Principal Component Analysis of Simulated Data

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Simulating 100 observations from a bivariate normal distribution.

The bivariate normal distribution has the following parameters:

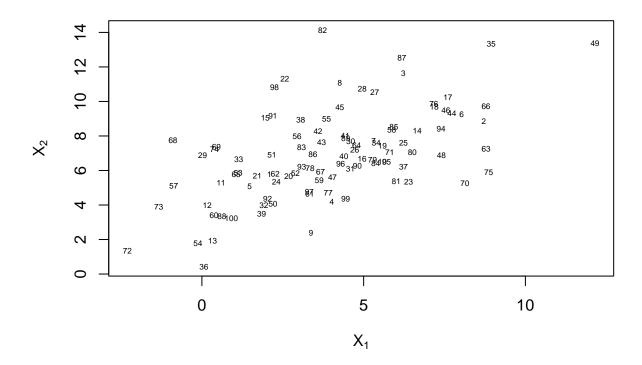
$$\mu = [47]$$

$$\Sigma = \begin{bmatrix} 10 & 6 \\ 6 & 8 \end{bmatrix}$$

We want to simulate 100 observations from this distribution. We will then plot the data and label the data points with the corresponding observation number.

```
mu = c(4, 7)
sigma = matrix(c(10, 6, 6, 8), byrow = TRUE, ncol = 2)
#This library contains the function "rmunorm" which generates random samples
#from a multivariate normal distribution.
library(mvtnorm)
#Set the seed for generating the same sequence of random variables for
#n(in our case 100) observations.
set.seed(123)
n = 100
#Use of function 'rmunorm' to generate the data
x = rmvnorm(n, mu, sigma)
head(x)
##
            [,1]
                      [,2]
## [1,] 2.085788 5.796222
## [2,] 8.712286 8.857059
## [3,] 6.224902 11.627028
## [4,] 4.013622 4.183931
## [5,] 1.478637
                  5.096696
## [6,] 8.027319 9.255103
dim(x)
## [1] 100
lbs = as.character(1:100)
plot(x, pch = 20, xlab = expression("X"[1]), ylab = expression("X"[2]),
     main = expression(paste("Sample from ", "N(", mu, ", ", Sigma, ")")),
     type="n")
text(x, labels = lbs, cex = 0.5)
```

Sample from $N(\mu, \Sigma)$



We now perform the covariance based PCA transformation to the data set.

Plot of the score matrix.

```
#We store the data in variable "score"
score = x_pca$scores
head(score)
```

```
## Comp.1 Comp.2

## [1,] -2.178272 -0.4622198

## [2,] 4.752625 1.8272928

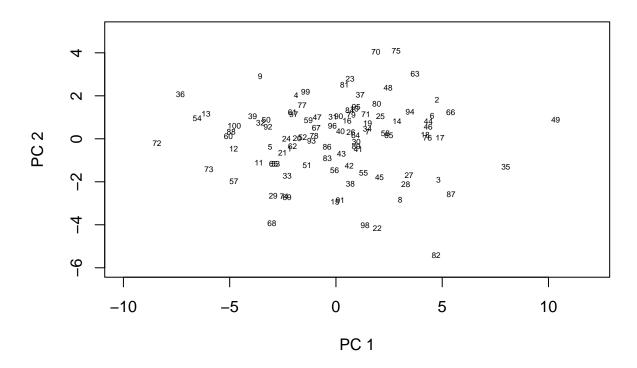
## [3,] 4.827310 -1.8948341

## [4,] -1.871092 2.0321071

## [5,] -3.099513 -0.3658647

## [6,] 4.524100 1.0687446
```

Score Matrix



We compare the plots of the original data and the score matrix data and describe the differences.

The data points were rotated and the data was centered by the y-axis.

Manual calculation of the score matrix.

Scores, that is, transformed variables are given by:

$$Y = (X - \mathbf{1}_n \bar{x}^\top) G$$

where G is the matrix of eigenvectors of the sample covariance and \bar{x} is the sample mean vector.

We wish to calculate the G and Y matrices without using any existing PCA functions.

```
n = nrow(x)
eig = eigen((n - 1) / n * cov(x)) #eigen of sample covariance
G = eig$vectors #eigen vectors
Y = as.matrix(sweep(x, 2, colMeans(x), "-")) %*% G #score matrix
head(G)
```

[,1] [,2]

```
## [1,] -0.7304868  0.6829268
## [2,] -0.6829268 -0.7304868

head(Y)

##        [,1]        [,2]
## [1,]        2.178272 -0.4622198
## [2,] -4.752625   1.8272928
## [3,] -4.827310 -1.8948341
## [4,]  1.871092  2.0321071
## [5,]  3.099513 -0.3658647
## [6,] -4.524100  1.0687446
```

Verifying that the G and Y matrices are calculated correctly.

We verify that the estimated scores and the loadings are equal (up to signs) in parts b) and e).

```
#Matrix G
#We store the data in variable "load"
load = x_pca$loadings
all(abs(round(G, 2)) == abs(round(load, 2)))
## [1] TRUE
#Matrix Y
all(abs(round(Y, 2)) == abs(round(score, 2)))
## [1] TRUE
```

PCA plot in the original data

Now we plot the directions of the first and second principal components to the original data.

```
center = x_pca$center
load = x_pca$loadings[]
load
##
           Comp.1
                      Comp.2
## [1,] 0.7304868 0.6829268
## [2,] 0.6829268 -0.7304868
arrows_xy = 10 * load + rep(1, 2) %*% t(x_pca$center)
arrows_xy
##
          Comp.1
                     Comp.2
## [1,] 11.29752 13.7754456
## [2,] 10.82192 -0.3586906
plot(x, xlim = c(-5, 15), ylim = c(-5, 20), pch = 21, bg = "tomato", cex = 0.5,
     xlab = expression("X"[1]), ylab = expression("X"[1]))
arrows(center[1], center[2], arrows_xy[, 1], arrows_xy[, 2], lwd = 2, col = c("green", "orange"), lengt
legend("topright", legend = c("PC 1", "PC 2"), col = c("green", "orange"), pch = 15, bty = "n", cex = 0
```

