

# Chapter 23

## The CLUSTER Procedure

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## Chapter 23

# The CLUSTER Procedure

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### Overview

The CLUSTER procedure hierarchically clusters the observations in a SAS data set using one of eleven methods. The CLUSTER procedure finds hierarchical clusters of the observations in a SAS data set. The data can be coordinates or distances. If the data are coordinates, PROC CLUSTER computes (possibly squared) Euclidean distances. If you want to perform a cluster analysis on non-Euclidean distance data, it is possible to do so by using a TYPE=DISTANCE data set as input. The %DISTANCE macro in the SAS/STAT sample library can compute many kinds of distance matrices.

One situation where analyzing non-Euclidean distance data can be useful is when you have categorical data, where the distance data are calculated using an association measure. For more information, see Example 23.5 on page 916.

The clustering methods available are average linkage, the centroid method, complete linkage, density linkage (including Wong's hybrid and  $k$ th-nearest-neighbor methods), maximum likelihood for mixtures of spherical multivariate normal distributions with equal variances but possibly unequal mixing proportions, the flexible-beta method, McQuitty's similarity analysis, the median method, single linkage, two-stage density linkage, and Ward's minimum-variance method.

All methods are based on the usual agglomerative hierarchical clustering procedure. Each observation begins in a cluster by itself. The two closest clusters are merged to form a new cluster that replaces the two old clusters. Merging of the two closest clusters is repeated until only one cluster is left. The various clustering methods differ in how the distance between two clusters is computed. Each method is described in the section "Clustering Methods" on page 854.

The CLUSTER procedure is not practical for very large data sets because, with most methods, the CPU time varies as the square or cube of the number of observations. The FASTCLUS procedure requires time proportional to the number of observations and can, therefore, be used with much larger data sets than PROC CLUSTER. If you want to cluster a very large data set hierarchically, you can use PROC FASTCLUS for a preliminary cluster analysis producing a large number of clusters and then use PROC CLUSTER to cluster the preliminary clusters hierarchically. This method is used to find clusters for the Fisher Iris data in Example 23.3, later in this chapter.

PROC CLUSTER displays a history of the clustering process, giving statistics useful for estimating the number of clusters in the population from which the data are sampled. PROC CLUSTER also creates an output data set that can be used by the TREE procedure to draw a tree diagram of the cluster hierarchy or to output the cluster membership at any desired level. For example, to obtain the six-cluster so-

lution, you could first use PROC CLUSTER with the OUTTREE= option then use this output data set as the input data set to the TREE procedure. With PROC TREE, specify NCLUSTERS=6 and the OUT= options to obtain the six-cluster solution and draw a tree diagram. For an example, see Example 66.1 in Chapter 66, “The TREE Procedure.”

Before you perform a cluster analysis on coordinate data, it is necessary to consider scaling or transforming the variables since variables with large variances tend to have more effect on the resulting clusters than those with small variances. The ACECLUS procedure is useful for performing linear transformations of the variables. You can also use the PRINCOMP procedure with the STD option, although in some cases it tends to obscure clusters or magnify the effect of error in the data when all components are retained. The STD option in the CLUSTER procedure standardizes the variables to mean 0 and standard deviation 1. Standardization is not always appropriate. See Milligan and Cooper (1987) for a Monte Carlo study on various methods of variable standardization. You should remove outliers before using PROC PRINCOMP or before using PROC CLUSTER with the STD option unless you specify the TRIM= option.

Nonlinear transformations of the variables may change the number of population clusters and should, therefore, be approached with caution. For most applications, the variables should be transformed so that equal differences are of equal practical importance. An interval scale of measurement is required if raw data are used as input. Ordinal or ranked data are generally not appropriate.

Agglomerative hierarchical clustering is discussed in all standard references on cluster analysis, for example, Anderberg (1973), Sneath and Sokal (1973), Hartigan (1975), Everitt (1980), and Spath (1980). An especially good introduction is given by Massart and Kaufman (1983). Anyone considering doing a hierarchical cluster analysis should study the Monte Carlo results of Milligan (1980), Milligan and Cooper (1985), and Cooper and Milligan (1988). Other essential, though more advanced, references on hierarchical clustering include Hartigan (1977, pp. 60–68; 1981), Wong (1982), Wong and Schaack (1982), and Wong and Lane (1983). Refer to Blashfield and Aldenderfer (1978) for a discussion of the confusing terminology in hierarchical cluster analysis.

## Getting Started

The following example demonstrates how you can use the CLUSTER procedure to compute hierarchical clusters of observations in a SAS data set.

Suppose you want to determine whether national figures for birth rates, death rates, and infant death rates can be used to determine certain types or categories of countries. You want to perform a cluster analysis to determine whether the observations can be formed into groups suggested by the data. Previous studies indicate that the clusters computed from this type of data can be elongated and elliptical. Thus, you need to perform some linear transformation on the raw data before the cluster analysis.

The following data\* from Rouncefield (1995) are birth rates, death rates, and infant death rates for 97 countries. The DATA step creates the SAS data set Poverty:

```
data Poverty;
  input Birth Death InfantDeath Country $20. @@;
  datalines;
24.7 5.7 30.8 Albania 12.5 11.9 14.4 Bulgaria
13.4 11.7 11.3 Czechoslovakia 12 12.4 7.6 Former_E._Germany
11.6 13.4 14.8 Hungary 14.3 10.2 16 Poland
13.6 10.7 26.9 Romania 14 9 20.2 Yugoslavia
17.7 10 23 USSR 15.2 9.5 13.1 Byelorussia_SSR
13.4 11.6 13 Ukrainian_SSR 20.7 8.4 25.7 Argentina
46.6 18 111 Bolivia 28.6 7.9 63 Brazil
23.4 5.8 17.1 Chile 27.4 6.1 40 Columbia
32.9 7.4 63 Ecuador 28.3 7.3 56 Guyana
34.8 6.6 42 Paraguay 32.9 8.3 109.9 Peru
18 9.6 21.9 Uruguay 27.5 4.4 23.3 Venezuela
29 23.2 43 Mexico 12 10.6 7.9 Belgium
13.2 10.1 5.8 Finland 12.4 11.9 7.5 Denmark
13.6 9.4 7.4 France 11.4 11.2 7.4 Germany
10.1 9.2 11 Greece 15.1 9.1 7.5 Ireland
9.7 9.1 8.8 Italy 13.2 8.6 7.1 Netherlands
14.3 10.7 7.8 Norway 11.9 9.5 13.1 Portugal
10.7 8.2 8.1 Spain 14.5 11.1 5.6 Sweden
12.5 9.5 7.1 Switzerland 13.6 11.5 8.4 U.K.
14.9 7.4 8 Austria 9.9 6.7 4.5 Japan
14.5 7.3 7.2 Canada 16.7 8.1 9.1 U.S.A.
40.4 18.7 181.6 Afghanistan 28.4 3.8 16 Bahrain
42.5 11.5 108.1 Iran 42.6 7.8 69 Iraq
22.3 6.3 9.7 Israel 38.9 6.4 44 Jordan
26.8 2.2 15.6 Kuwait 31.7 8.7 48 Lebanon
45.6 7.8 40 Oman 42.1 7.6 71 Saudi_Arabia
29.2 8.4 76 Turkey 22.8 3.8 26 United_Arab_Emirates
42.2 15.5 119 Bangladesh 41.4 16.6 130 Cambodia
21.2 6.7 32 China 11.7 4.9 6.1 Hong_Kong
30.5 10.2 91 India 28.6 9.4 75 Indonesia
23.5 18.1 25 Korea 31.6 5.6 24 Malaysia
36.1 8.8 68 Mongolia 39.6 14.8 128 Nepal
```

\*These data have been compiled from the United Nations Demographic Yearbook 1990 (United Nations publications, Sales No. E/F.91.XII.1, copyright 1991, United Nations, New York) and are reproduced with the permission of the United Nations.

30.3	8.1	107.7	Pakistan	33.2	7.7	45	Philippines
17.8	5.2	7.5	Singapore	21.3	6.2	19.4	Sri_Lanka
22.3	7.7	28	Thailand	31.8	9.5	64	Vietnam
35.5	8.3	74	Algeria	47.2	20.2	137	Angola
48.5	11.6	67	Botswana	46.1	14.6	73	Congo
38.8	9.5	49.4	Egypt	48.6	20.7	137	Ethiopia
39.4	16.8	103	Gabon	47.4	21.4	143	Gambia
44.4	13.1	90	Ghana	47	11.3	72	Kenya
44	9.4	82	Libya	48.3	25	130	Malawi
35.5	9.8	82	Morocco	45	18.5	141	Mozambique
44	12.1	135	Namibia	48.5	15.6	105	Nigeria
48.2	23.4	154	Sierra_Leone	50.1	20.2	132	Somalia
32.1	9.9	72	South_Africa	44.6	15.8	108	Sudan
46.8	12.5	118	Swaziland	31.1	7.3	52	Tunisia
52.2	15.6	103	Uganda	50.5	14	106	Tanzania
45.6	14.2	83	Zaire	51.1	13.7	80	Zambia
41.7	10.3	66	Zimbabwe				
;							

The data set **Poverty** contains the character variable **Country** and the numeric variables **Birth**, **Death**, and **InfantDeath**, which represent the birth rate per thousand, death rate per thousand, and infant death rate per thousand. The `$20.` in the **INPUT** statement specifies that the variable **Country** is a character variable with a length of 20. The double trailing at sign (`@@`) in the **INPUT** statement holds the input line for further iterations of the **DATA** step, specifying that observations are input from each line until all values are read.

Because the variables in the data set do not have equal variance, you must perform some form of scaling or transformation. One method is to standardize the variables to mean zero and variance one. However, when you suspect that the data contain elliptical clusters, you can use the **ACECLUS** procedure to transform the data such that the resulting within-cluster covariance matrix is spherical. The procedure obtains approximate estimates of the pooled within-cluster covariance matrix and then computes canonical variables to be used in subsequent analyses.

The following statements perform the **ACECLUS** transformation using the SAS data set **Poverty**. The **OUT=** option creates an output SAS data set called **Ace** to contain the canonical variable scores.

```
proc aceclus data=Poverty out=Ace p=.03 noprint;
    var Birth Death InfantDeath;
run;
```

The **P=** option specifies that approximately three percent of the pairs are included in the estimation of the within-cluster covariance matrix. The **NOPRINT** option suppresses the display of the output. The **VAR** statement specifies that the variables **Birth**, **Death**, and **InfantDeath** are used in computing the canonical variables.

The following statements invoke the **CLUSTER** procedure, using the SAS data set **ACE** created in the previous **PROC ACECLUS** run.

```

proc cluster data=Ace outtree=Tree method=ward
      ccc pseudo print=15;
      var can1 can2 can3 ;
      id Country;
run;

```

The OUTTREE= option creates an output SAS data set called **Tree** that can be used by the TREE procedure to draw a tree diagram. Ward's minimum-variance clustering method is specified by the METHOD= option. The CCC option displays the cubic clustering criterion, and the PSEUDO option displays pseudo  $F$  and  $t^2$  statistics. Only the last 15 generations of the cluster history are displayed, as defined by the PRINT= option.

The VAR statement specifies that the canonical variables computed in the ACECLUS procedure are used in the cluster analysis. The ID statement specifies that the variable **Country** should be added to the **Tree** output data set.

The results of this analysis are displayed in the following figures.

PROC CLUSTER first displays the table of eigenvalues of the covariance matrix for the three canonical variables (Figure 23.1). The first two columns list each eigenvalue and the difference between the eigenvalue and its successor. The last two columns display the individual and cumulative proportion of variation associated with each eigenvalue.

The CLUSTER Procedure				
Ward's Minimum Variance Cluster Analysis				
Eigenvalues of the Covariance Matrix				
	Eigenvalue	Difference	Proportion	Cumulative
1	64.5500051	54.7313223	0.8091	0.8091
2	9.8186828	4.4038309	0.1231	0.9321
3	5.4148519		0.0679	1.0000
Root-Mean-Square Total-Sample Standard Deviation = 5.156987				
Root-Mean-Square Distance Between Observations = 12.63199				

**Figure 23.1.** Table of Eigenvalues of the Covariance Matrix

As displayed in the last column, the first two canonical variables account for about 93% of the total variation. Figure 23.1 also displays the root mean square of the total sample standard deviation and the root mean square distance between observations.

Figure 23.2 displays the last 15 generations of the cluster history. First listed are the number of clusters and the names of the clusters joined. The observations are identified either by the ID value or by CL $n$ , where  $n$  is the number of the cluster. Next, PROC CLUSTER displays the number of observations in the new cluster and the semipartial  $R^2$ . The latter value represents the decrease in the proportion of variance accounted for by joining the two clusters.

The CLUSTER Procedure											
Ward's Minimum Variance Cluster Analysis											
Root-Mean-Square Total-Sample Standard Deviation = 5.156987											
Root-Mean-Square Distance Between Observations = 12.63199											
Cluster History											
NCL	-----Clusters Joined-----			FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	T i e
15	Oman	CL37		5	0.0039	.957	.933	6.03	132	12.1	
14	CL31	CL22		13	0.0040	.953	.928	5.81	131	9.7	
13	CL41	CL17		32	0.0041	.949	.922	5.70	131	13.1	
12	CL19	CL21		10	0.0045	.945	.916	5.65	132	6.4	
11	CL39	CL15		9	0.0052	.940	.909	5.60	134	6.3	
10	CL76	CL27		6	0.0075	.932	.900	5.25	133	18.1	
9	CL23	CL11		15	0.0130	.919	.890	4.20	125	12.4	
8	CL10	Afghanistan		7	0.0134	.906	.879	3.55	122	7.3	
7	CL9	CL25		17	0.0217	.884	.864	2.26	114	11.6	
6	CL8	CL20		14	0.0239	.860	.846	1.42	112	10.5	
5	CL14	CL13		45	0.0307	.829	.822	0.65	112	59.2	
4	CL16	CL7		28	0.0323	.797	.788	0.57	122	14.8	
3	CL12	CL6		24	0.0323	.765	.732	1.84	153	11.6	
2	CL3	CL4		52	0.1782	.587	.613	-.82	135	48.9	
1	CL5	CL2		97	0.5866	.000	.000	0.00	.	135	

**Figure 23.2.** Cluster Generation History and R-Square Values

Next listed is the squared multiple correlation,  $R^2$ , which is the proportion of variance accounted for by the clusters. Figure 23.2 shows that, when the data are grouped into three clusters, the proportion of variance accounted for by the clusters ( $R^2$ ) is about 77%. The approximate expected value of  $R^2$  is given in the column labeled “ERSQ.”

The next three columns display the values of the cubic clustering criterion (CCC), pseudo  $F$  (PSF), and  $t^2$  (PST2) statistics. These statistics are useful in determining the number of clusters in the data.

Values of the cubic clustering criterion greater than 2 or 3 indicate good clusters; values between 0 and 2 indicate potential clusters, but they should be considered with caution; large negative values can indicate outliers. In Figure 23.2, there is a local peak of the CCC when the number of clusters is 3. The CCC drops at 4 clusters and then steadily increases, levelling off at 11 clusters.

Another method of judging the number of clusters in a data set is to look at the pseudo  $F$  statistic (PSF). Relatively large values indicate a stopping point. Reading down the PSF column, you can see that this method indicates a possible stopping point at 11 clusters and another at 3 clusters.

A general rule for interpreting the values of the pseudo  $t^2$  statistic is to move down the column until you find the first value markedly larger than the previous value and move back up the column by one cluster. Moving down the PST2 column, you can see possible clustering levels at 11 clusters, 6 clusters, 3 clusters, and 2 clusters.

The final column in Figure 23.2 lists ties for minimum distance; a blank value indicates the absence of a tie.

These statistics indicate that the data can be clustered into 11 clusters or 3 clusters. The following statements examine the results of clustering the data into 3 clusters.



A graphical view of the clustering process can often be helpful in interpreting the clusters. The following statements use the TREE procedure to produce a tree diagram of the clusters:

```

options vsize=8in htext=1pct htitle=2.5pct;
axis1 order=(0 to 1 by 0.2);
proc tree data=Tree out=New nclusters=3
      graphics haxis=axis1 horizontal;
      height _rsq_;
      copy can1 can2 ;
      id country;
run;

```

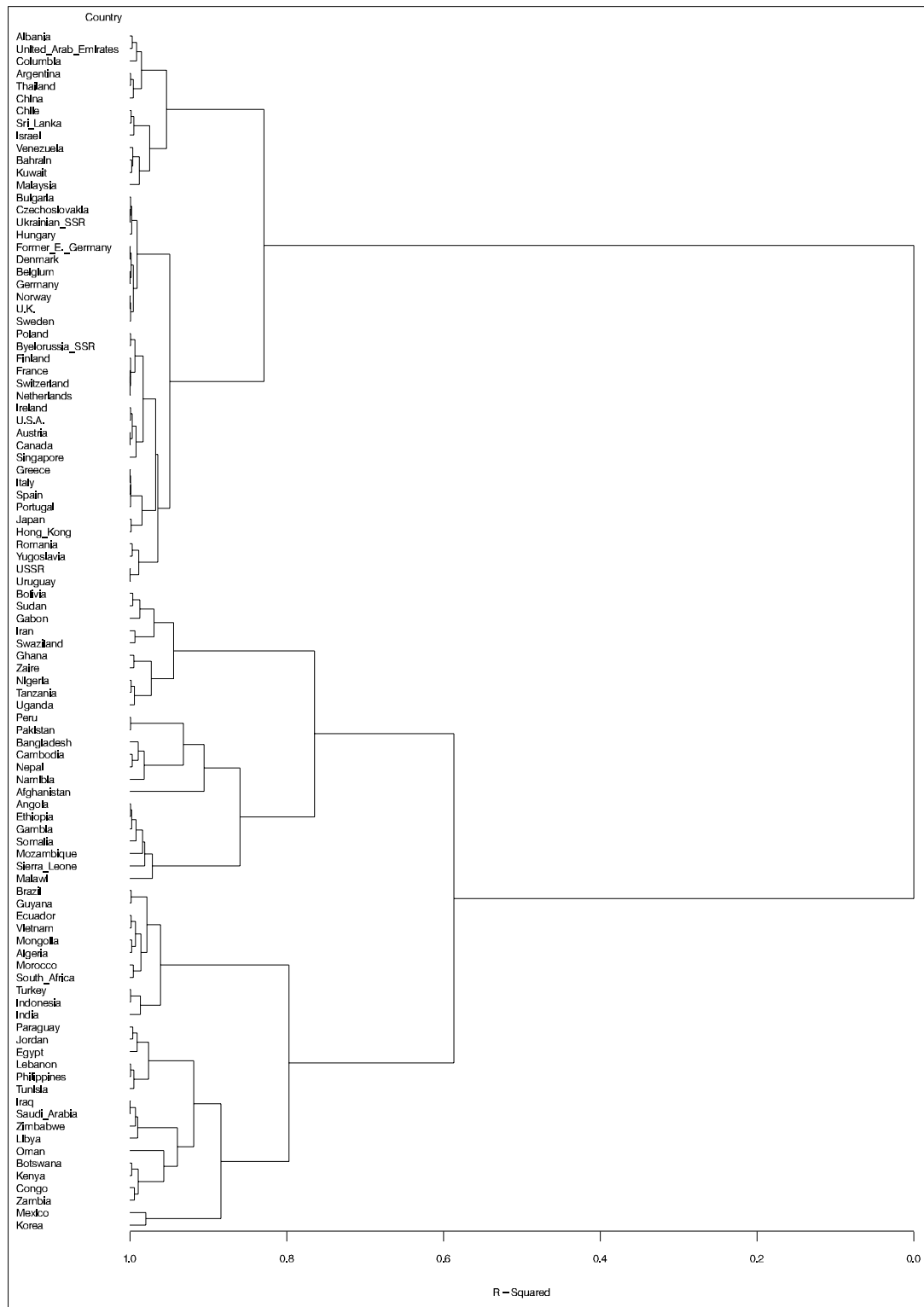
The AXIS1 statement defines axis parameters that are used in the TREE procedure. The ORDER= option specifies the data values in the order in which they should appear on the axis.

The preceding statements use the SAS data set *Tree* as input. The OUT= option creates an output SAS data set named *New* to contain information on cluster membership. The NCLUSTERS= option specifies the number of clusters desired in the data set *New*.

The GRAPHICS option directs the procedure to use high resolution graphics. The HAXIS= option specifies AXIS1 to customize the appearance of the horizontal axis. Use this option only when the GRAPHICS option is in effect. The HORIZONTAL option orients the tree diagram horizontally. The HEIGHT statement specifies the variable *\_RSQ\_* ( $R^2$ ) as the height variable.

The COPY statement copies the canonical variables *can1* and *can2* (computed in the ACECLUS procedure) into the output SAS data set *New*. Thus, the SAS output data set *New* contains information for three clusters and the first two of the original canonical variables.

Figure 23.3 displays the tree diagram. The figure provides a graphical view of the information in Figure 23.2. As the number of branches grows to the left from the root, the  $R^2$  approaches 1; the first three clusters (branches of the tree) account for over half of the variation (about 77%, from Figure 23.2). In other words, only three clusters are necessary to explain over three-fourths of the variation.



**Figure 23.3.** Tree Diagram of Clusters versus R-Square Values

The following statements invoke the GLOT procedure on the SAS data set `New`.

```

legend1 frame cframe=ligr cborder=black
      position=center value=(justify=center);

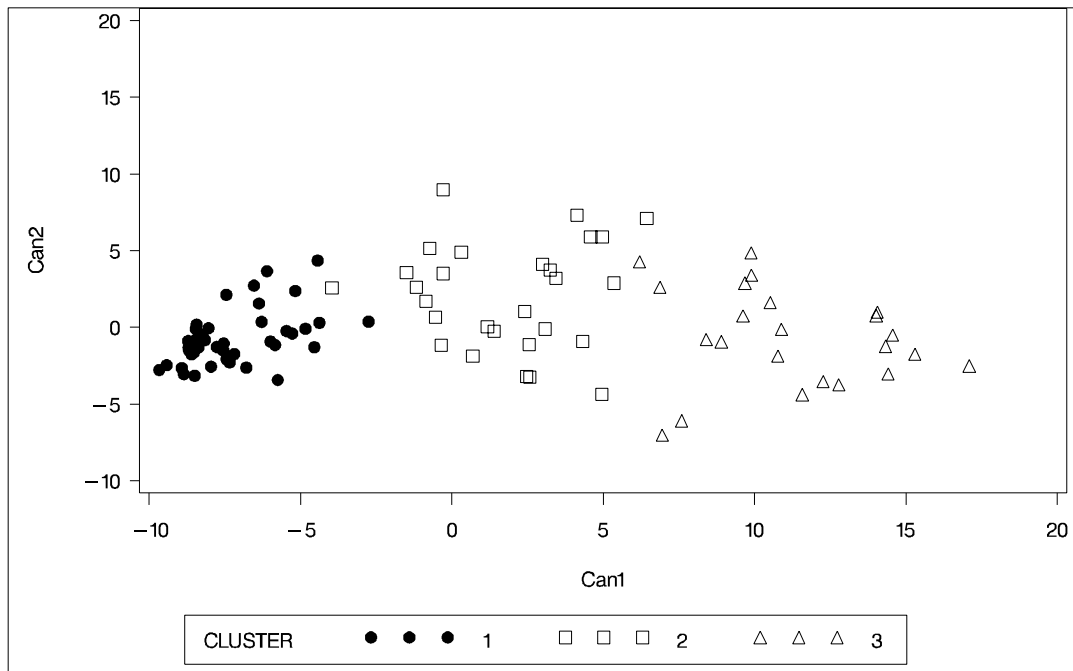
axis1 label=(angle=90 rotate=0) minor=none order=(-10 to 20 by 5);
axis2 minor=none order=(-10 to 20 by 5);

proc gplot data=New ;
  plot can2*can1=cluster/frame cframe=ligr
      legend=legend1 vaxis=axis1 haxis=axis2;
run;

```

The PLOT statement requests a plot of the two canonical variables, using the value of the variable `cluster` as the identification variable.

Figure 23.4 displays the separation of the clusters when three clusters are calculated. The plotting symbol is the cluster number.



**Figure 23.4.** Plot of Canonical Variables and Cluster for Three Clusters

The statistics in Figure 23.2, the tree diagram in Figure 23.3, and the plot of the canonical variables assist in the determination of clusters in the data. There seems to be reasonable separation in the clusters. However, you must use this information, along with experience and knowledge of the field, to help in deciding the correct number of clusters.

---

## Syntax

The following statements are available in the CLUSTER procedure.

```
PROC CLUSTER METHOD = name < options > ;
  BY variables ;
  COPY variables ;
  FREQ variable ;
  ID variable ;
  RMSSTD variable ;
  VAR variables ;
```

Only the PROC CLUSTER statement is required, except that the FREQ statement is required when the RMSSTD statement is used; otherwise the FREQ statement is optional. Usually only the VAR statement and possibly the ID and COPY statements are needed in addition to the PROC CLUSTER statement. The rest of this section provides detailed syntax information for each of the preceding statements, beginning with the PROC CLUSTER statement. The remaining statements are covered in alphabetical order.

---

## PROC CLUSTER Statement

```
PROC CLUSTER METHOD=name < options > ;
```

The PROC CLUSTER statement starts the CLUSTER procedure, identifies a clustering method, and optionally identifies details for clustering methods, data sets, data processing, and displayed output. The METHOD= specification determines the clustering method used by the procedure. Any one of the following 11 methods can be specified for *name*:

AVERAGE   AVE	requests average linkage (group average, unweighted pair-group method using arithmetic averages, UPGMA). Distance data are squared unless you specify the NOSQUARE option.
CENTROID   CEN	requests the centroid method (unweighted pair-group method using centroids, UPGMC, centroid sorting, weighted-group method). Distance data are squared unless you specify the NOSQUARE option.
COMPLETE   COM	requests complete linkage (furthest neighbor, maximum method, diameter method, rank order typal analysis). To reduce distortion of clusters by outliers, the TRIM= option is recommended.
DENSITY   DEN	requests density linkage, which is a class of clustering methods using nonparametric probability density estima-

	tion. You must also specify one of the K=, R=, or HYBRID options to indicate the type of density estimation to be used. See also the MODE= and DIM= options in this section.
EML	requests maximum-likelihood hierarchical clustering for mixtures of spherical multivariate normal distributions with equal variances but possibly unequal mixing proportions. Use METHOD=EML only with coordinate data. See the PENALTY= option on page 849. The NONORM option does not affect the reported likelihood values but does affect other unrelated criteria. The EML method is much slower than the other methods in the CLUSTER procedure.
FLEXIBLE   FLE	requests the Lance-Williams flexible-beta method. See the BETA= option in this section.
MCQUITTY   MCQ	requests McQuitty's similarity analysis, which is weighted average linkage, weighted pair-group method using arithmetic averages (WPGMA).
MEDIAN   MED	requests Gower's median method, which is weighted pair-group method using centroids (WPGMC). Distance data are squared unless you specify the NOSQUARE option.
SINGLE   SIN	requests single linkage (nearest neighbor, minimum method, connectedness method, elementary linkage analysis, or dendritic method). To reduce chaining, you can use the TRIM= option with METHOD=SINGLE.
TWOSTAGE   TWO	requests two-stage density linkage. You must also specify the K=, R=, or HYBRID option to indicate the type of density estimation to be used. See also the MODE= and DIM= options in this section.
WARD   WAR	requests Ward's minimum-variance method (error sum of squares, trace W). Distance data are squared unless you specify the NOSQUARE option. To reduce distortion by outliers, the TRIM= option is recommended. See the NONORM option.

The following table summarizes the options in the PROC CLUSTER statement.

Tasks	Options
<b>Specify input and output data sets</b>	
specify input data set	DATA=
create output data set	OUTTREE=
<b>Specify clustering methods</b>	
specify clustering method	METHOD=
beta for flexible beta method	BETA=
minimum number of members for modal clusters	MODE=
penalty coefficient for maximum-likelihood	PENALTY=
Wong's hybrid clustering method	HYBRID
<b>Control data processing prior to clustering</b>	
suppress computation of eigenvalues	NOEIGEN
suppress normalizing of distances	NONORM
suppress squaring of distances	NOSQUARE
standardize variables	STANDARD
omit points with low probability densities	TRIM=
<b>Control density estimation</b>	
dimensionality for estimates	DIM=
number of neighbors for $k$ th-nearest-neighbor	K=
radius of sphere of support for uniform-kernel	R=
<b>Suppress checking for ties</b>	NOTIE
<b>Control display of the cluster history</b>	
display cubic clustering criterion	CCC
suppress display of ID values	NOID
specify number of generations to display	PRINT=
display pseudo $F$ and $t^2$ statistics	PSEUDO
display root-mean-square standard deviation	RMSSTD
display $R^2$ and semipartial $R^2$	RSQUARE
<b>Control other aspects of output</b>	
suppress display of all output	NOPRINT
display simple summary statistics	SIMPLE

The following list provides details on these options.

#### **BETA= $n$**

specifies the beta parameter for METHOD=FLEXIBLE. The value of  $n$  should be less than 1, usually between 0 and  $-1$ . By default, BETA= $-0.25$ . Milligan (1987) suggests a somewhat smaller value, perhaps  $-0.5$ , for data with many outliers.

#### **CCC**

displays the cubic clustering criterion and approximate expected  $R^2$  under the uniform null hypothesis (Sarle 1983). The statistics associated with the RSQUARE option,  $R^2$  and semipartial  $R^2$ , are also displayed. The CCC option applies only to coordinate data. The CCC option is not appropriate with METHOD=SINGLE because of the method's tendency to chop off tails of distributions.

**DATA=SAS-data-set**

names the input data set containing observations to be clustered. By default, the procedure uses the most recently created SAS data set. If the data set is TYPE=DISTANCE, the data are interpreted as a distance matrix; the number of variables must equal the number of observations in the data set or in each BY group. The distances are assumed to be Euclidean, but the procedure accepts other types of distances or dissimilarities. If the data set is not TYPE=DISTANCE, the data are interpreted as coordinates in a Euclidean space, and Euclidean distances are computed. For more on TYPE=DISTANCE data sets, see Appendix A, “Special SAS Data Sets.”

You cannot use a TYPE=CORR data set as input to PROC CLUSTER, since the procedure uses dissimilarity measures. Instead, you can use a DATA step or the IML procedure to extract the correlation matrix from a TYPE=CORR data set and transform the values to dissimilarities such as  $1-r$  or  $1-r^2$ , where  $r$  is the correlation.

All methods produce the same results when used with coordinate data as when used with Euclidean distances computed from the coordinates. However, the DIM= option must be used with distance data if you specify METHOD=TWOSTAGE or METHOD=DENSITY or if you specify the TRIM= option.

Certain methods that are most naturally defined in terms of coordinates require *squared* Euclidean distances to be used in the combinatorial distance formulas (Lance and Williams 1967). For this reason, distance data are automatically squared when used with METHOD=AVERAGE, METHOD=CENTROID, METHOD=MEDIAN, or METHOD=WARD. If you want the combinatorial formulas to be applied to the (unsquared) distances with these methods, use the NOSQUARE option.

**DIM= $n$** 

specifies the dimensionality used when computing density estimates with the TRIM= option, METHOD=DENSITY, or METHOD=TWOSTAGE. The values of  $n$  must be greater than or equal to 1. The default is the number of variables if the data are coordinates; the default is 1 if the data are distances.

**HYBRID**

requests Wong’s (1982) hybrid clustering method in which density estimates are computed from a preliminary cluster analysis using the  $k$ -means method. The DATA= data set must contain means, frequencies, and root-mean-square standard deviations of the preliminary clusters (see the FREQ and RMSSTD statements). To use HYBRID, you must use either a FREQ statement or a DATA= data set that contains a \_FREQ\_ variable, and you must also use either an RMSSTD statement or a DATA= data set that contains a \_RMSSTD\_ variable.

The MEAN= data set produced by the FASTCLUS procedure is suitable for input to the CLUSTER procedure for hybrid clustering. Since this data set contains \_FREQ\_ and \_RMSSTD\_ variables, you can use it as input and then omit the FREQ and RMSSTD statements.

You must specify either METHOD=DENSITY or METHOD=TWOSTAGE with the HYBRID option. You cannot use this option in combination with the TRIM=, K=, or R= option.

**K=*n***

specifies the number of neighbors to use for *k*th-nearest-neighbor density estimation (Silverman 1986, pp. 19–21 and 96–99). The number of neighbors (*n*) must be at least two but less than the number of observations. See the **MODE=** option, which follows.

If you request an analysis that requires density estimation (the **TRIM=** option, **METHOD=DENSITY**, or **METHOD=TWOSTAGE**), you must specify one of the **K=**, **HYBRID**, or **R=** options.

**MODE=*n***

specifies that, when two clusters are joined, each must have at least *n* members for either cluster to be designated a modal cluster. If you specify **MODE=1**, each cluster must also have a maximum density greater than the fusion density for either cluster to be designated a modal cluster.

Use the **MODE=** option only with **METHOD=DENSITY** or **METHOD=TWOSTAGE**. With **METHOD=TWOSTAGE**, the **MODE=** option affects the number of modal clusters formed. With **METHOD=DENSITY**, the **MODE=** option does not affect the clustering process but does determine the number of modal clusters reported on the output and identified by the **\_MODE\_** variable in the output data set.

If you specify the **K=** option, the default value of **MODE=** is the same as the value of **K=** because the use of *k*th-nearest-neighbor density estimation limits the resolution that can be obtained for clusters with fewer than *k* members. If you do not specify the **K=** option, the default is **MODE=2**.

If you specify **MODE=0**, the default value is used instead of 0.

If you specify a **FREQ** statement or if a **\_FREQ\_** variable appears in the input data set, the **MODE=** value is compared with the number of actual observations in the clusters being joined, not with the sum of the frequencies in the clusters.

**NOEIGEN**

suppresses computation of eigenvalues for the cubic clustering criterion. Specifying the **NOEIGEN** option saves time if the number of variables is large, but it should be used only if the variables are nearly uncorrelated or if you are not interested in the cubic clustering criterion. If you specify the **NOEIGEN** option and the variables are highly correlated, the cubic clustering criterion may be very liberal. The **NOEIGEN** option applies only to coordinate data.

**NOID**

suppresses the display of ID values for the clusters joined at each generation of the cluster history.

**NONORM**

prevents the distances from being normalized to unit mean or unit root mean square with most methods. With **METHOD=WARD**, the **NONORM** option prevents the between-cluster sum of squares from being normalized by the total sum of squares to yield a squared semipartial correlation. The **NONORM** option does not affect the reported likelihood values with **METHOD=EML**, but it does affect other unrelated criteria, such as the **\_DIST\_** variable.



**NOPRINT**

suppresses the display of all output. Note that this option temporarily disables the Output Delivery System (ODS). For more information, see Chapter 15, “Using the Output Delivery System.”

**NOSQUARE**

prevents input distances from being squared with METHOD=AVERAGE, METHOD=CENTROID, METHOD=MEDIAN, or METHOD=WARD.

If you specify the NOSQUARE option with distance data, the data are assumed to be squared Euclidean distances for computing R-squared and related statistics defined in a Euclidean coordinate system.

If you specify the NOSQUARE option with coordinate data with METHOD=CENTROID, METHOD=MEDIAN, or METHOD=WARD, then the combinatorial formula is applied to unsquared Euclidean distances. The resulting cluster distances do not have their usual Euclidean interpretation and are, therefore, labeled “False” in the output.

**NOTIE**

prevents PROC CLUSTER from checking for ties for minimum distance between clusters at each generation of the cluster history. If your data are measured with such sufficient precision that ties are unlikely, then you can specify the NOTIE option to reduce slightly the time and space required by the procedure. See the section “Ties” on page 865.

**OUTTREE=SAS-data-set**

creates an output data set that can be used by the TREE procedure to draw a tree diagram. You must give the data set a two-level name to save it. Refer to *SAS Language Reference: Concepts* for a discussion of permanent data sets. If you omit the OUTTREE= option, the data set is named using the DATA $n$  convention and is not permanently saved. If you do not want to create an output data set, use OUTTREE=\_NULL\_.

**PENALTY= $p$** 

specifies the penalty coefficient used with METHOD=EML. See the section “Clustering Methods” on page 854. Values for  $p$  must be greater than zero. By default, PENALTY=2.

**PRINT= $n$  | P= $n$** 

specifies the number of generations of the cluster history to display. The P= option displays the latest  $n$  generations; for example, P=5 displays the cluster history from 1 cluster through 5 clusters. The value of P= must be a nonnegative integer. The default is to display all generations. Specify PRINT=0 to suppress the cluster history.

**PSEUDO**

displays pseudo  $F$  and  $t^2$  statistics. This option is effective only when the data are coordinates or when METHOD=AVERAGE, METHOD=CENTROID, or METHOD=WARD. See the section “Miscellaneous Formulas” on page 861. The PSEUDO option is not appropriate with METHOD=SINGLE because of the method’s tendency to chop off tails of distributions.

**R=*n***

specifies the radius of the sphere of support for uniform-kernel density estimation (Silverman 1986, pp. 11–13 and 75–94). The value of R= must be greater than zero.

If you request an analysis that requires density estimation (the TRIM= option, METHOD=DENSITY, or METHOD=TWOSTAGE), you must specify one of the K=, HYBRID, or R= options.

**RMSSTD**

displays the root-mean-square standard deviation of each cluster. This option is effective only when the data are coordinates or when METHOD=AVERAGE, METHOD=CENTROID, or METHOD=WARD. See the section “Miscellaneous Formulas” on page 861.

**RSQUARE | RSQ**

displays the  $R^2$  and semipartial  $R^2$ . This option is effective only when the data are coordinates or when METHOD=AVERAGE or METHOD=CENTROID. The  $R^2$  and semipartial  $R^2$  statistics are always displayed with METHOD=WARD. See the section “Miscellaneous Formulas” on page 861.

**SIMPLE | S**

displays means, standard deviations, skewness, kurtosis, and a coefficient of bimodality. The SIMPLE option applies only to coordinate data. See the section “Miscellaneous Formulas” on page 861.

**STANDARD | STD**

standardizes the variables to mean 0 and standard deviation 1. The STANDARD option applies only to coordinate data.

**TRIM=*p***

omits points with low estimated probability densities from the analysis. Valid values for the TRIM= option are  $0 \leq p < 100$ . If  $p < 1$ , then  $p$  is the proportion of observations omitted. If  $p \geq 1$ , then  $p$  is interpreted as a percentage. A specification of TRIM=10, which trims 10 percent of the points, is a reasonable value for many data sets. Densities are estimated by the  $k$ th-nearest-neighbor or uniform-kernel methods. Trimmed points are indicated by a negative value of the \_FREQ\_ variable in the OUTTREE= data set.

You must use either the K= or R= option when you use TRIM=. You cannot use the HYBRID option in combination with TRIM=, so you may want to use the DIM= option instead. If you specify the STANDARD option in combination with TRIM=, the variables are standardized both before and after trimming.

The TRIM= option is useful for removing outliers and reducing chaining. Trimming is highly recommended with METHOD=WARD or METHOD=COMPLETE because clusters from these methods can be severely distorted by outliers. Trimming is also valuable with METHOD=SINGLE since single linkage is the method most susceptible to chaining. Most other methods also benefit from trimming. However, trimming is unnecessary with METHOD=TWOSTAGE or METHOD=DENSITY when  $k$ th-nearest-neighbor density estimation is used.

Use of the TRIM= option may spuriously inflate the cubic clustering criterion and the pseudo  $F$  and  $t^2$  statistics. Trimming only outliers improves the accuracy of the statistics, but trimming saddle regions between clusters yields excessively large values.

---

## BY Statement

**BY variables ;**

You can specify a BY statement with PROC CLUSTER to obtain separate analyses on observations in groups defined by the BY variables. When a BY statement appears, the procedure expects the input data set to be sorted in order of the BY variables.

If your input data set is not sorted in ascending order, use one of the following alternatives:

- Sort the data using the SORT procedure with a similar BY statement.
- Specify the BY statement option NOTSORTED or DESCENDING in the BY statement for the CLUSTER procedure. The NOTSORTED option does not mean that the data are unsorted but rather that the data are arranged in groups (according to values of the BY variables) and that these groups are not necessarily in alphabetical or increasing numeric order.
- Create an index on the BY variables using the DATASETS procedure.

For more information on the BY statement, refer to the discussion in *SAS Language Reference: Concepts*. For more information on the DATASETS procedure, refer to the discussion in the *SAS Procedures Guide*.

---

## COPY Statement

**COPY variables ;**

The variables in the COPY statement are copied from the input data set to the OUTTREE= data set. Observations in the OUTTREE= data set that represent clusters of more than one observation from the input data set have missing values for the COPY variables.

---

## FREQ Statement

**FREQ** *variable* ;

If one variable in the input data set represents the frequency of occurrence for other values in the observation, specify the variable's name in a FREQ statement. PROC CLUSTER then treats the data set as if each observation appeared  $n$  times, where  $n$  is the value of the FREQ variable for the observation. Noninteger values of the FREQ variable are truncated to the largest integer less than the FREQ value.

If you omit the FREQ statement but the DATA= data set contains a variable called `_FREQ_`, then frequencies are obtained from the `_FREQ_` variable. If neither a FREQ statement nor a `_FREQ_` variable is present, each observation is assumed to have a frequency of one.

If each observation in the DATA= data set represents a cluster (for example, clusters formed by PROC FASTCLUS), the variable specified in the FREQ statement should give the number of original observations in each cluster.

If you specify the RMSSTD statement, a FREQ statement is required. A FREQ statement or `_FREQ_` variable is required when you specify the HYBRID option.

With most clustering methods, the same clusters are obtained from a data set with a FREQ variable as from a similar data set without a FREQ variable, if each observation is repeated as many times as the value of the FREQ variable in the first data set. The FLEXIBLE method can yield different results due to the nature of the combinatorial formula. The DENSITY and TWOSTAGE methods are also exceptions because two identical observations can be absorbed one at a time by a cluster with a higher density. If you are using a FREQ statement with either the DENSITY or TWOSTAGE method, see the MODE=option on page 848.

---

## ID Statement

**ID** *variable* ;

The values of the ID variable identify observations in the displayed cluster history and in the OUTTREE= data set. If the ID statement is omitted, each observation is denoted by `OB $n$` , where  $n$  is the observation number.

---

## RMSSTD Statement

**RMSSTD** *variable* ;

If the coordinates in the DATA= data set represent cluster means (for example, formed by the FASTCLUS procedure), you can obtain accurate statistics in the cluster histories for METHOD=AVERAGE, METHOD=CENTROID, or METHOD=WARD if the data set contains

- a variable giving the number of original observations in each cluster (see the discussion of the FREQ statement earlier in this chapter)
- a variable giving the root-mean-square standard deviation of each cluster

Specify the name of the variable containing root-mean-square standard deviations in the RMSSTD statement. If you specify the RMSSTD statement, you must also specify a FREQ statement.

If you omit the RMSSTD statement but the DATA= data set contains a variable called `_RMSSTD_`, then root-mean-square standard deviations are obtained from the `_RMSSTD_` variable.

An RMSSTD statement or `_RMSSTD_` variable is required when you specify the HYBRID option.

A data set created by FASTCLUS using the MEAN= option contains `_FREQ_` and `_RMSSTD_` variables, so you do not have to use FREQ and RMSSTD statements when using such a data set as input to the CLUSTER procedure.

---

## VAR Statement

**VAR** *variables* ;

The VAR statement lists numeric variables to be used in the cluster analysis. If you omit the VAR statement, all numeric variables not listed in other statements are used.

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## Details

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### Clustering Methods

The following notation is used, with lowercase symbols generally pertaining to observations and uppercase symbols pertaining to clusters:

$n$	number of observations
$v$	number of variables if data are coordinates
$G$	number of clusters at any given level of the hierarchy
$x_i$ or $\mathbf{x}_i$	$i$ th observation (row vector if coordinate data)
$C_K$	$K$ th cluster, subset of $\{1, 2, \dots, n\}$
$N_K$	number of observations in $C_K$
$\bar{\mathbf{x}}$	sample mean vector
$\bar{\mathbf{x}}_K$	mean vector for cluster $C_K$
$\ \mathbf{x}\ $	Euclidean length of the vector $\mathbf{x}$ , that is, the square root of the sum of the squares of the elements of $\mathbf{x}$
$T$	$\sum_{i=1}^n \ \mathbf{x}_i - \bar{\mathbf{x}}\ ^2$
$W_K$	$\sum_{i \in C_K} \ \mathbf{x}_i - \bar{\mathbf{x}}_K\ ^2$
$P_G$	$\sum W_J$ , where summation is over the $G$ clusters at the $G$ th level of the hierarchy
$B_{KL}$	$W_M - W_K - W_L$ if $C_M = C_K \cup C_L$
$d(\mathbf{x}, \mathbf{y})$	any distance or dissimilarity measure between observations or vectors $\mathbf{x}$ and $\mathbf{y}$
$D_{KL}$	any distance or dissimilarity measure between clusters $C_K$ and $C_L$

The distance between two clusters can be defined either directly or combinatorially (Lance and Williams 1967), that is, by an equation for updating a distance matrix when two clusters are joined. In all of the following combinatorial formulas, it is assumed that clusters  $C_K$  and  $C_L$  are merged to form  $C_M$ , and the formula gives the distance between the new cluster  $C_M$  and any other cluster  $C_J$ .

For an introduction to most of the methods used in the CLUSTER procedure, refer to Massart and Kaufman (1983).

#### Average Linkage

The following method is obtained by specifying METHOD=AVERAGE. The distance between two clusters is defined by

$$D_{KL} = \frac{1}{N_K N_L} \sum_{i \in C_K} \sum_{j \in C_L} d(x_i, x_j)$$

If  $d(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|^2$ , then

$$D_{KL} = \|\bar{\mathbf{x}}_K - \bar{\mathbf{x}}_L\|^2 + \frac{W_K}{N_K} + \frac{W_L}{N_L}$$

The combinatorial formula is

$$D_{JM} = \frac{N_K D_{JK} + N_L D_{JL}}{N_M}$$

In average linkage the distance between two clusters is the average distance between pairs of observations, one in each cluster. Average linkage tends to join clusters with small variances, and it is slightly biased toward producing clusters with the same variance.

Average linkage was originated by Sokal and Michener (1958).

### **Centroid Method**

The following method is obtained by specifying METHOD=CENTROID. The distance between two clusters is defined by

$$D_{KL} = \|\bar{\mathbf{x}}_K - \bar{\mathbf{x}}_L\|^2$$

If  $d(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|^2$ , then the combinatorial formula is

$$D_{JM} = \frac{N_K D_{JK} + N_L D_{JL}}{N_M} - \frac{N_K N_L D_{KL}}{N_M^2}$$

In the centroid method, the distance between two clusters is defined as the (squared) Euclidean distance between their centroids or means. The centroid method is more robust to outliers than most other hierarchical methods but in other respects may not perform as well as Ward's method or average linkage (Milligan 1980).

The centroid method was originated by Sokal and Michener (1958).

### **Complete Linkage**

The following method is obtained by specifying METHOD=COMPLETE. The distance between two clusters is defined by

$$D_{KL} = \max_{i \in C_K} \max_{j \in C_L} d(x_i, x_j)$$

The combinatorial formula is

$$D_{JM} = \max(D_{JK}, D_{JL})$$

In complete linkage, the distance between two clusters is the maximum distance between an observation in one cluster and an observation in the other cluster. Complete linkage is strongly biased toward producing clusters with roughly equal diameters, and it can be severely distorted by moderate outliers (Milligan 1980).

Complete linkage was originated by Sorensen (1948).

### Density Linkage

The phrase *density linkage* is used here to refer to a class of clustering methods using nonparametric probability density estimates (for example, Hartigan 1975, pp. 205–212; Wong 1982; Wong and Lane 1983). Density linkage consists of two steps:

1. A new dissimilarity measure,  $d^*$ , based on density estimates and adjacencies is computed. If  $x_i$  and  $x_j$  are adjacent (the definition of *adjacency* depends on the method of density estimation), then  $d^*(x_i, x_j)$  is the reciprocal of an estimate of the density midway between  $x_i$  and  $x_j$ ; otherwise,  $d^*(x_i, x_j)$  is infinite.
2. A single linkage cluster analysis is performed using  $d^*$ .

The CLUSTER procedure supports three types of density linkage: the  $k$ th-nearest-neighbor method, the uniform kernel method, and Wong's hybrid method. These are obtained by using METHOD=DENSITY and the K=, R=, and HYBRID options, respectively.

#### $k$ th-Nearest Neighbor Method

The  $k$ th-nearest-neighbor method (Wong and Lane 1983) uses  $k$ th-nearest neighbor density estimates. Let  $r_k(x)$  be the distance from point  $x$  to the  $k$ th-nearest observation, where  $k$  is the value specified for the K= option. Consider a closed sphere centered at  $x$  with radius  $r_k(x)$ . The estimated density at  $x$ ,  $f(x)$ , is the proportion of observations within the sphere divided by the volume of the sphere. The new dissimilarity measure is computed as

$$d^*(x_i, x_j) = \begin{cases} \frac{1}{2} \left( \frac{1}{f(x_i)} + \frac{1}{f(x_j)} \right) & \text{if } d(x_i, x_j) \leq \max(r_k(x_i), r_k(x_j)) \\ \infty & \text{otherwise} \end{cases}$$

Wong and Lane (1983) show that  $k$ th-nearest-neighbor density linkage is strongly set consistent for high-density (density-contour) clusters if  $k$  is chosen such that  $k/n \rightarrow 0$  and  $k/\ln(n) \rightarrow \infty$  as  $n \rightarrow \infty$ . Wong and Schaack (1982) discuss methods for estimating the number of population clusters using  $k$ th-nearest-neighbor clustering.

#### Uniform-Kernel Method

The uniform-kernel method uses uniform-kernel density estimates. Let  $r$  be the value specified for the R= option. Consider a closed sphere centered at point  $x$  with radius  $r$ . The estimated density at  $x$ ,  $f(x)$ , is the proportion of observations within the sphere divided by the volume of the sphere. The new dissimilarity measure is computed as

$$d^*(x_i, x_j) = \begin{cases} \frac{1}{2} \left( \frac{1}{f(x_i)} + \frac{1}{f(x_j)} \right) & \text{if } d(x_i, x_j) \leq r \\ \infty & \text{otherwise} \end{cases}$$

#### Wong's Hybrid Method

Wong's (1982) hybrid clustering method uses density estimates based on a preliminary cluster analysis by the  $k$ -means method. The preliminary clustering can be done



by the FASTCLUS procedure, using the MEAN= option to create a data set containing cluster means, frequencies, and root-mean-square standard deviations. This data set is used as input to the CLUSTER procedure, and the HYBRID option is specified with METHOD=DENSITY to request the hybrid analysis. The hybrid method is appropriate for very large data sets but should not be used with small data sets, say fewer than 100 observations in the original data. The term *preliminary cluster* refers to an observation in the DATA= data set.

For preliminary cluster  $C_K$ ,  $N_K$  and  $W_K$  are obtained from the input data set, as are the cluster means or the distances between the cluster means. Preliminary clusters  $C_K$  and  $C_L$  are considered adjacent if the midpoint between  $\bar{x}_K$  and  $\bar{x}_L$  is closer to either  $\bar{x}_K$  or  $\bar{x}_L$  than to any other preliminary cluster mean or, equivalently, if  $d^2(\bar{x}_K, \bar{x}_L) < d^2(\bar{x}_K, \bar{x}_M) + d^2(\bar{x}_L, \bar{x}_M)$  for all other preliminary clusters  $C_M$ ,  $M \neq K$  or  $L$ . The new dissimilarity measure is computed as

$$d^*(\bar{x}_K, \bar{x}_L) = \begin{cases} \frac{(W_K + W_L + \frac{1}{4}(N_K + N_L)d^2(\bar{x}_K, \bar{x}_L))^{\frac{v}{2}}}{(N_K + N_L)^{1 + \frac{v}{2}}} & \text{if } C_K \text{ and } C_L \text{ are adjacent} \\ \infty & \text{otherwise} \end{cases}$$

### Using the K= and R= Options

The values of the K= and R= options are called *smoothing parameters*. Small values of K= or R= produce jagged density estimates and, as a consequence, many modes. Large values of K= or R= produce smoother density estimates and fewer modes. In the hybrid method, the smoothing parameter is the number of clusters in the preliminary cluster analysis. The number of modes in the final analysis tends to increase as the number of clusters in the preliminary analysis increases. Wong (1982) suggests using  $n^{0.3}$  preliminary clusters, where  $n$  is the number of observations in the original data set. There is no general rule-of-thumb for selecting K= values. For all types of density linkage, you should repeat the analysis with several different values of the smoothing parameter (Wong and Schaack 1982).

There is no simple answer to the question of which smoothing parameter to use (Silverman 1986, pp. 43–61, 84–88, and 98–99). It is usually necessary to try several different smoothing parameters. A reasonable first guess for the R= option in many coordinate data sets is given by

$$\left[ \frac{2^{v+2}(v+2)\Gamma(\frac{v}{2}+1)}{nv^2} \right]^{\frac{1}{v+4}} \sqrt{\sum_{l=1}^v s_l^2}$$

where  $s_l^2$  is the standard deviation of the  $l$ th variable. The estimate for R= can be computed in a DATA step using the GAMMA function for  $\Gamma$ . This formula is derived under the assumption that the data are sampled from a multivariate normal distribution and tends, therefore, to be too large (oversmooth) if the true distribution is multimodal. Robust estimates of the standard deviations may be preferable if there are outliers. If the data are distances, the factor  $\sum s_l^2$  can be replaced by an average (mean, trimmed mean, median, root-mean-square, and so on) distance divided by  $\sqrt{2}$ . To prevent outliers from appearing as separate clusters, you can also specify K=2, or

more generally  $K=m$ ,  $m \geq 2$ , which in most cases forces clusters to have at least  $m$  members.

If the variables all have unit variance (for example, if the STANDARD option is used), Table 23.1 can be used to obtain an initial guess for the R= option:

**Table 23.1.** Reasonable First Guess for the R= Option for Standardized Data

Number of Observations	Number of Variables									
	1	2	3	4	5	6	7	8	9	10
20	1.01	1.36	1.77	2.23	2.73	3.25	3.81	4.38	4.98	5.60
35	0.91	1.24	1.64	2.08	2.56	3.08	3.62	4.18	4.77	5.38
50	0.84	1.17	1.56	1.99	2.46	2.97	3.50	4.06	4.64	5.24
75	0.78	1.09	1.47	1.89	2.35	2.85	3.38	3.93	4.50	5.09
100	0.73	1.04	1.41	1.82	2.28	2.77	3.29	3.83	4.40	4.99
150	0.68	0.97	1.33	1.73	2.18	2.66	3.17	3.71	4.27	4.85
200	0.64	0.93	1.28	1.67	2.11	2.58	3.09	3.62	4.17	4.75
350	0.57	0.85	1.18	1.56	1.98	2.44	2.93	3.45	4.00	4.56
500	0.53	0.80	1.12	1.49	1.91	2.36	2.84	3.35	3.89	4.45
750	0.49	0.74	1.06	1.42	1.82	2.26	2.74	3.24	3.77	4.32
1000	0.46	0.71	1.01	1.37	1.77	2.20	2.67	3.16	3.69	4.23
1500	0.43	0.66	0.96	1.30	1.69	2.11	2.57	3.06	3.57	4.11
2000	0.40	0.63	0.92	1.25	1.63	2.05	2.50	2.99	3.49	4.03

Since infinite  $d^*$  values occur in density linkage, the final number of clusters can exceed one when there are wide gaps between the clusters or when the smoothing parameter results in little smoothing.

Density linkage applies no constraints to the shapes of the clusters and, unlike most other hierarchical clustering methods, is capable of recovering clusters with elongated or irregular shapes. Since density linkage employs less prior knowledge about the shape of the clusters than do methods restricted to compact clusters, density linkage is less effective at recovering compact clusters from small samples than are methods that always recover compact clusters, regardless of the data.

### EML

The following method is obtained by specifying METHOD=EML. The distance between two clusters is given by

$$D_{KL} = nv \ln \left( 1 + \frac{B_{KL}}{P_G} \right) - 2 (N_M \ln(N_M) - N_K \ln(N_K) - N_L \ln(N_L))$$

The EML method joins clusters to maximize the likelihood at each level of the hierarchy under the following assumptions.

- multivariate normal mixture
- equal spherical covariance matrices
- unequal sampling probabilities

The EML method is similar to Ward's minimum-variance method but removes the bias toward equal-sized clusters. Practical experience has indicated that EML is somewhat biased toward unequal-sized clusters. You can specify the `PENALTY=` option to adjust the degree of bias. If you specify `PENALTY=p`, the formula is modified to

$$D_{KL} = nv \ln \left( 1 + \frac{B_{KL}}{P_G} \right) - p (N_M \ln(N_M) - N_K \ln(N_K) - N_L \ln(N_L))$$

The EML method was derived by W.S. Sarle of SAS Institute Inc. from the maximum-likelihood formula obtained by Symons (1981, p. 37, equation 8) for disjoint clustering. There are currently no other published references on the EML method.

### **Flexible-Beta Method**

The following method is obtained by specifying `METHOD=FLEXIBLE`. The combinatorial formula is

$$D_{JM} = (D_{JK} + D_{JL}) \frac{1-b}{2} + D_{KL}b$$

where  $b$  is the value of the `BETA=` option, or  $-0.25$  by default.

The flexible-beta method was developed by Lance and Williams (1967). See also Milligan (1987).

### **McQuitty's Similarity Analysis**

The following method is obtained by specifying `METHOD=MCQUITTY`. The combinatorial formula is

$$D_{JM} = \frac{D_{JK} + D_{JL}}{2}$$

The method was independently developed by Sokal and Michener (1958) and McQuitty (1966).

### **Median Method**

The following method is obtained by specifying `METHOD=MEDIAN`. If  $d(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|^2$ , then the combinatorial formula is

$$D_{JM} = \frac{D_{JK} + D_{JL}}{2} - \frac{D_{KL}}{4}$$

The median method was developed by Gower (1967).

### **Single Linkage**

The following method is obtained by specifying `METHOD=SINGLE`. The distance between two clusters is defined by

$$D_{KL} = \min_{i \in C_K} \min_{j \in C_L} d(x_i, x_j)$$

The combinatorial formula is

$$D_{JM} = \min(D_{JK}, D_{JL})$$

In single linkage, the distance between two clusters is the minimum distance between an observation in one cluster and an observation in the other cluster. Single linkage has many desirable theoretical properties (Jardine and Sibson 1971; Fisher and Van Ness 1971; Hartigan 1981) but has fared poorly in Monte Carlo studies (for example, Milligan 1980). By imposing no constraints on the shape of clusters, single linkage sacrifices performance in the recovery of compact clusters in return for the ability to detect elongated and irregular clusters. You must also recognize that single linkage tends to chop off the tails of distributions before separating the main clusters (Hartigan 1981). The notorious chaining tendency of single linkage can be alleviated by specifying the TRIM= option (Wishart 1969, pp. 296–298).

Density linkage and two-stage density linkage retain most of the virtues of single linkage while performing better with compact clusters and possessing better asymptotic properties (Wong and Lane 1983).

Single linkage was originated by Florek et al. (1951a, 1951b) and later reinvented by McQuitty (1957) and Sneath (1957).

### **Two-Stage Density Linkage**

If you specify METHOD=DENSITY, the modal clusters often merge before all the points in the tails have clustered. The option METHOD=TWOSTAGE is a modification of density linkage that ensures that all points are assigned to modal clusters before the modal clusters are allowed to join. The CLUSTER procedure supports the same three varieties of two-stage density linkage as of ordinary density linkage: *k*th-nearest neighbor, uniform kernel, and hybrid.

In the first stage, disjoint modal clusters are formed. The algorithm is the same as the single linkage algorithm ordinarily used with density linkage, with one exception: two clusters are joined only if at least one of the two clusters has fewer members than the number specified by the MODE= option. At the end of the first stage, each point belongs to one modal cluster.

In the second stage, the modal clusters are hierarchically joined by single linkage. The final number of clusters can exceed one when there are wide gaps between the clusters or when the smoothing parameter is small.

Each stage forms a tree that can be plotted by the TREE procedure. By default, the TREE procedure plots the tree from the first stage. To obtain the tree for the second stage, use the option HEIGHT=MODE in the PROC TREE statement. You can also produce a single tree diagram containing both stages, with the number of clusters as the height axis, by using the option HEIGHT=N in the PROC TREE statement. To produce an output data set from PROC TREE containing the modal clusters, use \_HEIGHT\_ for the HEIGHT variable (the default) and specify LEVEL=0.

Two-stage density linkage was developed by W.S. Sarle of SAS Institute Inc. There are currently no other published references on two-stage density linkage.

### **Ward's Minimum-Variance Method**

The following method is obtained by specifying METHOD=WARD. The distance between two clusters is defined by

$$D_{KL} = B_{KL} = \frac{\|\bar{\mathbf{x}}_K - \bar{\mathbf{x}}_L\|^2}{\frac{1}{N_K} + \frac{1}{N_L}}$$

If  $d(\mathbf{x}, \mathbf{y}) = \frac{1}{2}\|\mathbf{x} - \mathbf{y}\|^2$ , then the combinatorial formula is

$$D_{JM} = \frac{(N_J + N_K)D_{JK} + (N_J + N_L)D_{JL} - N_J D_{KL}}{N_J + N_M}$$

In Ward's minimum-variance method, the distance between two clusters is the ANOVA sum of squares between the two clusters added up over all the variables. At each generation, the within-cluster sum of squares is minimized over all partitions obtainable by merging two clusters from the previous generation. The sums of squares are easier to interpret when they are divided by the total sum of squares to give proportions of variance (squared semipartial correlations).

Ward's method joins clusters to maximize the likelihood at each level of the hierarchy under the following assumptions:

- multivariate normal mixture
- equal spherical covariance matrices
- equal sampling probabilities

Ward's method tends to join clusters with a small number of observations, and it is strongly biased toward producing clusters with roughly the same number of observations. It is also very sensitive to outliers (Milligan 1980).

Ward (1963) describes a class of hierarchical clustering methods including the minimum variance method.

---

## **Miscellaneous Formulas**

The root-mean-square standard deviation of a cluster  $C_K$  is

$$\text{RMSSTD} = \sqrt{\frac{W_K}{v(N_K - 1)}}$$

The  $R^2$  statistic for a given level of the hierarchy is

$$R^2 = 1 - \frac{P_G}{T}$$

The squared semipartial correlation for joining clusters  $C_K$  and  $C_L$  is

$$\text{semipartial } R^2 = \frac{B_{KL}}{T}$$

The bimodality coefficient is

$$b = \frac{m_3^2 + 1}{m_4 + \frac{3(n-1)^2}{(n-2)(n-3)}}$$

where  $m_3$  is skewness and  $m_4$  is kurtosis. Values of  $b$  greater than 0.555 (the value for a uniform population) may indicate bimodal or multimodal marginal distributions. The maximum of 1.0 (obtained for the Bernoulli distribution) is obtained for a population with only two distinct values. Very heavy-tailed distributions have small values of  $b$  regardless of the number of modes.

Formulas for the cubic-clustering criterion and approximate expected  $R^2$  are given in Sarle (1983).

The pseudo  $F$  statistic for a given level is

$$\text{pseudo } F = \frac{\frac{T - P_G}{G - 1}}{\frac{P_G}{n - G}}$$

The pseudo  $t^2$  statistic for joining  $C_K$  and  $C_L$  is

$$\text{pseudo } t^2 = \frac{B_{KL}}{\frac{W_K + W_L}{N_K + N_L - 2}}$$

The pseudo  $F$  and  $t^2$  statistics may be useful indicators of the number of clusters, but they are *not* distributed as  $F$  and  $t^2$  random variables. If the data are independently sampled from a multivariate normal distribution with a scalar covariance matrix and if the clustering method allocates observations to clusters randomly (which no clustering method actually does), then the pseudo  $F$  statistic is distributed as an  $F$  random variable with  $v(G - 1)$  and  $v(n - G)$  degrees of freedom. Under the same assumptions, the pseudo  $t^2$  statistic is distributed as an  $F$  random variable with  $v$  and  $v(N_K + N_L - 2)$  degrees of freedom. The pseudo  $t^2$  statistic differs computationally from Hotelling's  $T^2$  in that the latter uses a general symmetric covariance matrix instead of a scalar covariance matrix. The pseudo  $F$  statistic was suggested by Calinski and Harabasz (1974). The pseudo  $t^2$  statistic is related to the  $J_e(2)/J_e(1)$  statistic of Duda and Hart (1973) by

$$\frac{J_e(2)}{J_e(1)} = \frac{W_K + W_L}{W_M} = \frac{1}{1 + \frac{t^2}{N_K + N_L - 2}}$$

See Milligan and Cooper (1985) and Cooper and Milligan (1988) regarding the performance of these statistics in estimating the number of population clusters. Conservative tests for the number of clusters using the pseudo  $F$  and  $t^2$  statistics can be obtained by the Bonferroni approach (Hawkins, Muller, and ten Krooden 1982, pp. 337–340).

---

## Ultrametrics

A dissimilarity measure  $d(x, y)$  is called an *ultrametric* if it satisfies the following conditions:

- $d(x, x) = 0$  for all  $x$
- $d(x, y) \geq 0$  for all  $x, y$
- $d(x, y) = d(y, x)$  for all  $x, y$
- $d(x, y) \leq \max(d(x, z), d(y, z))$  for all  $x, y$ , and  $z$

Any hierarchical clustering method induces a dissimilarity measure on the observations, say  $h(x_i, x_j)$ . Let  $C_M$  be the cluster with the fewest members that contains both  $x_i$  and  $x_j$ . Assume  $C_M$  was formed by joining  $C_K$  and  $C_L$ . Then define  $h(x_i, x_j) = D_{KL}$ .

If the fusion of  $C_K$  and  $C_L$  reduces the number of clusters from  $g$  to  $g - 1$ , then define  $D_{(g)} = D_{KL}$ . Johnson (1967) shows that if

$$0 \leq D_{(n)} \leq D_{(n-1)} \leq \cdots \leq D_{(2)}$$

then  $h(\cdot, \cdot)$  is an ultrametric. A method that always satisfies this condition is said to be a *monotonic* or *ultrametric clustering method*. All methods implemented in PROC CLUSTER except CENTROID, EML, and MEDIAN are ultrametric (Milligan 1979; Batagelj 1981).

---

## Algorithms

Anderberg (1973) describes three algorithms for implementing agglomerative hierarchical clustering: stored data, stored distance, and sorted distance. The algorithms used by PROC CLUSTER for each method are indicated in Table 23.2. For METHOD=AVERAGE, METHOD=CENTROID, or METHOD=WARD, either the stored data or the stored distance algorithm can be used. For these methods, if the data are distances or if you specify the NOSQUARE option, the stored distance algorithm is used; otherwise, the stored data algorithm is used.

**Table 23.2.** Three Algorithms for Implementing Agglomerative Hierarchical Clustering

Stored Method	Algorithm		
	Stored Data	Stored Distance	Sorted Distance
AVERAGE	x	x	
CENTROID	x	x	
COMPLETE		x	
DENSITY			x
EML	x		
FLEXIBLE		x	
MCQUITTY		x	
MEDIAN		x	
SINGLE		x	
TWOSTAGE			x
WARD	x	x	

---

## Computational Resources

The CLUSTER procedure stores the data (including the COPY and ID variables) in memory or, if necessary, on disk. If eigenvalues are computed, the covariance matrix is stored in memory. If the stored distance or sorted distance algorithm is used, the distances are stored in memory or, if necessary, on disk.

With coordinate data, the increase in CPU time is roughly proportional to the number of variables. The VAR statement should list the variables in order of decreasing variance for greatest efficiency.

For both coordinate and distance data, the dominant factor determining CPU time is the number of observations. For density methods with coordinate data, the asymptotic time requirements are somewhere between  $n \ln(n)$  and  $n^2$ , depending on how the smoothing parameter increases. For other methods except EML, time is roughly proportional to  $n^2$ . For the EML method, time is roughly proportional to  $n^3$ .

PROC CLUSTER runs much faster if the data can be stored in memory and, if the stored distance algorithm is used, the distance matrix can be stored in memory as well. To estimate the bytes of memory needed for the data, use the following equation and round up to the nearest multiple of  $d$ .



$n(vd + 8d + i$	
$+ i$	if density estimation or the sorted distance algorithm used
$+ 3d$	if stored data algorithm used
$+ 3d$	if density estimation used
$+ \max(8, \text{length of ID variable})$	if ID variable used
$+ \text{length of ID variable}$	if ID variable used
$+ \text{sum of lengths of COPY variables})$	if COPY variables used

where

- $n$  is the number of observations
- $v$  is the number of variables
- $d$  is the size of a C variable of type *double*. For most computers,  $d = 8$ .
- $i$  is the size of a C variable of type *int*. For most computers,  $i = 4$ .

The number of bytes needed for the distance matrix is  $dn(n + 1)/2$ .

---

## Missing Values

If the data are coordinates, observations with missing values are excluded from the analysis. If the data are distances, missing values are not allowed in the lower triangle of the distance matrix. The upper triangle is ignored. For more on TYPE=DISTANCE data sets, see Appendix A, “Special SAS Data Sets.”

---

## Ties

At each level of the clustering algorithm, PROC CLUSTER must identify the pair of clusters with the minimum distance. Sometimes, usually when the data are discrete, there may be two or more pairs with the same minimum distance. In such cases the tie must be broken in some arbitrary way. If there are ties, then the results of the cluster analysis depend on the order of the observations in the data set. The presence of ties is reported in the SAS log and in the column of the cluster history labeled “Tie” unless the NOTIE option is specified.

PROC CLUSTER breaks ties as follows. Each cluster is identified by the smallest observation number among its members. For each pair of clusters, there is a smaller identification number and a larger identification number. If two or more pairs of clusters are tied for minimum distance between clusters, the pair that has the minimum larger identification number is merged. If there is a tie for minimum larger identification number, the pair that has the minimum smaller identification number is merged. This method for breaking ties is different from that used in Version 5. The change in the algorithm may produce changes in the resulting clusters.

A tie means that the level in the cluster history at which the tie occurred and possibly some of the subsequent levels are not uniquely determined. Ties that occur early in

the cluster history usually have little effect on the later stages. Ties that occur in the middle part of the cluster history are cause for further investigation. Ties late in the cluster history indicate important indeterminacies.

The importance of ties can be assessed by repeating the cluster analysis for several different random permutations of the observations. The discrepancies at a given level can be examined by crosstabulating the clusters obtained at that level for all of the permutations. See Example 23.4 for details.

---

## Size, Shape, and Correlation

In some biological applications, the organisms that are being clustered may be at different stages of growth. Unless it is the growth process itself that is being studied, differences in size among such organisms are not of interest. Therefore, distances among organisms should be computed in such a way as to control for differences in size while retaining information about differences in shape.

If coordinate data are measured on an interval scale, you can control for size by subtracting a measure of the overall size of each observation from each datum. For example, if no other direct measure of size is available, you could subtract the mean of each row of the data matrix, producing a row-centered coordinate matrix. An easy way to subtract the mean of each row is to use PROC STANDARD on the transposed coordinate matrix:

```
proc transpose data= coordinate-datatype ;
proc standard m=0;
proc transpose out=row-centered-coordinate-data;
```

Another way to remove size effects from interval-scale coordinate data is to do a principal component analysis and discard the first component (Blackith and Reyment 1971).

If the data are measured on a ratio scale, you can control for size by dividing each datum by a measure of overall size; in this case, the geometric mean is a more natural measure of size than the arithmetic mean. However, it is often more meaningful to analyze the logarithms of ratio-scaled data, in which case you can subtract the arithmetic mean after taking logarithms. You must also consider the dimensions of measurement. For example, if you have measures of both length and weight, you may need to cube the measures of length or take the cube root of the weights. Various other complications may also arise in real applications, such as different growth rates for different parts of the body (Sneath and Sokal 1973).

Issues of size and shape are pertinent to many areas besides biology (for example, Hamer and Cunningham 1981). Suppose you have data consisting of subjective ratings made by several different raters. Some raters may tend to give higher overall ratings than other raters. Some raters may also tend to spread out their ratings over more of the scale than do other raters. If it is impossible for you to adjust directly for rater differences, then distances should be computed in such a way as to control for both differences in size and variability. For example, if the data are considered to be measured on an interval scale, you can subtract the mean of each observation

and divide by the standard deviation, producing a row-standardized coordinate matrix. With some clustering methods, analyzing squared Euclidean distances from a row-standardized coordinate matrix is equivalent to analyzing the matrix of correlations among rows, since squared Euclidean distance is an affine transformation of the correlation (Hartigan 1975, p. 64).

If you do an analysis of row-centered or row-standardized data, you need to consider whether the columns (variables) should be standardized before centering or standardizing the rows, after centering or standardizing the rows, or both before and after. If you standardize the columns after standardizing the rows, then strictly speaking you are not analyzing shape because the profiles are distorted by standardizing the columns; however, this type of double standardization may be necessary in practice to get reasonable results. It is not clear whether iterating the standardization of rows and columns may be of any benefit.

The choice of distance or correlation measure should depend on the meaning of the data and the purpose of the analysis. Simulation studies that compare distance and correlation measures are useless unless the data are generated to mimic data from your field of application; conclusions drawn from artificial data cannot be generalized because it is possible to generate data such that distances that include size effects work better or such that correlations work better.

You can standardize the rows of a data set by using a DATA step or by using the TRANSPOSE and STANDARD procedures. You can also use PROC TRANSPOSE and then have PROC CORR create a TYPE=CORR data set containing a correlation matrix. If you want to analyze a TYPE=CORR data set with PROC CLUSTER, you must use a DATA step to perform the following steps:

1. Set the data set TYPE= to DISTANCE.
2. Convert the correlations to dissimilarities by computing  $1 - r$ ,  $\sqrt{1 - r}$ ,  $1 - r^2$ , or some other decreasing function.
3. Delete observations for which the variable \_TYPE\_ does not have the value 'CORR'.

See Example 23.6 for an analysis of a data set in which size information is detrimental to the classification.

---

## Output Data Set

The OUTTREE= data set contains one observation for each observation in the input data set, plus one observation for each cluster of two or more observations (that is, one observation for each node of the cluster tree). The total number of output observations is usually  $2n - 1$ , where  $n$  is the number of input observations. The density methods may produce fewer output observations when the number of clusters cannot be reduced to one.

The label of the OUTTREE= data set identifies the type of cluster analysis performed and is automatically displayed when the TREE procedure is invoked.

The variables in the OUTTREE= data set are as follows:

- the BY variables, if you use a BY statement
- the ID variable, if you use an ID statement
- the COPY variables, if you use a COPY statement
- **\_NAME\_**, a character variable giving the name of the node. If the node is a cluster, the name is **CL $n$** , where  $n$  is the number of the cluster. If the node is an observation, the name is **OB $n$** , where  $n$  is the observation number. If the node is an observation and the ID statement is used, the name is the formatted value of the ID variable.
- **\_PARENT\_**, a character variable giving the value of **\_NAME\_** of the parent of the node
- **\_NCL\_**, the number of clusters
- **\_FREQ\_**, the number of observations in the current cluster
- **\_HEIGHT\_**, the distance or similarity between the last clusters joined, as defined in the section “Clustering Methods” on page 854. The variable **\_HEIGHT\_** is used by the TREE procedure as the default height axis. The label of the **\_HEIGHT\_** variable identifies the between-cluster distance measure. For **METHOD=TWOSTAGE**, the **\_HEIGHT\_** variable contains the densities at which clusters joined in the first stage; for clusters formed in the second stage, **\_HEIGHT\_** is a very small negative number.

If the input data set contains coordinates, the following variables appear in the output data set:

- the variables containing the coordinates used in the cluster analysis. For output observations that correspond to input observations, the values of the coordinates are the same in both data sets except for some slight numeric error possibly introduced by standardizing and unstandardizing if the **STANDARD** option is used. For output observations that correspond to clusters of more than one input observation, the values of the coordinates are the cluster means.
- **\_ERSQ\_**, the approximate expected value of  $R^2$  under the uniform null hypothesis
- **\_RATIO\_**, equal to  $\frac{1-\text{\_ERSQ\_}}{1-\text{\_RSQ\_}}$
- **\_LOGR\_**, natural logarithm of **\_RATIO\_**
- **\_CCC\_**, the cubic clustering criterion

The variables **\_ERSQ\_**, **\_RATIO\_**, **\_LOGR\_**, and **\_CCC\_** have missing values when the number of clusters is greater than one-fifth the number of observations.

If the input data set contains coordinates and **METHOD=AVERAGE**, **METHOD=CENTROID**, or **METHOD=WARD**, then the following variables appear in the output data set.

- `_DIST_`, the Euclidean distance between the means of the last clusters joined
- `_AVLINK_`, the average distance between the last clusters joined

If the input data set contains coordinates or `METHOD=AVERAGE`, `METHOD=CENTROID`, or `METHOD=WARD`, then the following variables appear in the output data set:

- `_RMSSTD_`, the root-mean-square standard deviation of the current cluster
- `_SPRSQ_`, the semipartial squared multiple correlation or the decrease in the proportion of variance accounted for due to joining two clusters to form the current cluster
- `_RSQ_`, the squared multiple correlation
- `_PSF_`, the pseudo  $F$  statistic
- `_PST2_`, the pseudo  $t^2$  statistic

If `METHOD=EML`, then the following variable appears in the output data set:

- `_LNLR_`, the log-likelihood ratio

If `METHOD=TWOSTAGE` or `METHOD=DENSITY`, the following variable appears in the output data set:

- `_MODE_`, pertaining to the modal clusters. With `METHOD=DENSITY`, the `_MODE_` variable indicates the number of modal clusters contained by the current cluster. With `METHOD=TWOSTAGE`, the `_MODE_` variable gives the maximum density in each modal cluster and the fusion density,  $d^*$ , for clusters containing two or more modal clusters; for clusters containing no modal clusters, `_MODE_` is missing.

If nonparametric density estimates are requested (when `METHOD=DENSITY` or `METHOD=TWOSTAGE` and the `HYBRID` option is not used; or when the `TRIM=` option is used), the output data set contains

- `_DENS_`, the maximum density in the current cluster

---

## Displayed Output

If you specify the SIMPLE option and the data are coordinates, PROC CLUSTER produces simple descriptive statistics for each variable:

- the Mean
- the standard deviation, Std Dev
- the Skewness
- the Kurtosis
- a coefficient of Bimodality

If the data are coordinates and you do not specify the NOEIGEN option, PROC CLUSTER displays

- the Eigenvalues of the Correlation or Covariance Matrix
- the Difference between successive eigenvalues
- the Proportion of variance explained by each eigenvalue
- the Cumulative proportion of variance explained

If the data are coordinates, PROC CLUSTER displays the Root-Mean-Square Total-Sample Standard Deviation of the variables

If the distances are normalized, PROC CLUSTER displays one of the following, depending on whether squared or unsquared distances are used:

- the Root-Mean-Square Distance Between Observations
- the Mean Distance Between Observations

For the generations in the clustering process specified by the PRINT= option, PROC CLUSTER displays

- the Number of Clusters or NCL
- the names of the Clusters Joined. The observations are identified by the formatted value of the ID variable, if any; otherwise, the observations are identified by OB*n*, where *n* is the observation number. The CLUSTER procedure displays the entire value of the ID variable in the cluster history instead of truncating at 16 characters. Long ID values may be flowed onto several lines. Clusters of two or more observations are identified as CL*n*, where *n* is the number of clusters existing after the cluster in question is formed.
- the number of observations in the new cluster, Frequency of New Cluster or FREQ

If you specify the RMSSTD option and if the data are coordinates or if you specify METHOD=AVERAGE, METHOD=CENTROID, or METHOD=WARD, then PROC CLUSTER displays the root-mean-square standard deviation of the new cluster, RMS Std of New Cluster or RMS Std.

PROC CLUSTER displays the following items if you specify METHOD=WARD. It also displays them if you specify the RSQUARE option and either the data are coordinates or you specify METHOD=AVERAGE or METHOD=CENTROID:

- the decrease in the proportion of variance accounted for resulting from joining the two clusters, Semipartial R-Squared or SPRSQ. This equals the between-cluster sum of squares divided by the corrected total sum of squares.
- the squared multiple correlation, R-Squared or RSQ.  $R^2$  is the proportion of variance accounted for by the clusters.

If you specify the CCC option and the data are coordinates, PROC CLUSTER displays

- Approximate Expected R-Squared or ERSQ, the approximate expected value of  $R^2$  under the uniform null hypothesis
- the Cubic Clustering Criterion or CCC. The cubic clustering criterion and approximate expected  $R^2$  are given missing values when the number of clusters is greater than one-fifth the number of observations.

If you specify the PSEUDO option and if the data are coordinates or METHOD=AVERAGE, METHOD=CENTROID, or METHOD=WARD, then PROC CLUSTER displays

- Pseudo  $F$  or PSF, the pseudo  $F$  statistic measuring the separation among all the clusters at the current level
- Pseudo  $t^2$  or PST2, the pseudo  $t^2$  statistic measuring the separation between the two clusters most recently joined

If you specify the NOSQUARE option and METHOD=AVERAGE, PROC CLUSTER displays the (Normalized) Average Distance or (Norm) Aver Dist, the average distance between pairs of objects in the two clusters joined with one object from each cluster.

If you do not specify the NOSQUARE option and METHOD=AVERAGE, PROC CLUSTER displays the (Normalized) RMS Distance or (Norm) RMS Dist, the root-mean-square distance between pairs of objects in the two clusters joined with one object from each cluster.

If METHOD=CENTROID, PROC CLUSTER displays the (Normalized) Centroid Distance or (Norm) Cent Dist, the distance between the two cluster centroids.

If METHOD=COMPLETE, PROC CLUSTER displays the (Normalized) Maximum Distance or (Norm) Max Dist, the maximum distance between the two clusters.



If METHOD=DENSITY or METHOD=TWOSTAGE, PROC CLUSTER displays

- Normalized Fusion Density or Normalized Fusion Dens, the value of  $d^*$  as defined in the section “Clustering Methods” on page 854
- the Normalized Maximum Density in Each Cluster joined, including the Lesser or Min, and the Greater or Max, of the two maximum density values

If METHOD=EML, PROC CLUSTER displays

- Log Likelihood Ratio or LNLR
- Log Likelihood or LNLIKE

If METHOD=FLEXIBLE, PROC CLUSTER displays the (Normalized) Flexible Distance or (Norm) Flex Dist, the distance between the two clusters based on the Lance-Williams flexible formula.

If METHOD=MEDIAN, PROC CLUSTER displays the (Normalized) Median Distance or (Norm) Med Dist, the distance between the two clusters based on the median method.

If METHOD=MCQUITTY, PROC CLUSTER displays the (Normalized) McQuitty’s Similarity or (Norm) MCQ, the distance between the two clusters based on McQuitty’s similarity method.

If METHOD=SINGLE, PROC CLUSTER displays the (Normalized) Minimum Distance or (Norm) Min Dist, the minimum distance between the two clusters.

If you specify the NONORM option and METHOD=WARD, PROC CLUSTER displays the Between-Cluster Sum of Squares or BSS, the ANOVA sum of squares between the two clusters joined.

If you specify neither the NOTIE option nor METHOD=TWOSTAGE or METHOD=DENSITY, PROC CLUSTER displays Tie, where a T in the column indicates a tie for minimum distance and a blank indicates the absence of a tie.

After the cluster history, if METHOD=TWOSTAGE or METHOD=DENSITY, PROC CLUSTER displays the number of modal clusters.

---

## ODS Table Names

PROC CLUSTER assigns a name to each table it creates. You can use these names to reference the table when using the Output Delivery System (ODS) to select tables and create output data sets. These names are listed in the following table. For more information on ODS, see Chapter 15, “Using the Output Delivery System.”



**Table 23.3.** ODS Tables Produced in PROC CLUSTER

ODS Table Name	Description	Statement	Option
ClusterHistory	Obs or clusters joined, frequencies and other cluster statistics	PROC	default
SimpleStatistics	Simple statistics, before or after trimming	PROC	SIMPLE
EigenvalueTable	Eigenvalues of the CORR or COV matrix	PROC	default

## Examples

### Example 23.1. Cluster Analysis of Flying Mileages between Ten American Cities

This first example clusters ten American cities based on the flying mileages between them. Six clustering methods are shown with corresponding tree diagrams produced by the TREE procedure. The EML method cannot be used because it requires coordinate data. The other omitted methods produce the same clusters, although not the same distances between clusters, as one of the illustrated methods: complete linkage and the flexible-beta method yield the same clusters as Ward's method, McQuitty's similarity analysis produces the same clusters as average linkage, and the median method corresponds to the centroid method.

All of the methods suggest a division of the cities into two clusters along the east-west dimension. There is disagreement, however, about which cluster Denver should belong to. Some of the methods indicate a possible third cluster containing Denver and Houston. The following statements produce Output 23.1.1:

```

title 'Cluster Analysis of Flying Mileages Between 10 American Cities';
data mileages(type=distance);
  input (atlanta chicago denver houston losangeles
         miami newyork sanfran seattle washdc) (5.)
         @55 city $15.;
  datalines;
    0 ATLANTA
  587 0 CHICAGO
 1212 920 0 DENVER
  701 940 879 0 HOUSTON
 1936 1745 831 1374 0 LOS ANGELES
  604 1188 1726 968 2339 0 MIAMI
  748 713 1631 1420 2451 1092 0 NEW YORK
 2139 1858 949 1645 347 2594 2571 0 SAN FRANCISCO
 2182 1737 1021 1891 959 2734 2408 678 0 SEATTLE
  543 597 1494 1220 2300 923 205 2442 2329 0 WASHINGTON D.C.
;

```

```

/*----- Average linkage -----*/
proc cluster data=mileages method=average pseudo;
  id city;
run;

proc tree horizontal spaces=2;
  id city;
run;

/*----- Centroid method -----*/
proc cluster data=mileages method=centroid pseudo;
  id city;
run;

proc tree horizontal spaces=2;
  id city;
run;

/*----- Density linkage with 3rd-nearest-neighbor -----*/
proc cluster data=mileages method=density k=3;
  id city;
run;

proc tree horizontal spaces=2;
  id city;
run;

/*----- Single linkage -----*/
proc cluster data=mileages method=single;
  id city;
run;

proc tree horizontal spaces=2;
  id city;
run;

/*--- Two-stage density linkage with 3rd-nearest-neighbor ---*/
proc cluster data=mileages method=twostage k=3;
  id city;
run;

proc tree horizontal spaces=2;
  id city;
run;

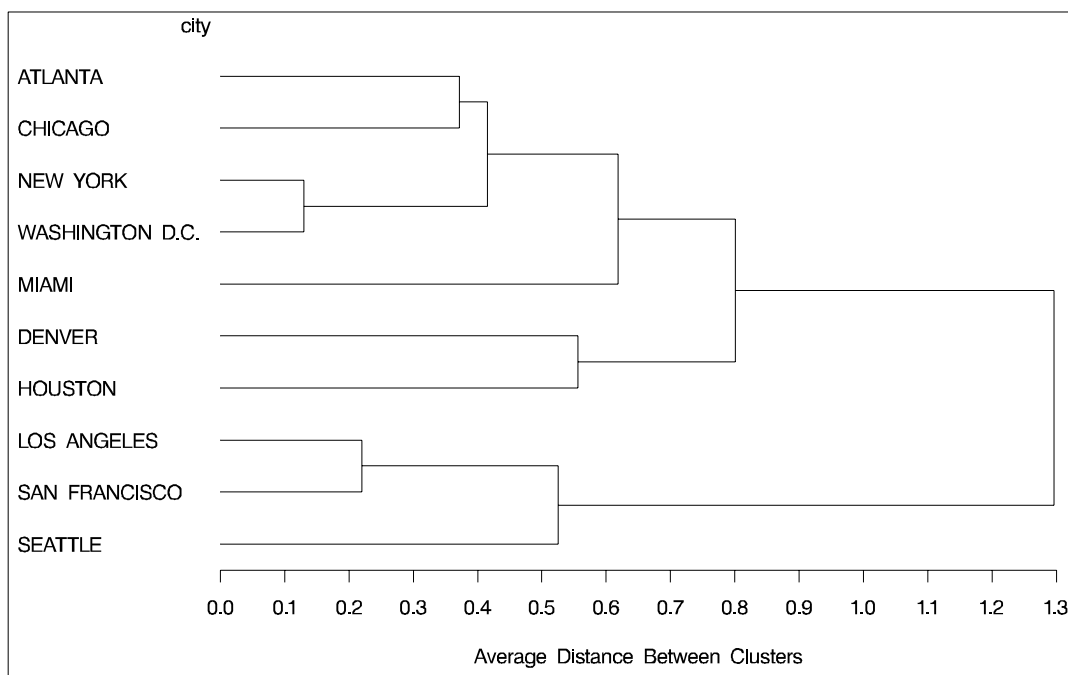
/* Ward's minimum variance with pseudo $F$ and $t^2$ statistics */
proc cluster data=mileages method=ward pseudo;
  id city;
run;

proc tree horizontal spaces=2;
  id city;
run;

```

**Output 23.1.1.** Statistics and Tree Diagrams for Six Different Clustering Methods

Cluster Analysis of Flying Mileages Between 10 American Cities							
The CLUSTER Procedure							
Average Linkage Cluster Analysis							
Root-Mean-Square Distance Between Observations = 1580.242							
Cluster History							
NCL	-----Clusters Joined-----		FREQ	PSF	PST2	Norm RMS Dist	T i e
9	NEW YORK	WASHINGTON D.C.	2	66.7	.	0.1297	
8	LOS ANGELES	SAN FRANCISCO	2	39.2	.	0.2196	
7	ATLANTA	CHICAGO	2	21.7	.	0.3715	
6	CL7	CL9	4	14.5	3.4	0.4149	
5	CL8	SEATTLE	3	12.4	7.3	0.5255	
4	DENVER	HOUSTON	2	13.9	.	0.5562	
3	CL6	MIAMI	5	15.5	3.8	0.6185	
2	CL3	CL4	7	16.0	5.3	0.8005	
1	CL2	CL5	10	.	16.0	1.2967	



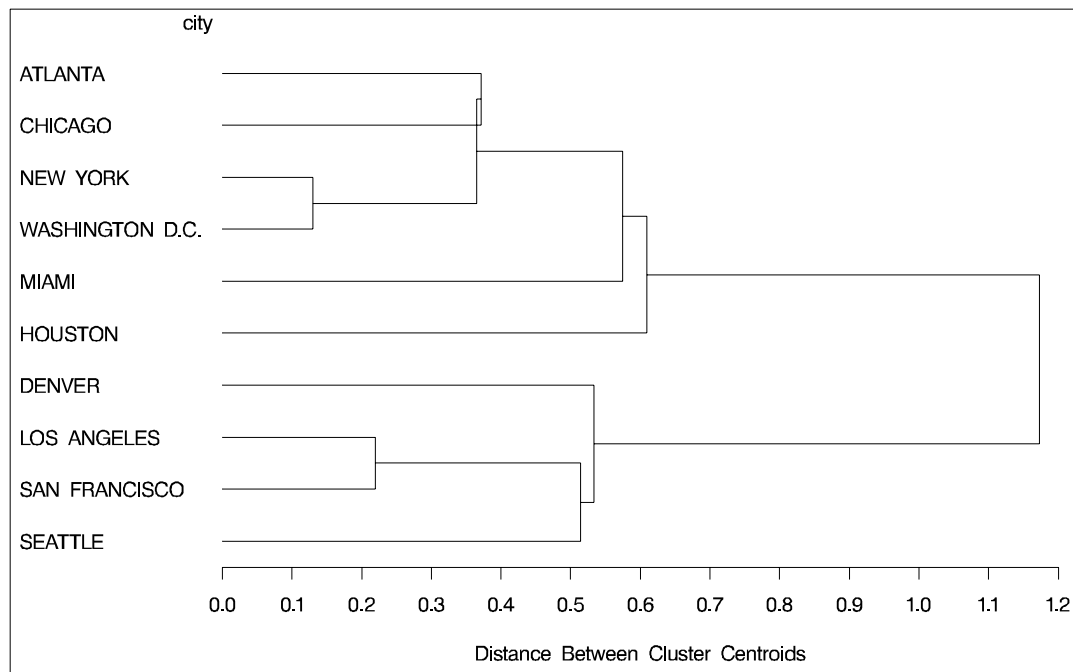
## Cluster Analysis of Flying Mileages Between 10 American Cities

The CLUSTER Procedure  
Centroid Hierarchical Cluster Analysis

Root-Mean-Square Distance Between Observations = 1580.242

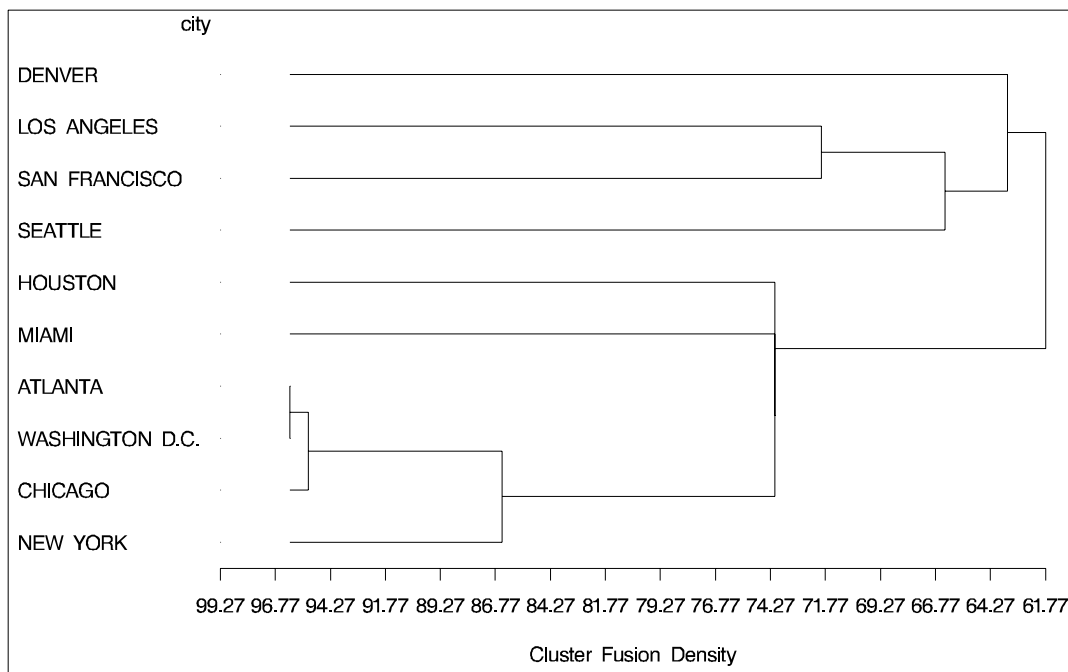
## Cluster History

NCL	-----Clusters Joined-----		FREQ	PSF	PST2	Norm Cent Dist	T i e
9	NEW YORK	WASHINGTON D.C.	2	66.7	.	0.1297	
8	LOS ANGELES	SAN FRANCISCO	2	39.2	.	0.2196	
7	ATLANTA	CHICAGO	2	21.7	.	0.3715	
6	CL7	CL9	4	14.5	3.4	0.3652	
5	CL8	SEATTLE	3	12.4	7.3	0.5139	
4	DENVER	CL5	4	12.4	2.1	0.5337	
3	CL6	MIAMI	5	14.2	3.8	0.5743	
2	CL3	HOUSTON	6	22.1	2.6	0.6091	
1	CL2	CL4	10	.	22.1	1.173	



Cluster Analysis of Flying Mileages Between 10 American Cities							
The CLUSTER Procedure							
Density Linkage Cluster Analysis							
K = 3							
Cluster History							
NCL	-----Clusters Joined-----		FREQ	Normalized Fusion Density	Maximum Density in Each Cluster		T
					Lesser	Greater	i
9	ATLANTA	WASHINGTON D.C.	2	96.106	92.5043	100.0	
8	CL9	CHICAGO	3	95.263	90.9548	100.0	
7	CL8	NEW YORK	4	86.465	76.1571	100.0	
6	CL7	MIAMI	5	74.079	58.8299	100.0	T
5	CL6	HOUSTON	6	74.079	61.7747	100.0	
4	LOS ANGELES	SAN FRANCISCO	2	71.968	65.3430	80.0885	
3	CL4	SEATTLE	3	66.341	56.6215	80.0885	
2	CL3	DENVER	4	63.509	61.7747	80.0885	
1	CL5	CL2	10	61.775	*	80.0885	

\* indicates fusion of two modal or multimodal clusters  
2 modal clusters have been formed.



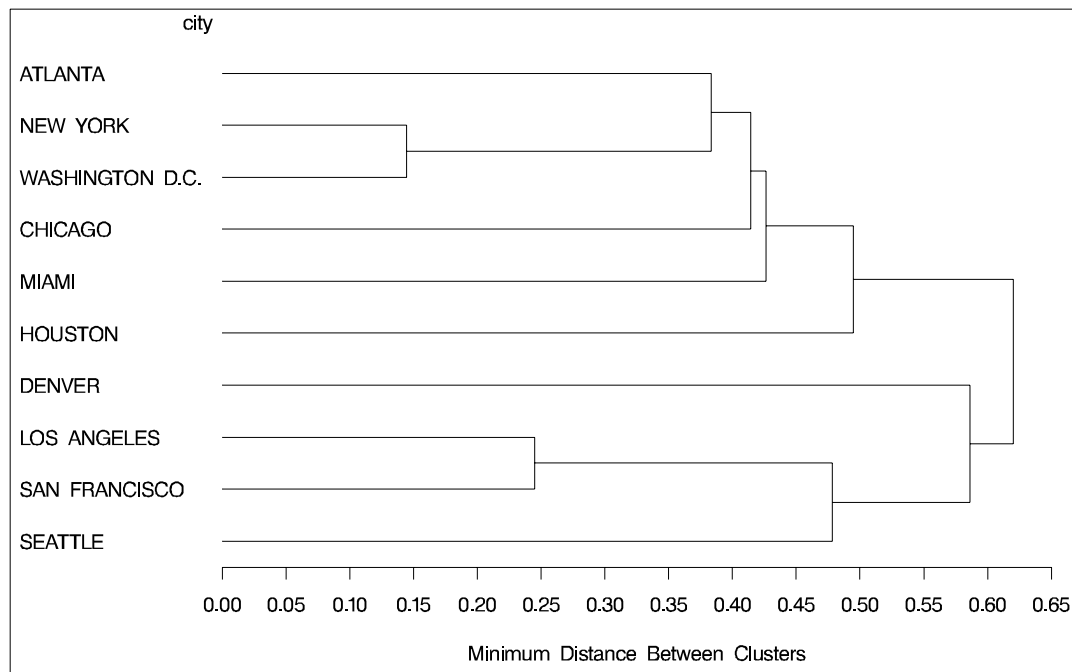
## Cluster Analysis of Flying Mileages Between 10 American Cities

The CLUSTER Procedure  
Single Linkage Cluster Analysis

Mean Distance Between Observations = 1417.133

## Cluster History

NCL	-----Clusters Joined-----		FREQ	Norm Min Dist	T i e
9	NEW YORK	WASHINGTON D.C.	2	0.1447	
8	LOS ANGELES	SAN FRANCISCO	2	0.2449	
7	ATLANTA	CL9	3	0.3832	
6	CL7	CHICAGO	4	0.4142	
5	CL6	MIAMI	5	0.4262	
4	CL8	SEATTLE	3	0.4784	
3	CL5	HOUSTON	6	0.4947	
2	DENVER	CL4	4	0.5864	
1	CL3	CL2	10	0.6203	



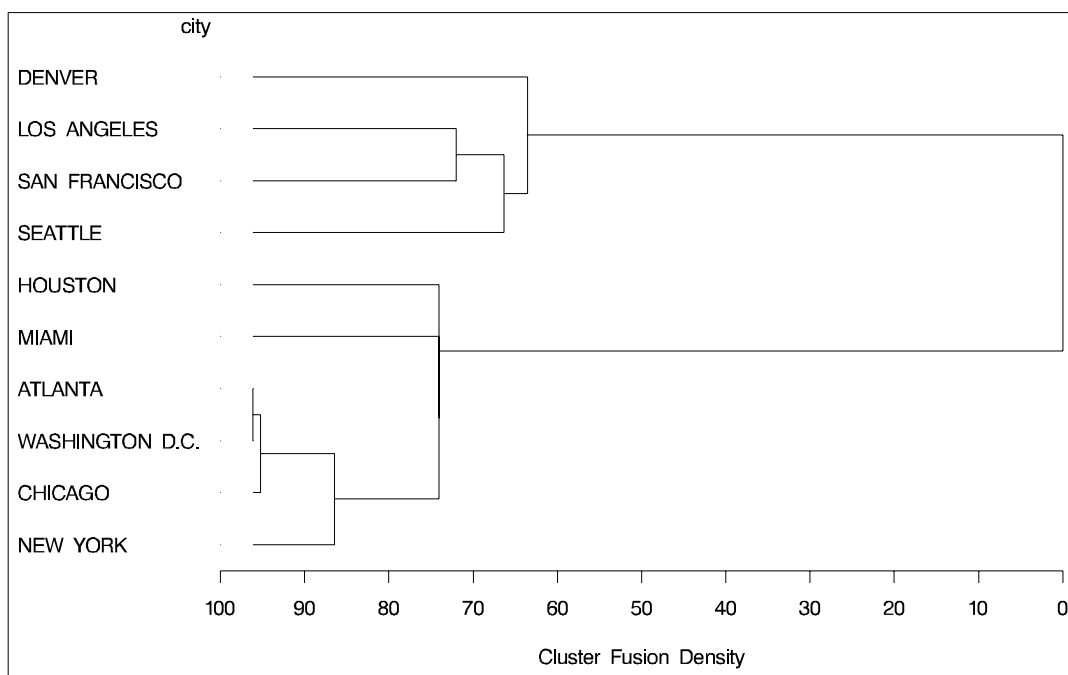
Cluster Analysis of Flying Mileages Between 10 American Cities

The CLUSTER Procedure  
Two-Stage Density Linkage Clustering

K = 3

Cluster History				Normalized Fusion Density		Maximum Density in Each Cluster		T
NCL	-----Clusters Joined-----		FREQ	Density	Lesser	Greater		
9	ATLANTA	WASHINGTON D.C.	2	96.106	92.5043	100.0		
8	CL9	CHICAGO	3	95.263	90.9548	100.0		
7	CL8	NEW YORK	4	86.465	76.1571	100.0		
6	CL7	MIAMI	5	74.079	58.8299	100.0		
5	CL6	HOUSTON	6	74.079	61.7747	100.0		
4	LOS ANGELES	SAN FRANCISCO	2	71.968	65.3430	80.0885		
3	CL4	SEATTLE	3	66.341	56.6215	80.0885		
2	CL3	DENVER	4	63.509	61.7747	80.0885		
1	CL5	CL2	10	61.775	80.0885	100.0		

2 modal clusters have been formed.



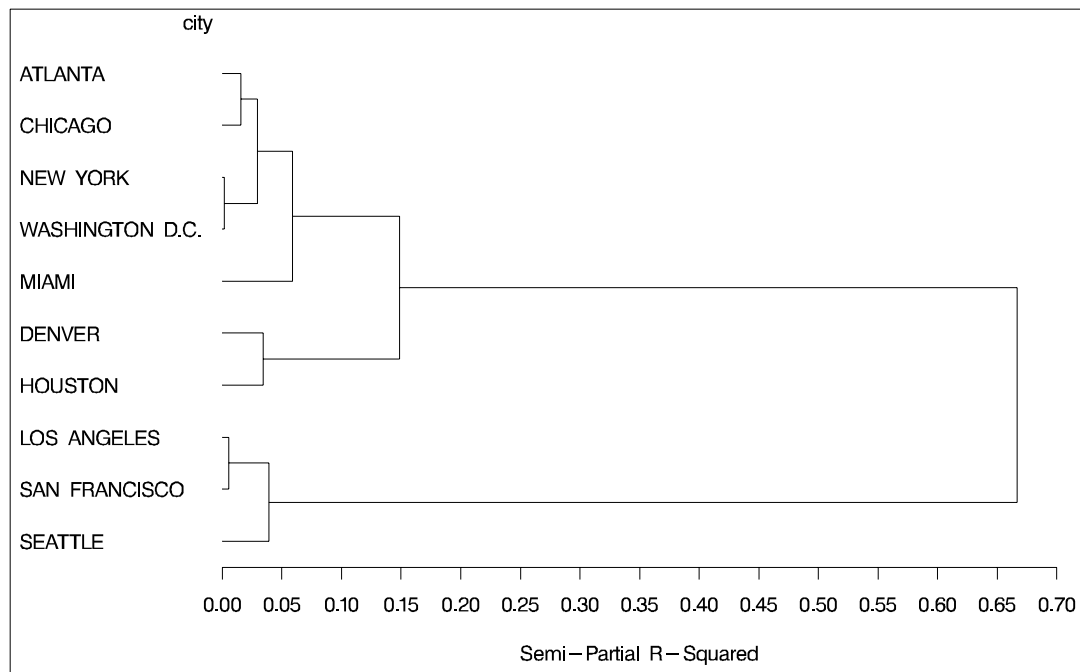
## Cluster Analysis of Flying Mileages Between 10 American Cities

The CLUSTER Procedure  
Ward's Minimum Variance Cluster Analysis

Root-Mean-Square Distance Between Observations = 1580.242

## Cluster History

NCL	-----Clusters Joined-----		FREQ	SPRSQ	RSQ	PSF	PST2	T i e
9	NEW YORK	WASHINGTON D.C.	2	0.0019	.998	66.7	.	
8	LOS ANGELES	SAN FRANCISCO	2	0.0054	.993	39.2	.	
7	ATLANTA	CHICAGO	2	0.0153	.977	21.7	.	
6	CL7	CL9	4	0.0296	.948	14.5	3.4	
5	DENVER	HOUSTON	2	0.0344	.913	13.2	.	
4	CL8	SEATTLE	3	0.0391	.874	13.9	7.3	
3	CL6	MIAMI	5	0.0586	.816	15.5	3.8	
2	CL3	CL5	7	0.1488	.667	16.0	5.3	
1	CL2	CL4	10	0.6669	.000	.	16.0	



## Example 23.2. Crude Birth and Death Rates

The following example uses the SAS data set **Poverty** created in the “Getting Started” section beginning on page 837. The data, from Rouncefield (1995), are birth rates, death rates, and infant death rates for 97 countries. Six cluster analyses are performed with eight methods. Scatter plots showing cluster membership at selected levels are produced instead of tree diagrams.

Each cluster analysis is performed by a macro called **ANALYZE**. The macro takes two arguments. The first, **&METHOD**, specifies the value of the **METHOD=** option to be used in the **PROC CLUSTER** statement. The second, **&NCL**, must be specified as a list of integers, separated by blanks, indicating the number of clusters desired



in each scatter plot. For example, the first invocation of ANALYZE specifies the AVERAGE method and requests plots of 3 and 8 clusters. When two-stage density linkage is used, the K= and R= options are specified as part of the first argument.

The ANALYZE macro first invokes the CLUSTER procedure with METHOD=&METHOD, where &METHOD represents the value of the first argument to ANALYZE. This part of the macro produces the PROC CLUSTER output shown.

The %DO loop processes &NCL, the list of numbers of clusters to plot. The macro variable &K is a counter that indexes the numbers within &NCL. The %SCAN function picks out the &Kth number in &NCL, which is then assigned to the macro variable &N. When &K exceeds the number of numbers in &NCL, %SCAN returns a null string. Thus, the %DO loop executes while &N is not equal to a null string. In the %WHILE condition, a null string is indicated by the absence of any nonblank characters between the comparison operator (NE) and the right parenthesis that terminates the condition.

Within the %DO loop, the TREE procedure creates an output data set containing &N clusters. The GPLOT procedure then produces a scatter plot in which each observation is identified by the number of the cluster to which it belongs. The TITLE2 statement uses double quotes so that &N and &METHOD can be used within the title. At the end of the loop, &K is incremented by 1, and the next number is extracted from &NCL by %SCAN.

For this example, plots are obtained only for average linkage. To generate plots for other methods, follow the example shown in the first macro call. The following statements produce Output 23.2.1 through Output 23.2.7.

```

title 'Cluster Analysis of Birth and Death Rates';

%macro analyze(method,ncl);
proc cluster data=poverty outtree=tree method=&method p=15 ccc pseudo;
  var birth death;
  title2;
run;
%let k=1;
%let n=%scan(&ncl,&k);
%do %while(&n NE);
  proc tree data=tree noprint out=out ncl=&n;
    copy birth death;
  run;
  legend1 frame cframe=ligr cborder=black
    position=center value=(justify=center);
  axis1 label=(angle=90 rotate=0) minor=none;
  axis2 minor=none;
  proc gplot;
    plot death*birth=cluster /
      frame cframe=ligr legend=legend1 vaxis=axis1 haxis=axis2;
    title2 "Plot of &n Clusters from METHOD=&METHOD";
  run;
  %let k=%eval(&k+1);
  %let n=%scan(&ncl,&k);
%end;
%mend;

```

```

%analyze(average,3 8)
%analyze(complete,3)
%analyze(single,7 10)
%analyze(two k=10,3)
%analyze(two k=18,2)

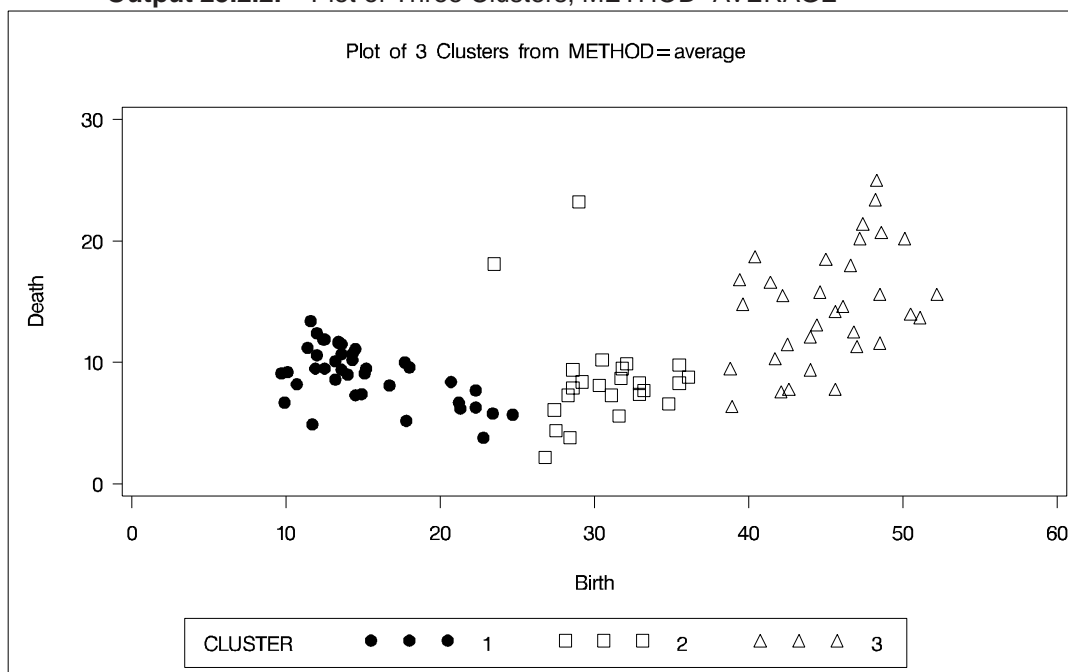
```

For average linkage, the CCC has peaks at 3, 8, 10, and 12 clusters, but the 3-cluster peak is lower than the 8-cluster peak. The pseudo  $F$  statistic has peaks at 3, 8, and 12 clusters. The pseudo  $t^2$  statistic drops sharply at 3 clusters, continues to fall at 4 clusters, and has a particularly low value at 12 clusters. However, there are not enough data to seriously consider as many as 12 clusters. Scatter plots are given for 3 and 8 clusters. The results are shown in Output 23.2.1 through Output 23.2.3. In Output 23.2.3, the eighth cluster consists of the two outlying observations, Mexico and Korea.

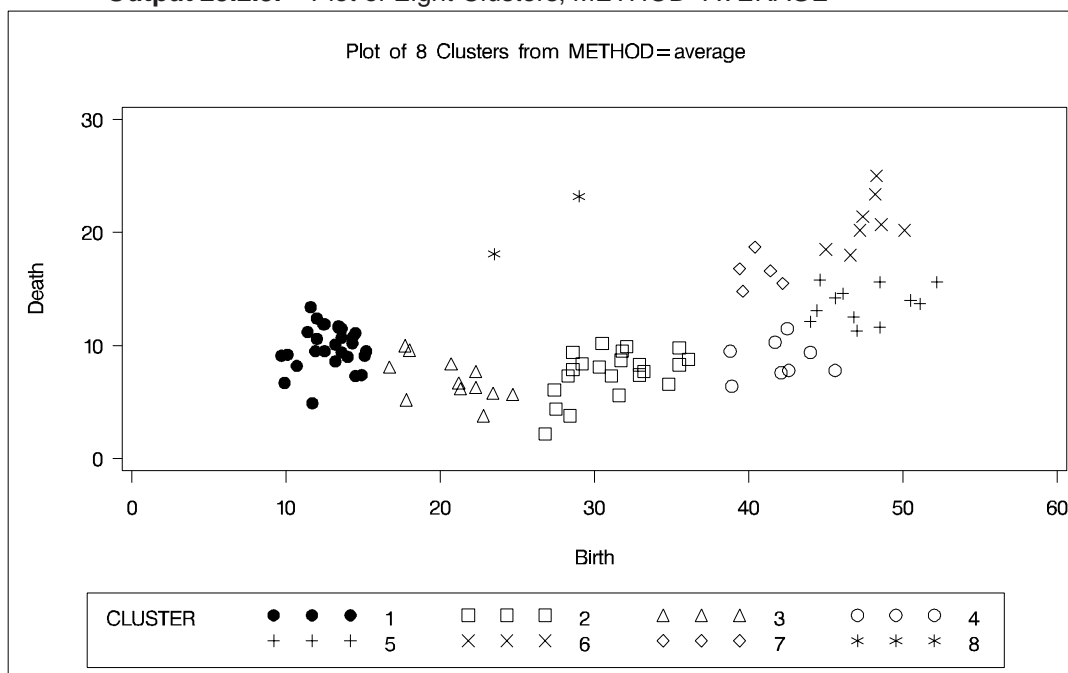
**Output 23.2.1.** Clusters for Birth and Death Rates: METHOD=AVERAGE

Cluster Analysis of Birth and Death Rates											
The CLUSTER Procedure											
Average Linkage Cluster Analysis											
Eigenvalues of the Covariance Matrix											
	Eigenvalue	Difference	Proportion	Cumulative							
1	189.106588	173.101020	0.9220	0.9220							
2	16.005568		0.0780	1.0000							
Root-Mean-Square Total-Sample Standard Deviation = 10.127											
Root-Mean-Square Distance Between Observations = 20.25399											
Cluster History											
NCL	--Clusters Joined--			FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Norm RMS Dist
15	CL27	CL20	18	0.0035	.980	.975	2.61	292	18.6	0.2325	
14	CL23	CL17	28	0.0034	.977	.972	1.97	271	17.7	0.2358	
13	CL18	CL54	8	0.0015	.975	.969	2.35	279	7.1	0.2432	
12	CL21	CL26	8	0.0015	.974	.966	2.85	290	6.1	0.2493	
11	CL19	CL24	12	0.0033	.971	.962	2.78	285	14.8	0.2767	
10	CL22	CL16	12	0.0036	.967	.957	2.84	284	17.4	0.2858	
9	CL15	CL28	22	0.0061	.961	.951	2.45	271	17.5	0.3353	
8	OB23	OB61	2	0.0014	.960	.943	3.59	302	.	0.3703	
7	CL25	CL11	17	0.0098	.950	.933	3.01	284	23.3	0.4033	
6	CL7	CL12	25	0.0122	.938	.920	2.63	273	14.8	0.4132	
5	CL10	CL14	40	0.0303	.907	.902	0.59	225	82.7	0.4584	
4	CL13	CL6	33	0.0244	.883	.875	0.77	234	22.2	0.5194	
3	CL9	CL8	24	0.0182	.865	.827	2.13	300	27.7	0.735	
2	CL5	CL3	64	0.1836	.681	.697	-.55	203	148	0.8402	
1	CL2	CL4	97	0.6810	.000	.000	0.00	.	203	1.3348	

**Output 23.2.2.** Plot of Three Clusters, METHOD=AVERAGE



**Output 23.2.3.** Plot of Eight Clusters, METHOD=AVERAGE



Complete linkage shows CCC peaks at 3, 8 and 12 clusters. The pseudo  $F$  statistic peaks at 3 and 12 clusters. The pseudo  $t^2$  statistic indicates 3 clusters.

The scatter plot for 3 clusters is shown. The results are shown in Output 23.2.4.

**Output 23.2.4.** Clusters for Birth and Death Rates: METHOD=COMPLETE

## Cluster Analysis of Birth and Death Rates

The CLUSTER Procedure  
Complete Linkage Cluster Analysis

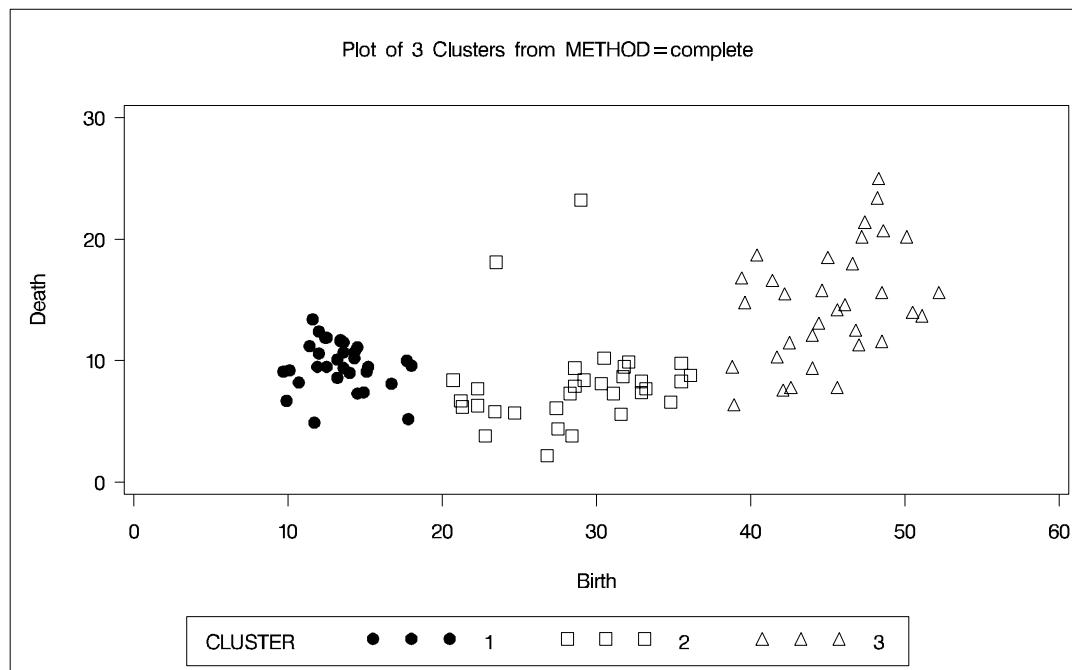
## Eigenvalues of the Covariance Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	189.106588	173.101020	0.9220	0.9220
2	16.005568		0.0780	1.0000

Root-Mean-Square Total-Sample Standard Deviation = 10.127  
Mean Distance Between Observations = 17.13099

## Cluster History

NCL	--Clusters Joined--		FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Norm Max Dist	T i e
15	CL22	CL33	8	0.0015	.983	.975	3.80	329	6.1	0.4092	
14	CL56	CL18	8	0.0014	.981	.972	3.97	331	6.6	0.4255	
13	CL30	CL44	8	0.0019	.979	.969	4.04	330	19.0	0.4332	
12	OB23	OB61	2	0.0014	.978	.966	4.45	340	.	0.4378	
11	CL19	CL24	24	0.0034	.974	.962	4.17	327	24.1	0.4962	
10	CL17	CL28	12	0.0033	.971	.957	4.18	325	14.8	0.5204	
9	CL20	CL13	16	0.0067	.964	.951	3.38	297	25.2	0.5236	
8	CL11	CL21	32	0.0054	.959	.943	3.44	297	19.7	0.6001	
7	CL26	CL15	13	0.0096	.949	.933	2.93	282	28.9	0.7233	
6	CL14	CL10	20	0.0128	.937	.920	2.46	269	27.7	0.8033	
5	CL9	CL16	30	0.0237	.913	.902	1.29	241	47.1	0.8993	
4	CL6	CL7	33	0.0240	.889	.875	1.38	248	21.7	1.2165	
3	CL5	CL12	32	0.0178	.871	.827	2.56	317	13.6	1.2326	
2	CL3		64	0.1900	.681	.697	- .55	203	167	1.5412	
1	CL2	CL4	97	0.6810	.000	.000	0.00	.	203	2.5233	

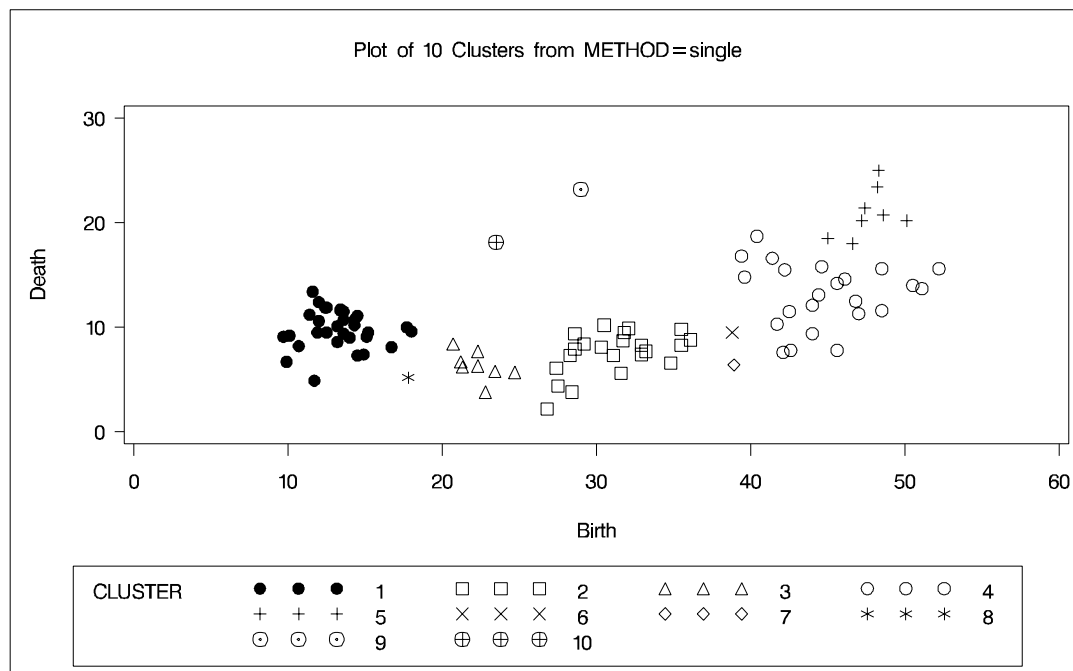
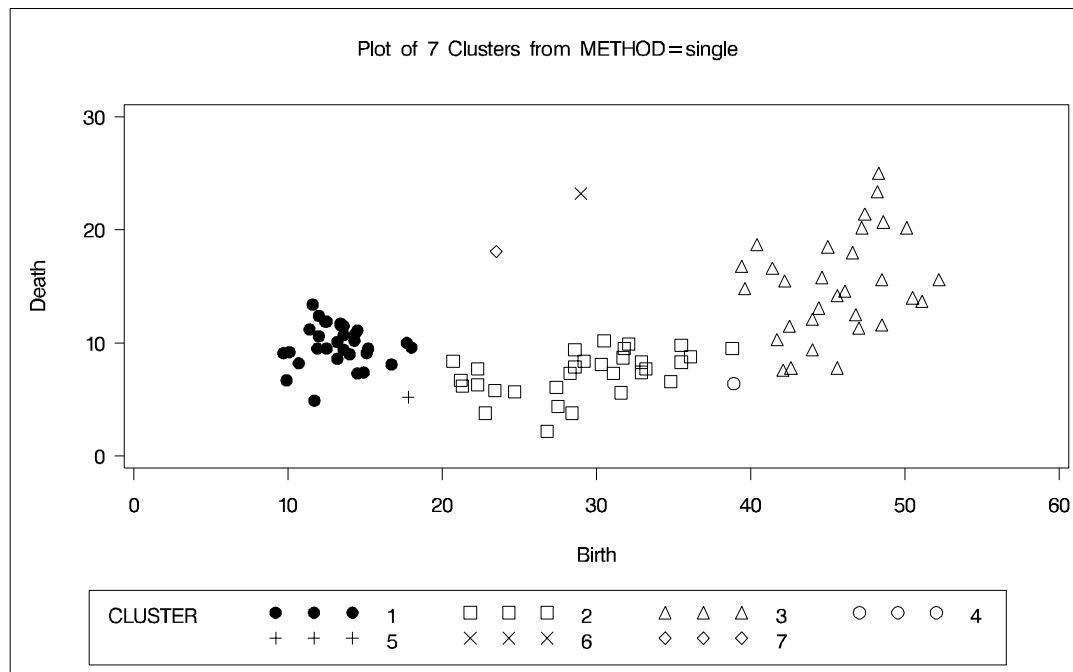


The CCC and pseudo  $F$  statistics are not appropriate for use with single linkage because of the method's tendency to chop off tails of distributions. The pseudo  $t^2$  statistic can be used by looking for *large* values and taking the number of clusters to be one greater than the level at which the large pseudo  $t^2$  value is displayed. For these data, there are large values at levels 6 and 9, suggesting 7 or 10 clusters.

The scatter plots for 7 and 10 clusters are shown. The results are shown in Output 23.2.5.

**Output 23.2.5.** Clusters for Birth and Death Rates: METHOD=SINGLE

Cluster Analysis of Birth and Death Rates											
The CLUSTER Procedure											
Single Linkage Cluster Analysis											
Eigenvalues of the Covariance Matrix											
			Eigenvalue	Difference	Proportion	Cumulative					
1			189.106588	173.101020	0.9220	0.9220					
2			16.005568		0.0780	1.0000					
Root-Mean-Square Total-Sample Standard Deviation = 10.127											
Mean Distance Between Observations = 17.13099											
Cluster History											
NCL	--Clusters Joined--		FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Norm Min Dist	T i e
15	CL37	CL19	8	0.0014	.968	.975	-2.3	178	6.6	0.1331	
14	CL20	CL23	15	0.0059	.962	.972	-3.1	162	18.7	0.1412	
13	CL14	CL16	19	0.0054	.957	.969	-3.4	155	8.8	0.1442	
12	CL26	OB58	31	0.0014	.955	.966	-2.7	165	4.0	0.1486	
11	OB86	CL18	4	0.0003	.955	.962	-1.6	183	3.8	0.1495	
10	CL13	CL11	23	0.0088	.946	.957	-2.3	170	11.3	0.1518	
9	CL22	CL17	30	0.0235	.923	.951	-4.7	131	45.7	0.1593	T
8	CL15	CL10	31	0.0210	.902	.943	-5.8	117	21.8	0.1593	
7	CL9	OB75	31	0.0052	.897	.933	-4.7	130	4.0	0.1628	
6	CL7	CL12	62	0.2023	.694	.920	-15	41.3	223	0.1725	
5	CL6	CL8	93	0.6681	.026	.902	-26	0.6	199	0.1756	
4	CL5	OB48	94	0.0056	.021	.875	-24	0.7	0.5	0.1811	T
3	CL4	OB67	95	0.0083	.012	.827	-15	0.6	0.8	0.1811	
2	OB23	OB61	2	0.0014	.011	.697	-13	1.0	.	0.4378	
1	CL3	CL2	97	0.0109	.000	.000	0.00	.	1.0	0.5815	



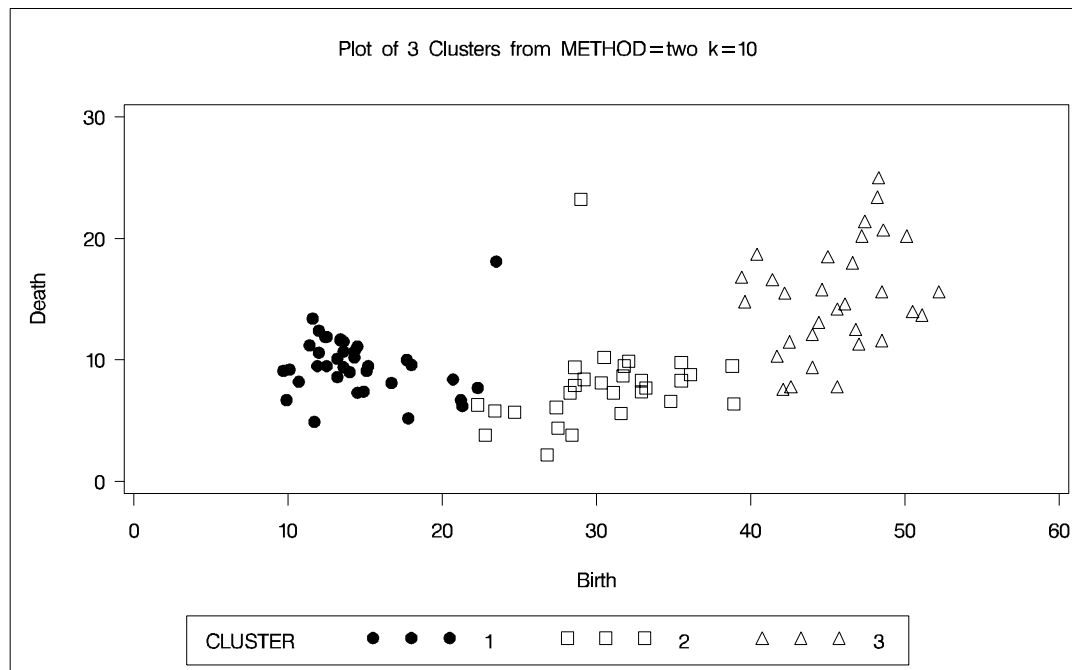
For  $k$ th-nearest-neighbor density linkage, the number of modes as a function of  $k$  is as follows (not all of these analyses are shown):

$k$	modes
3	13
4	6
5-7	4
8-15	3
16-21	2
22+	1

Thus, there is strong evidence of 3 modes and an indication of the possibility of 2 modes. Uniform-kernel density linkage gives similar results. For  $K=10$  (10th-nearest-neighbor density linkage), the scatter plot for 3 clusters is shown; and for  $K=18$ , the scatter plot for 2 clusters is shown. The results are shown in Output 23.2.6.

**Output 23.2.6.** Clusters for Birth and Death Rates: METHOD=TWOSTAGE,  $K=10$

Cluster Analysis of Birth and Death Rates												
The CLUSTER Procedure												
Two-Stage Density Linkage Clustering												
Eigenvalues of the Covariance Matrix												
		Eigenvalue	Difference	Proportion	Cumulative							
1		189.106588	173.101020	0.9220	0.9220							
2		16.005568		0.0780	1.0000							
K = 10												
Root-Mean-Square Total-Sample Standard Deviation =					10.127							
Cluster History												
NCL	--Clusters	Joined--	FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Normalized Fusion Density	Maximum Density in Each Cluster	T i e
										Lesser	Greater	
15	CL16	OB94	22	0.0015	.921	.975	-11	68.4	1.4	9.2234	6.7927	15.3069
14	CL19	OB49	28	0.0021	.919	.972	-11	72.4	1.8	8.7369	5.9334	33.4385
13	CL15	OB52	23	0.0024	.917	.969	-10	76.9	2.3	8.5847	5.9651	15.3069
12	CL13	OB96	24	0.0018	.915	.966	-9.3	83.0	1.6	7.9252	5.4724	15.3069
11	CL12	OB93	25	0.0025	.912	.962	-8.5	89.5	2.2	7.8913	5.4401	15.3069
10	CL11	OB78	26	0.0031	.909	.957	-7.7	96.9	2.5	7.787	5.4082	15.3069
9	CL10	OB76	27	0.0026	.907	.951	-6.7	107	2.1	7.7133	5.4401	15.3069
8	CL9	OB77	28	0.0023	.904	.943	-5.5	120	1.7	7.4256	4.9017	15.3069
7	CL8	OB43	29	0.0022	.902	.933	-4.1	138	1.6	6.927	4.4764	15.3069
6	CL7	OB87	30	0.0043	.898	.920	-2.7	160	3.1	4.932	2.9977	15.3069
5	CL6	OB82	31	0.0055	.892	.902	-1.1	191	3.7	3.7331	2.1560	15.3069
4	CL22	OB61	37	0.0079	.884	.875	0.93	237	10.6	3.1713	1.6308	100.0
3	CL14	OB23	29	0.0126	.872	.827	2.60	320	10.4	2.0654	1.0744	33.4385
2	CL4	CL3	66	0.2129	.659	.697	-1.3	183	172	12.409	33.4385	100.0
1	CL2	CL5	97	0.6588	.000	.000	0.00	.	183	10.071	15.3069	100.0
3 modal clusters have been formed.												

**Output 23.2.7.** Clusters for Birth and Death Rates: METHOD=TWOSTAGE, K=18

```

Cluster Analysis of Birth and Death Rates

The CLUSTER Procedure
Two-Stage Density Linkage Clustering

Eigenvalues of the Covariance Matrix

Eigenvalue    Difference    Proportion    Cumulative
1      189.106588    173.101020      0.9220      0.9220
2       16.005568      0.0780      0.0780      1.0000

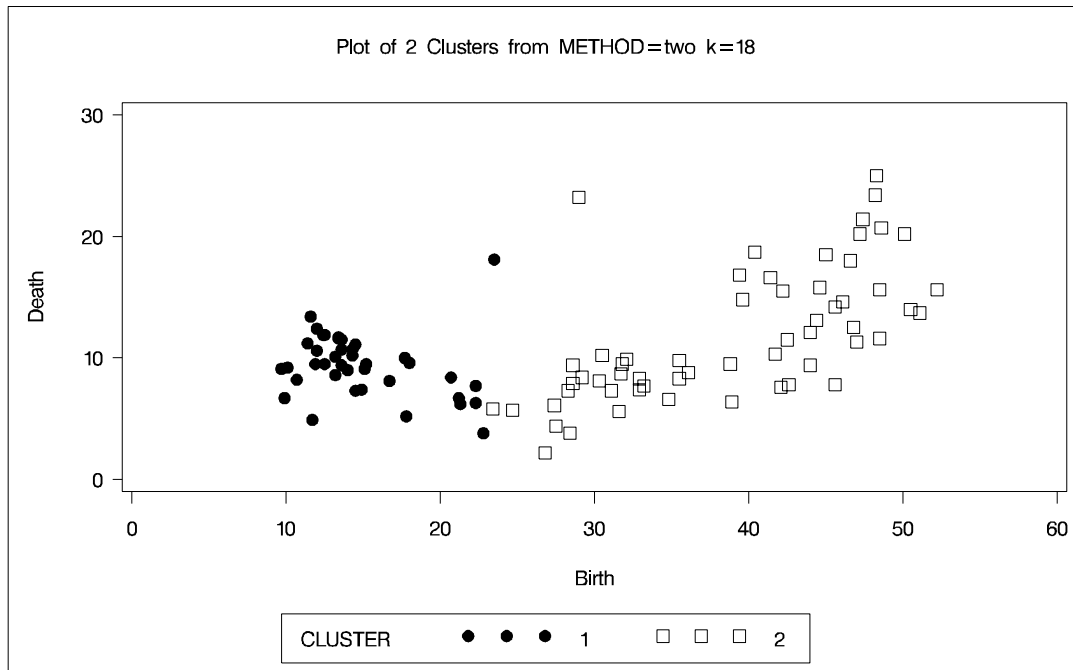
K = 18
Root-Mean-Square Total-Sample Standard Deviation = 10.127

```

Cluster History										Normalized Fusion Density	Maximum Density in Each Cluster		T i e
NCL	--Clusters	Joined--	FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2		Lesser	Greater	
15	CL16	OB72	46	0.0107	.799	.975	-21	23.3	3.0	10.118	7.7445	23.4457	T
14	CL15	OB94	47	0.0098	.789	.972	-21	23.9	2.7	9.676	7.1257	23.4457	
13	CL14	OB51	48	0.0037	.786	.969	-20	25.6	1.0	9.409	6.8398	23.4457	
12	CL13	OB96	49	0.0099	.776	.966	-19	26.7	2.6	9.409	6.8398	23.4457	
11	CL12	OB76	50	0.0114	.764	.962	-19	27.9	2.9	8.8136	6.3138	23.4457	
10	CL11	OB77	51	0.0021	.762	.957	-18	31.0	0.5	8.6593	6.0751	23.4457	
9	CL10	OB78	52	0.0103	.752	.951	-17	33.3	2.5	8.6007	6.0976	23.4457	
8	CL9	OB43	53	0.0034	.748	.943	-16	37.8	0.8	8.4964	5.9160	23.4457	
7	CL8	OB93	54	0.0109	.737	.933	-15	42.1	2.6	8.367	5.7913	23.4457	
6	CL7	OB88	55	0.0110	.726	.920	-13	48.3	2.6	7.916	5.3679	23.4457	
5	CL6	OB87	56	0.0120	.714	.902	-12	57.5	2.7	6.6917	4.3415	23.4457	T
4	CL20	OB61	39	0.0077	.707	.875	-9.8	74.7	8.3	6.2578	3.2882	100.0	
3	CL5	OB82	57	0.0138	.693	.827	-5.0	106	3.0	5.3605	3.2834	23.4457	
2	CL3	OB23	58	0.0117	.681	.697	-5.4	203	2.5	3.2687	1.7568	23.4457	
1	CL2	CL4	97	0.6812	.000	.000	0.00	.	203	13.764	23.4457	100.0	

2 modal clusters have been formed.





In summary, most of the clustering methods indicate 3 or 8 clusters. Most methods agree at the 3-cluster level, but at the other levels, there is considerable disagreement about the composition of the clusters. The presence of numerous ties also complicates the analysis; see Example 23.4.

### Example 23.3. Cluster Analysis of Fisher Iris Data

The iris data published by Fisher (1936) have been widely used for examples in discriminant analysis and cluster analysis. The sepal length, sepal width, petal length, and petal width are measured in millimeters on fifty iris specimens from each of three species, *Iris setosa*, *I. versicolor*, and *I. virginica*. Mezzich and Solomon (1980) discuss a variety of cluster analyses of the iris data.

This example analyzes the iris data by Ward's method and two-stage density linkage and then illustrates how the FASTCLUS procedure can be used in combination with PROC CLUSTER to analyze large data sets.

```

title 'Cluster Analysis of Fisher (1936) Iris Data';
proc format;
  value specname
    1='Setosa      '
    2='Versicolor'
    3='Virginica  ';
run;

data iris;
  input SepalLength SepalWidth PetalLength PetalWidth Species @@;
  format Species specname.;
  label SepalLength='Sepal Length in mm.'
```

```

        SepalWidth ='Sepal Width in mm.'
        PetalLength='Petal Length in mm.'
        PetalWidth  ='Petal Width in mm.';
    symbol = put(species, specname10.);
    datalines;
50 33 14 02 1 64 28 56 22 3 65 28 46 15 2 67 31 56 24 3
63 28 51 15 3 46 34 14 03 1 69 31 51 23 3 62 22 45 15 2
59 32 48 18 2 46 36 10 02 1 61 30 46 14 2 60 27 51 16 2
65 30 52 20 3 56 25 39 11 2 65 30 55 18 3 58 27 51 19 3
68 32 59 23 3 51 33 17 05 1 57 28 45 13 2 62 34 54 23 3
77 38 67 22 3 63 33 47 16 2 67 33 57 25 3 76 30 66 21 3
49 25 45 17 3 55 35 13 02 1 67 30 52 23 3 70 32 47 14 2
64 32 45 15 2 61 28 40 13 2 48 31 16 02 1 59 30 51 18 3
55 24 38 11 2 63 25 50 19 3 64 32 53 23 3 52 34 14 02 1
49 36 14 01 1 54 30 45 15 2 79 38 64 20 3 44 32 13 02 1
67 33 57 21 3 50 35 16 06 1 58 26 40 12 2 44 30 13 02 1
77 28 67 20 3 63 27 49 18 3 47 32 16 02 1 55 26 44 12 2
50 23 33 10 2 72 32 60 18 3 48 30 14 03 1 51 38 16 02 1
61 30 49 18 3 48 34 19 02 1 50 30 16 02 1 50 32 12 02 1
61 26 56 14 3 64 28 56 21 3 43 30 11 01 1 58 40 12 02 1
51 38 19 04 1 67 31 44 14 2 62 28 48 18 3 49 30 14 02 1
51 35 14 02 1 56 30 45 15 2 58 27 41 10 2 50 34 16 04 1
46 32 14 02 1 60 29 45 15 2 57 26 35 10 2 57 44 15 04 1
50 36 14 02 1 77 30 61 23 3 63 34 56 24 3 58 27 51 19 3
57 29 42 13 2 72 30 58 16 3 54 34 15 04 1 52 41 15 01 1
71 30 59 21 3 64 31 55 18 3 60 30 48 18 3 63 29 56 18 3
49 24 33 10 2 56 27 42 13 2 57 30 42 12 2 55 42 14 02 1
49 31 15 02 1 77 26 69 23 3 60 22 50 15 3 54 39 17 04 1
66 29 46 13 2 52 27 39 14 2 60 34 45 16 2 50 34 15 02 1
44 29 14 02 1 50 20 35 10 2 55 24 37 10 2 58 27 39 12 2
47 32 13 02 1 46 31 15 02 1 69 32 57 23 3 62 29 43 13 2
74 28 61 19 3 59 30 42 15 2 51 34 15 02 1 50 35 13 03 1
56 28 49 20 3 60 22 40 10 2 73 29 63 18 3 67 25 58 18 3
49 31 15 01 1 67 31 47 15 2 63 23 44 13 2 54 37 15 02 1
56 30 41 13 2 63 25 49 15 2 61 28 47 12 2 64 29 43 13 2
51 25 30 11 2 57 28 41 13 2 65 30 58 22 3 69 31 54 21 3
54 39 13 04 1 51 35 14 03 1 72 36 61 25 3 65 32 51 20 3
61 29 47 14 2 56 29 36 13 2 69 31 49 15 2 64 27 53 19 3
68 30 55 21 3 55 25 40 13 2 48 34 16 02 1 48 30 14 01 1
45 23 13 03 1 57 25 50 20 3 57 38 17 03 1 51 38 15 03 1
55 23 40 13 2 66 30 44 14 2 68 28 48 14 2 54 34 17 02 1
51 37 15 04 1 52 35 15 02 1 58 28 51 24 3 67 30 50 17 2
63 33 60 25 3 53 37 15 02 1
;

```

The following macro, SHOW, is used in the subsequent analyses to display cluster results. It invokes the FREQ procedure to crosstabulate clusters and species. The CANDISC procedure computes canonical variables for discriminating among the clusters, and the first two canonical variables are plotted to show cluster membership. See Chapter 21, “The CANDISC Procedure,” for a canonical discriminant analysis of the iris species.

```

%macro show;
proc freq;
    tables cluster*species;
run;
proc candisc noprint out=can;
    class cluster;
    var petal: sepal;;
run;
legend1 frame cframe=ligr cborder=black
    position=center value=(justify=center);
axis1 label=(angle=90 rotate=0) minor=none;
axis2 minor=none;
proc gplot;
    plot can2*can1=cluster /
        frame cframe=ligr legend=legend1 vaxis=axis1 haxis=axis2;
run;
%mend;

```

The first analysis clusters the iris data by Ward's method and plots the CCC and pseudo  $F$  and  $t^2$  statistics. The CCC has a local peak at 3 clusters but a higher peak at 5 clusters. The pseudo  $F$  statistic indicates 3 clusters, while the pseudo  $t^2$  statistic suggests 3 or 6 clusters. For large numbers of clusters, Version 6 of the SAS System produces somewhat different results than previous versions of PROC CLUSTER. This is due to changes in the treatment of ties. Results are identical for 5 or fewer clusters.

The TREE procedure creates an output data set containing the 3-cluster partition for use by the SHOW macro. The FREQ procedure reveals 16 misclassifications. The results are shown in Output 23.3.1.

```

title2 'By Ward''s Method';
proc cluster data=iris method=ward print=15 ccc pseudo;
    var petal: sepal;;
    copy species;
run;
legend1 frame cframe=ligr cborder=black
    position=center value=(justify=center);
axis1 label=(angle=90 rotate=0) minor=none order=(0 to 600 by 100);
axis2 minor=none order=(1 to 30 by 1);
axis3 label=(angle=90 rotate=0) minor=none order=(0 to 7 by 1);
proc gplot;
    plot _ccc*_ncl_ /
        frame cframe=ligr legend=legend1 vaxis=axis3 haxis=axis2;
    plot _psf*_ncl_ _pst2*_ncl_ /overlay
        frame cframe=ligr legend=legend1 vaxis=axis1 haxis=axis2;
run;

proc tree noprint ncl=3 out=out;
    copy petal: sepal: species;
run;

%show;

```

**Output 23.3.1.** Cluster Analysis of Fisher Iris Data: CLUSTER with  
METHOD=WARD

Cluster Analysis of Fisher (1936) Iris Data  
By Ward's Method

The CLUSTER Procedure  
Ward's Minimum Variance Cluster Analysis

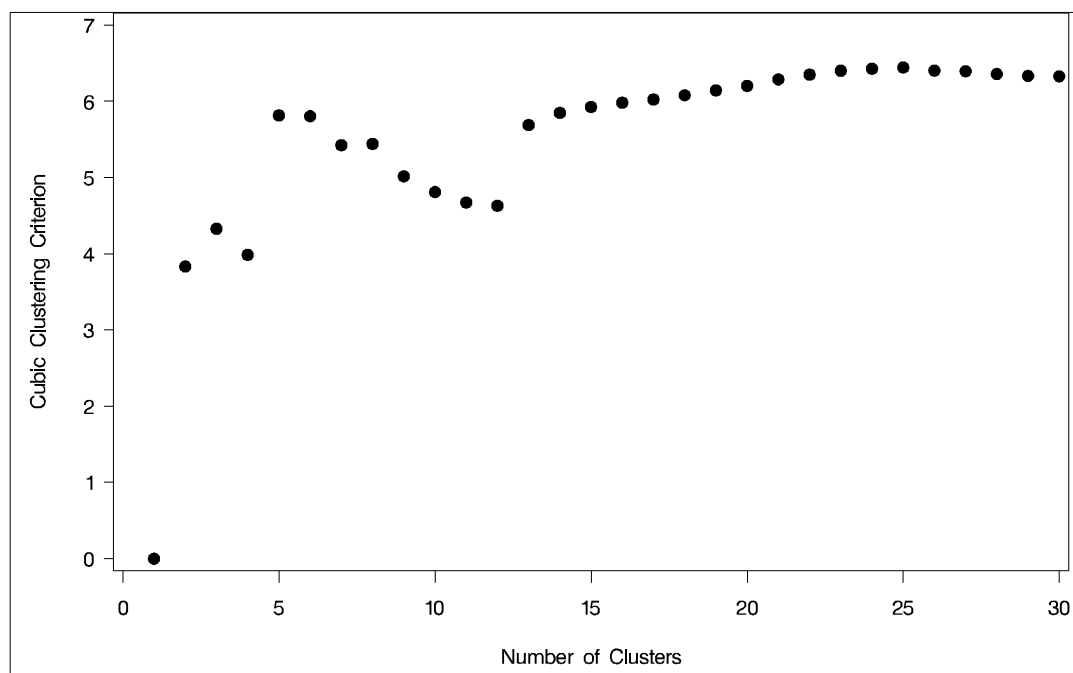
Eigenvalues of the Covariance Matrix

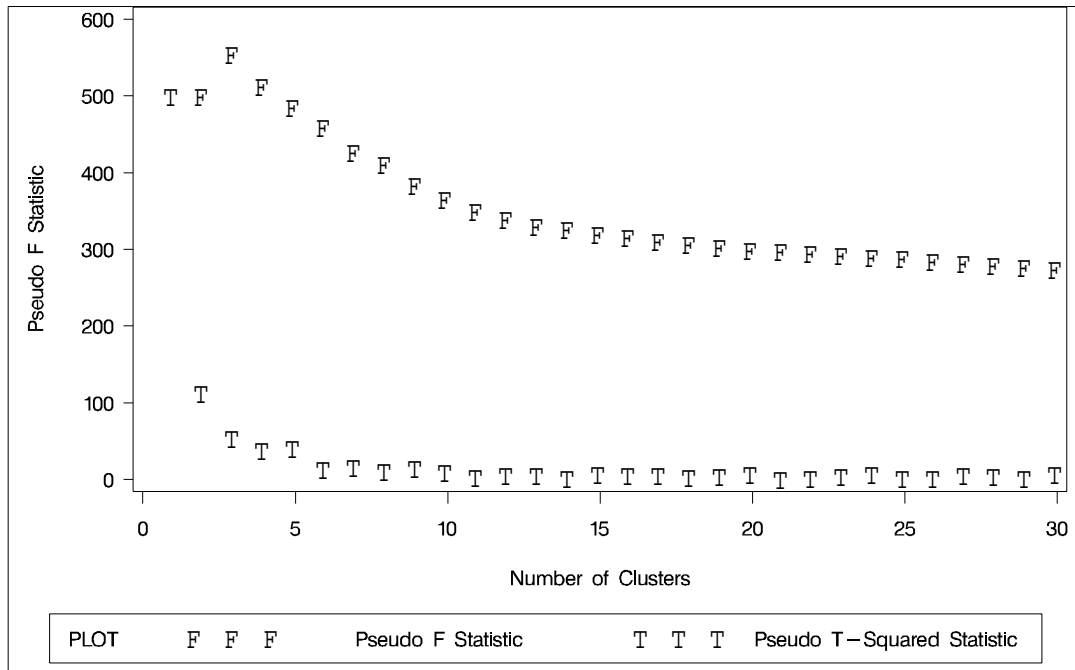
	Eigenvalue	Difference	Proportion	Cumulative
1	422.824171	398.557096	0.9246	0.9246
2	24.267075	16.446125	0.0531	0.9777
3	7.820950	5.437441	0.0171	0.9948
4	2.383509		0.0052	1.0000

Root-Mean-Square Total-Sample Standard Deviation = 10.69224  
Root-Mean-Square Distance Between Observations = 30.24221

Cluster History

NCL	--Clusters Joined--		FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	T i e
15	CL24	CL28	15	0.0016	.971	.958	5.93	324	9.8	
14	CL21	CL53	7	0.0019	.969	.955	5.85	329	5.1	
13	CL18	CL48	15	0.0023	.967	.953	5.69	334	8.9	
12	CL16	CL23	24	0.0023	.965	.950	4.63	342	9.6	
11	CL14	CL43	12	0.0025	.962	.946	4.67	353	5.8	
10	CL26	CL20	22	0.0027	.959	.942	4.81	368	12.9	
9	CL27	CL17	31	0.0031	.956	.936	5.02	387	17.8	
8	CL35	CL15	23	0.0031	.953	.930	5.44	414	13.8	
7	CL10	CL47	26	0.0058	.947	.921	5.43	430	19.1	
6	CL8	CL13	38	0.0060	.941	.911	5.81	463	16.3	
5	CL9	CL19	50	0.0105	.931	.895	5.82	488	43.2	
4	CL12	CL11	36	0.0172	.914	.872	3.99	515	41.0	
3	CL6	CL7	64	0.0301	.884	.827	4.33	558	57.2	
2	CL4	CL3	100	0.1110	.773	.697	3.83	503	116	
1	CL5	CL2	150	0.7726	.000	.000	0.00	.	503	



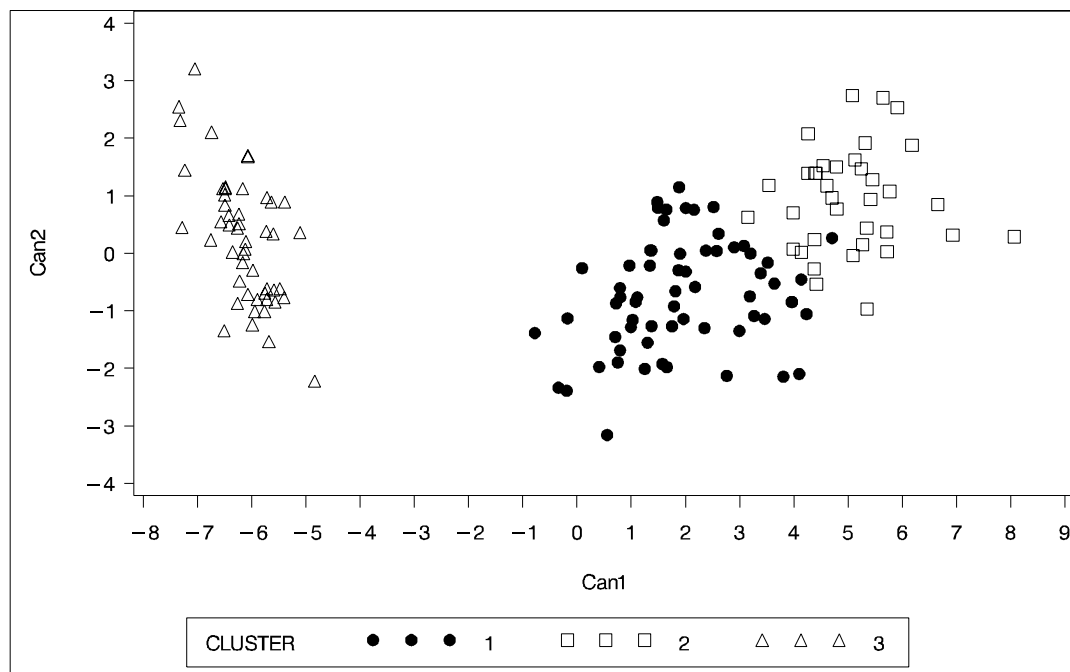


# Cluster Analysis of Fisher (1936) Iris Data

## The FREQ Procedure

### Table of CLUSTER by Species

CLUSTER		Species			
Frequency	Percent				
Row Pct	Col Pct	Setosa	Versicol or	Virginic a	Total
1		0	49	15	64
		0.00	32.67	10.00	42.67
		0.00	76.56	23.44	
		0.00	98.00	30.00	
2		0	1	35	36
		0.00	0.67	23.33	24.00
		0.00	2.78	97.22	
		0.00	2.00	70.00	
3		50	0	0	50
		33.33	0.00	0.00	33.33
		100.00	0.00	0.00	
		100.00	0.00	0.00	
Total		50	50	50	150
		33.33	33.33	33.33	100.00



The second analysis uses two-stage density linkage. The raw data suggest 2 or 6 modes instead of 3:

<i>k</i>	modes
3	12
4-6	6
7	4
8	3
9-50	2
51+	1

However, the ACECLUS procedure can be used to reveal 3 modes. This analysis uses  $K=8$  to produce 3 clusters for comparison with other analyses. There are only 6 misclassifications. The results are shown in Output 23.3.2.

```

title2 'By Two-Stage Density Linkage';
proc cluster data=iris method=twostage k=8 print=15 ccc pseudo;
  var petal: sepal;;
  copy species;
run;

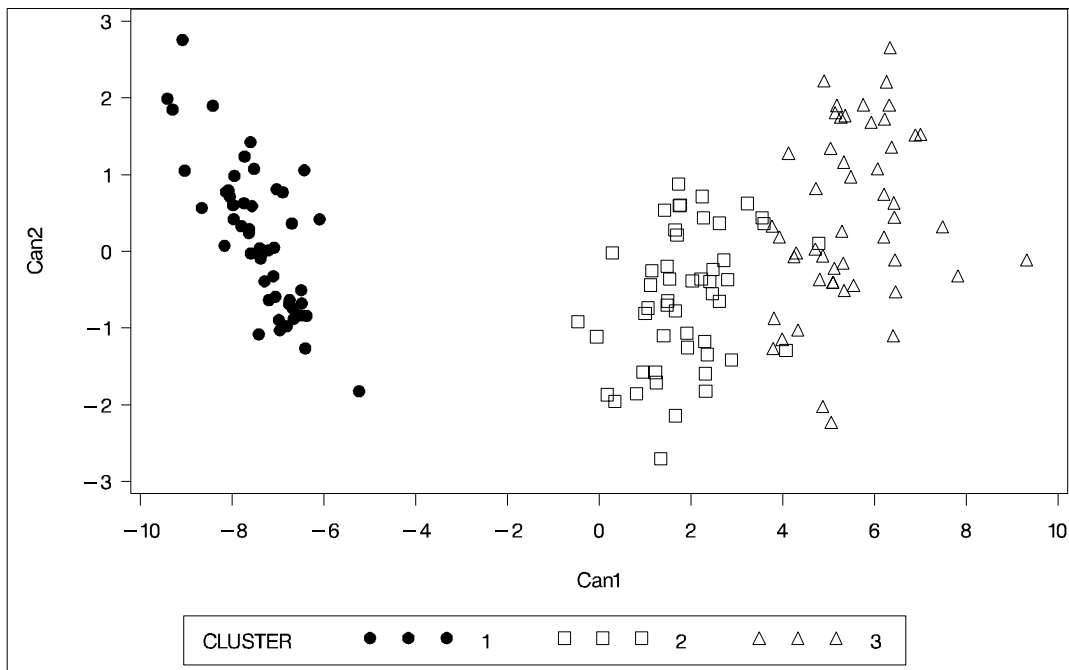
proc tree noprint ncl=3 out=out;
  copy petal: sepal: species;
run;

%show;
```

**Output 23.3.2.** Cluster Analysis of Fisher Iris Data: CLUSTER with METHOD=TWOSTAGE

Cluster Analysis of Fisher (1936) Iris Data													
By Two-Stage Density Linkage													
The CLUSTER Procedure													
Two-Stage Density Linkage Clustering													
Eigenvalues of the Covariance Matrix													
			Eigenvalue	Difference	Proportion	Cumulative							
	1		422.824171	398.557096	0.9246	0.9246							
	2		24.267075	16.446125	0.0531	0.9777							
	3		7.820950	5.437441	0.0171	0.9948							
	4		2.383509		0.0052	1.0000							
K = 8													
Root-Mean-Square Total-Sample Standard Deviation = 10.69224													
Cluster History													
NCL	--Clusters Joined--		FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Normalized Fusion Density	Maximum Density in Each Cluster	T i e	
											Lesser	Greater	
15	CL17	OB127	44	0.0025	.916	.958	-11	105	3.4	0.3903	0.2066	3.5156	
14	CL16	OB137	50	0.0023	.913	.955	-11	110	5.6	0.3637	0.1837	100.0	
13	CL15	OB74	45	0.0029	.910	.953	-10	116	3.7	0.3553	0.2130	3.5156	
12	CL28	OB49	46	0.0036	.907	.950	-8.0	122	5.2	0.3223	0.1736	8.3678	T
11	CL12	OB85	47	0.0036	.903	.946	-7.6	130	4.8	0.3223	0.1736	8.3678	
10	CL11	OB98	48	0.0033	.900	.942	-7.1	140	4.1	0.2879	0.1479	8.3678	
9	CL13	OB24	46	0.0037	.896	.936	-6.5	152	4.4	0.2802	0.2005	3.5156	
8	CL10	OB25	49	0.0019	.894	.930	-5.5	171	2.2	0.2699	0.1372	8.3678	
7	CL8	OB121	50	0.0035	.891	.921	-4.5	194	4.0	0.2586	0.1372	8.3678	
6	CL9	OB45	47	0.0042	.886	.911	-3.3	225	4.6	0.1412	0.0832	3.5156	
5	CL6	OB39	48	0.0049	.882	.895	-1.7	270	5.0	0.107	0.0605	3.5156	
4	CL5	OB21	49	0.0049	.877	.872	0.35	346	4.7	0.0969	0.0541	3.5156	
3	CL4	OB90	50	0.0047	.872	.827	3.28	500	4.1	0.0715	0.0370	3.5156	
2	CL3	CL7	100	0.0993	.773	.697	3.83	503	91.9	2.6277	3.5156	8.3678	
3 modal clusters have been formed.													

Cluster Analysis of Fisher (1936) Iris Data					
The FREQ Procedure					
Table of CLUSTER by Species					
CLUSTER	Species				
Frequency					
Percent					
Row Pct					
Col Pct	Setosa	Versicol or	Virginic a	Total	
1	50	0	0	50	
	33.33	0.00	0.00	33.33	
	100.00	0.00	0.00		
	100.00	0.00	0.00		
2	0	47	3	50	
	0.00	31.33	2.00	33.33	
	0.00	94.00	6.00		
	0.00	94.00	6.00		
3	0	3	47	50	
	0.00	2.00	31.33	33.33	
	0.00	6.00	94.00		
	0.00	6.00	94.00		
Total	50	50	50	150	
	33.33	33.33	33.33	100.00	



The CLUSTER procedure is not practical for very large data sets because, with most methods, the CPU time varies as the square or cube of the number of observations. The FASTCLUS procedure requires time proportional to the number of observations and can, therefore, be used with much larger data sets than PROC CLUSTER. If you want to hierarchically cluster a very large data set, you can use PROC FASTCLUS for a preliminary cluster analysis producing a large number of clusters and then use PROC CLUSTER to hierarchically cluster the preliminary clusters.

FASTCLUS automatically creates variables `_FREQ_` and `_RMSSTD_` in the `MEAN=` output data set. These variables are then automatically used by PROC CLUSTER in the computation of various statistics.

The iris data are used to illustrate the process of clustering clusters. In the preliminary analysis, PROC FASTCLUS produces ten clusters, which are then crosstabulated with species. The data set containing the preliminary clusters is sorted in preparation for later merges. The results are shown in Output 23.3.3.

```

title2 'Preliminary Analysis by FASTCLUS';
proc fastclus data=iris summary maxc=10 maxiter=99 converge=0
    mean=mean out=prelim cluster=preclus;
    var petal: sepal;;
run;

proc freq;
    tables preclus*species;
run;

proc sort data=prelim;
    by preclus;
run;

```



**Output 23.3.3.** Preliminary Analysis of Fisher Iris Data

Cluster Analysis of Fisher (1936) Iris Data						
Preliminary Analysis by FASTCLUS						
The FASTCLUS Procedure						
Replace=FULL Radius=0 Maxclusters=10 Maxiter=99 Converge=0						
Cluster Summary						
Cluster	Frequency	RMS Std Deviation	Maximum Distance from Seed to Observation	Radius Exceeded	Nearest Cluster	Distance Between Cluster Centroids
1	9	2.7067	8.2027		5	8.7362
2	19	2.2001	7.7340		4	6.2243
3	18	2.1496	6.2173		8	7.5049
4	4	2.5249	5.3268		2	6.2243
5	3	2.7234	5.8214		1	8.7362
6	7	2.2939	5.1508		2	9.3318
7	17	2.0274	6.9576		10	7.9503
8	18	2.2628	7.1135		3	7.5049
9	22	2.2666	7.5029		8	9.0090
10	33	2.0594	10.0033		7	7.9503
Pseudo F Statistic = 370.58						
Observed Over-All R-Squared = 0.95971						
Approximate Expected Over-All R-Squared = 0.82928						
Cubic Clustering Criterion = 27.077						
WARNING: The two values above are invalid for correlated variables.						

Cluster Analysis of Fisher (1936) Iris Data  
Preliminary Analysis by FASTCLUS

The FREQ Procedure

Table of PRECLUS by Species

PRECLUS(Cluster)		Species		
Frequency	Percent			
Row Pct	Col Pct	Setosa	Versicol or	Virginic a
1	0	0	9	9
	0.00	0.00	6.00	6.00
	0.00	0.00	100.00	
	0.00	0.00	18.00	
2	0	19	0	19
	0.00	12.67	0.00	12.67
	0.00	100.00	0.00	
	0.00	38.00	0.00	
3	0	18	0	18
	0.00	12.00	0.00	12.00
	0.00	100.00	0.00	
	0.00	36.00	0.00	
4	0	3	1	4
	0.00	2.00	0.67	2.67
	0.00	75.00	25.00	
	0.00	6.00	2.00	
5	0	0	3	3
	0.00	0.00	2.00	2.00
	0.00	0.00	100.00	
	0.00	0.00	6.00	
6	0	7	0	7
	0.00	4.67	0.00	4.67
	0.00	100.00	0.00	
	0.00	14.00	0.00	
7	17	0	0	17
	11.33	0.00	0.00	11.33
	100.00	0.00	0.00	
	34.00	0.00	0.00	
8	0	3	15	18
	0.00	2.00	10.00	12.00
	0.00	16.67	83.33	
	0.00	6.00	30.00	
9	0	0	22	22
	0.00	0.00	14.67	14.67
	0.00	0.00	100.00	
	0.00	0.00	44.00	
10	33	0	0	33
	22.00	0.00	0.00	22.00
	100.00	0.00	0.00	
	66.00	0.00	0.00	
Total	50	50	50	150
	33.33	33.33	33.33	100.00

The following macro, CLUS, clusters the preliminary clusters. There is one argument to choose the METHOD= specification to be used by PROC CLUSTER. The TREE procedure creates an output data set containing the 3-cluster partition, which is sorted and merged with the OUT= data set from PROC FASTCLUS to determine to which cluster each of the original 150 observations belongs. The SHOW macro is then used to display the results. In this example, the CLUS macro is invoked using

Ward's method, which produces 16 misclassifications, and Wong's hybrid method, which produces 22 misclassifications. The results are shown in Output 23.3.4 and Output 23.3.5.

```
%macro clus(method);
proc cluster data=mean method=&method ccc pseudo;
  var petal: sepal;;
  copy preclus;
run;
proc tree noprint ncl=3 out=out;
  copy petal: sepal: preclus;
run;
proc sort data=out;
  by preclus;
run;
data clus;
  merge prelim out;
  by preclus;
run;
%show;
%mend;

title2 'Clustering Clusters by Ward''s Method';
%clus(ward);

title2 'Clustering Clusters by Wong''s Hybrid Method';
%clus(twostage hybrid);
```

Output 23.3.4. Clustering Clusters: with Ward's Method

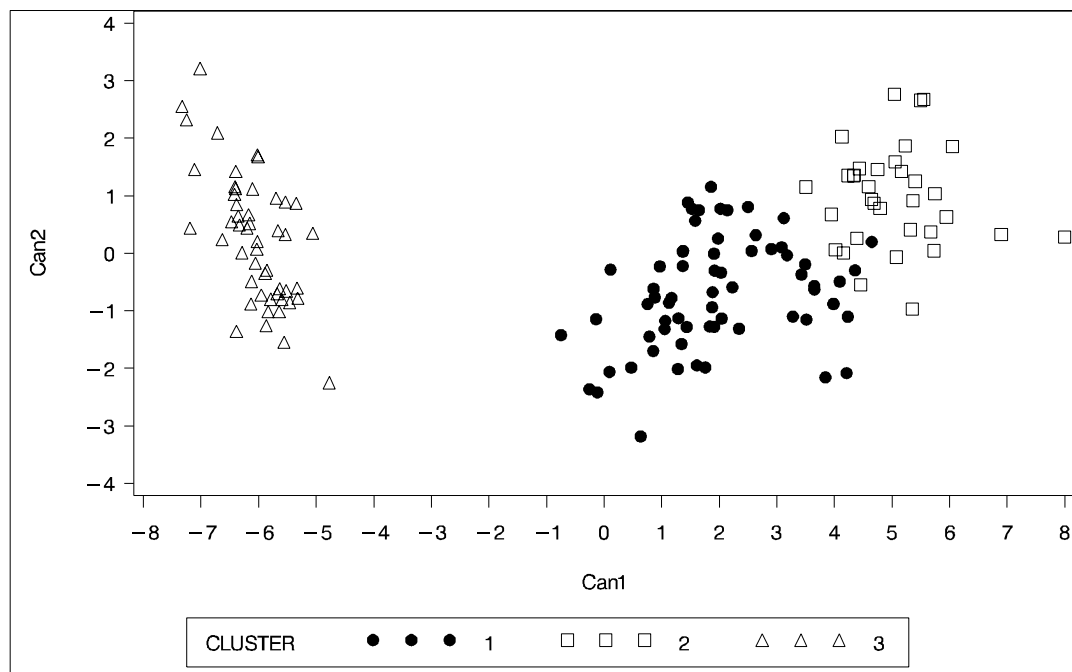
Cluster Analysis of Fisher (1936) Iris Data									
Clustering Clusters by Ward's Method									
The CLUSTER Procedure									
Ward's Minimum Variance Cluster Analysis									
Eigenvalues of the Covariance Matrix									
	Eigenvalue		Difference		Proportion		Cumulative		
1	416.976349		398.666421		0.9501		0.9501		
2	18.309928		14.952922		0.0417		0.9918		
3	3.357006		3.126943		0.0076		0.9995		
4	0.230063				0.0005		1.0000		
Root-Mean-Square Total-Sample Standard Deviation = 10.69224									
Root-Mean-Square Distance Between Observations = 30.24221									
Cluster History									
NCL	--Clusters Joined--		FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2
9	OB2	OB4	23	0.0019	.958	.932	6.26	400	6.3
8	OB1	OB5	12	0.0025	.955	.926	6.75	434	5.8
7	CL9	OB6	30	0.0069	.948	.918	6.28	438	19.5
6	OB3	OB8	36	0.0074	.941	.907	6.21	459	26.0
5	OB7	OB10	50	0.0104	.931	.892	6.15	485	42.2
4	CL8	OB9	34	0.0162	.914	.870	4.28	519	39.3
3	CL7	CL6	66	0.0318	.883	.824	4.39	552	59.7
2	CL4	CL3	100	0.1099	.773	.695	3.94	503	113
1	CL2	CL5	150	0.7726	.000	.000	0.00	.	503

## Cluster Analysis of Fisher (1936) Iris Data

## The FREQ Procedure

## Table of CLUSTER by Species

CLUSTER	Species			Total
	Setosa	Versicol or	Virginic a	
1	0	50	16	66
	0.00	33.33	10.67	44.00
	0.00	75.76	24.24	
	0.00	100.00	32.00	
2	0	0	34	34
	0.00	0.00	22.67	22.67
	0.00	0.00	100.00	
	0.00	0.00	68.00	
3	50	0	0	50
	33.33	0.00	0.00	33.33
	100.00	0.00	0.00	
	100.00	0.00	0.00	
Total	50	50	50	150
	33.33	33.33	33.33	100.00



## Output 23.3.5. Clustering Clusters: PROC CLUSTER with Wong's Hybrid Method

```

Cluster Analysis of Fisher (1936) Iris Data
Clustering Clusters by Wong's Hybrid Method

The CLUSTER Procedure
Two-Stage Density Linkage Clustering

Eigenvalues of the Covariance Matrix

Eigenvalue    Difference    Proportion    Cumulative
1    416.976349    398.666421    0.9501    0.9501
2    18.309928    14.952922    0.0417    0.9918
3     3.357006     3.126943    0.0076    0.9995
4     0.230063     0.0005    0.0005    1.0000
Root-Mean-Square Total-Sample Standard Deviation = 10.69224

```

```

Cluster History

Normalized      Maximum Density      T
Fusion          in Each Cluster      i
Density          Lesser      Greater      e

NCL  --Clusters Joined--  FREQ  SPRSQ  RSQ  ERSQ  CCC  PSF  PST2  Normalized      Maximum Density      T
                                FREQ  SPRSQ  RSQ  ERSQ  CCC  PSF  PST2  Density          Lesser      Greater      e

9  OB10  OB7          50  0.0104  .949  .932  3.81  330  42.2    40.24  58.2179    100.0
8  OB3   OB8          36  0.0074  .942  .926  3.22  329  26.0    27.981  39.4511    48.4350
7  OB2   OB4          23  0.0019  .940  .918  4.24  373   6.3    23.775   8.9675    46.3026
6  CL8   OB9          58  0.0194  .921  .907  2.13  334  46.3    20.724  46.8846    48.4350
5  CL7   OB6          30  0.0069  .914  .892  3.09  383  19.5    13.303  17.6360    46.3026
4  CL6   OB1          67  0.0292  .884  .870  1.21  372  41.0    8.4137  10.8758    48.4350
3  CL4   OB5          70  0.0138  .871  .824  3.33  494  12.3    5.1855   6.2890    48.4350
2  CL3   CL5         100  0.0979  .773  .695  3.94  503  89.5    19.513  46.3026    48.4350
1  CL2   CL9         150  0.7726  .000  .000  0.00   .  503    1.3337  48.4350    100.0

3 modal clusters have been formed.

```

## Cluster Analysis of Fisher (1936) Iris Data

## The FREQ Procedure

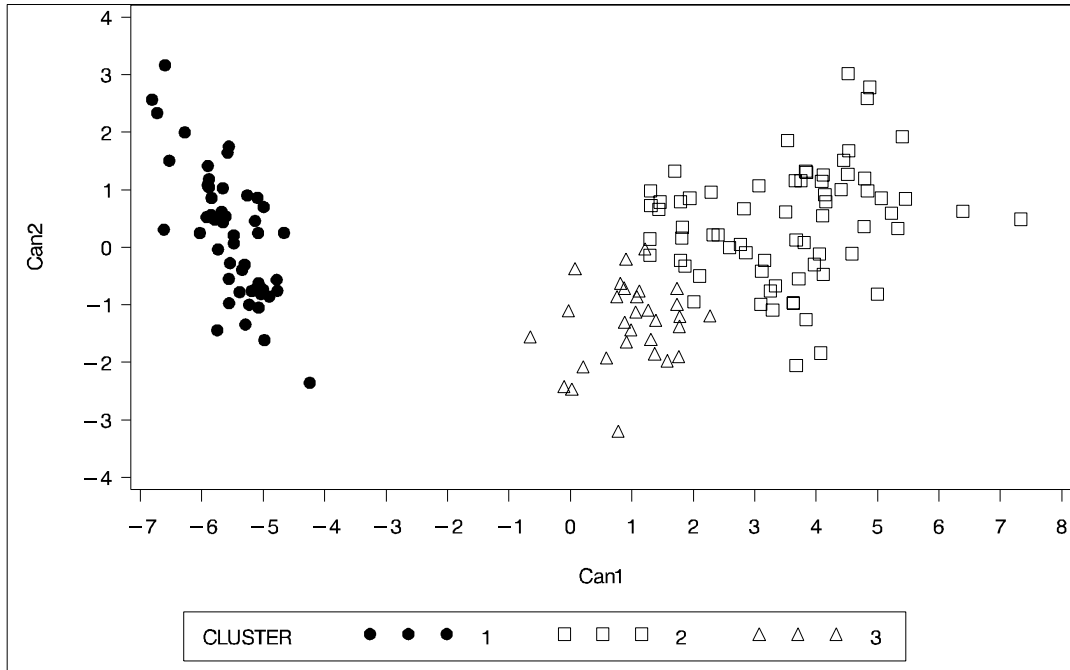
## Table of CLUSTER by Species

```

CLUSTER      Species

Frequency|
Percent  |
Row Pct  |
Col Pct  |Setosa  |Versicol|Virginic| Total
          |   or   |   a    |
-----+-----+-----+-----+
1 |          50 |          0 |          0 |          50
  |          33.33 |          0.00 |          0.00 |          33.33
  |          100.00 |          0.00 |          0.00 |
  |          100.00 |          0.00 |          0.00 |
-----+-----+-----+-----+
2 |          0 |          21 |          49 |          70
  |          0.00 |          14.00 |          32.67 |          46.67
  |          0.00 |          30.00 |          70.00 |
  |          0.00 |          42.00 |          98.00 |
-----+-----+-----+-----+
3 |          0 |          29 |          1 |          30
  |          0.00 |          19.33 |          0.67 |          20.00
  |          0.00 |          96.67 |          3.33 |
  |          0.00 |          58.00 |          2.00 |
-----+-----+-----+-----+
Total |          50 |          50 |          50 |          150
      |          33.33 |          33.33 |          33.33 |          100.00

```



### Example 23.4. Evaluating the Effects of Ties

If, at some level of the cluster history, there is a tie for minimum distance between clusters, then one or more levels of the sample cluster tree are not uniquely determined. This example shows how the degree of indeterminacy can be assessed.

Mammals have four kinds of teeth: incisors, canines, premolars, and molars. The following data set gives the number of teeth of each kind on one side of the top and bottom jaws for 32 mammals.

Since all eight variables are measured in the same units, it is not strictly necessary to rescale the data. However, the canines have much less variance than the other kinds of teeth and, therefore, have little effect on the analysis if the variables are not standardized. An average linkage cluster analysis is run with and without standardization to allow comparison of the results. The results are shown in Output 23.4.1 and Output 23.4.2.

```

title 'Hierarchical Cluster Analysis of Mammals'' Teeth Data';
title2 'Evaluating the Effects of Ties';
data teeth;
  input mammal $ 1-16
    @21 (v1-v8) (1.);
  label v1='Top incisors'
    v2='Bottom incisors'
    v3='Top canines'
    v4='Bottom canines'
    v5='Top premolars'
    v6='Bottom premolars'
    v7='Top molars'
    v8='Bottom molars';

```

```

      datalines;
BROWN BAT      23113333
MOLE            32103333
SILVER HAIR BAT 23112333
PIGMY BAT      23112233
HOUSE BAT      23111233
RED BAT        13112233
PIKA           21002233
RABBIT         21003233
BEAVER         11002133
GROUNDHOG      11002133
GRAY SQUIRREL  11001133
HOUSE MOUSE    11000033
PORCUPINE      11001133
WOLF           33114423
BEAR           33114423
RACCOON        33114432
MARTEN         33114412
WEASEL         33113312
WOLVERINE      33114412
BADGER         33113312
RIVER OTTER    33114312
SEA OTTER      32113312
JAGUAR         33113211
COUGAR         33113211
FUR SEAL       32114411
SEA LION       32114411
GREY SEAL      32113322
ELEPHANT SEAL  21114411
REINDEER       04103333
ELK            04103333
DEER           04003333
MOOSE          04003333
;

proc cluster data=teeth method=average nonorm
              outtree=_null_;
  var v1-v8;
  id mammal;
  title3 'Raw Data';
run;

proc cluster data=teeth std method=average nonorm
              outtree=_null_;
  var v1-v8;
  id mammal;
  title3 'Standardized Data';
run;

```

## Output 23.4.1. Average Linkage Analysis of Mammals' Teeth Data: Raw Data

Hierarchical Cluster Analysis of Mammals' Teeth Data  
Evaluating the Effects of Ties  
Raw Data

The CLUSTER Procedure  
Average Linkage Cluster Analysis

Eigenvalues of the Covariance Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	3.76799365	2.33557185	0.5840	0.5840
2	1.43242180	0.91781899	0.2220	0.8061
3	0.51460281	0.08414950	0.0798	0.8858
4	0.43045331	0.30021485	0.0667	0.9525
5	0.13023846	0.03814626	0.0202	0.9727
6	0.09209220	0.04216914	0.0143	0.9870
7	0.04992305	0.01603541	0.0077	0.9947
8	0.03388764		0.0053	1.0000

Root-Mean-Square Total-Sample Standard Deviation = 0.898027

Cluster History

Cluster History				T i e	
NCL	-----Clusters Joined-----		FREQ	RMS Dist	
31	BEAVER	GROUNDHOG	2	0	T
30	GRAY SQUIRREL	PORCUPINE	2	0	T
29	WOLF	BEAR	2	0	T
28	MARTEN	WOLVERINE	2	0	T
27	WEASEL	BADGER	2	0	T
26	JAGUAR	COUGAR	2	0	T
25	FUR SEAL	SEA LION	2	0	T
24	REINDEER	ELK	2	0	T
23	DEER	MOOSE	2	0	
22	BROWN BAT	SILVER HAIR BAT	2	1	T
21	PIGMY BAT	HOUSE BAT	2	1	T
20	PIKA	RABBIT	2	1	T
19	CL31	CL30	4	1	T
18	CL28	RIVER OTTER	3	1	T
17	CL27	SEA OTTER	3	1	T
16	CL24	CL23	4	1	
15	CL21	RED BAT	3	1.2247	
14	CL17	GREY SEAL	4	1.291	
13	CL29	RACCOON	3	1.4142	T
12	CL25	ELEPHANT SEAL	3	1.4142	
11	CL18	CL14	7	1.5546	
10	CL22	CL15	5	1.5811	
9	CL20	CL19	6	1.8708	T
8	CL11	CL26	9	1.9272	
7	CL8	CL12	12	2.2278	
6	MOLE	CL13	4	2.2361	
5	CL9	HOUSE MOUSE	7	2.4833	
4	CL6	CL7	16	2.5658	
3	CL10	CL16	9	2.8107	
2	CL3	CL5	16	3.7054	
1	CL2	CL4	32	4.2939	



**Output 23.4.2.** Average Linkage Analysis of Mammals' Teeth Data: Standardized Data

```

Hierarchical Cluster Analysis of Mammals' Teeth Data
Evaluating the Effects of Ties
Standardized Data

The CLUSTER Procedure
Average Linkage Cluster Analysis

Eigenvalues of the Correlation Matrix

      Eigenvalue    Difference    Proportion    Cumulative
1      4.74153902    3.27458808      0.5927      0.5927
2      1.46695094    0.70824118      0.1834      0.7761
3      0.75870977    0.25146252      0.0948      0.8709
4      0.50724724    0.30264737      0.0634      0.9343
5      0.20459987    0.05925818      0.0256      0.9599
6      0.14534169    0.03450100      0.0182      0.9780
7      0.11084070    0.04606994      0.0139      0.9919
8      0.06477076                      0.0081      1.0000

```

```

The data have been standardized to mean 0 and variance 1
Root-Mean-Square Total-Sample Standard Deviation =      1

```

```

Cluster History

      NCL      -----Clusters Joined-----      FREQ      RMS      T
              Dist      e
31      BEAVER      GROUNDHOG      2      0      T
30      GRAY SQUIRREL      PORCUPINE      2      0      T
29      WOLF      BEAR      2      0      T
28      MARTEN      WOLVERINE      2      0      T
27      WEASEL      BADGER      2      0      T
26      JAGUAR      COUGAR      2      0      T
25      FUR SEAL      SEA LION      2      0      T
24      REINDEER      ELK      2      0      T
23      DEER      MOOSE      2      0
22      PIGMY BAT      RED BAT      2      0.9157
21      CL28      RIVER OTTER      3      0.9169
20      CL31      CL30      4      0.9428      T
19      BROWN BAT      SILVER HAIR BAT      2      0.9428      T
18      PIKA      RABBIT      2      0.9428
17      CL27      SEA OTTER      3      0.9847
16      CL22      HOUSE BAT      3      1.1437
15      CL21      CL17      6      1.3314
14      CL25      ELEPHANT SEAL      3      1.3447
13      CL19      CL16      5      1.4688
12      CL15      GREY SEAL      7      1.6314
11      CL29      RACCOON      3      1.692
10      CL18      CL20      6      1.7357
9      CL12      CL26      9      2.0285
8      CL24      CL23      4      2.1891
7      CL9      CL14      12      2.2674
6      CL10      HOUSE MOUSE      7      2.317
5      CL11      CL7      15      2.6484
4      CL13      MOLE      6      2.8624
3      CL4      CL8      10      3.5194
2      CL3      CL6      17      4.1265
1      CL2      CL5      32      4.7753

```

There are ties at 16 levels for the raw data but at only 10 levels for the standardized data. There are more ties for the raw data because the increments between successive values are the same for all of the raw variables but different for the standardized variables.

One way to assess the importance of the ties in the analysis is to repeat the analysis on several random permutations of the observations and then to see to what extent the results are consistent at the interesting levels of the cluster history. Three macros are presented to facilitate this process.

```

/* ----- */
/*
/* The macro CLUSPERM randomly permutes observations and
/* does a cluster analysis for each permutation.
/* The arguments are as follows:
/*
/* data      data set name
/* var       list of variables to cluster
/* id        id variable for proc cluster
/* method    clustering method (and possibly other options)
/* nperm     number of random permutations.
/*
/* ----- */
%macro CLUSPERM(data,var,id,method,nperm);
/* -----CREATE TEMPORARY DATA SET WITH RANDOM NUMBERS----- */
data _temp_;
  set &data;
  array _random_ _ran_1-_ran_&nperm;
  do over _random_;
    _random_ = ranuni(835297461);
  end;
run;
/* -----PERMUTE AND CLUSTER THE DATA----- */
%do n=1 %to &nperm;
  proc sort data=_temp_ (keep=_ran_&n &var &id) out=_perm_;
    by _ran_&n;
  run;
  proc cluster method=&method noprint outtree=_tree_&n;
    var &var;
    id &id;
  run;
%end;
%mend;

/* ----- */
/*
/* The macro PLOTPERM plots various cluster statistics
/* against the number of clusters for each permutation.
/* The arguments are as follows:
/*
/* stats     names of variables from tree data set
/* nclus     maximum number of clusters to be plotted
/* nperm     number of random permutations.
/*
/* ----- */
%macro PLOTPERM(stat,nclus,nperm);
/* ---CONCATENATE TREE DATA SETS FOR 20 OR FEWER CLUSTERS--- */
data _plot_;
  set %do n=1 %to &nperm; _tree_&n(in=_in_&n) %end; ;
  if _ncl_ <= &nclus;
  %do n=1 %to &nperm;
    if _in_&n then _perm_ = &n;
  %end;
  label _perm_ = 'permutation number';

```

```

        keep _ncl_ &stat _perm_;
run;
/* ---PLOT THE REQUESTED STATISTICS BY NUMBER OF CLUSTERS--- */

proc plot;
    plot (&stat)*_ncl_=_perm_ /vpos=26;
    title2 'Symbol is value of _PERM_';
run;
%mend;

/* ----- */
/*
/* The macro TREEPERM generates cluster-membership variables
/* for a specified number of clusters for each permutation.
/* PROC PRINT lists the objects in each cluster-combination,
/* and PROC TABULATE gives the frequencies and means. The
/* arguments are as follows:
/*
/*      var      list of variables to cluster
/*              (no "-" or ":" allowed)
/*      id        id variable for proc cluster
/*      meanfmt   format for printing means in PROC TABULATE
/*      nclus     number of clusters desired
/*      nperm     number of random permutations.
/*
/* ----- */
%macro TREEPERM(var,id,meanfmt,nclus,nperm);
/* -----CREATE DATA SETS GIVING CLUSTER MEMBERSHIP----- */
%do n=1 %to &nperm;
    proc tree data=_tree_&n noprint n=&nclus
        out=_out_&n(drop=clusname
                    rename=(cluster=_clus_&n));
        copy &var;
        id &id;
    run;
    proc sort;
        by &id &var;
    run;
%end;
/* -----MERGE THE CLUSTER VARIABLES----- */
data _merge_;
    merge
        %do n=1 %to &nperm;
            _out_&n
        %end; ;
    by &id &var;
    length all_clus $ %eval(3*&nperm);
    %do n=1 %to &nperm;
        substr( all_clus, %eval(1+(&n-1)*3), 3) =
            put( _clus_&n, 3.);
    %end;
run;

```

```

/* -----PRINT AND TABULATE CLUSTER COMBINATIONS----- */
proc sort;
  by _clus_;;
run;
proc print;
  var &var;
  id &id;
  by all_clus notsorted;
run;
proc tabulate order=data formchar='          ';
  class all_clus;
  var &var;
  table all_clus, n='FREQ'*f=5. mean*f=&meanfmt*(&var) /
    rts=%eval(&nperm*3+1);
run;
%mend;

```

To use these, it is first convenient to define a macro, VLIST, listing the teeth variables, since the forms V1-V8 or V: cannot be used with the TABULATE procedure in the TREEPERM macro:

```

/* -TABULATE does not accept hyphens or colons in VAR lists- */
%let vlist=v1 v2 v3 v4 v5 v6 v7 v8;

```

The CLUSPERM macro is then called to analyze ten random permutations. The PLOTPERM macro plots the pseudo  $F$  and  $t^2$  statistics and the cubic clustering criterion. Since the data are discrete, the pseudo  $F$  statistic and the cubic clustering criterion can be expected to increase as the number of clusters increases, so local maxima or large jumps in these statistics are more relevant than the global maximum in determining the number of clusters. For the raw data, only the pseudo  $t^2$  statistic indicates the possible presence of clusters, with the 4-cluster level being suggested. Hence, the TREEPERM macro is used to analyze the results at the 4-cluster level:

```

title3 'Raw Data';

/* -----CLUSTER RAW DATA WITH AVERAGE LINKAGE----- */
%clusperm( teeth, &vlist, mammal, average, 10);

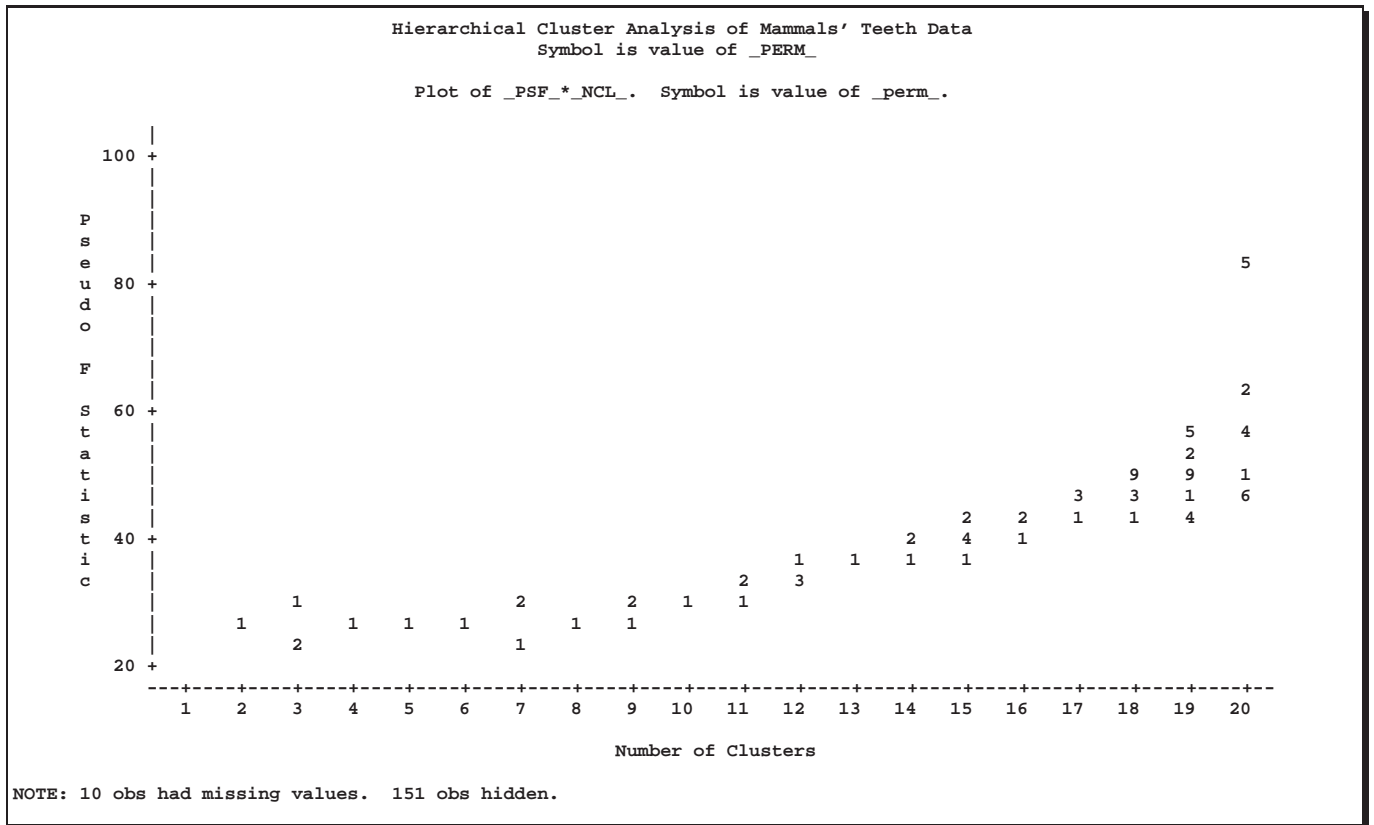
/* -----PLOT STATISTICS FOR THE LAST 20 LEVELS----- */
%plotperm( _psf_ _pst2_ _ccc_, 20, 10);

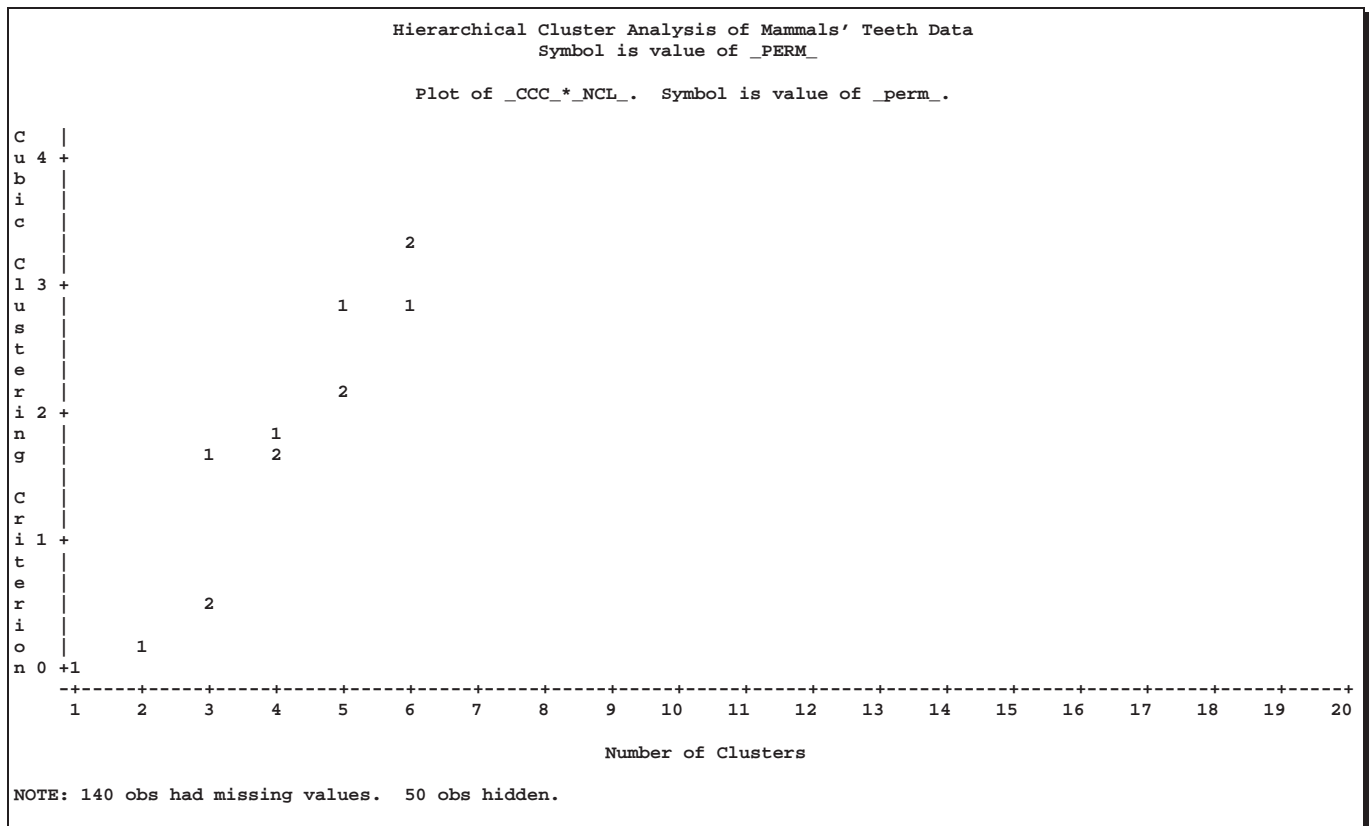
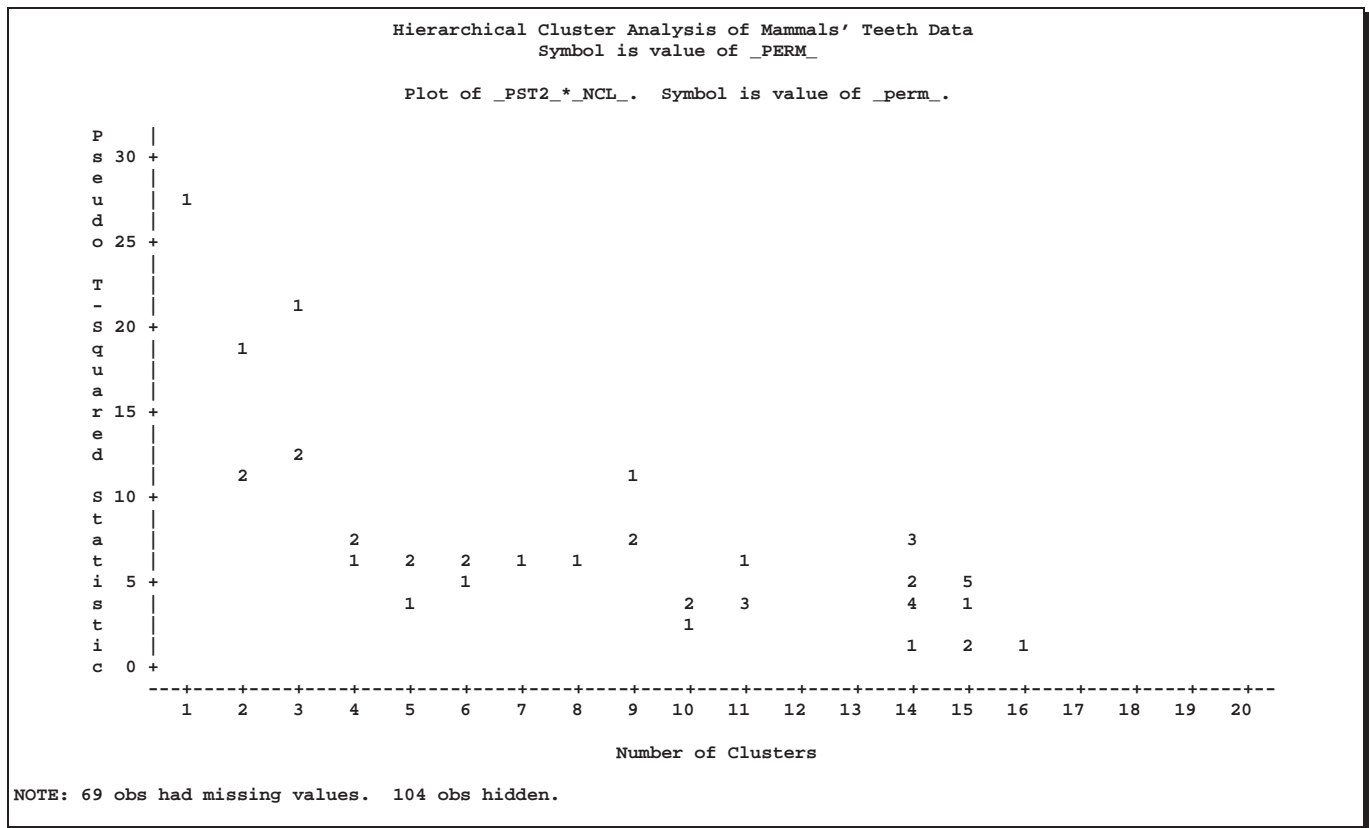
/* -----ANALYZE THE 4-CLUSTER LEVEL----- */
%treeperm( &vlist, mammal, 9.1, 4, 10);

```

The results are shown in Output 23.4.3.

**Output 23.4.3.** Analysis of Ten Random Permutations of Raw Mammals' Teeth Data: Indeterminacy at the 4-Cluster Level





----- all_clus=' 1 3 1 1 1 3 3 3 2 3' -----									
mammal	v1	v2	v3	v4	v5	v6	v7	v8	
DEER	0	4	0	0	3	3	3	3	
ELK	0	4	1	0	3	3	3	3	
MOOSE	0	4	0	0	3	3	3	3	
REINDEER	0	4	1	0	3	3	3	3	
----- all_clus=' 2 2 2 2 2 2 1 2 1 1' -----									
mammal	v1	v2	v3	v4	v5	v6	v7	v8	
BADGER	3	3	1	1	3	3	1	2	
BEAR	3	3	1	1	4	4	2	3	
COUGAR	3	3	1	1	3	2	1	1	
ELEPHANT SEAL	2	1	1	1	4	4	1	1	
FUR SEAL	3	2	1	1	4	4	1	1	
GREY SEAL	3	2	1	1	3	3	2	2	
JAGUAR	3	3	1	1	3	2	1	1	
MARTEN	3	3	1	1	4	4	1	2	
RACCOON	3	3	1	1	4	4	3	2	
RIVER OTTER	3	3	1	1	4	3	1	2	
SEA LION	3	2	1	1	4	4	1	1	
SEA OTTER	3	2	1	1	3	3	1	2	
WEASEL	3	3	1	1	3	3	1	2	
WOLF	3	3	1	1	4	4	2	3	
WOLVERINE	3	3	1	1	4	4	1	2	
----- all_clus=' 2 4 2 2 4 2 1 2 1 1' -----									
mammal	v1	v2	v3	v4	v5	v6	v7	v8	
MOLE	3	2	1	0	3	3	3	3	
----- all_clus=' 3 1 3 3 3 1 2 1 3 2' -----									
mammal	v1	v2	v3	v4	v5	v6	v7	v8	
BEAVER	1	1	0	0	2	1	3	3	
GRAY SQUIRREL	1	1	0	0	1	1	3	3	
GROUNDHOG	1	1	0	0	2	1	3	3	
HOUSE MOUSE	1	1	0	0	0	0	3	3	
PORCUPINE	1	1	0	0	1	1	3	3	
----- all_clus=' 3 4 3 3 4 1 2 1 3 2' -----									
mammal	v1	v2	v3	v4	v5	v6	v7	v8	
PIKA	2	1	0	0	2	2	3	3	
RABBIT	2	1	0	0	3	2	3	3	
----- all_clus=' 4 4 4 4 4 4 4 4 4 4' -----									
mammal	v1	v2	v3	v4	v5	v6	v7	v8	
BROWN BAT	2	3	1	1	3	3	3	3	
HOUSE BAT	2	3	1	1	1	2	3	3	
PIGMY BAT	2	3	1	1	2	2	3	3	
RED BAT	1	3	1	1	2	2	3	3	
SILVER HAIR BAT	2	3	1	1	2	3	3	3	

												Mean								
												FREQ	Top incisors	Bottom incisors	Top canines	Bottom canines	Top premolars	Bottom premolars	Top molars	Bottom molars
all_clus																				
1	3	1	1	1	3	3	3	2	3		4	0.0	4.0	0.5	0.0	3.0	3.0	3.0	3.0	
2	2	2	2	2	2	1	2	1	1		15	2.9	2.6	1.0	1.0	3.6	3.4	1.3	1.8	
2	4	2	2	4	2	1	2	1	1		1	3.0	2.0	1.0	0.0	3.0	3.0	3.0	3.0	
3	1	3	3	3	1	2	1	3	2		5	1.0	1.0	0.0	0.0	1.2	0.8	3.0	3.0	
3	4	3	3	4	1	2	1	3	2		2	2.0	1.0	0.0	0.0	2.5	2.0	3.0	3.0	
4	4	4	4	4	4	4	4	4	4		5	1.8	3.0	1.0	1.0	2.0	2.4	3.0	3.0	

From the TABULATE and PRINT output, you can see that two types of clustering are obtained. In one case, the mole is grouped with the carnivores, while the pika and rabbit are grouped with the rodents. In the other case, both the mole and the lagomorphs are grouped with the bats.

Next, the analysis is repeated with the standardized data. The pseudo  $F$  and  $t^2$  statistics indicate 3 or 4 clusters, while the cubic clustering criterion shows a sharp rise up to 4 clusters and then levels off up to 6 clusters. So the TREEPERM macro is used again at the 4-cluster level. In this case, there is no indeterminacy, as the same four clusters are obtained with every permutation, although in different orders. It must be emphasized, however, that lack of indeterminacy in no way indicates validity. The results are shown in Output 23.4.4.

```

title3 'Standardized Data';

/*-----CLUSTER STANDARDIZED DATA WITH AVERAGE LINKAGE-----*/
%clusperm( teeth, &vlist, mammal, average std, 10);

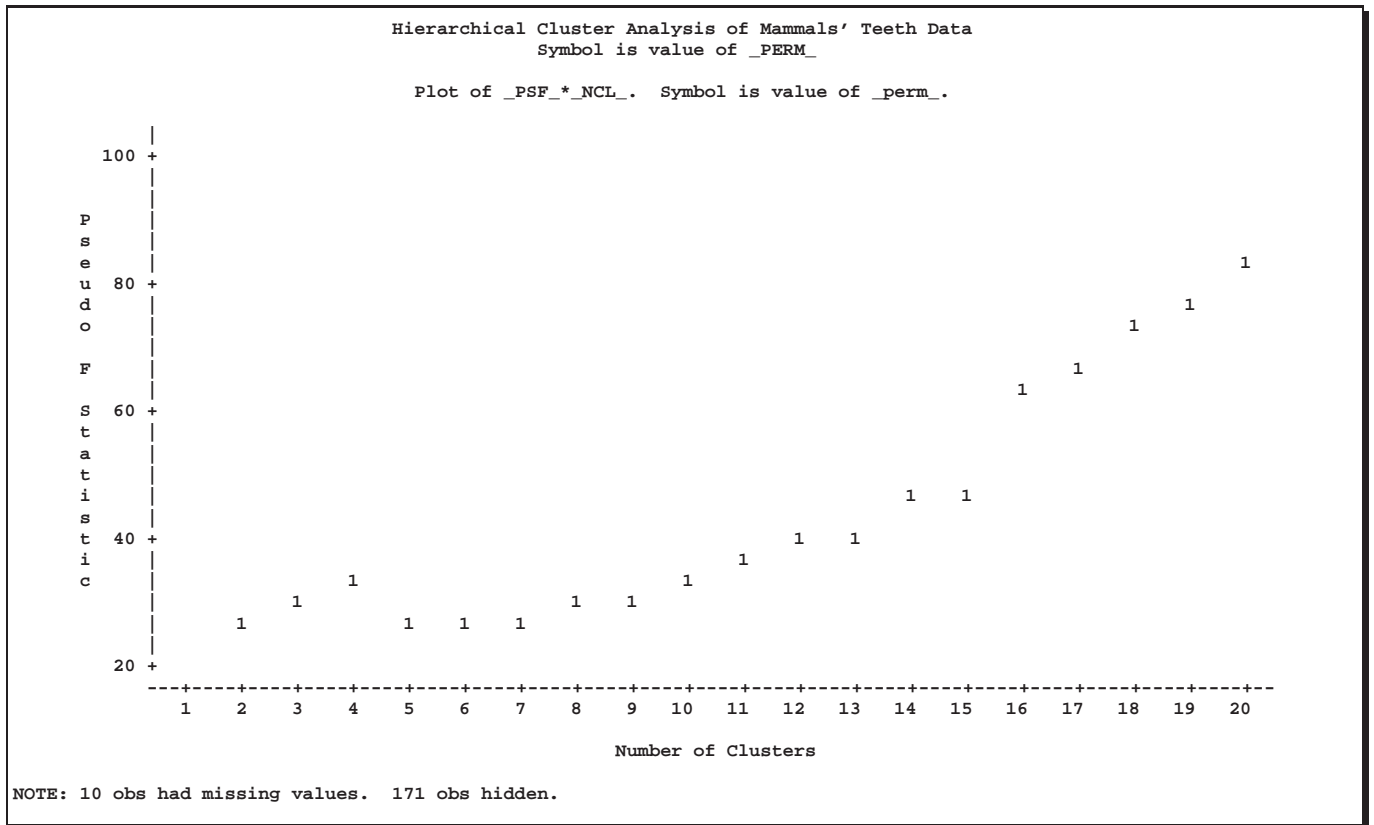
/*-----PLOT STATISTICS FOR THE LAST 20 LEVELS-----*/
%plotperm( _psf_ _pst2_ _ccc_, 20, 10);

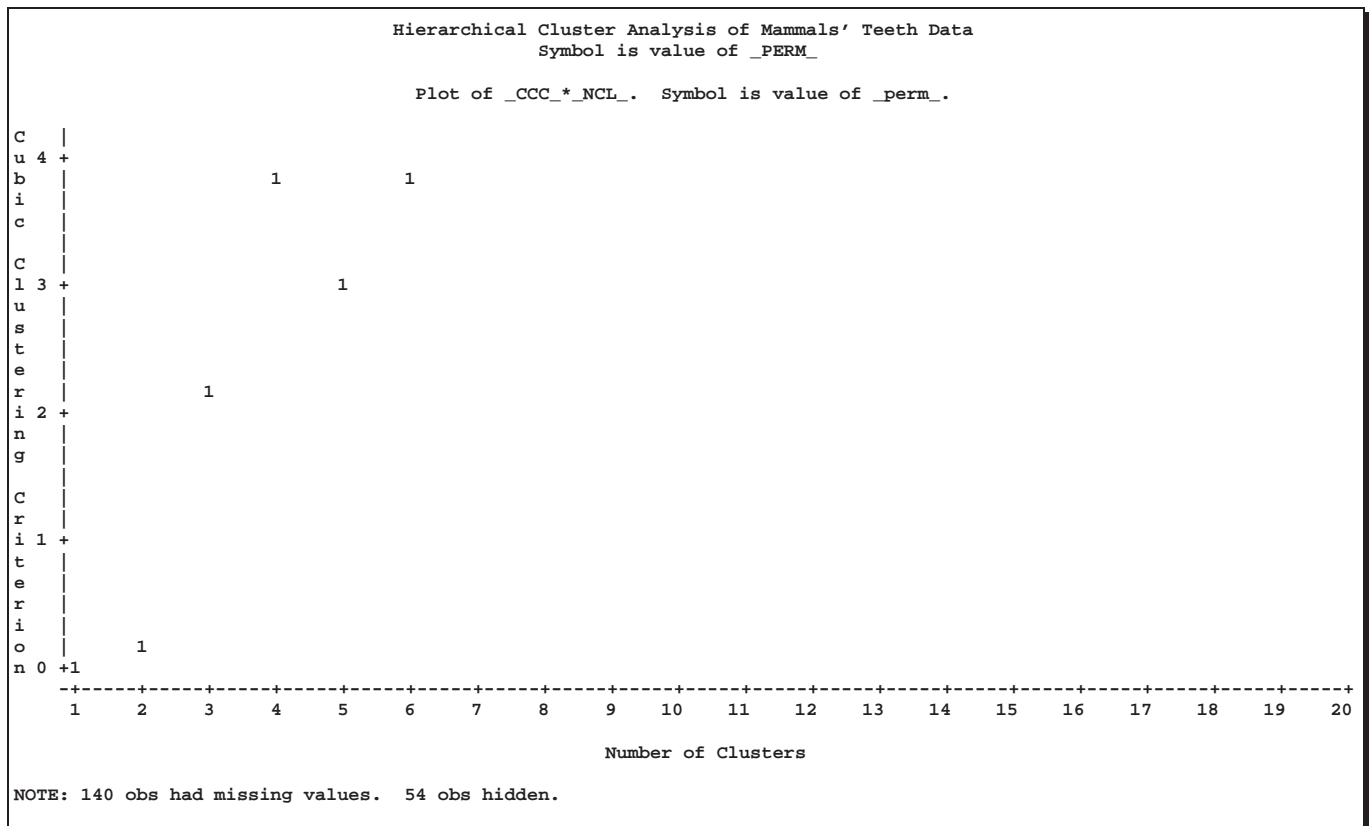
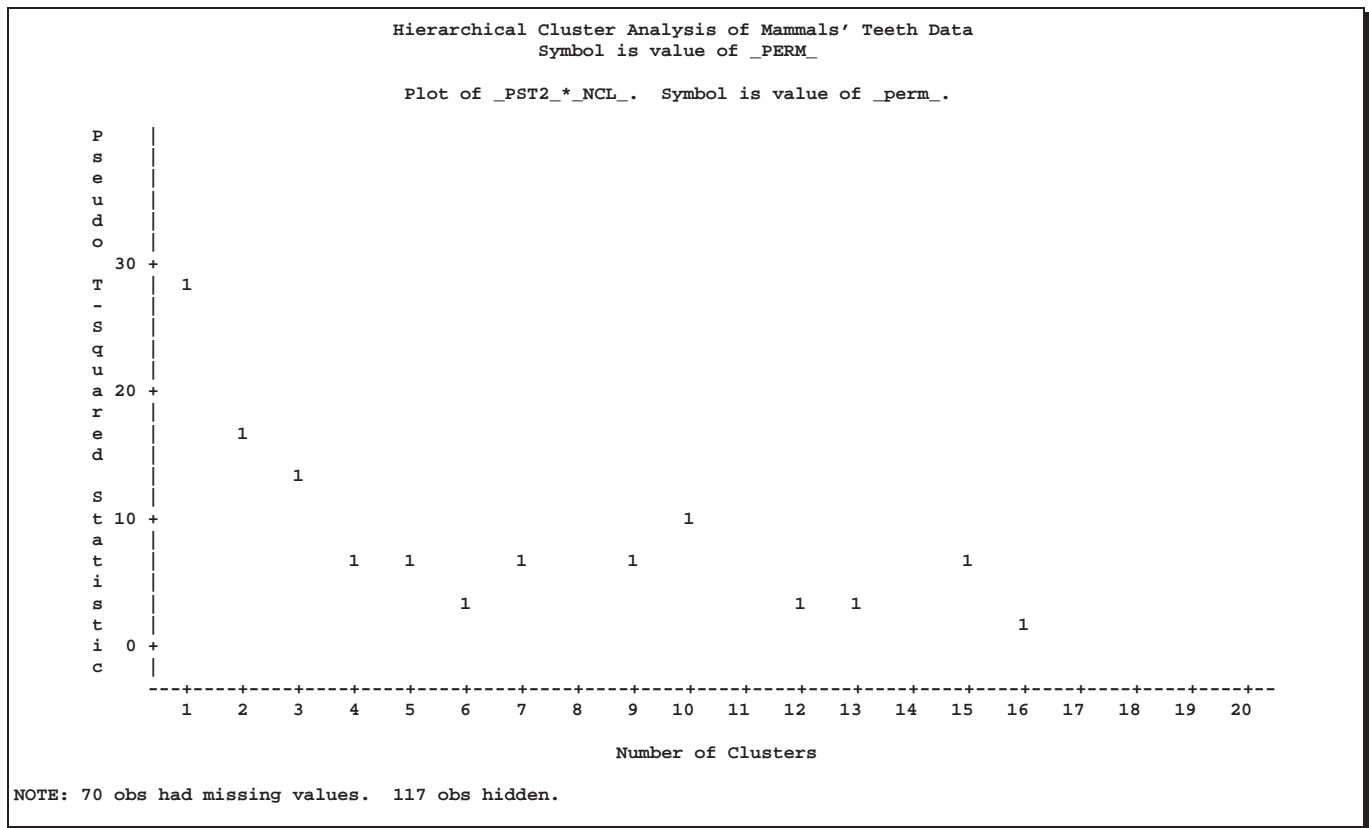
/*-----ANALYZE THE 4-CLUSTER LEVEL-----*/
%treeperm( &vlist, mammal, 9.1, 4, 10);

```



**Output 23.4.4.** Analysis of Ten Random Permutations of Standardized Mammals' Teeth Data: No Indeterminacy at the 4-Cluster Level





----- all_clus=' 1 3 1 1 1 3 3 3 2 3' -----									
mammal	v1	v2	v3	v4	v5	v6	v7	v8	
DEER	0	4	0	0	3	3	3	3	
ELK	0	4	1	0	3	3	3	3	
MOOSE	0	4	0	0	3	3	3	3	
REINDEER	0	4	1	0	3	3	3	3	
----- all_clus=' 2 2 2 2 2 2 1 2 1 1' -----									
mammal	v1	v2	v3	v4	v5	v6	v7	v8	
BADGER	3	3	1	1	3	3	1	2	
BEAR	3	3	1	1	4	4	2	3	
COUGAR	3	3	1	1	3	2	1	1	
ELEPHANT SEAL	2	1	1	1	4	4	1	1	
FUR SEAL	3	2	1	1	4	4	1	1	
GREY SEAL	3	2	1	1	3	3	2	2	
JAGUAR	3	3	1	1	3	2	1	1	
MARTEN	3	3	1	1	4	4	1	2	
RACCOON	3	3	1	1	4	4	3	2	
RIVER OTTER	3	3	1	1	4	3	1	2	
SEA LION	3	2	1	1	4	4	1	1	
SEA OTTER	3	2	1	1	3	3	1	2	
WEASEL	3	3	1	1	3	3	1	2	
WOLF	3	3	1	1	4	4	2	3	
WOLVERINE	3	3	1	1	4	4	1	2	
----- all_clus=' 3 1 3 3 3 1 2 1 3 2' -----									
mammal	v1	v2	v3	v4	v5	v6	v7	v8	
BEAVER	1	1	0	0	2	1	3	3	
GRAY SQUIRREL	1	1	0	0	1	1	3	3	
GROUNDHOG	1	1	0	0	2	1	3	3	
HOUSE MOUSE	1	1	0	0	0	0	3	3	
PIKA	2	1	0	0	2	2	3	3	
PORCUPINE	1	1	0	0	1	1	3	3	
RABBIT	2	1	0	0	3	2	3	3	
----- all_clus=' 4 4 4 4 4 4 4 4 4 4' -----									
mammal	v1	v2	v3	v4	v5	v6	v7	v8	
BROWN BAT	2	3	1	1	3	3	3	3	
HOUSE BAT	2	3	1	1	1	2	3	3	
MOLE	3	2	1	0	3	3	3	3	
PIGMY BAT	2	3	1	1	2	2	3	3	
RED BAT	1	3	1	1	2	2	3	3	
SILVER HAIR BAT	2	3	1	1	2	3	3	3	
Mean									
	FREQ	Top incisors	Bottom incisors	Top canines	Bottom canines	Top premolars	Bottom premolars	Top molars	Bottom molars
all_clus									
1 3 1 1 1 3 3 3 2 3	4	0.0	4.0	0.5	0.0	3.0	3.0	3.0	3.0
2 2 2 2 2 2 1 2 1 1	15	2.9	2.6	1.0	1.0	3.6	3.4	1.3	1.8
3 1 3 3 3 1 2 1 3 2	7	1.3	1.0	0.0	0.0	1.6	1.1	3.0	3.0
4 4 4 4 4 4 4 4 4 4	6	2.0	2.8	1.0	0.8	2.2	2.5	3.0	3.0

## Example 23.5. Computing a Distance Matrix

A wide variety of distance and similarity measures are used in cluster analysis (Anderberg 1973, Sneath and Sokal 1973). If your data are in coordinate form and you want to use a non-Euclidean distance for clustering, you can compute a distance matrix using a DATA step or the IML procedure.

Similarity measures must be converted to dissimilarities before being used in PROC CLUSTER. Such conversion can be done in a variety of ways, such as taking reciprocals or subtracting from a large value. The choice of conversion method depends on the application and the similarity measure.

In the following example, the observations are states. Binary-valued variables correspond to various grounds for divorce and indicate whether the grounds for divorce apply in each of the states.

The %DISTANCE\* macro is used to compute the Jaccard coefficient (Anderberg 1973, pp. 89, 115, and 117) between each pair of states. The Jaccard coefficient is defined as the number of variables that are coded as 1 for both states divided by the number of variables that are coded as 1 for either or both states. The Jaccard coefficient is converted to a distance measure by subtracting it from 1.

```
%include '<location of SAS/STAT sample library>/xmacro.sas';
%include '<location of SAS/STAT sample library>/distnew.sas';

options ls=120 ps=60;
data divorce;
  title 'Grounds for Divorce';
  input state $15.
        (incompat cruelty desertn non_supp alcohol
         felony impotenc insanity separate) (1.) @@;
  if mod(_n_,2) then input +4 @@; else input;
  datalines;
ALABAMA      111111111      ALASKA      111011110
ARIZONA      100000000      ARKANSAS    011111111
CALIFORNIA   100000010      COLORADO   100000000
CONNECTICUT  111111011      DELAWARE   100000001
FLORIDA      100000010      GEORGIA    111011110
HAWAII       100000001      IDAHO      111111011
ILLINOIS     011011100      INDIANA    100001110
IOWA         100000000      KANSAS     111011110
KENTUCKY     100000000      LOUISIANA  000001001
MAINE        111110110      MARYLAND   011001111
MASSACHUSETTS 111111101      MICHIGAN   100000000
MINNESOTA    100000000      MISSISSIPPI 111011110
MISSOURI     100000000      MONTANA    100000000
```

\*The %DISTANCE macro computes various measures of distance, dissimilarity, or similarity between the observations (rows) of a SAS data set. These proximity measures are stored as a lower triangular matrix or a square matrix in an output data set that can then be used as input to the CLUSTER, MDS or MODECLUS procedures. The input data sets may contain numeric or character variables or both, depending on which proximity measure is used. The macro is documented in the macro comments and can be found in the SAS/STAT sample library.

NEBRASKA	100000000	NEVADA	100000011
NEW HAMPSHIRE	111111100	NEW JERSEY	011011011
NEW MEXICO	111000000	NEW YORK	011001001
NORTH CAROLINA	000000111	NORTH DAKOTA	111111110
OHIO	111011101	OKLAHOMA	111111110
OREGON	100000000	PENNSYLVANIA	011001110
RHODE ISLAND	111111101	SOUTH CAROLINA	011010001
SOUTH DAKOTA	011111000	TENNESSEE	111111100
TEXAS	111001011	UTAH	011111110
VERMONT	011101011	VIRGINIA	010001001
WASHINGTON	100000001	WEST VIRGINIA	111011011
WISCONSIN	100000001	WYOMING	100000011

```

;

%distance(data=divorce, id=state, options=nomiss, out=distjacc,
          shape=square, method=djaccard, var=incompat--separate);

proc print data=distjacc(obs=10);
  id state; var alabama--georgia;
  title2 'First 10 states';
run;
title2;

proc cluster data=distjacc method=centroid
  pseudo outtree=tree;
  id state;
  var alabama--wyoming;
run;

proc tree data=tree noprint n=9 out=out;
  id state;
run;

proc sort;
  by state;
run;

data clus;
  merge divorce out;
  by state;
run;

proc sort;
  by cluster;
run;

proc print;
  id state;
  var incompat--separate;
  by cluster;
run;
```

**Output 23.5.1.** Computing a Distance Matrix

Grounds for Divorce First 10 states										
state	ALABAMA	ALASKA	ARIZONA	ARKANSAS	CALIFORNIA	COLORADO	CONNECTICUT	DELAWARE	FLORIDA	GEORGIA
ALABAMA	0.00000	0.22222	0.88889	0.11111	0.77778	0.88889	0.11111	0.77778	0.77778	0.22222
ALASKA	0.22222	0.00000	0.85714	0.33333	0.71429	0.85714	0.33333	0.87500	0.71429	0.00000
ARIZONA	0.88889	0.85714	0.00000	1.00000	0.50000	0.00000	0.87500	0.50000	0.50000	0.85714
ARKANSAS	0.11111	0.33333	1.00000	0.00000	0.88889	1.00000	0.22222	0.88889	0.88889	0.33333
CALIFORNIA	0.77778	0.71429	0.50000	0.88889	0.00000	0.50000	0.75000	0.66667	0.00000	0.71429
COLORADO	0.88889	0.85714	0.00000	1.00000	0.50000	0.00000	0.87500	0.50000	0.50000	0.85714
CONNECTICUT	0.11111	0.33333	0.87500	0.22222	0.75000	0.87500	0.00000	0.75000	0.75000	0.33333
DELAWARE	0.77778	0.87500	0.50000	0.88889	0.66667	0.50000	0.75000	0.00000	0.66667	0.87500
FLORIDA	0.77778	0.71429	0.50000	0.88889	0.00000	0.50000	0.75000	0.66667	0.00000	0.71429
GEORGIA	0.22222	0.00000	0.85714	0.33333	0.71429	0.85714	0.33333	0.87500	0.71429	0.00000

Grounds for Divorce

The CLUSTER Procedure

Centroid Hierarchical Cluster Analysis

Root-Mean-Square Distance Between Observations = 0.694873

Cluster History						Norm	T
NCL	-----Clusters Joined-----		FREQ	PSF	PST2	Cent Dist	i e
49	ARIZONA	COLORADO	2	.	.	0	T
48	CALIFORNIA	FLORIDA	2	.	.	0	T
47	ALASKA	GEORGIA	2	.	.	0	T
46	DELAWARE	HAWAII	2	.	.	0	T
45	CONNECTICUT	IDAHO	2	.	.	0	T
44	CL49	IOWA	3	.	.	0	T
43	CL47	KANSAS	3	.	.	0	T
42	CL44	KENTUCKY	4	.	.	0	T
41	CL42	MICHIGAN	5	.	.	0	T
40	CL41	MINNESOTA	6	.	.	0	T
39	CL43	MISSISSIPPI	4	.	.	0	T
38	CL40	MISSOURI	7	.	.	0	T
37	CL38	MONTANA	8	.	.	0	T
36	CL37	NEBRASKA	9	.	.	0	T
35	NORTH DAKOTA	OKLAHOMA	2	.	.	0	T
34	CL36	OREGON	10	.	.	0	T
33	MASSACHUSETTS	RHODE ISLAND	2	.	.	0	T
32	NEW HAMPSHIRE	TENNESSEE	2	.	.	0	T
31	CL46	WASHINGTON	3	.	.	0	T
30	CL31	WISCONSIN	4	.	.	0	T
29	NEVADA	WYOMING	2	.	.	0	
28	ALABAMA	ARKANSAS	2	1561	.	0.1599	T
27	CL33	CL32	4	479	.	0.1799	T
26	CL39	CL35	6	265	.	0.1799	T
25	CL45	WEST VIRGINIA	3	231	.	0.1799	
24	MARYLAND	PENNSYLVANIA	2	199	.	0.2399	
23	CL28	UTAH	3	167	3.2	0.2468	
22	CL27	OHIO	5	136	5.4	0.2698	
21	CL26	MAINE	7	111	8.9	0.2998	
20	CL23	CL21	10	75.2	8.7	0.3004	
19	CL25	NEW JERSEY	4	71.8	6.5	0.3053	T
18	CL19	TEXAS	5	69.1	2.5	0.3077	
17	CL20	CL22	15	48.7	9.9	0.3219	
16	NEW YORK	VIRGINIA	2	50.1	.	0.3598	
15	CL18	VERMONT	6	49.4	2.9	0.3797	
14	CL17	ILLINOIS	16	47.0	3.2	0.4425	
13	CL14	CL15	22	29.2	15.3	0.4722	
12	CL48	CL29	4	29.5	.	0.4797	T
11	CL13	CL24	24	27.6	4.5	0.5042	
10	CL11	SOUTH DAKOTA	25	28.4	2.4	0.5449	
9	LOUISIANA	CL16	3	30.3	3.5	0.5844	
8	CL34	CL30	14	23.3	.	0.7196	
7	CL8	CL12	18	19.3	15.0	0.7175	
6	CL10	SOUTH CAROLINA	26	21.4	4.2	0.7384	
5	CL6	NEW MEXICO	27	24.0	4.7	0.8303	
4	CL5	INDIANA	28	28.9	4.1	0.8343	
3	CL4	CL9	31	31.7	10.9	0.8472	
2	CL3	NORTH CAROLINA	32	55.1	4.1	1.0017	
1	CL2	CL7	50	.	55.1	1.0663	

## Grounds for Divorce

## ----- CLUSTER=1 -----

state	incompat	cruelty	desertn	non_supp	alcohol	felony	impotenc	insanity	separate
ARIZONA	1	0	0	0	0	0	0	0	0
COLORADO	1	0	0	0	0	0	0	0	0
IOWA	1	0	0	0	0	0	0	0	0
KENTUCKY	1	0	0	0	0	0	0	0	0
MICHIGAN	1	0	0	0	0	0	0	0	0
MINNESOTA	1	0	0	0	0	0	0	0	0
MISSOURI	1	0	0	0	0	0	0	0	0
MONTANA	1	0	0	0	0	0	0	0	0
NEBRASKA	1	0	0	0	0	0	0	0	0
OREGON	1	0	0	0	0	0	0	0	0

## ----- CLUSTER=2 -----

state	incompat	cruelty	desertn	non_supp	alcohol	felony	impotenc	insanity	separate
CALIFORNIA	1	0	0	0	0	0	0	1	0
FLORIDA	1	0	0	0	0	0	0	1	0
NEVADA	1	0	0	0	0	0	0	1	1
WYOMING	1	0	0	0	0	0	0	1	1

## ----- CLUSTER=3 -----

state	incompat	cruelty	desertn	non_supp	alcohol	felony	impotenc	insanity	separate
ALABAMA	1	1	1	1	1	1	1	1	1
ALASKA	1	1	1	0	1	1	1	1	0
ARKANSAS	0	1	1	1	1	1	1	1	1
CONNECTICUT	1	1	1	1	1	1	0	1	1
GEORGIA	1	1	1	0	1	1	1	1	0
IDAHO	1	1	1	1	1	1	0	1	1
ILLINOIS	0	1	1	0	1	1	1	0	0
KANSAS	1	1	1	0	1	1	1	1	0
MAINE	1	1	1	1	1	0	1	1	0
MARYLAND	0	1	1	0	0	1	1	1	1
MASSACHUSETTS	1	1	1	1	1	1	1	0	1
MISSISSIPPI	1	1	1	0	1	1	1	1	0
NEW HAMPSHIRE	1	1	1	1	1	1	1	0	0
NEW JERSEY	0	1	1	0	1	1	0	1	1
NORTH DAKOTA	1	1	1	1	1	1	1	1	0
OHIO	1	1	1	0	1	1	1	0	1
OKLAHOMA	1	1	1	1	1	1	1	1	0
PENNSYLVANIA	0	1	1	0	0	1	1	1	0
RHODE ISLAND	1	1	1	1	1	1	1	0	1
SOUTH DAKOTA	0	1	1	1	1	1	0	0	0
TENNESSEE	1	1	1	1	1	1	1	0	0
TEXAS	1	1	1	0	0	1	0	1	1
UTAH	0	1	1	1	1	1	1	1	0
VERMONT	0	1	1	1	0	1	0	1	1
WEST VIRGINIA	1	1	1	0	1	1	0	1	1

## ----- CLUSTER=4 -----

state	incompat	cruelty	desertn	non_supp	alcohol	felony	impotenc	insanity	separate
DELAWARE	1	0	0	0	0	0	0	0	1
HAWAII	1	0	0	0	0	0	0	0	1
WASHINGTON	1	0	0	0	0	0	0	0	1
WISCONSIN	1	0	0	0	0	0	0	0	1



----- CLUSTER=5 -----									
state	incompat	cruelty	desertn	non_supp	alcohol	felony	impotenc	insanity	separate
LOUISIANA	0	0	0	0	0	1	0	0	1
NEW YORK	0	1	1	0	0	1	0	0	1
VIRGINIA	0	1	0	0	0	1	0	0	1
----- CLUSTER=6 -----									
state	incompat	cruelty	desertn	non_supp	alcohol	felony	impotenc	insanity	separate
SOUTH CAROLINA	0	1	1	0	1	0	0	0	1
----- CLUSTER=7 -----									
state	incompat	cruelty	desertn	non_supp	alcohol	felony	impotenc	insanity	separate
NEW MEXICO	1	1	1	0	0	0	0	0	0
----- CLUSTER=8 -----									
state	incompat	cruelty	desertn	non_supp	alcohol	felony	impotenc	insanity	separate
INDIANA	1	0	0	0	0	1	1	1	0
----- CLUSTER=9 -----									
state	incompat	cruelty	desertn	non_supp	alcohol	felony	impotenc	insanity	separate
NORTH CAROLINA	0	0	0	0	0	0	1	1	1

## Example 23.6. Size, Shape, and Correlation

The following example shows the analysis of a data set in which size information is detrimental to the classification. Imagine that an archaeologist of the future is excavating a 20th century grocery store. The archaeologist has discovered a large number of boxes of various sizes, shapes, and colors and wants to do a preliminary classification based on simple external measurements: height, width, depth, weight, and the predominant color of the box. It is known that a given product may have been sold in packages of different size, so the archaeologist wants to remove the effect of size from the classification. It is not known whether color is relevant to the use of the products, so the analysis should be done both with and without color information.

Unknown to the archaeologist, the boxes actually fall into six general categories according to the use of the product: breakfast cereals, crackers, laundry detergents, Little Debbie snacks, tea, and toothpaste. These categories are shown in the analysis so that you can evaluate the effectiveness of the classification.

Since there is no reason for the archaeologist to assume that the true categories have equal sample sizes or variances, the centroid method is used to avoid undue bias. Each analysis is done with Euclidean distances after suitable transformations of the data. Color is coded as five dummy variables with values of 0 or 1. The DATA step is as follows:

```
options ls=120;
title 'Cluster Analysis of Grocery Boxes';
data grocery2;
```

```

length name $35    /* name of product */
      class $16    /* category of product */
      unit $1      /* unit of measurement for weights:
                    g=gram
                    o=ounce
                    l=lb
                    all weights are converted to grams */
      color $8     /* predominant color of box */
      height 8     /* height of box in cm. */
      width 8      /* width of box in cm. */
      depth 8      /* depth of box (front to back) in cm. */
      weight 8     /* weight of box in grams */
      c_white c_yellow c_red c_green c_blue 4;
                    /* dummy variables */

retain class;
drop unit;

/*--- read name with possible embedded blanks ---*/
input name & @;

/*--- if name starts with "---",          ---*/
/*--- it's really a category value        ---*/
if substr(name,1,3) = '---' then do;
  class = substr(name,4,index(substr(name,4),'-')-1);
  delete;
  return;
end;

/*--- read the rest of the variables ---*/
input height width depth weight unit color;

/*--- convert weights to grams ---*/
select (unit);
  when ('l') weight = weight * 454;
  when ('o') weight = weight * 28.3;
  when ('g') ;
  otherwise put 'Invalid unit ' unit;
end;

/*--- use 0/1 coding for dummy variables for colors ---*/
c_white = (color = 'w');
c_yellow = (color = 'y');
c_red = (color = 'r');
c_green = (color = 'g');
c_blue = (color = 'b');

datalines;

---Breakfast cereals---

Cheerios          32.5 22.4  8.4  567 g y
Cheerios          30.3 20.4  7.2  425 g y
Cheerios          27.5 19   6.2  283 g y
Cheerios          24.1 17.2  5.3  198 g y

```

Special K	30.1	20.5	8.5	18	o	w
Special K	29.6	19.2	6.7	12	o	w
Special K	23.4	16.6	5.7	7	o	w
Corn Flakes	33.7	25.4	8	24	o	w
Corn Flakes	30.2	20.6	8.4	18	o	w
Corn Flakes	30	19.1	6.6	12	o	w
Grape Nuts	21.7	16.3	4.9	680	g	w
Shredded Wheat	19.7	19.9	7.5	283	g	y
Shredded Wheat, Spoon Size	26.6	19.6	5.6	510	g	r
All-Bran	21.1	14.3	5.2	13.8	o	y
Froot Loops	30.2	20.8	8.5	19.7	o	r
Froot Loops	25	17.7	6.4	11	o	r

---Crackers---

Wheatsworth	11.1	25.2	5.5	326	g	w
Ritz	23.1	16	5.3	340	g	r
Ritz	23.1	20.7	5.2	454	g	r
Premium Saltines	11	25	10.7	454	g	w
Waverly Wafers	14.4	22.5	6.2	454	g	g

---Detergent---

Arm & Hammer Detergent	38.8	30	16.9	25	l	y
Arm & Hammer Detergent	39.5	25.8	11	14.2	l	y
Arm & Hammer Detergent	33.7	22.8	7	7	l	y
Arm & Hammer Detergent	27.8	19.4	6.3	4	l	y
Tide	39.4	24.8	11.3	9.2	l	r
Tide	32.5	23.2	7.3	4.5	l	r
Tide	26.5	19.9	6.3	42	o	r
Tide	19.3	14.6	4.7	17	o	r

---Little Debbie---

Figaroos	13.5	18.6	3.7	12	o	y
Swiss Cake Rolls	10.1	21.8	5.8	13	o	w
Fudge Brownies	11	30.8	2.5	12	o	w
Marshmallow Supremes	9.4	32	7	10	o	w
Apple Delights	11.2	30.1	4.9	15	o	w
Snack Cakes	13.4	32	3.4	13	o	b
Nutty Bar	13.2	18.5	4.2	12	o	y
Lemon Stix	13.2	18.5	4.2	9	o	w
Fudge Rounds	8.1	28.3	5.4	9.5	o	w

---Tea---

Celestial Saesonings Mint Magic	7.8	13.8	6.3	49	g	b
Celestial Saesonings Cranberry Cove	7.8	13.8	6.3	46	g	r
Celestial Saesonings Sleepy Time	7.8	13.8	6.3	37	g	g
Celestial Saesonings Lemon Zinger	7.8	13.8	6.3	56	g	y
Bigelow Lemon Lift	7.7	13.4	6.9	40	g	y
Bigelow Plantation Mint	7.7	13.4	6.9	35	g	g
Bigelow Earl Grey	7.7	13.4	6.9	35	g	b
Luzianne	8.9	22.8	6.4	6	o	r

Luzianne	18.4	20.2	6.9	8	o r
Luzianne Decaffeinated	8.9	22.8	6.4	5.25	o g
Lipton Tea Bags	17.1	20	6.7	8	o r
Lipton Tea Bags	11.5	14.4	6.6	3.75	o r
Lipton Tea Bags	6.7	10	5.7	1.25	o r
Lipton Family Size Tea Bags	13.7	24	9	12	o r
Lipton Family Size Tea Bags	8.7	20.8	8.2	6	o r
Lipton Family Size Tea Bags	8.9	11.1	8.2	3	o r
Lipton Loose Tea	12.7	10.9	5.4	8	o r

---Paste, Tooth---

Colgate	4.4	22	3.5	7	o r
Colgate	3.6	15.6	3.3	3	o r
Colgate	4.2	18.3	3.5	5	o r
Crest	4.3	21.7	3.7	6.4	o w
Crest	4.3	17.4	3.6	4.6	o w
Crest	3.5	15.2	3.2	2.7	o w
Crest	3.0	10.9	2.8	.85	o w
Arm & Hammer	4.4	17	3.7	5	o w

;

```
data grocery;
  length name $16;
  set grocery2;
```

The FORMAT procedure is used to define to formats to make the output easier to read. The STARS. format is used for graphical crosstabulations in the TABULATE procedure. The \$COLOR format displays the names of the colors instead of just the first letter.

```
/*----- formats and macros for displaying -----*/
/*----- cluster results -----*/
proc format; value stars
  0='          ',
  1='          #',
  2='          ##',
  3='          ###',
  4='          ####',
  5='          #####',
  6='          #####',
  7='          #####',
  8='          #####',
  9='          #####',
  10='          #####',
  11='          #####',
  12='          #####',
  13='          #####',
  14='          #####',
  15-high='>#####';
run;
```

```

proc format; value $color
  'w'='White'
  'y'='Yellow'
  'r'='Red'
  'g'='Green'
  'b'='Blue';
run;

```

Since a full display of the results of each cluster analysis would be very long, a macro is used with five macro variables to select parts of the output. The macro variables are set to select only the PROC CLUSTER output and the crosstabulation of clusters and true categories for the first two analyses. The example could be run with different settings of the macro variables to show the full output or other selected parts.

```

%let cluster=1; /* 1=show CLUSTER output, 0=don't */
%let tree=0; /* 1=print TREE diagram, 0=don't */
%let list=0; /* 1=list clusters, 0=don't */
%let crosstab=1; /* 1=crosstabulate clusters and classes,
                  0=don't */
%let crosscol=0; /* 1=crosstabulate clusters and colors,
                  0=don't */

/*--- define macro with options for TREE ---*/
%macro treeopt;
  %if &tree %then h page=1;
  %else noprint;
%mend;

/*--- define macro with options for CLUSTER ---*/
%macro clusopt;
  %if &cluster %then pseudo ccc p=20;
  %else noprint;
%mend;

/*----- macro for showing cluster results -----*/
%macro show(n); /* n=number of clusters
                to show results for */

proc tree data=tree %treeopt n=&n out=out;
  id name;
  copy class height width depth weight color;
run;

%if &list %then %do;
  proc sort;
    by cluster;
  run;

  proc print;
    var class name height width depth weight color;
    by cluster clusname;
  run;
%end;

```

```

    %if &crosstab %then %do;
        proc tabulate noseps /* formchar='          ' */;
            class class cluster;
            table cluster, class*n='
                '*f=stars./rts=10 misstext=' ';
        run;
    %end;

    %if &crosscol %then %do;
        proc tabulate noseps /* formchar='          ' */;
            class color cluster;
            table cluster, color*n='
                '*f=stars./rts=10 misstext=' ';
            format color $color.;
        run;
    %end;
%mend;

```

The first analysis uses the variables height, width, depth, and weight in standardized form to show the effect of including size information. The CCC, pseudo  $F$ , and pseudo  $t^2$  statistics indicate 10 clusters. Most of the clusters do not correspond closely to the true categories, and four of the clusters have only one or two observations.

```

/*****
/*
/*      Analysis 1: standardized box measurements      */
/*
/*
/*****
title2 'Analysis 1: Standardized data';
proc cluster data=grocery m=cen std %clusopt outtree=tree;
    var height width depth weight;
    id name;
    copy class color;
run;

%show(10);

```

## Output 23.6.1. Analysis of Standardized Data

```

Cluster Analysis of Grocery Boxes
Analysis 1: Standardized data

The CLUSTER Procedure
Centroid Hierarchical Cluster Analysis

Eigenvalues of the Correlation Matrix

```

	Eigenvalue	Difference	Proportion	Cumulative
1	2.44512438	1.64456210	0.6113	0.6113
2	0.80056228	0.33149770	0.2001	0.8114
3	0.46906458	0.18381582	0.1173	0.9287
4	0.28524876		0.0713	1.0000

```

The data have been standardized to mean 0 and variance 1
Root-Mean-Square Total-Sample Standard Deviation = 1
Root-Mean-Square Distance Between Observations = 2.828427

```

```

Cluster Analysis of Grocery Boxes
Analysis 1: Standardized data

The CLUSTER Procedure
Centroid Hierarchical Cluster Analysis

```

```

The data have been standardized to mean 0 and variance 1
Root-Mean-Square Total-Sample Standard Deviation = 1
Root-Mean-Square Distance Between Observations = 2.828427

```

## Cluster History

NCL	-----Clusters Joined-----	FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Norm Cent Dist	T i e
20	CL22 Lipton Family Si	11	0.0028	.974	.	.	85.4	4.5	0.3073	
19	CL36 Corn Flakes	5	0.0026	.972	.	.	83.7	15.3	0.3146	
18	CL24 CL41	12	0.0080	.964	.	.	70.2	10.0	0.3316	
17	CL18 CL30	18	0.0144	.949	.	.	53.8	12.7	0.3343	
16	Marshmallow Supr CL29	3	0.0024	.947	.	.	55.8	4.7	0.3363	
15	CL50 CL33	7	0.0055	.941	.	.	55.0	24.4	0.346	
14	CL46 CL15	10	0.0069	.934	.	.	53.7	8.1	0.3192	
13	CL27 Lipton Family Si	6	0.0035	.931	.	.	56.1	6.3	0.362	
12	CL31 CL16	5	0.0075	.923	.861	8.03	55.8	6.6	0.4416	
11	CL19 CL23	7	0.0102	.913	.848	7.59	54.6	12.7	0.4713	
10	Arm & Hammer Det Tide	2	0.0037	.909	.835	8.36	59.1	.	0.4781	
9	CL11 CL17	25	0.0393	.870	.819	4.72	45.2	19.3	0.4918	
8	CL13 CL14	16	0.0329	.837	.801	2.95	40.4	23.7	0.5215	
7	CL8 CL20	27	0.0629	.774	.779	-.31	32.0	25.9	0.5467	
6	CL7 Crest	28	0.0112	.763	.752	0.61	36.7	2.4	0.6003	
5	CL9 CL6	53	0.1879	.575	.718	-5.9	19.6	43.4	0.6641	
4	CL5 CL21	55	0.0345	.541	.672	-5.2	23.2	4.5	0.745	
3	CL4 CL12	60	0.1137	.427	.602	-5.3	22.4	14.5	0.8769	
2	CL3 CL10	62	0.1511	.276	.471	-4.3	23.2	15.8	1.5559	
1	CL2 Arm & Hammer Det	63	0.2759	.000	.000	0.00	.	23.2	2.948	

	class					
	Breakfast cereal	Crackers	Detergent	Little Debbie	Paste, Tooth	Tea
CLUSTER						
1						#####
2		##		#		###
3	####		##			
4				###	#####	
5	#####	##	###			##
6				####		
7		#				#
8			##			
9					#	
10			#			

The second analysis uses logarithms of height, width, depth, and the cube root of weight; the cube root is used for consistency with the linear measures. The rows are then centered to remove size information. Finally, the columns are standardized to have a standard deviation of 1. There is no compelling a priori reason to standardize the columns, but if they are not standardized, height dominates the analysis because of its large variance. The STANDARD procedure is used instead of the STD option in PROC CLUSTER so that a subsequent analysis can separately standardize the dummy variables for color.

```

/*****
/*
/*      Analysis 2: standardized row-centered logarithms      */
/*
/*
/*****

title2 'Row-centered logarithms';
data shape;
  set grocery;
  array x height width depth weight;
  array l l_height l_width l_depth l_weight;
                                /* logarithms */
  weight=weight**(1/3); /* take cube root to conform with
                        the other linear measurements */
  do over l;                /* take logarithms */
    l=log(x);
  end;
  mean=mean( of l(*)); /* find row mean of logarithms */
  do over l;
    l=l-mean;          /* center row */
  end;
run;

title2 'Analysis 2: Standardized row-centered logarithms';
proc standard data=shape out=shapstan m=0 s=1;
  var l_height l_width l_depth l_weight;
run;

```



```

proc cluster data=shapstan m=cen %clusopt outtree=tree;
  var l_height l_width l_depth l_weight;
  id name;
  copy class height width depth weight color;
run;

%show(8);

```

The results of the second analysis are shown for eight clusters. Clusters 1 through 4 correspond fairly well to tea, toothpaste, breakfast cereals, and detergents. Crackers and Little Debbie products are scattered among several clusters.

**Output 23.6.2.** Analysis of Standardized Row-Centered Logarithms

Cluster Analysis of Grocery Boxes												
Analysis 2: Standardized row-centered logarithms												
The CLUSTER Procedure												
Centroid Hierarchical Cluster Analysis												
Eigenvalues of the Covariance Matrix												
	Eigenvalue	Difference	Proportion	Cumulative								
1	1.94931049	0.34845395	0.4873	0.4873								
2	1.60085654	1.15102358	0.4002	0.8875								
3	0.44983296	0.44983296	0.1125	1.0000								
4	0.00000000		0.0000	1.0000								
Root-Mean-Square Total-Sample Standard Deviation = 1												
Root-Mean-Square Distance Between Observations = 2.828427												
Cluster History												
NCL	-----Clusters Joined-----			FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Norm Cent Dist	T i e
20	CL29	All-Bran		4	0.0017	.977	.	.	94.7	2.9	0.2658	
19	CL26	CL27		8	0.0045	.972	.	.	85.4	8.4	0.3047	
18	Fudge Rounds	Crest		2	0.0016	.971	.	.	87.2	.	0.3193	
17	Fudge Brownies	Snack Cakes		2	0.0018	.969	.	.	89.1	.	0.3331	
16	Arm & Hammer Det	Lipton Loose Tea		2	0.0019	.967	.	.	91.3	.	0.3434	
15	CL23	CL18		5	0.0050	.962	.	.	86.5	4.8	0.3587	
14	CL37	CL21		5	0.0051	.957	.	.	83.5	10.4	0.3613	
13	CL30	CL24		9	0.0068	.950	.	.	79.2	12.9	0.3682	
12	CL32	CL20		16	0.0142	.936	.892	5.75	67.6	29.3	0.3826	
11	CL22	Apple Delights		4	0.0037	.932	.881	6.31	71.4	3.2	0.3901	
10	CL11	CL31		7	0.0090	.923	.869	6.17	70.8	6.3	0.4032	
9	CL33	CL13		11	0.0092	.914	.853	6.25	71.7	7.6	0.4181	
8	CL19	CL16		10	0.0131	.901	.835	6.12	71.4	10.9	0.503	
7	CL14	CL9		16	0.0297	.871	.813	4.63	63.1	15.6	0.5173	
6	CL10	CL15		12	0.0329	.838	.785	3.69	59.1	13.6	0.5916	
5	CL6	CL28		19	0.0557	.783	.748	2.01	52.2	15.8	0.6252	
4	CL12	CL8		26	0.0885	.694	.697	-.16	44.6	48.8	0.6679	
3	CL5	CL17		21	0.0459	.648	.617	1.21	55.3	7.4	0.8863	
2	CL4	CL7		42	0.2841	.364	.384	-.56	34.9	60.3	0.9429	
1	CL2	CL3		63	0.3640	.000	.000	0.00	.	34.9	0.8978	

	class					
	Breakfast cereal	Crackers	Detergent	Little Debbie	Paste, Tooth	Tea
CLUSTER						
1		#				#####
2					#####	
3	#####	##				
4	#		#####			#
5				##	#	##
6	#					####
7		##		####		
8				##		

The third analysis is similar to the second analysis except that the rows are standardized rather than just centered. There is a clear indication of seven clusters from the CCC, pseudo  $F$ , and pseudo  $t^2$  statistics. The clusters are listed as well as crosstabulated with the true categories and colors.

```

/*****
/*
/* Analysis 3: standardized row-standardized logarithms */
/*
/*
/*****

%let list=1;
%let crosscol=1;

title2 'Row-standardized logarithms';
data std;
  set grocery;
  array x height width depth weight;
  array l l_height l_width l_depth l_weight;
  /* logarithms */
  weight=weight**(1/3); /* take cube root to conform with
                        the other linear measurements */
  do over l;
    l=log(x);          /* take logarithms */
  end;
  mean=mean( of l(*)); /* find row mean of logarithms */
  std=std( of l(*));   /* find row standard deviation */
  do over l;
    l=(l-mean)/std;    /* standardize row */
  end;
run;

title2 'Analysis 3: Standardized row-standardized logarithms';
proc standard data=std out=stdstan m=0 s=1;
  var l_height l_width l_depth l_weight;
run;

proc cluster data=stdstan m=cen %clusopt outtree=tree;
  var l_height l_width l_depth l_weight;
  id name;

```

```

copy class height width depth weight color;
run;

%show(7);

```

The output from the third analysis shows that cluster 1 contains 9 of the 17 teas. Cluster 2 contains all of the detergents plus Grape Nuts, a very heavy cereal. Cluster 3 includes all of the toothpastes and one Little Debbie product that is of very similar shape, although roughly twice as large. Cluster 4 has most of the cereals, Ritz crackers (which come in a box very similar to most of the cereal boxes), and Lipton Loose Tea (all the other teas in the sample come in tea bags). Clusters 5 and 6 each contain several Luzianne and Lipton teas and one or two miscellaneous items. Cluster 7 includes most of the Little Debbie products and two types of crackers. Thus, the crackers are not identified and the teas are broken up into three clusters, but the other categories correspond to single clusters. This analysis classifies toothpaste and Little Debbie products slightly better than the second analysis,

**Output 23.6.3.** Analysis of Standardized Row-Standardized Logarithms

Cluster Analysis of Grocery Boxes												
Analysis 3: Standardized row-standardized logarithms												
The CLUSTER Procedure												
Centroid Hierarchical Cluster Analysis												
Eigenvalues of the Covariance Matrix												
		Eigenvalue	Difference	Proportion	Cumulative							
	1	2.42684848	0.94583675	0.6067	0.6067							
	2	1.48101173	1.38887193	0.3703	0.9770							
	3	0.09213980	0.09213980	0.0230	1.0000							
	4	-.00000000		-0.0000	1.0000							
Root-Mean-Square Total-Sample Standard Deviation = 1												
Root-Mean-Square Distance Between Observations = 2.828427												
Cluster History												
NCL	-----Clusters Joined-----			FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Norm Cent Dist	T i e
20	CL35	CL33		8	0.0024	.990	.	.	229	32.0	0.1923	
19	CL22	Ritz		5	0.0010	.989	.	.	224	2.9	0.2014	
18	CL44	CL27		6	0.0018	.987	.	.	206	20.5	0.2073	
17	CL18	CL26		9	0.0025	.985	.	.	187	6.4	0.1956	
16	Fudge Rounds	Crest		2	0.0009	.984	.	.	192	.	0.24	
15	CL24	CL23		5	0.0029	.981	.	.	177	7.8	0.2753	
14	CL25	Waverly Wafers		4	0.0021	.979	.	.	175	7.7	0.2917	
13	CL30	CL19		17	0.0101	.969	.	.	130	41.0	0.2974	
12	CL16	CL31		9	0.0049	.964	.932	5.49	124	20.5	0.3121	
11	CL21	Lipton Family Si		4	0.0029	.961	.924	5.81	129	8.2	0.3445	
10	CL41	CL11		6	0.0045	.957	.915	5.94	130	5.0	0.323	
9	CL29	Lipton Tea Bags		4	0.0031	.953	.904	6.52	138	20.3	0.3603	
8	CL14	CL15		9	0.0101	.943	.890	6.08	131	10.7	0.3761	
7	CL20	Lipton Family Si		9	0.0047	.939	.872	6.89	143	11.7	0.4063	
6	CL13	CL9		21	0.0272	.911	.848	5.23	117	30.0	0.5101	
5	CL6	CL17		30	0.0746	.837	.814	1.30	74.3	42.2	0.606	
4	CL10	CL7		15	0.0440	.793	.764	1.40	75.3	36.4	0.6152	
3	CL8	CL12		18	0.0642	.729	.681	2.02	80.6	44.0	0.6648	
2	CL3	CL4		33	0.2580	.471	.470	0.01	54.2	54.4	0.9887	
1	CL5	CL2		63	0.4707	.000	.000	0.00	.	54.2	0.9636	

----- CLUSTER=1 CLUSNAME=CL7 -----							
Obs	class	name	height	width	depth	weight	color
1	Tea	Bigelow Plantati	7.7	13.4	6.9	3.27107	g
2	Tea	Bigelow Earl Gre	7.7	13.4	6.9	3.27107	b
3	Tea	Celestial Saeson	7.8	13.8	6.3	3.65931	b
4	Tea	Celestial Saeson	7.8	13.8	6.3	3.58305	r
5	Tea	Bigelow Lemon Li	7.7	13.4	6.9	3.41995	y
6	Tea	Celestial Saeson	7.8	13.8	6.3	3.82586	y
7	Tea	Celestial Saeson	7.8	13.8	6.3	3.33222	g
8	Tea	Lipton Tea Bags	6.7	10.0	5.7	3.28271	r
9	Tea	Lipton Family Si	8.9	11.1	8.2	4.39510	r
----- CLUSTER=2 CLUSNAME=CL17 -----							
Obs	class	name	height	width	depth	weight	color
10	Detergent	Tide	26.5	19.9	6.3	10.5928	r
11	Detergent	Tide	19.3	14.6	4.7	7.8357	r
12	Detergent	Tide	32.5	23.2	7.3	12.6889	r
13	Breakfast cereal	Grape Nuts	21.7	16.3	4.9	8.7937	w
14	Detergent	Arm & Hammer Det	33.7	22.8	7.0	14.7023	y
15	Detergent	Arm & Hammer Det	27.8	19.4	6.3	12.2003	y
16	Detergent	Arm & Hammer Det	38.8	30.0	16.9	22.4732	y
17	Detergent	Tide	39.4	24.8	11.3	16.1045	r
18	Detergent	Arm & Hammer Det	39.5	25.8	11.0	18.6115	y
----- CLUSTER=3 CLUSNAME=CL12 -----							
Obs	class	name	height	width	depth	weight	color
19	Paste, Tooth	Colgate	3.6	15.6	3.3	4.39510	r
20	Paste, Tooth	Crest	3.5	15.2	3.2	4.24343	w
21	Paste, Tooth	Crest	4.3	17.4	3.6	5.06813	w
22	Paste, Tooth	Arm & Hammer	4.4	17.0	3.7	5.21097	w
23	Paste, Tooth	Colgate	4.2	18.3	3.5	5.21097	r
24	Paste, Tooth	Crest	4.3	21.7	3.7	5.65790	w
25	Paste, Tooth	Colgate	4.4	22.0	3.5	5.82946	r
26	Little Debbie	Fudge Rounds	8.1	28.3	5.4	6.45411	w
27	Paste, Tooth	Crest	3.0	10.9	2.8	2.88670	w

----- CLUSTER=4 CLUSNAME=CL13 -----							
Obs	class	name	height	width	depth	weight	color
28	Breakfast cereal	Cheerios	27.5	19.0	6.2	6.56541	y
29	Breakfast cereal	Froot Loops	25.0	17.7	6.4	6.77735	r
30	Breakfast cereal	Special K	30.1	20.5	8.5	7.98644	w
31	Breakfast cereal	Corn Flakes	30.2	20.6	8.4	7.98644	w
32	Breakfast cereal	Special K	29.6	19.2	6.7	6.97679	w
33	Breakfast cereal	Corn Flakes	30.0	19.1	6.6	6.97679	w
34	Breakfast cereal	Froot Loops	30.2	20.8	8.5	8.23034	r
35	Breakfast cereal	Cheerios	30.3	20.4	7.2	7.51847	y
36	Breakfast cereal	Cheerios	24.1	17.2	5.3	5.82848	y
37	Breakfast cereal	Corn Flakes	33.7	25.4	8.0	8.79021	w
38	Breakfast cereal	Special K	23.4	16.6	5.7	5.82946	w
39	Breakfast cereal	Cheerios	32.5	22.4	8.4	8.27677	y
40	Breakfast cereal	Shredded Wheat,	26.6	19.6	5.6	7.98957	r
41	Crackers	Ritz	23.1	16.0	5.3	6.97953	r
42	Breakfast cereal	All-Bran	21.1	14.3	5.2	7.30951	y
43	Tea	Lipton Loose Tea	12.7	10.9	5.4	6.09479	r
44	Crackers	Ritz	23.1	20.7	5.2	7.68573	r
----- CLUSTER=5 CLUSNAME=CL10 -----							
Obs	class	name	height	width	depth	weight	color
45	Tea	Luzianne	8.9	22.8	6.4	5.53748	r
46	Tea	Luzianne Decaffe	8.9	22.8	6.4	5.29641	g
47	Crackers	Premium Saltines	11.0	25.0	10.7	7.68573	w
48	Tea	Lipton Family Si	8.7	20.8	8.2	5.53748	r
49	Little Debbie	Marshmallow Supr	9.4	32.0	7.0	6.56541	w
50	Tea	Lipton Family Si	13.7	24.0	9.0	6.97679	r

----- CLUSTER=6 CLUSNAME=CL9 -----							
Obs	class	name	height	width	depth	weight	color
51	Tea	Luzianne	18.4	20.2	6.9	6.09479	r
52	Tea	Lipton Tea Bags	17.1	20.0	6.7	6.09479	r
53	Breakfast cereal	Shredded Wheat	19.7	19.9	7.5	6.56541	y
54	Tea	Lipton Tea Bags	11.5	14.4	6.6	4.73448	r
----- CLUSTER=7 CLUSNAME=CL8 -----							
Obs	class	name	height	width	depth	weight	color
55	Crackers	Wheatworth	11.1	25.2	5.5	6.88239	w
56	Little Debbie	Swiss Cake Rolls	10.1	21.8	5.8	7.16545	w
57	Little Debbie	Figaroos	13.5	18.6	3.7	6.97679	y
58	Little Debbie	Nutty Bar	13.2	18.5	4.2	6.97679	y
59	Little Debbie	Apple Delights	11.2	30.1	4.9	7.51552	w
60	Little Debbie	Lemon Stix	13.2	18.5	4.2	6.33884	w
61	Little Debbie	Fudge Brownies	11.0	30.8	2.5	6.97679	w
62	Little Debbie	Snack Cakes	13.4	32.0	3.4	7.16545	b
63	Crackers	Waverly Wafers	14.4	22.5	6.2	7.68573	g

----- class -----						
	Breakfast cereal	Crackers	Detergent	Little Debbie	Paste, Tooth	Tea
CLUSTER						
1						#####
2	#		#####			
3				#	#####	
4	#####	##				#
5		#		#		####
6	#					###
7		##		#####		

	color				
	Blue	Green	Red	White	Yellow
CLUSTER					
1	##	##	###		##
2			####	#	####
3			###	#####	
4			#####	#####	#####
5		#	###	##	
6			###		#
7	#	#		#####	##

The last several analyses include color. Obviously, the dummy variables must not be included in calculations to standardize the rows. If the five dummy variables are simply standardized to variance 1.0 and included with the other variables, color dominates the analysis. The dummy variables should be scaled to a smaller variance, which must be determined by trial and error. Four analyses are done using PROC STANDARD to scale the dummy variables to a standard deviation of 0.2, 0.3, 0.4, or 0.8. The cluster listings are suppressed.

Since dummy variables drastically violate the normality assumption on which the CCC depends, the CCC tends to indicate an excessively large number of clusters.

```

/*****
/*
/* Analyses 4-7: standardized row-standardized logs & color */
/*
/*****
%let list=0;
%let crosscol=1;

title2
  'Analysis 4: Standardized row-standardized
    logarithms and color (s=.2)';
proc standard data=stdstan out=stdstan m=0 s=.2;
  var c_;
run;

proc cluster data=stdstan m=cen %clusopt outtree=tree;
  var l_height l_width l_depth l_weight c_;
  id name;
  copy class height width depth weight color;
run;

%show(7);

title2
  'Analysis 5: Standardized row-standardized
    logarithms and color (s=.3)';
proc standard data=stdstan out=stdstan m=0 s=.3;
  var c_;
run;

```

```

proc cluster data=stdstan m=cen %clusopt outtree=tree;
  var l_height l_width l_depth l_weight c_;;
  id name;
  copy class height width depth weight color;
run;

%show(6);

title2
  'Analysis 6: Standardized row-standardized
    logarithms and color (s=.4)';
proc standard data=stdstan out=stdstan m=0 s=.4;
  var c_;;
run;

proc cluster data=stdstan m=cen %clusopt outtree=tree;
  var l_height l_width l_depth l_weight c_;;
  id name;
  copy class height width depth weight color;
run;

%show(3);

title2
  'Analysis 7: Standardized row-standardized
    logarithms and color (s=.8)';
proc standard data=stdstan out=stdstan m=0 s=.8;
  var c_;;
run;

proc cluster data=stdstan m=cen %clusopt outtree=tree;
  var l_height l_width l_depth l_weight c_;;
  id name;
  copy class height width depth weight color;
run;

%show(10);

```

Using PROC STANDARD on the dummy variables with  $S=0.2$  causes four of the Little Debbie products to join the toothpastes. Using  $S=0.3$  causes one of the tea clusters to merge with the breakfast cereals while three cereals defect to the detergents. Using  $S=0.4$  produces three clusters consisting of (1) cereals and detergents, (2) Little Debbie products and toothpaste, and (3) teas, with crackers divided among all three clusters and a few other misclassifications. With  $S=0.8$ , ten clusters are indicated, each entirely monochrome. So,  $S=0.2$  or  $S=0.3$  degrades the classification,  $S=0.4$  yields a good but perhaps excessively coarse classification, and higher values of the  $S=$  option produce clusters that are determined mainly by color.

## Output 23.6.4. Analysis of Standardized Row-Standardized Logarithms and Color

Cluster Analysis of Grocery Boxes  
Analysis 4: Standardized row-standardized logarithms and color (s=.2)

The CLUSTER Procedure  
Centroid Hierarchical Cluster Analysis

Eigenvalues of the Covariance Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	2.43584975	0.94791932	0.5800	0.5800
2	1.48793042	1.39363531	0.3543	0.9342
3	0.09429511	0.03686218	0.0225	0.9567
4	0.05743293	0.01036136	0.0137	0.9704
5	0.04707157	0.00489503	0.0112	0.9816
6	0.04217654	0.00693298	0.0100	0.9916
7	0.03524355	0.03524355	0.0084	1.0000
8	-.00000000	0.00000000	-0.0000	1.0000
9	-.00000000		-0.0000	1.0000

Root-Mean-Square Total-Sample Standard Deviation = 0.68313  
Root-Mean-Square Distance Between Observations = 2.898275

Cluster History

NCL	-----Clusters Joined-----	FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Norm Cent Dist	T i e
20	CL46 Lemon Stix	3	0.0016	.968	.	.	67.5	11.9	0.2706	
19	Luzianne Lipton Family Si	2	0.0014	.966	.	.	69.7	.	0.2995	
18	CL25 CL37	6	0.0041	.962	.	.	67.1	5.0	0.3081	
17	CL33 CL35	16	0.0099	.952	.	.	57.2	16.7	0.3196	
16	CL19 Luzianne Decaffe	3	0.0024	.950	.	.	59.2	1.7	0.3357	
15	CL30 CL16	5	0.0042	.946	.	.	59.5	2.7	0.3299	
14	CL27 CL18	8	0.0057	.940	.	.	58.9	4.2	0.3429	
13	CL20 Fudge Brownies	4	0.0031	.937	.	.	61.7	3.6	0.3564	
12	CL24 Lipton Tea Bags	4	0.0031	.934	.905	3.23	65.2	4.7	0.359	
11	CL39 CL28	6	0.0068	.927	.896	3.17	65.9	12.1	0.3743	
10	CL13 Snack Cakes	5	0.0036	.923	.886	3.62	70.8	2.3	0.3755	
9	CL11 CL32	13	0.0176	.906	.874	2.70	64.8	16.0	0.4107	
8	CL14 Lipton Family Si	9	0.0052	.900	.859	3.29	71.0	2.6	0.4265	
7	Waverly Wafers CL10	6	0.0052	.895	.841	4.09	79.8	2.4	0.4378	
6	CL17 CL12	20	0.0248	.870	.817	3.52	76.6	19.7	0.4898	
5	CL15 CL8	14	0.0326	.838	.783	3.08	75.0	14.0	0.5607	
4	CL6 CL21	30	0.0743	.764	.734	1.35	63.5	35.6	0.5877	
3	CL9 CL7	19	0.0579	.706	.653	2.17	72.0	22.8	0.6611	
2	CL4 CL3	49	0.3632	.343	.450	-2.6	31.8	73.0	0.9838	
1	CL2 CL5	63	0.3426	.000	.000	0.00	.	31.8	0.9876	

	class					
	Breakfast cereal	Crackers	Detergent	Little Debbie	Paste, Tooth	Tea
CLUSTER						
1	##		#####			
2		#		####	#####	
3	#####	##				#
4	#					###
5		#		#####		
6						#####
7		#				####



	color				
	Blue	Green	Red	White	Yellow
CLUSTER					
1			####	#	####
2			###	#####	
3			#####	#####	####
4			###		#
5	#	#		##	##
6	##	##	###		##
7		#	###	#	

Cluster Analysis of Grocery Boxes  
Analysis 5: Standardized row-standardized logarithms and color (s=.3)

The CLUSTER Procedure  
Centroid Hierarchical Cluster Analysis

Eigenvalues of the Covariance Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	2.44752302	0.95026671	0.5500	0.5500
2	1.49725632	1.36701945	0.3365	0.8865
3	0.13023687	0.02135049	0.0293	0.9157
4	0.10888637	0.00867367	0.0245	0.9402
5	0.10021271	0.00628821	0.0225	0.9627
6	0.09392449	0.02196469	0.0211	0.9838
7	0.07195981	0.07195981	0.0162	1.0000
8	0.00000000	0.00000000	0.0000	1.0000
9	-.00000000		-0.0000	1.0000

Root-Mean-Square Total-Sample Standard Deviation = 0.703167  
Root-Mean-Square Distance Between Observations = 2.983287

Cluster History

NCL	-----Clusters Joined-----		FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Norm Cent Dist	T i e
20	CL24	CL28	4	0.0038	.953	.	.	45.7	2.7	0.3448	
19	Grape Nuts	CL23	6	0.0033	.950	.	.	46.0	3.5	0.3477	
18	CL46	Lemon Stix	3	0.0027	.947	.	.	47.1	21.9	0.3558	
17	CL21	Lipton Tea Bags	4	0.0031	.944	.	.	48.2	2.5	0.3577	
16	CL39	CL33	6	0.0064	.937	.	.	46.9	12.1	0.3637	
15	CL19	CL29	14	0.0152	.922	.	.	40.6	12.4	0.3707	
14	CL18	Fudge Brownies	4	0.0035	.919	.	.	42.5	2.5	0.3813	
13	CL16	CL25	13	0.0175	.901	.	.	38.0	13.7	0.4103	
12	CL22	Lipton Family Si	5	0.0049	.896	.875	1.76	40.0	3.2	0.4353	
11	CL12	CL37	7	0.0089	.887	.865	1.71	40.9	4.6	0.4397	
10	CL20	Luzianne Decaffe	5	0.0056	.882	.854	2.02	43.9	2.5	0.4669	
9	CL26	CL17	16	0.0222	.859	.841	1.20	41.3	16.6	0.479	
8	CL32	CL11	9	0.0125	.847	.826	1.31	43.5	4.5	0.4988	
7	CL14	Snack Cakes	5	0.0070	.840	.806	1.95	49.0	3.3	0.519	
6	Waverly Wafers	CL7	6	0.0077	.832	.782	2.79	56.6	2.3	0.5366	
5	CL9	CL15	30	0.0716	.761	.749	0.54	46.1	28.3	0.5452	
4	CL10	CL8	14	0.0318	.729	.700	1.21	52.9	8.6	0.5542	
3	CL5	CL6	36	0.0685	.660	.622	1.50	58.3	14.2	0.6516	
2	CL13	CL4	27	0.2008	.460	.427	0.90	51.9	46.6	0.9611	
1	CL3	CL2	63	0.4595	.000	.000	0.00	.	51.9	0.9609	

	class					
	Breakfast cereal	Crackers	Detergent	Little Debbie	Paste, Tooth	Tea
CLUSTER						
1	###	##	#####			#
2		#		####	#####	
3	#####					###
4		#		####		
5						#####
6		#				####

	color				
	Blue	Green	Red	White	Yellow
CLUSTER					
1			#####	#	####
2			###	#####	
3			####	#####	####
4	#	#		##	##
5	##	##	###		##
6		#	###	#	

Cluster Analysis of Grocery Boxes  
Analysis 6: Standardized row-standardized logarithms and color (s=.4)

The CLUSTER Procedure  
Centroid Hierarchical Cluster Analysis

Eigenvalues of the Covariance Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	2.46469435	0.95296119	0.5135	0.5135
2	1.51173316	1.28149311	0.3149	0.8284
3	0.23024005	0.04306536	0.0480	0.8764
4	0.18717469	0.01766446	0.0390	0.9154
5	0.16951023	0.01827481	0.0353	0.9507
6	0.15123542	0.06582379	0.0315	0.9822
7	0.08541162	0.08541162	0.0178	1.0000
8	-.00000000	0.00000000	-0.0000	1.0000
9	-.00000000		-0.0000	1.0000

Root-Mean-Square Total-Sample Standard Deviation = 0.730297  
Root-Mean-Square Distance Between Observations = 3.098387

Cluster History

NCL	-----Clusters Joined-----		FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Norm Cent Dist	T i e
20	CL29	CL44	10	0.0074	.955	.	.	47.7	8.2	0.3789	
19	CL38	Lipton Family Si	3	0.0031	.952	.	.	48.1	9.3	0.3792	
18	CL25	CL41	11	0.0155	.936	.	.	38.8	36.7	0.4192	
17	CL23	CL43	10	0.0120	.924	.	.	35.0	11.6	0.4208	
16	Grape Nuts	CL26	6	0.0050	.919	.	.	35.6	5.8	0.4321	
15	CL19	CL31	5	0.0074	.912	.	.	35.4	5.3	0.4362	
14	Premium Saltines	CL27	4	0.0046	.907	.	.	36.8	2.9	0.4374	
13	CL18	CL20	21	0.0352	.872	.	.	28.4	19.7	0.4562	
12	CL13	CL16	27	0.0372	.835	.839	-.37	23.4	12.0	0.4968	
11	CL21	CL17	15	0.0289	.806	.828	-1.5	21.6	13.6	0.5183	
10	CL14	CL15	9	0.0200	.786	.815	-1.8	21.6	7.2	0.5281	
9	Waverly Wafers	Luzianne Decaffe	2	0.0047	.781	.801	-1.2	24.1	.	0.5425	
8	CL10	CL24	12	0.0243	.757	.785	-1.3	24.5	5.8	0.5783	
7	CL12	CL46	29	0.0224	.735	.765	-1.3	25.8	5.3	0.6105	
6	CL8	CL37	14	0.0220	.712	.740	-1.1	28.3	4.0	0.6313	
5	CL6	CL32	16	0.0251	.687	.707	-.78	31.9	3.9	0.6664	
4	CL11	CL9	17	0.0287	.659	.660	-.04	38.0	7.0	0.7098	
3	CL4	Snack Cakes	18	0.0180	.641	.584	2.21	53.5	3.2	0.7678	
2	CL3	CL5	34	0.2175	.423	.400	0.67	44.8	31.4	0.8923	
1	CL7	CL2	63	0.4232	.000	.000	0.00	.	44.8	0.9156	

	class					
	Breakfast cereal	Crackers	Detergent	Little Debbie	Paste, Tooth	Tea
CLUSTER						
1	>#####	##	#####	##		#
2		##		#####	#####	#
3		#				>#####

	color				
	Blue	Green	Red	White	Yellow
CLUSTER					
1			#####	#####	#####
2	#	##	###	#####	
3	##	##	#####	#	##

Cluster Analysis of Grocery Boxes  
 Analysis 7: Standardized row-standardized logarithms and color (s=.8)

The CLUSTER Procedure  
 Centroid Hierarchical Cluster Analysis

Eigenvalues of the Covariance Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	2.61400794	0.93268930	0.3631	0.3631
2	1.68131864	0.77645948	0.2335	0.5966
3	0.90485916	0.22547234	0.1257	0.7222
4	0.67938683	0.00292216	0.0944	0.8166
5	0.67646466	0.12119211	0.0940	0.9106
6	0.55527255	0.46658428	0.0771	0.9877
7	0.08868827	0.08868827	0.0123	1.0000
8	-.00000000	0.00000000	-0.0000	1.0000
9	-.00000000		-0.0000	1.0000

Root-Mean-Square Total-Sample Standard Deviation = 0.894427  
 Root-Mean-Square Distance Between Observations = 3.794733

Cluster History

NCL	-----Clusters Joined-----		FREQ	SPRSQ	RSQ	ERSQ	CCC	PSF	PST2	Norm Cent Dist	T i e
20	CL29	CL44	10	0.0049	.970	.	.	72.7	8.2	0.3094	
19	CL38	Lipton Family Si	3	0.0021	.968	.	.	73.3	9.3	0.3096	
18	CL21	CL23	12	0.0153	.952	.	.	53.0	15.0	0.4029	
17	Waverly Wafers	Luzianne Decaffe	2	0.0032	.949	.	.	53.8	.	0.443	
16	CL27	CL24	6	0.0095	.940	.	.	48.9	10.4	0.444	
15	CL19	CL16	9	0.0136	.926	.	.	43.0	6.1	0.4587	
14	CL41	Grape Nuts	7	0.0058	.920	.	.	43.6	51.2	0.4591	
13	CL26	CL46	7	0.0105	.910	.	.	42.1	22.0	0.4769	
12	CL25	CL13	12	0.0205	.889	.743	16.5	37.3	13.8	0.467	
11	CL18	Premium Saltines	13	0.0093	.880	.726	16.7	38.2	4.0	0.5586	
10	CL17	CL37	4	0.0134	.867	.706	16.5	38.3	7.9	0.6454	
9	CL14	CL20	17	0.0567	.810	.684	11.0	28.8	52.6	0.6534	
8	CL12	CL9	29	0.0828	.727	.659	5.03	20.9	20.7	0.604	
7	CL11	CL43	16	0.0359	.691	.631	4.25	20.9	14.4	0.6758	
6	CL15	CL31	11	0.0263	.665	.598	4.24	22.6	8.0	0.7065	
5	CL7	CL6	27	0.1430	.522	.557	-1.7	15.8	28.2	0.8247	
4	CL8	CL5	56	0.2692	.253	.507	-9.1	6.6	31.5	0.7726	
3	Snack Cakes	CL32	3	0.0216	.231	.435	-6.6	9.0	46.0	1.0027	
2	CL4	CL10	60	0.1228	.108	.289	-5.6	7.4	9.5	1.0096	
1	CL2	CL3	63	0.1083	.000	.000	0.00	.	7.4	1.0839	

CLUSTER	class					
	Breakfast cereal	Crackers	Detergent	Little Debbie	Paste, Tooth	Tea
1	###	##	####			#
2		##		#####	#####	
3	#####					
4	#####		####	##		
5					###	
6						#####
7		#				###
8						##
9						##
10				#		

	color				
	Blue	Green	Red	White	Yellow
CLUSTER					
1			#####		
2				#####	
3				#####	
4					#####
5			###		
6			#####		
7		####			
8	##				
9					##
10	#				

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