mm.		1.063386525	1.063386525
		11.80141844	13.62721631
		47	47
Pearson Correlation Coefficients			
Prob >  r  under H0: Rho=0			
Number of Observations			
		Sepal Length	Sepal Width
PetalLength		0.22335	0.22014
Petal Length in mm.		0.1229	0.1285
		49	49
PetalWidth		0.25726	0.27539
Petal Width in mm.		0.0775	0.0582
		48	48

## Example 3: Computing Cronbach's Coefficient Alpha

### Procedure features:

PROC CORR statement options:

ALPHA  
NOCORR  
NOMISS

This example

- computes Cronbach's coefficient alpha for a multiple-item mixed-rating scale
- suppresses Pearson correlation statistics
- excludes observations with missing values using listwise deletion.

This example does not examine the correlation matrix but assumes that all items are positively correlated. Normally, you want to examine the correlation and covariance matrices to make sure that all variables are positively correlated. Positive correlation is needed because items measure a common entity. You exclude negatively correlated items from the analysis because they do not measure the same construct.

### Program

```
options nodate pageno=1 linesize=80 pagesize=60;
```

The data set PYSCHDAT contains responses to a questionnaire assessing the mental stability of 30 randomly selected female psychiatric patients.\* Each observation represents one patient. The scale includes seven items. The LABEL statement provides a label for each item. Seven observations contain missing values.

```
data psychdat;
  input Age Anxiety Depression Sleep Sex Life WeightChange @@;
  label age          = 'age in years'
        anxiety      = 'anxiety level'
        depression    = 'depression level'
        sleep         = 'normal sleep (1=y 2=n)'
        sex           = 'sexual (1=n 2=y)'
        life          = 'suicidal (1=n 2=y)'
        weightchange  = 'recent weight change';
  datalines;
39 2  2  2  2  2  4.9 41 2  2  2  2  2  2.2
42 3  3  .  2  2  4.0 30 2  2  2  2  2 -2.6
35 2  1  1  2  1 -0.3 44 .  1  2  1  1  0.9
31 2  2  .  2  2 -1.5 39 3  2  2  2  1  3.5
35 3  2  2  2  2 -1.2 33 2  2  2  2  2  0.8
38 2  1  1  1  1 -1.9 31 2  2  2  .  1  5.5
```

\*

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```

40 3 2 2 2 1 2.7 44 2 2 2 2 2 4.4
43 3 2 2 2 2 3.2 32 1 1 1 2 1 -1.5
32 1 2 2 . 1 -1.9 43 4 3 2 2 2 8.3
46 3 2 2 2 2 3.6 30 2 2 2 2 1 1.4
34 3 3 . 2 2 . 37 3 2 2 2 1 .
35 2 1 2 2 1 -1.0 45 2 2 2 2 2 6.5
35 2 2 2 2 1 -2.1 31 2 2 2 2 1 -0.4
32 2 2 2 2 1 -1.9 44 2 2 2 2 2 3.7
40 3 3 2 2 2 4.5 42 3 3 2 2 2 4.2
;

```

ALPHA computes Cronbach's alpha and invokes PEARSON. NOCORR suppresses Pearson correlation statistics. NOMISS excludes observations with missing values. Omitting a VAR statement causes PROC CORR to use all numeric variables.

```
proc corr data=psychdat alpha nocorr nomiss;
```

The TITLE statement specifies a title for the report.

```

title1 'Mental Stability Scale for Female Psychiatric Patients';
run;

```

## Output

The correlation report includes descriptive statistics and Cronbach's coefficient alpha, the correlation between the variable and the total of the remaining variables, and Cronbach's coefficient alpha using the remaining variables for both the raw variables and the standardized variables. These calculations use the 23 observations without missing values.

Because the variances of some variables vary widely, you use the standardized scores to estimate reliability. The overall standardized alpha of .85 is an acceptable reliability coefficient. This is greater than Nunnally's suggested value of .70.

The standardized alpha provides information on how each item reflects the reliability of the scale. Notice that the standardized alpha decreases after removing Depression from the construct. Therefore, this variable appears strongly correlated with other items in the scale. The standardized alpha increases slightly after removing Sex from the construct. Thus, removing this variable from the scale makes the construct more reliable.

Mental Stability Scale for Female Psychiatric Patients					1
The CORR Procedure					
7 Variables:	Age	Anxiety	Depression	Sleep	Sex
	Life	WeightChange			
Simple Statistics					
Variable	N	Mean	Std Dev	Sum	
Age	23	37.91304	5.13378	872.00000	
Anxiety	23	2.34783	0.64728	54.00000	
Depression	23	1.95652	0.56232	45.00000	
Sleep	23	1.86957	0.34435	43.00000	
Sex	23	1.95652	0.20851	45.00000	
Life	23	1.56522	0.50687	36.00000	
WeightChange	23	1.78261	3.06381	41.00000	
Simple Statistics					
Variable	Minimum	Maximum	Label		
Age	30.00000	46.00000	age in years		
Anxiety	1.00000	4.00000	anxiety level		
Depression	1.00000	3.00000	depression level		
Sleep	1.00000	2.00000	normal sleep (1=y 2=n)		
Sex	1.00000	2.00000	sexual (1=n 2=y)		
Life	1.00000	2.00000	suicidal (1=n 2=y)		
WeightChange	-2.60000	8.30000	recent weight change		
Cronbach Coefficient Alpha					
	Variables	Alpha			
	-----	-----			
	Raw	0.627754			
	Standardized	0.845339			

Mental Stability Scale for Female Psychiatric Patients				
The CORR Procedure				
Cronbach Coefficient Alpha with Deleted Variable				
Raw Variables			Standardized Variables	
Deleted Variable	Correlation with Total	Alpha	Correlation with Total	Alpha
Age	0.742614	0.557515	0.546856	0.832207

Cronbach Coefficient Alpha with Deleted Variable				
Deleted Variable	Label			
Age	age in years			

Cronbach Coefficient Alpha with Deleted Variable				
Raw Variables			Standardized Variables	
Deleted Variable	Correlation with Total	Alpha	Correlation with Total	Alpha
Anxiety	0.577129	0.600944	0.590851	0.825643
Depression	0.554983	0.608273	0.770956	0.797610
Sleep	0.378930	0.630242	0.618367	0.821482
Sex	0.155115	0.642017	0.333368	0.862537
Life	0.622207	0.607333	0.625338	0.820421
WeightChange	0.843939	0.341006	0.749261	0.801087

Cronbach Coefficient Alpha with Deleted Variable				
Deleted Variable	Label			
Anxiety	anxiety level			
Depression	depression level			
Sleep	normal sleep (1=y 2=n)			
Sex	sexual (1=n 2=y)			
Life	suicidal (1=n 2=y)			
WeightChange	recent weight change			

## Example 4: Storing Partial Correlations in an Output Data Set

**Procedure features:**

PROC CORR statement options:

COV  
 KENDALL  
 NOSIMPLE  
 OUTP=  
 SPEARMAN

PARTIAL statement

VAR statement

**Data set:** FITNESS on page 301

---

This example

- suppresses descriptive statistics
- calculates three types of partial correlation coefficients
- calculates a partial covariance matrix
- excludes observations with missing values using listwise deletion
- selects the analysis variables
- creates an output data set with Pearson correlation statistics.

See Output 12.4 on page 299 for a listing of the output data set.

## Program

```
options nodate pageno=1 linesize=120 pagesize=60;
```

SPEARMAN and KENDALL request correlation statistics. COV calculates the covariance matrix and invokes PEARSON. NOSIMPLE suppresses descriptive statistics. OUT= creates the FITCORR data set that contains Pearson correlation statistics.

```
proc corr data=fitness spearman kendall cov nosimple
      outp=fitcorr;
```

The VAR statement specifies the analysis variables and the order to print them.

```
var weight oxygen runtime;
```

The PARTIAL statement calculates partial correlations using Age as the controlling variable.

```
partial age;
```

The LABEL statement associates a label with each variable for the duration of the PROC step.

```
label age      = 'Age of subject'
      weight   = 'Wt in kg'
      runtime  = '1.5 mi in minutes'
      oxygen   = 'O2 use';
```

The TITLE statement specifies a title for the report.

```
title1 'Partial Correlations for a Fitness and Exercise Study';
run;
```

## Output

The report includes a partial covariance matrix and partial correlations for Pearson's rho, Spearman's rho, and Kendall's tau-b. The  $p$ -values for Kendall's tau-b are not available. Because observations with missing data are excluded, PROC CORR uses 28 observations to calculate correlation coefficients.

Partial Correlations for a Fitness and Exercise Study					1
The CORR Procedure					
1	Partial Variables:	Age			
3	Variables:	Weight	Oxygen	Runtime	
Partial Covariance Matrix, DF = 26					
		Weight	Oxygen	Runtime	
Weight	Wt in kg	72.43742055	-12.75113194	2.06766763	
Oxygen	O2 use	-12.75113194	27.01654904	-5.59370556	
Runtime	1.5 mi in minutes	2.06766763	-5.59370556	1.94512451	
Pearson Partial Correlation Coefficients, N = 28					
Prob >  r  under H0: Partial Rho=0					
		Weight	Oxygen	Runtime	
Weight		1.00000	-0.28824	0.17419	
Wt in kg			0.1448	0.3849	
Oxygen		-0.28824	1.00000	-0.77163	
O2 use		0.1448		<.0001	
Runtime		0.17419	-0.77163	1.00000	
1.5 mi in minutes		0.3849	<.0001		
Spearman Partial Correlation Coefficients, N = 28					
Prob >  r  under H0: Partial Rho=0					
		Weight	Oxygen	Runtime	
Weight		1.00000	-0.16407	0.08708	
Wt in kg			0.4135	0.6658	
Oxygen		-0.16407	1.00000	-0.67112	
O2 use		0.4135		0.0001	
Runtime		0.08708	-0.67112	1.00000	
1.5 mi in minutes		0.6658	0.0001		
Kendall Partial Tau b Correlation Coefficients, N = 28					
		Weight	Oxygen	Runtime	
Weight		1.00000	-0.09021	0.02854	
Wt in kg					
Oxygen		-0.09021	1.00000	-0.52158	
O2 use					
Runtime		0.02854	-0.52158	1.00000	
1.5 mi in minutes					

---

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The correct bibliographic citation for this manual is as follows: SAS Institute Inc., SAS® *Procedures Guide, Version 8*, Cary, NC: SAS Institute Inc., 1999. 1729 pp.

**SAS® Procedures Guide, Version 8**

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ISBN 1-58025-482-9

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1st printing, October 1999

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