DSBA 5122: Visual Analytics

Class 7: Multidimensional & Dimensionality Reduction

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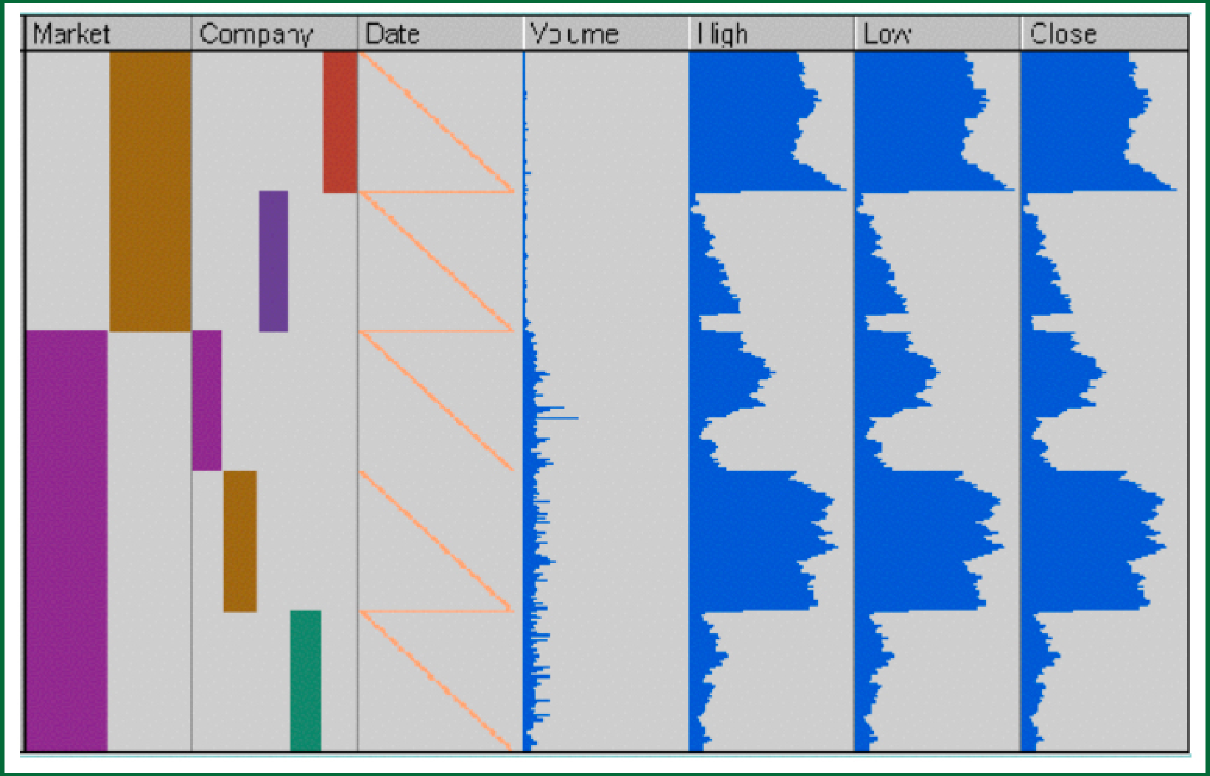
Multidimensional Data: Cairo Ch. 9 and Wilke Ch. 12



Rao and Card, 1994

Summary information

```
glimpse(mpg)
```

```
## Observations: 234
## Variables: 11
## $ manufacturer <chr> "audi", "audi", "audi", "audi", "audi", "audi", "au…
## $ model        <chr> "a4", "a4", "a4", "a4", "a4", "a4", "a4", "a4 quatt…
## $ displ        <dbl> 1.8, 1.8, 2.0, 2.0, 2.8, 2.8, 3.1, 1.8, 1.8, 2.0, 2…
## $ year         <int> 1999, 1999, 2008, 2008, 1999, 1999, 2008, 1999, 199…
## $ cyl          <int> 4, 4, 4, 4, 6, 6, 6, 4, 4, 4, 4, 6, 6, 6, 6, 6, 6, …
## $ trans        <chr> "auto(l5)", "manual(m5)", "manual(m6)", "auto(av)",…
## $ drv          <chr> "f", "f", "f", "f", "f", "f", "f", "4", "4", "4", "…
## $ cty          <int> 18, 21, 20, 21, 16, 18, 18, 18, 16, 20, 19, 15, 17,…
## $ hwy          <int> 29, 29, 31, 30, 26, 26, 27, 26, 25, 28, 27, 25, 25,…
## $ fl           <chr> "p", "p", "p", "p", "p", "p", "p", "p", "p", "p", "…
## $ class        <chr> "compact", "compact", "compact", "compact", "compac…
```

skimr package

```r
library(skimr)
skim(mpg)
```

```
## Skim summary statistics
##  n obs: 234
##  n variables: 11
##
## ── Variable type:character ────────────────────────────────────────────────────────
##     variable missing complete   n min max empty n_unique
##        class       0      234 234   3  10     0        7
##          drv       0      234 234   1   1     0        3
##           fl       0      234 234   1   1     0        5
##  manufacturer      0      234 234   4  10     0       15
##        model       0      234 234   2  22     0       38
##        trans       0      234 234   8  10     0       10
##
## ── Variable type:integer ──────────────────────────────────────────────────────────
##  variable missing complete   n    mean   sd   p0  p25    p50  p75 p100
##      cty       0      234 234   16.86 4.26    9   14   17     19   35
##      cyl       0      234 234    5.89 1.61    4    4    6      8    8
##      hwy       0      234 234   23.44 5.95   12   18   24     27   44
##     year       0      234 234 2003.5   4.51 1999 1999 2003.5 2008 2008
##     hist
##  ▂▃▃▃▁▁▁▁
##  ▃▁▁▃▁▁▁▃
##  ▁▂▁▂▁▁▁▁
##  ▃▁▁▁▁▁▁▃
##
## ── Variable type:numeric ──────────────────────────────────────────────────────────
##  variable missing complete   n mean   sd  p0 p25 p50 p75 p100     hist
##     displ       0      234 234 3.47 1.29 1.6 2.4 3.3 4.6    7 ▇▇▅▅▅▂▁▁
```

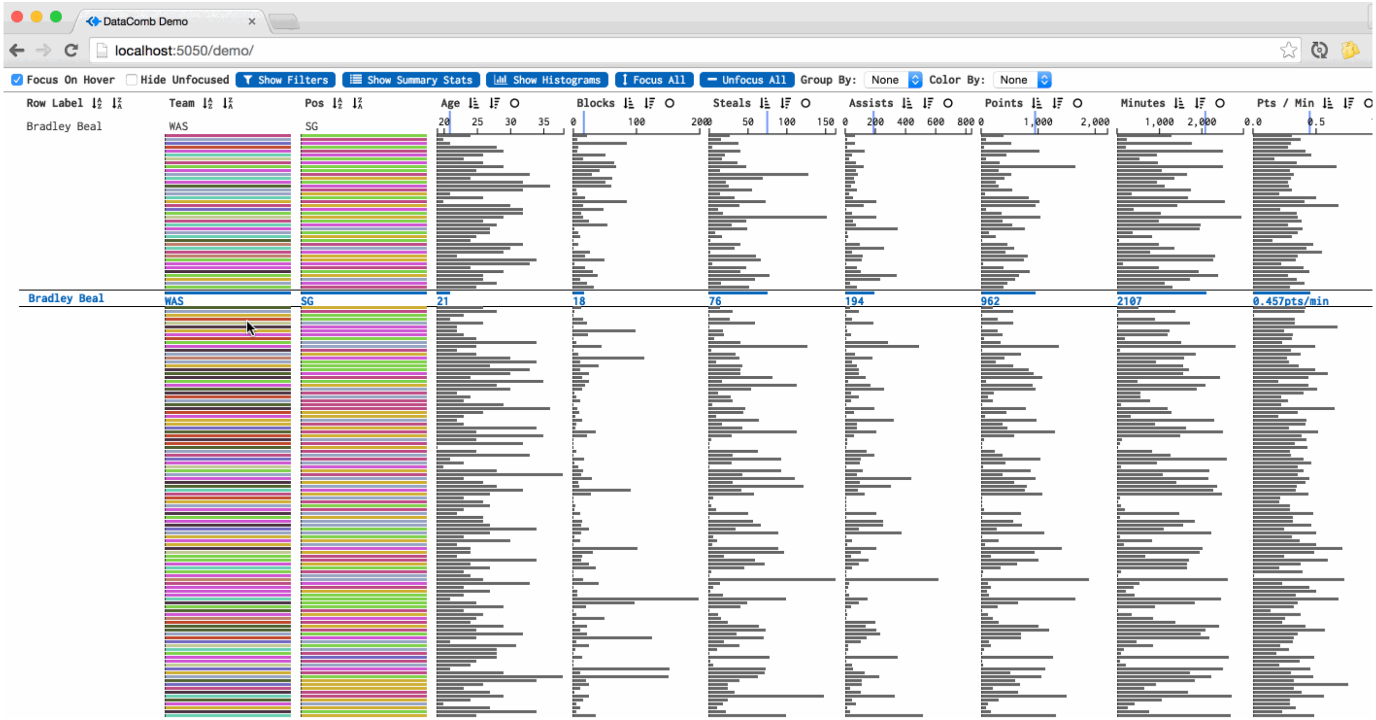
Table based

```r
library(formattable)

head(df)
```

```
##   id   name age grade test1_score test2_score final_score registered
## 1  1    Bob  28     C         8.9         9.1         9.0       TRUE
## 2  2 Ashley  27     A         9.5         9.1         9.3      FALSE
## 3  3  James  30     A         9.6         9.2         9.4       TRUE
## 4  4  David  28     C         8.9         9.1         9.0      FALSE
## 5  5  Jenny  29     B         9.1         8.9         9.0       TRUE
## 6  6   Hans  29     B         9.3         8.5         8.9       TRUE
```

```r
f <- formattable(df, list(
  age = color_tile("white", "orange"),
  grade = formatter("span", style = x ~ ifelse(x == "A",
    style(color = "green", font.weight = "bold"), NA)),
  area(col = c(test1_score, test2_score)) ~ normalize_bar("pink", 0.2),
  final_score = formatter("span",
    style = x ~ style(color = ifelse(rank(-x) <= 3, "green", "gray")),
    x ~ sprintf("%.2f (rank: %02d)", x, rank(-x))),
  registered = formatter("span",
    style = x ~ style(color = ifelse(x, "green", "red")),
    x ~ icontext(ifelse(x, "ok", "remove"), ifelse(x, "Yes", "No")))
))

# to make work in Rmarkdown/xaringan
f %>%
  as.htmlwidget() %>%
  frameWidget()
```

datacomb package



https://github.com/cmpolis/datacomb

Heatmaps

```
library(d3heatmap)

d3heatmap(mtcars, scale = "column", colors = "YlOrRd")
```

Scatterplot matrix

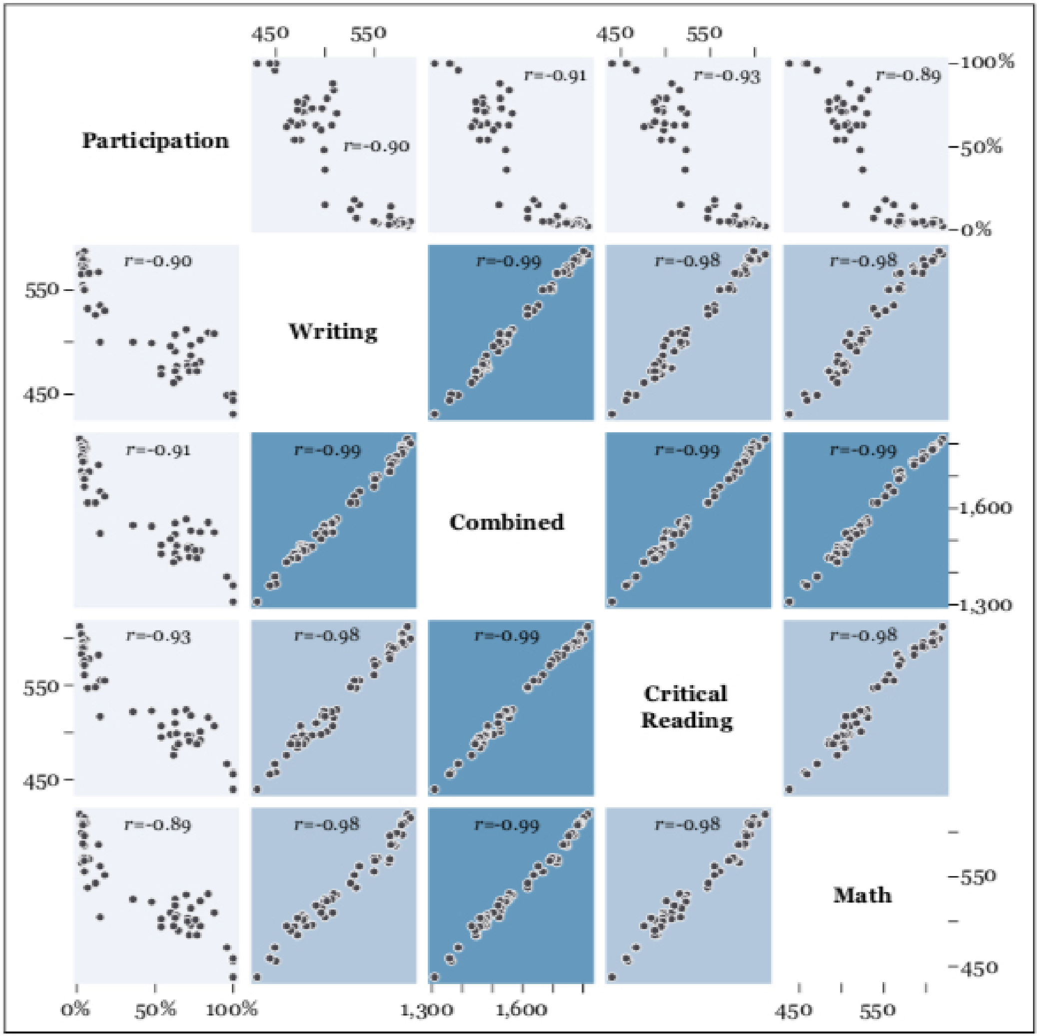


Figure 9.11
A scatter plot matrix. Even if I have calculated *r* for each of the panels, always be aware that outliers can greatly influence this statistic.

Scatterplot matrix

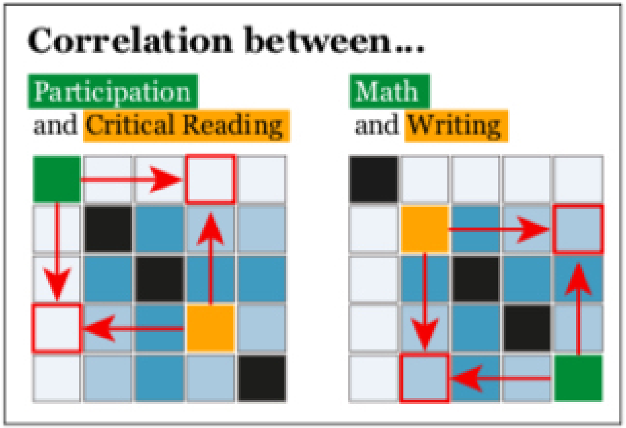


Figure 9.12 How to read a scatter plot matrix.

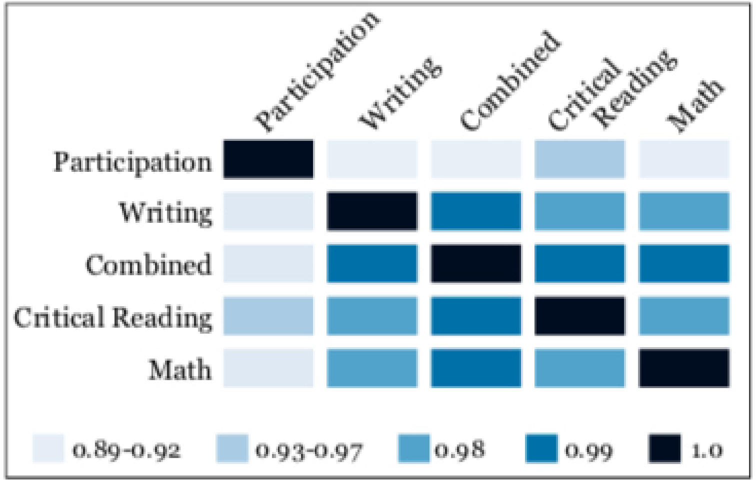


Figure 9.13 A simple heat map based on a correlation matrix.

Scatterplot matrix

```
library(pairsD3)
pairsD3(iris[,1:4], group=iris[,5])
```

Parallel coordinates:

Radar (Star) Plot

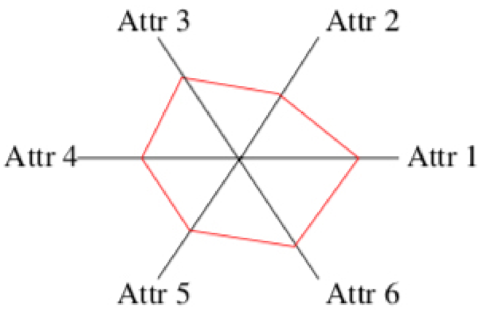


Fig. 4.9 Star plot.

City	Precip. average	Temp. average	Temp. max average	Temp. min average	Record max	Record min
Athens	37	17	21	13	42	−3
Bucharest	58	11	16	5	49	−23
Canberra	62	12	19	6	42	−10
Dublin	74	10	12	6	28	−7
Helsinki	63	5	8	1	31	−36
Hong Kong	218	23	25	21	37	2
London	75	10	13	5	35	−13
Madrid	45	13	20	7	40	−10
Mexico City	63	17	23	11	32	−3
Moscow	59	4	8	1	35	−42
New York	118	12	17	8	40	−18
Porto	126	14	18	10	34	−2
Rio de Janeiro	109	25	30	20	43	7
Rome	80	15	20	11	37	−7
Tunis	44	18	23	13	46	−1
Zurich	107	9	12	6	35	−20

Table 4.1 Annual climatic values in Celsius of some world cities. Values from http://www.weatherbase.com.

Radar (Star) Plot

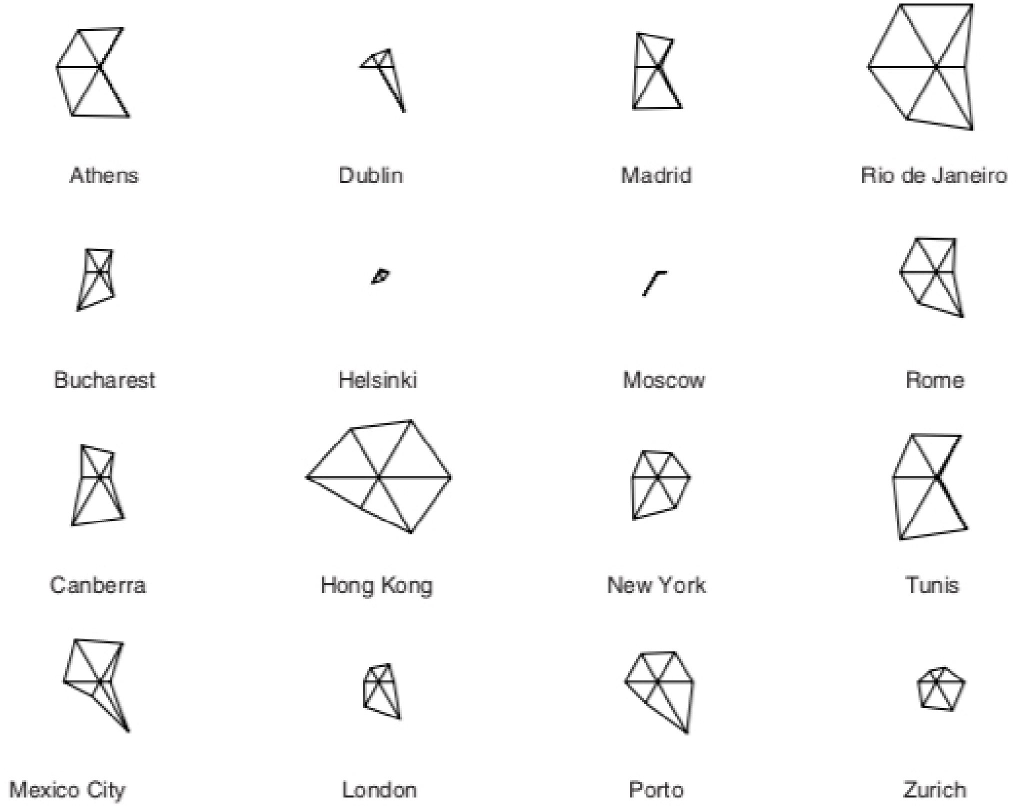


Fig. 4.10 Star plot of the annual climatic data of some cities. Image generated by the S-PLUS tool.

Chernoff Faces

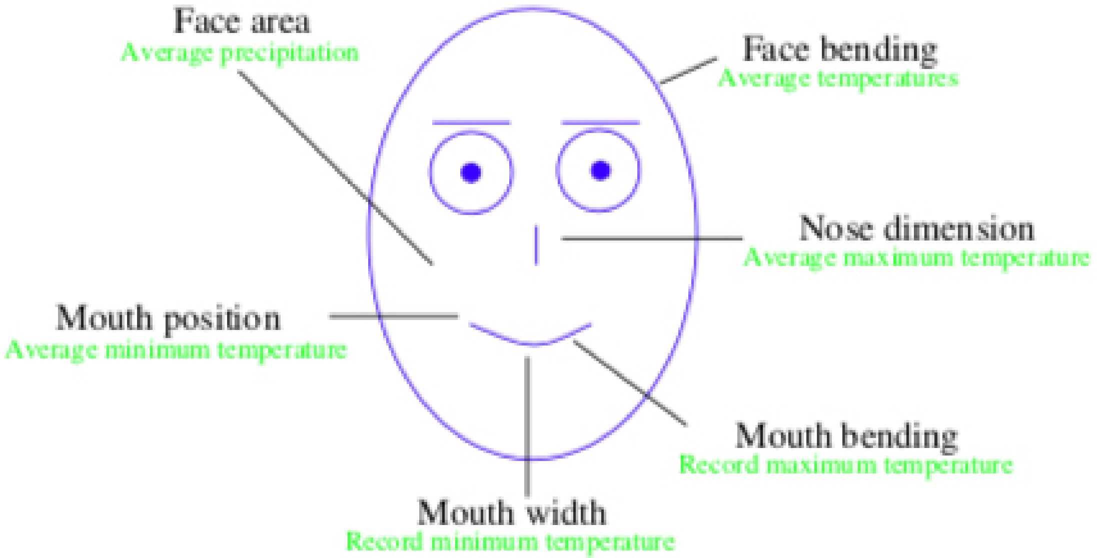


Fig. 4.11 Chernoff face.

Chernoff Faces

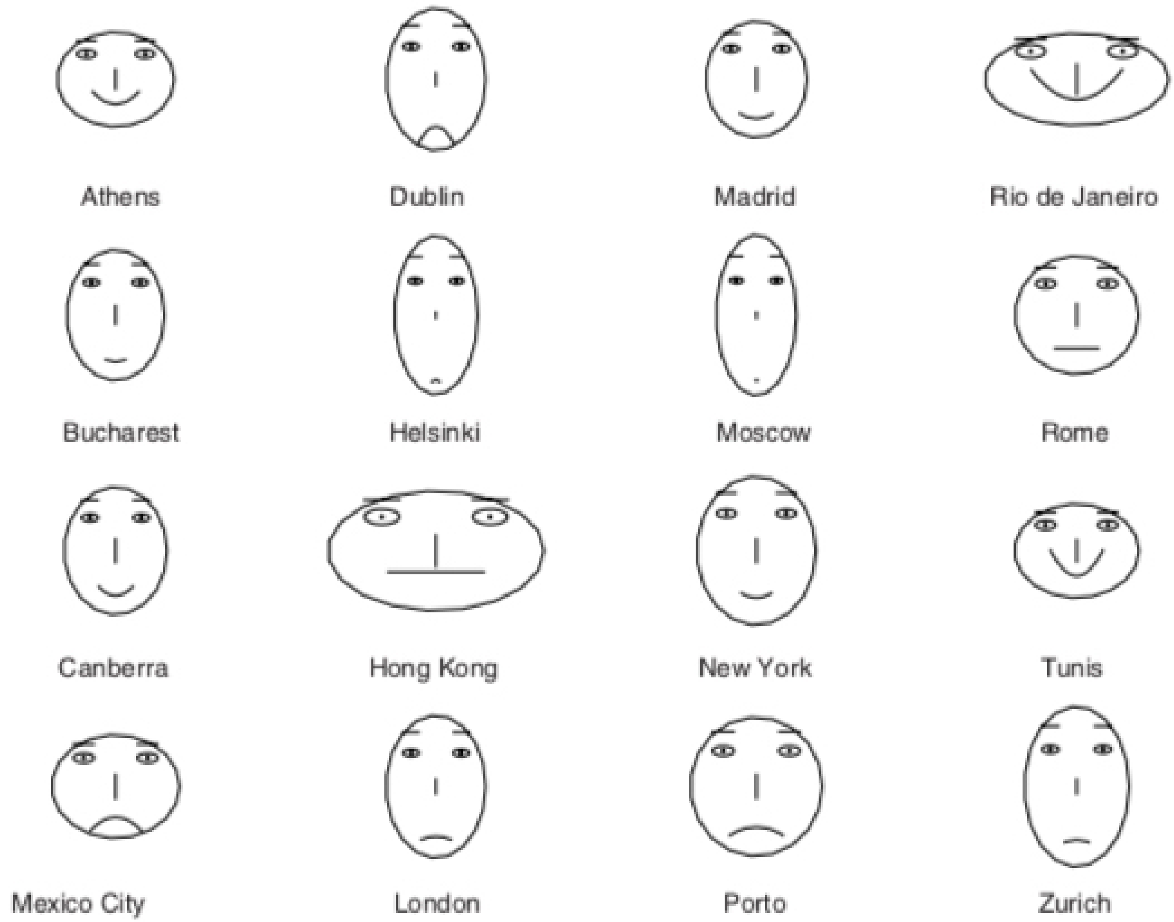
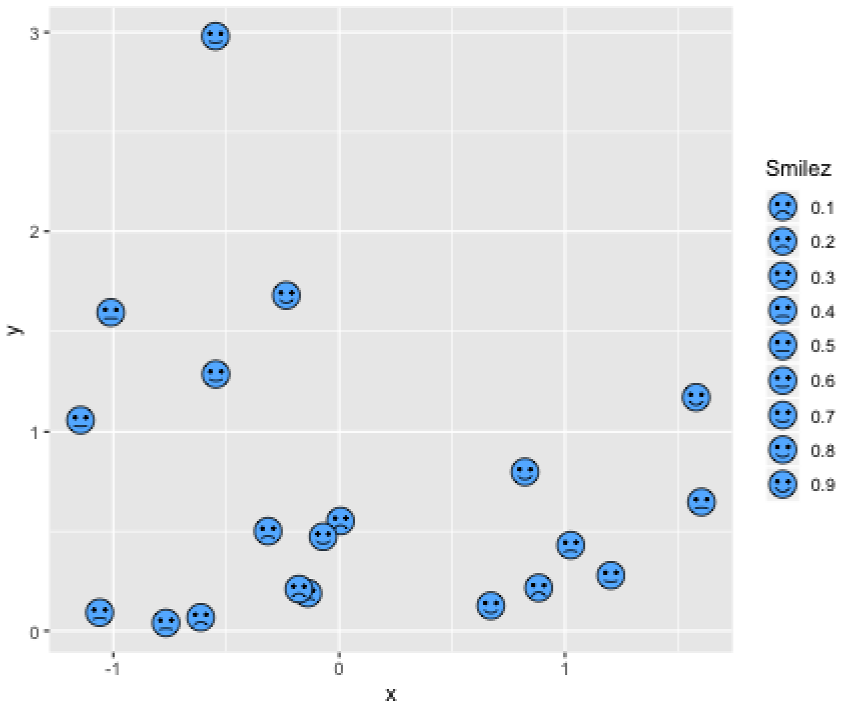


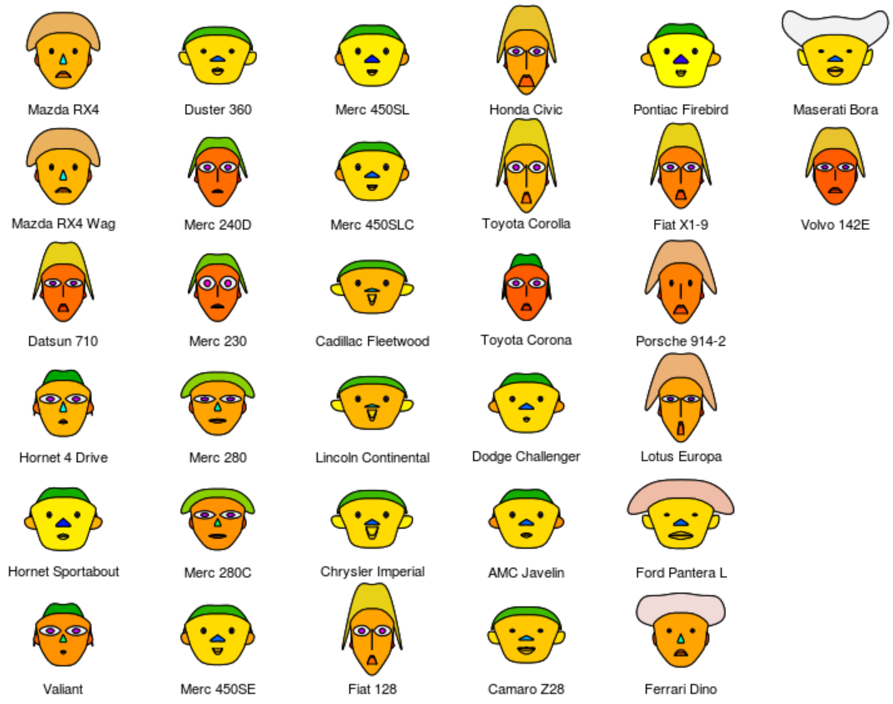
Fig. 4.12 Climatic data of some cities represented by Chernoff faces. Image generated by the S-PLUS statistics tool.

Chernoff Faces: ggChernoff

```
#devtools::install_github('Selbosh/ggChernoff')
library(ggChernoff)
ggplot(data.frame(x = rnorm(20), y = rexp(20), z = runif(20))) +
  aes(x, y, smile = z) +
  geom_chernoff(fill = 'steelblue1') +
  scale_smile_continuous('Smilez', breaks = 0:10/10, midpoint = .5)
```



DfaceR Shiny App



https://oddhypothesis.shinyapps.io/DFaceR/

Dimensionality Reduction:

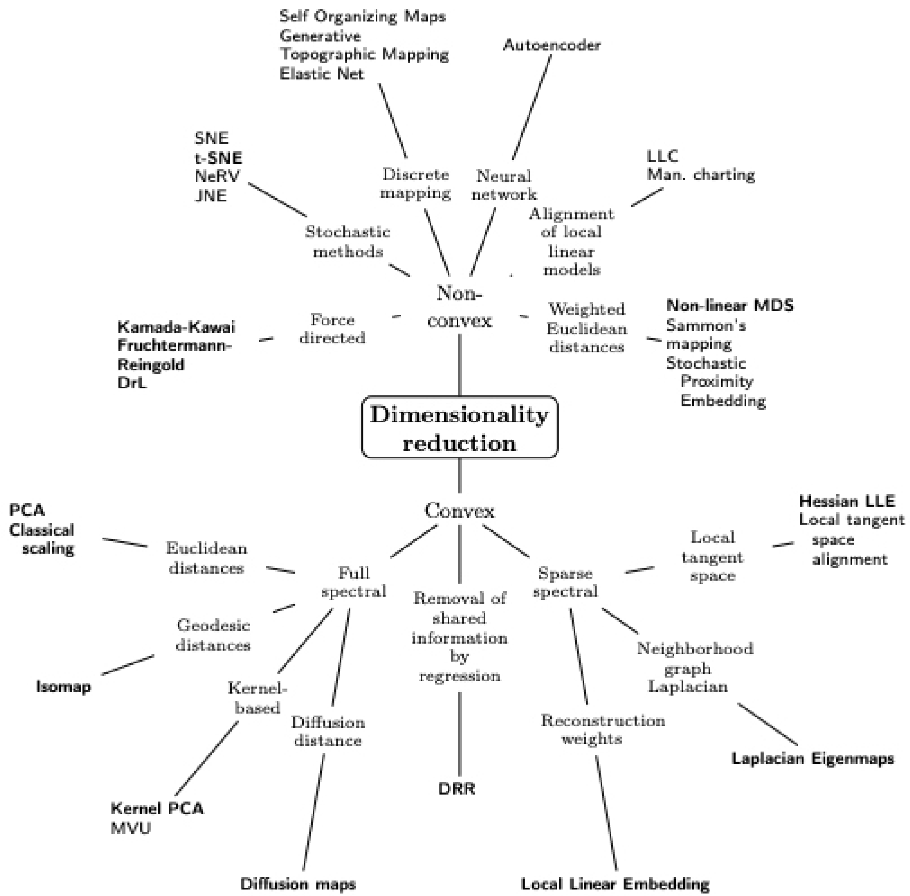
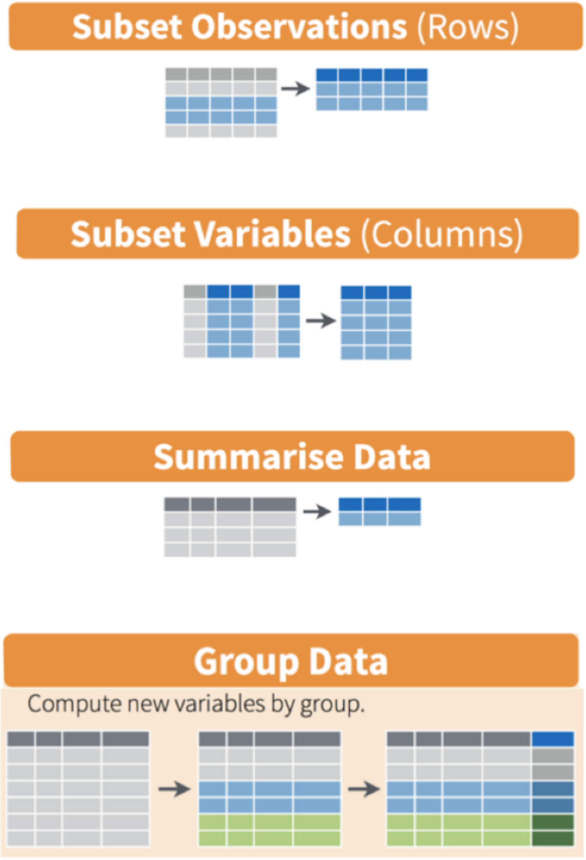


Figure 1: Classification of dimensionality reduction methods. Methods in bold face are implemented in **dimRed**. Modified from Van Der Maaten et al. (2009).

Simplest approach: `dplyr`

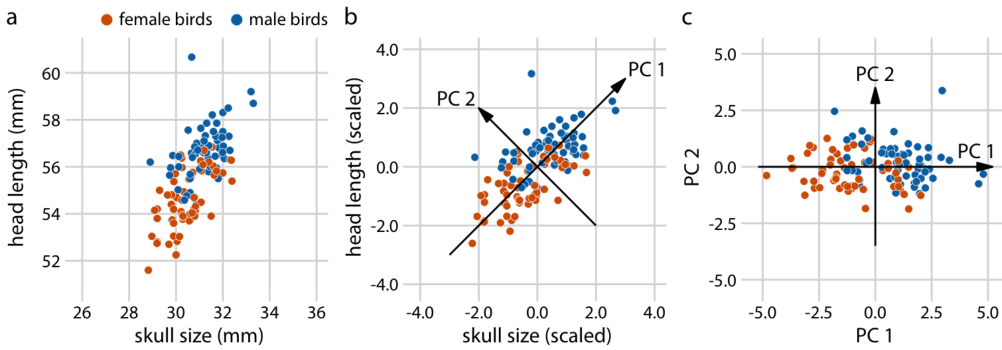


Dimensionality Reduction

There exist many algorithms for projecting n-dimensions to 2D:

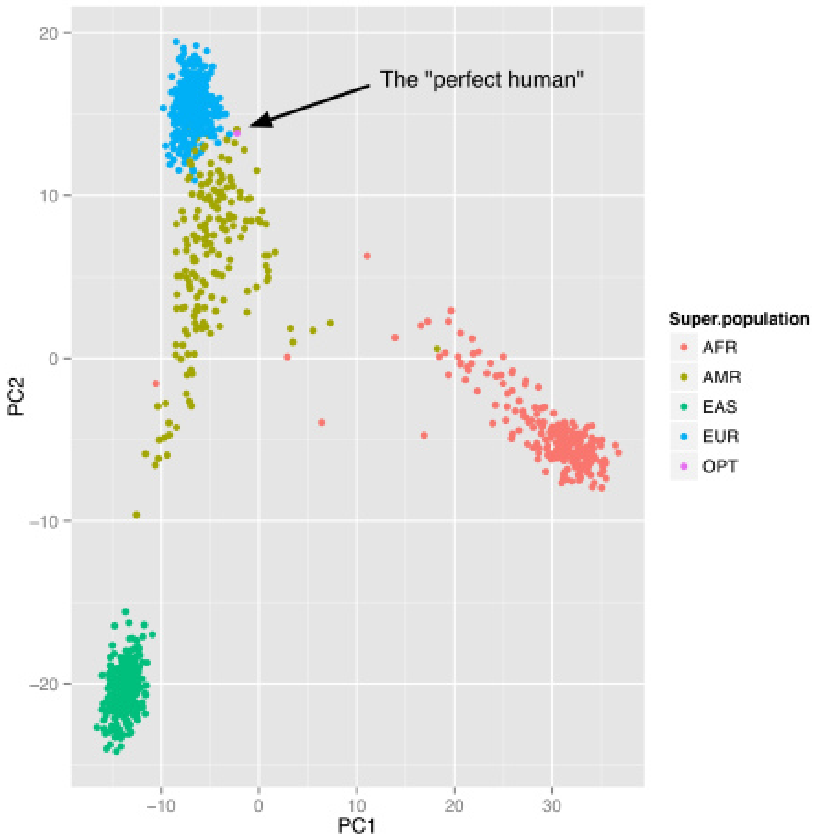
- Principal components analysis (PCA)
- Multi-dimensional scaling (MDS)
- Linear discriminant analysis (LDA)
- t-Distributed Stochastic Neighbor Embedding (t-SNE)

Principal Components



- Introduces a new set of variables (PC's) by **linear combination of the original variables** and standardized (zero mean and unit variance).
- The PCs are uncorrelated and ordered (first feature most important, etc.)
- Usually, key data features can be seen from first 2-3 PC's.

Case Study 1: Perfect Human



Lior Patcher's Dec 2014 blog post / see definition of "Repute" genes (good/bad)

Case Study 1: Perfect Human

Lior Patcher's Dec 2014 blog post

Case Study 2: Tyler Bradley's blog post

```
us_arrests %>%
  head()
```

```
## # A tibble: 6 x 5
##   state      murder assault urbanpop  rape
##   <chr>       <dbl>   <int>    <int> <dbl>
## 1 Alabama      13.2     236       58  21.2
## 2 Alaska       10       263       48  44.5
## 3 Arizona       8.1     294       80  31
## 4 Arkansas      8.8     190       50  19.5
## 5 California    9       276       91  40.6
## 6 Colorado      7.9     204       78  38.7
```

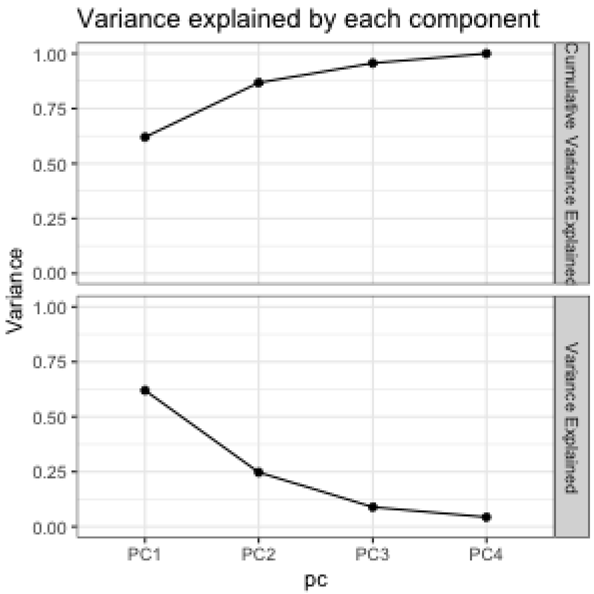
```
us_arrests_pca <- us_arrests %>%
  nest() %>%
  mutate(pca = map(data, ~ prcomp(.x %>% select(-state),
                                  center = TRUE, scale = TRUE)),
         pca_aug = map2(pca, data, ~augment(.x, data = .y)))

us_arrests_pca %>%
  head()
```

```
## # A tibble: 1 x 3
##   data              pca          pca_aug
##   <list>            <list>       <list>
## 1 <tibble [50 × 5]> <S3: prcomp> <tibble [50 × 10]>
```

PCA

```
var_exp <- us_arrests_pca %>%
  unnest(pca_aug) %>%
  summarize_at(.vars = vars(contains("PC")),
               .funs = funs(var)) %>%
  gather(key = pc, value = variance) %>%
  mutate(var_exp = variance/sum(variance),
         cum_var_exp = cumsum(var_exp),
         pc = str_replace(pc, ".fitted", ""))

var_exp
```

```
## # A tibble: 4 x 4
##   pc    variance var_exp cum_var_exp
##   <chr>    <dbl>   <dbl>       <dbl>
## 1 PC1      2.48   0.620        0.620
## 2 PC2      0.990  0.247        0.868
## 3 PC3      0.357  0.0891       0.957
## 4 PC4      0.173  0.0434       1
```



PCA with `ggbiplot`

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

PCA with ggbiplot

```r
t <- "First two principal components of PCA on USArrests dataset"

us_arrests_pca %>%
  mutate(pca_graph = map2(.x = pca, .y = data,
      ~ autoplot(.x, loadings = TRUE, loadings.label = TRUE,
                 loadings.label.repel = TRUE,
                 data = .y, label = TRUE,
                 label.label = "state",
                 label.repel = TRUE) +
        theme_bw() +
        labs(x = "Principal Component 1",
             y = "Principal Component 2",
             title = t)
    )
  ) %>%
  pull(pca_graph)
```