LNCC
Laboratório Nacional de
Computação Científica

Jornada de Ciência de Dados
11 anos!

CEFET/RJ

EXPLORATORY ANALYSIS

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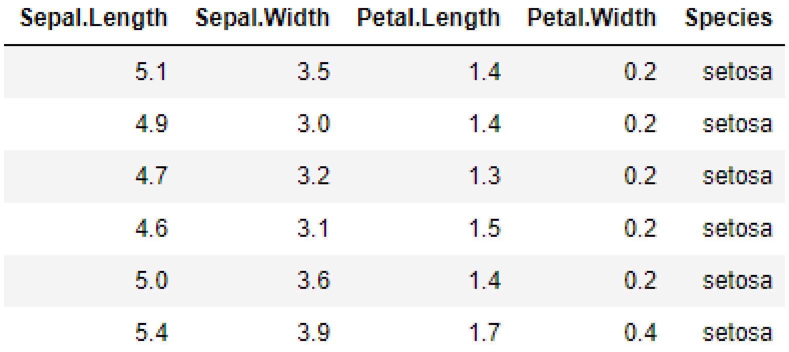
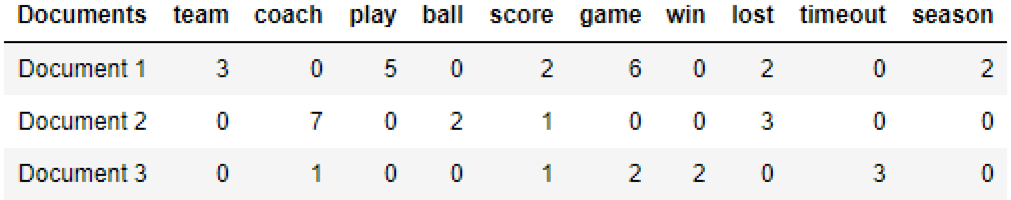
Types of Data Sets

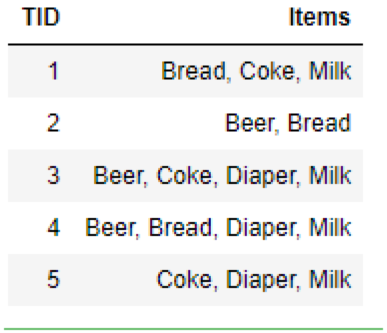
- Record
  - Relational datasets
- Matrix
  - numerical matrix, crosstabs
- Documents
  - texts, term-frequency vector
- Transactions
- Graph and network
  - World Wide Web
  - Social or information networks
- Ordered
  - Temporal data: time-series
  - Sequential data: transaction sequences
- Spatial, image, and multimedia
  - Spatial data: maps
  - Images
  - Videos



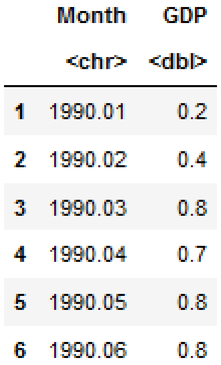
Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
5.1	3.5	1.4	0.2	setosa
4.9	3.0	1.4	0.2	setosa
4.7	3.2	1.3	0.2	setosa
4.6	3.1	1.5	0.2	setosa
5.0	3.6	1.4	0.2	setosa
5.4	3.9	1.7	0.4	setosa



Documents	team	coach	play	ball	score	game	win	lost	timeout	season
Document 1	3	0	5	0	2	6	0	2	0	2
Document 2	0	7	0	2	1	0	0	3	0	0
Document 3	0	1	0	0	1	2	2	0	3	0



TID	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk



	Month	GDP
	<chr>	<dbl>
1	1990.01	0.2
2	1990.02	0.4
3	1990.03	0.8
4	1990.04	0.7
5	1990.05	0.8
6	1990.06	0.8

[1] J. Han, J. Pei, and H. Tong, Data Mining: Concepts and Techniques, 4th edition. Cambridge, MA: Morgan Kaufmann, 2022.

Important Characteristics of Structured Data

- Dimensionality
  - Curse of dimensionality
- Sparsity
  - Only presence counts
- Resolution
  - Patterns depend on the scale
  - Aggregated data
- Distribution
  - Centrality and dispersion

[1] J. Han, J. Pei, and H. Tong, Data Mining: Concepts and Techniques, 4th edition. Cambridge, MA: Morgan Kaufmann, 2022.

Relational data

- Data sets are made up of data objects
- A data object represents an entity
  - sales database: customers, store items, sales
  - medical database: patients, treatments, illness
  - university database: students, professors, courses
- Attributes describe data objects
- Database
  - rows: data objects (tuples)
  - columns: attributes

[1] J. Han, J. Pei, and H. Tong, Data Mining: Concepts and Techniques, 4th edition. Cambridge, MA: Morgan Kaufmann, 2022.

Attributes

- Attribute (or dimensions, features, variables)
  - a data field, representing a characteristic or feature of a data object
  - E.g., customer_ID, name, address
- Types: Nominal, Binary, Ordinal, Numeric

[1] J. Han, J. Pei, and H. Tong, Data Mining: Concepts and Techniques, 4th edition. Cambridge, MA: Morgan Kaufmann, 2022.

Attribute Types

- Nominal: categories, states, or “names of things”
  - Hair_color = {auburn, black, blond, brown, grey, red, white}
  - marital status, occupation, ID numbers, zip codes
- Binary
  - Attribute with only two states (0 and 1)
  - Symmetric binary: both outcomes equally important
    - e.g., gender
  - Asymmetric binary: outcomes not equally important
    - e.g., medical test (positive vs. negative)
    - Convention: assign 1 to the most important outcome (e.g., HIV positive)
- Ordinal
  - Values have a meaningful order (ranking), but magnitude between successive values is not known
  - Size = {small, medium, large}, grades, army rankings

[1] J. Han, J. Pei, and H. Tong, Data Mining: Concepts and Techniques, 4th edition. Cambridge, MA: Morgan Kaufmann, 2022.

Numeric Attribute Types

- Quantity (integer or real-valued)
- Interval
    - Measured on a scale of equal-sized units
    - Values have order
        - E.g., the temperature in C°or F°, calendar dates
    - No true zero-point
- Ratio
    - Inherent zero-point
    - We can speak of values as being an order of magnitude larger than the unit of measurement (10 K is twice as high as 5 K).
        - e.g., the temperature in Kelvin, length, counts, monetary quantities

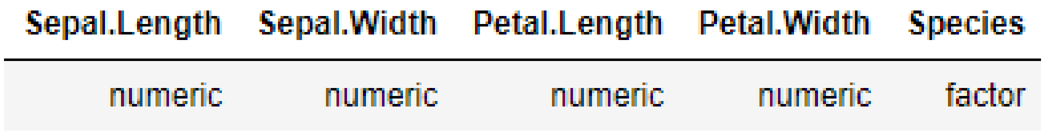
[1] J. Han, J. Pei, and H. Tong, Data Mining: Concepts and Techniques, 4th edition. Cambridge, MA: Morgan Kaufmann, 2022.

Discrete vs. Continuous Attributes

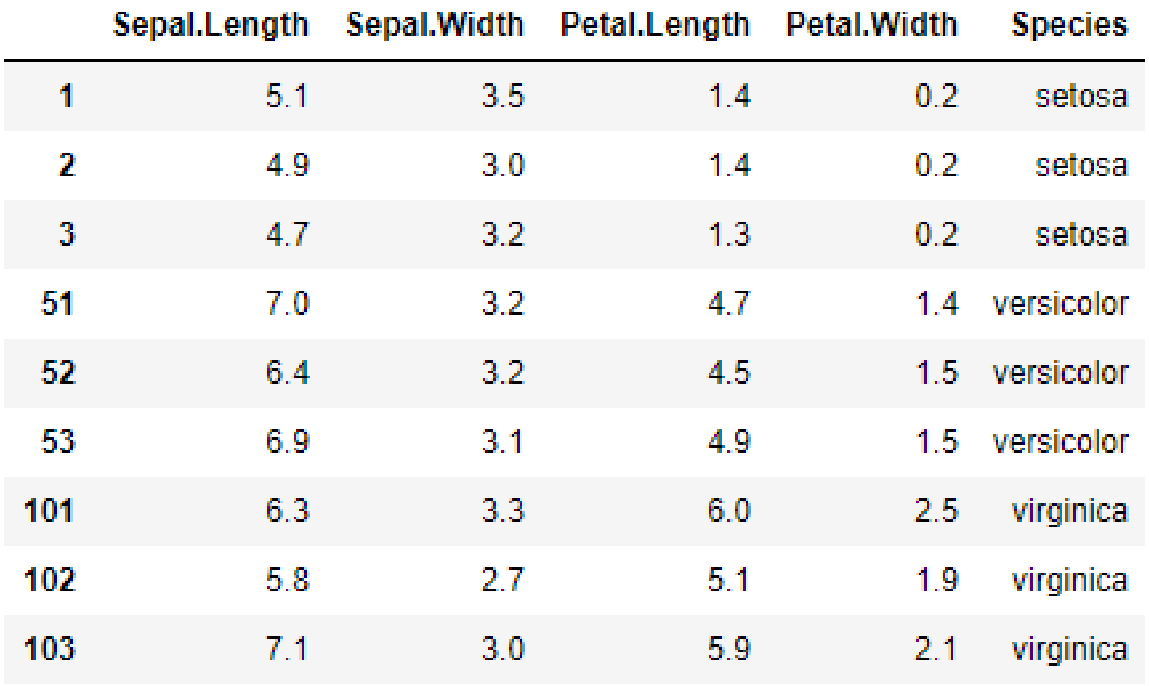
- Discrete Attribute
  - Has only a finite or countably infinite set of values
  - Sometimes, represented as integer variables
- Continuous Attribute
  - Has real numbers as attribute values
    - E.g., temperature, height, or weight
  - Practically, real values can only be measured and represented using a finite number of digits
  - Continuous attributes are typically represented as floating-point variables

[1] J. Han, J. Pei, and H. Tong, Data Mining: Concepts and Techniques, 4th edition. Cambridge, MA: Morgan Kaufmann, 2022.

Iris Dataset



Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
numeric	numeric	numeric	numeric	factor



	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
51	7.0	3.2	4.7	1.4	versicolor
52	6.4	3.2	4.5	1.5	versicolor
53	6.9	3.1	4.9	1.5	versicolor
101	6.3	3.3	6.0	2.5	virginica
102	5.8	2.7	5.1	1.9	virginica
103	7.1	3.0	5.9	2.1	virginica

[1] Kaggle, 2020, *Iris Species*, https://www.kaggle.com/uciml/iris.

Basic Statistical Descriptions of Data

- Motivation
  - To better understand the data:
    - central tendency, variation and spread
- Data centrality and dispersion characteristics
  - median, max, min, quantiles, outliers, variance
- Numerical dimensions correspond to sorted intervals
  - Boxplot or quantile analysis on sorted intervals

[1] R.J. Larsen and M.L. Marx, 2017, *An Introduction to Mathematical Statistics and Its Applications*. Pearson Education.

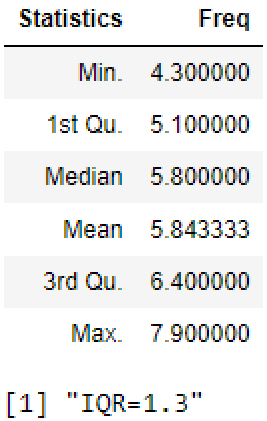
Descriptive Measures

- Centrality
  - Mean (algebraic measure)
    - $\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$
  - Median
    - Middle value if an odd number of values, or weighted average of the middle two values otherwise
  - Mode
    - The value that occurs most frequently in the data
    - Unimodal, bimodal, trimodal
- Dispersion
  - Variance and standard deviation
    - Variance: (algebraic, scalable computation)
    - Standard deviation (σ): square root of the variance (σ^2)
      - $\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n} = \frac{\sum_{i=1}^{n} {x_i}^2}{n} - \mu^2$

[1] R.J. Larsen and M.L. Marx, 2017, *An Introduction to Mathematical Statistics and Its Applications*. Pearson Education.

Measuring the Dispersion of Data

- Quartiles, outliers and boxplots
  - Quartiles: Q_1 (25th percentile), Q_3 (75th percentile)
  - Inter-quartile range: IQR = $Q_3 – Q_1$
  - Five numbers summary: min, Q_1, median, Q_3, max
  - Boxplot



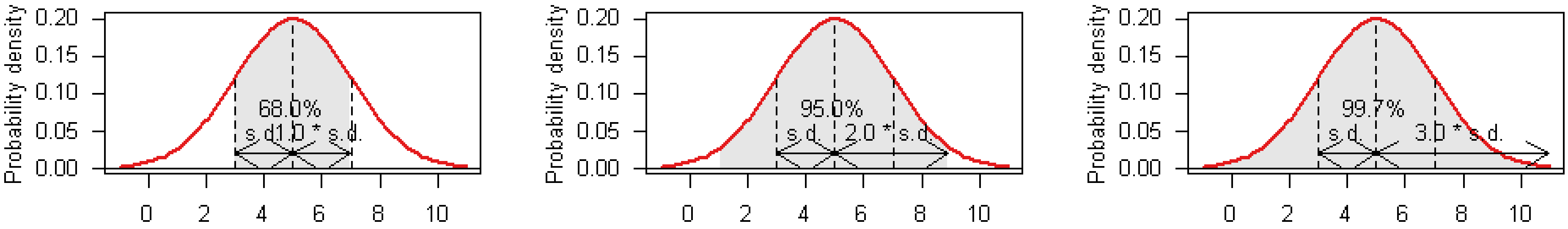
Statistics	Freq
Min.	4.300000
1st Qu.	5.100000
Median	5.800000
Mean	5.843333
3rd Qu.	6.400000
Max.	7.900000

```
[1] "IQR=1.3"
```

[1] R.J. Larsen and M.L. Marx, 2017, *An Introduction to Mathematical Statistics and Its Applications*. Pearson Education.

Properties of Normal Distribution Curve

- The normal (distribution) curve
  - From μ–σ to μ+σ: contains about 68% of the measurements (μ: mean, σ: standard deviation)
  - From μ–2σ to μ+2σ: contains about 95% of it
  - From μ–3σ to μ+3σ: contains about 99.7% of it
  - When distribution is normal, values below -2.698σ or greater than 2.698σ are considered outliers



[1] R.J. Larsen and M.L. Marx, 2017, *An Introduction to Mathematical Statistics and Its Applications*. Pearson Education.

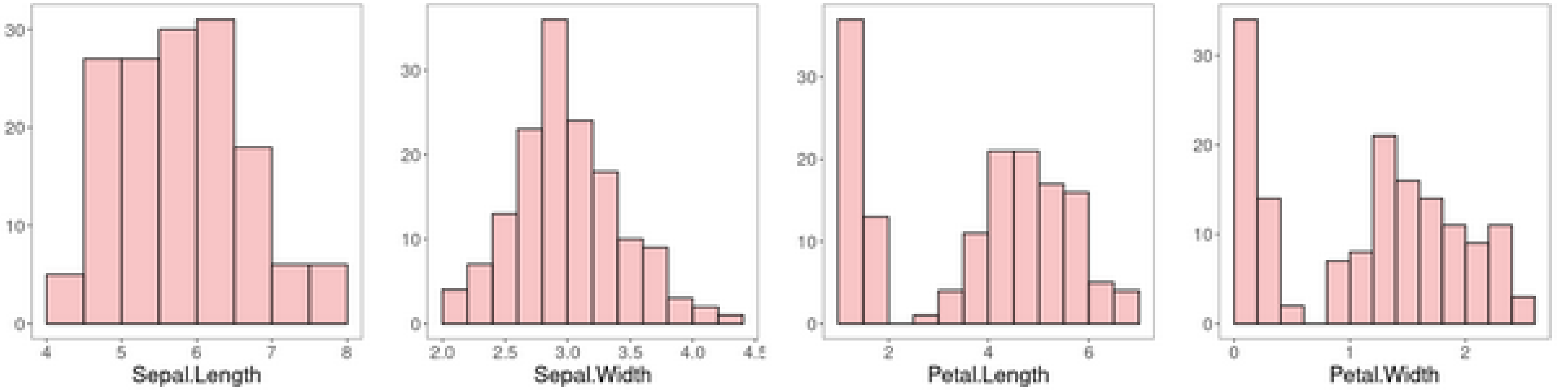
Graphic Displays of Basic Statistical Descriptions

- Histogram
- Boxplot
- Density distribution

[1] R.J. Larsen and M.L. Marx, 2017, *An Introduction to Mathematical Statistics and Its Applications*. Pearson Education.

Histogram Analysis

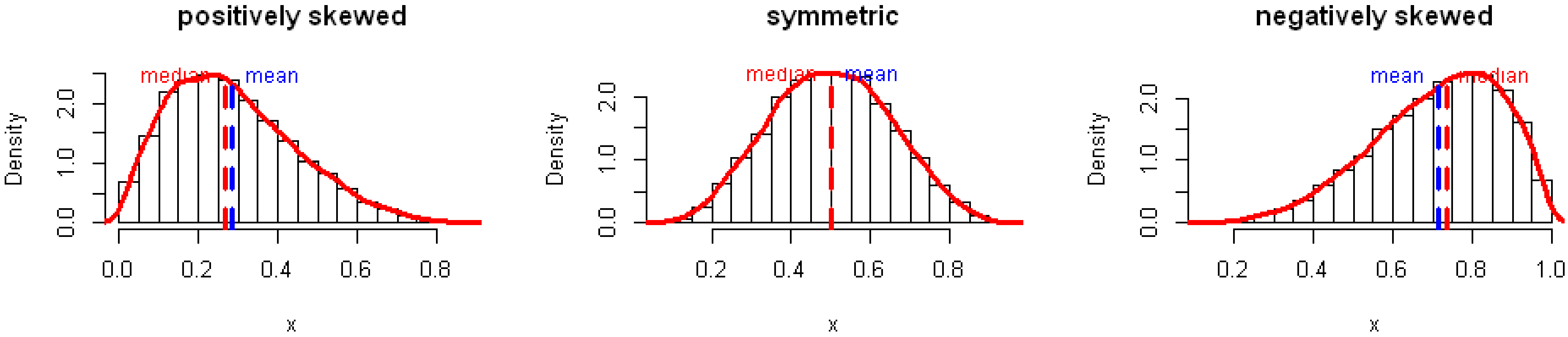
- The histogram displays values of tabulated frequencies
- It shows what proportion of cases into each category
- The area of the bar that denotes the value
  - It is a crucial property when the categories are not of uniform width
- The categories specify non-overlapping intervals of some variable
- The categories (bars) must be adjacent



[1] R.J. Larsen and M.L. Marx, 2017, An Introduction to Mathematical Statistics and Its Applications. Pearson Education.

Symmetric vs. Skewed Data

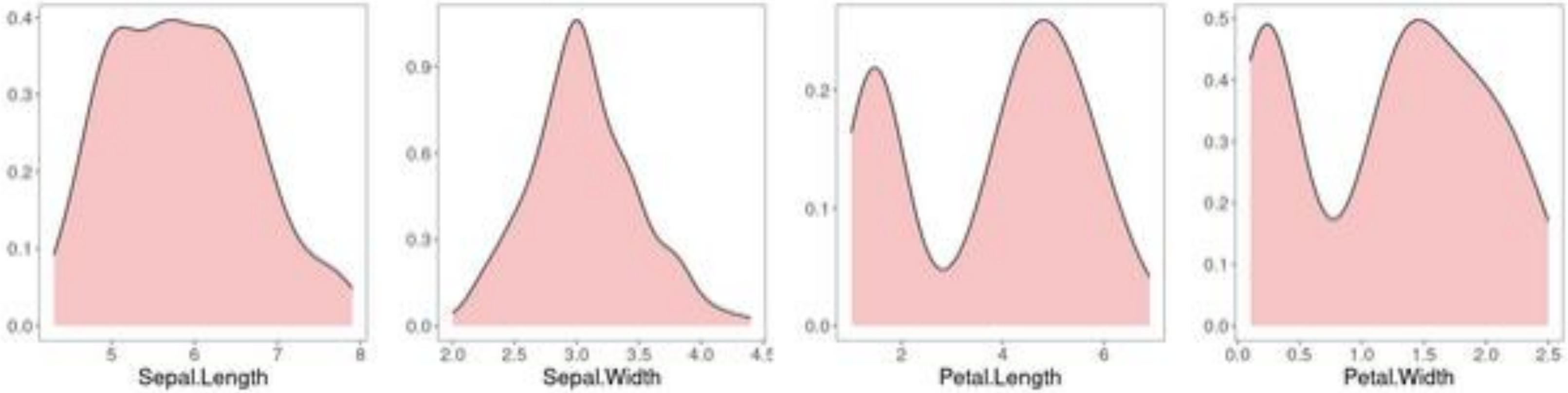
- Median and mean for:
  - positive, symmetric, and negatively skewed data



[1] R.J. Larsen and M.L. Marx, 2017, An Introduction to Mathematical Statistics and Its Applications. Pearson Education.

Probability Density

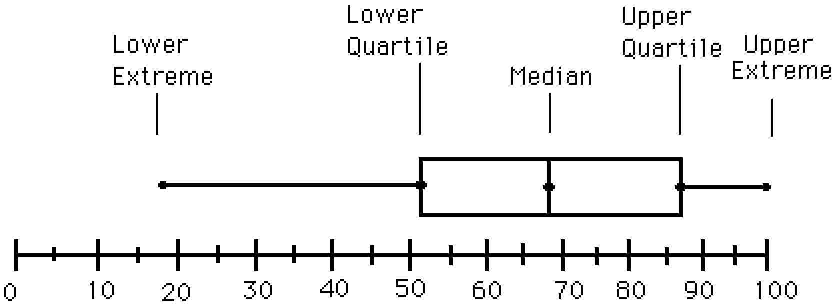
- Computes and draws kernel density estimate, which is a smoothed version of the histogram. This is a useful alternative to the histogram for continuous data that comes from an underlying smooth distribution.



[1] K.J. Keen, 2018, *Graphics for Statistics and Data Analysis with R*. CRC Press.

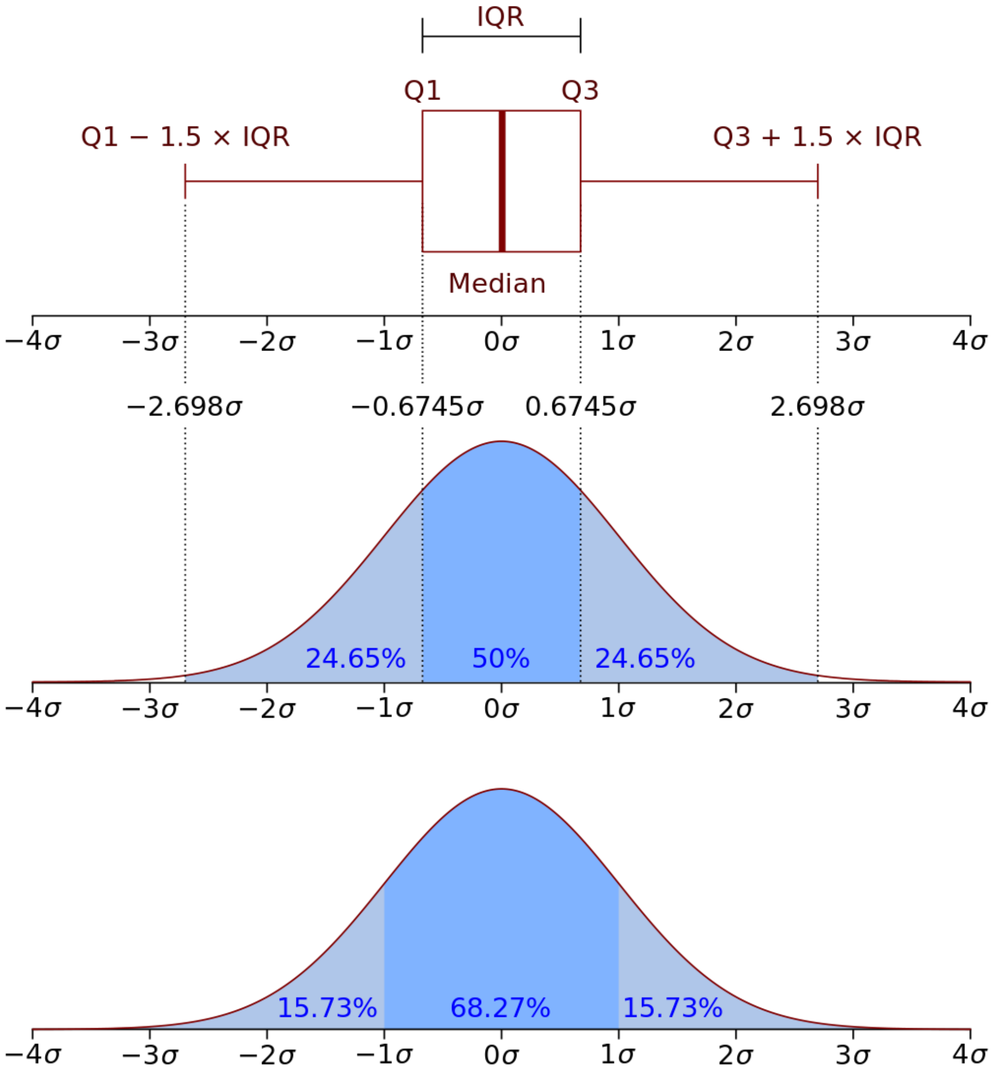
Boxplot Analysis

- In descriptive statistics, a box plot is a method for graphically depicting groups of numerical data through their quartiles. Box plots may also have lines extending from the boxes (whiskers), indicating variability outside the upper and lower quartiles (outliers)
- Five-number summary of a distribution
  - Min., Q1, Median, Q3, Max.
- Boxplot
  - Data is represented with a box
  - The ends of the box are at the first and third quartiles, i.e., the height of the box is IQR
  - Whiskers: two lines outside the box extended to Minimum and Maximum
  - Outliers are values:
    - higher than Q3 + 1.5 x IQR
    - lower than Q1 - 1.5 x IQR



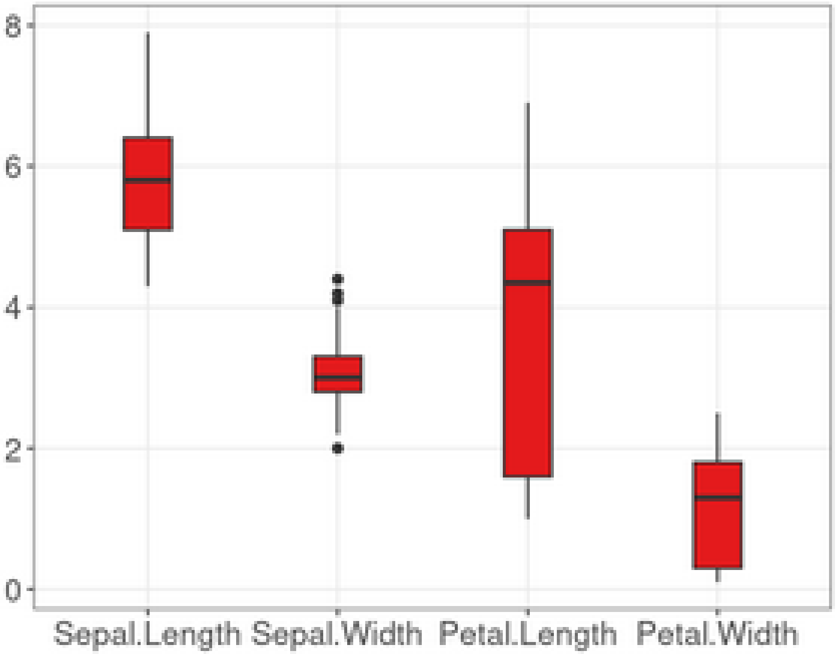
- [1] R. McGill, J.W. Tukey, and W.A. Larsen, 1978, Variations of box plots, *American Statistician*, v. 32, n. 1, p. 12–16.

Outliers in Boxplot



[1] R.J. Larsen and M.L. Marx, 2017, *An Introduction to Mathematical Statistics and Its Applications*. Pearson Education.
https://en.wikipedia.org/wiki/Box_plot

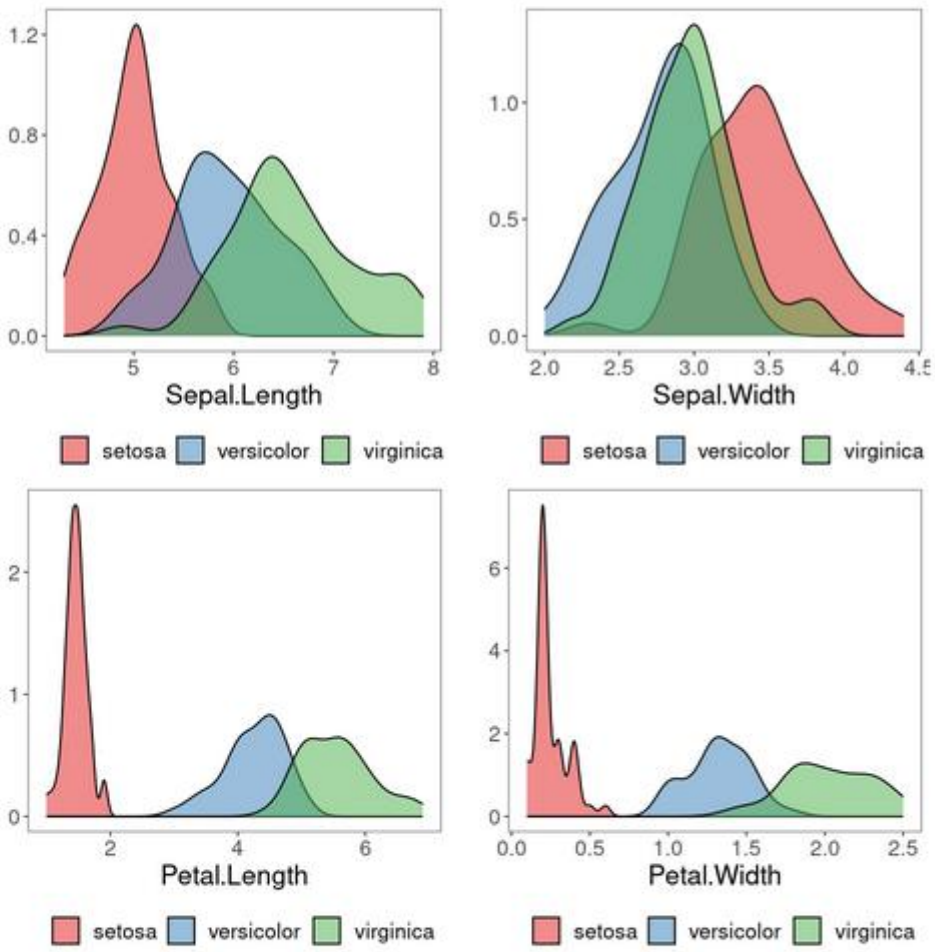
Example of boxplot for iris dataset



[1] K.J. Keen, 2018, *Graphics for Statistics and Data Analysis with R*. CRC Press.

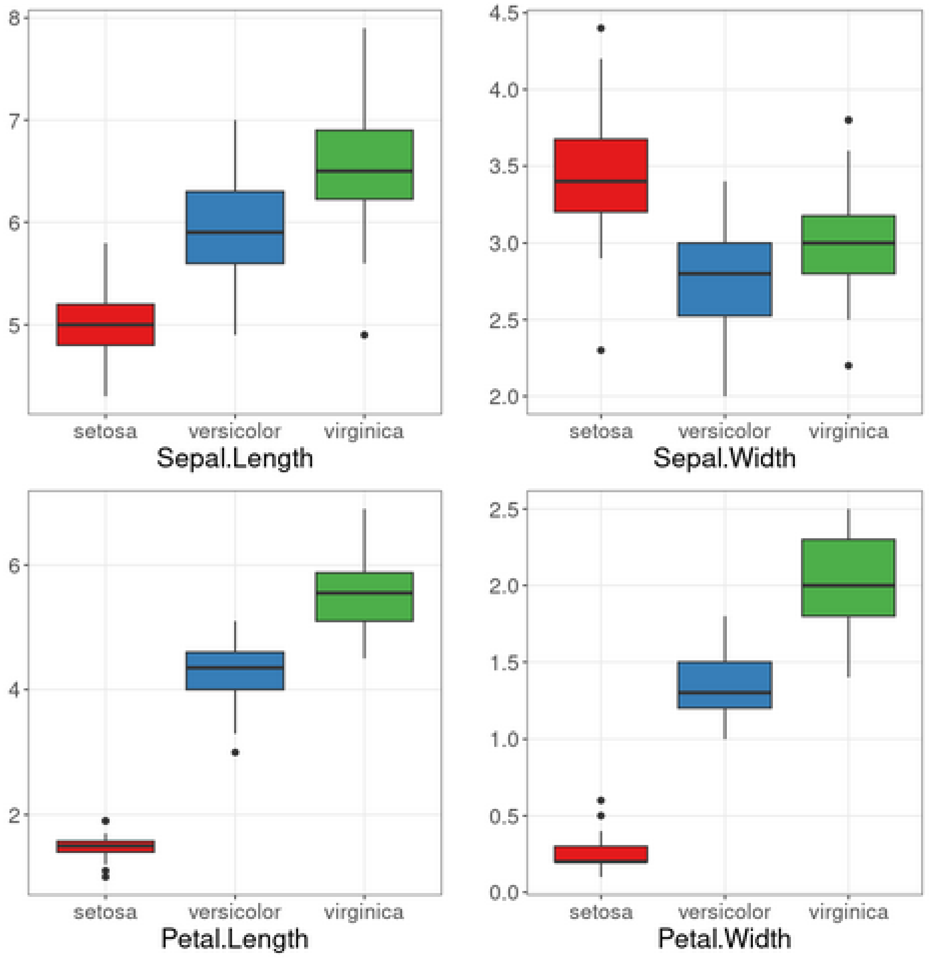
Exploratory analysis for Classification problem

Density distributions with class label



[1] K.J. Keen, 2018, *Graphics for Statistics and Data Analysis with R*. CRC Press.

Boxplot with class label



[1] K.J. Keen, 2018, *Graphics for Statistics and Data Analysis with R*. CRC Press.

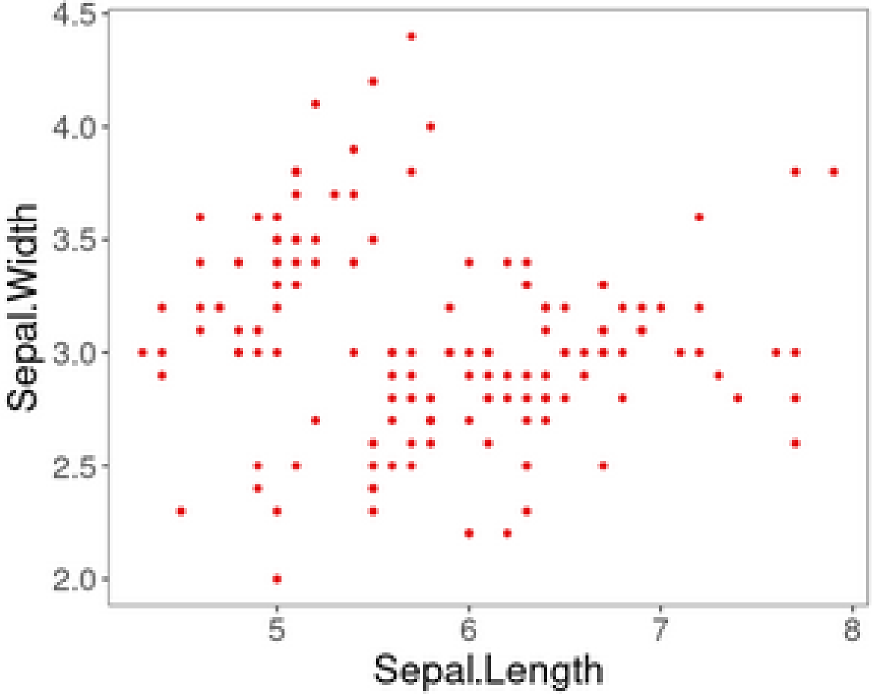
Graphic Displays of Basic Statistical Descriptions

- Scatter plot
- Correlation analysis
- Scatter matrix

[1] K.J. Keen, 2018, *Graphics for Statistics and Data Analysis with R*. CRC Press.

Scatter plot

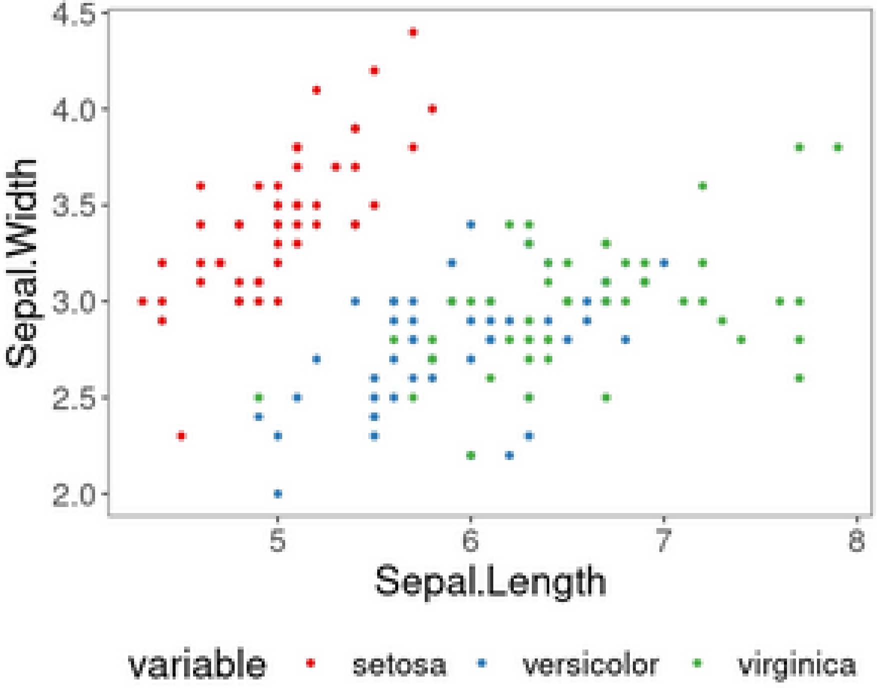
- Provides the first look at bivariate data to see clusters of points, outliers
- Each pair of values is treated as a pair of coordinates and plotted as points in the plane



[1] K.J. Keen, 2018, *Graphics for Statistics and Data Analysis with R*. CRC Press.

Scatter plot with class label

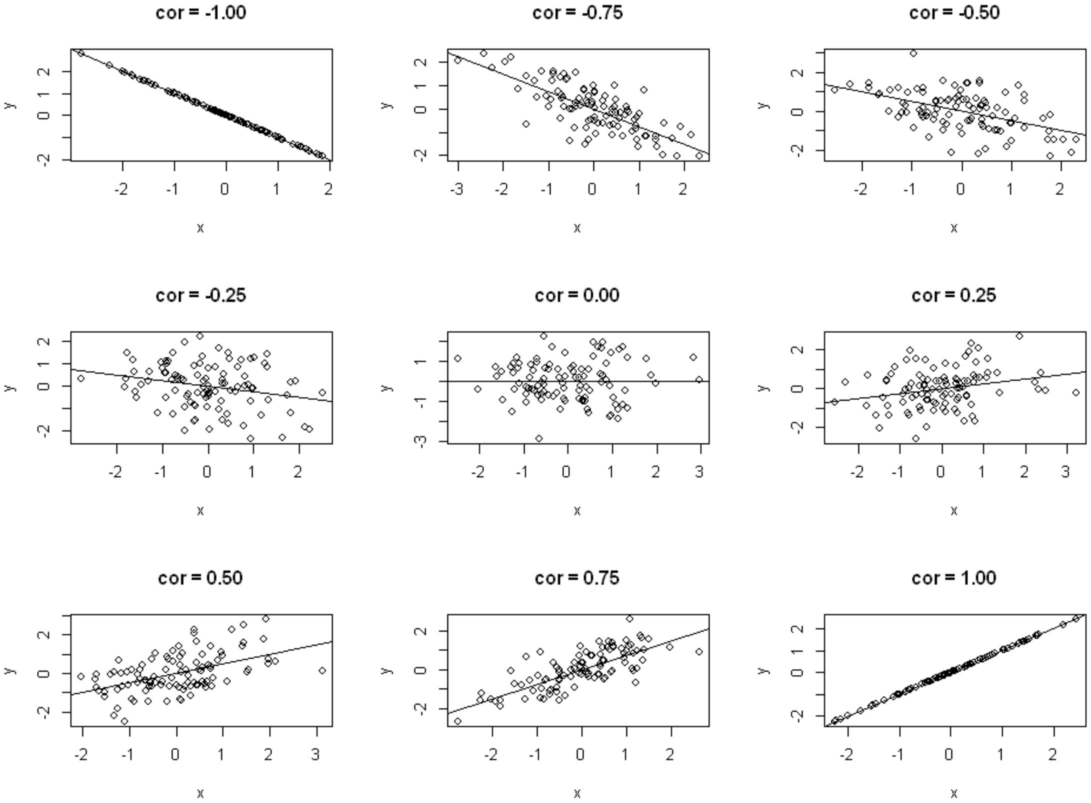
- Provides the first look at bivariate data to see clusters of points, outliers
- Each pair of values is treated as a pair of coordinates and plotted as points in the plane



[1] K.J. Keen, 2018, *Graphics for Statistics and Data Analysis with R*. CRC Press.

Data correlation

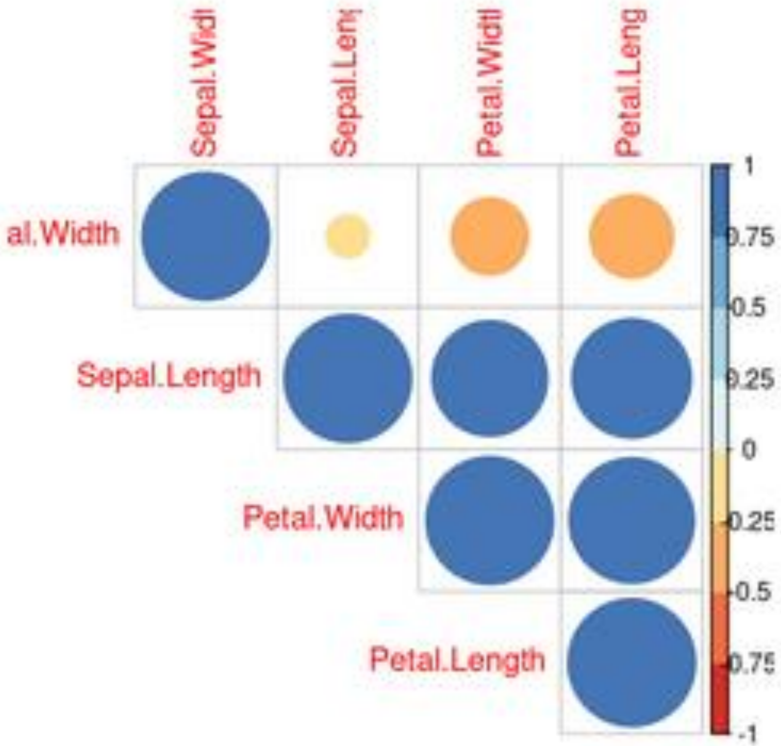
- The first row presents negatively correlated data
- The second row presents uncorrelated data
- The third row presents positively correlated data



[1] K.J. Keen, 2018, *Graphics for Statistics and Data Analysis with R*. CRC Press.

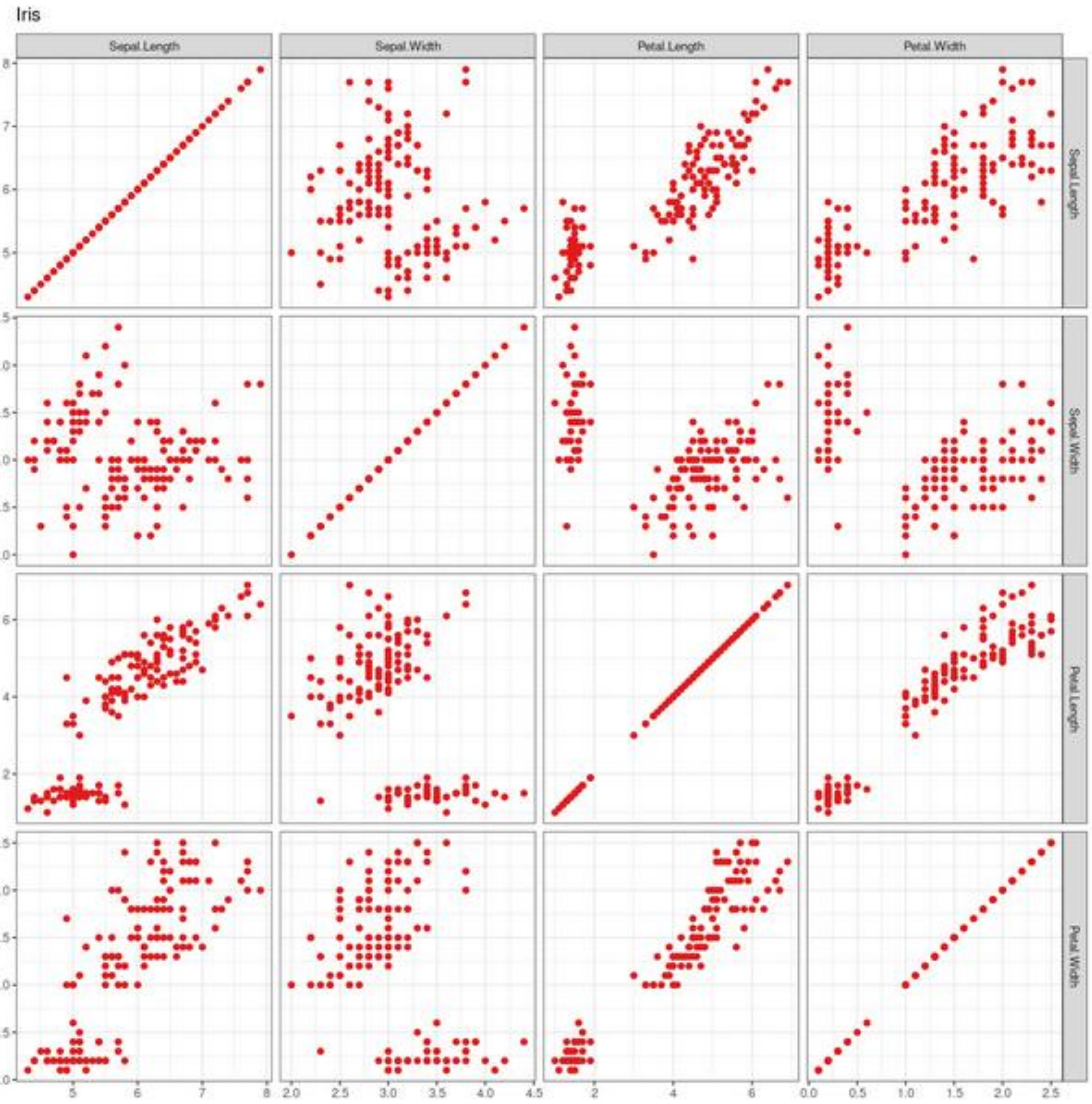
Correlation analysis

- The correlation plots are used to display the pairwise correlation among all numerical attributes of a dataset



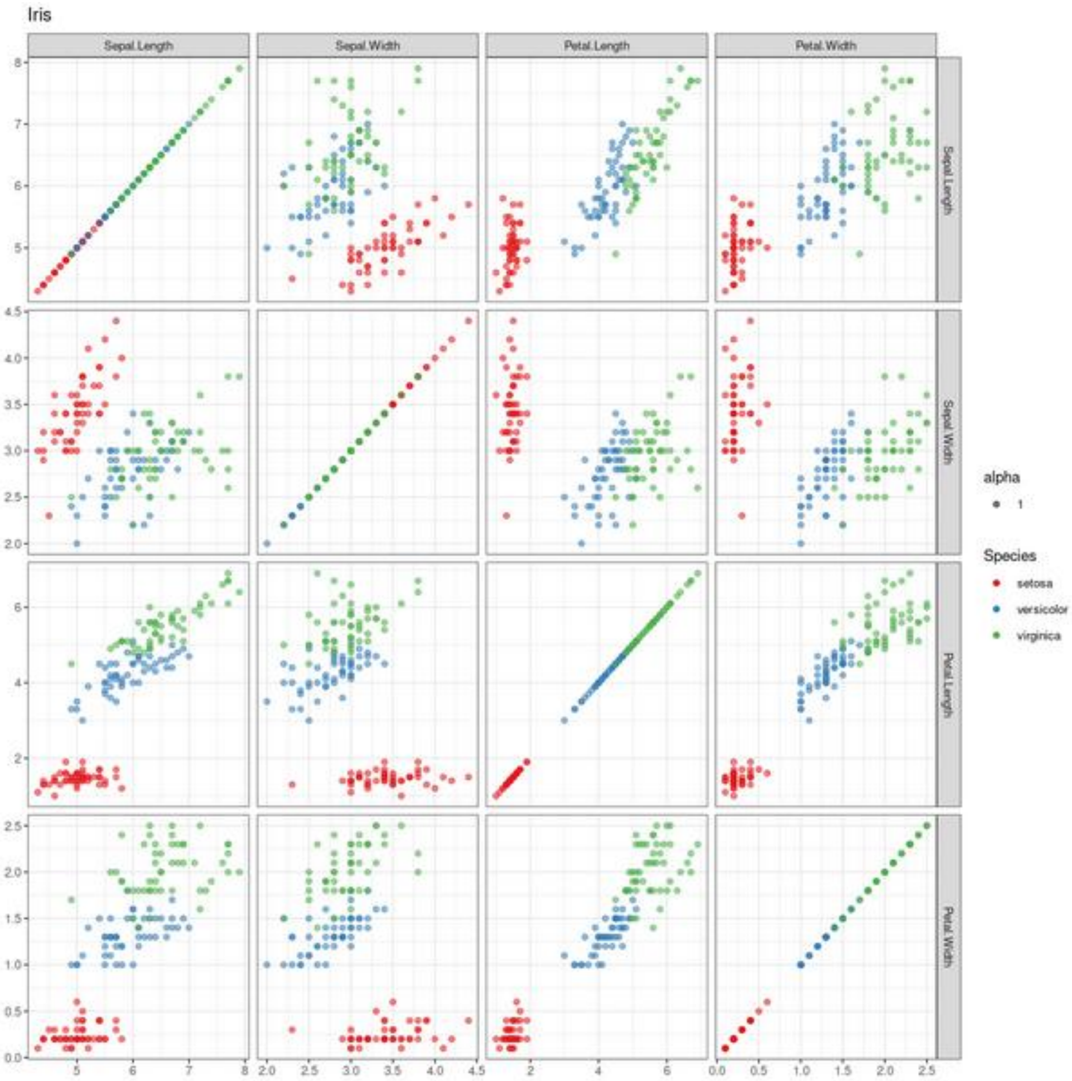
[1] M. Friendly, 2002, Corrgrams: Exploratory displays for correlation matrices, *American Statistician*, v. 56, n. 4, p. 316–324.

Scatter Matrix plot



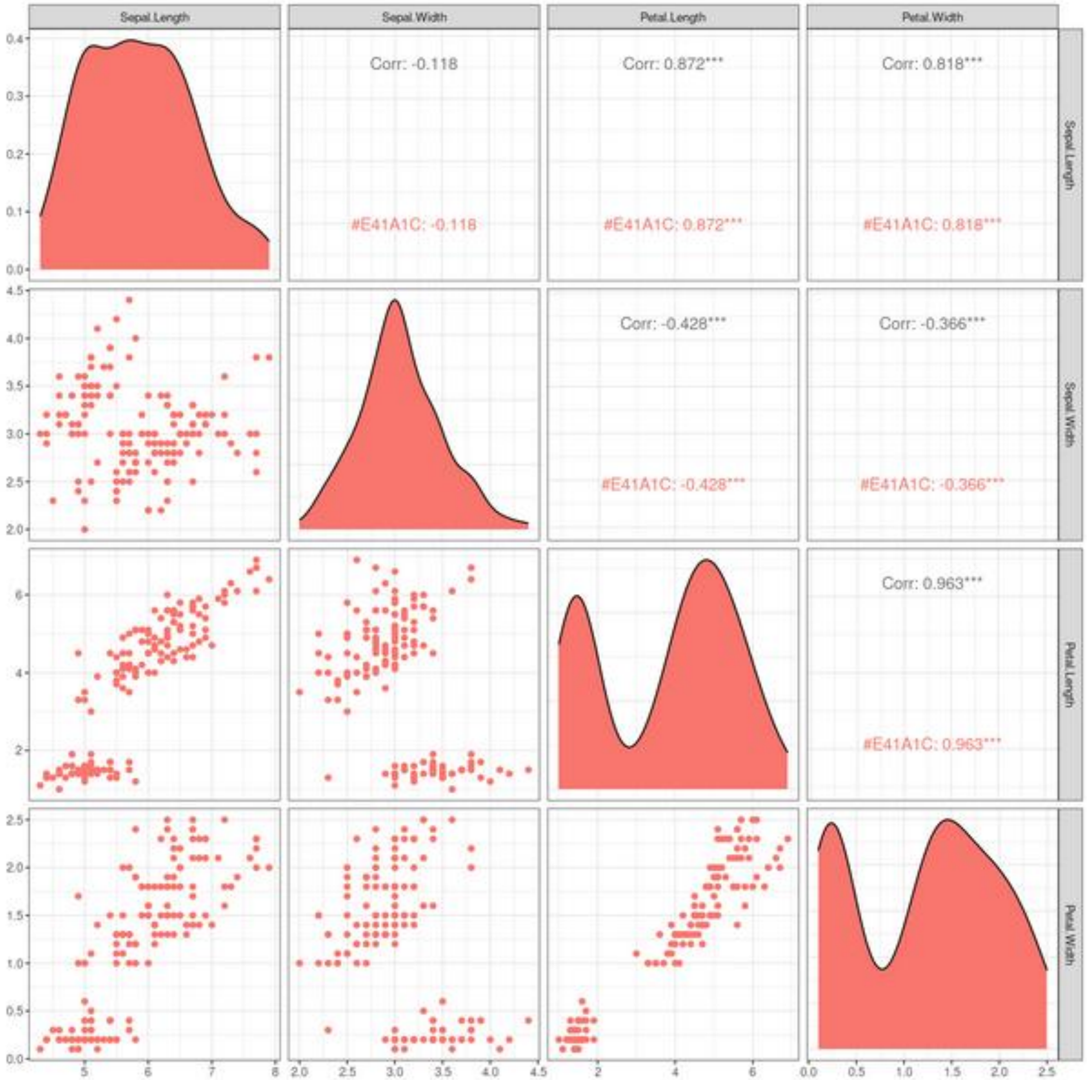
[1] N. Elmqvist, P. Dragicevic, and J.-D. Fekete, 2008, Rolling the dice: Multidimensional visual exploration using scatterplot matrix navigation, *IEEE Transactions on Visualization and Computer Graphics*, v. 14, n. 6, p. 1141–1148.

Scatter Matrix plot with a class label



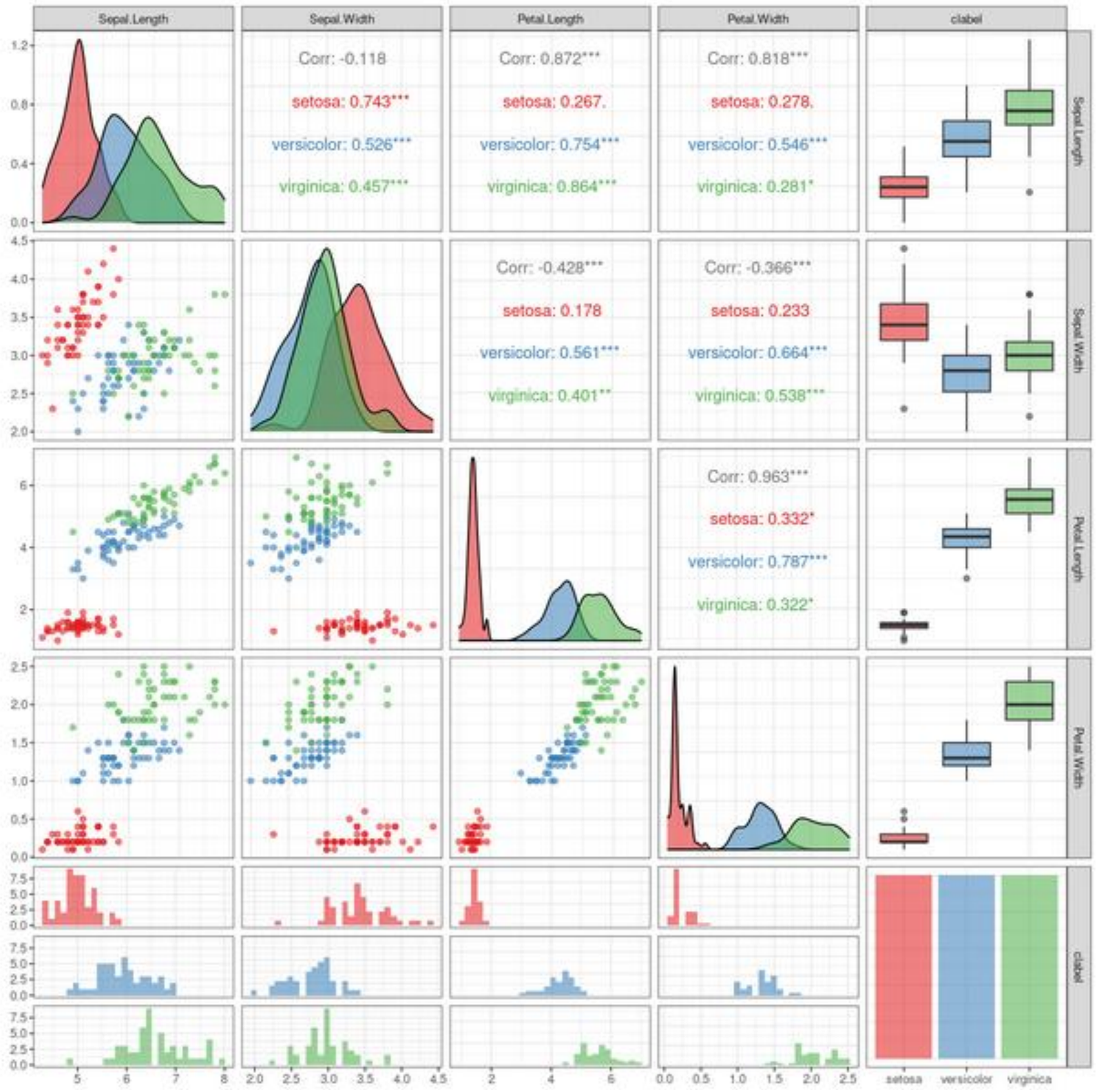
[1] N. Elmqvist, P. Dragicevic, and J.-D. Fekete, 2008, Rolling the dice: Multidimensional visual exploration using scatterplot matrix navigation, IEEE Transactions on Visualization and Computer Graphics, v. 14, n. 6, p. 1141–1148.

Advanced Scatter Matrix plot



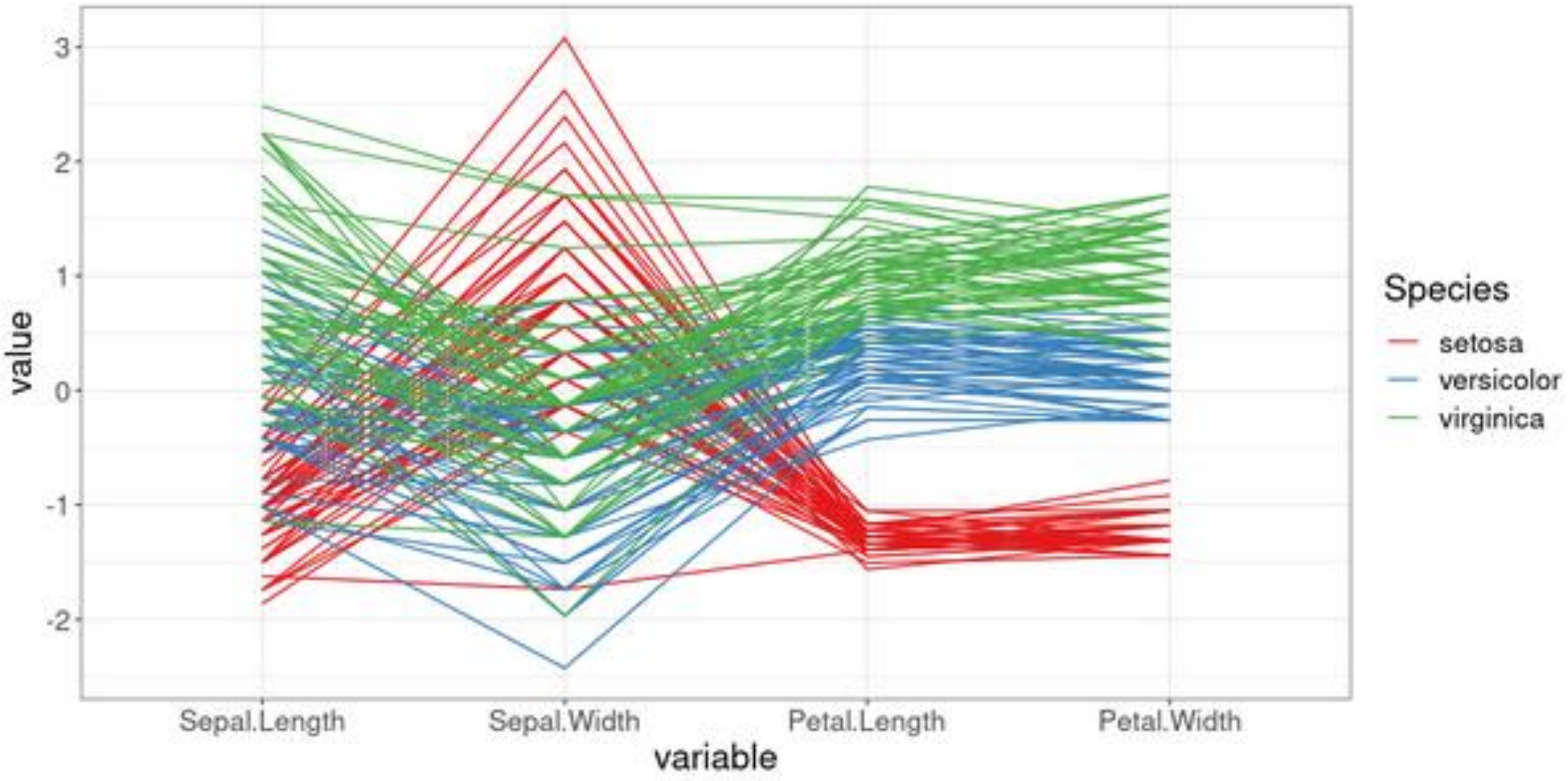
[1] D.A. Keim, M.C. Hao, U. Dayal, H. Janetzko, and P. Bak, 2010, Generalized scatter plots, Information Visualization, v. 9, n. 4, p. 301–311.

Advanced Scatter Matrix plot with a class label



[1] D.A. Keim, M.C. Hao, U. Dayal, H. Janetzko, and P. Bak, 2010, Generalized scatter plots, Information Visualization, v. 9, n. 4, p. 301–311.

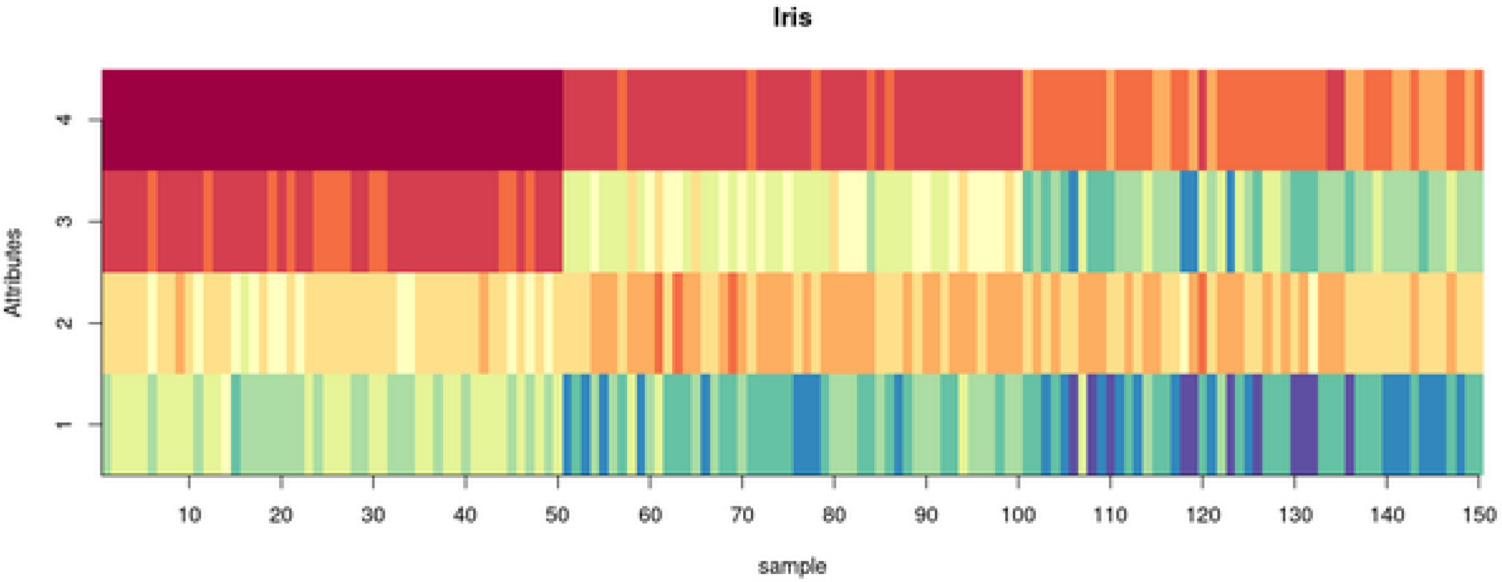
Parallel Coordinates of a Data Set



[1] A. Inselberg and B. Dimsdale, 1990, Parallel coordinates: A tool for visualizing multi-dimensional geometry, In: *IEEE Conference on Visualization - Visualization '90*, p. 361–378

Pixel-Oriented Visualization Techniques

- For a data set of m dimensions, create m windows on the screen, one for each dimension
- The m dimension values of a record are mapped to m pixels at the corresponding positions in the windows
- The colors of the pixels reflect the corresponding values



[1] D.A. Keim, 2000, Designing pixel-oriented visualization techniques: theory and applications, IEEE Transactions on Visualization and Computer Graphics, v. 6, n. 1, p. 59–78.

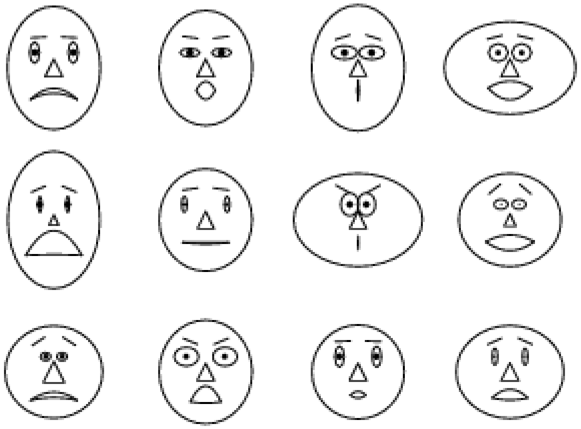
Icon-Based Visualization Techniques

- Visualization of the data values as features of icons
- Typical visualization methods
  - Chernoff faces
  - Salience
- General techniques
  - Shape coding: Use shape to represent certain information encoding
  - Color icons: Use color icons to encode more information
  - Tile bars: Use small icons to represent the relevant feature vectors in document retrieval

[1] J. Han, J. Pei, and H. Tong, Data Mining: Concepts and Techniques, 4th edition. Cambridge, MA: Morgan Kaufmann, 2022.

Chernoff Faces

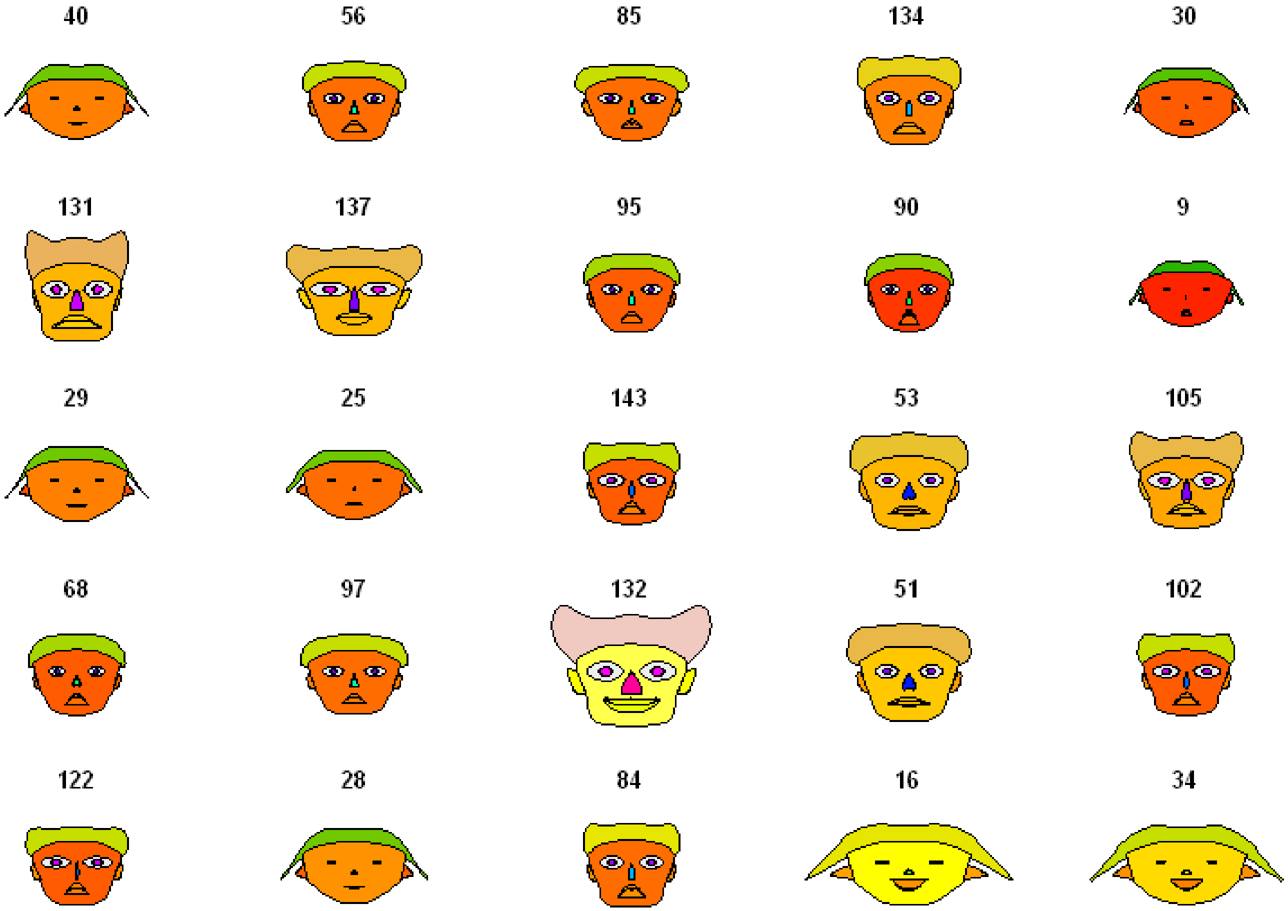
- A way to display variables on a two-dimensional surface
  - Let x be eyebrow slant, y be eye size, z be nose length
- The figure shows faces produced using ten characteristics: head eccentricity, eye size, eye spacing, eye eccentricity, pupil size, eyebrow slant, nose size, mouth shape, mouth size, and mouth opening):
  - Each assigned one of 10 possible values



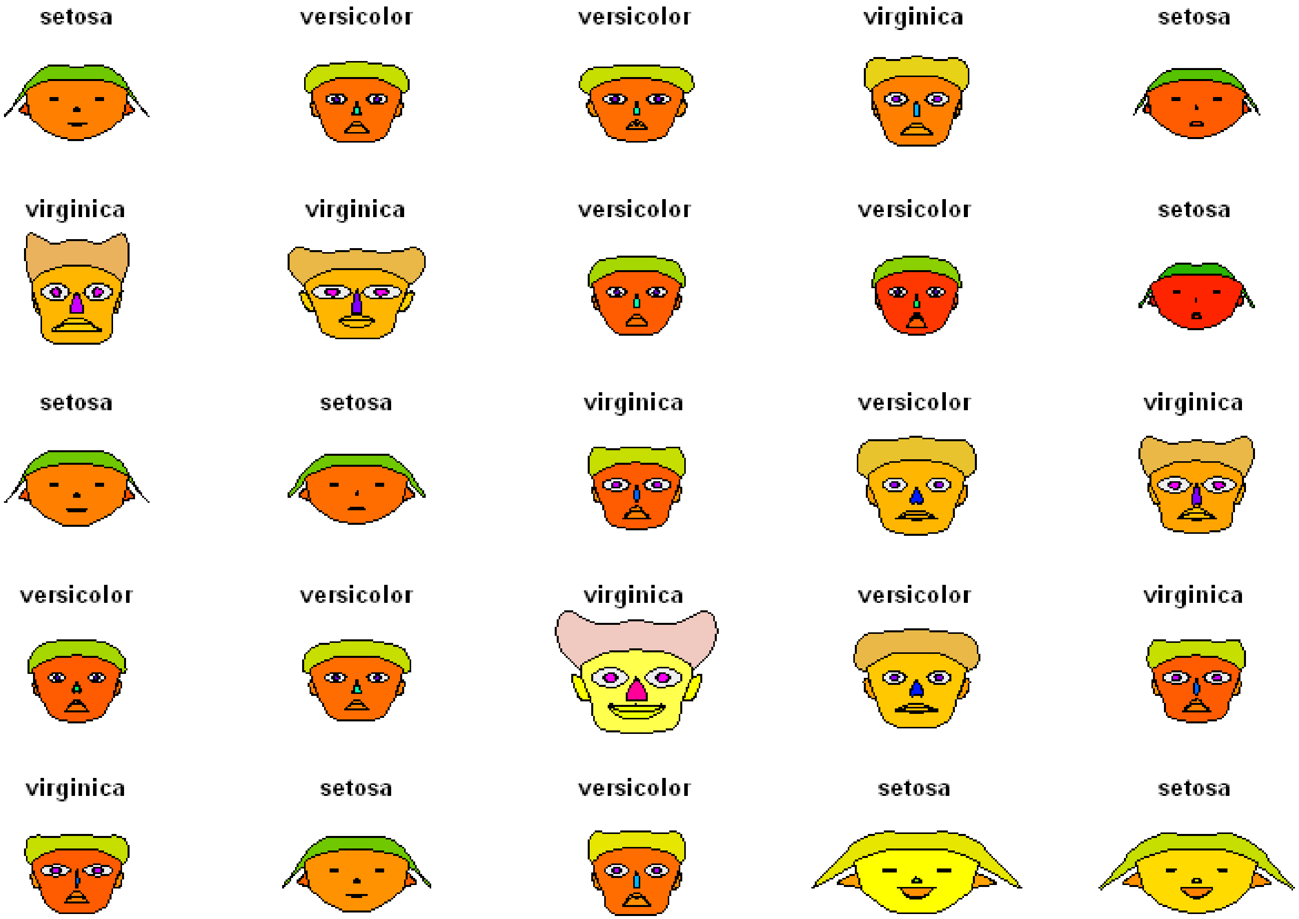
Gonick, L. and Smith, W. The Cartoon Guide to Statistics. New York: Harper Perennial, p. 212, 1993

Weisstein, Eric W. "Chernoff Face." From MathWorld -A Wolfram Web Resource. mathworld.wolfram.com/ChernoffFace.html

Chernoff Faces example with the Iris dataset
Can you see any pattern?

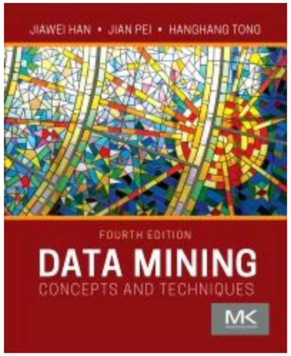


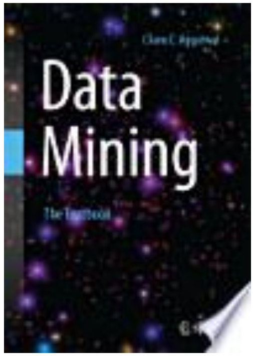
Chernoff Faces example with the Iris dataset (displaying class label)

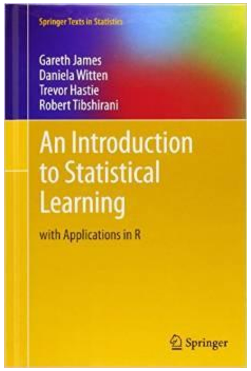


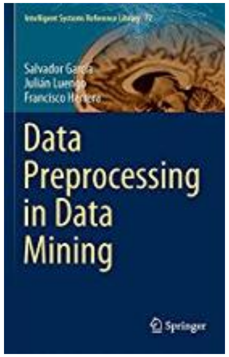
Main References

Código: https://github.com/eogasawara/analise-dados/blob/main/examples/4-ExploratoryAnalysis.md








Intelligent Systems Reference Library 72
Salvador García
Julián Luengo
Francisco Herrera
Data Preprocessing in Data Mining
Springer

Slides e vídeos em: https://eic.cefet-rj.br/~eogasawara/analise-de-dados

Further readings

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