# DSA 8070 R Session 1: Exploratory Analysis of Multivariate Data

# Whitney Huang, Clemson University

# Contents

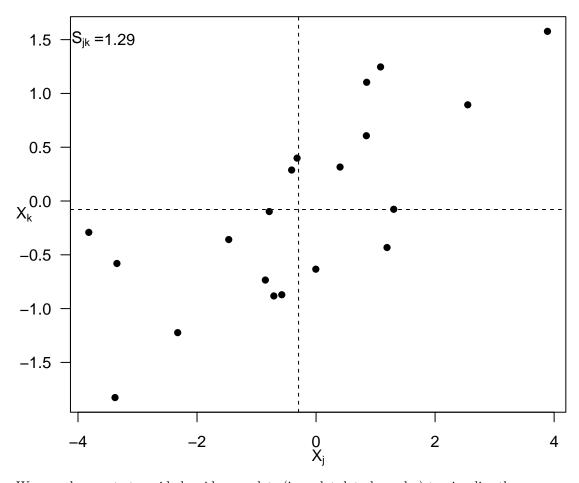
Descriptive Statistics	1
Sample covariance visualization	1
Sample and population covariance	3
Bivariate Data Example	4
Generliazed Variance	4
Graphs and Visualization	Ę
pairs	Ę
ggpairs	6
3D Scatter Plot	7
Parallel Coordinate Plot	8
Chernoff Faces	Ć
Visualizing Summary Statistics	12

# **Descriptive Statistics**

#### Sample covariance visualization

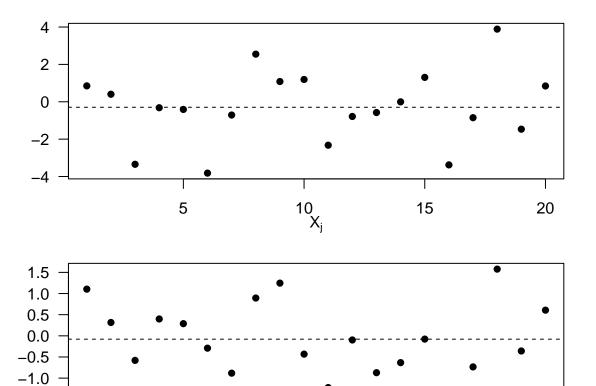
Here, we simulate a bivariate dataset from a bivariate normal distribution with a mean vector of  $(0,0)^T$  and variances of 4 and 1, respectively. Furthermore, the two variables are positively correlated, with a population covariance of 1.4 (resulting in a population correlation of  $\frac{1.4}{\sqrt{4} \times \sqrt{1}} = 0.7$ ). We will use a scatterplot to visualize the covariance.

```
set.seed(123)
library(MASS)
dat <- mvrnorm(n = 20, mu = c(0, 0), Sigma = matrix(c(4, 1.4, 1.4, 1), 2))
n <- dim(dat)[1]
par(mar = c(3.6, 3.6, 0.8, 0.6), las = 1)
plot(dat, pch = 16, las = 1, xlab = "", ylab = "")
mtext(expression(X[j]), 1, line = 2); mtext(expression(X[k]), 2, line = 2)
text(-3.8, 1.5, expression(paste(S[jk], " = ")))
text(-3.3, 1.5, round(cov(dat[, 1], dat[, 2]), 2))
abline(h = mean(dat[, 2]), lty = 2); abline(v = mean(dat[, 1]), lty = 2)</pre>
```



We can also create two side-by-side run plots (i.e., plot data by order) to visualize the co-movement.

```
par(mfrow = c(2, 1), mar = c(3.6, 3.6, 0.8, 0.6), las = 1)
plot(1:n, dat[, 1], pch = 16, xlab = "", ylab = "")
abline(h = mean(dat[, 1]), lty = 2)
mtext(expression(X[j]), 1, line = 2)
plot(1:n, dat[, 2], pch = 16, xlab = "", ylab = "")
abline(h = mean(dat[, 2]), lty = 2)
mtext(expression(X[k]), 1, line = 2)
```



# Sample and population covariance

5

-1.5

Here, we simulate data with size sample n=20 from a bivariate normal distribution with population covariance  $\rho_{12}=0$ . For each simulated data set, we calculate the sample covariance  $s_{12}$  and repeat this process 1,000 times.

15

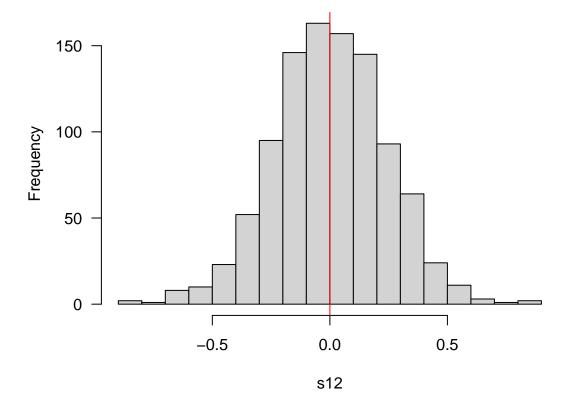
20

10

 $\boldsymbol{X}_{k}$ 

The main purpose of this exercise is to demonstrate that one can conduct a *Monte Carlo* experiment to approximate the *sampling distribution* of  $s_{12}$  when two variables are independent to each other.

```
dat <- replicate(1000, mvrnorm(n = 20, mu = c(0, 0), Sigma = matrix(c(1, 0, 0, 1), 2)))
s12 <- apply(dat, 3, function(x) cov(x[, 1], x[, 2]))
hist(s12, 20, las = 1, main = "")
abline(v = 0, col = "red")</pre>
```



### Bivariate Data Example

```
data <- cbind(x1 = c(42, 52, 88, 58, 60), x2 = c(4, 5, 7, 4, 5))
(means <- apply(data, 2, mean))</pre>
## x1 x2
## 60
cov(data)
##
       x1
            x2
## x1 294 19.0
## x2 19
          1.5
cor(data)
##
             x1
## x1 1.0000000 0.9047619
## x2 0.9047619 1.0000000
```

#### Generliazed Variance

The generalized variance is the determinant of the covariance matrix - it reflects the overall spread (volume) of the data in multivariate space.

```
data(mtcars)
vars <- which(names(mtcars) %in% c("mpg", "disp", "hp", "drat", "wt"))
car <- mtcars[, vars]; S <- cov(car)
(genVar <- det(S))</pre>
```

## [1] 3951786

## [1] 3.108855

- With fixed variances, stronger correlations (positive or negative) reduce the generalized variance.
- If variables are uncorrelated, it equals the product of their variances.

```
set.seed(123)
dat <- mvrnorm(n = 100, mu = c(0, 0), Sigma = matrix(c(4, 1.4, 1.4, 1), 2))
det(cov(dat))

## [1] 1.585516

set.seed(123)
dat1 <- mvrnorm(n = 100, mu = c(0, 0), Sigma = matrix(c(4, 0, 0, 1), 2))
det(cov(dat1))</pre>
```

**Sample vs. Population** Population values come from the true covariance matrix; sample values use the sample covariance and vary due to random sampling but converge to the population value as sample size grows.

```
det(cov(dat))
## [1] 1.585516

det(matrix(c(4, 1.4, 1.4, 1), 2))
## [1] 2.04

det(cov(dat1))
## [1] 3.108855

det(matrix(c(4, 0, 0, 1), 2))
## [1] 4
```

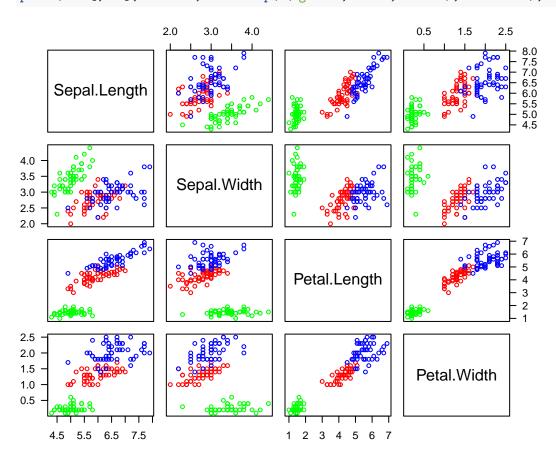
### Graphs and Visualization

pairs

#### head(iris)

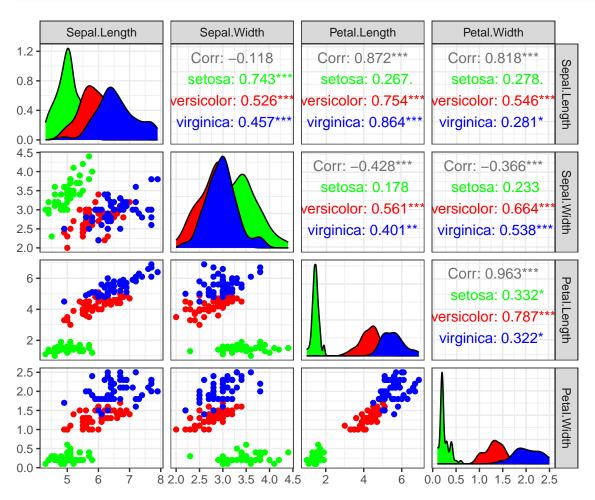
```
Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1
              5.1
                          3.5
                                       1.4
                                                   0.2 setosa
              4.9
                          3.0
## 2
                                       1.4
                                                   0.2 setosa
## 3
              4.7
                          3.2
                                       1.3
                                                   0.2 setosa
                                                   0.2 setosa
## 4
              4.6
                          3.1
                                       1.5
## 5
              5.0
                          3.6
                                       1.4
                                                   0.2 setosa
## 6
              5.4
                          3.9
                                       1.7
                                                   0.4 setosa
```

```
pairs(iris[, -5], las = 1, col = rep(c("green", "red", "blue"), each = 50), cex = 0.8)
```

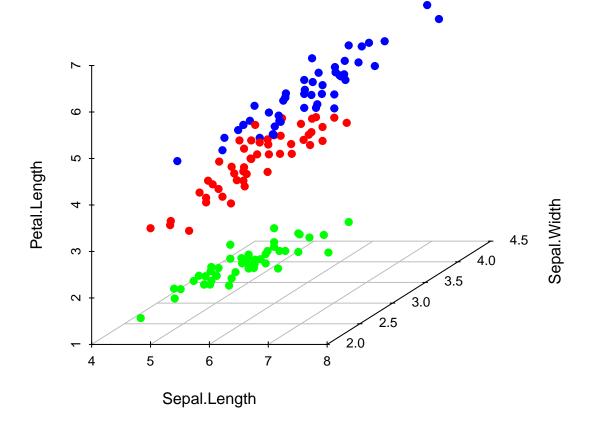


#### ggpairs

```
scale_color_manual(values = c("green", "red", "blue"))
}
```

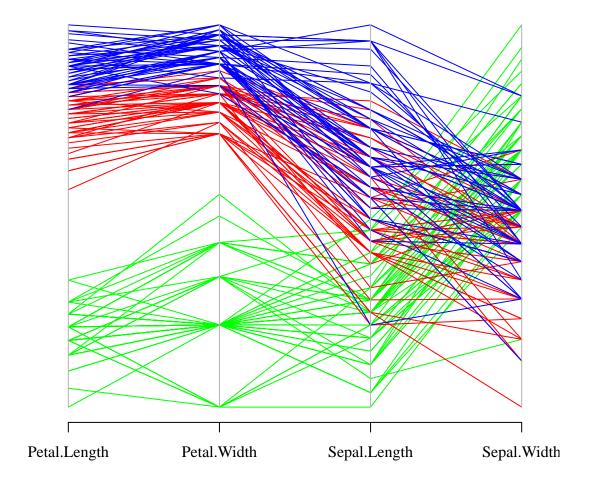


#### 3D Scatter Plot



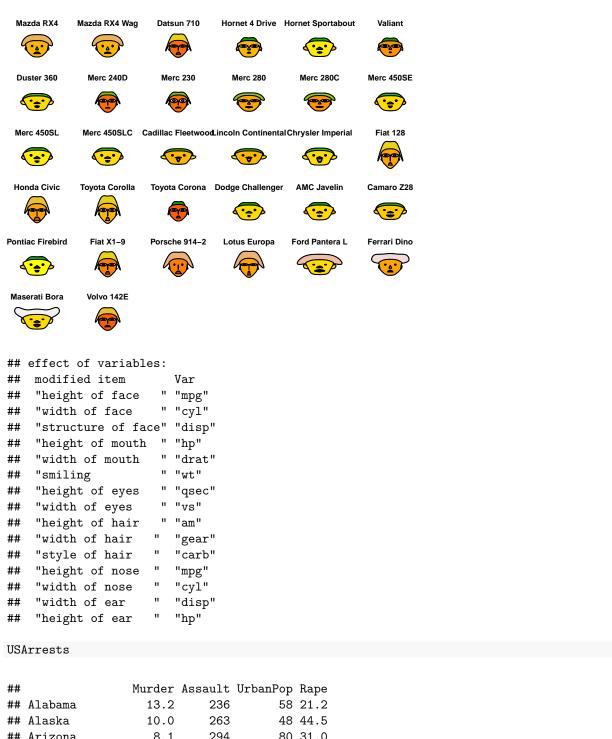
# Parallel Coordinate Plot

```
dat <- iris[, 1:4]
par(mar = c(3, 3.5, 0.5, 1), mgp = c(2, 1, 0), las = 1,
    family = "serif", font = 3)
parcoord(log(dat)[, c(3, 4, 1, 2)], # Order the axes
col = rep(c("green", "red", "blue"), each = 50))</pre>
```



# Chernoff Faces

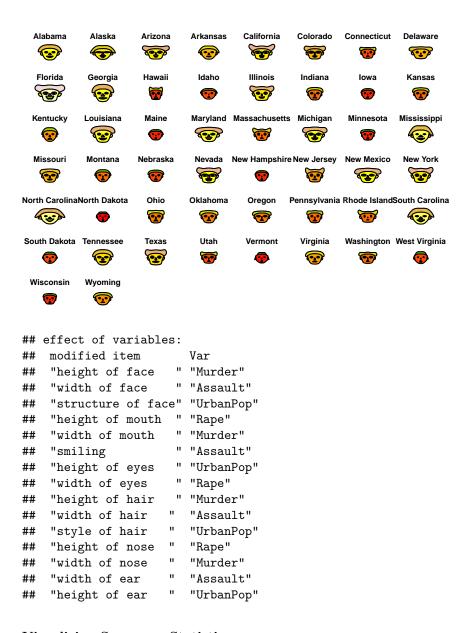
```
library(aplpack)
par(mar = rep(0, 4))
faces(mtcars, cex = 0.8)
```



##		Murder	Assault	UrbanPop	Rape
##	Alabama	13.2	236	58	21.2
##	Alaska	10.0	263	48	44.5
##	Arizona	8.1	294	80	31.0
##	Arkansas	8.8	190	50	19.5
##	California	9.0	276	91	40.6
##	Colorado	7.9	204	78	38.7
##	Connecticut	3.3	110	77	11.1
##	Delaware	5.9	238	72	15.8
##	Florida	15.4	335	80	31.9
##	Georgia	17.4	211	60	25.8
##	Hawaii	5.3	46	83	20.2
##	Idaho	2.6	120	54	14.2

##	Illinois	10.4	249	83 24.0
##	Indiana	7.2	113	65 21.0
##	Iowa	2.2	56	57 11.3
##	Kansas	6.0	115	66 18.0
##	Kentucky	9.7	109	52 16.3
##	Louisiana	15.4	249	66 22.2
##	Maine	2.1	83	51 7.8
##	Maryland	11.3	300	67 27.8
##	Massachusetts	4.4	149	85 16.3
##	Michigan	12.1	255	74 35.1
##	Minnesota	2.7	72	66 14.9
##	Mississippi	16.1	259	44 17.1
##	Missouri	9.0	178	70 28.2
##	Montana	6.0	109	53 16.4
##	Nebraska	4.3	102	62 16.5
##	Nevada	12.2	252	81 46.0
##	New Hampshire	2.1	57	56 9.5
##	New Jersey	7.4	159	89 18.8
##	New Mexico	11.4	285	70 32.1
##	New York	11.1	254	86 26.1
##	North Carolina	13.0	337	45 16.1
##	North Dakota	0.8	45	44 7.3
##	Ohio	7.3	120	75 21.4
##	Oklahoma	6.6	151	68 20.0
##	Oregon	4.9	159	67 29.3
##	Pennsylvania	6.3	106	72 14.9
##	Rhode Island	3.4	174	87 8.3
##	South Carolina	14.4	279	48 22.5
##	South Dakota	3.8	86	45 12.8
##	Tennessee	13.2	188	59 26.9
##	Texas	12.7	201	80 25.5
##	Utah	3.2	120	80 22.9
##	Vermont	2.2	48	32 11.2
##	Virginia	8.5	156	63 20.7
##	Washington	4.0	145	73 26.2
##	West Virginia	5.7	81	39 9.3
##	Wisconsin	2.6	53	66 10.8
##	Wyoming	6.8	161	60 15.6

faces(USArrests, cex = 0.8)



#### Visualizing Summary Statistics

