

DSA 8070 R Session 1: Characterizing and Displaying Multivariate Data

Whitney

Contents

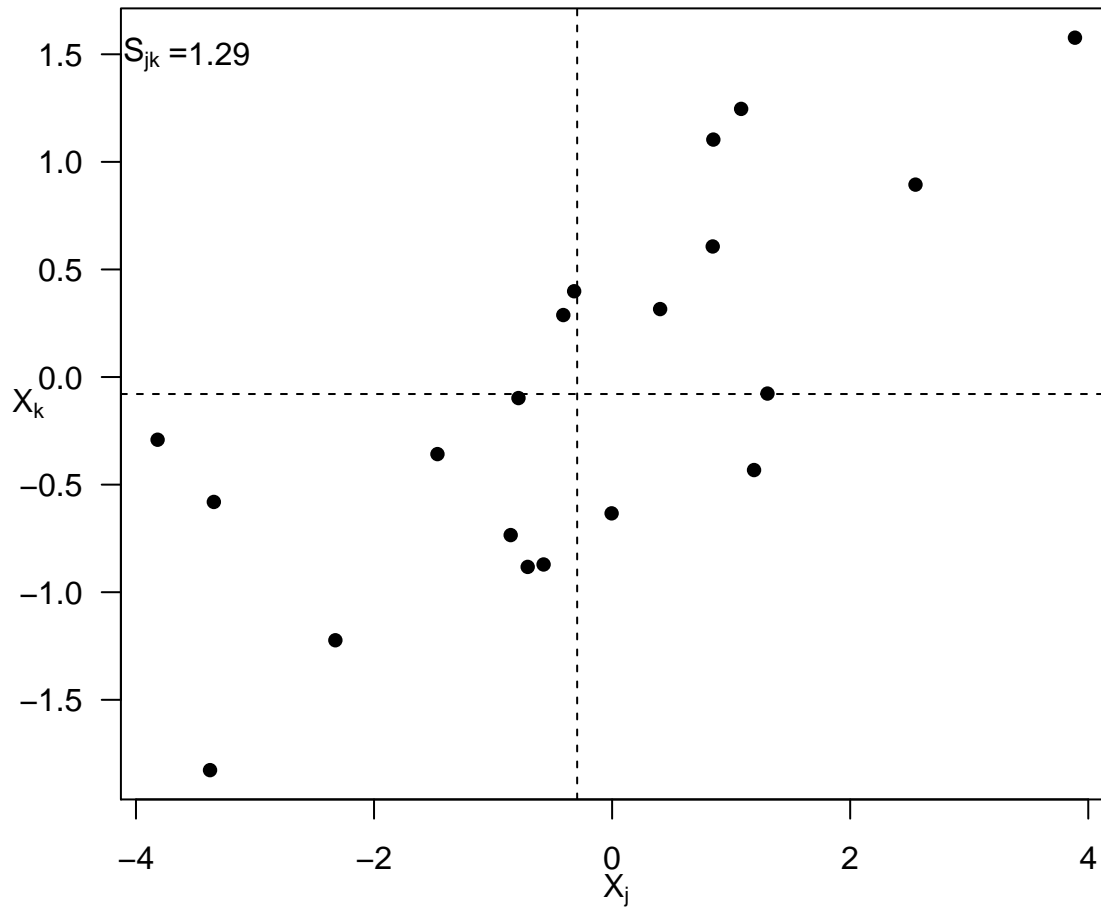
Descriptive Statistics	1
Sample covariance visualization	1
Sample and population covariance	3
Bivariate Data Example	4
Generalized Variance	4
Graphs and Visualization	5
pairs	5
ggpairs	5
3D Scatter Plot	7
Chernoff Faces	7
Visualizing Summary Statistics	10

Descriptive Statistics

Sample covariance visualization

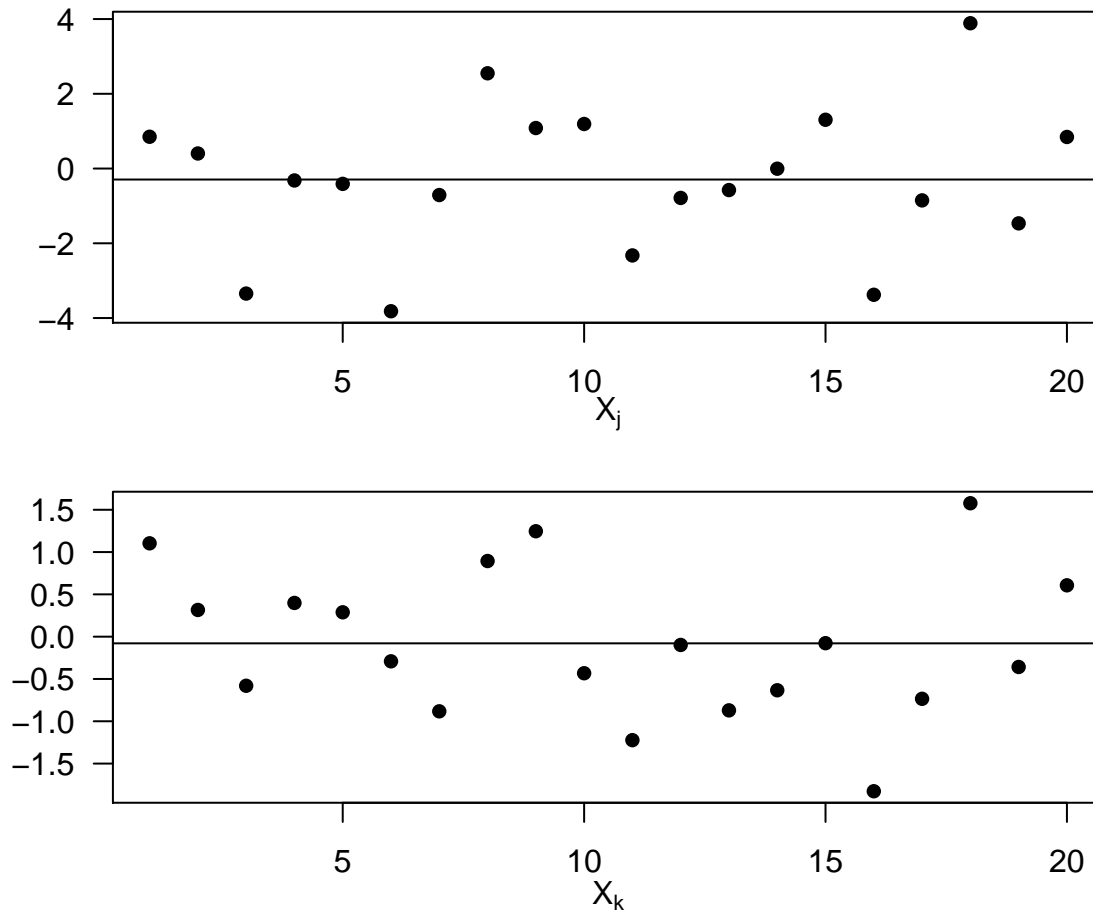
Here, we simulate a bivariate dataset that follows a bivariate normal distribution with a mean vector of $(0, 0)^T$ and variances of 4 and 1, respectively. Furthermore, these two variables are positively correlated with a population covariance of 1.4 (resulting in a population correlation of $\frac{1.4}{\sqrt{4 \times 1}} = 0.7$). 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)
```



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]))
mtext(expression(X[j]), 1, line = 2)
plot(1:n, dat[, 2], pch = 16, xlab = "", ylab = "")
abline(h = mean(dat[, 2]))
mtext(expression(X[k]), 1, line = 2)
```

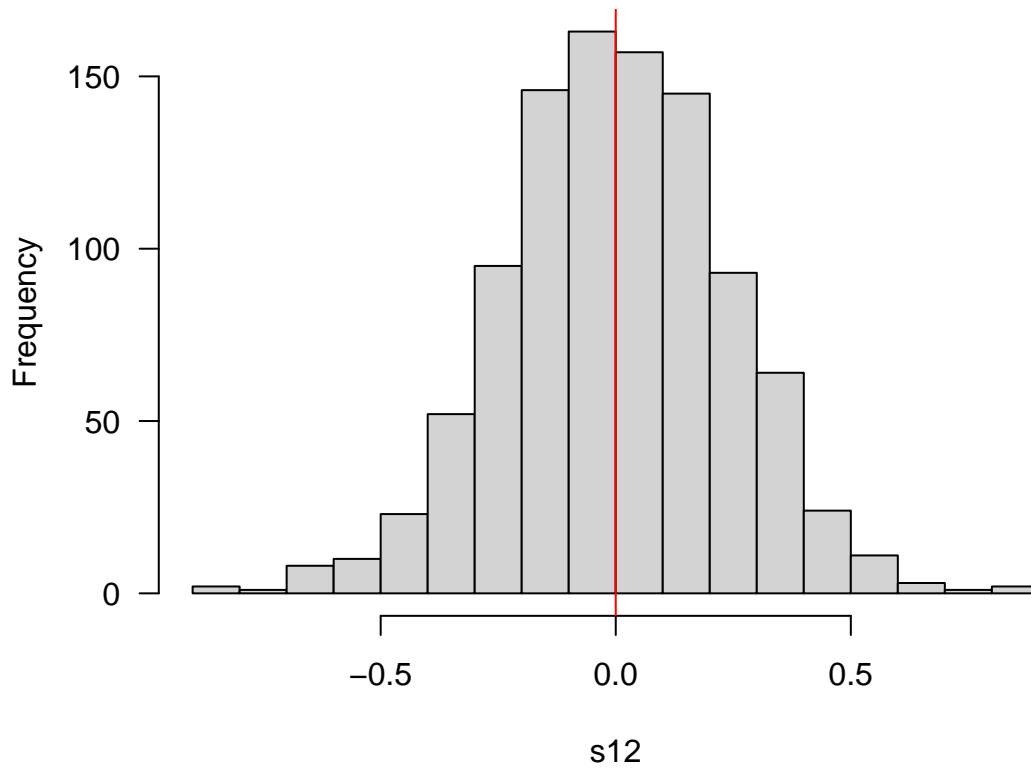


Sample and population covariance

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.

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")
```



Bivariate Data Example

```
data <- cbind(x1 = c(42, 52, 88, 58, 60), x2 = c(4, 5, 7, 4, 5))
(means <- apply(data, 2, mean))
```

```
## x1 x2
## 60 5
```

```
cov(data)
```

```
##      x1  x2
## x1 294 19.0
## x2  19  1.5
```

```
cor(data)
```

```
##          x1          x2
## x1 1.0000000 0.9047619
## x2 0.9047619 1.0000000
```

Generalized Variance

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

```
## [1] 3951786
```

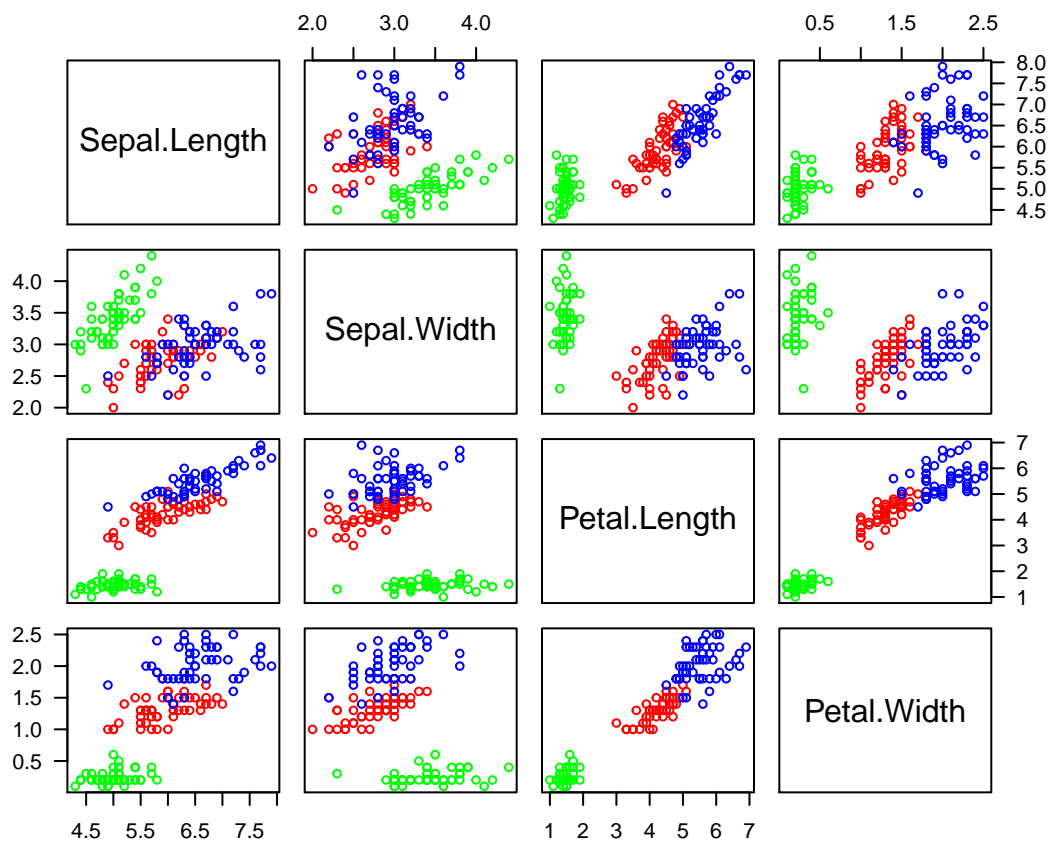
Graphs and Visualization

pairs

```
head(iris)
```

```
## Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1 5.1 3.5 1.4 0.2 setosa
## 2 4.9 3.0 1.4 0.2 setosa
## 3 4.7 3.2 1.3 0.2 setosa
## 4 4.6 3.1 1.5 0.2 setosa
## 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

```
library(GGally)
```

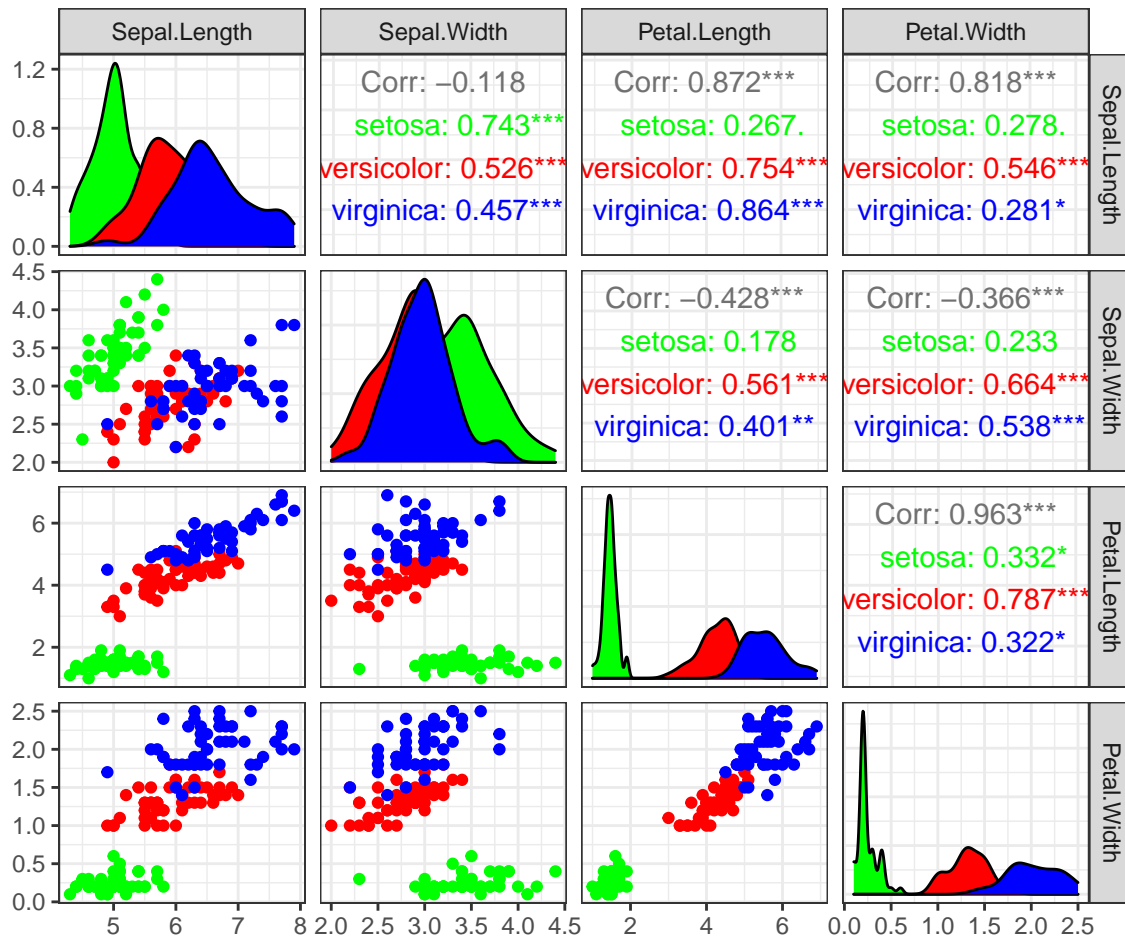
```
## Loading required package: ggplot2

## Warning: replacing previous import 'lifecycle::last_warnings' by
## 'rlang::last_warnings' when loading 'tibble'

## Warning: replacing previous import 'lifecycle::last_warnings' by
## 'rlang::last_warnings' when loading 'pillar'

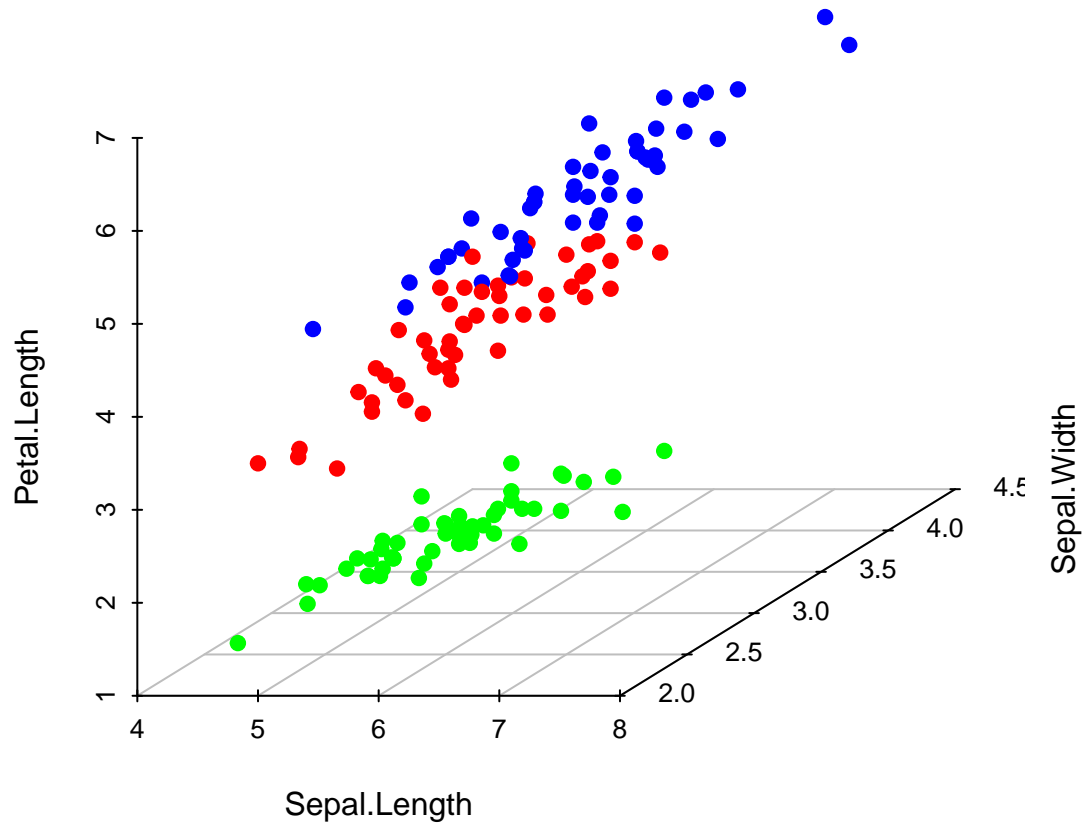
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg      ggplot2
```

```
library(ggplot2)
p <- ggpairs(iris[, -5], aes(color = iris$Species)) + theme_bw()
# Change color manually.
# Loop through each plot changing relevant scales
for(i in 1:p$nrow) {
  for(j in 1:p$ncol){
    p[i, j] <- p[i, j] +
      scale_fill_manual(values = c("green", "red", "blue")) +
      scale_color_manual(values = c("green", "red", "blue"))
  }
}
p
```



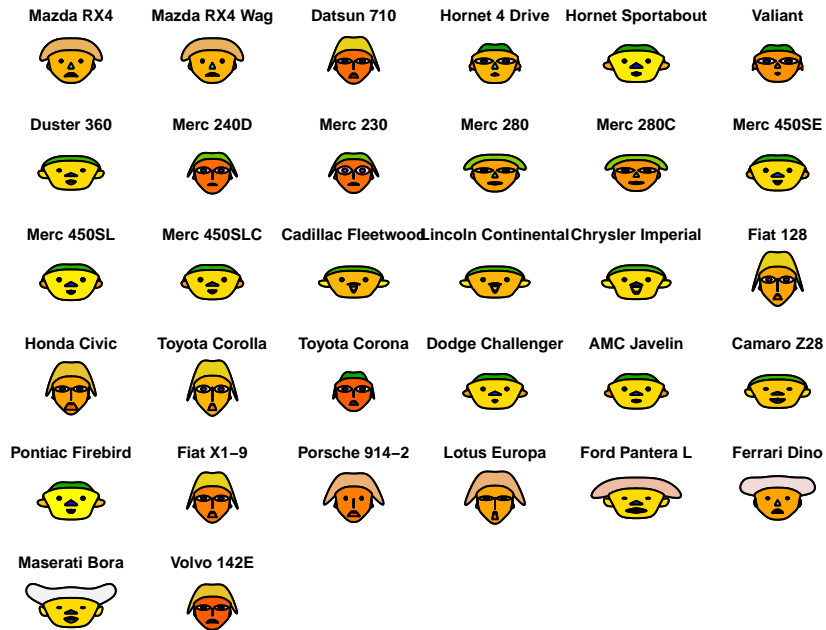
3D Scatter Plot

```
library(scatterplot3d)
scatterplot3d(iris[, 1:3], pch = 19, color = rep(c("green", "red", "blue"), each = 50), grid = TRUE, bo
```



Chernoff Faces

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



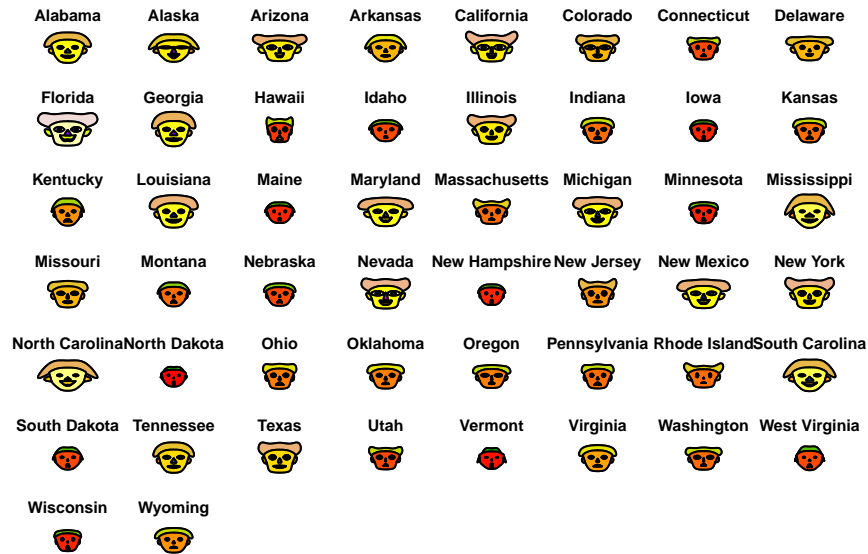
```
## effect of variables:
## modified item      Var
## "height of face"  "mpg"
## "width of face"   "cyl"
## "structure of face" "disp"
## "height of mouth" "hp"
## "width of mouth"  "drat"
## "smiling"         "wt"
## "height of eyes"  "qsec"
## "width of eyes"   "vs"
## "height of hair"  "am"
## "width of hair"   "gear"
## "style of hair"   "carb"
## "height of nose"  "mpg"
## "width of nose"   "cyl"
## "width of ear"    "disp"
## "height of ear"   "hp"
```

USArrests

```
##           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)
```



```
## effect of variables:
## modified item      Var
## "height of face   " "Murder"
## "width of face    " "Assault"
## "structure of face" "UrbanPop"
## "height of mouth  " "Rape"
## "width of mouth   " "Murder"
## "smiling          " "Assault"
## "height of eyes   " "UrbanPop"
## "width of eyes    " "Rape"
## "height of hair   " "Murder"
## "width of hair    " "Assault"
## "style of hair    " "UrbanPop"
## "height of nose   " "Rape"
## "width of nose    " "Murder"
## "width of ear     " "Assault"
## "height of ear    " "UrbanPop"
```

Visualizing Summary Statistics

```
library(ggcorrplot)
# Compute a correlation matrix
corr <- round(cor(car), 1)
# Visualize
ggcorrplot(corr, p.mat = cor_pmat(car),
            hc.order = TRUE, type = "lower",
            color = c("#FC4E07", "white", "#00AFBB"),
            outline.col = "white", lab = TRUE)
```

