RSDA Package version 2.0

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Installing the Package

```
#install.packages("RSDA",dependencies=TRUE)
suppressWarnings(suppressMessages(library(RSDA)))
# ?RSDA
```

How to read a Symbolic Table from a CSV file with RSDA?

```
setwd("~/Google Drive/MDCurso/Datos")
ex3 <- read.sym.table('tsym1.csv', header=TRUE, sep=';',dec='.', row.names=1)
ex3
```

```
# A Symbolic Data Table :  7  x  7
        F1      F2                     F3   F4        F5          F6      F7
Case1  2.8   [1,2] M1:10% M2:70% M3:20%    6     {a,d}      [0,90]  [9,24]
Case2  1.4   [3,9] M1:60% M2:30% M3:10%    8   {b,c,d}    [-90,98]  [-9,9]
Case3  3.2  [-1,4] M1:20% M2:20% M3:60%   -7     {a,b}     [65,90] [65,70]
Case4 -2.1   [0,2]  M1:90% M2:0% M3:10%    0 {a,b,c,d}     [45,89] [25,67]
Case5   -3 [-4,-2]  M1:60% M2:0% M3:40% -9.5       {d}     [20,40]  [9,40]
Case6  0.1 [10,21]  M1:0% M2:70% M3:30%   -1   {a,b,c}       [5,8]   [5,8]
Case7    9  [4,21] M1:20% M2:20% M3:60%  0.5     {a,d} [3.14,6.76]   [4,6]
```

How to save a Symbolic Table in a CSV file with RSDA?

```
setwd("~/Google Drive/MDCurso/Datos")
write.sym.table(ex3, file='tsymtemp.csv', sep=';',dec='.', row.names=TRUE,col.names=TRUE)
```

Symbolic Data Frame Example in RSDA

```
data(example3)
example3
```

```
# A Symbolic Data Table :  7  x  7
        F1      F2                     F3   F4         F5          F6
Case1  2.8   [1,2] M1:10% M2:70% M3:20%     6 {e,g,i,k}      [0,90]
Case2  1.4   [3,9] M1:60% M2:30% M3:10%     8 {a,b,c,d}    [-90,98]
Case3  3.2  [-1,4] M1:20% M2:20% M3:60%    -7 {2,b,1,c}     [65,90]
Case4 -2.1   [0,2]  M1:90% M2:0% M3:10%     0 {a,3,4,c}     [45,89]
Case5   -3 [-4,-2]  M1:60% M2:0% M3:40%  -9.5 {e,g,i,k}     [20,40]
Case6  0.1 [10,21]  M1:0% M2:70% M3:30%    -1   {e,1,i}       [5,8]
Case7    9  [4,21] M1:20% M2:20% M3:60%   0.5   {e,a,2} [3.14,6.76]
           F7
Case1  [9,24]
Case2  [-9,9]
Case3 [65,70]
Case4 [25,67]
Case5  [9,40]
Case6   [5,8]
Case7   [4,6]
```

```
example3[2,]
```

```
# A Symbolic Data Table :  1  x  7
       F1    F2                     F3 F4        F5       F6     F7
Case2 1.4 [3,9] M1:60% M2:30% M3:10%   8 {a,b,c,d} [-90,98] [-9,9]
```

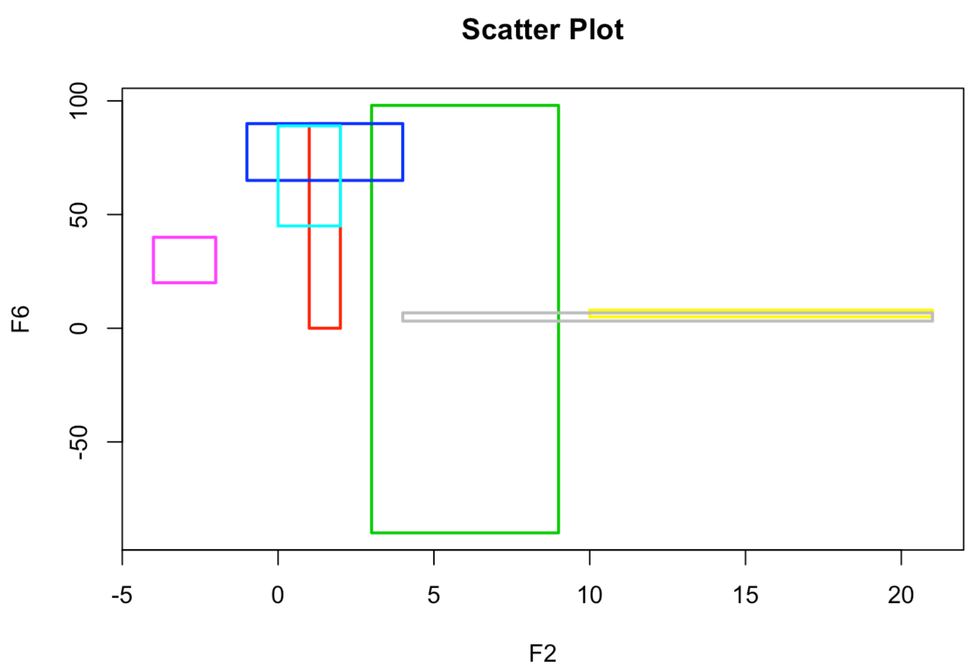
```
example3[,3]
```

```
# A Symbolic Data Table :  7  x  1
                         F3
Case1 M1:10% M2:70% M3:20%
Case2 M1:60% M2:30% M3:10%
Case3 M1:20% M2:20% M3:60%
Case4  M1:90% M2:0% M3:10%
Case5  M1:60% M2:0% M3:40%
Case6  M1:0% M2:70% M3:30%
Case7 M1:20% M2:20% M3:60%
```

```
example3[2:3,5]
```

```
# A Symbolic Data Table :  2  x  1
             F5
Case2 {a,b,c,d}
Case3 {2,b,1,c}
```

```
sym.scatterplot(example3[,2], example3[,6], col='blue', main='Scatter Plot')
```



How to generated a symbolic data table from a classic data table in RSDA?

Example 1

```
data(ex1_db2so)
ex1_db2so
```

```
        state sex county group age
1     Florida   M      2     6   3
2  California   F      4     3   4
3       Texas   M     12     3   4
4     Florida   F      2     3   4
5       Texas   M      4     6   4
6       Texas   F      2     3   3
7     Florida   M      6     3   4
8     Florida   F      2     6   4
9  California   M      2     3   6
10 California   F     21     3   4
11 California   M      2     3   4
12 California   M      2     6   7
13      Texas   F     23     3   4
14    Florida   M      2     3   4
15    Florida   F     12     7   4
16      Texas   M      2     3   8
17 California   F      3     7   9
```

```
18 California   M      2     3  11
19 California   M      1     3  11
```

```
result <- classic.to.sym(ex1_db2so, concept=c("state", "sex"),
                    variables=c("county", "group", "age","age","age"),
                    variables.types=c("$C", "$I", "$H","$M", "$S"))
```

```
Loading required package: tcltk
```

```
Warning: Quoted identifiers should have class SQL, use DBI::SQL() if the
caller performs the quoting.
```

```
result
```

```
# A Symbolic Data Table :  6  x  5
             county group
California.F   9.33 [3,7]
California.M    1.8 [3,6]
Florida.F      5.33 [3,7]
Florida.M      3.33 [3,6]
Texas.F        12.5 [3,3]
Texas.M           6 [3,6]
                                                                                     age
California.F [3,4):0% [4,5):38% [5,6):0% [6,7):12% [7,8):12% [8,9):0% [9,10):12% [10,11]:25%
California.M    [3,4):17% [4,5):83% [5,6):0% [6,7):0% [7,8):0% [8,9):0% [9,10):0% [10,11]:0%
Florida.F      [3,4):20% [4,5):60% [5,6):0% [6,7):0% [7,8):0% [8,9):20% [9,10):0% [10,11]:0%
Florida.M    [3,4):0% [4,5):38% [5,6):0% [6,7):12% [7,8):12% [8,9):0% [9,10):12% [10,11]:25%
Texas.F         [3,4):17% [4,5):83% [5,6):0% [6,7):0% [7,8):0% [8,9):0% [9,10):0% [10,11]:0%
Texas.M        [3,4):20% [4,5):60% [5,6):0% [6,7):0% [7,8):0% [8,9):20% [9,10):0% [10,11]:0%
                                                  age        age
California.F   3:0% 4:67% 6:0% 7:0% 8:0% 9:33% 11:0%       {4,9}
California.M 3:0% 4:20% 6:20% 7:20% 8:0% 9:0% 11:40%  {4,6,7,11}
Florida.F      3:0% 4:100% 6:0% 7:0% 8:0% 9:0% 11:0%         {4}
Florida.M      3:33% 4:67% 6:0% 7:0% 8:0% 9:0% 11:0%       {3,4}
Texas.F        3:50% 4:50% 6:0% 7:0% 8:0% 9:0% 11:0%       {3,4}
Texas.M        3:0% 4:67% 6:0% 7:0% 8:33% 9:0% 11:0%       {4,8}
```

Example 2

```
data(USCrime)
dim(USCrime)
```

```
[1] 1994  103
```

```
head(USCrime)
```

```
  state fold population householdsize racepctblack racePctWhite
1     8    1       0.19          0.33         0.02         0.90
2    53    1       0.00          0.16         0.12         0.74
3    24    1       0.00          0.42         0.49         0.56
4    34    1       0.04          0.77         1.00         0.08
5    42    1       0.01          0.55         0.02         0.95
6     6    1       0.02          0.28         0.06         0.54
  racePctAsian racePctHisp agePct12t21 agePct12t29 agePct16t24 agePct65up
1         0.12        0.17        0.34        0.47        0.29       0.32
2         0.45        0.07        0.26        0.59        0.35       0.27
3         0.17        0.04        0.39        0.47        0.28       0.32
4         0.12        0.10        0.51        0.50        0.34       0.21
5         0.09        0.05        0.38        0.38        0.23       0.36
6         1.00        0.25        0.31        0.48        0.27       0.37
  numbUrban pctUrban medIncome pctWWage pctWFarmSelf pctWInvInc pctWSocSec
1      0.20      1.0      0.37     0.72         0.34       0.60       0.29
2      0.02      1.0      0.31     0.72         0.11       0.45       0.25
3      0.00      0.0      0.30     0.58         0.19       0.39       0.38
4      0.06      1.0      0.58     0.89         0.21       0.43       0.36
5      0.02      0.9      0.50     0.72         0.16       0.68       0.44
6      0.04      1.0      0.52     0.68         0.20       0.61       0.28
  pctWPubAsst pctWRetire medFamInc perCapInc whitePerCap blackPerCap
1        0.15       0.43      0.39      0.40        0.39        0.32
2        0.29       0.39      0.29      0.37        0.38        0.33
3        0.40       0.84      0.28      0.27        0.29        0.27
4        0.20       0.82      0.51      0.36        0.40        0.39
5        0.11       0.71      0.46      0.43        0.41        0.28
6        0.15       0.25      0.62      0.72        0.76        0.77
  indianPerCap AsianPerCap OtherPerCap HispPerCap NumUnderPov
1         0.27        0.27        0.36       0.41        0.08
2         0.16        0.30        0.22       0.35        0.01
3         0.07        0.29        0.28       0.39        0.01
```

4	0.16	0.25	0.36	0.44	0.01
5	0.00	0.74	0.51	0.48	0.00
6	0.28	0.52	0.48	0.60	0.01

	PctPopUnderPov	PctLess9thGrade	PctNotHSGrad	PctBSorMore	PctUnemployed
1	0.19	0.10	0.18	0.48	0.27
2	0.24	0.14	0.24	0.30	0.27
3	0.27	0.27	0.43	0.19	0.36
4	0.10	0.09	0.25	0.31	0.33
5	0.06	0.25	0.30	0.33	0.12
6	0.12	0.13	0.12	0.80	0.10

	PctEmploy	PctEmplManu	PctEmplProfServ	PctOccupManu	PctOccupMgmtProf
1	0.68	0.23	0.41	0.25	0.52
2	0.73	0.57	0.15	0.42	0.36
3	0.58	0.32	0.29	0.49	0.32
4	0.71	0.36	0.45	0.37	0.39
5	0.65	0.67	0.38	0.42	0.46
6	0.65	0.19	0.77	0.06	0.91

	MalePctDivorce	MalePctNevMarr	FemalePctDiv	TotalPctDiv	PersPerFam
1	0.68	0.40	0.75	0.75	0.35
2	1.00	0.63	0.91	1.00	0.29
3	0.63	0.41	0.71	0.70	0.45
4	0.34	0.45	0.49	0.44	0.75
5	0.22	0.27	0.20	0.21	0.51
6	0.49	0.57	0.61	0.58	0.44

	PctFam2Par	PctKids2Par	PctYoungKids2Par	PctTeen2Par	PctWorkMomYoungKids
1	0.55	0.59	0.61	0.56	0.74
2	0.43	0.47	0.60	0.39	0.46
3	0.42	0.44	0.43	0.43	0.71
4	0.65	0.54	0.83	0.65	0.85
5	0.91	0.91	0.89	0.85	0.40
6	0.62	0.69	0.87	0.53	0.30

	PctWorkMom	NumIlleg	PctIlleg	NumImmig	PctImmigRecent	PctImmigRec5
1	0.76	0.04	0.14	0.03	0.24	0.27
2	0.53	0.00	0.24	0.01	0.52	0.62
3	0.67	0.01	0.46	0.00	0.07	0.06
4	0.86	0.03	0.33	0.02	0.11	0.20
5	0.60	0.00	0.06	0.00	0.03	0.07
6	0.43	0.00	0.11	0.04	0.30	0.35

	PctImmigRec8	PctImmigRec10	PctRecentImmig	PctRecImmig5	PctRecImmig8
1	0.37	0.39	0.07	0.07	0.08
2	0.64	0.63	0.25	0.27	0.25
3	0.15	0.19	0.02	0.02	0.04
4	0.30	0.31	0.05	0.08	0.11
5	0.20	0.27	0.01	0.02	0.04
6	0.43	0.47	0.50	0.50	0.56

	PctRecImmig10	PctSpeakEnglOnly	PctNotSpeakEnglWell	PctLargHouseFam
1	0.08	0.89	0.06	0.14
2	0.23	0.84	0.10	0.16
3	0.05	0.88	0.04	0.20
4	0.11	0.81	0.08	0.56
5	0.05	0.88	0.05	0.16
6	0.57	0.45	0.28	0.25

	PctLargHouseOccup	PersPerOccupHous	PersPerOwnOccHous	PersPerRentOccHous
1	0.13	0.33	0.39	0.28
2	0.10	0.17	0.29	0.17
3	0.20	0.46	0.52	0.43
4	0.62	0.85	0.77	1.00
5	0.19	0.59	0.60	0.37
6	0.19	0.29	0.53	0.18

	PctPersOwnOccup	PctPersDenseHous	PctHousLess3BR	MedNumBR	HousVacant
1	0.55	0.09	0.51	0.5	0.21
2	0.26	0.20	0.82	0.0	0.02
3	0.42	0.15	0.51	0.5	0.01
4	0.94	0.12	0.01	0.5	0.01
5	0.89	0.02	0.19	0.5	0.01
6	0.39	0.26	0.73	0.0	0.02

	PctHousOccup	PctHousOwnOcc	PctVacantBoarded	PctVacMore6Mos
1	0.71	0.52	0.05	0.26
2	0.79	0.24	0.02	0.25
3	0.86	0.41	0.29	0.30
4	0.97	0.96	0.60	0.47
5	0.89	0.87	0.04	0.55
6	0.84	0.30	0.16	0.28

	MedYrHousBuilt	PctHousNoPhone	PctWOFullPlumb	OwnOccLowQuart	OwnOccMedVal
1	0.65	0.14	0.06	0.22	0.19
2	0.65	0.16	0.00	0.21	0.20
3	0.52	0.47	0.45	0.18	0.17
4	0.52	0.11	0.11	0.24	0.21
5	0.73	0.05	0.14	0.31	0.31
6	0.25	0.02	0.05	0.94	1.00

	OwnOccHiQuart	RentLowQ	RentMedian	RentHighQ	MedRent	MedRentPctHousInc
1	0.18	0.36	0.35	0.38	0.34	0.38
2	0.21	0.42	0.38	0.40	0.37	0.29
3	0.16	0.27	0.29	0.27	0.31	0.48
4	0.19	0.75	0.70	0.77	0.89	0.63

```
5         0.30     0.40       0.36      0.38    0.38               0.22
6         1.00     0.67       0.63      0.68    0.62               0.47
  MedOwnCostPctInc MedOwnCostPctIncNoMtg NumInShelters NumStreet
1             0.46                  0.25          0.04         0
2             0.32                  0.18          0.00         0
3             0.39                  0.28          0.00         0
4             0.51                  0.47          0.00         0
5             0.51                  0.21          0.00         0
6             0.59                  0.11          0.00         0
  PctForeignBorn PctBornSameState PctSameHouse85 PctSameCity85
1           0.12             0.42           0.50          0.51
2           0.21             0.50           0.34          0.60
3           0.14             0.49           0.54          0.67
4           0.19             0.30           0.73          0.64
5           0.11             0.72           0.64          0.61
6           0.70             0.42           0.49          0.73
  PctSameState85 LandArea PopDens PctUsePubTrans LemasPctOfficDrugUn
1           0.64     0.12    0.26           0.20                0.32
2           0.52     0.02    0.12           0.45                0.00
3           0.56     0.01    0.21           0.02                0.00
4           0.65     0.02    0.39           0.28                0.00
5           0.53     0.04    0.09           0.02                0.00
6           0.64     0.01    0.58           0.10                0.00
  ViolentCrimesPerPop
1                0.20
2                0.67
3                0.43
4                0.12
5                0.03
6                0.14
```

```
result  <- classic.to.sym(USCrime, concept="state",
                          variables=c("NumInShelters", "NumImmig", "ViolentCrimesPerPop","ViolentCrimesPerPop"),
                          variables.types=c("$I", "$I","$I","$H"))
result
```

```
# A Symbolic Data Table :  46  x  4
   NumInShelters    NumImmig ViolentCrimesPerPop
1       [0,0.32]    [0,0.04]            [0.01,1]
2    [0.01,0.18] [0.01,0.09]         [0.05,0.36]
4          [0,1]    [0,0.57]         [0.05,0.57]
5       [0,0.08]    [0,0.02]            [0.02,1]
6          [0,1]       [0,1]            [0.01,1]
8       [0,0.68]    [0,0.23]         [0.07,0.75]
9       [0,0.79]    [0,0.14]            [0,0.94]
10   [0.01,0.01] [0.01,0.01]         [0.37,0.37]
11         [1,1] [0.39,0.39]               [1,1]
12      [0,0.52]       [0,1]            [0.06,1]
13         [0,1]    [0,0.09]               [0,1]
16      [0,0.09]    [0,0.01]         [0.02,0.18]
18      [0,0.33]    [0,0.09]            [0.01,1]
19      [0,0.18]    [0,0.04]            [0,0.65]
20   [0.12,0.12] [0.08,0.08]         [0.36,0.36]
21      [0,0.47]    [0,0.03]         [0.03,0.69]
22      [0,0.46]    [0,0.14]            [0.05,1]
23      [0,0.11]    [0,0.02]         [0.01,0.28]
24      [0,0.67]    [0,0.16]             [0.2,1]
25         [0,1]    [0,0.77]            [0,0.88]
27      [0,0.62]    [0,0.15]         [0.04,0.75]
28      [0,0.05]    [0,0.01]         [0.05,0.96]
29      [0,0.35]    [0,0.08]            [0.02,1]
32      [0,0.34]    [0,0.18]         [0.11,0.42]
33      [0,0.09]    [0,0.04]         [0.01,0.26]
34         [0,1]    [0,0.38]            [0.01,1]
35      [0,0.15]    [0,0.14]         [0.12,0.66]
36         [0,1]       [0,1]            [0,0.87]
37      [0,0.31]     [0,0.1]         [0.06,0.91]
38      [0,0.07]    [0,0.01]         [0.02,0.05]
39      [0,0.58]    [0,0.16]               [0,1]
40      [0,0.59]    [0,0.13]         [0.05,0.57]
41      [0,0.91]    [0,0.22]         [0.05,0.76]
42         [0,1]     [0,0.7]               [0,1]
44      [0,0.14]    [0,0.21]            [0,0.61]
45      [0,0.12]    [0,0.02]            [0.06,1]
46      [0,0.09]    [0,0.01]         [0.02,0.18]
47      [0,0.21]    [0,0.06]         [0.01,0.81]
48       [0,0.7]    [0,0.84]            [0.01,1]
49      [0,0.32]    [0,0.09]         [0.02,0.33]
50      [0,0.05]    [0,0.01]         [0.01,0.07]
51      [0,0.22]    [0,0.14]         [0.04,0.67]
53         [0,1]    [0,0.45]         [0.03,0.76]
54      [0,0.09]    [0,0.01]         [0.01,0.56]
55       [0,0.3]     [0,0.2]             [0,0.4]
56      [0,0.03]    [0,0.01]         [0.06,0.27]
```

```
                                                                                                                                        ViolentCrimesPerPo
1    [0,0.1):21% [0.1,0.2):16% [0.2,0.3):12% [0.3,0.4):9% [0.4,0.5):5% [0.5,0.6):14% [0.6,0.7):5% [0.7,0.8):0% [0.8,0.9):2% [0.9,1]:16
2       [0,0.1):33% [0.1,0.2):0% [0.2,0.3):0% [0.3,0.4):67% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
4    [0,0.1):25% [0.1,0.2):25% [0.2,0.3):10% [0.3,0.4):25% [0.4,0.5):10% [0.5,0.6):5% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
5     [0,0.1):32% [0.1,0.2):12% [0.2,0.3):20% [0.3,0.4):12% [0.4,0.5):4% [0.5,0.6):8% [0.6,0.7):4% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:8
6      [0,0.1):8% [0.1,0.2):24% [0.2,0.3):24% [0.3,0.4):16% [0.4,0.5):9% [0.5,0.6):8% [0.6,0.7):5% [0.7,0.8):1% [0.8,0.9):2% [0.9,1]:4
8      [0,0.1):20% [0.1,0.2):48% [0.2,0.3):12% [0.3,0.4):4% [0.4,0.5):4% [0.5,0.6):0% [0.6,0.7):4% [0.7,0.8):8% [0.8,0.9):0% [0.9,1]:0
9       [0,0.1):74% [0.1,0.2):14% [0.2,0.3):6% [0.3,0.4):1% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):1% [0.8,0.9):1% [0.9,1]:1
10      [0,0.1):0% [0.1,0.2):0% [0.2,0.3):0% [0.3,0.4):100% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
11      [0,0.1):0% [0.1,0.2):0% [0.2,0.3):0% [0.3,0.4):0% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:100
12   [0,0.1):6% [0.1,0.2):18% [0.2,0.3):18% [0.3,0.4):9% [0.4,0.5):8% [0.5,0.6):10% [0.6,0.7):10% [0.7,0.8):3% [0.8,0.9):8% [0.9,1]:11
13  [0,0.1):11% [0.1,0.2):14% [0.2,0.3):11% [0.3,0.4):19% [0.4,0.5):16% [0.5,0.6):14% [0.6,0.7):3% [0.7,0.8):8% [0.8,0.9):3% [0.9,1]:3
16      [0,0.1):29% [0.1,0.2):71% [0.2,0.3):0% [0.3,0.4):0% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
18     [0,0.1):44% [0.1,0.2):21% [0.2,0.3):17% [0.3,0.4):2% [0.4,0.5):4% [0.5,0.6):6% [0.6,0.7):2% [0.7,0.8):0% [0.8,0.9):2% [0.9,1]:2
19     [0,0.1):55% [0.1,0.2):20% [0.2,0.3):5% [0.3,0.4):5% [0.4,0.5):5% [0.5,0.6):0% [0.6,0.7):10% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
20      [0,0.1):0% [0.1,0.2):0% [0.2,0.3):0% [0.3,0.4):100% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
21   [0,0.1):12% [0.1,0.2):27% [0.2,0.3):23% [0.3,0.4):12% [0.4,0.5):15% [0.5,0.6):4% [0.6,0.7):8% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
22    [0,0.1):5% [0.1,0.2):5% [0.2,0.3):5% [0.3,0.4):23% [0.4,0.5):14% [0.5,0.6):18% [0.6,0.7):14% [0.7,0.8):0% [0.8,0.9):9% [0.9,1]:9
23       [0,0.1):88% [0.1,0.2):6% [0.2,0.3):6% [0.3,0.4):0% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
24    [0,0.1):0% [0.1,0.2):0% [0.2,0.3):42% [0.3,0.4):0% [0.4,0.5):17% [0.5,0.6):17% [0.6,0.7):8% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:17
25     [0,0.1):41% [0.1,0.2):30% [0.2,0.3):12% [0.3,0.4):6% [0.4,0.5):3% [0.5,0.6):2% [0.6,0.7):2% [0.7,0.8):2% [0.8,0.9):2% [0.9,1]:0
27    [0,0.1):29% [0.1,0.2):43% [0.2,0.3):14% [0.3,0.4):0% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):14% [0.8,0.9):0% [0.9,1]:0
28    [0,0.1):11% [0.1,0.2):32% [0.2,0.3):26% [0.3,0.4):16% [0.4,0.5):5% [0.5,0.6):5% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:5
29     [0,0.1):36% [0.1,0.2):31% [0.2,0.3):19% [0.3,0.4):7% [0.4,0.5):2% [0.5,0.6):2% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:2
32     [0,0.1):0% [0.1,0.2):40% [0.2,0.3):40% [0.3,0.4):0% [0.4,0.5):20% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
33      [0,0.1):76% [0.1,0.2):19% [0.2,0.3):5% [0.3,0.4):0% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
34      [0,0.1):53% [0.1,0.2):27% [0.2,0.3):9% [0.3,0.4):3% [0.4,0.5):0% [0.5,0.6):1% [0.6,0.7):2% [0.7,0.8):0% [0.8,0.9):1% [0.9,1]:3
35   [0,0.1):0% [0.1,0.2):20% [0.2,0.3):30% [0.3,0.4):20% [0.4,0.5):0% [0.5,0.6):10% [0.6,0.7):20% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
36    [0,0.1):33% [0.1,0.2):20% [0.2,0.3):13% [0.3,0.4):11% [0.4,0.5):9% [0.5,0.6):4% [0.6,0.7):4% [0.7,0.8):0% [0.8,0.9):7% [0.9,1]:0
37    [0,0.1):4% [0.1,0.2):7% [0.2,0.3):24% [0.3,0.4):17% [0.4,0.5):15% [0.5,0.6):15% [0.6,0.7):9% [0.7,0.8):4% [0.8,0.9):2% [0.9,1]:2
38      [0,0.1):100% [0.1,0.2):0% [0.2,0.3):0% [0.3,0.4):0% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
39      [0,0.1):52% [0.1,0.2):29% [0.2,0.3):3% [0.3,0.4):3% [0.4,0.5):4% [0.5,0.6):2% [0.6,0.7):4% [0.7,0.8):1% [0.8,0.9):0% [0.9,1]:3
40     [0,0.1):25% [0.1,0.2):39% [0.2,0.3):14% [0.3,0.4):8% [0.4,0.5):8% [0.5,0.6):6% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
41     [0,0.1):35% [0.1,0.2):42% [0.2,0.3):19% [0.3,0.4):0% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):3% [0.8,0.9):0% [0.9,1]:0
42      [0,0.1):63% [0.1,0.2):21% [0.2,0.3):6% [0.3,0.4):3% [0.4,0.5):2% [0.5,0.6):2% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):1% [0.9,1]:2
44      [0,0.1):58% [0.1,0.2):19% [0.2,0.3):8% [0.3,0.4):8% [0.4,0.5):4% [0.5,0.6):0% [0.6,0.7):4% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
45 [0,0.1):14% [0.1,0.2):11% [0.2,0.3):18% [0.3,0.4):0% [0.4,0.5):0% [0.5,0.6):11% [0.6,0.7):14% [0.7,0.8):14% [0.8,0.9):7% [0.9,1]:11
46      [0,0.1):67% [0.1,0.2):33% [0.2,0.3):0% [0.3,0.4):0% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
47    [0,0.1):14% [0.1,0.2):23% [0.2,0.3):20% [0.3,0.4):17% [0.4,0.5):9% [0.5,0.6):3% [0.6,0.7):6% [0.7,0.8):6% [0.8,0.9):3% [0.9,1]:0
48    [0,0.1):18% [0.1,0.2):28% [0.2,0.3):21% [0.3,0.4):16% [0.4,0.5):4% [0.5,0.6):6% [0.6,0.7):3% [0.7,0.8):3% [0.8,0.9):1% [0.9,1]:1
49     [0,0.1):71% [0.1,0.2):12% [0.2,0.3):12% [0.3,0.4):4% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
50      [0,0.1):100% [0.1,0.2):0% [0.2,0.3):0% [0.3,0.4):0% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
51     [0,0.1):30% [0.1,0.2):30% [0.2,0.3):18% [0.3,0.4):9% [0.4,0.5):3% [0.5,0.6):6% [0.6,0.7):3% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
53    [0,0.1):28% [0.1,0.2):25% [0.2,0.3):20% [0.3,0.4):15% [0.4,0.5):2% [0.5,0.6):5% [0.6,0.7):2% [0.7,0.8):2% [0.8,0.9):0% [0.9,1]:0
54     [0,0.1):36% [0.1,0.2):29% [0.2,0.3):21% [0.3,0.4):0% [0.4,0.5):7% [0.5,0.6):7% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
55      [0,0.1):77% [0.1,0.2):18% [0.2,0.3):2% [0.3,0.4):2% [0.4,0.5):2% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
56     [0,0.1):43% [0.1,0.2):43% [0.2,0.3):14% [0.3,0.4):0% [0.4,0.5):0% [0.5,0.6):0% [0.6,0.7):0% [0.7,0.8):0% [0.8,0.9):0% [0.9,1]:0
```

Converting a SODAS 1.0 *.SDS files to RSDA files

Example

```
setwd("~/Google Drive/MDCurso/Datos")
hani3101 <- SDS.to.RSDA(file.path="hani3101.sds")
```

```
Preprocessing file
Converting data to JSON format
Processing variable 1: R3101
Processing variable 2: RNINO12
Processing variable 3: RNINO3
Processing variable 4: RNINO4
Processing variable 5: RNINO34
Processing variable 6: RSOI
```

```
hani3101
```

```
# A Symbolic Data Table :  32  x  6
                                                     R3101
X1971  X2:21% X4:18% X3:15% X5:14% X6:7% X7:0% X8:0% X1:24% X9:0%
X1972   X2:30% X4:14% X3:19% X5:4% X6:0% X7:0% X8:0% X1:32% X9:0%
X1973  X2:16% X4:12% X3:20% X5:12% X6:7% X7:2% X8:1% X1:30% X9:0%
X1974  X2:13% X4:15% X3:22% X5:11% X6:7% X7:1% X8:0% X1:32% X9:0%
X1975 X2:14% X4:14% X3:18% X5:14% X6:10% X7:2% X8:0% X1:28% X9:0%
X1976    X2:26% X4:6% X3:23% X5:4% X6:1% X7:0% X8:0% X1:41% X9:0%
X1977   X2:28% X4:14% X3:10% X5:3% X6:1% X7:0% X8:0% X1:43% X9:0%
X1978   X2:25% X4:15% X3:19% X5:9% X6:0% X7:0% X8:0% X1:31% X9:0%
X1979  X2:20% X4:15% X3:19% X5:12% X6:6% X7:2% X8:0% X1:26% X9:0%
X1980   X2:21% X4:16% X3:31% X5:7% X6:0% X7:0% X8:0% X1:24% X9:0%
```

```
X1981  X2:16% X4:25% X3:16% X5:16% X6:4% X7:2% X8:0% X1:21% X9:0%
X1982   X2:18% X4:18% X3:19% X5:8% X6:2% X7:0% X8:0% X1:34% X9:0%
X1983   X2:34% X4:9% X3:20% X5:11% X6:2% X7:0% X8:0% X1:25% X9:0%
X1984  X2:19% X4:14% X3:20% X5:11% X6:5% X7:1% X8:0% X1:30% X9:0%
X1985   X2:18% X4:19% X3:21% X5:9% X6:1% X7:1% X8:0% X1:30% X9:0%
X1986   X2:22% X4:10% X3:23% X5:5% X6:2% X7:0% X8:1% X1:37% X9:0%
X1987   X2:18% X4:19% X3:24% X5:6% X6:0% X7:0% X8:0% X1:33% X9:0%
X1988 X2:14% X4:10% X3:13% X5:15% X6:12% X7:0% X8:1% X1:34% X9:0%
X1989   X2:20% X4:20% X3:22% X5:9% X6:0% X7:0% X8:0% X1:28% X9:0%
X1990    X2:25% X4:7% X3:28% X5:7% X6:4% X7:0% X8:0% X1:29% X9:0%
X1991    X2:24% X4:9% X3:24% X5:8% X6:1% X7:0% X8:0% X1:35% X9:0%
X1992   X2:33% X4:10% X3:18% X5:2% X6:0% X7:0% X8:0% X1:36% X9:0%
X1993  X2:16% X4:18% X3:21% X5:10% X6:2% X7:0% X8:0% X1:33% X9:0%
X1994   X2:30% X4:11% X3:18% X5:7% X6:1% X7:0% X8:0% X1:33% X9:0%
X1995  X2:20% X4:10% X3:18% X5:13% X6:9% X7:2% X8:0% X1:27% X9:0%
X1996  X2:17% X4:18% X3:13% X5:17% X6:8% X7:2% X8:1% X1:26% X9:0%
X1997  X2:22% X4:15% X3:15% X5:10% X6:3% X7:0% X8:0% X1:36% X9:0%
X1998  X2:24% X4:16% X3:15% X5:16% X6:7% X7:4% X8:1% X1:18% X9:0%
X1999 X2:17% X4:15% X3:14% X5:10% X6:15% X7:7% X8:0% X1:21% X9:0%
X2000   X2:16% X4:16% X3:20% X5:9% X6:7% X7:3% X8:0% X1:29% X9:0%
X2001   X2:24% X4:12% X3:16% X5:9% X6:6% X7:1% X8:1% X1:31% X9:0%
X2002   X2:22% X4:8% X3:14% X5:13% X6:7% X7:2% X8:0% X1:33% X9:0%
                    RNINO12                RNINO3               RNINO4
X1971  X1:17% X2:83% X3:0%  X2:83% X3:0% X1:17%  X2:100% X3:0% X1:0%
X1972  X1:0% X2:25% X3:75%  X2:25% X3:75% X1:0%   X2:92% X3:8% X1:0%
X1973  X1:67% X2:33% X3:0%  X2:25% X3:0% X1:75%  X2:58% X3:0% X1:42%
X1974  X1:17% X2:83% X3:0%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X1975  X1:42% X2:58% X3:0%  X2:42% X3:0% X1:58%  X2:33% X3:0% X1:67%
X1976  X1:0% X2:67% X3:33%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X1977  X1:0% X2:100% X3:0%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X1978  X1:0% X2:100% X3:0%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X1979  X1:0% X2:100% X3:0%   X2:92% X3:8% X1:0%  X2:100% X3:0% X1:0%
X1980   X1:8% X2:92% X3:0%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X1981   X1:8% X2:92% X3:0%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X1982  X1:0% X2:33% X3:67%  X2:17% X3:83% X1:0%   X2:92% X3:8% X1:0%
X1983  X1:0% X2:58% X3:42%  X2:75% X3:25% X1:0%  X2:100% X3:0% X1:0%
X1984  X1:33% X2:67% X3:0%  X2:75% X3:0% X1:25%  X2:100% X3:0% X1:0%
X1985  X1:42% X2:58% X3:0%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X1986  X1:0% X2:75% X3:25%  X2:67% X3:33% X1:0%   X2:92% X3:8% X1:0%
X1987  X1:0% X2:67% X3:33%  X2:33% X3:67% X1:0%  X2:67% X3:33% X1:0%
X1988  X1:50% X2:50% X3:0%  X2:17% X3:0% X1:83%  X2:50% X3:0% X1:50%
X1989   X1:8% X2:92% X3:0%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X1990  X1:0% X2:100% X3:0%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X1991  X1:0% X2:83% X3:17%  X2:50% X3:50% X1:0%  X2:58% X3:42% X1:0%
X1992  X1:0% X2:83% X3:17%  X2:83% X3:17% X1:0%  X2:100% X3:0% X1:0%
X1993   X1:8% X2:92% X3:0%   X2:92% X3:8% X1:0%  X2:100% X3:0% X1:0%
X1994  X1:17% X2:83% X3:0%  X2:100% X3:0% X1:0%  X2:50% X3:50% X1:0%
X1995  X1:17% X2:83% X3:0%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X1996  X1:58% X2:33% X3:8%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X1997  X1:0% X2:0% X3:100%  X2:0% X3:100% X1:0%  X2:83% X3:17% X1:0%
X1998  X1:8% X2:67% X3:25%  X2:75% X3:8% X1:17%  X2:42% X3:0% X1:58%
X1999  X1:50% X2:50% X3:0%  X2:50% X3:0% X1:50%  X2:58% X3:0% X1:42%
X2000  X1:17% X2:75% X3:8%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X2001 X1:33% X2:50% X3:17%  X2:100% X3:0% X1:0%  X2:100% X3:0% X1:0%
X2002   X1:8% X2:92% X3:0%  X2:83% X3:17% X1:0%  X2:58% X3:42% X1:0%
                   RNINO34                RSOI
X1971 X2:100% X3:0% X1:0%  X2:75% X1:0% X3:25%
X1972 X2:33% X3:67% X1:0%  X2:33% X1:67% X3:0%
X1973 X2:25% X3:0% X1:75%  X2:42% X1:0% X3:58%
X1974 X2:100% X3:0% X1:0%  X2:67% X1:0% X3:33%
X1975 X2:33% X3:0% X1:67%  X2:17% X1:0% X3:83%
X1976 X2:100% X3:0% X1:0%  X2:58% X1:33% X3:8%
X1977 X2:100% X3:0% X1:0%  X2:33% X1:67% X3:0%
X1978 X2:100% X3:0% X1:0%   X2:92% X1:0% X3:8%
X1979 X2:100% X3:0% X1:0%  X2:67% X1:25% X3:8%
X1980 X2:100% X3:0% X1:0%   X2:92% X1:8% X3:0%
X1981 X2:100% X3:0% X1:0%  X2:83% X1:0% X3:17%
X1982  X2:8% X3:92% X1:0%   X2:8% X1:92% X3:0%
X1983  X2:92% X3:8% X1:0%   X2:92% X1:0% X3:8%
X1984 X2:67% X3:0% X1:33%  X2:83% X1:0% X3:17%
X1985 X2:100% X3:0% X1:0%   X2:92% X1:8% X3:0%
X1986 X2:50% X3:50% X1:0%  X2:50% X1:50% X3:0%
X1987 X2:42% X3:58% X1:0%  X2:58% X1:42% X3:0%
X1988 X2:0% X3:0% X1:100%  X2:25% X1:0% X3:75%
X1989 X2:100% X3:0% X1:0%  X2:75% X1:17% X3:8%
X1990 X2:100% X3:0% X1:0%  X2:75% X1:17% X3:8%
X1991 X2:42% X3:58% X1:0%  X2:33% X1:67% X3:0%
X1992  X2:92% X3:8% X1:0%  X2:50% X1:50% X3:0%
X1993  X2:92% X3:8% X1:0%  X2:50% X1:50% X3:0%
X1994 X2:75% X3:25% X1:0%  X2:42% X1:58% X3:0%
X1995 X2:100% X3:0% X1:0%   X2:92% X1:0% X3:8%
X1996 X2:100% X3:0% X1:0%  X2:75% X1:8% X3:17%
X1997 X2:17% X3:83% X1:0%  X2:0% X1:100% X3:0%
X1998 X2:33% X3:0% X1:67%  X2:33% X1:0% X3:67%
X1999 X2:50% X3:0% X1:50%  X2:58% X1:0% X3:42%
```

```
X2000 X2:100% X3:0% X1:0%  X2:58% X1:0% X3:42%
X2001 X2:100% X3:0% X1:0%  X2:83% X1:17% X3:0%
X2002 X2:50% X3:50% X1:0%  X2:58% X1:42% X3:0%
```

```
# We can save the file in CSV to RSDA format as follows:
write.sym.table(hani3101, file='hani3101.csv', sep=';',dec='.', row.names=TRUE,col.names=TRUE)
```

Converting a SODAS 2.0 *.XML files to RSDA files

Example

```
setwd("~/Google Drive/MDCurso/Datos")
abalone<-SODAS.to.RSDA("abalone.xml")
```

```
Processing variable 1: LENGTH
Processing variable 2: DIAMETER
Processing variable 3: HEIGHT
Processing variable 4: WHOLE_WEIGHT
Processing variable 5: SHUCKED_WEIGHT
Processing variable 6: VISCERA_WEIGHT
Processing variable 7: SHELL_WEIGHT
```

```
abalone
```

```
# A Symbolic Data Table :  24  x  7
             LENGTH    DIAMETER      HEIGHT WHOLE_WEIGHT SHUCKED_WEIGHT
F_4-6   [0.28,0.66]  [0.2,0.48] [0.07,0.18]  [0.08,1.37]    [0.03,0.64]
F_7-9    [0.3,0.74] [0.22,0.58] [0.02,1.13]  [0.15,2.25]    [0.06,1.16]
F_10-12 [0.34,0.78] [0.26,0.63] [0.06,0.23]   [0.2,2.66]    [0.07,1.49]
F_13-15 [0.39,0.82]  [0.3,0.65]  [0.1,0.25]  [0.26,2.51]    [0.11,1.23]
F_16-18  [0.4,0.74]  [0.32,0.6]  [0.1,0.24]   [0.35,2.2]    [0.12,0.84]
F_22-24  [0.45,0.8] [0.38,0.63] [0.14,0.22]  [0.64,2.53]    [0.16,0.93]
F_19-21 [0.49,0.72] [0.36,0.58] [0.12,0.21]  [0.68,2.12]    [0.16,0.82]
F_25-29  [0.55,0.7] [0.46,0.58] [0.18,0.22]  [1.21,1.81]    [0.32,0.71]
I_1-3   [0.08,0.24] [0.06,0.18] [0.01,0.06]     [0,0.07]       [0,0.03]
I_4-6   [0.13,0.58]  [0.1,0.45]    [0,0.15]  [0.01,0.89]        [0,0.5]
I_7-9   [0.26,0.67]   [0.2,0.5]    [0,0.18]   [0.08,1.3]      [0.03,0.6]
I_13-15 [0.32,0.66] [0.24,0.52] [0.08,0.19]  [0.16,1.69]    [0.06,0.72]
I_10-12 [0.34,0.72] [0.26,0.55] [0.08,0.22]  [0.17,2.05]    [0.07,0.77]
I_16-18 [0.44,0.65] [0.33,0.52]  [0.12,0.2]  [0.44,1.63]    [0.16,0.63]
I_19-21 [0.45,0.58] [0.36,0.44] [0.12,0.18]  [0.41,1.18]    [0.11,0.39]
M_1-3   [0.16,0.21] [0.11,0.15] [0.04,0.05]  [0.02,0.04]    [0.01,0.02]
M_4-6   [0.16,0.53] [0.12,0.41] [0.02,0.16]  [0.02,0.81]    [0.01,0.32]
M_7-9    [0.2,0.72] [0.16,0.57]  [0.04,0.2]  [0.04,2.33]    [0.02,1.25]
M_10-12 [0.29,0.78] [0.22,0.63] [0.06,0.52]  [0.12,2.78]    [0.04,1.35]
M_13-15 [0.35,0.76]  [0.26,0.6] [0.08,0.24]  [0.21,2.55]     [0.1,1.35]
M_16-18 [0.42,0.78]  [0.32,0.6] [0.12,0.24]  [0.35,2.83]    [0.11,1.15]
M_19-21 [0.49,0.74] [0.38,0.59] [0.13,0.23]  [0.57,2.13]    [0.22,0.87]
M_22-24 [0.52,0.69]  [0.4,0.54] [0.14,0.22]  [0.75,1.84]    [0.25,0.74]
M_25-29  [0.6,0.66]  [0.5,0.54]  [0.2,0.22]  [1.06,2.18]    [0.38,0.75]
        VISCERA_WEIGHT SHELL_WEIGHT
F_4-6      [0.02,0.29]  [0.02,0.34]
F_7-9      [0.03,0.45]  [0.04,0.56]
F_10-12    [0.04,0.53]  [0.07,0.73]
F_13-15    [0.05,0.52]   [0.09,0.8]
F_16-18    [0.09,0.48]     [0.12,1]
F_22-24    [0.11,0.59]  [0.24,0.71]
F_19-21    [0.13,0.45]   [0.2,0.85]
F_25-29     [0.2,0.32]  [0.48,0.52]
I_1-3         [0,0.01]     [0,0.02]
I_4-6         [0,0.19]     [0,0.35]
I_7-9      [0.01,0.32]  [0.02,0.39]
I_13-15     [0.03,0.4]  [0.05,0.42]
I_10-12    [0.02,0.44]  [0.06,0.66]
I_16-18    [0.07,0.34]  [0.13,0.53]
I_19-21    [0.07,0.22]  [0.16,0.32]
M_1-3         [0,0.01]     [0,0.01]
M_4-6         [0,0.15]     [0,0.35]
M_7-9      [0.01,0.54]  [0.02,0.52]
M_10-12    [0.03,0.76]  [0.04,0.68]
M_13-15    [0.05,0.57]  [0.06,0.76]
M_16-18    [0.06,0.48]   [0.13,0.9]
M_19-21    [0.12,0.49]  [0.17,0.58]
M_22-24    [0.13,0.35]  [0.26,0.58]
M_25-29    [0.19,0.39]  [0.38,0.88]
```

Basic statistics in RSDA

The symbolic mean

```
data(example3)
mean(example3[,1])
```

```
[1] 1.628571
```

```
mean(example3[,2])
```

```
[1] 5
```

```
mean(example3[,2], method='interval')
```

```
      F2     F2.1
1.857143 8.142857
```

The symbolic median

```
data(example3)
median(example3[,1])
```

```
[1] 1.4
```

```
median(example3[,2])
```

```
[1] 1.5
```

```
median(example3[,6],method='interval')
```

```
  F6 F6.1
   5   89
```

The symbolic variance and standard deviation

```
data(example3)
var(example3[,1])
```

```
[1] 15.98238
```

```
var(example3[,2])
```

```
[1] 90.66667
```

```
var(example3[,6])
```

```
[1] 1872.358
```

```
var(example3[,6],method='interval')
```

```
      F6     F6.1
2408.966 1670.509
```

```
var(example3[,6],method='billard')
```

```
[1] 1355.143
```

```
data(example3)
sd(example3[,1])
```

```
[1] 3.997797
```

```
sd(example3[,2])
```

```
[1] 6.733003
```

```
sd(example3[,6])
```

```
[1] 30.59704
```

```
sd(example3[,6],method='interval')
```

```
      F6     F6.1
49.08121 40.87186
```

```
sd(example3[,6],method='billard')
```

```
[1] 36.81226
```

Symbolic Correlation

```
data(example3)
cor(example3[,1], example3[,4],method='centers')
```

```
[1] 0.2864553
```

```
cor(example3[,2],example3[,6],method='centers')
```

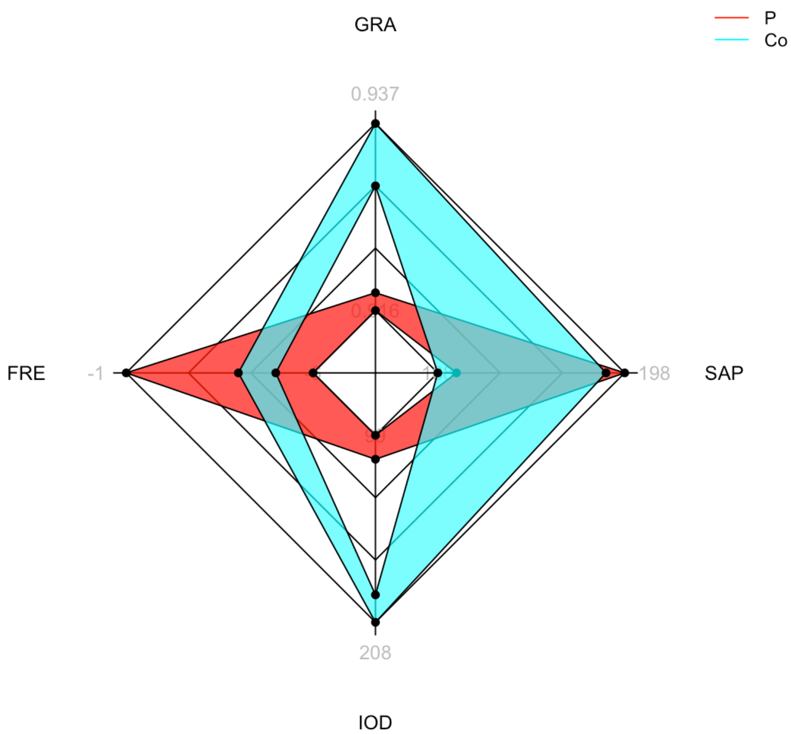
```
[1] -0.6693648
```

```
cor(example3[,2],example3[,6],method='billard')
```

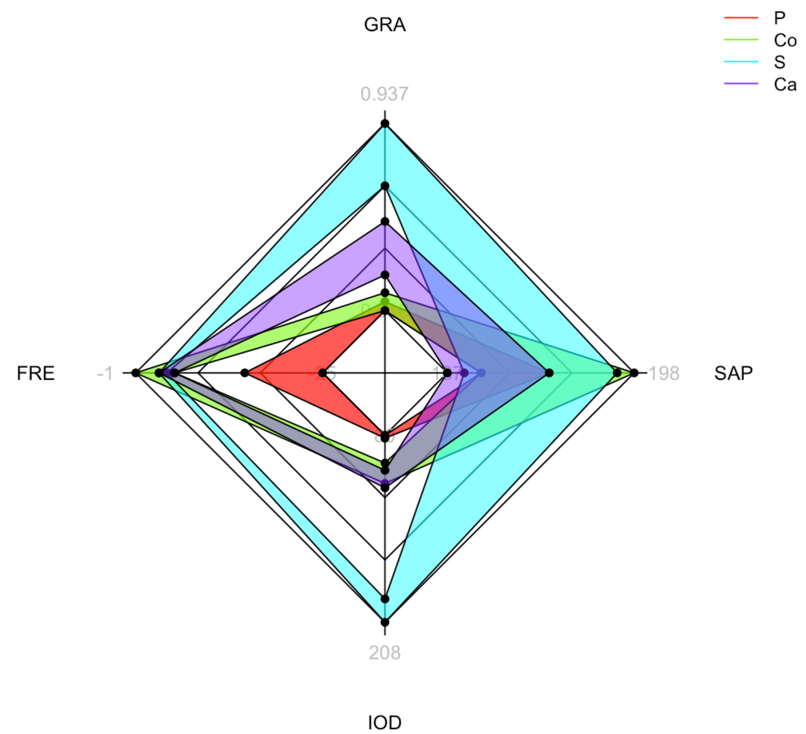
```
[1] -0.6020041
```

Radar plot for interval varibles.

```
data(oils)
sym.radar.plot(oils[2:3,])
```

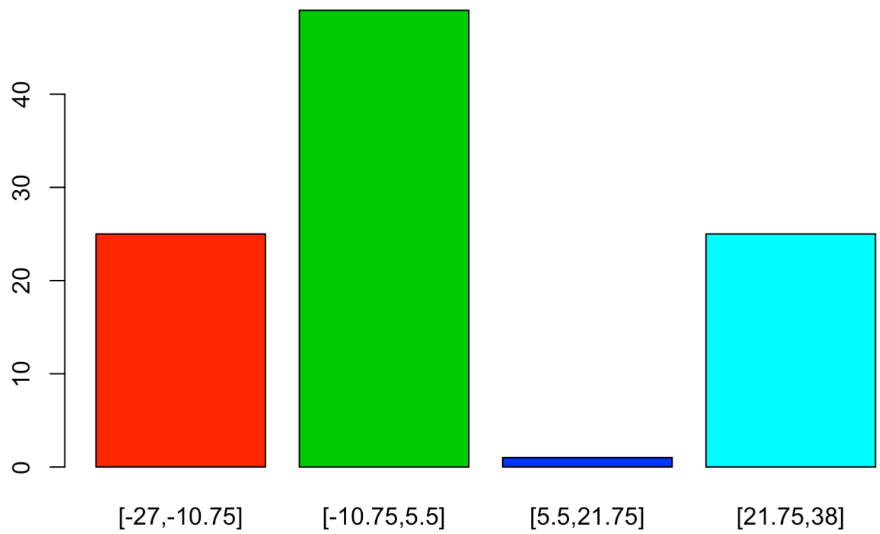



```
data(oils)
sym.radar.plot(oils[2:5,])
```



Histogram for interval variables.

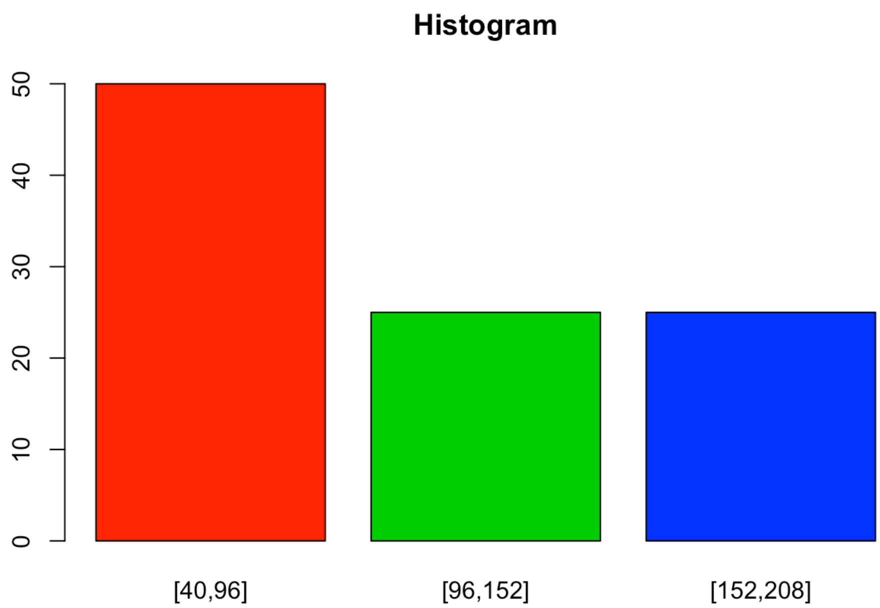
```
data(oils)
res <- interval.histogram.plot(oils[,2],n.bins = 4,col=c(2,3,4,5))
```




```
res
```

```
## $frequency
## [1] 25 49  1 25
##
## $histogram
##      [,1]
## [1,]  0.7
## [2,]  1.9
## [3,]  3.1
## [4,]  4.3
```

```
data("oils")
res <- interval.histogram.plot(oils[,3],n.bins = 3, main = "Histogram",col=c(2,3,4))
```

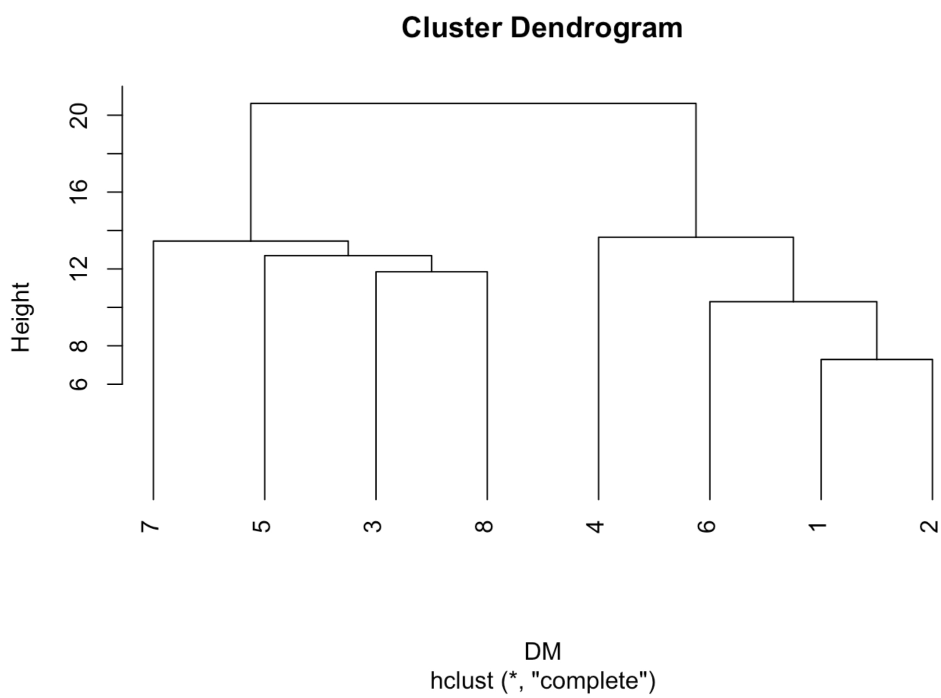


```
res
```

```
## $frequency
## [1] 50 25 25
##
## $histogram
##      [,1]
## [1,]  0.7
## [2,]  1.9
## [3,]  3.1
```

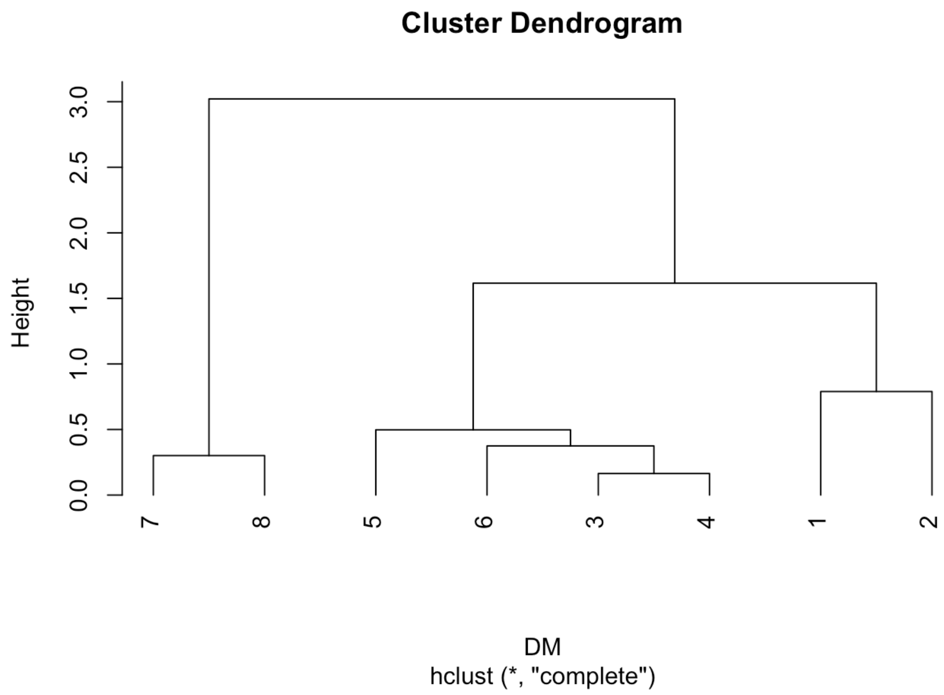
Distances in RSDA

```
data("oils")
DM<-dist.interval(sym.data=oils,variables=c(1:4),method = "Gowda.Diday")
DM<-DM$Gowda.Diday
model<-hclust(DM)
plot(model,hang = -1)
```

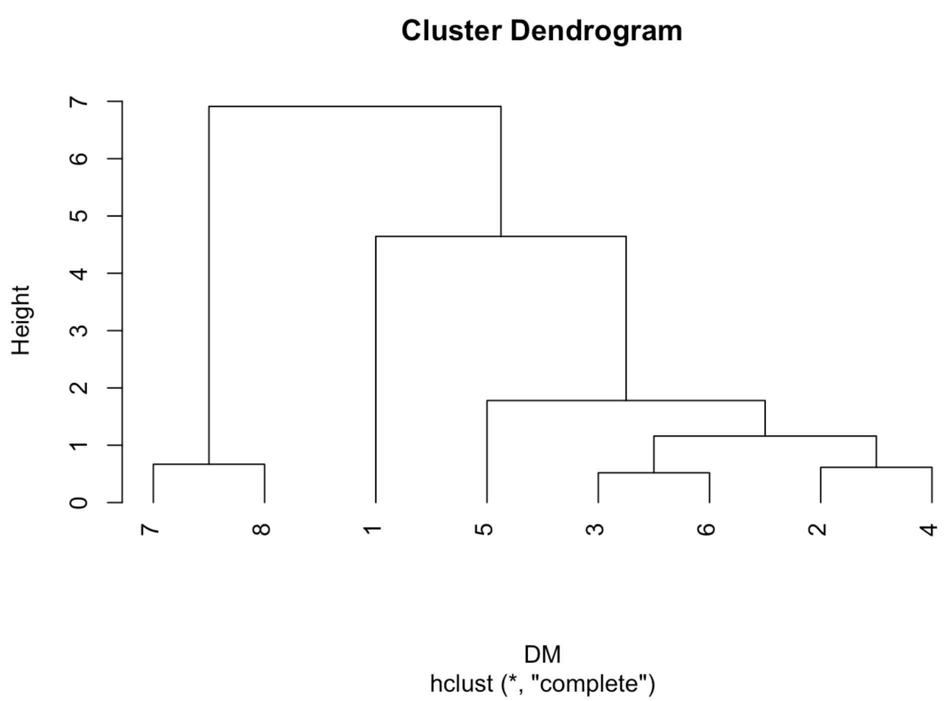



```
DM<-dist.interval(sym.data=oils,variables=c(1:4),method = "Ichino")
DM<-DM$Ichino
model<-hclust(DM)
plot(model,hang = -1)
```

```
DM<-dist.interval(oils,c(1:4),method = "Ichino")
DM<-DM$Ichino
model<-hclust(DM)
plot(model,hang = -1)
```




```
DM<-dist.interval(sym.data=oils,variables=c(1,2,4),gamma=0.5,method="Hausdorff",normalize=FALSE,
SpanNormalize=TRUE,euclidea=TRUE,q=2)
DM<-DM$Hausdorff
model<-hclust(DM)
plot(model,hang = -1)
```



Symbolic Regression

Example 1

```
data(int_prost_train)
data(int_prost_test)
res.cm<-sym.lm(lpsa~.,sym.data=int_prost_train,method='cm')
```

```
pred.cm<-predictsym.lm(res.cm,int_prost_test,method='cm')
RMSE.L(sym.var(int_prost_test,9),pred.cm$Fitted)
```

```
[1] 0.7229999
```

```
RMSE.U(sym.var(int_prost_test,9),pred.cm$Fitted)
```

```
[1] 0.7192467
```

```
R2.L(sym.var(int_prost_test,9),pred.cm$Fitted)
```

```
[1] 0.501419
```

```
R2.U(sym.var(int_prost_test,9),pred.cm$Fitted)
```

```
[1] 0.5058389
```

```
deter.coefficient(sym.var(int_prost_test,9),pred.cm$Fitted)
```

```
[1] 0.4962964
```

Example 2

```
data(int_prost_train)
data(int_prost_test)
res.cm<-sym.lm(lpsa~.,sym.data=int_prost_train,method='crm')
pred.cm<-predictsym.lm(res.cm,int_prost_test,method='crm')
RMSE.L(sym.var(int_prost_test,9),pred.cm$Fitted)
```

```
[1] 0.7212187
```

```
RMSE.U(sym.var(int_prost_test,9),pred.cm$Fitted)
```

```
[1] 0.7209186
```

```
R2.L(sym.var(int_prost_test,9),pred.cm$Fitted)
```

```
[1] 0.5034327
```

```
R2.U(sym.var(int_prost_test,9),pred.cm$Fitted)
```

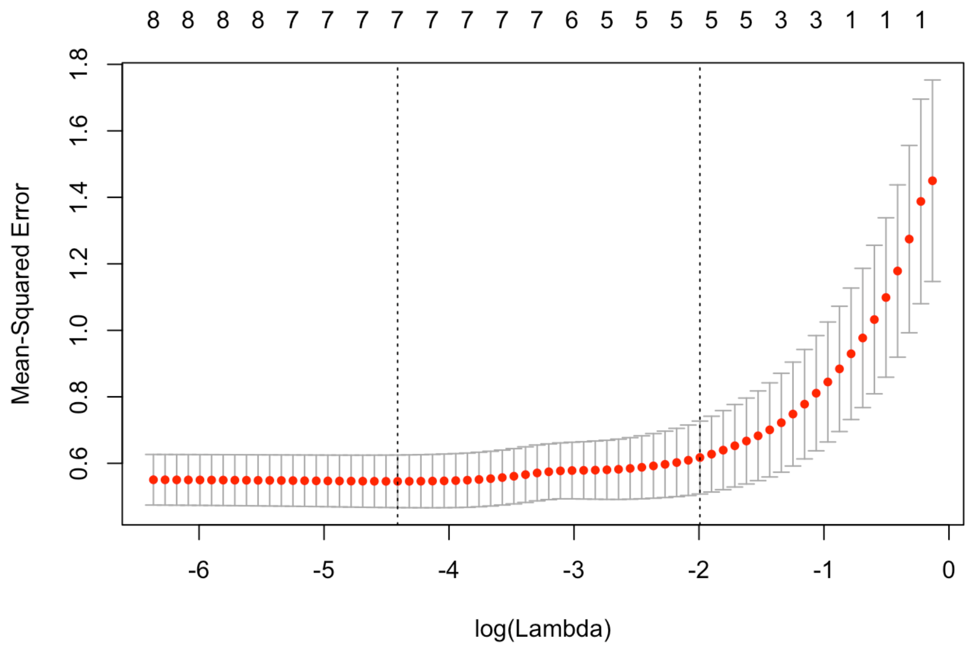
```
[1] 0.5039147
```

```
deter.coefficient(sym.var(int_prost_test,9),pred.cm$Fitted)
```

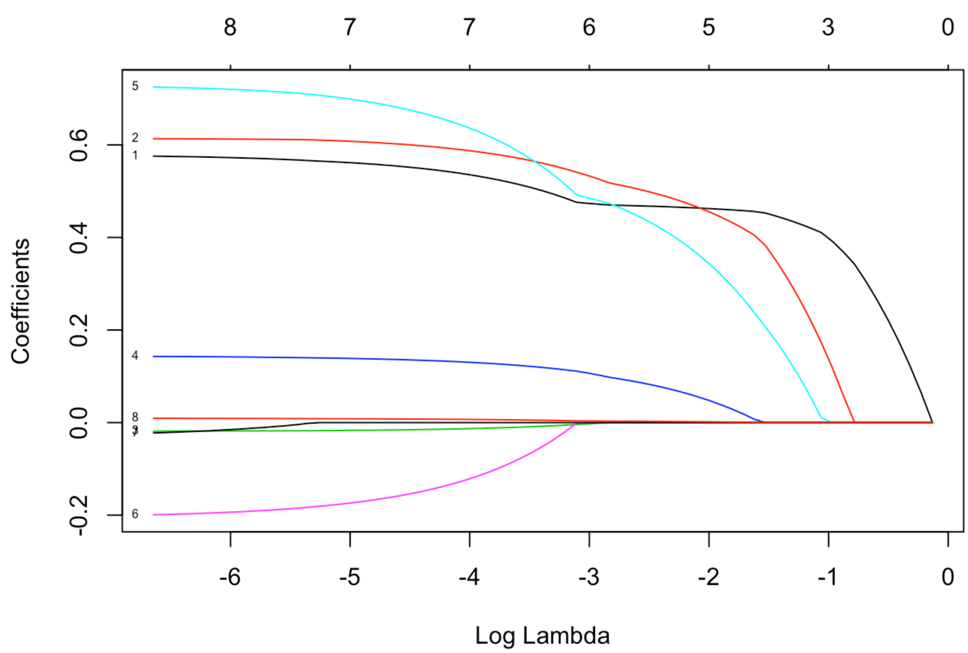
```
[1] 0.4962964
```

Example 3 - LASSO

```
data(int_prost_train)
data(int_prost_test)
res.cm.lasso<-sym.glm(sym.data=int_prost_train,response=9,method='cm',
                      alpha=1,nfolds=10,grouped=TRUE)
pred.cm.lasso<-predictsym.glm(res.cm.lasso,response=9,int_prost_test,method='cm')
plot(res.cm.lasso)
```




```
plot(res.cm.lasso$glmnet.fit, "lambda", label=TRUE)
```




```
RMSE.L(sym.var(int_prost_test,9),pred.cm.lasso)
```

```
[1] 0.7042827
```

```
RMSE.U(sym.var(int_prost_test,9),pred.cm.lasso)
```

```
[1] 0.7009571
```

```
R2.L(sym.var(int_prost_test,9),pred.cm.lasso)
```

```
[1] 0.5270353
```

```
R2.U(sym.var(int_prost_test,9),pred.cm.lasso)
```

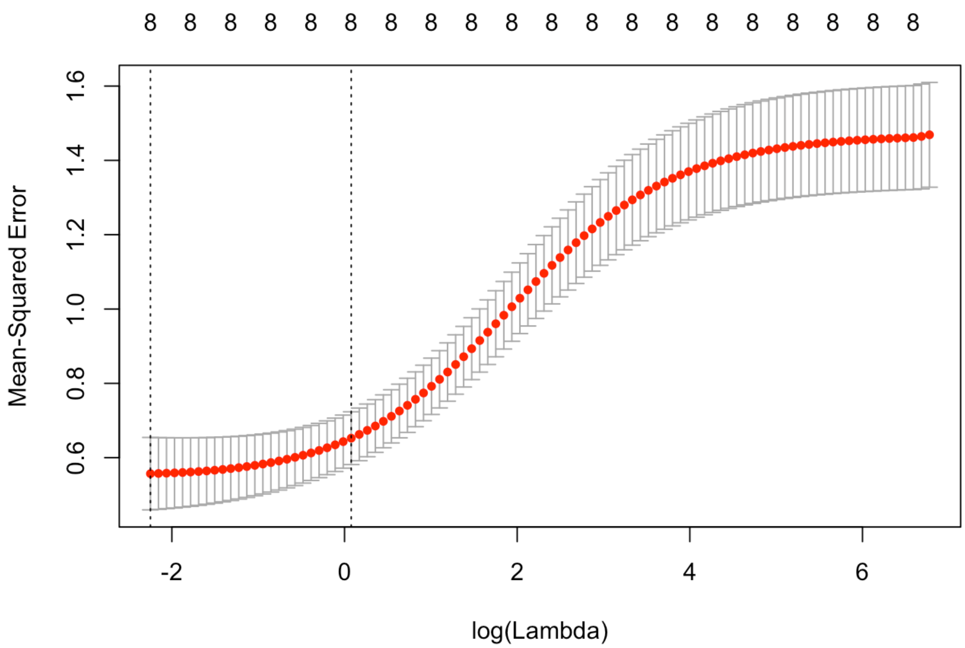
```
[1] 0.5309621
```

```
deter.coefficient(sym.var(int_prost_test,9),pred.cm.lasso)
```

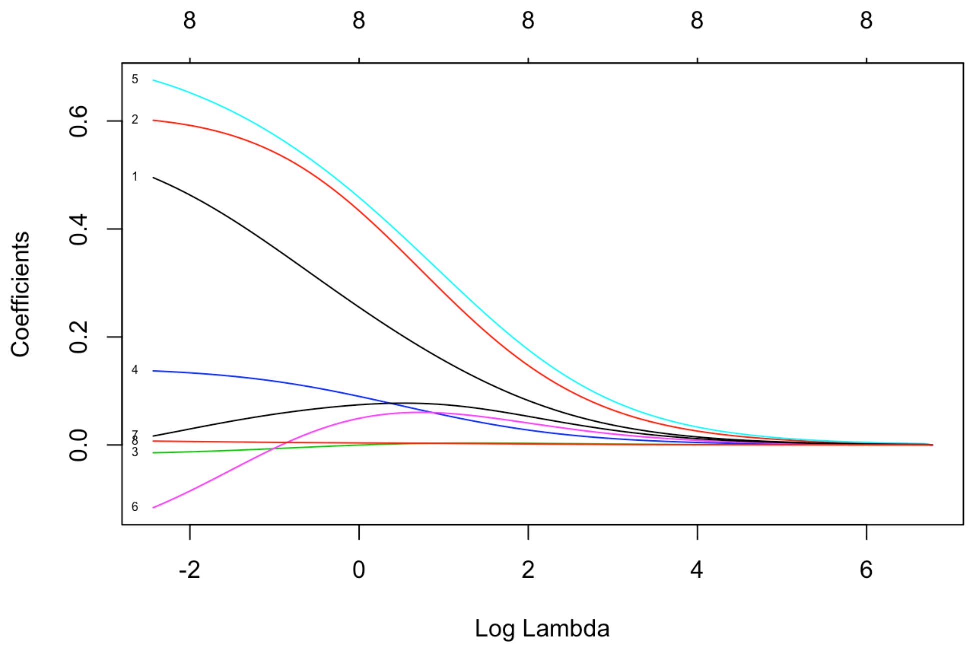
```
[1] 0.4914187
```

Example 4 - RIDGE

```
data(int_prost_train)
data(int_prost_test)
res.cm.ridge<-sym.glm(sym.data=int_prost_train,response=9,method='cm',
                      alpha=0,nfolds=10,grouped=TRUE)
pred.cm.ridge<-predictsym.glm(res.cm.ridge,response=9,int_prost_test,method='cm')
plot(res.cm.ridge)
```




```
plot(res.cm.ridge$glmnet.fit, "lambda", label=TRUE)
```




```
RMSE.L(sym.var(int_prost_test,9),pred.cm.ridge)
```

```
[1] 0.7018444
```

```
RMSE.U(sym.var(int_prost_test,9),pred.cm.ridge)
```

```
[1] 0.6988044
```

```
R2.L(sym.var(int_prost_test,9),pred.cm.ridge)
```

```
[1] 0.5311717
```

```
R2.U(sym.var(int_prost_test,9),pred.cm.ridge)
```

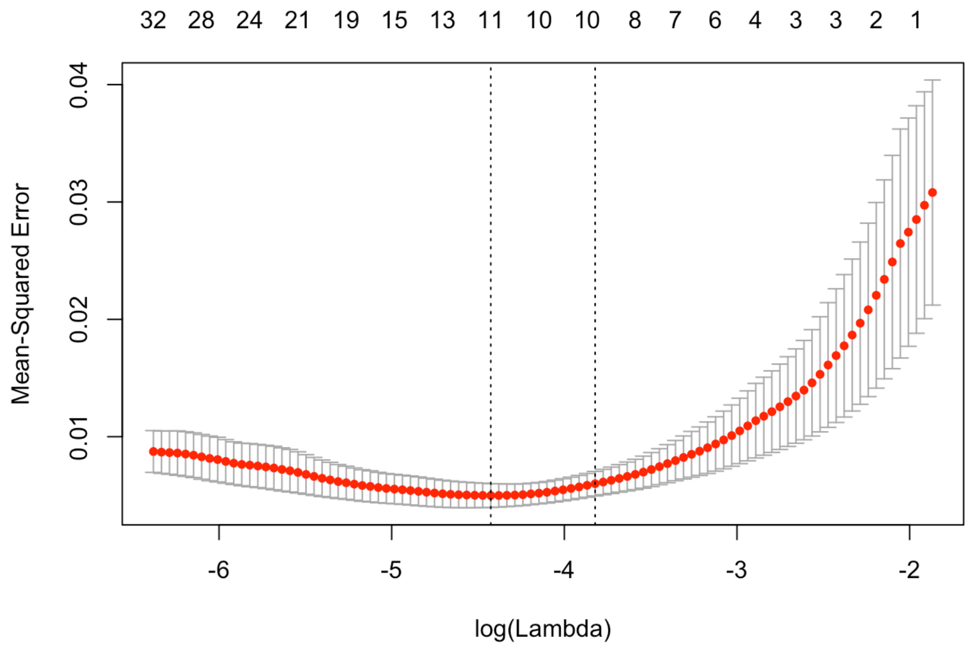
```
[1] 0.5347125
```

```
deter.coefficient(sym.var(int_prost_test,9),pred.cm.ridge)
```

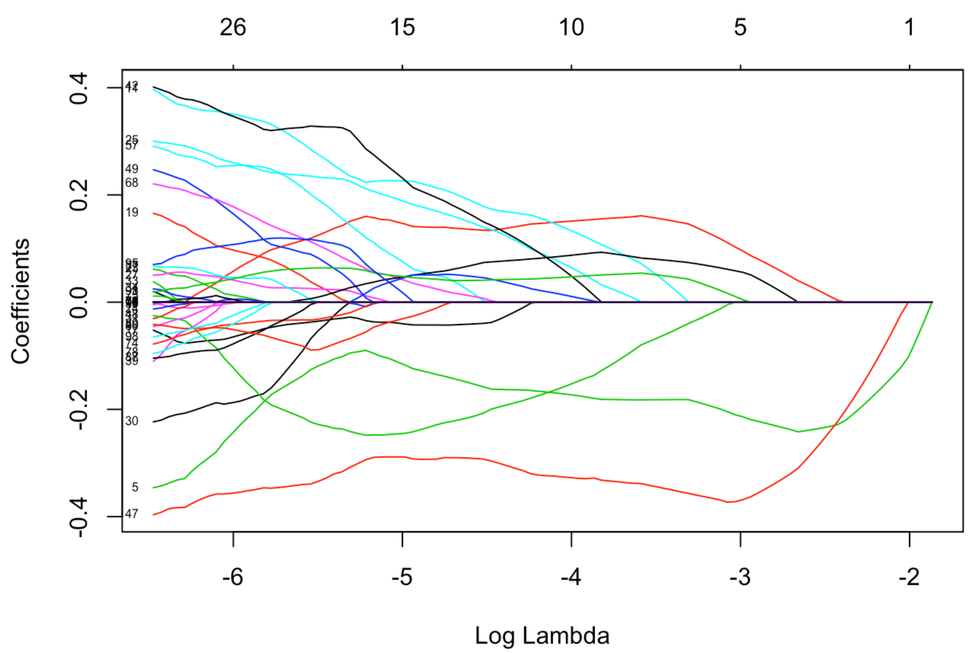
```
[1] 0.4778964
```

Example 5 - LASSO

```
data(uscrime_int)
car.data<-uscrime_int
res.cm.lasso<-sym.glm(sym.data=car.data,response=102,method='cm',alpha=1,
                                      nfolds=10,grouped=TRUE)
plot(res.cm.lasso)
```




```
plot(res.cm.lasso$glmnet.fit, "lambda", label=TRUE)
```




```
pred.cm.lasso<-predictsym.glm(res.cm.lasso,response=102,car.data,method='cm')
RMSE.L(sym.var(car.data,102),pred.cm.lasso)
```

```
[1] 0.35871
```

```
RMSE.U(sym.var(car.data,102),pred.cm.lasso)
```

```
[1] 0.3760611
```

```
R2.L(sym.var(car.data,102),pred.cm.lasso)
```

```
[1] 0.2248573
```

```
R2.U(sym.var(car.data,102),pred.cm.lasso)
```

```
[1] 0.6771767
```

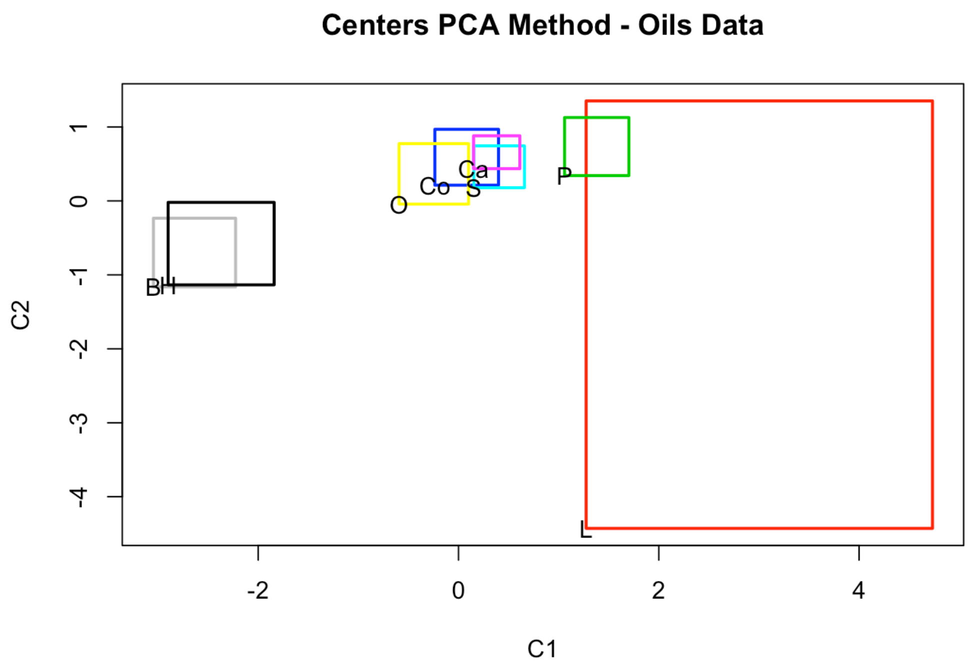
```
deter.coefficient(sym.var(car.data,102),pred.cm.lasso)
```

```
[1] 0.7571673
```

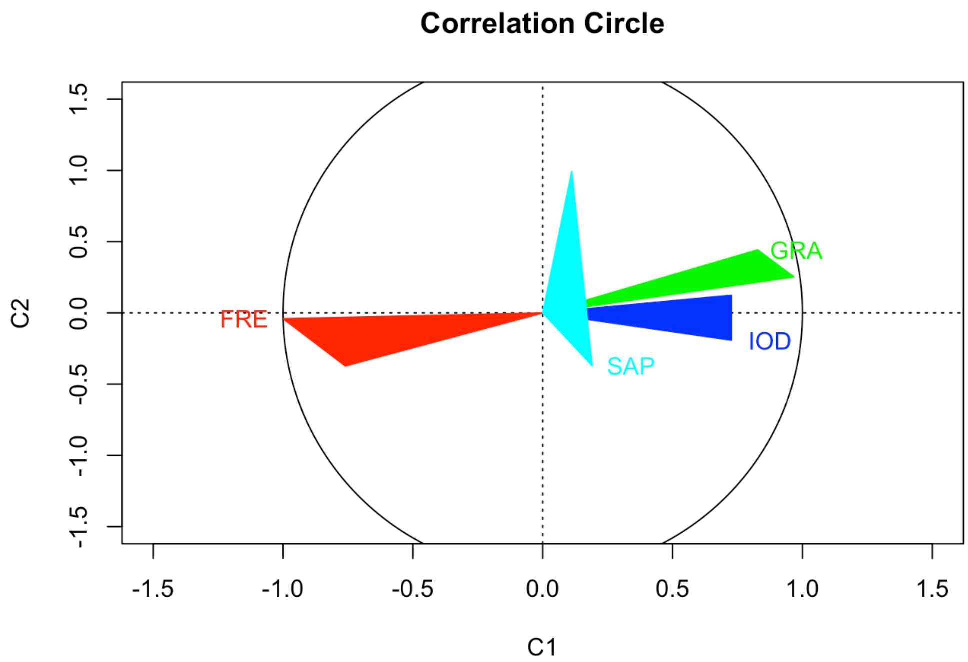
Interval Principal Components Analysis.

Example 1

```
data(oils)
res <- sym.interval.pca(oils,'centers')
sym.scatterplot(res$Sym.Components[,1], res$Sym.Components[,2],
                 labels=TRUE,col='red',main='Centers PCA Method - Oils Data')
```

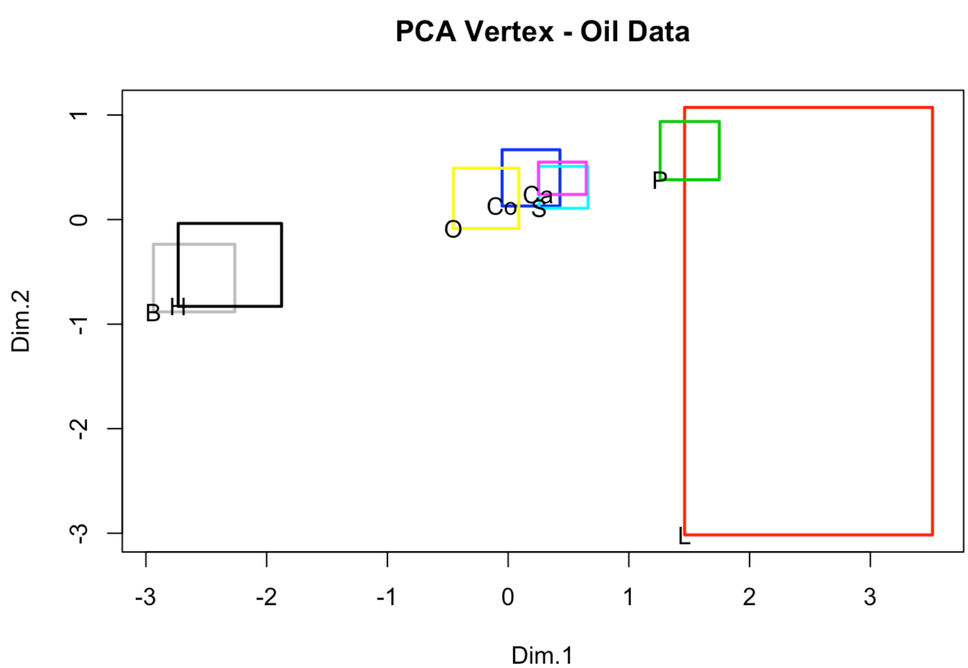



```
 sym.circle.plot(res$Sym.Prin.Correlations)
```



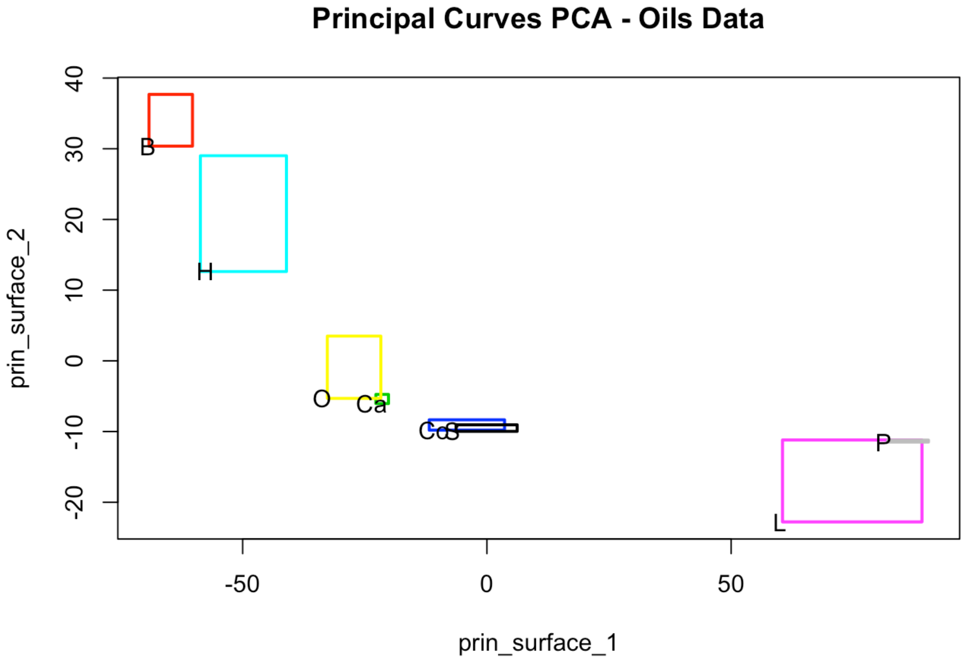
Example 2

```
res <- sym.interval.pca(oils,'tops')
sym.scatterplot(res$Sym.Components[,1],res$Sym.Components[,2],
                labels=TRUE,col='red',main='PCA Vertex - Oil Data')
```



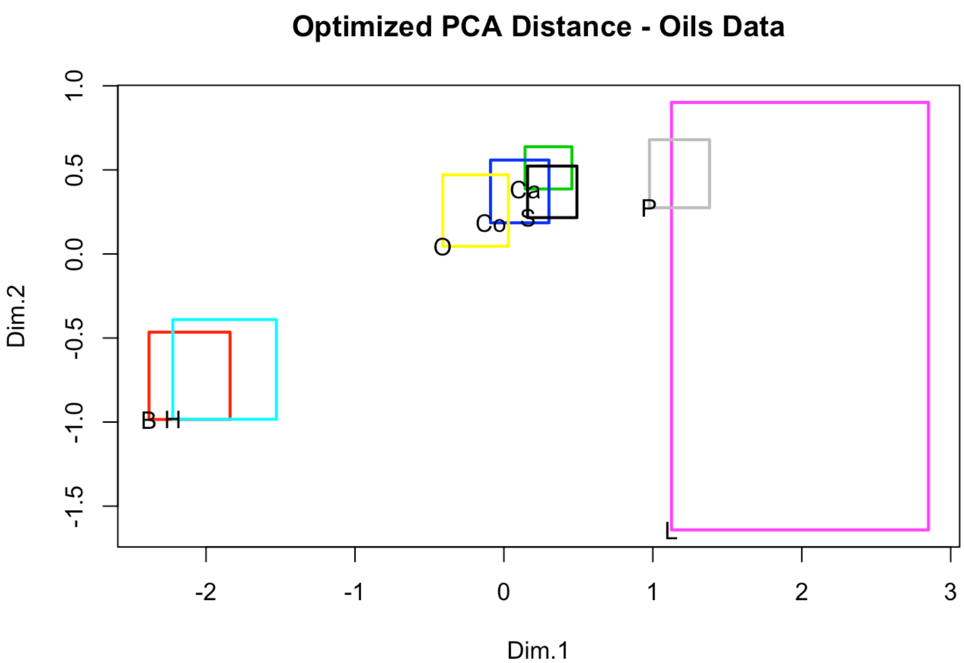
Example 3

```
res <- sym.interval.pca(oils,'principal.curves')
sym.scatterplot(res$sym.prin.curve[,1],res$sym.prin.curve[,2],
                labels=TRUE,col='red',main='Principal Curves PCA - Oils Data')
```

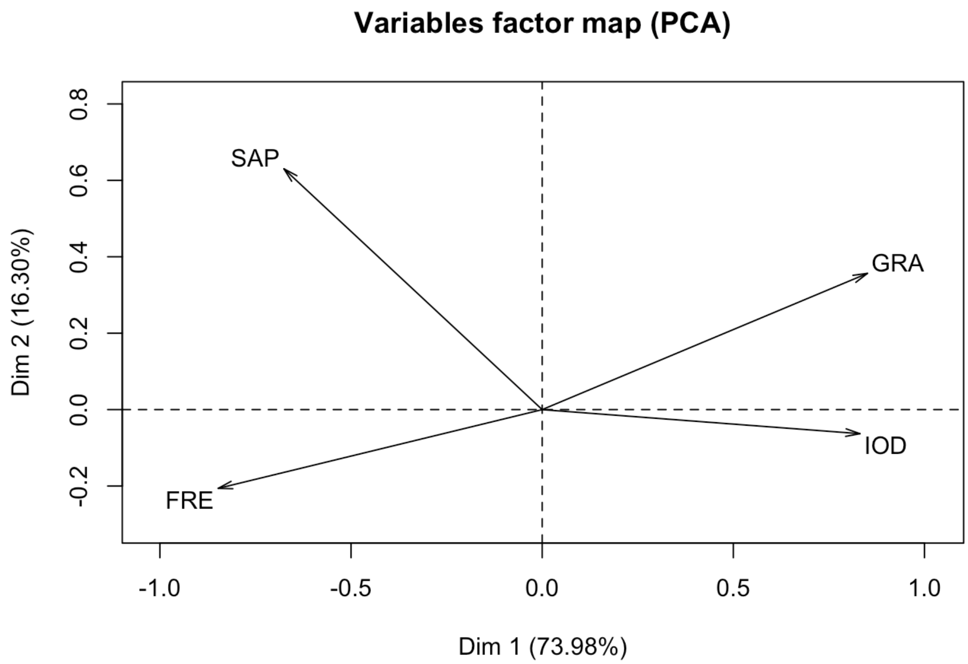


Example 4

```
res <- sym.interval.pca(oils,'optimized.distance')
sym.scatterplot(res$Sym.Components[,1] , res$Sym.Components[,2],
labels = TRUE,col='red',main='Optimized PCA Distance - Oils Data')
```

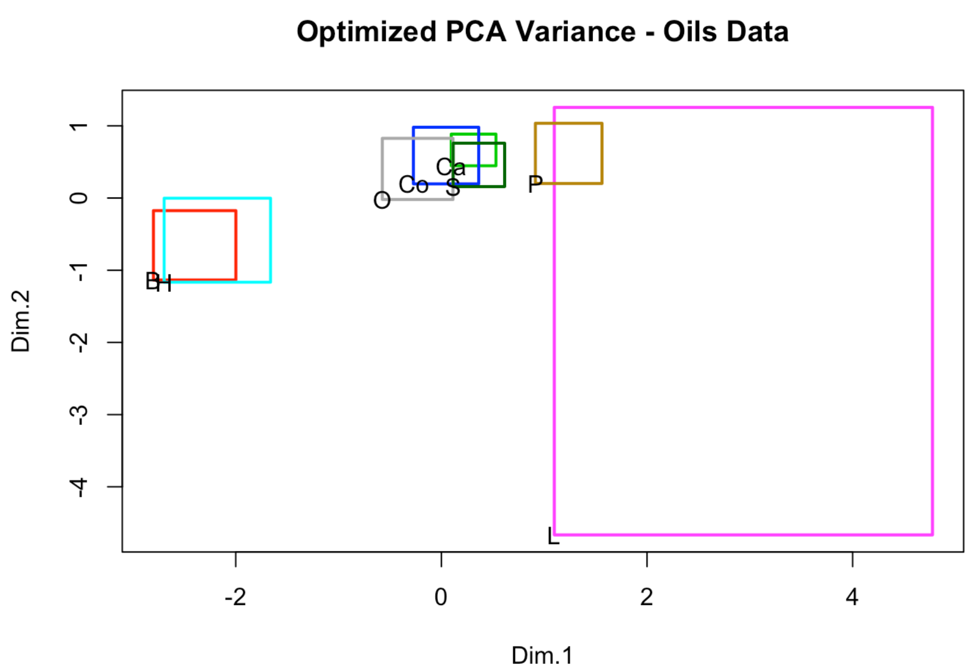



```
plot(res$pca.min,choix = "var")
```

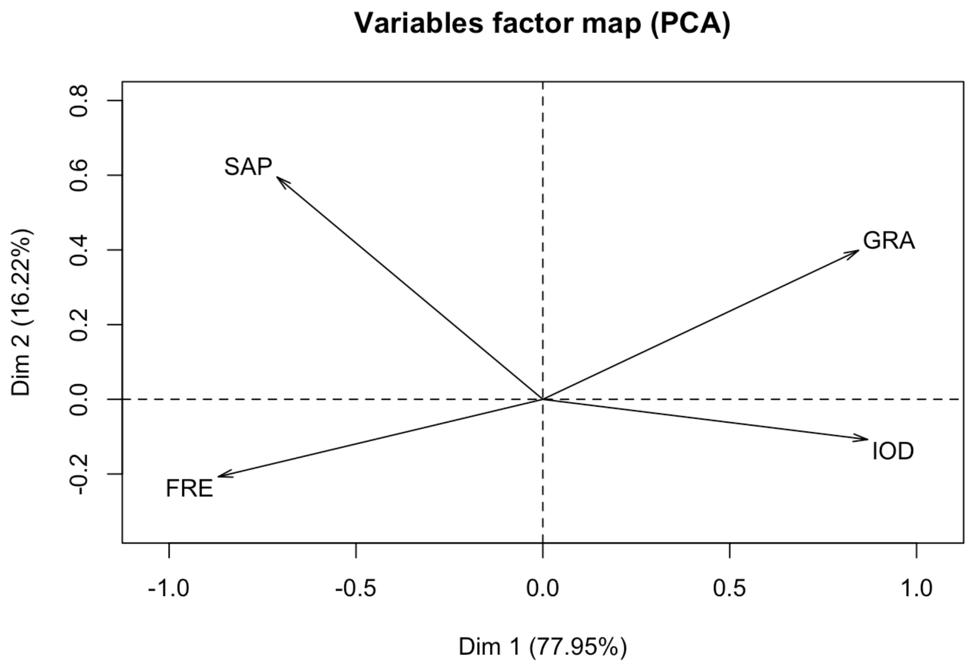


Example 5

```
res <- sym.interval.pca(oils,'optimized.variance')
sym.scatterplot(res$Sym.Components[,1] ,res$Sym.Components[,2],
labels = TRUE,col='red',main='Optimized PCA Variance - Oils Data')
```




```
plot(res$pca.min,choix = "var")
```



Symbolic Correspondance Analysis

Example 1

```
data(ex_cfa1)
res<-sym.cfa(ex_cfa1)
cfa.scatterplot(sym.var(res,1),sym.var(res,2),num.gr1=ex_cfa1$N,
                        labels=TRUE,col='red',main='CFA')
```