

Contents

1	Introduction to Course	1
2	Overview of Course	1
3	Data Reduction	2
3.1	Variable Redundancy	3
3.2	Data Reduction in Exploratory Graphics	5
4	Principal Component Analysis	5
4.1	Introduction	5
4.2	Mathematical background of PCA	5
4.3	Number of Extracted Components	6
4.4	Characteristics of Principal Components	6
4.5	Total Variance in the context of PCA	7
4.6	Orthogonal versus Oblique Solutions	7
4.7	Sampling adequacy (KMO Statistic)	7
4.8	Bartlett's Test for Sphericity	8
4.9	Determining the Number of Meaningful Components to Retain	8
4.10	The Eigenvalue-One Criterion	8
4.10.1	Advantages and Disadvantages	9
4.11	The scree test	9
4.11.1	Advantages and Disadvantages	9
4.12	Proportion of Variance Accounted For	10
4.12.1	Advantages and Disadvantages	10
4.13	The Interpretability Criteria	11

1 Introduction to Course

Advances in data collection and storage capabilities during the past decades have led to an information overload in most sciences. Researchers working in domains as diverse as engineering, astronomy, biology, remote sensing, economics, and consumer transactions, face larger and larger observations and simulations on a daily basis.

Such datasets, in contrast with smaller, more traditional datasets that have been studied extensively in the past, present new challenges in data analysis. Traditional statistical methods break down partly because of the increase in the number of observations, but mostly because of the increase in the number of variables associated with each observation. The dimension of the data is the number of variables that are measured on each observation.

(I Fodor, LLNL, USA, June 2002).

2 Overview of Course

To ground the students in Applied Multivariate Analysis. This module serves business and mathematics students. It introduces the mathematical statistical ideas behind

- Principal Component Analysis,

- Factor Analysis,
- Cluster Analysis,
- Discrimination Function,
- The Multiple Linear Logistic function.

The students learn how to implement these techniques in SPSS to become competent in the analysis of a wide variety of multivariate data structures.

3 Data Reduction

Data Reduction or Dimensionality Reduction pertains to analytic methods (typically multivariate exploratory techniques such as Factor Analysis, Multidimensional Scaling, Cluster Analysis, Canonical Correlation, or Neural Networks) that involve reducing the dimensionality of a data set by extracting a number of underlying factors, dimensions, clusters, etc., that can account for the variability in the (multidimensional) data set.

For example, in poorly designed questionnaires, all responses provided by the participants on a large number of variables (scales, questions, or dimensions) could be explained by a very limited number of "trivial" or artifactual factors. For example, two such underlying factors could be: (1) the respondent's attitude towards the study (positive or negative) and (2) the "social desirability" factor (a response bias representing a tendency to respond in a socially desirable manner).

3.1 Variable Redundancy

A specific (but fictitious) example of research will now be presented to illustrate the concept of variable redundancy introduced earlier. Imagine that you have developed a 7-item measure of job satisfaction. The *instrument* is reproduced here:

Please respond to each of the following statements by placing a rating in the space to the left of the statement. In making your ratings, use any number from 1 to 7 in which 1=strongly disagree and 7=strongly agree.

----- 1. My supervisor treats me with consideration.

----- 2. My supervisor consults me concerning important decisions that affect my work.

----- 3. My supervisors give me recognition when I do a good job.

----- 4. My supervisor gives me the support I need to do my job well.

----- 5. My pay is fair.

----- 6. My pay is appropriate, given the amount of responsibility that comes with my job.

----- 7. My pay is comparable to the pay earned by other employees whose jobs are similar to mine.

Notice that items 1-4 all deal with the same topic: the employees satisfaction with their supervisors. In this way, items 1-4 are somewhat redundant to one another. Similarly, notice that items 5-7 also all seem to deal with the same topic: the employees satisfaction with their pay. Empirical findings may further support the notion that there is redundancy in the seven items. Assume that you administer the questionnaire to 200 employees and compute all possible correlations between responses to the 7 items. The resulting fictitious correlations are reproduced in the table below.

When correlations among several variables are computed, they are typically summarized in the form of a correlation matrix, such as the one reproduced in the previous table. This is an appropriate opportunity to review just how a correlation matrix is interpreted.

The rows and columns of the table correspond to the seven variables included in the analysis: Row 1 (and column 1) represents variable 1, row 2 (and column 2) represents variable 2, and so forth. Where a given row and column intersect, you will find the correlation between the two corresponding variables. For example, where the row for variable 2 intersects with the column for variable 1, you find a correlation of 0.75; this means that the correlation between variables 1 and 2 is 0.75. The correlations show that the seven items seem to hang together in two distinct groups.

First, notice that items 1-4 show relatively strong correlations with one another. This could be because items 1-4 are measuring the same construct. In the same way, items 5-7 correlate strongly with one another (a possible indication that they all measure the same construct as well). Even more interesting, notice that items 1-4 demonstrate very weak correlations with items 5-7. This is what you would expect to see if items 1-4 and items 5-7 were measuring two different constructs.

Correlations among Seven Job Satisfaction Items

Variable	Correlations						
	1	2	3	4	5	6	7
1	1.00						
2	.75	1.00					
3	.83	.82	1.00				
4	.68	.92	.88	1.00			
5	.03	.01	.04	.01	1.00		
6	.05	.02	.05	.07	.89	1.00	
7	.02	.06	.00	.03	.91	.76	1.00

Note : N = 200.

Figure 1: Questionnaire

Given this apparent redundancy, it is likely that the seven items of the questionnaire are not really measuring seven different constructs; more likely, items 1-4 are measuring a single construct that could reasonably be labelled *satisfaction with supervision* while items 5-7 are measuring a different construct that could be labelled *satisfaction with pay*.

If responses to the seven items actually displayed the redundancy suggested by the pattern of correlations, it would be advantageous to somehow reduce the number of variables in this data set, so that (in a sense) items 1-4 are collapsed into a single new variable that reflects the employees satisfaction with supervision, and items 5-7 are collapsed into a single new variable that reflects satisfaction with pay.

We could then use these two new artificial variables (rather than the seven original variables) as predictor variables in multiple regression, or in any other type of analysis.

In essence, this is what is accomplished by principal component analysis: it allows you to reduce a set of observed variables into a smaller set of artificial variables called principal components. The resulting principal components may then be used in subsequent analyses.

3.2 Data Reduction in Exploratory Graphics

The term can also refer in **exploratory graphics** to “Data Reduction by unbiased decreasing of the sample size”. This type of Data Reduction is applied in exploratory graphical data analysis of extremely large data sets. The size of the data set can obscure an existing pattern (especially in large line graphs or scatterplots) due to the density of markers or lines. Then, it can be useful to plot only a representative subset of the data (so that the pattern is not hidden by the number of point markers) to reveal the otherwise obscured but still reliable pattern.

4 Principal Component Analysis

4.1 Introduction

Principal component analysis is appropriate when you have obtained measures on a number of (possibly) correlated observed variables and wish to develop a smaller number of artificial uncorrelated variables called **principal components** that will account for most of the variance in the observed variables. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. The principal components may then be used as predictor or criterion variables in subsequent analyses.

Traditionally, principal component analysis is performed can be performed on raw data, on the symmetric **Covariance matrix** or on the symmetric **Correlation matrix**. (The covariance matrix contains scaled sums of squares and cross products. A correlation matrix is like a covariance matrix but first the variables, i.e. the columns, have been standardized.)

If raw data is used, the procedure will create the original correlation matrix or covariance matrix, as specified by the user. If the correlation matrix is used, the variables are standardized and the total variance will equal the number of variables used in the analysis (because each standardized variable has a variance equal to 1). If the covariance matrix is used, the variables will remain in their original metric. However, one must take care to use variables whose variances and scales are similar. Unlike **factor analysis**, which analyzes the common variance, the original matrix in a principal components analysis analyzes the total variance. Also, principal components analysis assumes that each original measure is collected without measurement error.

4.2 Mathematical background of PCA

Principal Component Analysis is a linear **dimensionality reduction** technique, which identifies orthogonal directions of maximum variance in the original data, and projects the data into a lower-dimensionality space formed of a sub-set of the highest-variance components (Bishop, 1995).

The mathematical technique used in PCA is called **eigen analysis**. Technically, a principal component can be defined as a linear combination of optimally-weighted observed variables. Software packages compute solutions for these weights by using a special type of equation called an **eigenequation**. The weights produced by these eigenequations are optimal weights in the sense that, for a given set of data, no other set of weights could produce a set of components that are more successful in accounting for variance in the observed variables. The weights are

created so as to satisfy a principle of least squares that is similar (but not identical) to the principle of least squares used in multiple regression.

Remarks

- The words ***linear combination*** refer to the fact that scores on a component are created by adding together scores on the observed variables being analyzed.
- ***Optimally weighted*** refers to the fact that the observed variables are weighted in such a way that the resulting components account for a maximal amount of variance in the data set.

4.3 Number of Extracted Components

The preceding section may have created the impression that, if a principal component analysis were performed on data from the 7-item job satisfaction questionnaire, only two components would be created. However, such an impression would not be entirely correct.

In reality, the number of components extracted in a principal component analysis *is equal* to the number of observed variables being analyzed. This means that an analysis of your 7-item questionnaire would actually result in seven components, not two.

However, in most analyses, only the first few components account for meaningful amounts of variance, so only these first few components are retained, interpreted, and used in subsequent analyses (such as in multiple regression analyses). For example, in your analysis of the 7-item job satisfaction questionnaire, it is likely that only the first two components would account for a meaningful amount of variance; therefore only these would be retained for interpretation. You would assume that the remaining five components accounted for only trivial amounts of variance. These latter components would therefore not be retained, interpreted, or further analyzed.

4.4 Characteristics of Principal Components

The first component extracted in a principal component analysis accounts for a maximal amount of total variance in the observed variables. Under typical conditions, this means that the first component will be correlated with at least some of the observed variables. In fact it may be correlated with many.

The second component extracted will have two important characteristics. First, this component will account for a maximal amount of variance in the data set that was not accounted for by the first component. Again under typical conditions, this means that the second component will be correlated with some of the observed variables that did not display strong correlations with component 1. The second characteristic of the second component is that it will be uncorrelated with the first component. If you were to compute the correlation between components 1 and 2, that correlation should be close to zero.

The remaining components that are extracted in the analysis display the same two characteristics: each component accounts for a maximal amount of variance in the observed variables that was not accounted for by the preceding components, and is uncorrelated with all of the preceding components. A principal component analysis proceeds in this fashion, with each new component accounting for progressively smaller and smaller amounts of variance (this is why

only the first few components are usually retained and interpreted). When the analysis is complete, the resulting components will display varying degrees of correlation with the observed variables, but are completely uncorrelated with one another.

4.5 Total Variance in the context of PCA

To understand the meaning of **total variance** as it is used in a principal component analysis, remember that the observed variables are standardized in the course of the analysis. This means that each variable is transformed so that it has a mean of zero and a variance of one.

The total variance in the data set is simply the sum of the variances of these observed variables. Because they have been standardized to have a variance of one, each observed variable contributes one unit of variance to the total variance in the data set. Because of this, the total variance in a principal component analysis *will always be equal* to the number of observed variables being analyzed.

For example, if seven variables are being analyzed, the total variance will equal seven. The components that are extracted in the analysis will partition this variance: perhaps the first component will account for 3.2 units of total variance; perhaps the second component will account for 2.1 units. The analysis continues in this way until all of the variance in the data set (i.e. the remaining 1.7 units). has been accounted for.

4.6 Orthogonal versus Oblique Solutions

This course will discuss only principal component analysis that result in **orthogonal solutions**. An orthogonal solution is one in which the components remain uncorrelated (orthogonal means uncorrelated).

It is possible to perform a principal component analysis that results in correlated components. Such a solution is called an **oblique solution**. In some situations, oblique solutions are superior to orthogonal solutions because they produce cleaner, more easily-interpreted results. However, oblique solutions are also somewhat more complicated to interpret, compared to orthogonal solutions. For this reason, we will focus only on the interpretation of orthogonal solutions

4.7 Sampling adequacy (KMO Statistic)

Measured by the Kaiser-Meyer-Olkin (KMO) statistics, sampling adequacy predicts if the analyses are likely to perform well, based on correlation and partial correlation. KMO can also be used to assess which variables to drop from the model because they are too multi-collinear.

There is a KMO statistic for each individual variable, and their sum is the KMO overall statistic. KMO varies from 0 to 1.0 and KMO overall should be 0.60 or higher to proceed with factor analysis. Values below 0.5 imply that factor analysis or PCA may not be appropriate. (Approach to overcoming this: If it is not, drop the **indicator variables** with the lowest individual KMO statistic values, until KMO overall rises above 0.60.)

Kaiser-Meyer-OlkinTo compute KMO overall, the numerator is the sum of squared correlations of all variables in the analysis (except the 1.0 self-correlations of variables with themselves, of course). The denominator is this same sum plus the sum of squared partial correlations of each variable i with each variable j , controlling for others in the analysis. The concept is that

the partial correlations should not be very large if one is to expect distinct factors to emerge from factor analysis.

4.8 Bartlett's Test for Sphericity

Bartlett's measure tests the null hypothesis that the original correlation matrix is an identity matrix. For PCA and factor analysis to work we need some relationships between variables and if the R- matrix were an identity matrix then all correlation coefficients would be zero. Therefore, we want this test to be significant (i.e. have a significance value less than 0.05). A significant test tells us that the correlation matrix is not an identity matrix; therefore, there are some relationships between the variables we hope to include in the analysis. For these data, Bartlett's test is highly significant ($p < 0.001$), and therefore factor analysis is appropriate.

4.9 Determining the Number of Meaningful Components to Retain

Earlier it was stated that the number of components extracted is equal to the number of variables being analyzed, necessitating that you decide just how many of these components are truly meaningful and worthy of being retained for further analysis.

In general, you expect that only the first few components will account for meaningful amounts of variance, and that the later components will tend to account for only trivial variance.

The next step of the analysis, therefore, is to determine how many meaningful components should be retained for interpretation. The following section will describe four criteria that may be used in making this decision:

- the eigenvalue-one criterion,
- the scree test,
- the proportion of variance accounted for,
- the interpretability criterion.

4.10 The Eigenvalue-One Criterion

In principal component analysis, one of the most commonly used criteria for solving the number-of-components problem is the eigenvalue-one criterion, also known as the Kaiser criterion (Kaiser, 1960). With this approach, you retain and interpret any component with an eigenvalue greater than 1.00.

The rationale for this criterion is straightforward. Each observed variable contributes one unit of variance to the total variance in the data set. Any component that displays an eigenvalue greater than 1.00 is accounting for a greater amount of variance than had been contributed by one variable. Such a component is therefore accounting for a meaningful amount of variance, and is worthy of being retained.

On the other hand, a component with an eigenvalue less than 1.00 is accounting for less variance than had been contributed by one variable. The purpose of principal component analysis is to reduce a number of observed variables into a relatively smaller number of components; this cannot be effectively achieved if you retain components that account for less variance than had been contributed by individual variables. For this reason, components with eigenvalues less than 1.00 are viewed as trivial, and are not retained.

4.10.1 Advantages and Disadvantages

The eigenvalue-one criterion has a number of positive features that have contributed to its popularity. Perhaps the most important reason for its widespread use is its simplicity: You do not make any subjective decisions, but merely retain components with eigenvalues greater than one.

On the positive side, it has been shown that this criterion very often results in retaining the correct number of components, particularly when a small to moderate number of variables are being analyzed and the variable communalities are high. Stevens (1986) reviews studies that have investigated the accuracy of the eigenvalue-one criterion, and recommends its use when less than 30 variables are being analyzed and communalities are greater than .70, or when the analysis is based on over 250 observations and the mean communality is greater than or equal to 0.60.

There are a number of problems associated with the eigenvalue-one criterion, however. As was suggested in the preceding paragraph, it can lead to retaining the wrong number of components under circumstances that are often encountered in research (e.g., when many variables are analyzed, when communalities are small).

Also, the mindless application of this criterion can lead to retaining a certain number of components when the actual difference in the eigenvalues of successive components is only trivial. For example, if component 2 displays an eigenvalue of 1.001 and component 3 displays an eigenvalue of 0.999, then component 2 will be retained but component 3 will not; this may mislead you into believing that the third component was meaningless when, in fact, it accounted for almost exactly the same amount of variance as the second component.

In short, the eigenvalue-one criterion can be helpful when used judiciously, but the thoughtless application of this approach can lead to serious errors of interpretation.

4.11 The scree test

With the scree test (Cattell, 1966), you plot the eigenvalues associated with each component and look for a break between the components with relatively large eigenvalues and those with small eigenvalues. The components that appear before the break are assumed to be meaningful and are retained for rotation; those appearing after the break are assumed to be unimportant and are not retained.

Remark: The word scree refers to the loose rubble that lies at the base of a cliff. When performing a scree test, you normally hope that the scree plot will take the form of a cliff: At the top will be the eigenvalues for the few meaningful components, followed by a break (the edge of the cliff). At the bottom of the cliff will lie the scree: eigenvalues for the trivial components.

Sometimes a scree plot will display several large breaks. When this is the case, you should look for the last big break before the eigenvalues begin to level off. Only the components that appear before this last large break should be retained.

4.11.1 Advantages and Disadvantages

The scree test can be expected to provide reasonably accurate results, provided the sample is large (over 200) and most of the variable communalities are large (Stevens, 1986). However, this criterion has its own weaknesses as well, most notably the ambiguity that is often displayed

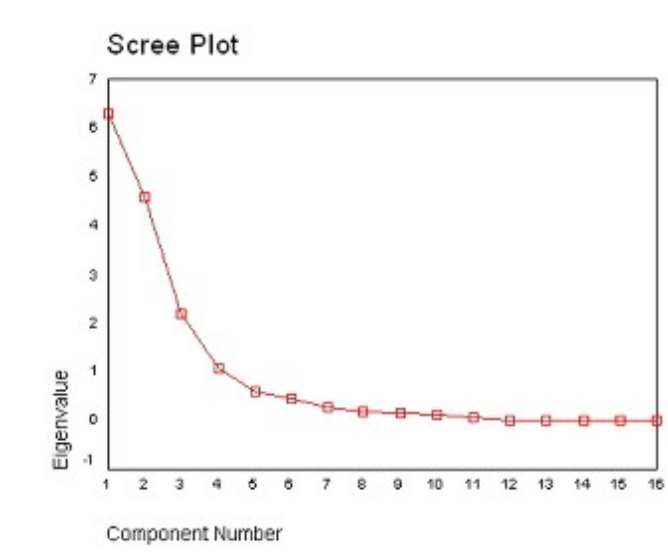


Figure 2: Example of a Scree Plot

by scree plots under typical research conditions: Very often, it is difficult to determine exactly where in the scree plot a break exists, or even if a break exists at all.

4.12 Proportion of Variance Accounted For

A third criterion in solving the number of factors problem involves retaining a component if it accounts for a specified proportion (or percentage) of variance in the data set. For example, you may decide to retain any component that accounts for at least 5% or 10% of the total variance. This proportion can be calculated with a simple formula:

$$\text{Proportion} = \frac{\text{Eigenvalue for the component of interest}}{\text{Total eigenvalues of the correlation matrix}}$$

In principal component analysis, the total eigenvalues of the correlation matrix is equal to the total number of variables being analyzed (because each variable contributes one unit of variance to the analysis).

An alternative criterion is to retain enough components so that the cumulative percent of variance accounted for is equal to some minimal value. Suppose that, in a PCA procedure, that components 1, 2, 3, and 4 accounted for approximately 37%, 33%, 13%, and 10% of the total variance, respectively.

Suppose that it was required to account for 90% of the variance. Adding these percentages together results in a sum of 93%. This means that the cumulative percent of variance accounted for by components 1, 2, 3, and 4 is 93%.

4.12.1 Advantages and Disadvantages

The proportion of variance criterion has a number of positive features. For example, in most cases, you would not want to retain a group of components that, combined, account for only

Eigenvalues of the Correlation Matrix				
	Eigenvalue	Difference	Proportion	Cumulative
1	3.88155846	2.24699126	0.4313	0.4313
2	1.63456720	0.57436630	0.1816	0.6129
3	1.06020090	0.10480537	0.1178	0.7307
4	0.95539554	0.42415968	0.1062	0.8369
5	0.53123586	0.10477119	0.0590	0.8959
6	0.42646467	0.13882496	0.0474	0.9433
7	0.28763971	0.16930381	0.0320	0.9752
8	0.11833590	0.01373414	0.0131	0.9884
9	0.10460176		0.0116	1.0000

Figure 3: Eigenvalue Table

a minority of the variance in the data set (say, 30%). Nonetheless, many critical values discussed earlier are obviously arbitrary. Because of these and related problems, this approach has sometimes been criticized for its subjectivity (Kim and Mueller, 1978).

4.13 The Interpretability Criteria

Perhaps the most important criterion for solving the *number of-components* problem is the interpretability criterion: interpreting the substantive meaning of the retained components and verifying that this interpretation makes sense in terms of what is known about the constructs under investigation.

The following list provides four rules to follow in doing this. (A later section shows how to actually interpret the results of a principal component analysis; the following rules will be more meaningful after you have completed that section).

1. Are there at least three variables (items) with significant loadings on each retained component? A solution is less satisfactory if a given component is measured by less than three variables.
2. Do the variables that load on a given component share the same conceptual meaning? For example, if three questions on a survey all load on component 1, do all three of these questions seem to be measuring the same construct?
3. Do the variables that load on different components seem to be measuring different constructs? For example, if three questions load on component 1, and three other questions load on component 2, do the first three questions seem to be measuring a construct that is conceptually different from the construct measured by the last three questions?
4. Does the rotated factor pattern demonstrate simple structure? Simple structure means that the pattern possesses two characteristic:
 - (a) Most of the variables have relatively high factor loadings on only one component, and near zero loadings on the other components, and

- (b) most components have relatively high factor loadings for some variables, and near-zero loadings for the remaining variables.