

15th International Conference
Applications of Computer Algebra

Teaching Principal Components Analysis with Minitab

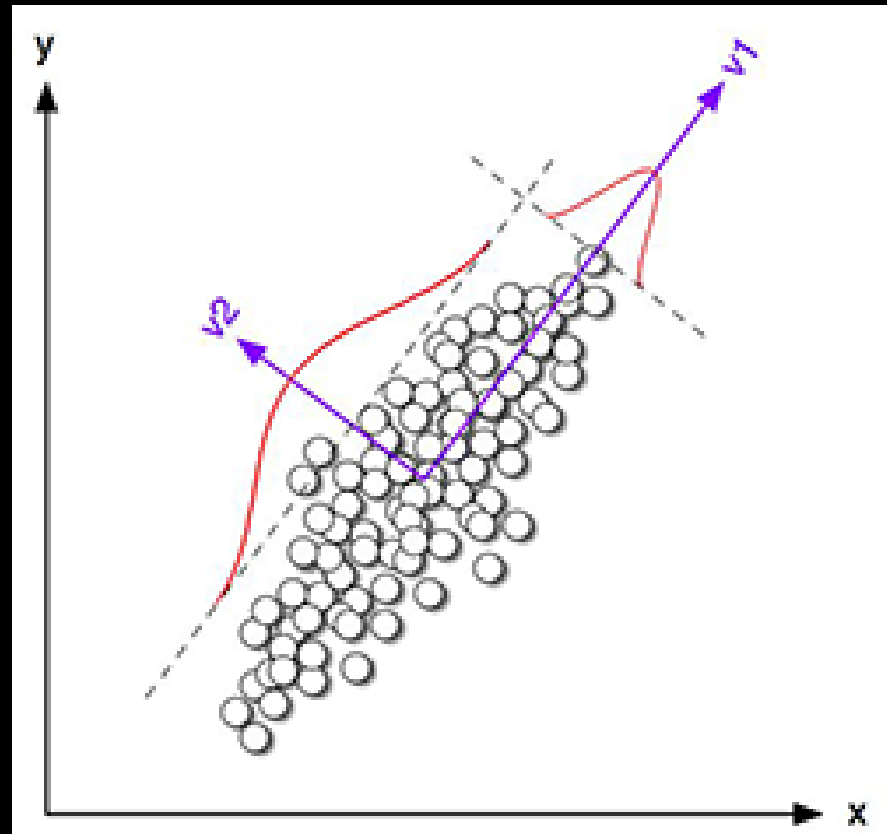
Dr. Jaime Curts

The University of Texas Pan American

ACA 2009 to be held June 25-28, 2009
at École de Technologie Supérieure (ETS),
Université du Québec, Montréal, Québec, Canada

Introduction

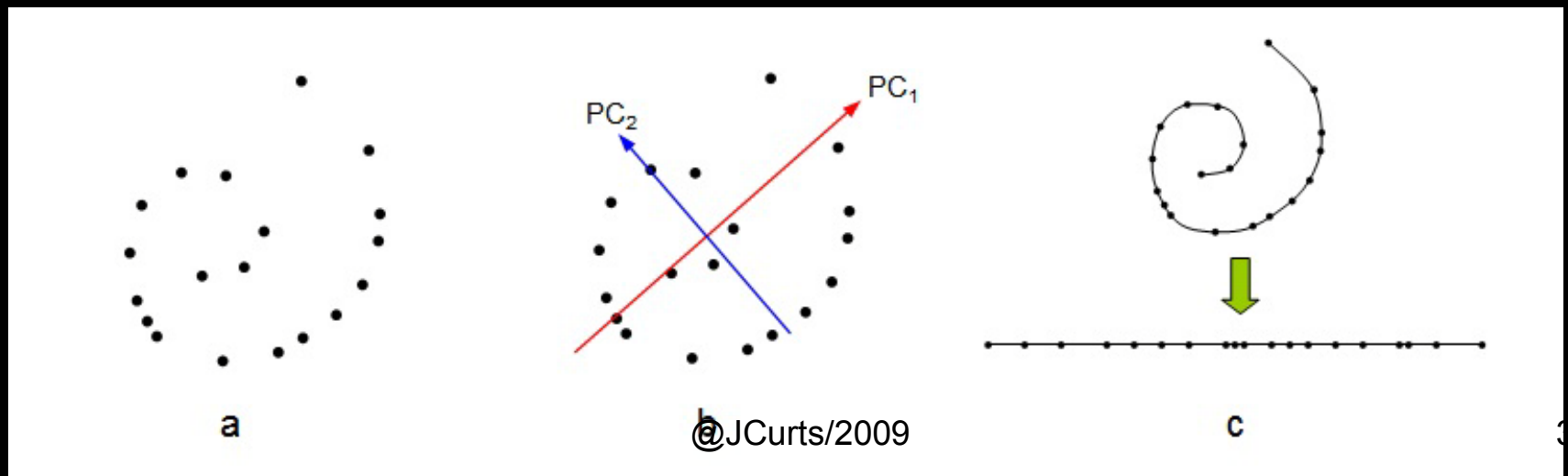
The purpose of this presentation is to introduce the logical and arithmetic operators and simple matrix functions of Minitab® –a well-known software package for teaching statistics- as a computer-aid to teach Principal Components Analysis (PCA) to graduate students in the field of Education.



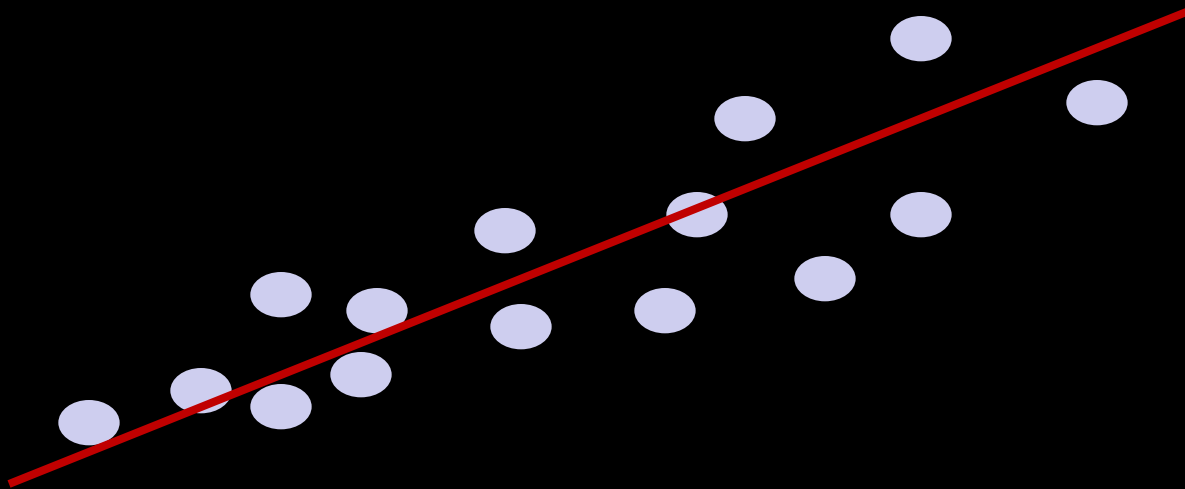
PCA, originally proposed by Pearson (1901) is a mathematical technique –a vector space transform- that has its roots in linear algebra and in statistics.

Its main purpose is to reduce a correlated multidimensional data set to an uncorrelated lower dimensional space with maximum variance.

PCA concepts can be a roadblock for non-mathematical oriented students, since statistical definitions (i.e., variance-covariance, correlation) need to be connected to matrix algebra (eigenvectors of a variance-covariance matrix) and to graphical vector representation (including matrix rotation).



- Given m points in a n dimensional space, for large n , how does one project on to a low dimensional space while preserving broad trends in the data and allowing it to be visualized?
- Choose a line that fits the data so the points are spread



File Edit Data Calc Stat Graph Editor Tools Window Help

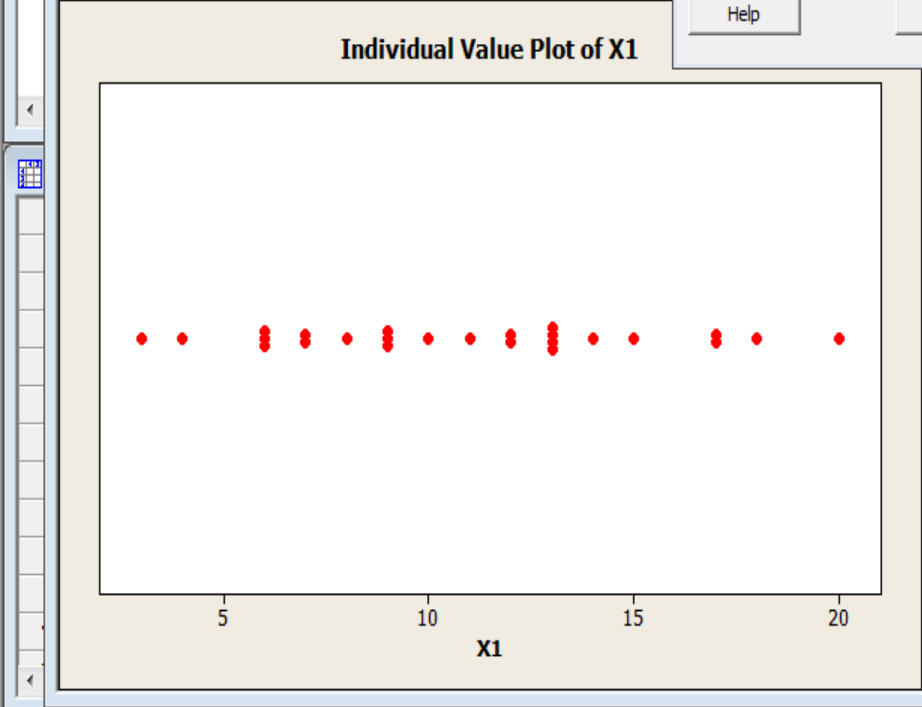
Save Print Copy Paste Undo Redo Find Help Minitab

Session

Descriptive Statistics: X1, X2

Variable	Mean	StDev	Variance
X1	10.880	4.503	20.277
X2	10.680	4.905	24.060

Individual Value Plot of X1



Display Descriptive Statistics

Variables:
X1 X2

By variables (optional):

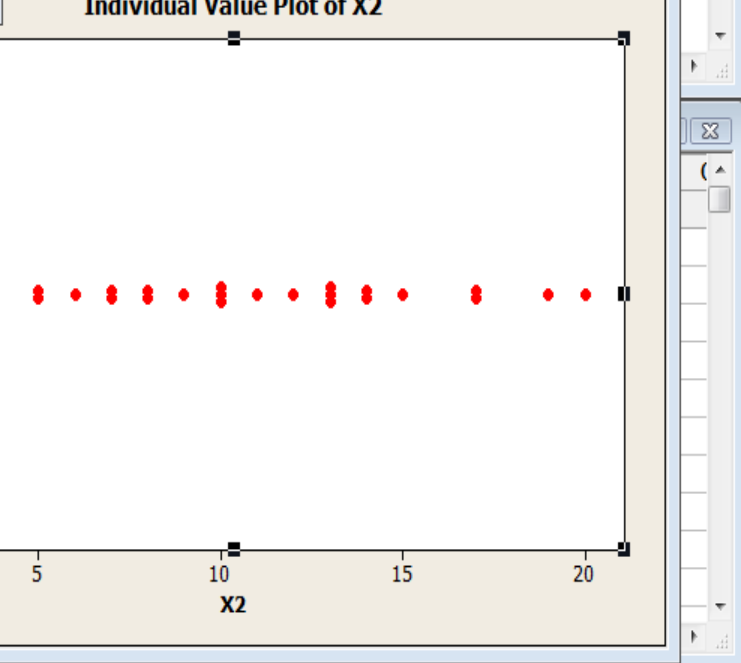
Select Statistics... Graphs... Help OK Cancel

Descriptive Statistics - Statistics

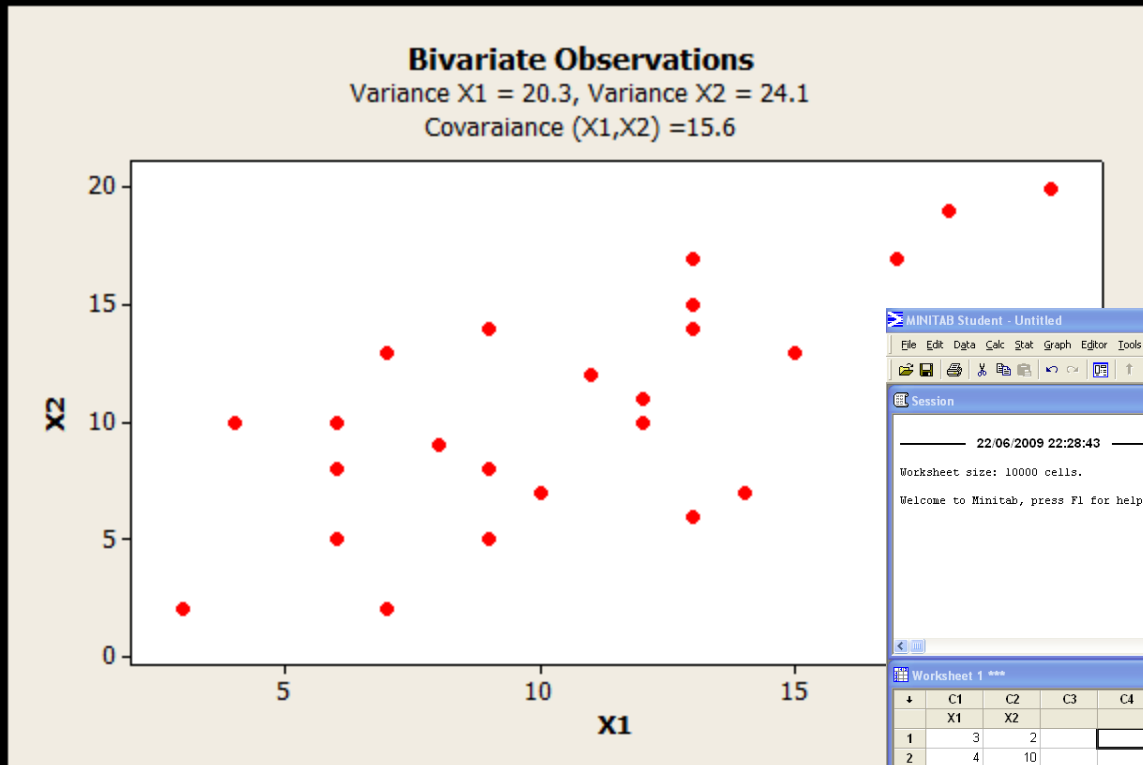
Mean Trimmed mean N nonmissing
 SE of mean Sum N missing
 Standard deviation Minimum N total
 Variance Maximum Cumulative N
 Coefficient of variation Range Percent
 Cumulative percent
 First quartile Sum of squares
 Median Skewness
 Third quartile Kurtosis
 Interquartile range MSSD
 Mode

Help OK Cancel

Individual Value Plot of X2



A sample of n observations in the 2-D space



MINITAB Student - Untitled

Session

22.06.2009 22:28:43

Worksheet size: 10000 cells.

Welcome to Minitab, press F1 for help.

Scatterplots

Simple With Groups With Regression With Regression and Groups

With Connect Line With Connect and Groups

Help OK Cancel

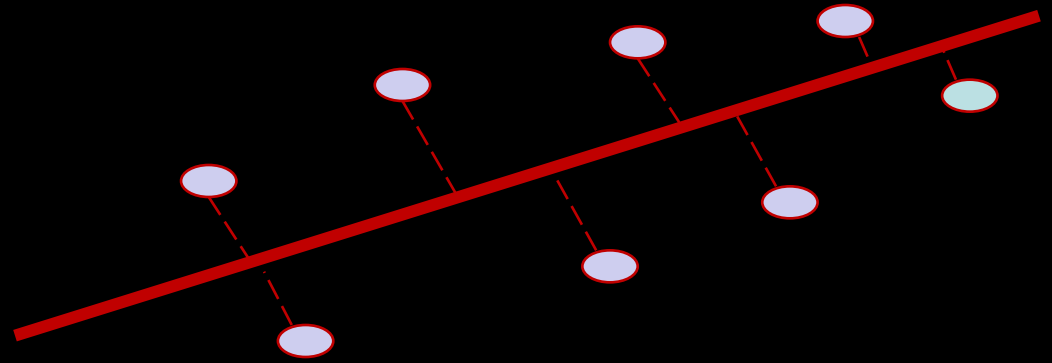
	C1	C2	C3	C4	C5
	X1	X2			
1	3	2			
2	4	10			
3	6	5			
4	6	8			
5	6	10			
6	7	2			
7	7	13			
8	8	9			
9	9	5			
10	9	8			

Project... Draw scatterplots

11:02 AM

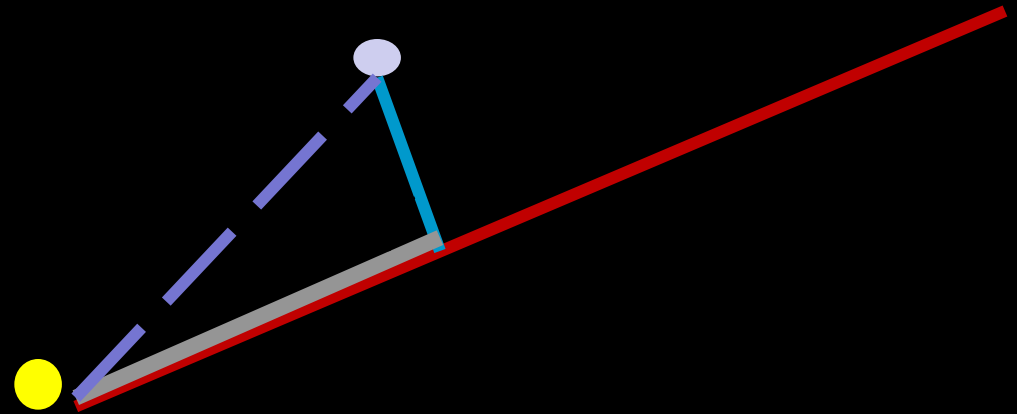
Goal: to account for the variation in a sample in as few variables as possible, to some accuracy

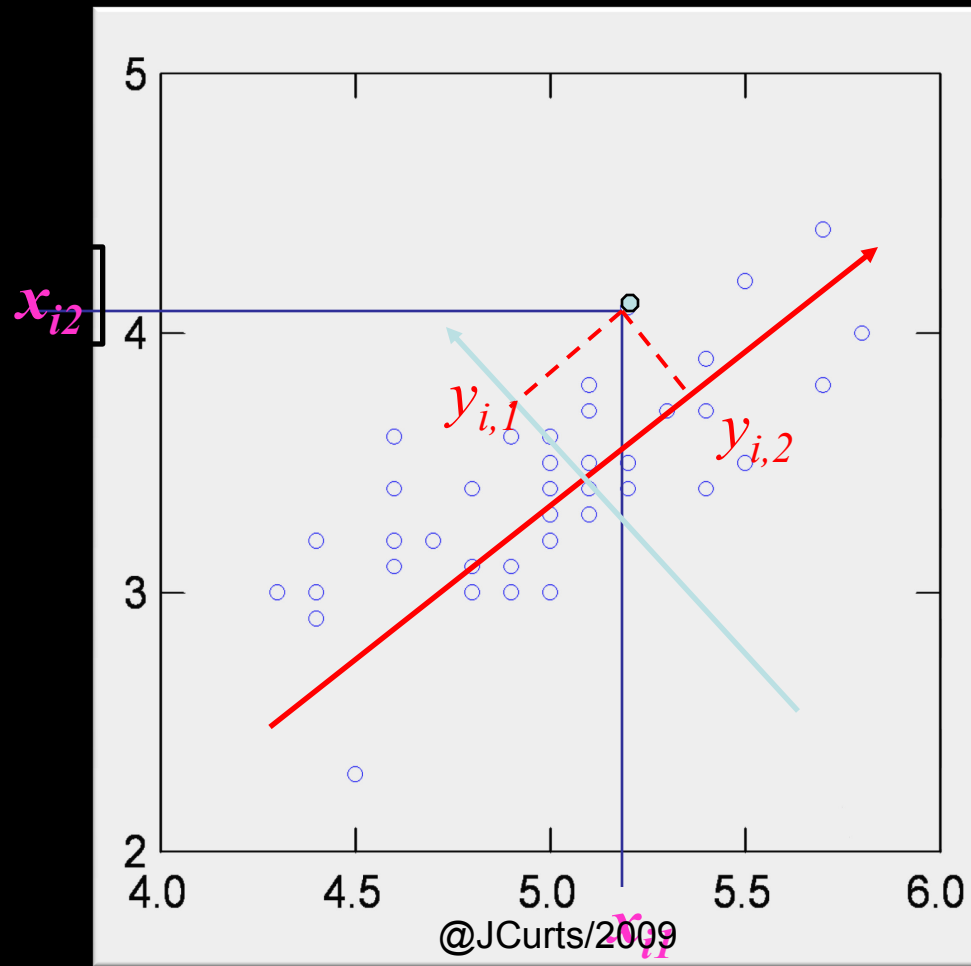
Formally, minimize sum of squares of distances to the line.



Why sum of squares?
Because it allows fast minimization, assuming the line passes through 0

Minimizing sum of squares of distances to the line is the same as maximizing the sum of squares of the projections on that line, thanks to Pythagoras.





Y1 and Y2 are new coordinates.

- Y1 represents the direction where the data values have the largest uncertainty.
- Y2 is perpendicular to Y1.

To find Y1 and Y2, we need to make transformation from X1 and X2. To simplify the discussion, we move the origin to (\bar{x}_1, \bar{x}_2) and redefine the (X1,X2) coordinate as

$x_1 = X_1 - \bar{x}_1$, $x_2 = X_2 - \bar{x}_2$, so that the origin is (0,0).

The relationship is illustrated in the following graph. We would like to present the data of a given lab, $p = (x_1, x_2)$ in terms of $p = (y_1, y_2)$.

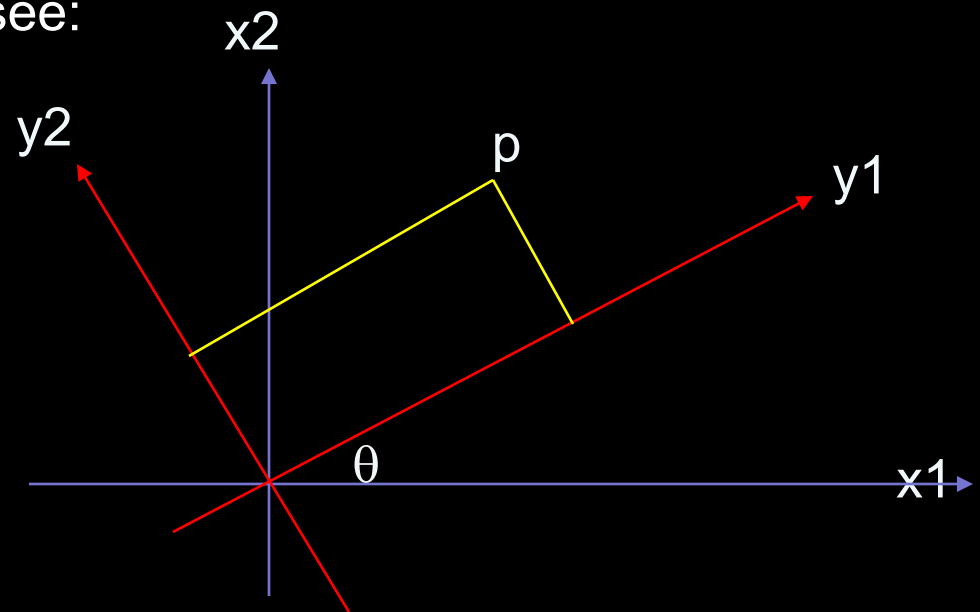
From basic geometry relations, we see:

$$y_1 = (\cos\theta) x_1 + (\sin\theta) x_2$$

$$y_2 = (-\sin\theta) x_1 + (\cos\theta) x_2$$

The angle θ is determined so that the observations along the Y1 axis has the largest variability.

But HOW?



File Edit Data Calc Stat Graph Editor Tools Window Help

Session

Descriptive Statistics: X1, X2, Z1, Z2, Y1 with thet, Y1 with thet, ...

Variable	N	N*	Mean	StDev	Variance
X1	25	0	10.880	4.503	20.277
X2	25	0	10.680	4.905	24.060
Z1	25	0	0.000	1.000	1.000
Z2	25	0	0.000	1.000	1.000
Y1 with theta = 5	25	0	-7.155	3.909	15.277
Y1 with theta = 10	25	0	-14.94	5.97	35.62
Y1 with theta = 45	25	0	14.80	6.08	36.95
Y1 = theta = 90	25	0	4.673	3.289	10.814

Calculator

Store result in variable: C8

Expression:
 $\text{COS}(90) * X1 + \text{SIN}(90) * X2$

Functions:
 All functions
 Absolute value
 Antilog
 Any
 Arcsine
 Arccosine
 Arctangent

7 8 9 + = <>
 4 5 6 - < >
 1 2 3 * <= >=
 0 . [] / And
 ** Or
 () Not

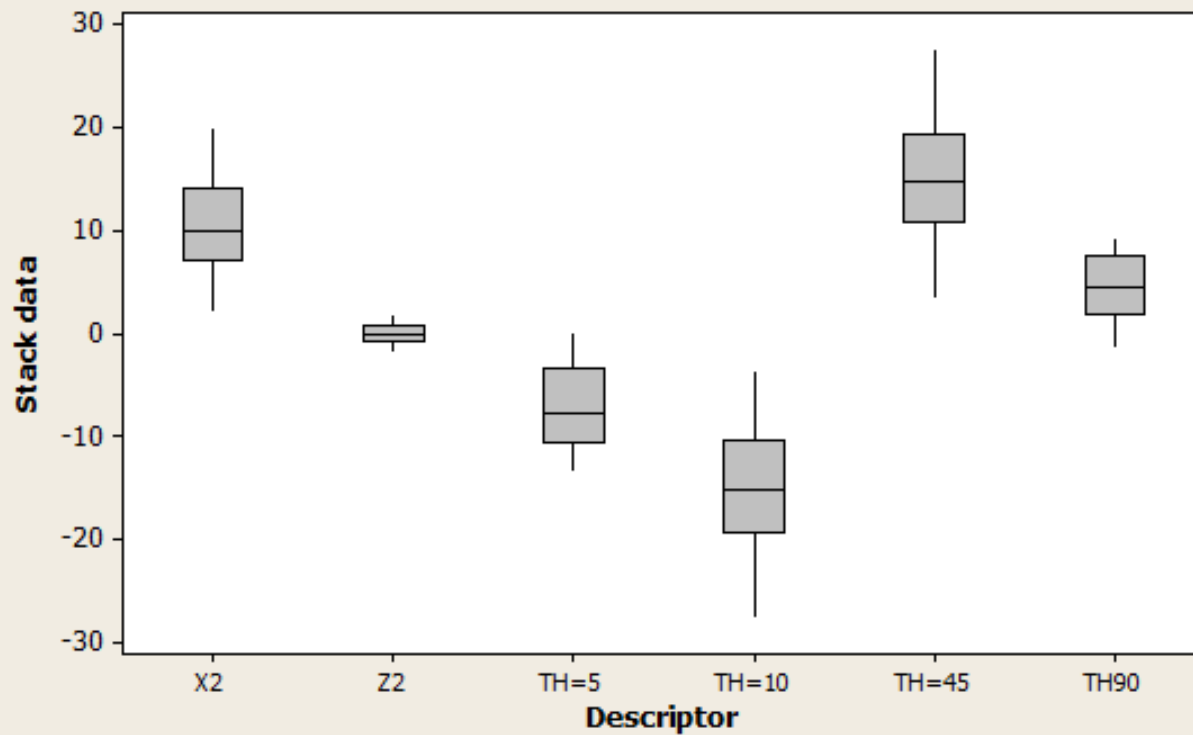
Assign as a formula

Help OK Cancel

ACA data one.MTW ***

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
	X1	X2	Z1	Z2	Y1 with theta = 5	Y1 with theta = 10	Y1 with theta = 45	Y1 = theta = 90							
16	13	6	0.47080	-0.95411	-2.0659	-14.1721	11.9346	-0.46098							
17	13	14	0.47080	0.67685	-9.7373	-18.5242	18.7418	6.69100							
18	13	15	0.47080	0.88072	-10.6963	-19.0682	19.5927	7.58499							
19	13	17	0.47080	1.28846	-12.6141	-20.1563	21.2945	9.37299							
20	14	7	0.69288	-0.75024	-2.7412	-15.5551	13.3108	-0.01505							
21	15	13	0.91495	0.47298	-8.2111	-19.6583	18.9416	4.90085							
22	17	13	1.35911	0.47298	-7.6438	-21.3365	19.9922	4.00471							
23	17	17	1.35911	1.28846	-11.4795	-23.5126	23.3958	7.58069							
24	18	19	1.58118	1.69619	-13.1136	-25.4397	25.6230	8.92061							
25	20	20	2.02533	1.90006	-13.5052	-27.6619	27.5245	8.91846							

Boxplot of Stack data



For any given value of theta, then, it is a simple matter to work out the values of Y1 for each of our twenty observations. **When θ is 5 degrees**, for example, the calculations are:

Z1	Z2	New Variable Y1
1.90	0.47	1.94
0.99	0.85	1.06
1.22	0.09	1.22
0.54	-0.68	0.47
0.31	0.47	0.35
0.08	-1.25	-0.03
-0.15	-0.30	-0.17
-0.60	0.09	-0.59
-1.06	-1.63	-1.20
-1.29	-1.25	-1.39
-1.74	-1.63	-1.88
-1.52	-1.06	-1.60
0.76	0.47	0.80
1.90	2.57	2.12
0.31	0.28	0.33
-0.38	-0.10	-0.38
-0.15	0.66	-0.09
-0.15	0.85	-0.07
-0.38	0.66	-0.32
-0.60	0.47	-0.56

Mean (X1) = 7.65; VAR (X1) = 19.23

Mean (Z1) = Mean (Z2) = 0;

Variance (Z1) = Variance (Z2) = 1

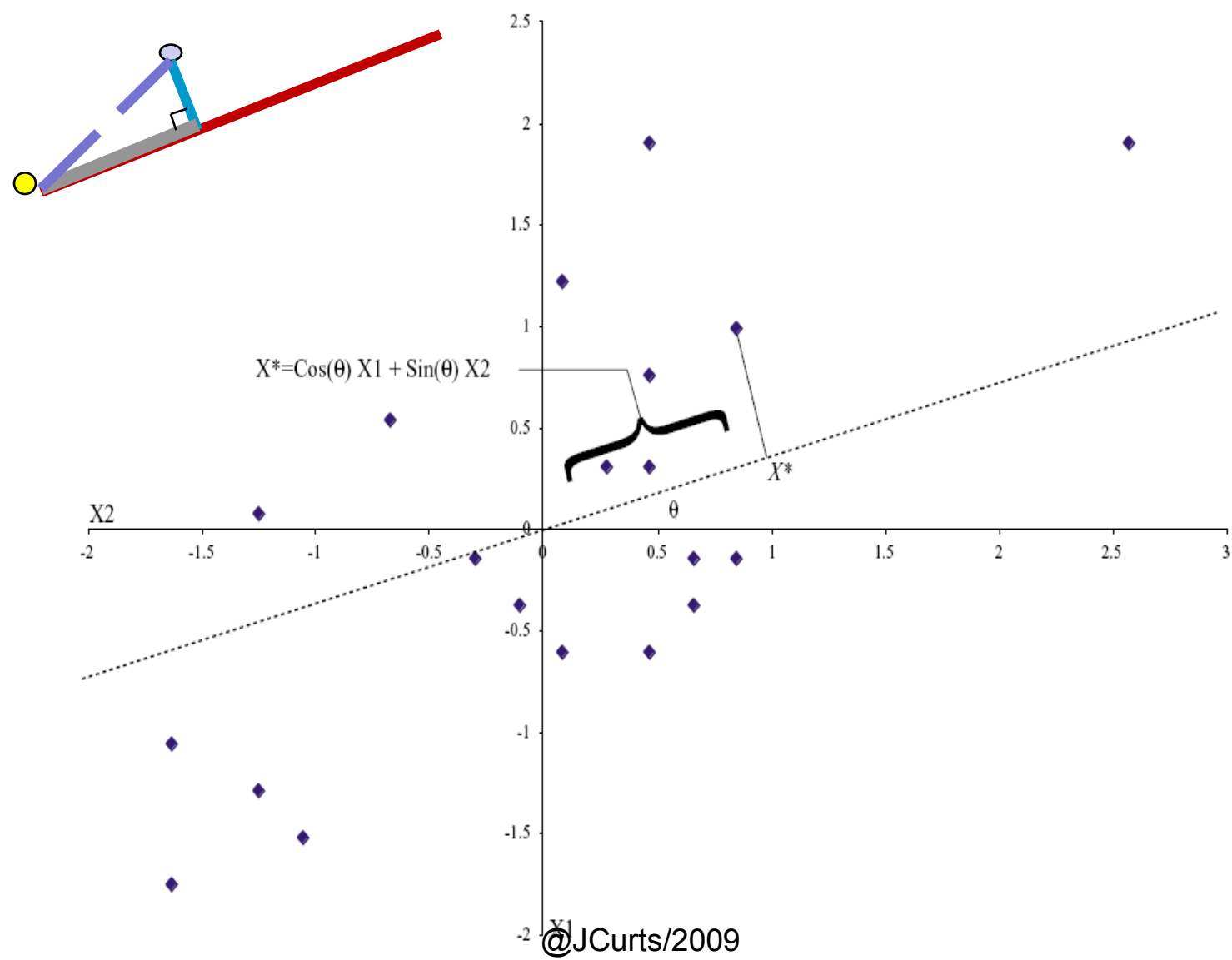
VAR (Y1) = (cos θ) x1 + (sin θ) x2 = 1.12

Note that each of the **original variables** has a **variance** of **1.0**, but **the variance of the new axis is 1.12**, which constitutes more than half of the total variance for the entire dataset (e.g., 1.12/2.00 or 56%).

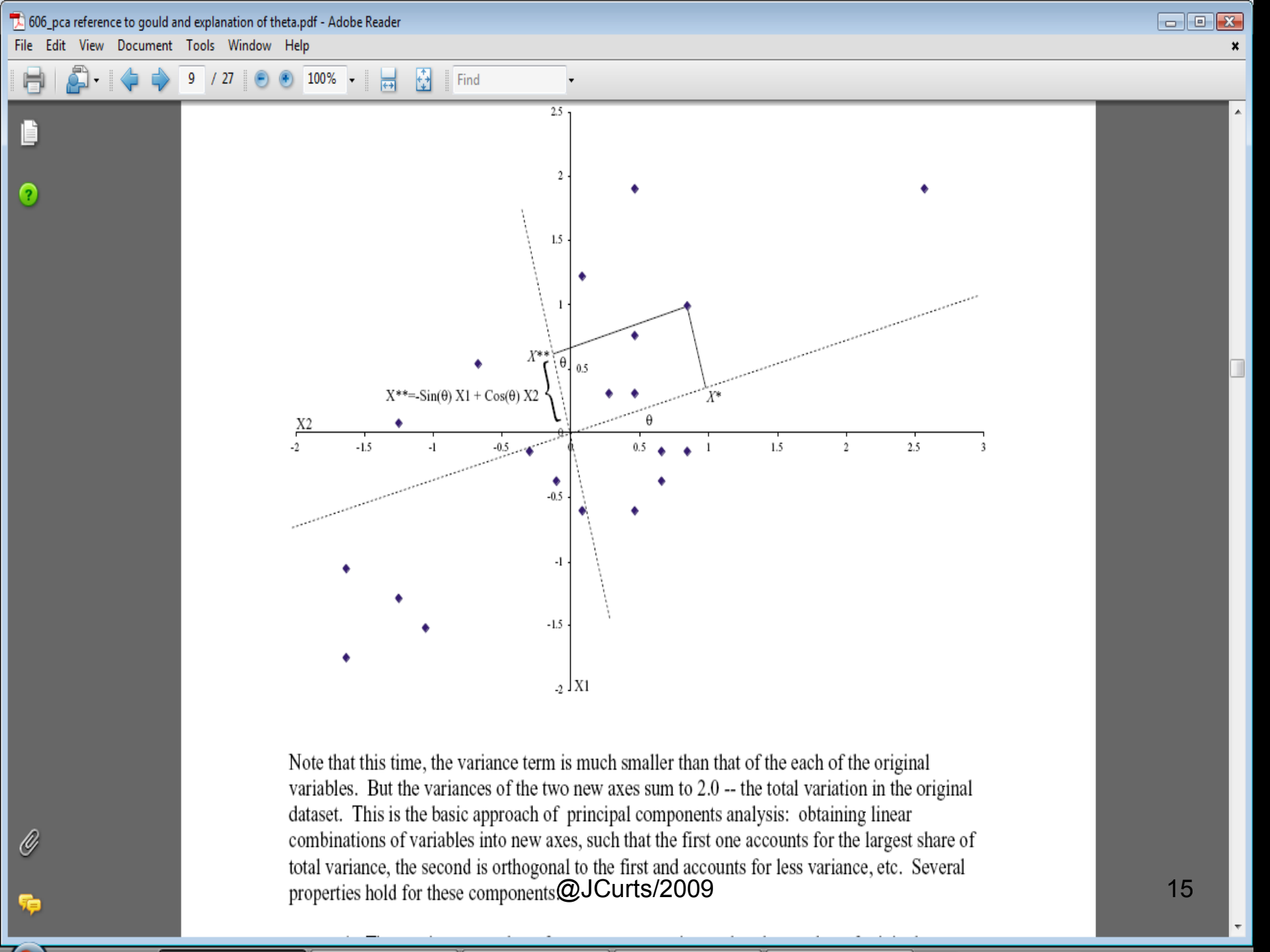
Each value of theta will yield a different set of scores on Y1, and will also result in distinct values for the variance term. If we calculate transformed values and variances for different values of theta, we can compare the variance of the new axis to the total for our dataset.

Note that as we increase the angle, the new variable accounts for an increasing fraction of total variance, until 45 degrees, and then declines; by the time theta is 90 degrees, the new axis is equivalent to X2, and, not surprisingly, its proportion of variance is back to 1.00 or 50.0%.

Theta	Var (Y1)	Proportion
5	1.121	56.0%
10	1.238	61.9%
15	1.348	67.4%
20	1.447	72.4%
25	1.533	76.7%
30	1.603	80.1%
35	1.654	82.7%
40	1.685	84.3%
45	1.696	84.8%
50	1.685	84.3%
55	1.654	82.7%
60	1.603	80.1%
65	1.533	76.7%
70	1.447	72.4%
75	1.348	67.4%
80	1.238	61.9%
85	1.121	56.0%
90	1.000	50.0%



@JCurts/2009



Note that this time, the variance term is much smaller than that of the each of the original variables. But the variances of the two new axes sum to 2.0 -- the total variation in the original dataset. This is the basic approach of principal components analysis: obtaining linear combinations of variables into new axes, such that the first one accounts for the largest share of total variance, the second is orthogonal to the first and accounts for less variance, etc. Several properties hold for these components. @JCurts/2009

The transformation from (x_1, x_2) to (y_1, y_2) results several nice properties

1. The variability along y_1 is largest.
2. Y_1 and y_2 are uncorrelated, that is, orthogonal.
3. The confidence region based on (y_1, y_2) is easy to construct, and provide useful interpretations of the two sample plots.

Questions remain unanswered are

1. How to determine the angle θ so that the variability of observations along the y_1 axis is maximized?
2. How to construct the ellipse for confidence region with different levels of confidences?
3. How to interpret the two-sample plots?

✓ How to determine the Y1 and Y2 axis so that the variability of observations along the Y1 axis is maximized and Y2 is orthogonal to Y1?

✓ Rewrite the linear relation between (Y1, Y2) and (x1, x2) in matrix notation:

$$Y1 = (\cos\theta) x1 + (\sin\theta) x2$$

$$Y2 = (-\sin\theta) x1 + (\cos\theta) x2$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} (\cos\theta)x_1 + (\sin\theta)x_2 \\ (-\sin\theta)x_1 + (\cos\theta)x_2 \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} A_1'X \\ A_2'X \end{bmatrix} = AX$$

NOTE: X is bivariate, so is Y, and

$$V(X) = \begin{bmatrix} V(x_1) & Cov(x_1, x_2) \\ Cov(x_1, x_2) & V(x_2) \end{bmatrix}, \quad V(Y) = A'V(X)A = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

λ_1 and λ_2 are called the eigen values. Which are the solutions of
And, $V(Y1) = \lambda_1$, $V(Y2) = \lambda_2$, Correlation between Y1 and Y2 = 0.

$$|V(X) - \lambda I| = 0$$

λ_1 and λ_2 are called the eigen values. Which are the solutions of
 And, $V(Y1) = \lambda_1$, $V(Y2) = \lambda_2$, Correlation between Y1 and Y2 = 0.

The angle $\theta =$ $(.5) \arctan\left(\frac{2\rho\sigma_1\sigma_2}{\sigma_1^2 - \sigma_2^2}\right)$ if $\sigma_1 \neq \sigma_2$

when $\sigma_1 = \sigma_2$, $\theta = 45^\circ$ The angle $\theta = \arctan\left(\frac{\lambda_1 - \sigma_1^2}{\rho\sigma_1\sigma_2}\right)$

Note the angle depends on the correlation between X1 and X2 , as well as, on the variances of X1 and X2, respectively.

- When ρ is close to zero, the angle is also close to zero. If $V(X1)$ and $V(X2)$ are close, then, the scatter plots are scattered like a circle. That is, there is no clear major principal component.
- When ρ is close to zero and $V(X1)$ is much larger than $V(X2)$, then, the angle will be close to zero, and the data points are likely to be parallel to the X-axis. On the other hand, if $V(X1)$ is much smaller than $V(X2)$, the angle will be close to 90° , and the data points will be more likely parallel to the Y-axis.

Consider, now, we actually observe the following two sample data:

$$\begin{bmatrix} x_{11} & x_{21} \\ x_{12} & x_{22} \\ x_{13} & x_{23} \\ \vdots & \vdots \\ x_{1n} & x_{2n} \end{bmatrix}$$

The sample means are given by

$$\begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}$$

The sample variance-covariance matrix is given by

$$\hat{V}(X) = \begin{bmatrix} s_1^2 & rS_1S_2 \\ rS_1S_2 & s_2^2 \end{bmatrix}$$

r is the Pearson's correlation coefficient, and S^2 is the sample variance. S is the sample standard deviation.

$V(Y)$ is the solution of

$$|\hat{V}(X) - \lambda I| = 0$$

The solutions for λ are given by

$$\frac{(s_1^2 + s_2^2) \pm \sqrt{(s_1^2 + s_2^2)^2 - 4(1-r^2)s_1^2s_2^2}}{2}$$

NOTE: $V(Y1) + V(Y2) = \lambda_1 + \lambda_2 = s_1^2 + s_2^2 = V(X1) + V(X2)$

Using the sample data, the angle is estimated by

$$\theta = (.5) \arctan \left(\frac{2rs_1s_2}{s_1^2 - s_2^2} \right)$$

$$s_1 \neq s_2$$

$$= \arctan \left(\frac{\lambda_1 - s_1^2}{rs_1s_2} \right)$$

Correlation and Covariance Matrix

MINITAB Student - Untitled

File Edit Data Calc Stat Graph Editor Tools Window Help

Worksheet 1

	C1	C2
	X1	X2
1	3	2
2	4	10
3	6	5
4	6	8
5	6	10
6	7	2

Bivariate Observations
 Variance X1 = 20.3, Variance X2 = 24.1
 Covariance (X1,X2) = 15.6

Correlation dialog box:

Variables: X1 X2

Display p-values

Store matrix (display nothing)

Buttons: Select, Help, OK, Cancel

Diagram illustrating the flow of data analysis:

Original data matrix \rightarrow Correlation matrix \rightarrow Factor matrix

Original data matrix:

Objects	v_1	v_2	...	v_k
O_1				
O_2				
O_3				
O_4				
\vdots				
O_n				

Correlation matrix:

Variables	v_1	v_2	...	v_k
v_1				
v_2				
\vdots				
v_k				

Factor matrix:

Factors	F_1	F_2	...	F_m
v_1				
v_2				
\vdots				
v_k				

Session

Variable	N	N*	Mean	StDev	Variance
X1	25	0	10.880	4.503	20.277
X2	25	0	10.680	4.905	24.060
Z1	25	0	0.000	1.000	1.000
Z2	25	0	0.000	1.000	1.000
Y1 with theta = 5	25	0	-7.155	3.909	15.277
Y1 with theta = 10	25	0	-14.94	5.97	35.62
Y1 with theta = 45	25	0	14.80	6.08	36.95
Y1 = theta = 90	25	0	4.673	3.289	10.814

Boxplot of Stack data

Eigen Analysis

Analyze matrix: COVA1

Storage

Column of eigenvalues: c11

Matrix of eigenvectors: m3

Select

Help

OK

Cancel

ACA data one.MTW ***

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
	X1	X2	Z1	Z2	Y1 with theta = 5	Y1 with theta = 10	Y1 with theta = 45	Y1 = theta = 90	Stack data	Descriptor					
16	13	6	0.47080	-0.95411	-2.0659	-14.1721	11.9346	-0.46098	6.0000	1					
17	13	14	0.47080	0.67685	-9.7373	-18.5242	18.7418	6.69100	14.0000	1					
18	13	15	0.47080	0.88072	-10.6963	-19.0682	19.5927	7.58499	15.0000	1					
19	13	17	0.47080	1.28846	-12.6141	-20.1563	21.2945	9.37299	17.0000	1					
20	14	7	0.69288	-0.75024	-2.7412	-15.5551	13.3108	-0.01505	7.0000	1					
21	15	13	0.91495	0.47298	-8.2111	-19.6583	18.9416	4.90085	13.0000	1					
22	17	13	1.35911	0.47298	-7.6438	-21.3365	19.9922	4.00471	13.0000	1					
23	17	17	1.35911	1.28846	-11.4795	-23.5126	23.3958	7.58069	17.0000	1					
24	18	19	1.58118	1.69619	-13.1136	-25.4397	25.6230	8.92061	19.0000	1					
25	20	20	2.02533	1.90006	-13.5052	-27.6619	27.5245	8.91846	20.0000	1					

Boxplot of Stack data
print

Data Display

Matrix CORR1

```
1.00000  0.70560
0.70560  1.00000
```

Matrix COVA1

```
20.2767  15.585
15.5850  24.060
```

Matrix M3

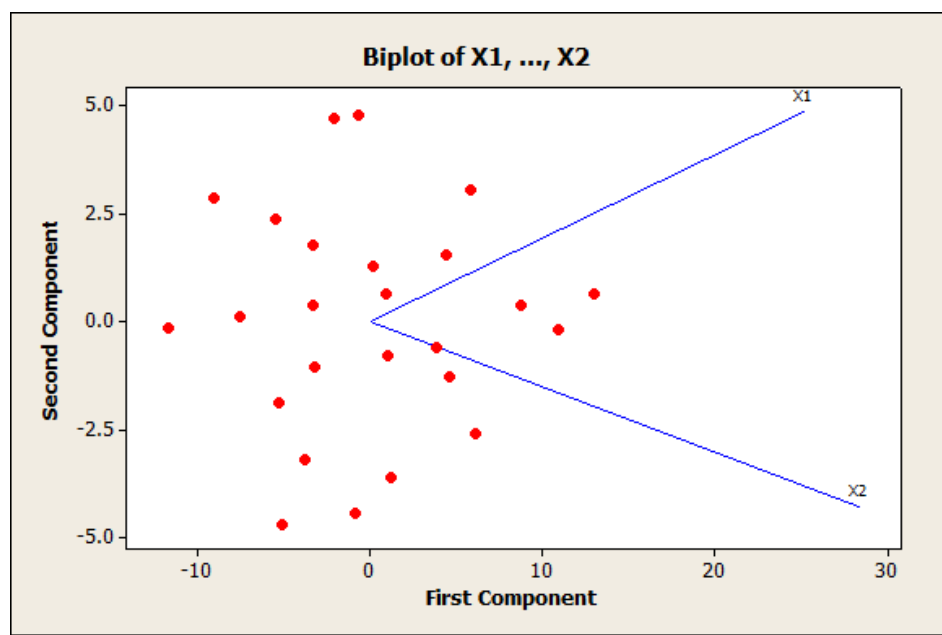
```
0.663139  0.748496
0.748496 -0.663139
```

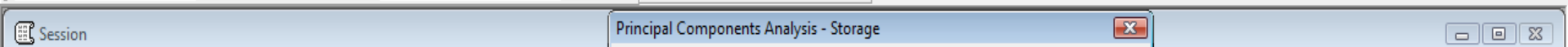
Principal Component Analysis: X1, X2

Eigenanalysis of the Covariance Matrix

```
Eigenvalue  37.868  6.469
Proportion  0.854  0.146
Cumulative  0.854  1.000
```

Variable	PC1	PC2
X1	0.663	0.748
X2	0.748	-0.663





Principal Components Analysis

Variables:
X1 X2

Number of components to compute:

Type of Matrix
 Correlation
 Covariance

Select Graphs... Storage...
 Help OK Cancel

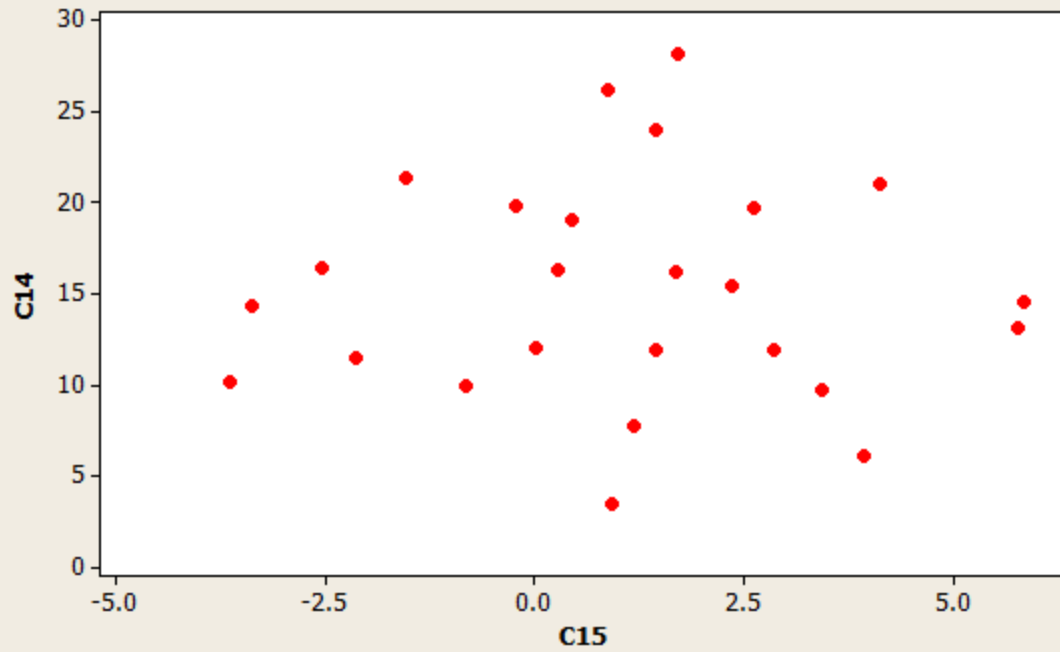
Principal Components Analysis - Storage

C1 X1 Coefficients: c12 c13
 C2 X2
 C3 Z1
 C4 Z2
 C5 Y1 with theta = Scores: c14 c15
 C6 Y1 with theta =
 C7 Y1 with theta =
 C8 Y1 = theta = 90
 C9 Stack data Eigenvalues: c16
 C10 Descriptor
 C11
 C12
 C13
 C14
 C15
 C16

Select Help OK Cancel

		C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	
	a = 45	Y1 = theta = 90	Stack data	Descriptor									
1	-1.76959	-1.0669	-3.6053	3.2778	0.44377	2.0000	1	37.8677	0.663139	0.748496	3.4864	0.91921	37.8677
2	-0.13863	-8.4546	-8.7965	10.6103	7.14767	10.0000	1	6.4690	0.748496	-0.663139	10.1375	-3.63741	6.4690
3	-1.15798	-3.0926	-7.7545	7.4064	1.78154	5.0000	1				7.7213	1.17528	
4	-0.54637	-5.9694	-9.3866	9.9592	4.46353	8.0000	1				9.9668	-0.81414	
5	-0.13863	-7.8873	-10.4746	11.6610	6.25152	10.0000	1				11.4638	-2.14041	
6	-1.76959	0.0678	-6.9615	5.3791	-1.34852	2.0000	1				6.1390	3.91320	
7	0.47298	-10.4804	-12.9458	14.7390	8.48544	13.0000	1				14.3724	-3.38134	
8	-0.34250	-6.3610	-11.6088	11.8607	4.46138	9.0000	1				12.0416	0.01972	
9	-1.15798	-2.2417	-10.2717	8.9824	0.43732	5.0000	1				9.7107	3.42077	
10	-0.54637	-5.1184	-11.9038	11.5351	3.11931	8.0000	1				11.9562	1.43135	

Scatterplot of C14 vs C15



Pearson correlation of C14 and C15 = -0.000

Thanks.....

jbcurts@utpa.edu