

# R-Language: Data Visualization

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**PREPARED FOR**

Engineering Students

All Engineering College

*(R-Language)*

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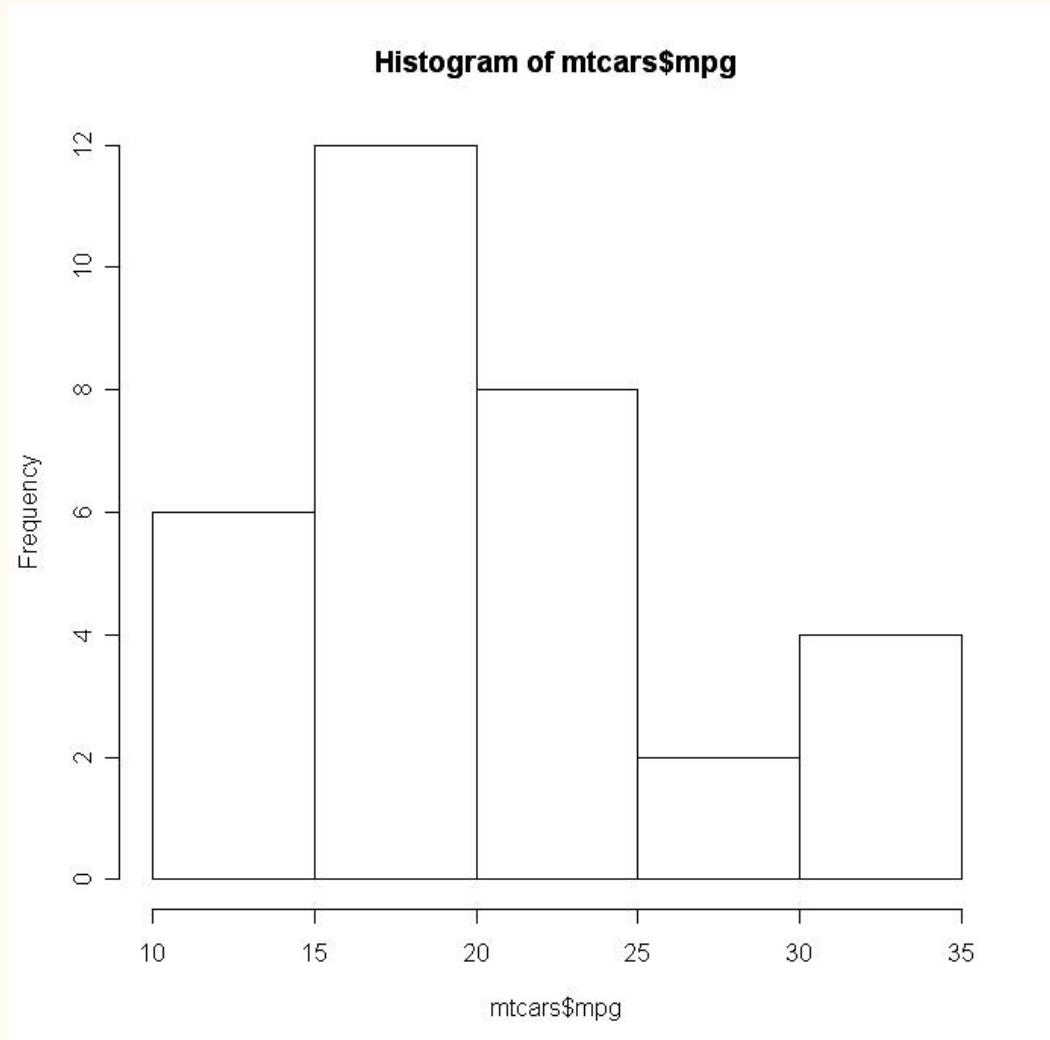
All libraries and functions can be download  
from:

<http://www.r-project.org/>



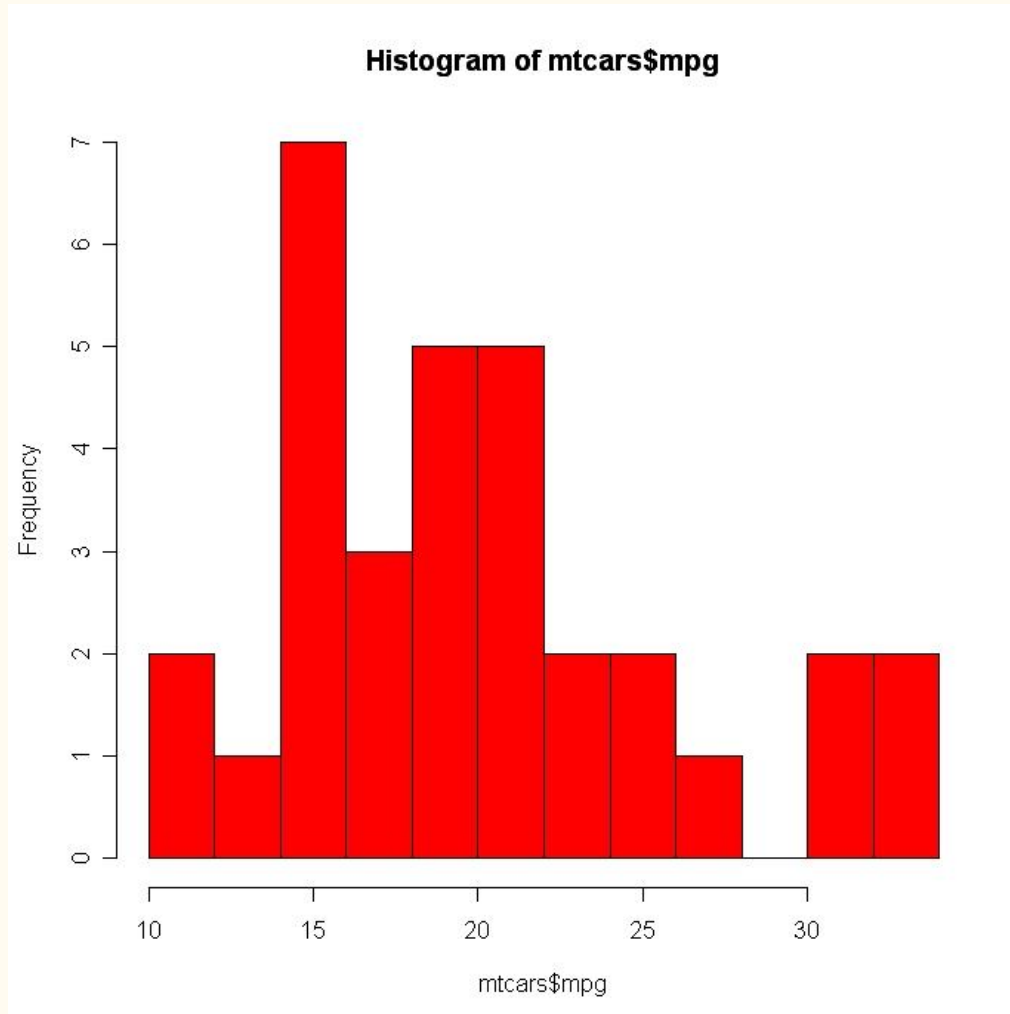
# Histogram

```
> library(datasets)
> mtcars
> hist(mtcars$mpg)
```



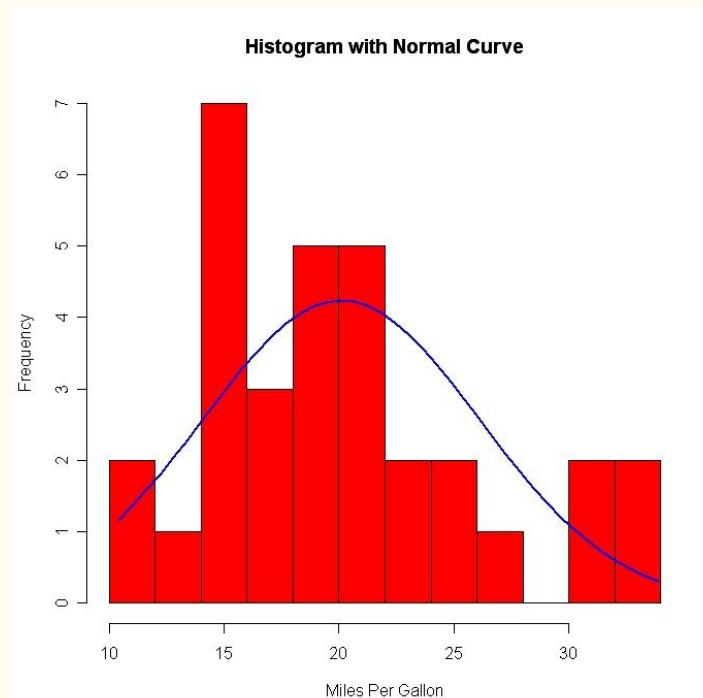
# Coloured histogram

```
> hist(mtcars$mpg, breaks=12, col="red")
```



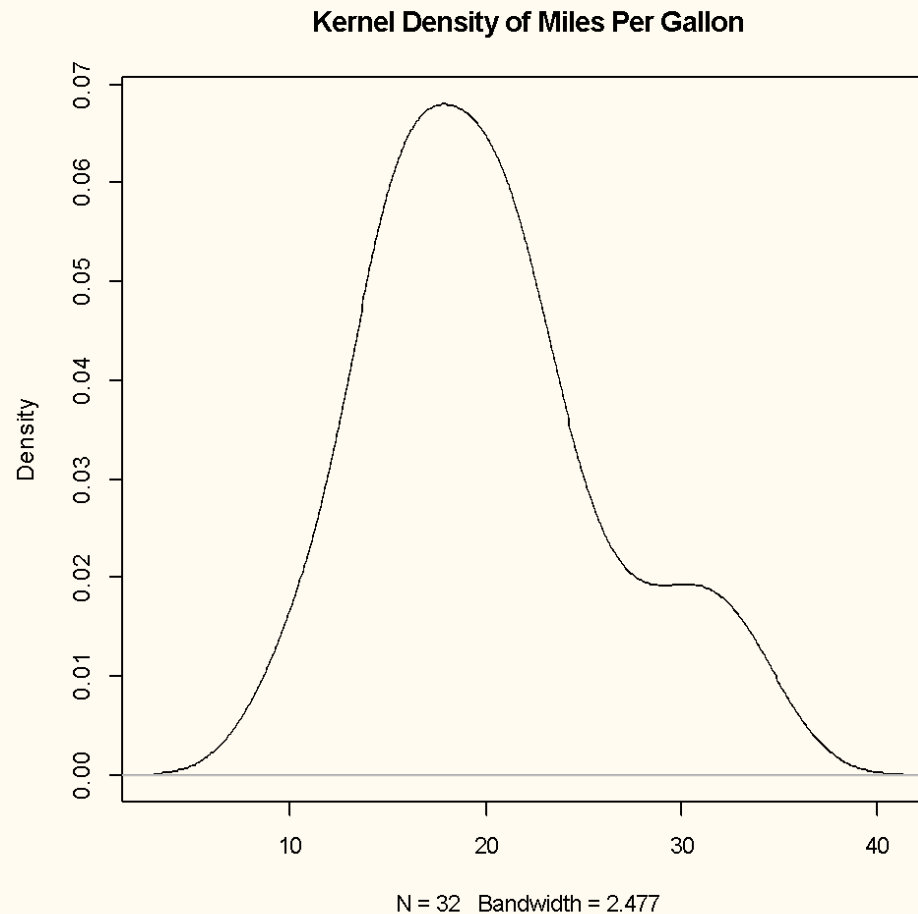
# Histogram with normal curve

```
> x <- mtcars$mpg
> h <- hist(x, breaks=10, col="red", xlab="Miles Per Gallon", main=
  "Histogram with Normal Curve")
> xfit <- seq(min(x), max(x), length=40)
> yfit <- dnorm(xfit, mean=mean(x), sd=sd(x))
> yfit <- yfit * diff(h$mids[1:2]) * length(x)
> lines(xfit, yfit, col="blue", lwd=2)
```



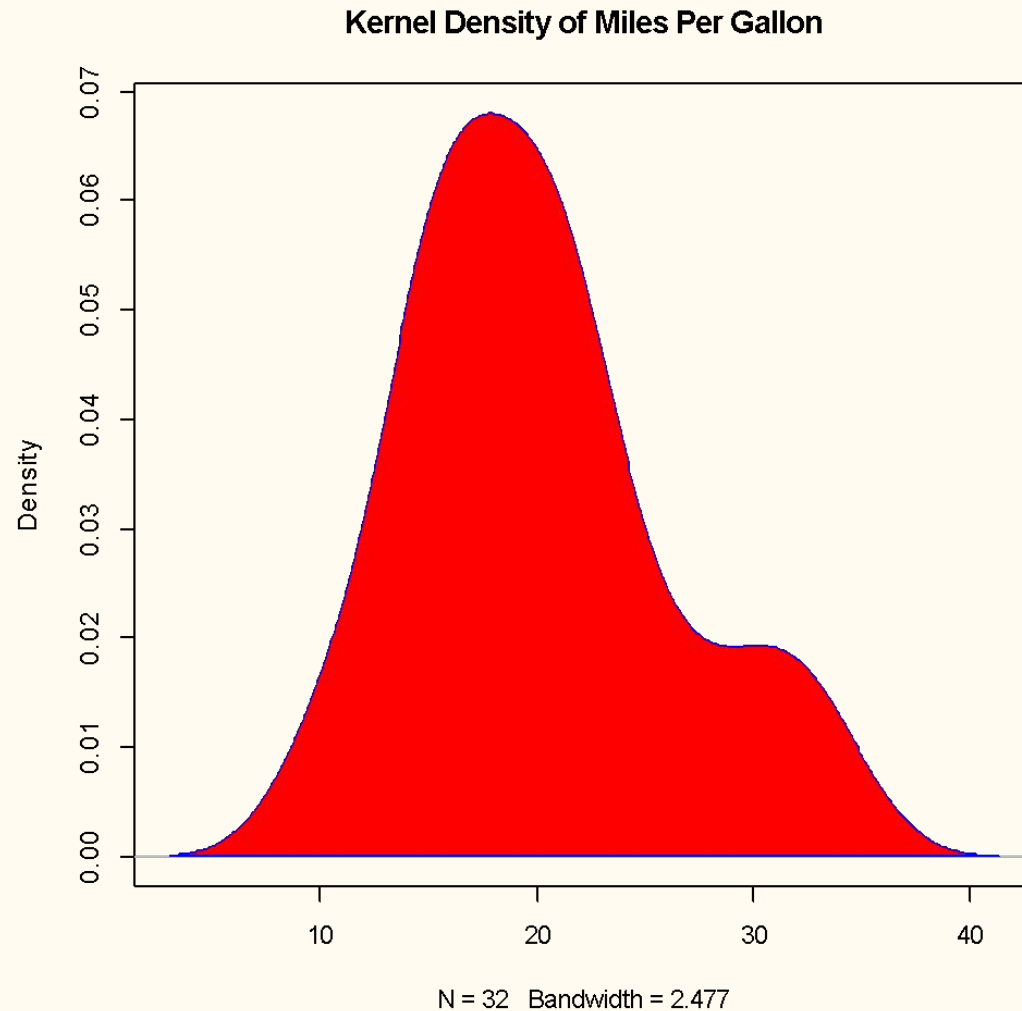
# Density Plot

```
> d <- density(mtcars$mpg)
> plot(d, main="Kernel Density of Miles Per Gallon")
```



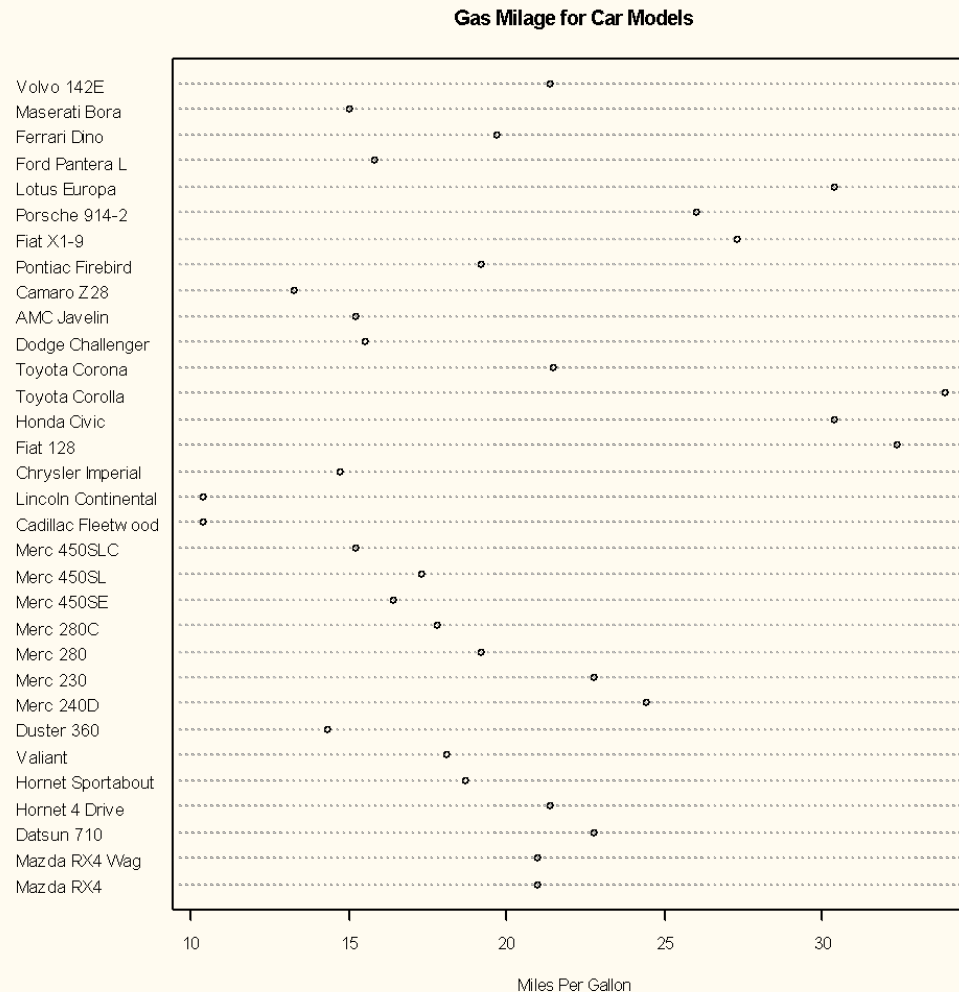
# Filled Density Plot

```
> polygon(d, col="red", border="blue")
```



# Dot Plot

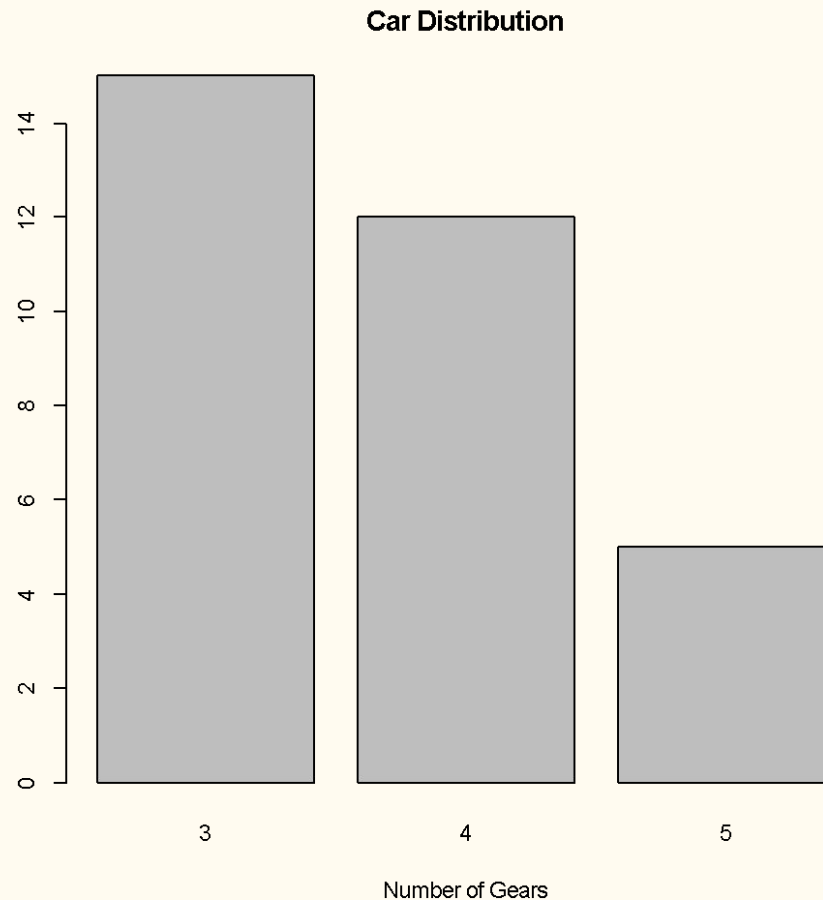
```
> dotchart(mtcars$mpg, labels=row.names(mtcars), cex=.7, main="Gas  
Milage for Car Models", xlab="Miles Per Gallon")
```





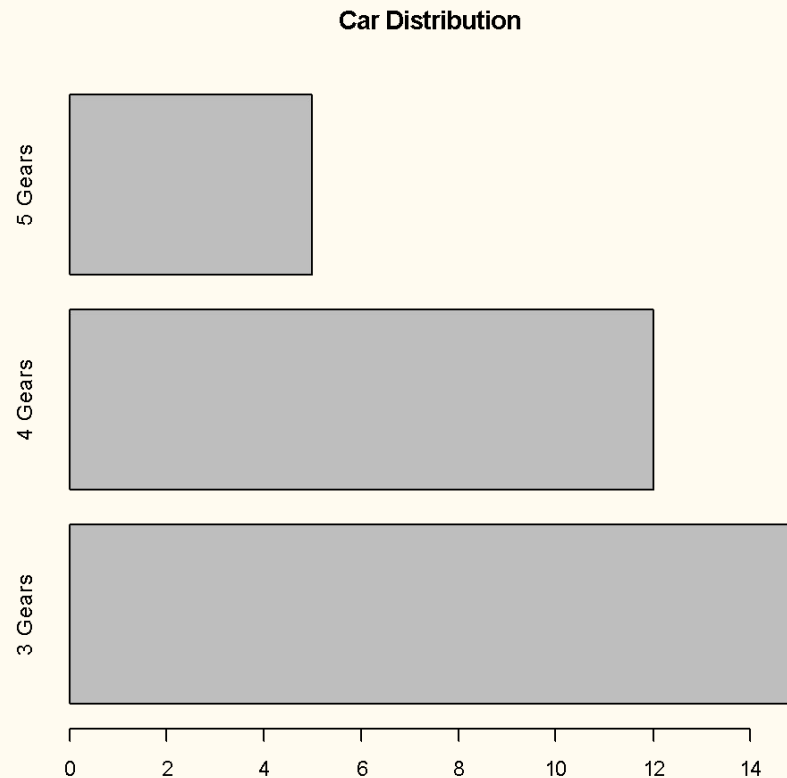
# Simple Bar Plot

```
> counts <- table(mtcars$gear)      # Simple Bar Plot  
> barplot(counts, main="Car Distribution",  
           xlab="Number of Gears")
```



# Simple Horizontal Bar Plot with Added Labels

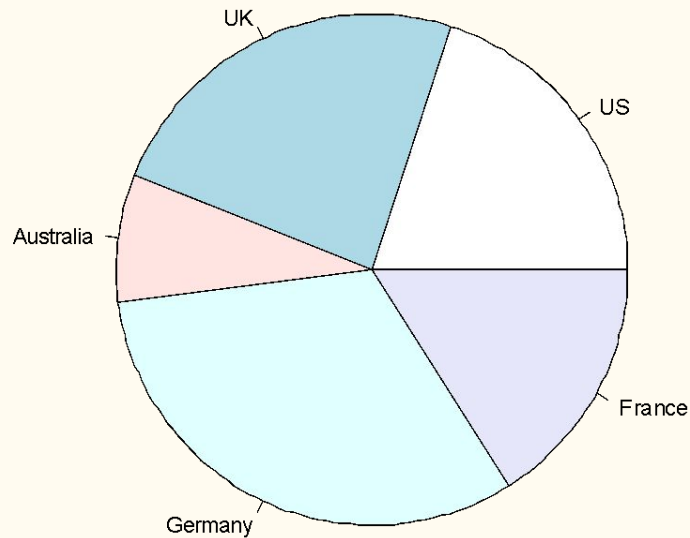
```
> counts <- table(mtcars$gear)
> barplot(counts, main="Car Distribution", horiz=TRUE,
  names.arg=c("3 Gears", "4 Gears", "5 Gears"))
```



# Simple Pie Chart

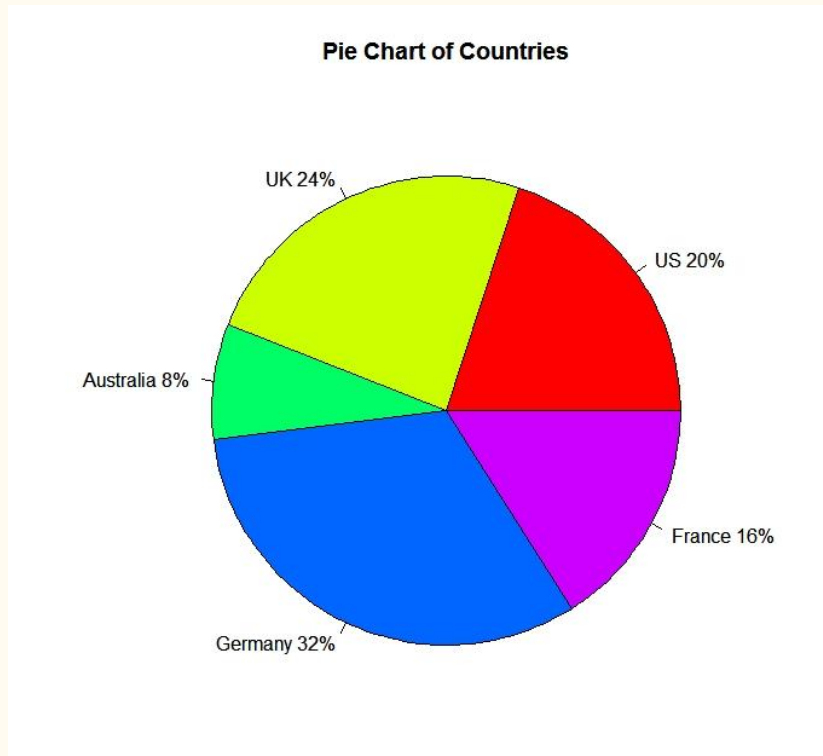
```
> slices <- c(10, 12, 4, 16, 8)           # Simple Pie Chart  
> lbls <- c("US", "UK", "Australia", "Germany", "France")  
> pie(slices, labels = lbls, main="Pie Chart of Countries")
```

**Pie Chart of Countries**



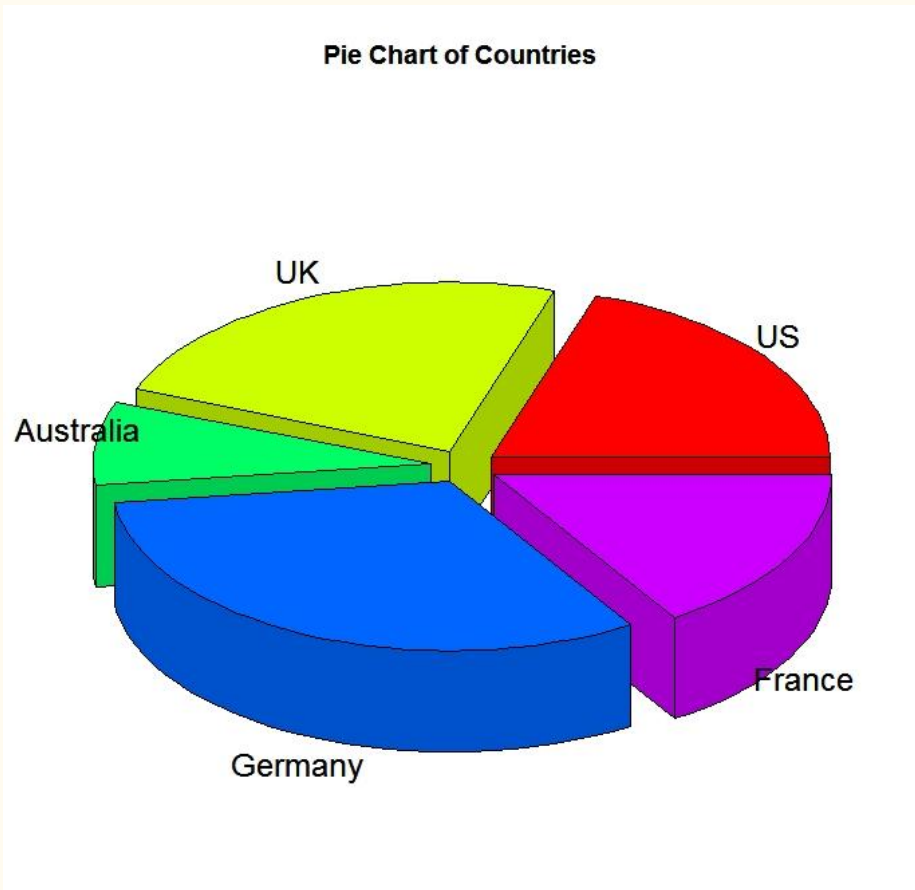
# Pie Chart with Annotated Percentages

```
> slices <- c(10, 12, 4, 16, 8)
> lbls <- c("US", "UK", "Australia", "Germany", "France")
> pct <- round(slices/sum(slices)*100)
> lbls <- paste(lbls, pct)      # add percents to labels
> lbls <- paste(lbls,"%",sep="") # ad % to labels
> pie(slices,labels = lbls, col=rainbow(length(lbls)),
     main="Pie Chart of Countries")
```



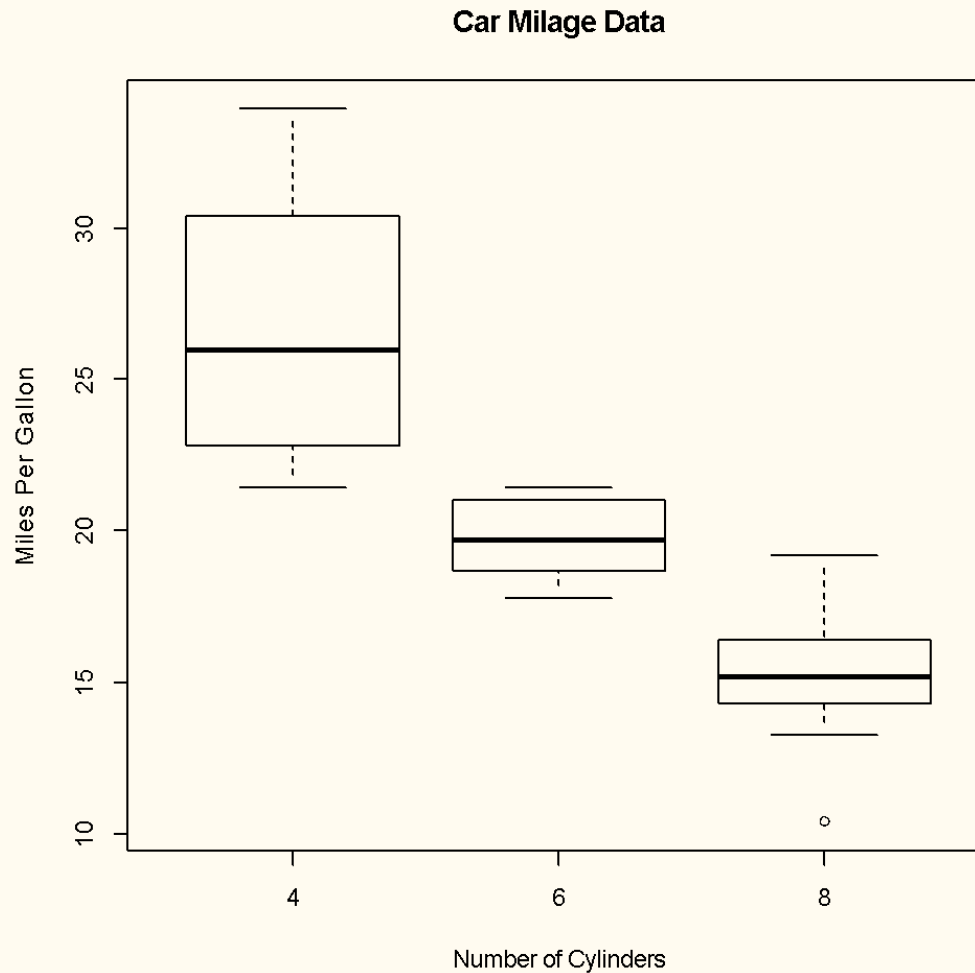
# 3D Pie Chart

```
> library(plotrix)
> slices <- c(10, 12, 4, 16, 8)
> lbls <- c("US", "UK", "Australia", "Germany", "France")
> pie3D(slices, labels=lbls, explode=0.1, main="Pie Chart of  
Countries ")
```



# Boxplot

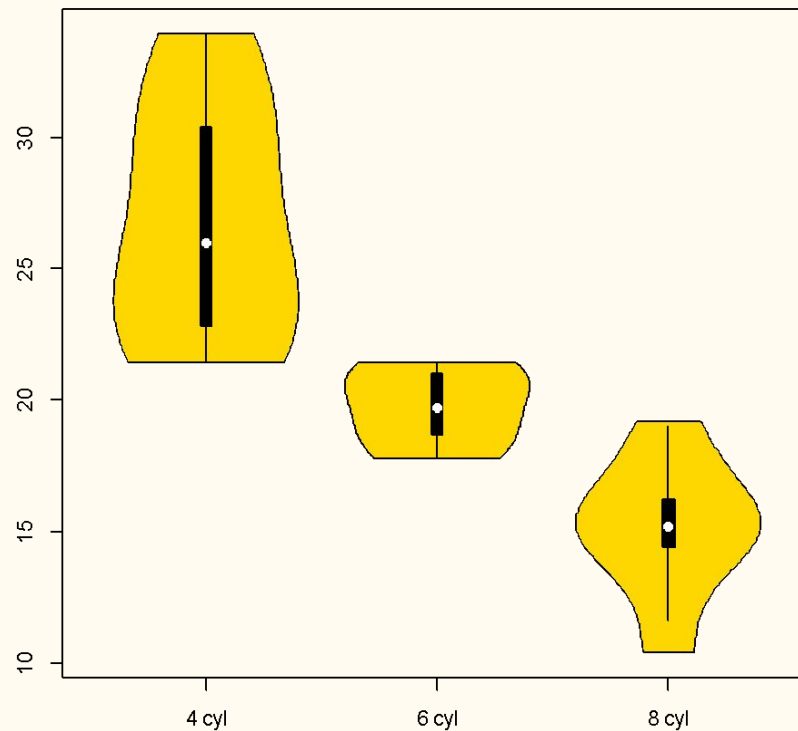
```
> boxplot(mpg~cyl,data=mtcars, main="Car Milage Data",  
          xlab="Number of Cylinders", ylab="Miles Per Gallon")
```



# Violin plot

```
> library(vioplot)
> x1 <- mtcars$mpg[mtcars$cyl==4]
> x2 <- mtcars$mpg[mtcars$cyl==6]
> x3 <- mtcars$mpg[mtcars$cyl==8]
> vioplot(x1, x2, x3, names=c("4 cyl", "6 cyl", "8 cyl"), col="gold")
> title("Violin Plots of Miles Per Gallon")
```

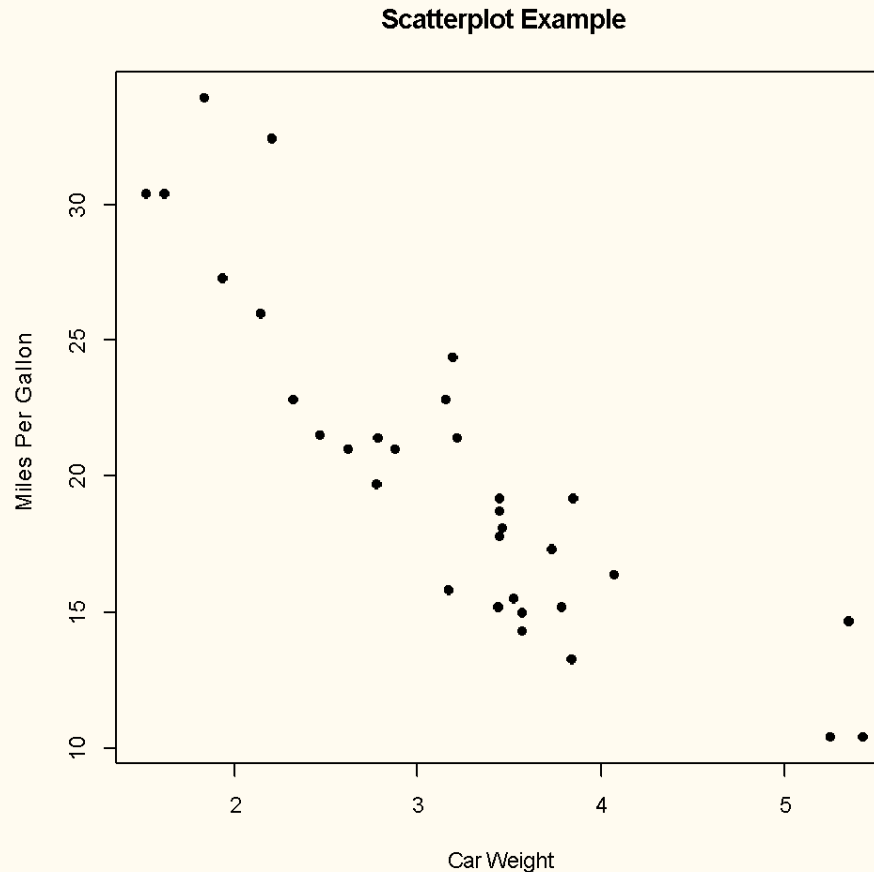
**Violin Plots of Miles Per Gallon**



# Simple Scatterplot

```
> attach(mtcars)
```

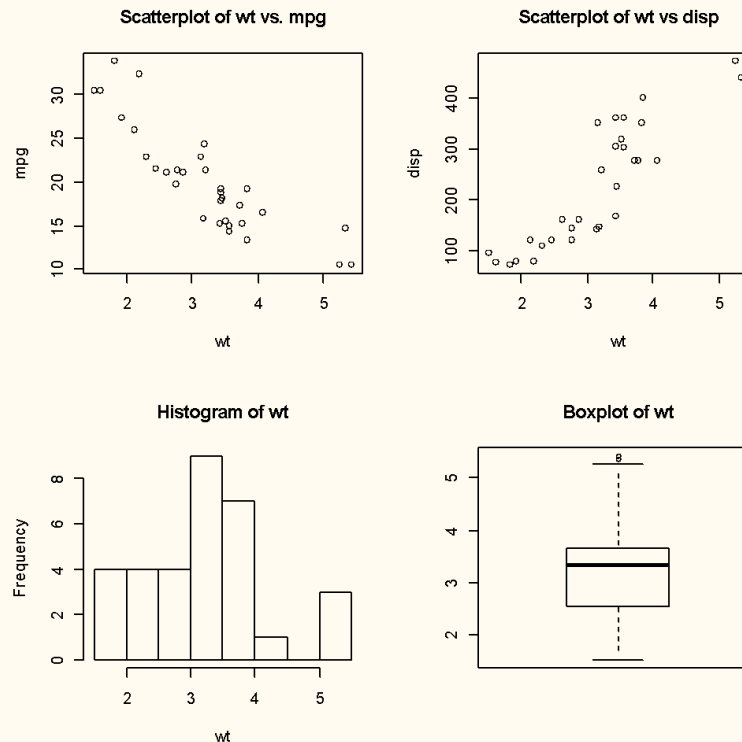
```
> plot(wt, mpg, main="Scatterplot Example", xlab="Car  
Weight ", ylab="Miles Per Gallon ", pch=19)
```





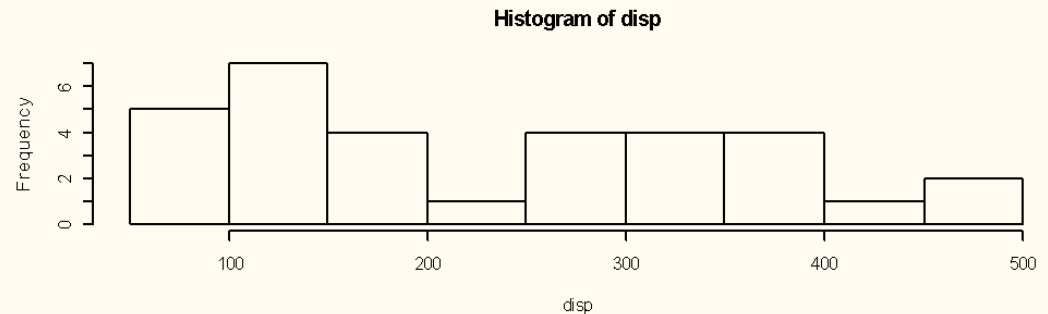
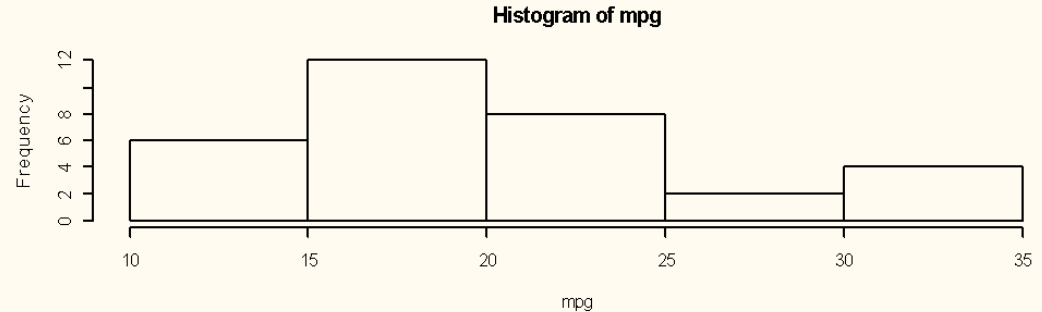
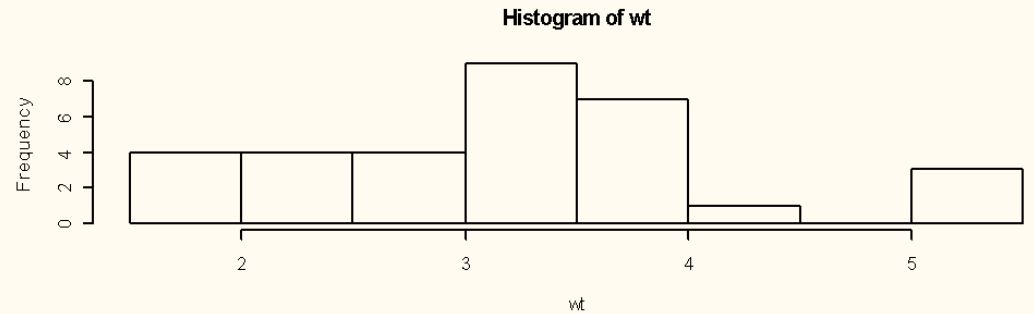
# Combining Plots

```
> attach(mtcars)
> par(mfrow=c(2,2))
> plot(wt,mpg, main="Scatterplot of wt vs. mpg")
> plot(wt,disp, main="Scatterplot of wt vs disp")
> hist(wt, main="Histogram of wt")
> boxplot(wt, main="Boxplot of wt")
```



# 3 figures arranged in 3 rows and 1 column

```
> attach(mtcars)
> par(mfrow=c(3,1))
> hist(wt)
> hist(mpg)
> hist(dis)
```



# **Visualizing tools for two-way contingency tables**

# Binomial distribution in R

For arandom variable  $X$ , binomial distributed with  $n=10$  and success of probability  $\pi=0.3$ , the probability  $P(X=2)$  is computed as:

```
> dbinom(2, 10, 0.3)
```

with the cumulative probability  $P(X \leq 2)$  by:

```
> pbinom(2, 10, 0.3)
```

The corresponding function on the vector of all possible outcomes  $x=(0,1,\dots,5)$  is computed as:

```
> x <- 0:5
```

```
> dbinom(x, 5, 0.1)
```

```
> dbinom(x, 5, 0.1)
```

The probability mass function can be plotted by the command:

```
> plot(x, dbinom(x,5,0.1), type="h", ylim=c(0,1), lwd=5, lend=3,  
      frame.plot=F, xaxt="n", main="0.1", ylab="P(X=x)")
```

```
> axis(1, at=x, pos=c(0,0))
```

# Multinomial distribution in R

Consider a trial with  $K$  possible outcomes,  $K \geq 2$ , denoted by  $A_1, A_2, \dots, A_K$

The number of outcomes  $K$  is fixed and the probability for each of them to occur is positive and constant across independent trials, equal to  $\pi_k$ ,  $k=1, \dots, K$ , with

$$\sum_{k=1}^K \pi_k = 1$$

The  $K$  outcomes are all possible levels of a categorical variable  $X$ , taking values in  $\{1, 2, \dots, K\}$

For a random sample of  $n$  independent trials, let  $(N_1, \dots, N_K)$  be the random category frequencies of  $X$

To obtain probabilities for  $(N_1, N_2) \sim M(10; (0.35, 0.25))$ , the probability  $P(3, 2, 5)$  is calculated by:

```
> x<- c(3,2,5); dmultinom(x,prob=c(0.35, 0.2, 0.4))
```

# Poisson distribution in R

For Poisson distribution, if  $X \sim P(2)$ , then:

```
> dpois(3, 2)
```

calculates  $P(X=3)=0.18$

$P(X>4)$  is computed as:

```
> 1-dpois(4, 2)
```

# Creating frequency table

```
> library(vcd)          # opening the vcd library
> Arthritis              # opening Arthritis dataset
> head(Arthritis, 7)     # firts 7 observations
> names(Arthritis)       # list variables names
> str(Arthritis)         # data structure

> library(datasets)     # opening the datasets library
> HairEyeColor           # HaiEyeColor data set
> sum(HairEyeColor)      # number of cases
> structable(HaiEyeColor) # table structure
> summary(HairEyeColor)  # data summary
> structable(Hair+Sex~Eye, HairEyeColor)
    # specify col~row variables
```

# Test of independence

```
> HairEye <- margin.table(HairEyeColor, c(1, 2))  
      # two-way table: Hair x Eye  
  
> HairEye          # printing two-way table  
> sum(HairEye)      # number of cases  
> chisq.test(HairEye)  # chi-square test for two-way table  
> assocstats(HairEye)  # independence coefficients
```



# Analysis of association for nominal data

- Nominal data are usually presented in a contingency table
- Joint distribution in a two-way contingency table for two variables, each with 2 category (dichotomous variable):
  - $X$  (row variable) with categories:  $h=1,2$
  - $Y$  (column variable) with categories  $j=1,2$is presented in a two-way table 2x2:

Categories of $X$	Categories of $Y$		
	$Y_1$	$Y_2$	$n_{h.}$
$X_1$	$n_{11}$	$n_{12}$	$n_{1.}$
$X_2$	$n_{21}$	$n_{22}$	$n_{2.}$
$n_{.j}$	$n_{.1}$	$n_{.2}$	$n$

# 2x2 contingency table

- The total number of observations is defined as:  $n = n_{..} = \sum_{h=1}^2 \sum_{j=1}^2 n_{hj}$
- Row marginals:  $n_{h\bullet} = \sum_{j=1}^2 n_{hj}$
- Column marginals:  $n_{\bullet j} = \sum_{h=1}^2 n_{hj}$
- Example :

Smoking	Gender		
	Female	Male	$n_{h\bullet}$
Yes	50	100	$n_{1\bullet}$
No	250	200	$n_{2\bullet}$
$n_{\bullet j}$	$n_{\bullet 1}$	$n_{\bullet 2}$	$n$

# Probability 2x2 table

- For any contingency table we can have probability table:

Categories of $X$	Categories of $Y$		
	$Y_1$	$Y_2$	$p_{h\bullet}$
$X_1$	$p_{11}$	$p_{12}$	$p_{1\bullet}$
$X_2$	$p_{21}$	$p_{22}$	$p_{2\bullet}$
$p_{\bullet j}$	$p_{\bullet 1}$	$p_{\bullet 2}$	1

where: 
$$p_{h\bullet} = \sum_{j=1}^2 p_{hj} = \sum_{j=1}^2 \frac{n_{hj}}{n}$$

and: 
$$p_{\bullet j} = \sum_{h=1}^2 p_{hj} = \sum_{h=1}^2 \frac{n_{hj}}{n}$$

In case  $X$  and  $Y$  are independent:  $p_{hj} = p_{h\bullet} \cdot p_{\bullet j}$

Estimated expected cell counts are: 
$$\hat{m}_{hj} = n \cdot p_{h\bullet} \cdot p_{\bullet j} = \frac{n_{h\bullet} \cdot n_{\bullet j}}{n}$$

# *HxJ* contingency table

- The total number of observations is defined as:  $n = n_{..} = \sum_{h=1}^H \sum_{j=1}^J n_{hj}$
- Row marginals:  $n_{h\bullet} = \sum_{j=1}^J n_{hj}$
- Column marginals:  $n_{\bullet j} = \sum_{h=1}^H n_{hj}$

Categories of $X$	Categories of $Y$			$n_{h\bullet}$
	$Y_1$	...	$Y_J$	
$X_1$	$n_{11}$	...	$n_{1J}$	$n_{1\bullet}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$X_H$	$n_{H1}$	...	$n_{HJ}$	$n_{H\bullet}$
$n_{\bullet j}$	$n_{\bullet 1}$	...	$n_{\bullet J}$	$n$

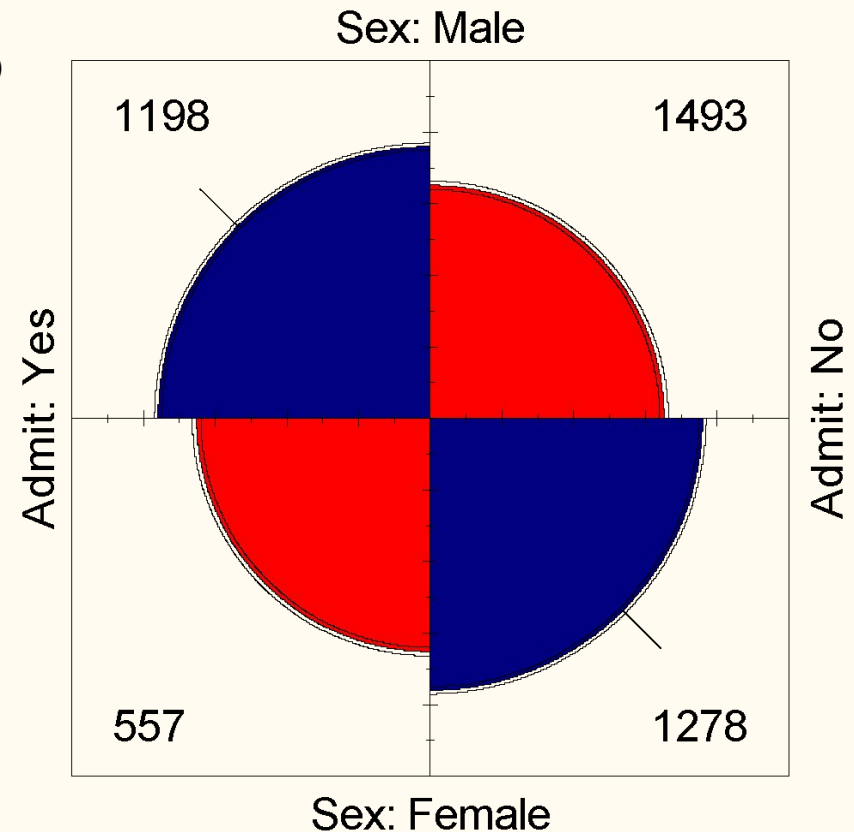
# Probability table $H \times J$

Categories of $X$	Categories of $Y$			$p_{h\bullet}$
	$Y_1$	...	$Y_J$	
$X_1$	$p_{11}$	...	$p_{1J}$	$p_{1\bullet}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$X_H$	$p_{H1}$	...	$p_{HJ}$	$p_{H\bullet}$
$p_{\bullet j}$	$p_{\bullet 1}$	...	$p_{\bullet J}$	1

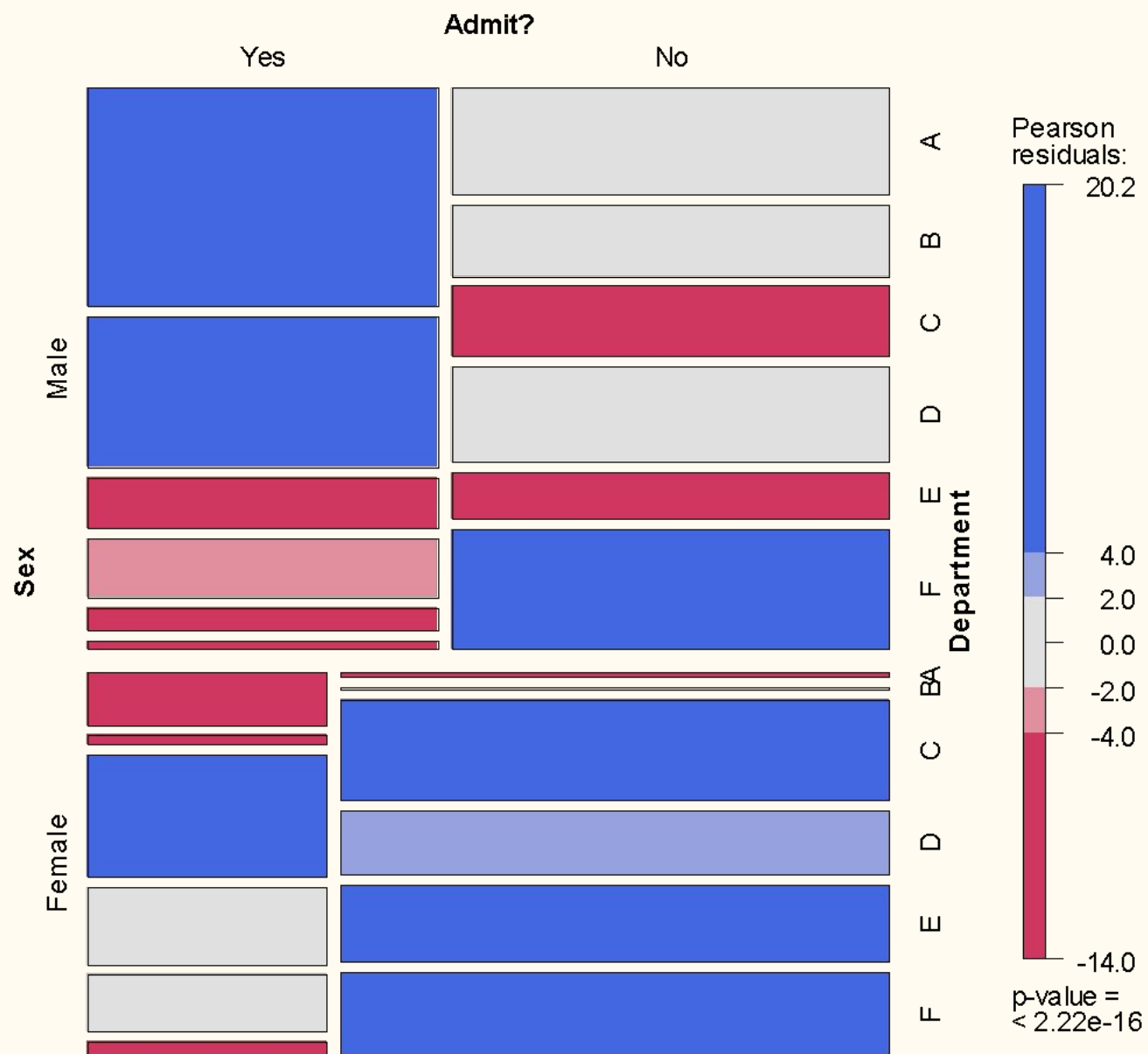
- $p_{hj} = P(X = n_h, Y = n_j)$  are probabilities of falling into  $hj$ -cell
- Expected cell counts are defined as:  $m_{hj} = n \cdot p_{hj}$

# Fourfold plot

```
> library(datasets)
> library(vcd)
> x <- aperm(UCBAdmissions, c(2, 1, 3))
> dimnames(x)[[2]] <- c("Yes", "No")
> names(dimnames(x)) <- c("Sex", "Admit", "Department")
> ftable(x)
> fourfold(margin.table(x, c(1, 2)))
```



```
> mosaic(x, shade=TRUE)
```

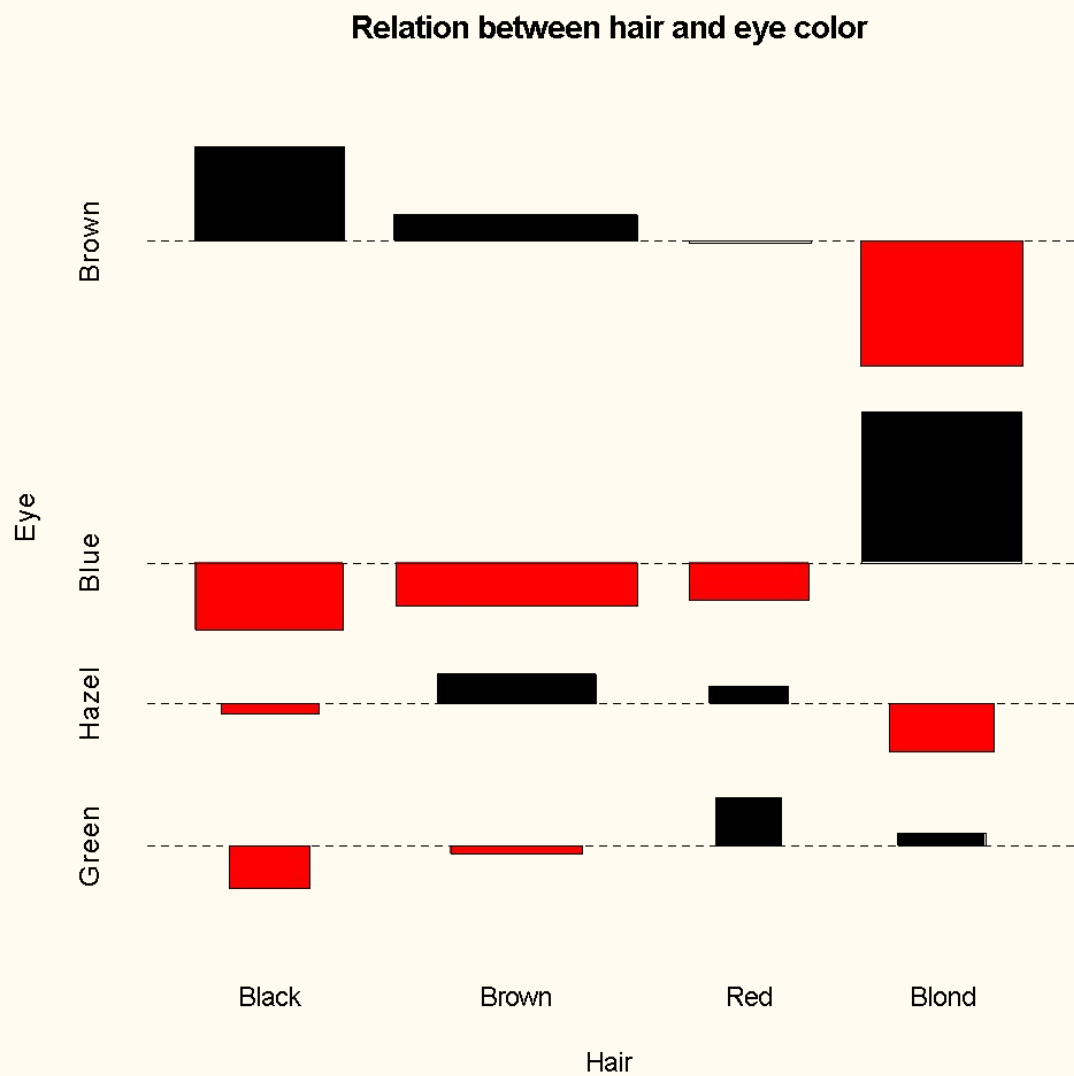


```
> library(graphics)
> x <- margin.table(HairEyeColor, c(1, 2))
> x
```

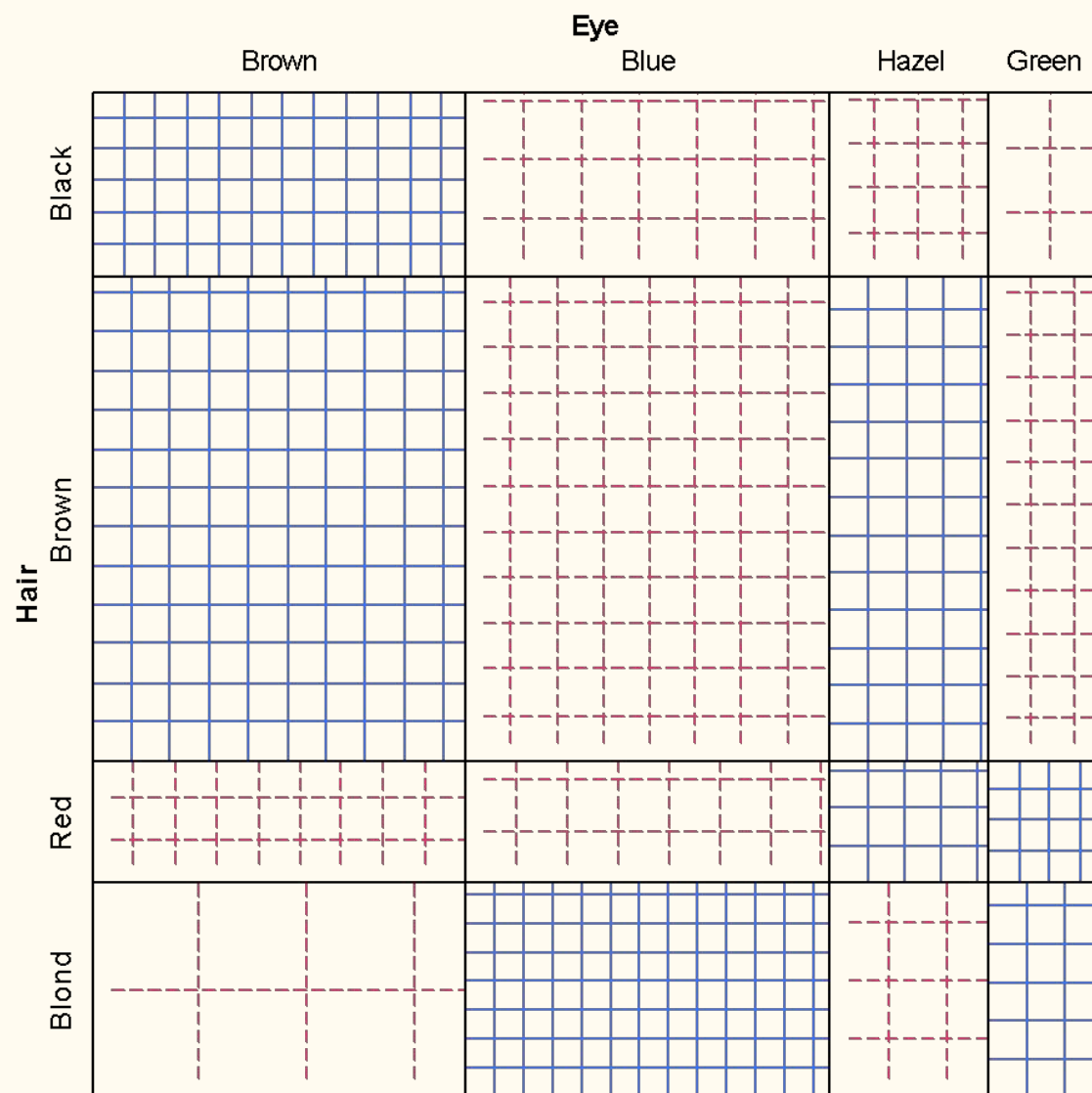
```
Eye
Hair   Brown Blue Hazel Green
Black   68   20   15    5
Brown  119   84   54   29
Red     26   17   14   14
Blond    7   94   10   16
```



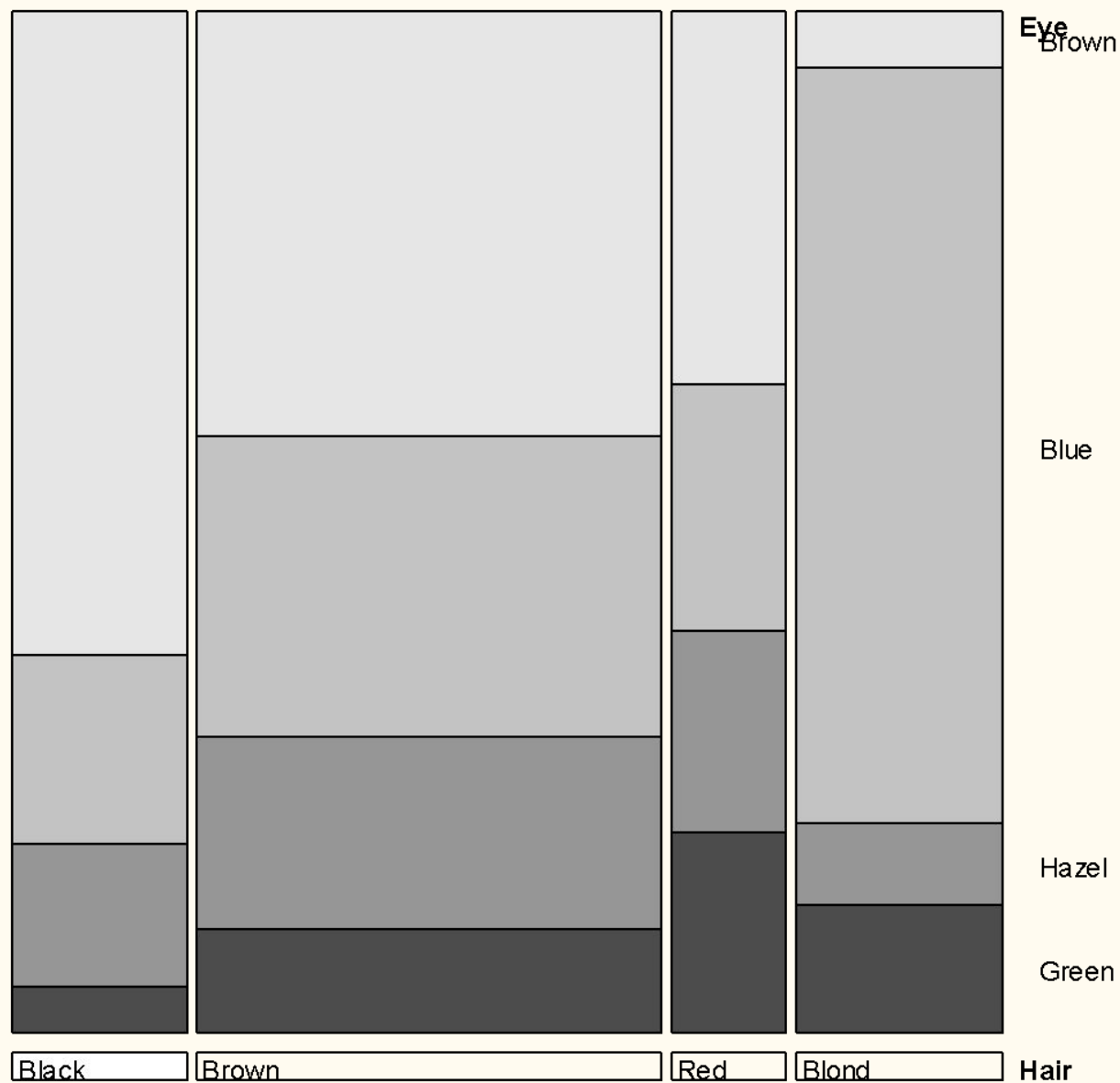
```
> assocplot(x, main = "Relation between hair and eye color")
```



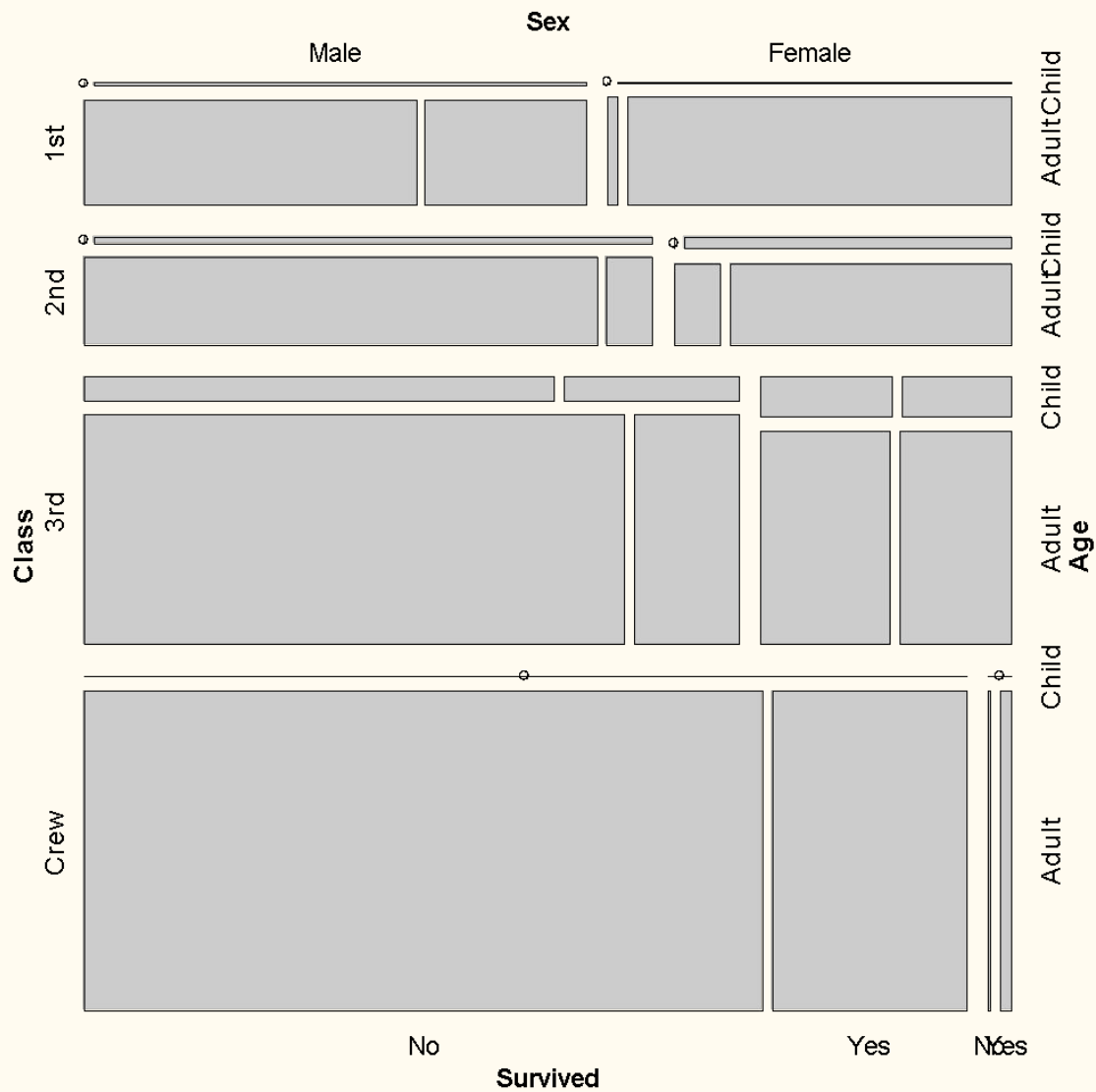
```
> sieve(x, shade=TRUE)
```



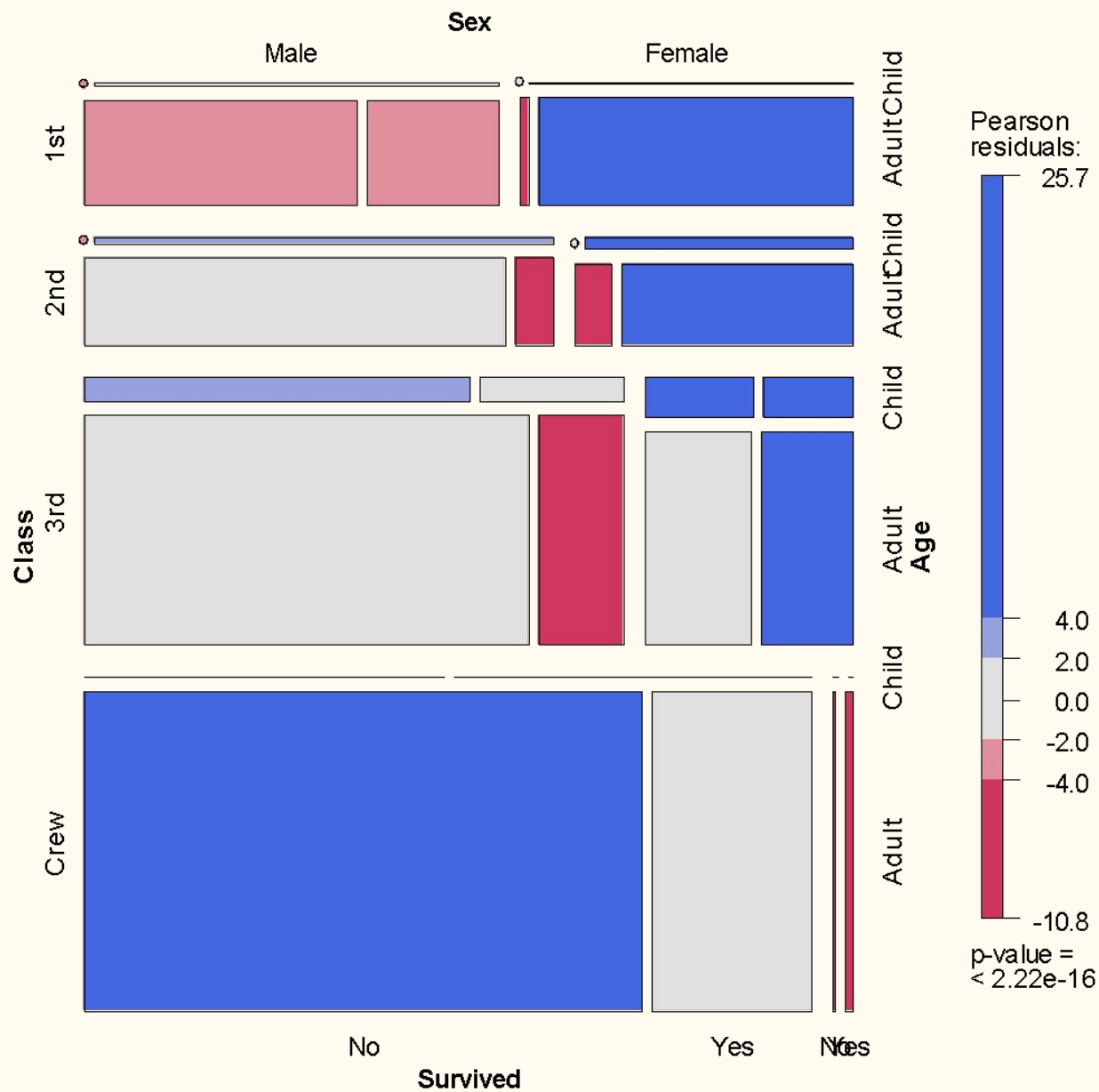
```
> doubledecker(x)
```



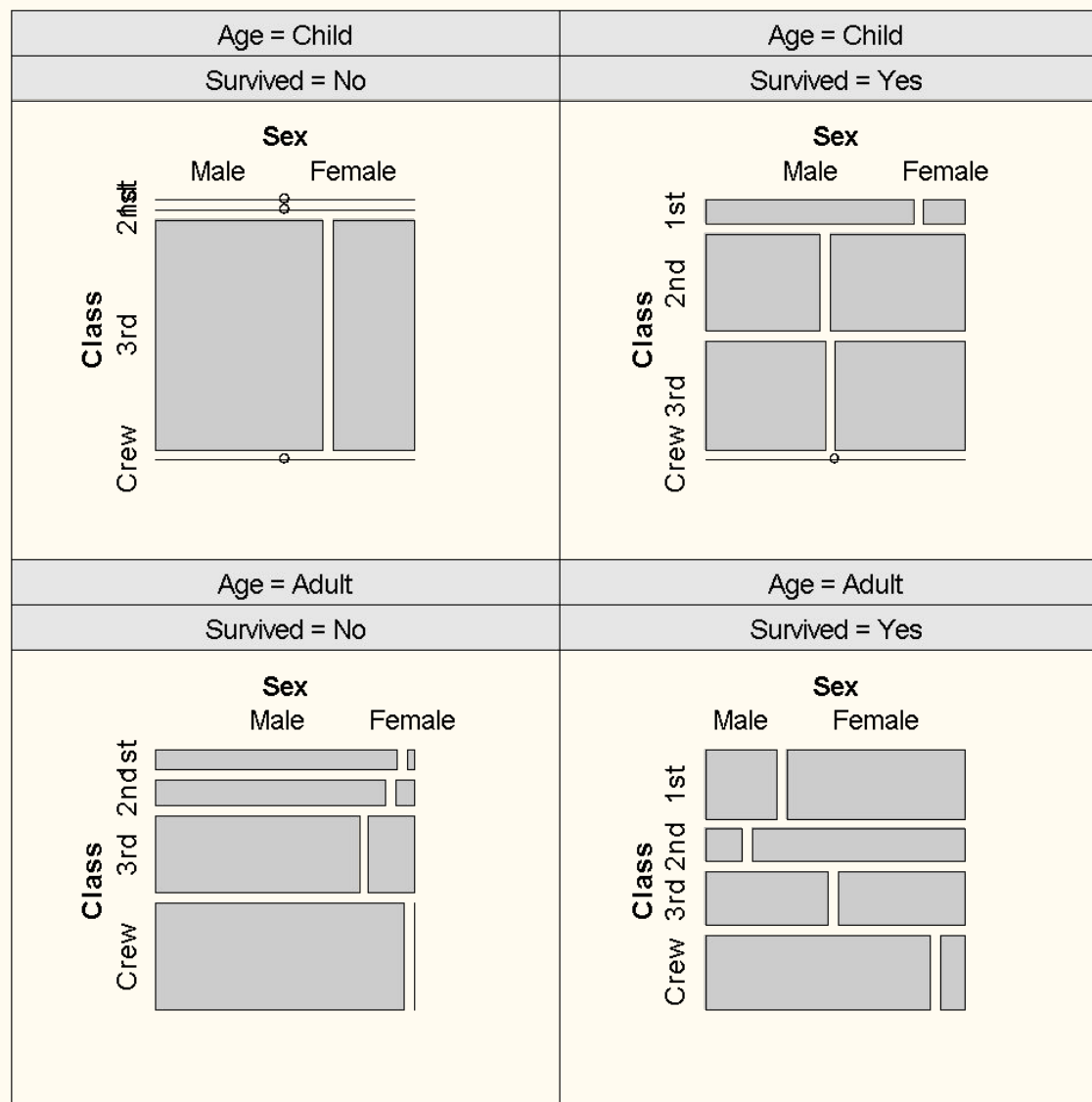
```
> library(vcd) # opens the library for visualizing
> mosaic(Titanic)
```



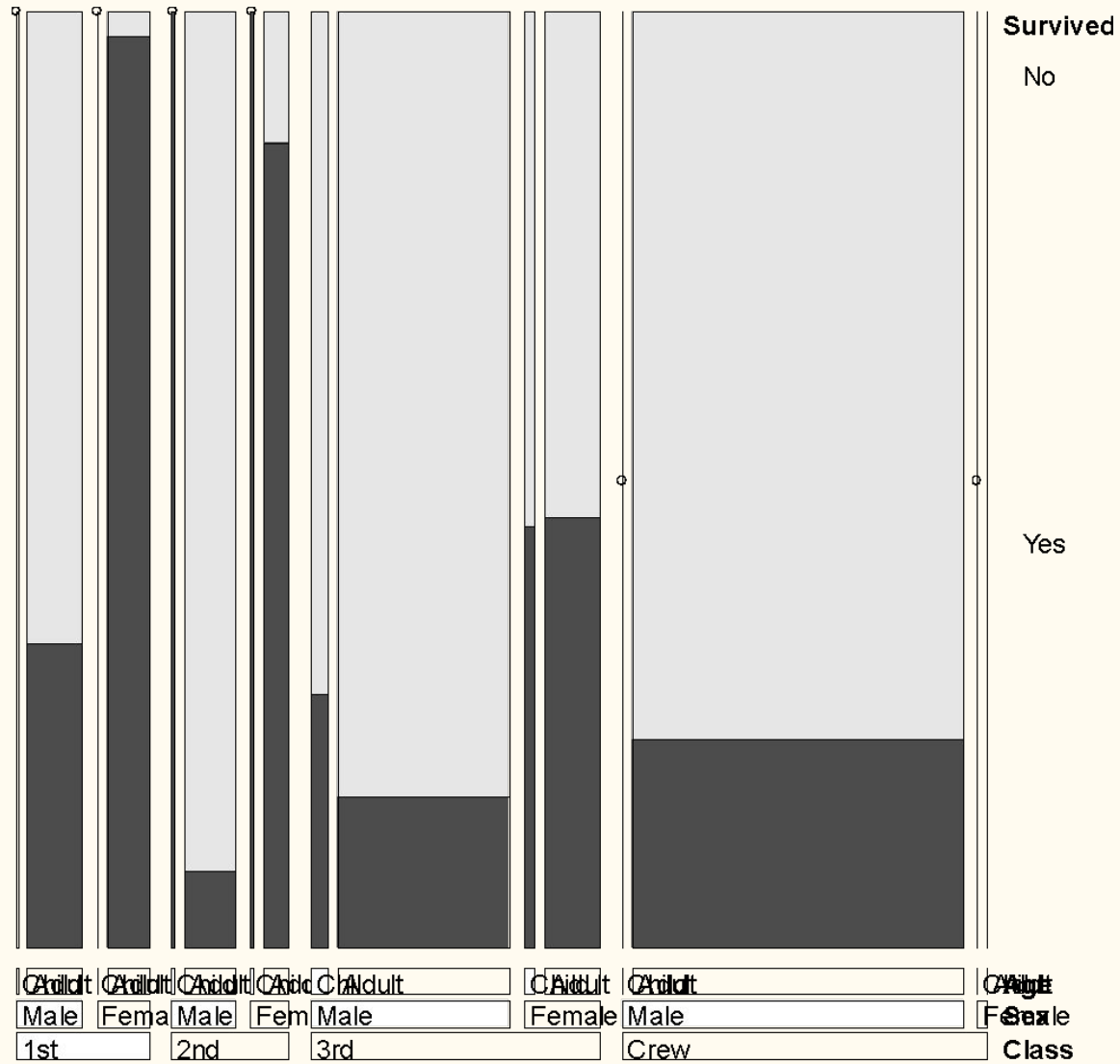
```
> mosaic(Titanic, shade=TRUE)
```



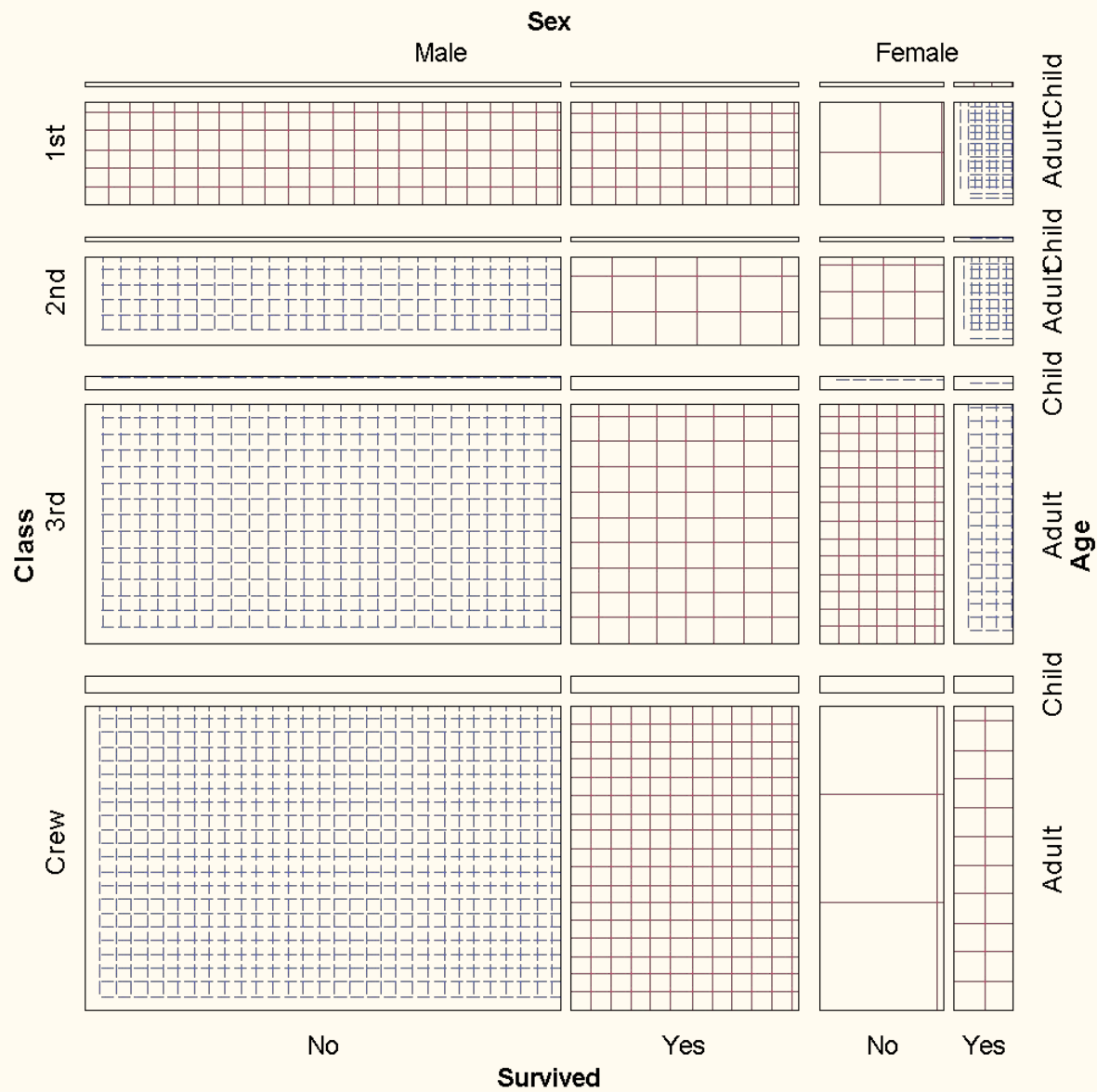
```
> cotabplot(Titanic)
```



```
> doubledecker(Titanic)
```



```
> sieve(Titanic)
> sieve(Titanic, shade=TRUE)
```





# Kappa agreement coefficient

- Agreement symmetric table  $H \times H$

Person 1	Person 2			$n_{h\bullet}$
	1	...	$H$	
1	$n_{11}$	...	$n_{1H}$	$n_{1\bullet}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$H$	$n_{H1}$	...	$n_{HH}$	$n_{H\bullet}$
$n_{h\bullet}$	$n_{\bullet 1}$	...	$n_{\bullet H}$	$n$

- Cohen's Kappa:

$$\kappa = \frac{\theta_1 - \theta_2}{1 - \theta_2} = \frac{\sum_{h=1}^H p_{hh} - \sum_{h=1}^H p_{h\bullet} p_{\bullet h}}{1 - \sum_{h=1}^H p_{h\bullet} p_{\bullet h}}$$

where:  $\theta_1 = \sum_{h=1}^H p_{hh}$ ,  $\theta_2 = \sum_{h=1}^H p_{h\bullet} p_{\bullet h}$

# Agreement interpretation

- Kappa coefficient agreement can range from  $[0,1]$  with 0 indicating no agreement, and 1 indicating perfect agreement
  - perfect agreement :  $0,75 < \kappa \leq 1$
  - good agreement :  $0,4 < \kappa \leq 0,75$
  - poor agreement :  $0 < \kappa \leq 0,4$

# Example - agreement

- Student teachers rated by Supervisors

Rating by Supervisor 1	Rating by Supervisor 2			$n_{h\bullet}$
	Authoritarian	Democratic	Permissive	
Authoritarian	17	4	8	29
Democratic	5	12	0	17
Permissive	10	3	13	26
$n_{h\bullet}$	32	19	21	72

$$\theta_1 = \sum_{h=1}^H p_{hh} = \frac{17}{72} + \frac{12}{72} + \frac{13}{72} = 0.583$$

$$\theta_2 = \sum_{h=1}^H p_{h\bullet} p_{\bullet h} = \frac{32}{72} \cdot \frac{29}{72} + \frac{19}{72} \cdot \frac{17}{72} + \frac{21}{72} \cdot \frac{26}{72} = 0.347$$

$$\kappa = \frac{\theta_1 - \theta_2}{1 - \theta_2} = \frac{\sum_{h=1}^H p_{hh} - \sum_{h=1}^H p_{h\bullet} p_{\bullet h}}{1 - \sum_{h=1}^H p_{h\bullet} p_{\bullet h}} = \frac{0.583 - 0.347}{1 - 0.347} = 0.362$$

The supervisors agree poorly

# Measure of agreement

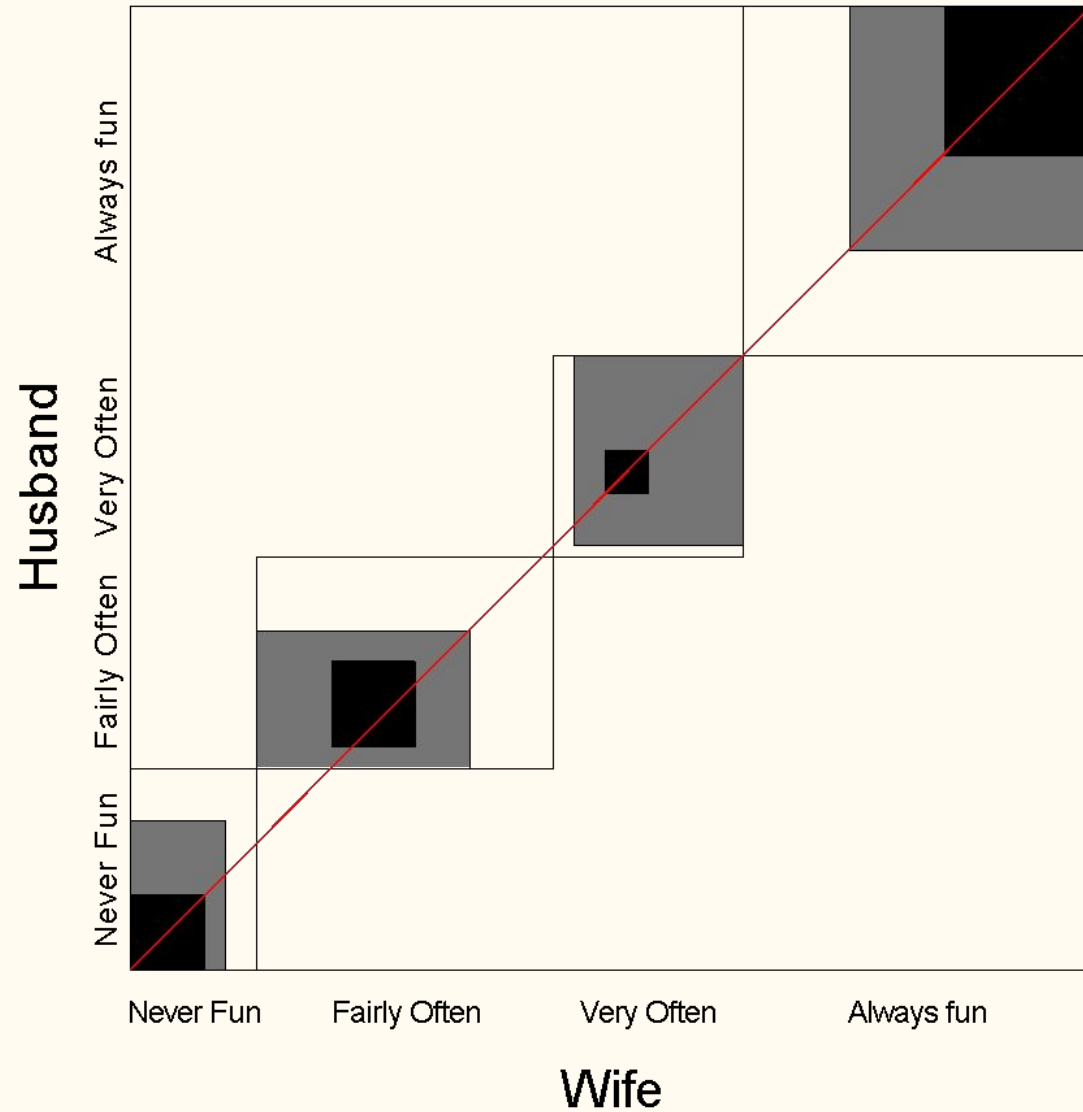
```
> library(vcd)          # opening the vcd library
> SexualFun              # opening dataset
> ?SexualFun             # information on data
> Kappa(SexualFun)       # Kappa coefficient for data
```

Z- test are obtained by dividing Kappa coefficient by its asymptotic standard error (ASE)

```
> confint(Kappa(SexualFun))  # confidence intervals for for Kappa
> agreementplot(SexualFun)   # agreement plot
```

We have thus produced an agreement plot, also called a Bangdiwala's Observer Agreement Chart. Note that our agreement plot is a representation of a  $k \times k$  confusion matrix. The observed and expected diagonal elements are represented by superposed black and white rectangles, respectively. The extent to which the rectangles are above or below the line indicates the extent of any disagreement (above and/or below indicates direction of the disagreement).

# Agreement plot



# Correspondence analysis in R

```
> library(ca)          # package for correspondence analysis
> data(smoke)          # dataset in Greenacre (1984)
> smoke

# Table containing 5 rows (staff group) and 4 columns (smoking
# categories), giving the frequencies of smoking categories in each
# staff group in a fictional organization
```

	none	light	medium	heavy
SM	4	2	3	2
JM	4	3	7	4
SE	25	10	12	4
JE	18	24	33	13
SC	10	6	7	2

```
> summary(smoke)    # summary statistics for smoke data set
```

	none	light	medium	heavy
Min.	: 4.0	Min. : 2	Min. : 3.0	Min. : 2
1st Qu.:	4.0	1st Qu.: 3	1st Qu.: 7.0	1st Qu.: 2
Median	:10.0	Median : 6	Median : 7.0	Median : 4
Mean	:12.2	Mean : 9	Mean :12.4	Mean : 5
3rd Qu.:	18.0	3rd Qu.:10	3rd Qu.:12.0	3rd Qu.: 4
Max.	:25.0	Max. :24	Max. :33.0	Max. :13

```
> summary(ca(smoke)) # summary of correspondence analysis
```

```
Principal inertias (eigenvalues):
```

```
dim      value      %      cum%      scree plot
1       0.074759   87.8   87.8   *****
2       0.010017   11.8   99.5   ***
3       0.000414    0.5  100.0
Total: 0.085190 100.0
```

Eigenvalues and relative percentages of explained inertia are given for all available dimensions. Additionally, cumulated percentages and a scree plot are shown

```
Rows:
```

	name	mass	qlt	inr	k=1	cor	ctr	k=2	cor	ctr
1	SM	57	893	31	-66	92	3	-194	800	214
2	JM	93	991	139	259	526	84	-243	465	551
3	SE	264	1000	450	-381	999	512	-11	1	3
4	JE	456	1000	308	233	942	331	58	58	152
5	SC	130	999	71	-201	865	70	79	133	81

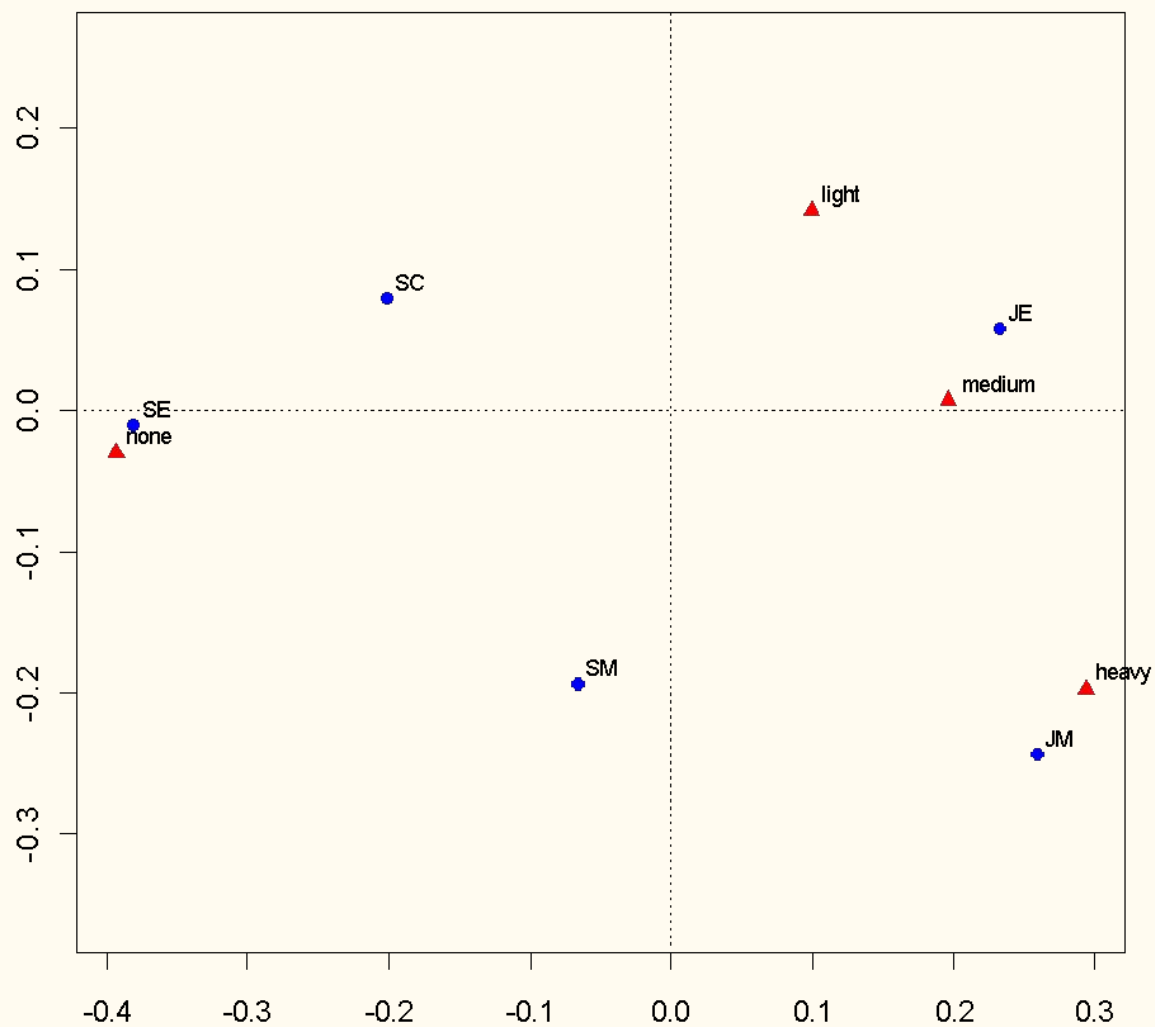
```
Columns:
```

	name	mass	qlt	inr	k=1	cor	ctr	k=2	cor	ctr
1	none	316	1000	577	-393	994	654	-30	6	29
2	lght	233	984	83	99	327	31	141	657	463
3	medm	321	983	148	196	982	166	7	1	2
4	hevz	130	995	192	294	684	150	-198	310	506

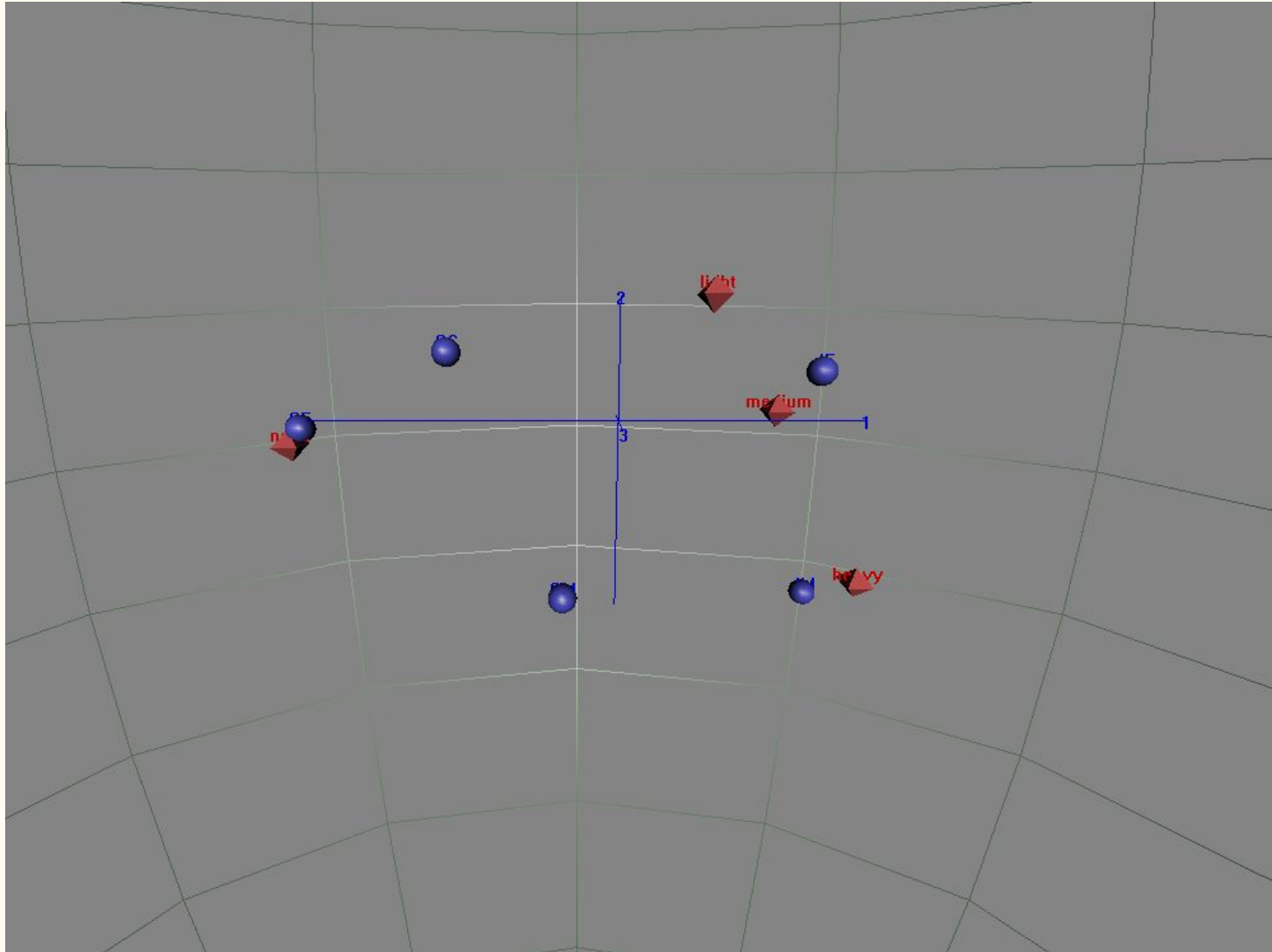
The items given in Rows and Columns include the principal coordinates for the first two dimensions ( $k=1$  and  $k=2$ ). Squared correlations (cor) and contributions (ctr) for the points are displayed next to the coordinates. Notice that the quantities in these tables are multiplied by 1000 (e.g., the coordinates and masses) which for the cor and ctr quantities means they are expressed in permills. The total quality (qlt) is given with respect to the dimensionality of the solution, i.e. in this case it is the sum of the squared correlations over the two included dimensions.



```
> plot(ca(smoke)) # perception map in 2-dimensional space
```



```
> plot3d.ca(ca(smoke, nd=3))
```



# Multiple correspondence analysis

```
> library(mjca) # package for multiple correspondence analysis
> library(MASS)  # package with dataset for MCA
> farms
```

```
Mois Manag Use Manure
1      M1      SF  U2      C4
2      M1      BF  U2      C2
3      M2      SF  U2      C4
4      M2      SF  U2      C4
5      M1      HF  U1      C2
6      M1      HF  U2      C2
7      M1      HF  U3      C3
8      M5      HF  U3      C3
9      M4      HF  U1      C1
10     M2      BF  U1      C1
11     M1      BF  U3      C1
12     M4      SF  U2      C2
13     M5      SF  U2      C3
14     M5      NM  U3      C0
15     M5      NM  U2      C0
16     M5      SF  U3      C3
17     M2      NM  U1      C0
18     M1      NM  U1      C0
19     M5      NM  U1      C0
20     M5      NM  U1      C0
```

```
# The farms data frame has 20 rows and 4
columns. The rows are farms on the Dutch island
of Terschelling and the columns are factors
describing the management of grassland.
```

```
> mjca(farms)           # multiple correspondence analysis
```

```
Eigenvalues:
```

	1	2	3	4	5
Value	0.284327	0.16559	0.126682	0.030975	0.006463
Percentage	37.21%	21.67%	16.58%	4.05%	0.85%

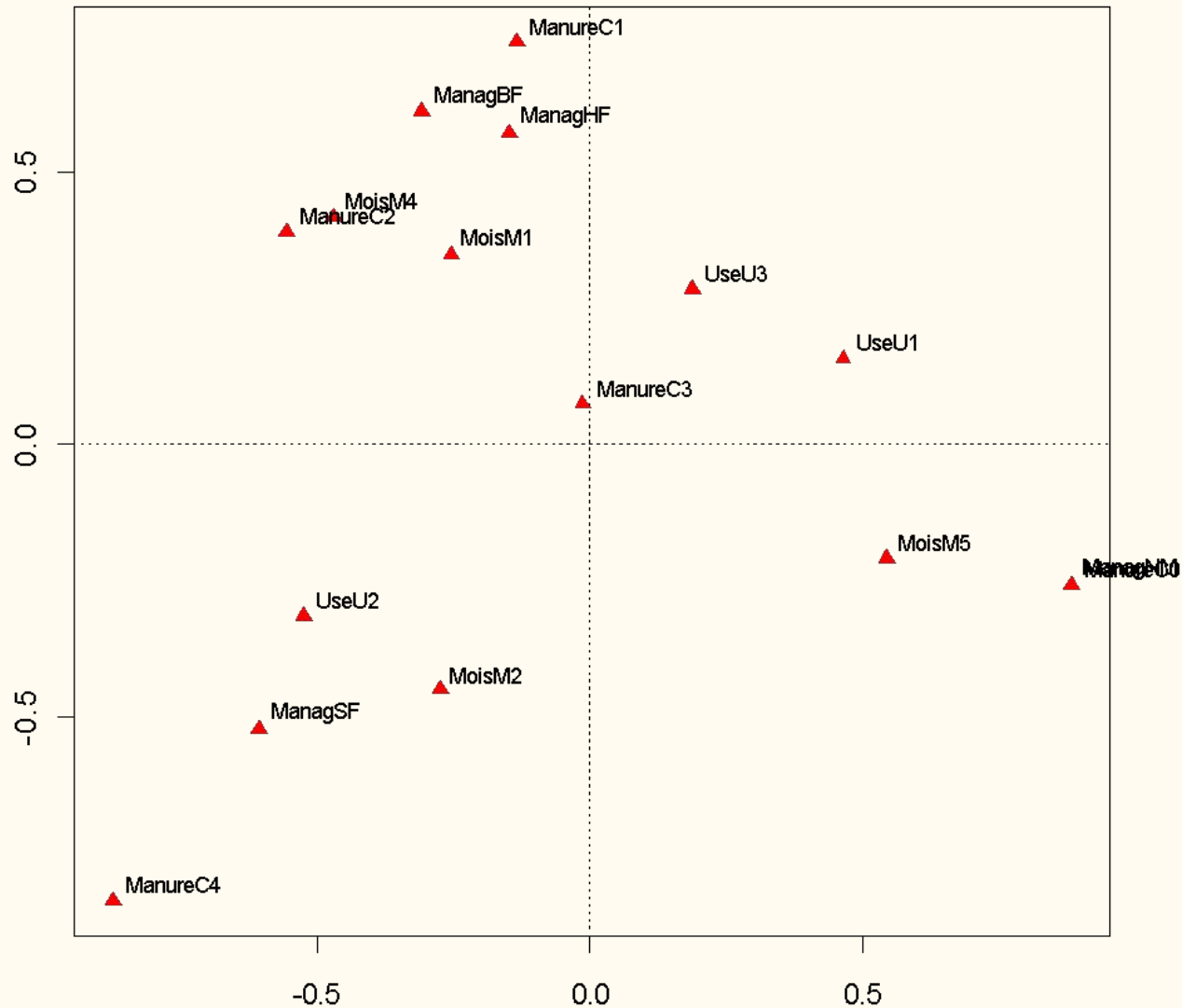
```
Columns:
```

	MoisM1	MoisM2	MoisM4	MoisM5	ManagBF	ManagHF	ManagNM	ManagSF	UseU1	UseU2	UseU3	ManureC0	ManureC1	ManureC2	ManureC3	ManureC4
Mass	0.087500	0.050000	0.025000	0.087500	0.037500	0.062500	0.075000	0.075000	0.087500	0.100000	0.062500	0.075000	0.037500	0.050000	0.050000	0.037500
ChiDist	0.814187	1.233824	1.738483	0.932488	1.504183	1.073157	1.183761	1.092225	0.897437	0.842730	1.102162	1.183761	1.563049	1.269051	1.325264	1.661301
Inertia	0.030896	0.046429	0.034325	0.063039	0.056393	0.044630	0.109061	0.081283	0.053061	0.059590	0.051640	0.109061	0.068430	0.054266	0.067229	0.089550
Dim. 1	-0.477737	-0.516208	-0.881543	1.024582	-0.578179	-0.275410	1.656951	-1.138353	0.871706	-0.984867	0.355398	1.656951	-0.251812	-1.041621	-0.023472	-1.641966
Dim. 2	0.855155	-1.109824	1.024338	-0.513638	1.501013	1.402503	-0.635768	-1.283491	0.385416	-0.774909	0.700272	-0.635768	1.814494	0.956973	0.179838	-2.058706

```
> plot(mjca(farms))# perception map in two-dimensional space
```

```
> plot(mjca(farms), what=c("none", "all"))
```

# Multiple correspondence analysis plot



# Let`s build table on our own

```
> gender<-c("female","male")
> gender<- factor(rep(gender, rep(64, length(gender))),
  levels=gender)
> region <- factor(rep(rep(c("lodzkie","mazowieckie", "malopolskie",
  "slaskie", "lubelskie", "podkarpackie", "podlaskie",
  "swietokszyskie", "lubuskie", "wielkopolskie",
  "zachodniopomorskie", "dolnoslaskie", "opolskie",
  "kujawsko-pomorskie", "pomorskie", "warminsko-mazurskie"),
  c(4,4,4,4,4,4,4,4,4,4,4,4,4,4,4,4)),2),
  levels=c("lodzkie","mazowieckie", "malopolskie", "slaskie",
  "lubelskie", "podkarpackie", "podlaskie", "swietokszyskie",
  "lubuskie", "wielkopolskie", "zachodniopomorskie", "dolnoslaskie",
  "opolskie", "kujawsko-pomorskie","pomorskie",
  "warminsko-mazurskie"))
> education <- factor(rep(c("higher", "higher vocational", "high
  school","lower vocational"), 32), levels=c("higher", "higher
  vocational", "high school","lower vocational"))
```

>

```
freq<-c(1,2,3,1,2,3,4,3,4,5,1,2,3,4,2,3,4,6,7,8,1,2,3,2,1,3,4,5,
4,5,6,5,6,5,6,5,6,5,6,7,6,7,6,7,6,6,5,4,3,2,2,2,1,2,3,4,5,6,5,4,
3,4,5,6,1,2,3,1,2,3,4,3,4,5,1,
2,3,4,2,3,4,6,7,8,1,2,3,2,1,3,4,5,4,5,6,5,6,5,6,5,6,5,6,7,6,7,6,
7,6,6,5,4,3,2,2,2,1,2,3,4,5,6,5,4,3,4,5,6)
```

```
> data <- data.frame(gender, region, education, Freq)
```

```
> data
```

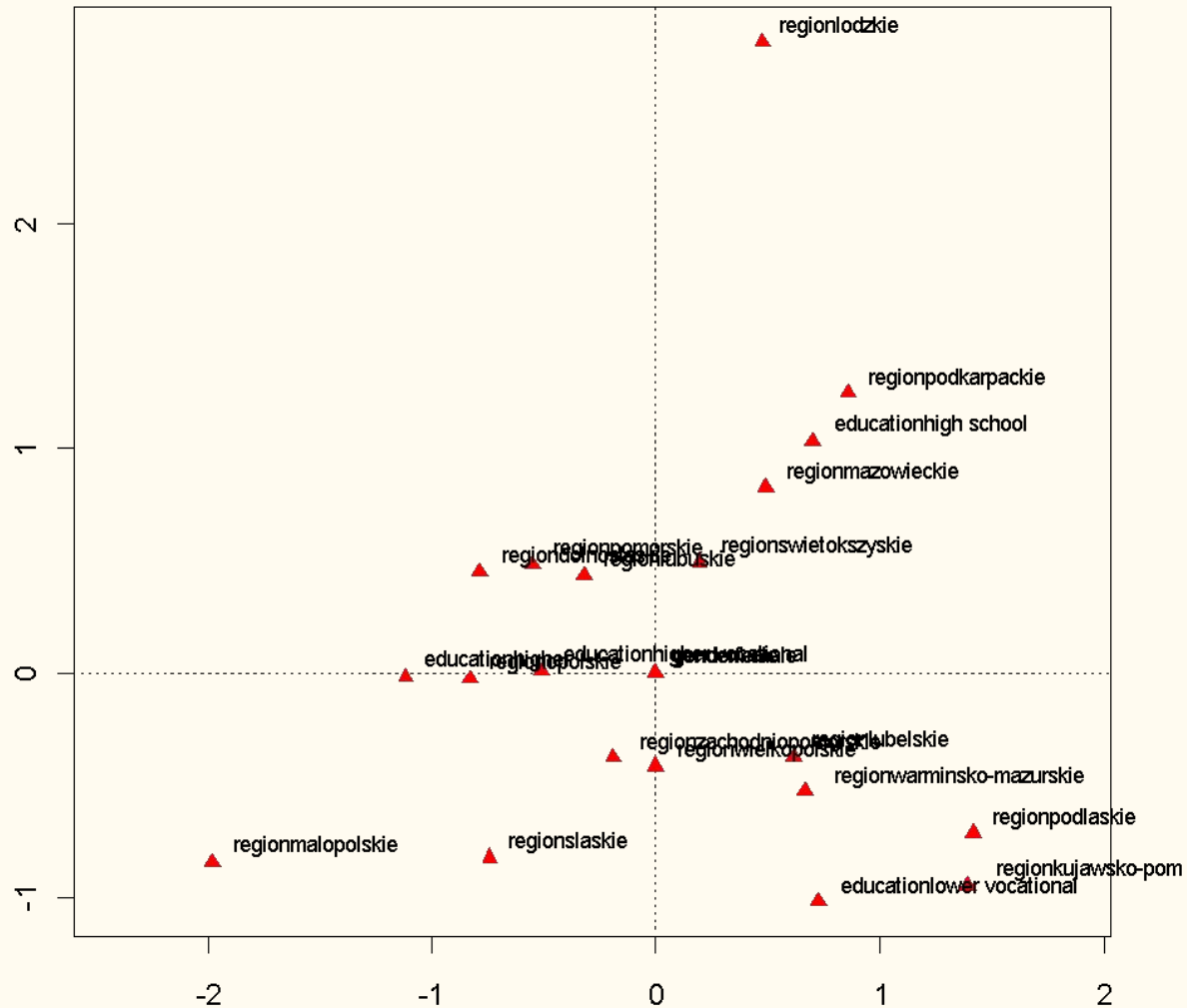
	gender	region	education	Freq
1	female	lodzkie	higher	1
2	female	lodzkie	higher vocational	2
3	female	lodzkie	high school	3
4	female	lodzkie	lower vocational	1
5	female	mazowieckie	higher	2
6	female	mazowieckie	higher vocational	3
7	female	mazowieckie	high school	4
8	female	mazowieckie	lower vocational	3
9	female	malopolskie	higher	4
10	female	malopolskie	higher vocational	5
11	female	malopolskie	high school	1
12	female	malopolskie	lower vocational	2
13	female	slaskie	higher	3
14	female	slaskie	higher vocational	4
15	female	slaskie	high school	2

```
> library(ca)
> library(vcdExtra)
> data<- expand.dft(data)

> mjca(data)
> summary(mjca(data))
> data.mjca<- mjca(data, lambda="indicator")
> plot(data.mjca, what=c("none", "all"))
```



# Perception map



# Correspondence analysis

## Example in FactoMineR

```
> data<- matrix(c(13,142,106,30,408,117,241,573,94), byrow=T,
  ncol=3)
> dimnames(data) <- list(In_an_ideal_family=c("Both parents work",
  "Husband works more", "Only the husband works"),
  Activity_for_a_mother_when_the_children_goes_to_school=c("Stay
  at home", "Part-time-work", "Full-time work"))
> summary(data)
> res.test.chi2<- chisq.test(data[,1:3])
  # Chi-square test using only first their columns
> res.test.chi2          # Chi-square result
> round(res.test.chi2$expected,1)      # Expected cell counts

> round(res.test.chi2$residuals^2, 2)
> round(100*res.test.chi2$residuals^2/res.test.chi2$stat, 2)
```

```
dd<- rbind(data,apply(data[,1:3],2,sum)) # Row totals
dd
round(prop.table(as.matrix(dd), margin=1),3)
# Row profiles for data
dd<- cbind(data,apply(data[,1:3],2,sum))
# Column totals
dd
round(prop.table(as.matrix(dd), margin=2),3)
# Column profiles for data

res.ca<-CA(data[,1:3]) # Correspondence analysis

plot(res.ca, invisilbe="col") # Graph representing the rows
plot(res.ca, invisible="row") # Graph representing the columns

res.ca$row$inertia # inertia for row
res.ca$col$inertia # inertia for column
```

спасибо  
danke 謝謝  
ngiyabonga  
teşekkür ederim  
dank je  
gracias  
tapadh leat  
mochchakkeram  
go raibh maith agat  
arigatō  
takk  
dakujem  
merci  
ευχαριστώ  
감사합니다  
terima kasih  
kop khun krap  
sukriya  
sagolun  
unogob  
dziękuję  
hvala  
mauriuru  
bedankt  
obrigado

*Any Question?*