CEFET/RJ

Exploratory Analysis

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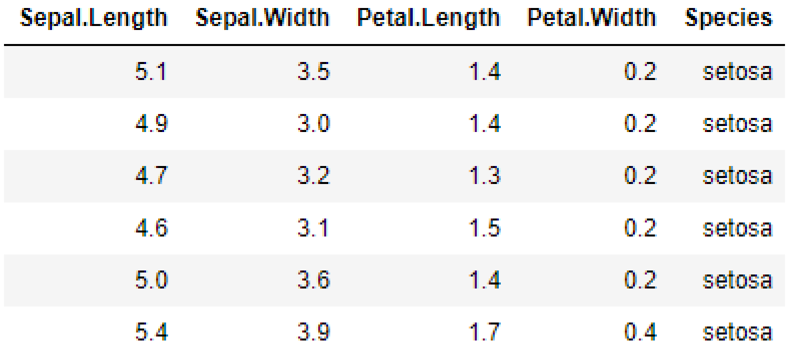
Goals of Exploratory Data Analysis (EDA)

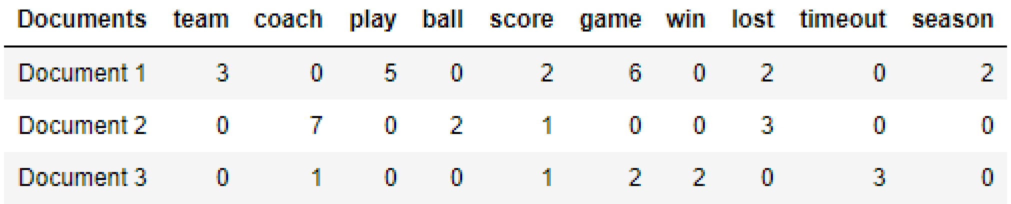
- Understand the structure and quality of the data
- Identify patterns, anomalies, and outliers
- Reveal relationships between variables
- Support decisions about:
- Preprocessing (e.g., normalization)
- Feature selection
- Model choice
- 📌 EDA helps you make sense of your data before modeling begins

Types of Data Sets

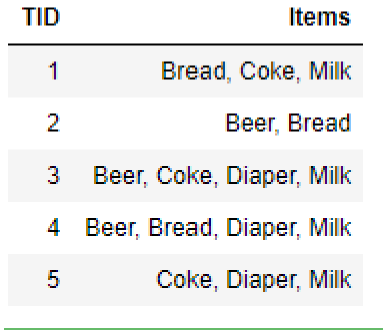
- Record
  - Relational datasets
- Matrix
  - numerical matrix, crosstabs
- Documents
  - texts, term-frequency vector
- Transactions
- Graph and network
  - World Wide Web
  - Social or information networks
- Ordered
  - Temporal data: time-series
  - Sequential data: transaction sequences
- Spatial,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



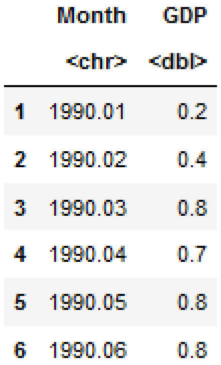
Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
5.1	3.5	1.4	0.2	setosa
4.9	3.0	1.4	0.2	setosa
4.7	3.2	1.3	0.2	setosa
4.6	3.1	1.5	0.2	setosa
5.0	3.6	1.4	0.2	setosa
5.4	3.9	1.7	0.4	setosa



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

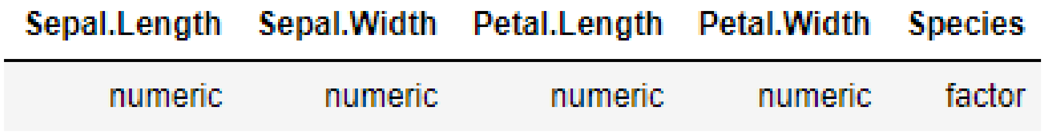
[1] J. Han, J. Pei, and H. Tong, Data Mining: Concepts and Techniques, 4th edition. Cambridge, MA: Morgan Kaufmann, 2022.

Why Attribute Types Matter

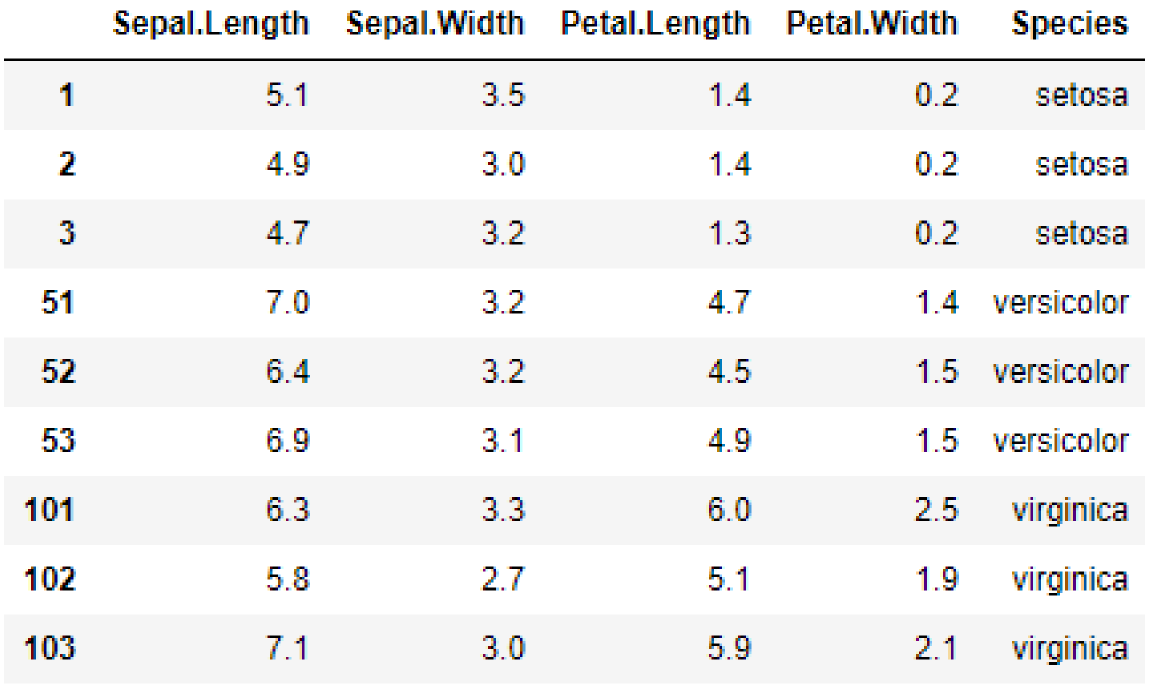
- Affects:
  - Which distance measures can be used (e.g., Euclidean vs. Hamming)
  - Which statistical summaries are valid
  - What kind of encoding or transformation is needed
- Example:
  - You wouldn’t calculate a mean for hair color (nominal)
  - You may normalize a weight (continuous numeric), but not a ZIP code
- 📌 Understanding attribute types helps prevent misuse of techniques

Iris Dataset

- The Iris dataset is a classic example in data science, used for classification tasks. It contains measurements of three species of Iris flowers across four features: sepal length, sepal width, petal length, and petal width



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



	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
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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

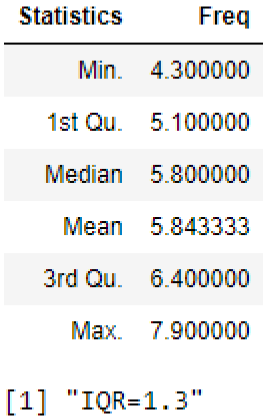
- Descriptive measures provide key statistical summaries of data, including central tendency and dispersion. These form the basis for many EDA techniques
- Central tendency
  - Mean (algebraic measure)
    - $\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$
  - Median
    - Middle value if an odd number of values, 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)
      - $\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n} = \frac{\sum_{i=1}^{n} {x_i}^2}{n} - \mu^2$
- Shape: skewness, kurtosis
- These measures allow for quick comparison across variables and help detect anomalies

[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

Sepal.length



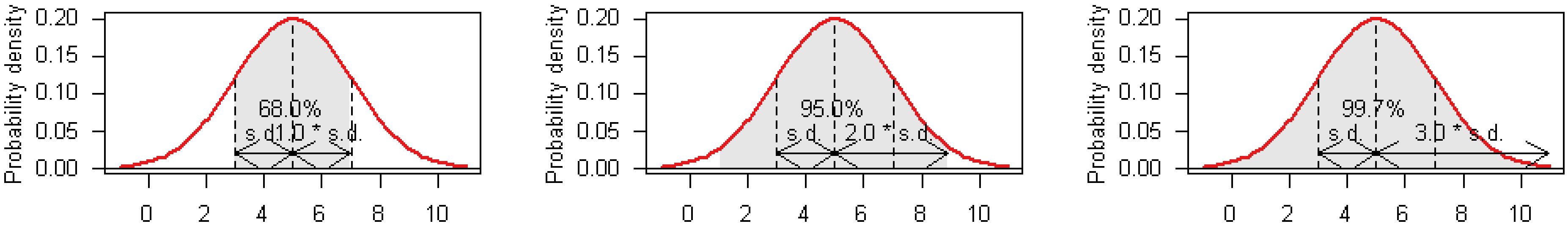
Statistics	Freq
Min.	4.300000
1st Qu.	5.100000
Median	5.800000
Mean	5.843333
3rd Qu.	6.400000
Max.	7.900000

```
[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 is symmetric, bell-shaped, and centered around its mean
- This reference shape is used to evaluate whether real-world data is normally distributed, which impacts statistical method assumptions
- 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.

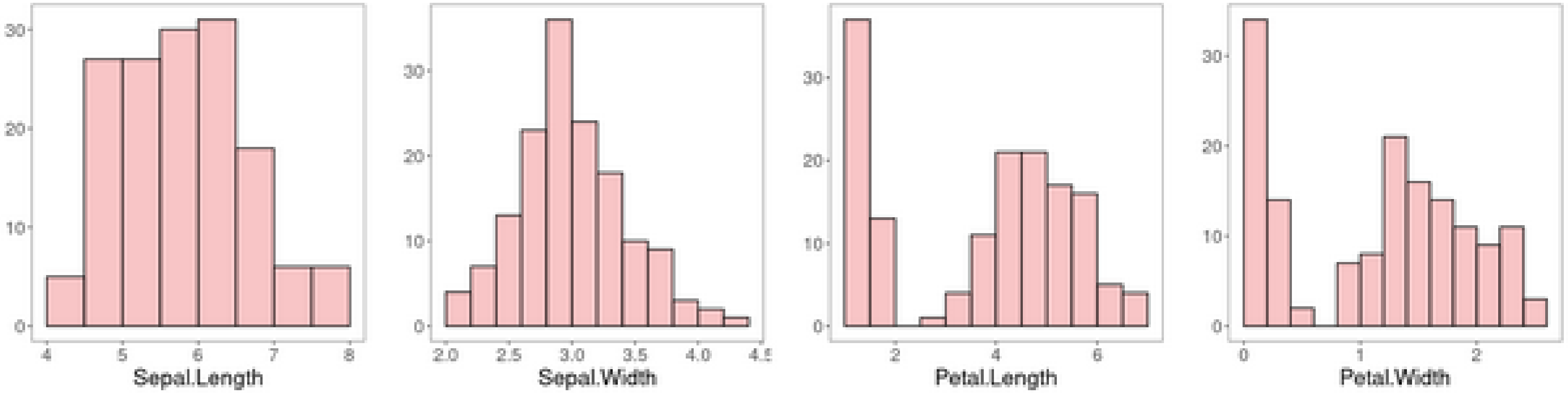
Graphic Displays of Basic Statistical Descriptions

- These graphics provide visual summaries of data distribution:
  - Histogram
  - Boxplot
  - Density distribution
- They are essential tools in exploratory data analysis for revealing shape, spread, and potential outliers

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

Histogram Analysis

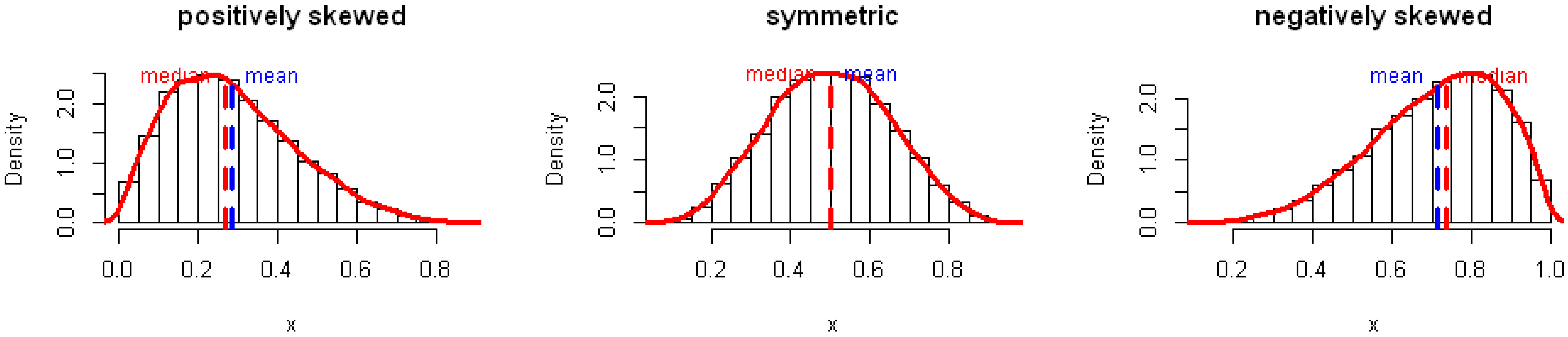
- The histogram displays values of tabulated frequencies
- It shows what proportion of cases into each category
- The area of the bar that denotes the value
  - It is a crucial property when the categories are not of uniform width
- The categories specify non-overlapping intervals of some variable
-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

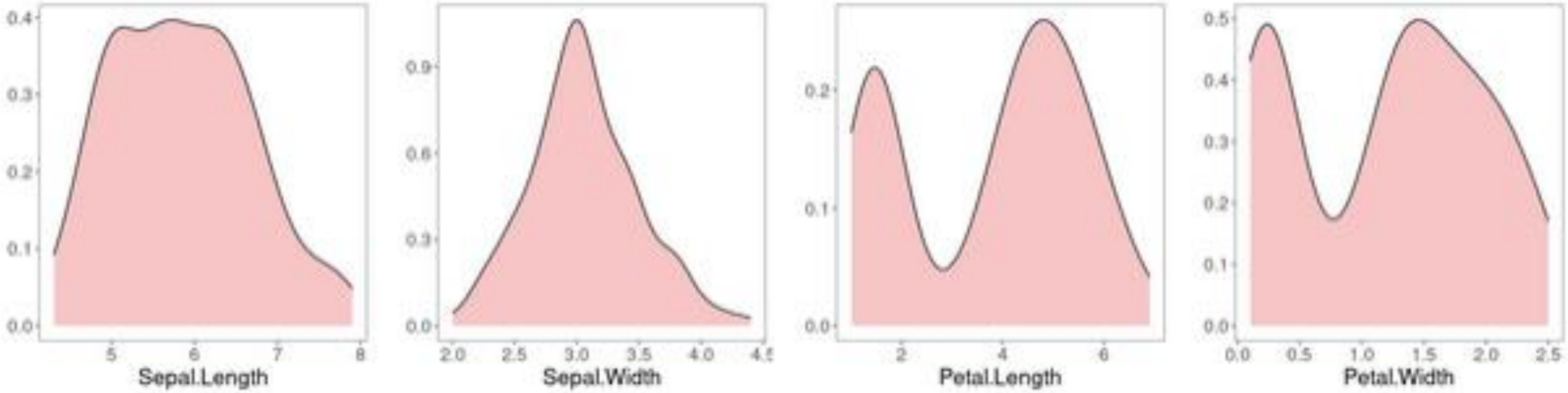
- Median and mean for:
  - positive, symmetric, and negatively skewed data



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

Probability Density

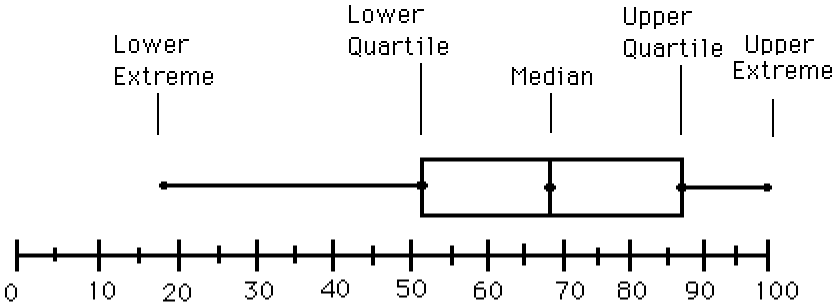
- Computes and draws kernel density estimate, which is a smoothed version of the histogram. This is a useful alternative to the histogram for continuous data that comes from an underlying smooth distribution.



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

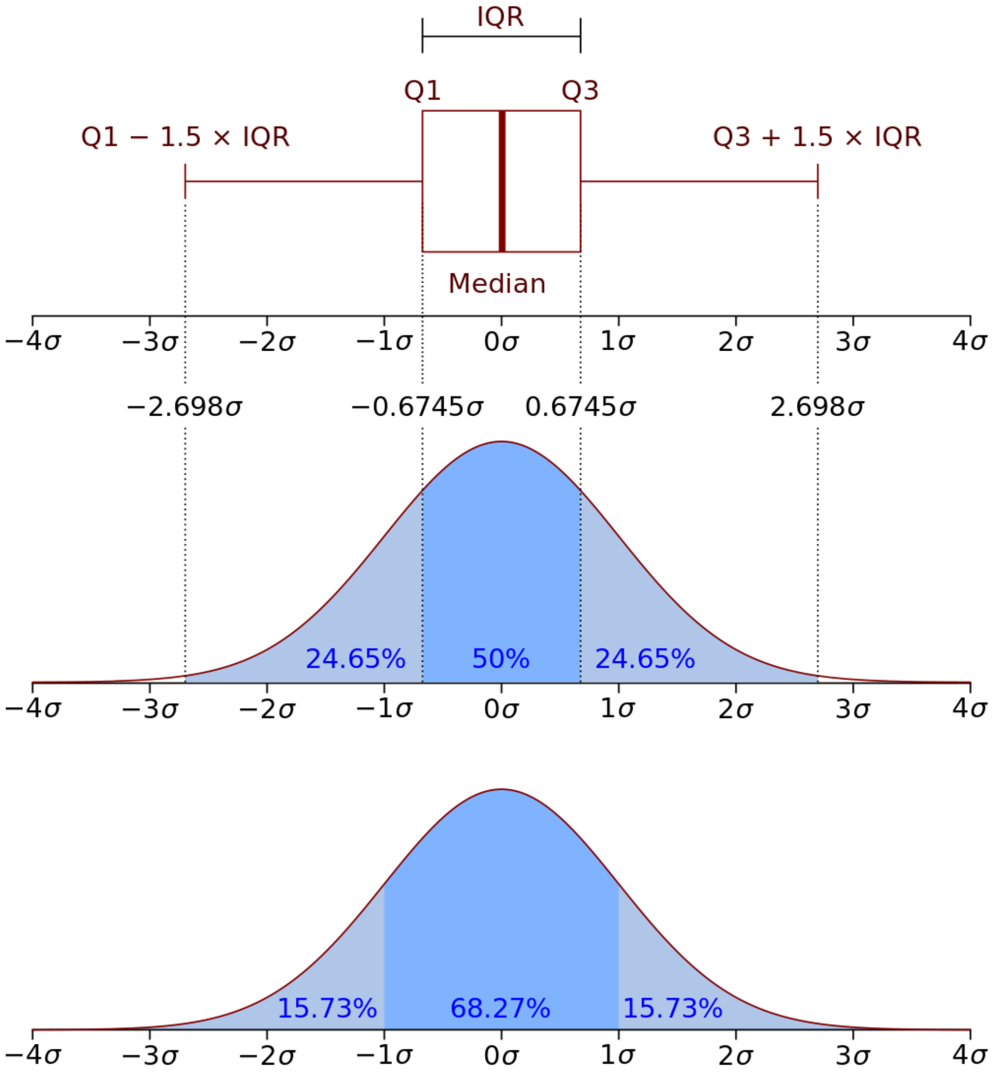
Boxplot Analysis

- 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 or 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.

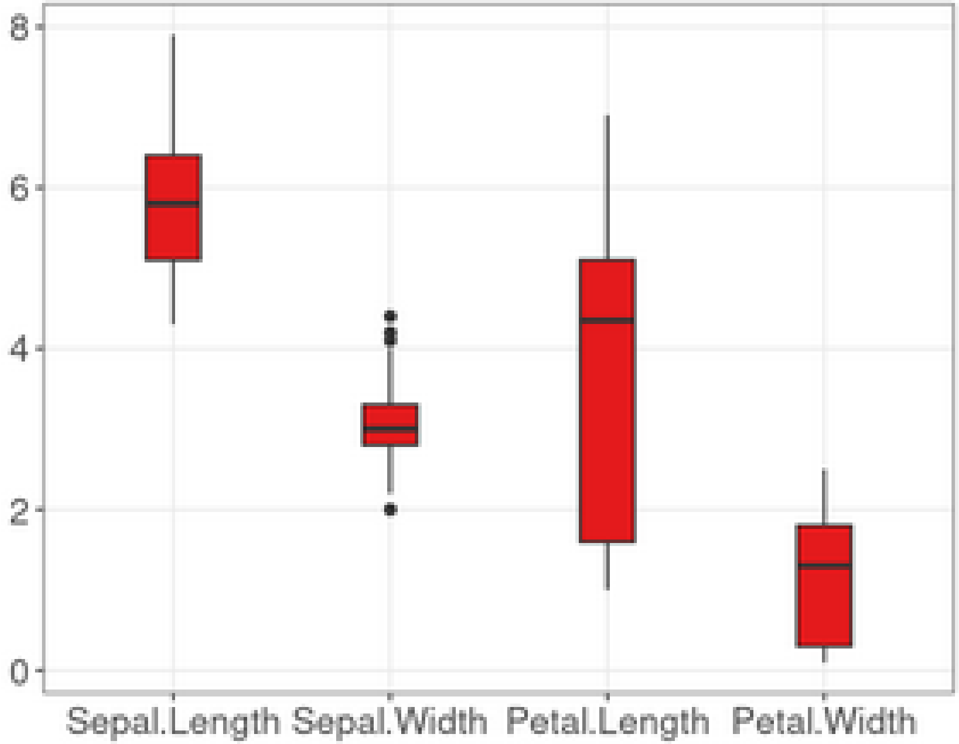
Outliers in Boxplot



[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

- Boxplots are especially useful for comparing distributions between groups, identifying outliers, and spotting data skewness.
- They are widely used in both EDA and reporting

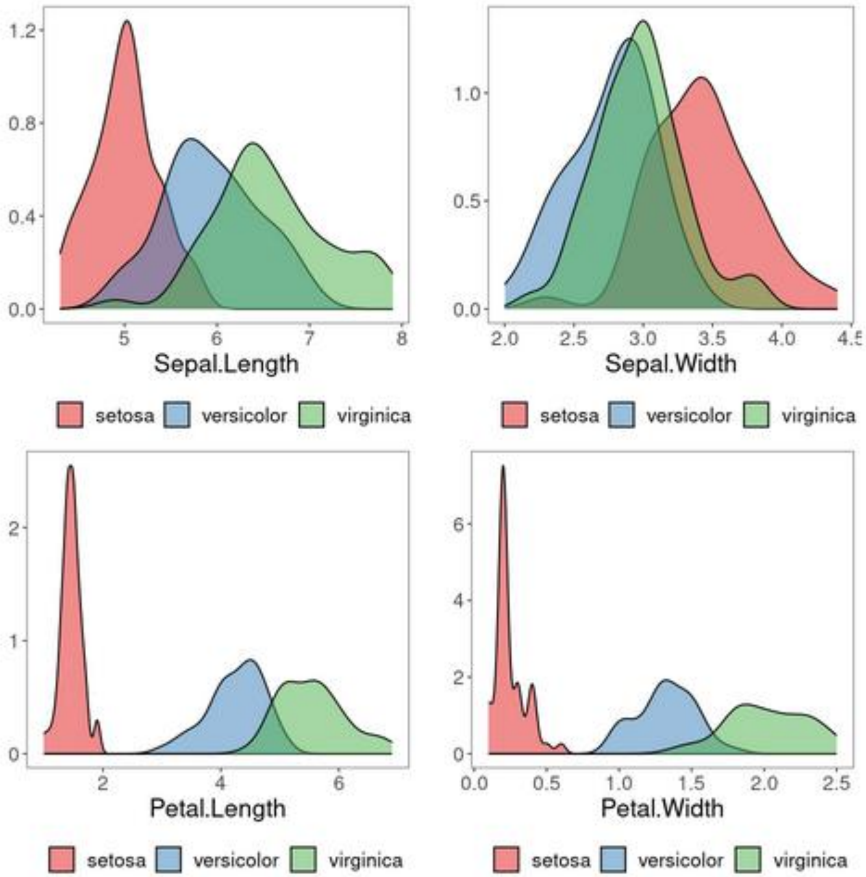


[1] K.J. Keen, 2018, *Graphics for Statistics and Data Analysis with R*. CRC Press.

Exploratory analysis for Classification problem

Density distributions with class label

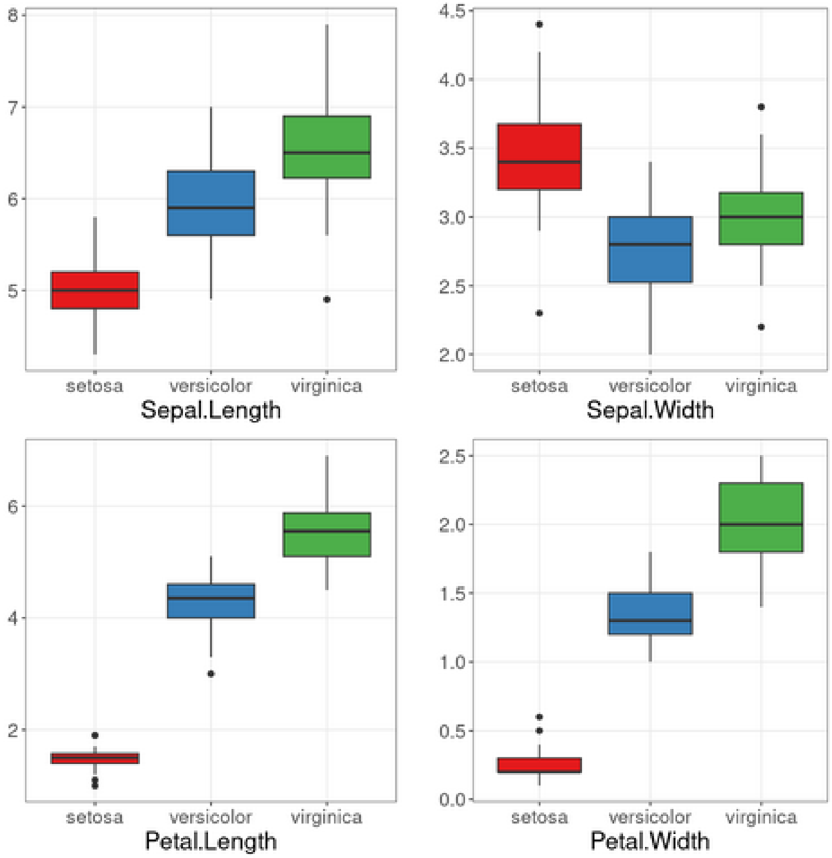
- Density plots show the probability distribution of a variable. When paired with class labels, they reveal how different classes may overlap or separate in feature space



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

Boxplot with class label

- These boxplots illustrate how the distribution of a numeric variable differs between classes
- It's a useful method to visualize variance and detect potential discriminative power



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

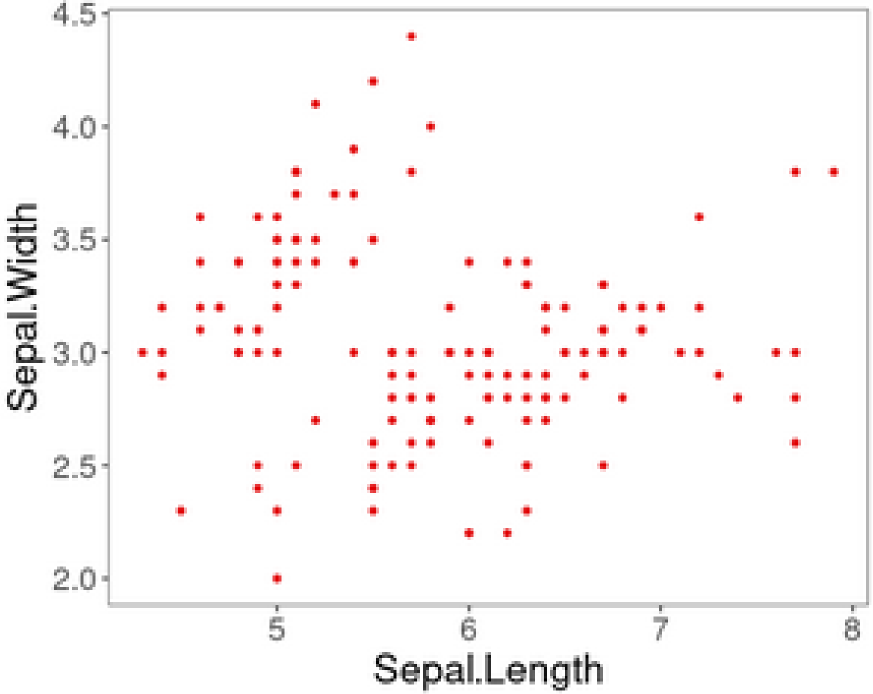
Graphic Displays of Basic Statistical Descriptions

- These visual tools show relationships between pairs of variables:
  - Scatter plot
    - Scatter plots reveal clusters and outliers
  - Correlation analysis
    - Correlation plots quantify the direction and strength of linear relationships
  - Scatter matrix
    - Scatter matrices scale this pairwise comparison to multivariate data

[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.

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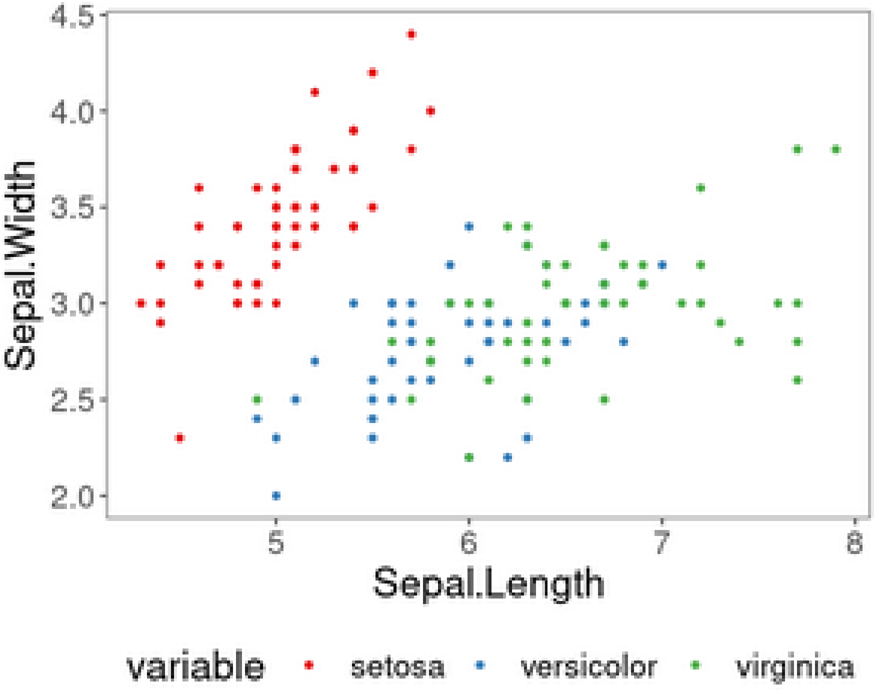
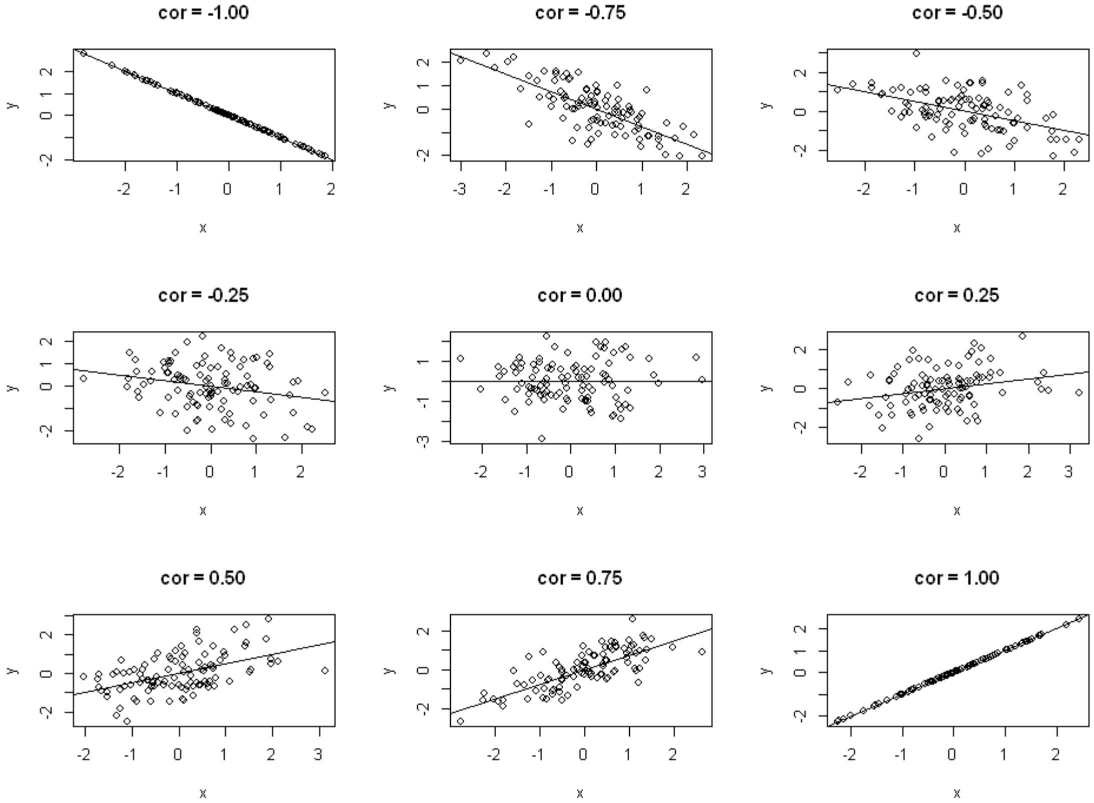


[1] K.J. Keen, 2018, *Graphics for Statistics and Data Analysis with R*. CRC Press.

Data correlation

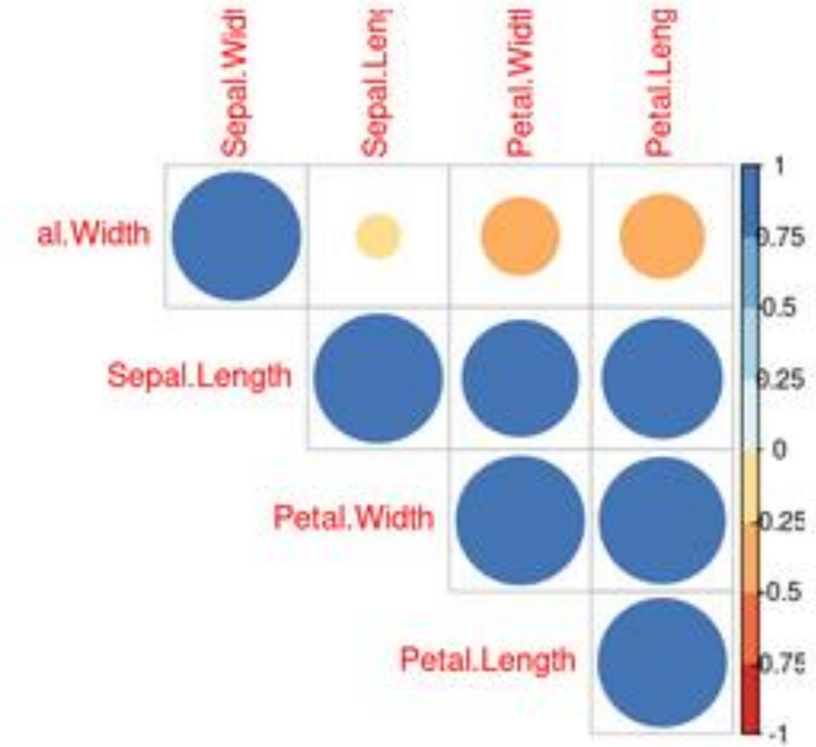
- The first row presents negatively correlated data
- The second row presents uncorrelated data
- The third row presents positively correlated data



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

Correlation analysis

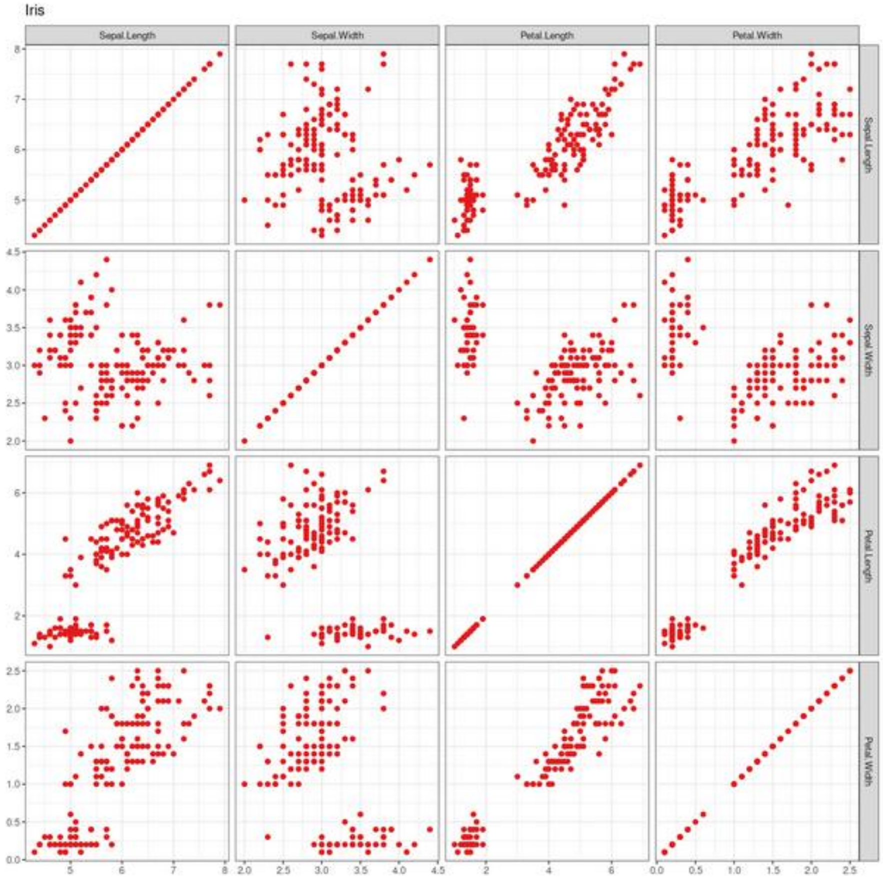
- The correlation plots are used to display the pairwise correlation among all numerical attributes of a dataset



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

Scatter Matrix plot

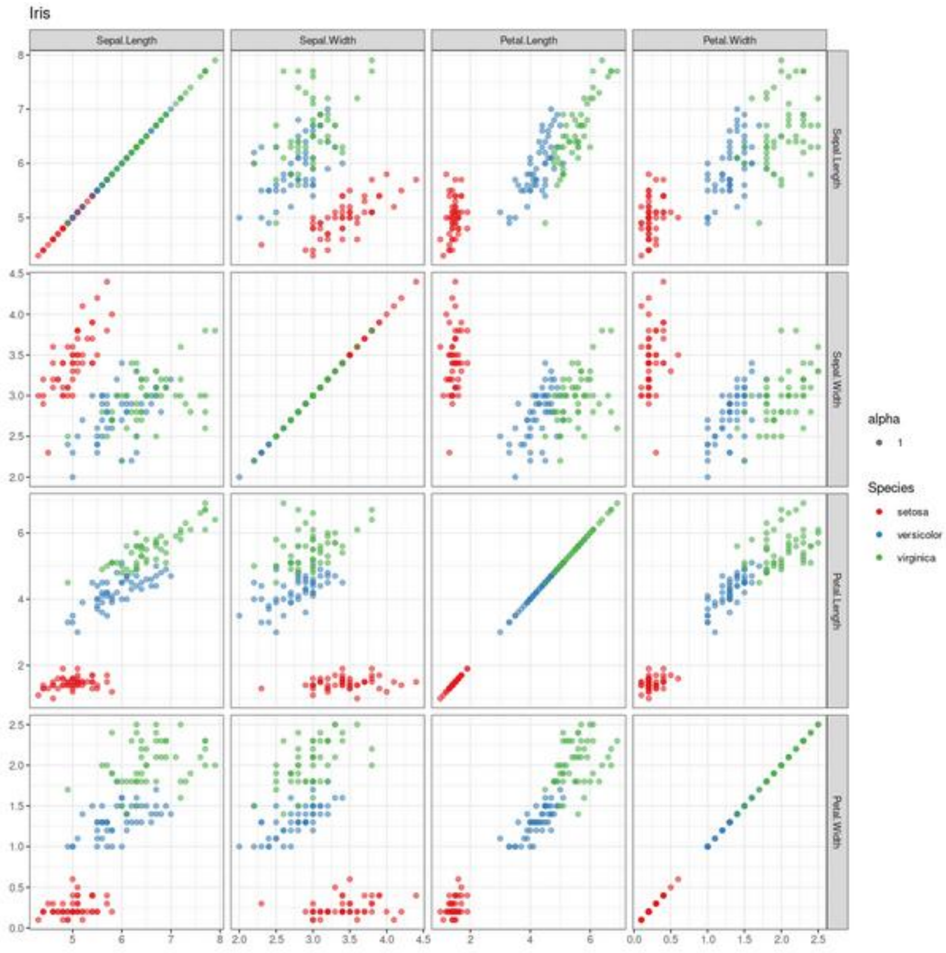
- A scatter matrix is a grid of scatterplots for each pair of variables
- It is useful for spotting correlations and grouping tendencies among multiple features



[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

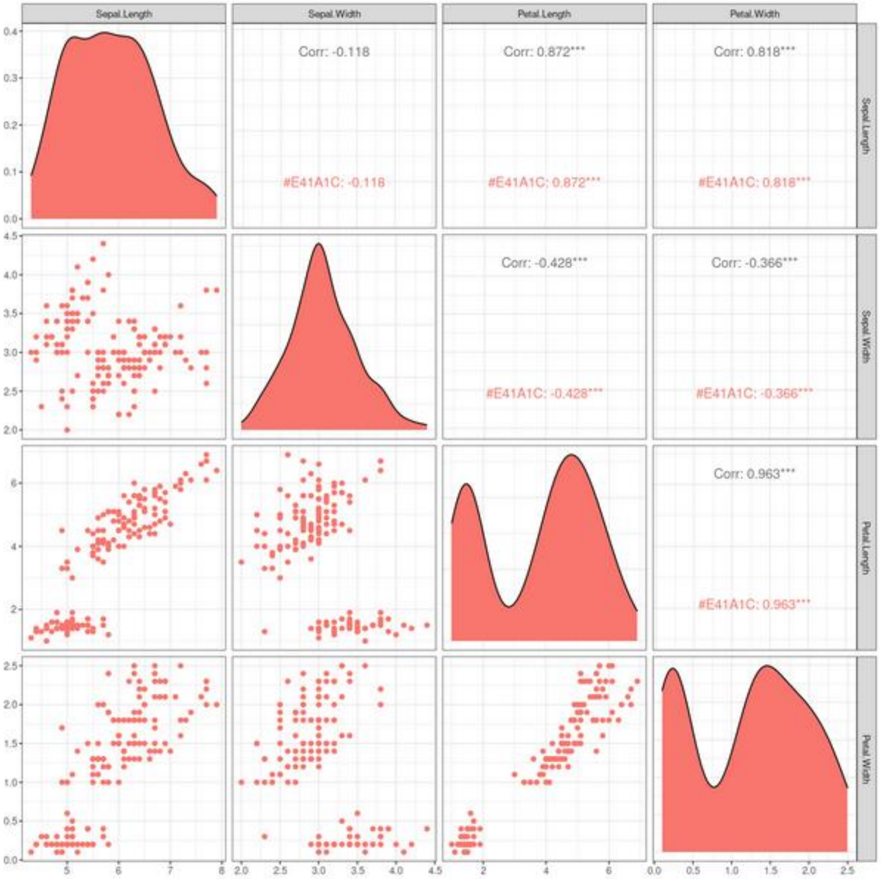
- By adding class labels to a scatter matrix, we can assess how well the classes are separated across different feature combinations



[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

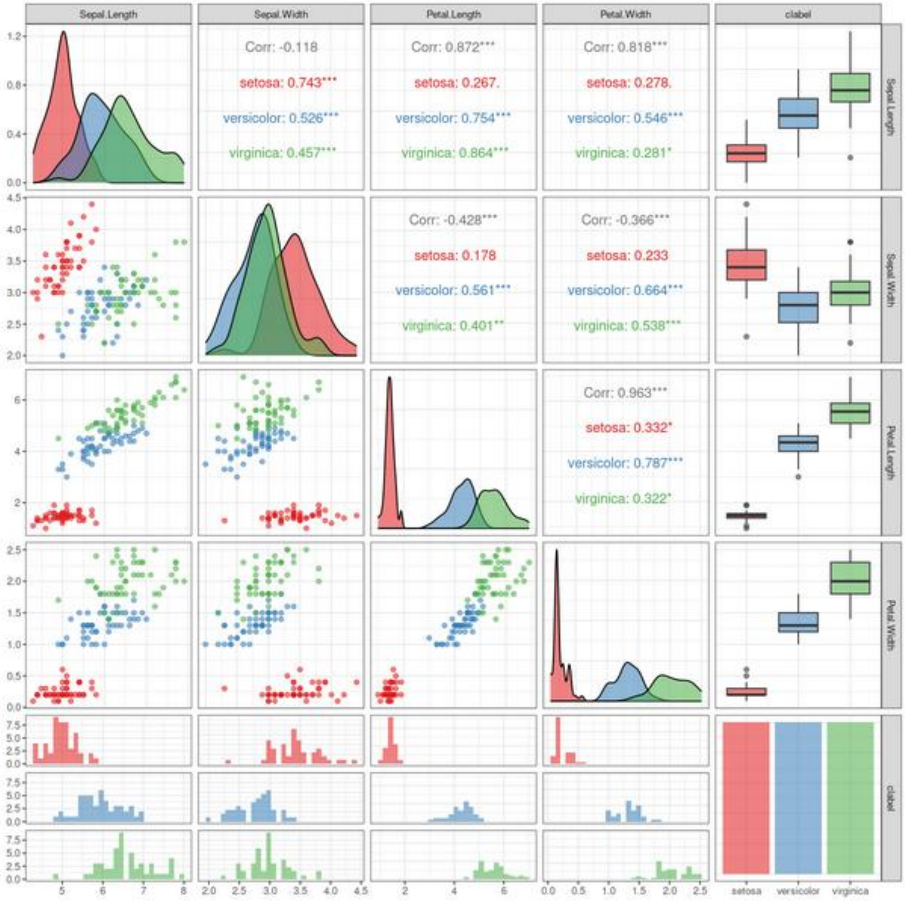
- This version of a scatter matrix includes enhancements such as density overlays or smoothed patterns to better reveal underlying structure in multidimensional data



[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

- A more expressive scatter matrix plot where class labels help identify clusters and improve pattern recognition across variables



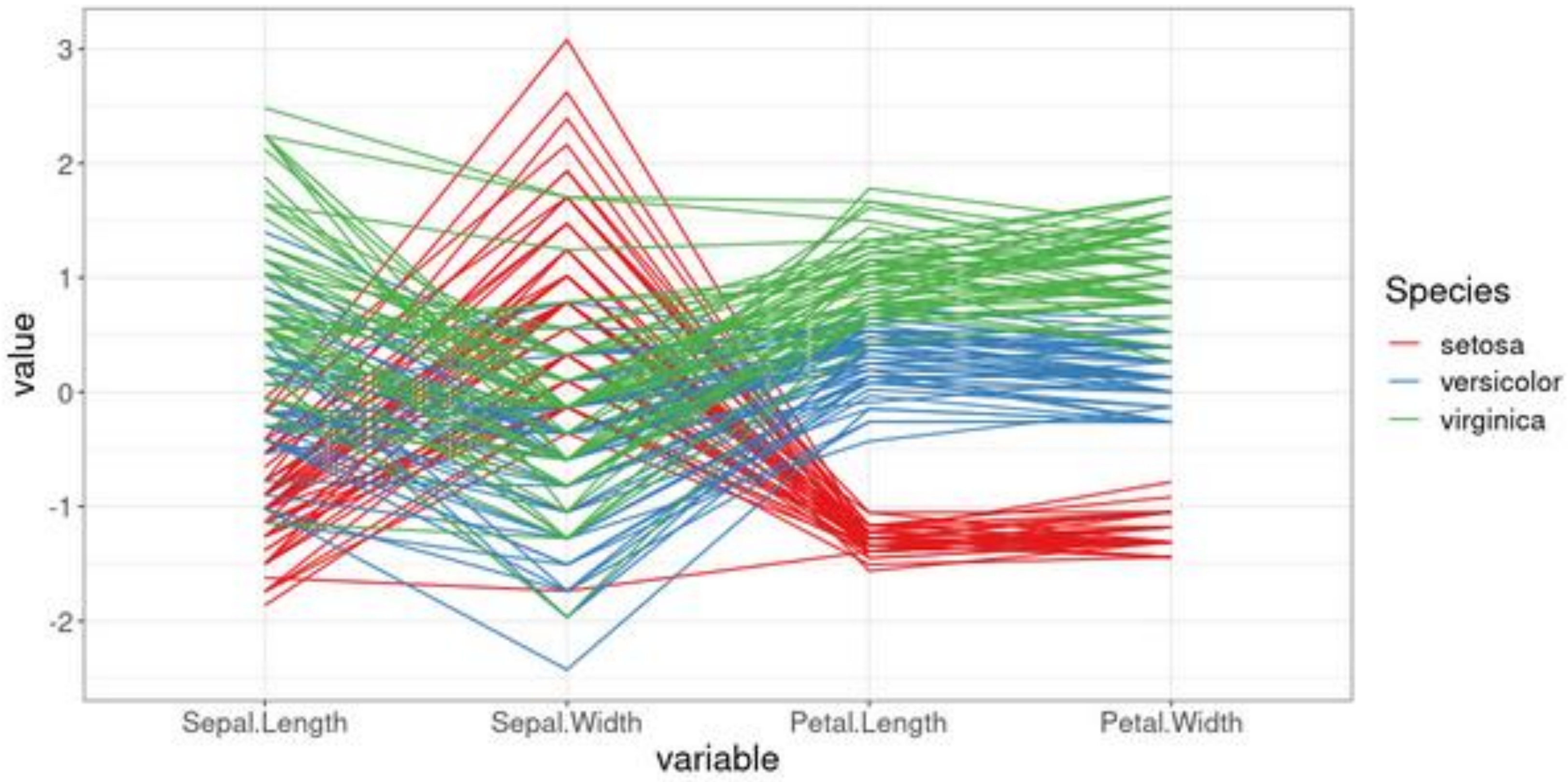
[1] D.A. Keim, M.C. Hao, U. Dayal, H. Janetzko, and P. Bak, 2010, Generalized scatter plots, Information Visualization, v. 9, n. 4, p. 301–311.

EDA and Data Preprocessing

- EDA informs preprocessing steps:
  - Missing value handling
  - Outlier removal
  - Scaling (e.g., standardization)
- Guides:
  - Which features may need encoding or transformation
  - Whether data is ready for modeling
  - 📌 EDA is not isolated—it feeds directly into building better models

Parallel Coordinates of a Data Set

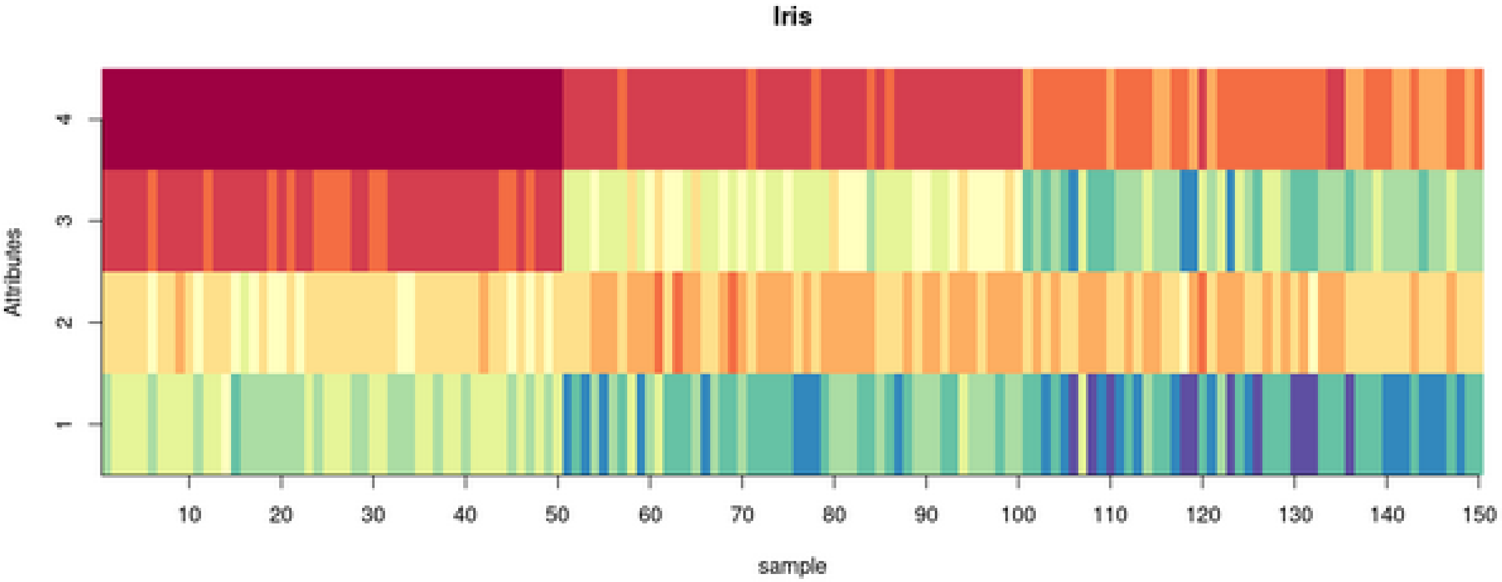
- Parallel coordinates allow the visualization of multivariate data by mapping each variable to a vertical axis. Lines connecting points help identify patterns across dimensions



[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

- Pixel-oriented techniques represent each data point as a colored pixel in small multiples, allowing visualization of very large, high-dimensional datasets efficiently
  - 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.

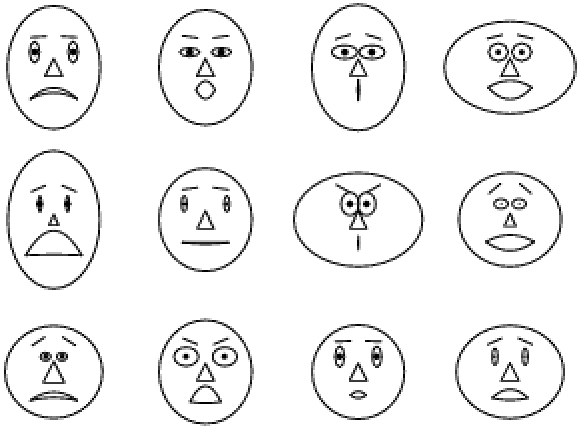
Icon-Based Visualization Techniques

- Icon-based methods use symbolic representations to encode multiple variables visually
- They offer intuitive pattern recognition in complex data
- 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

- Chernoff faces assign variable values to facial features. This metaphor makes it easier for humans to detect similarities or anomalies across high-dimensional data
- 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

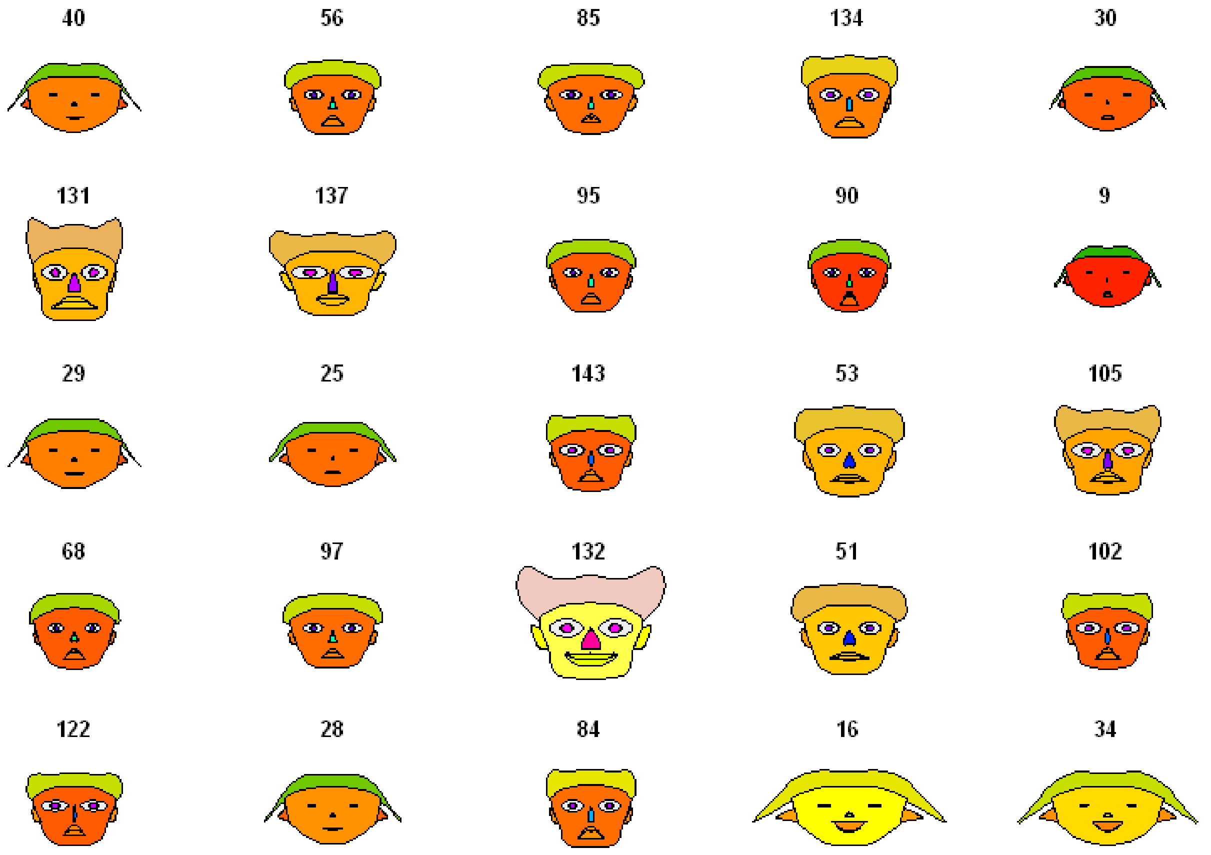


Gonick, L. and Smith, W. The Cartoon Guide to Statistics. New York: Harper Perennial, p. 212, 1993

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

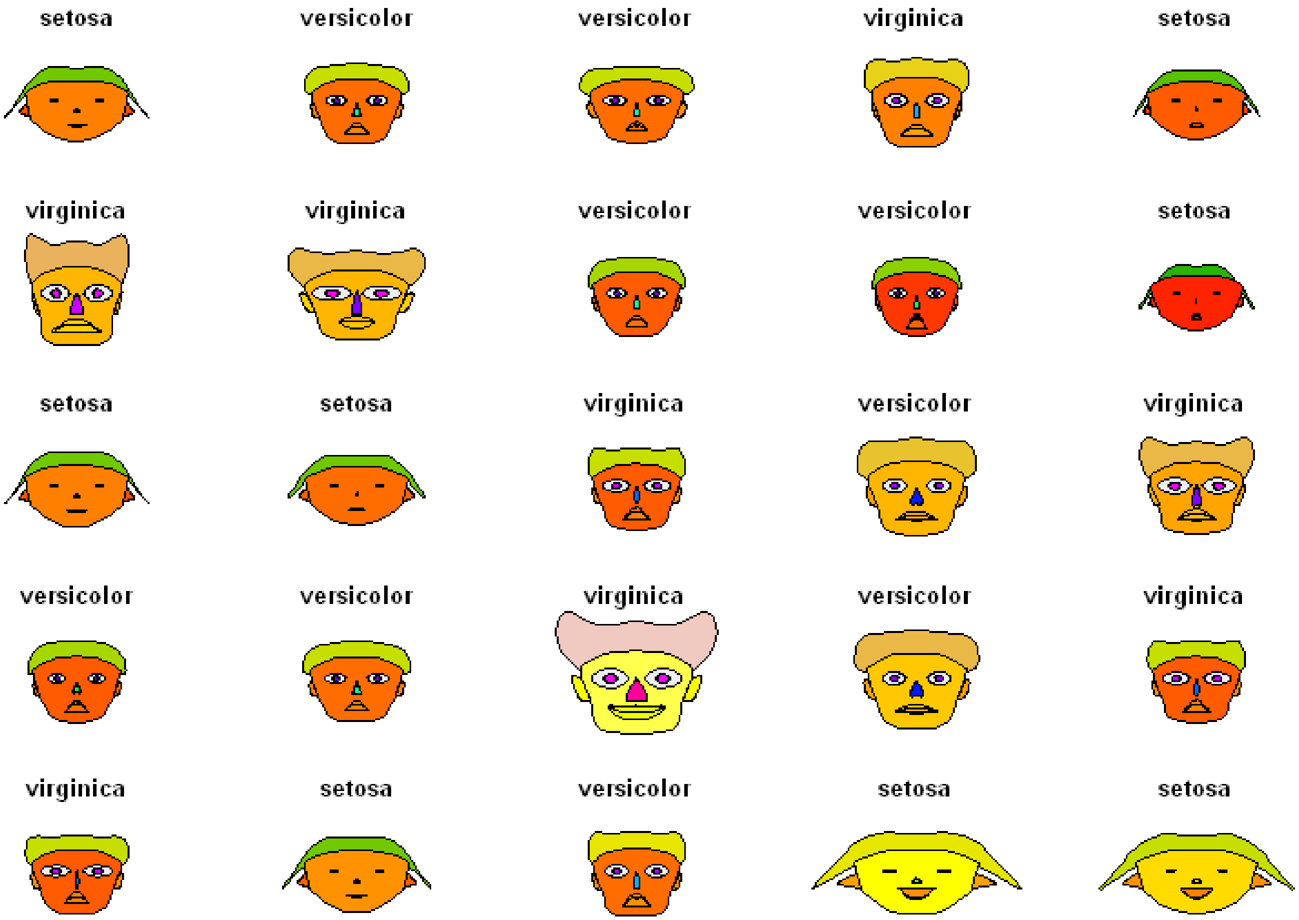
Chernoff Faces example with the Iris dataset

- This visualization maps multiple variables to facial features
- Groupings in facial expressions may reflect similarities in multivariate data

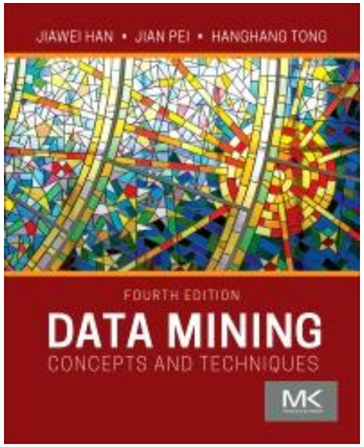


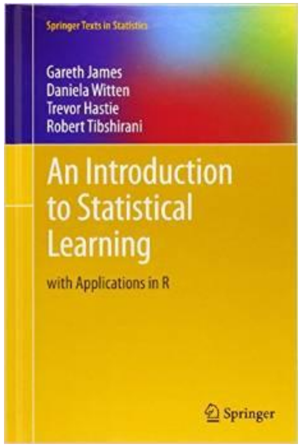
Chernoff Faces example with the Iris dataset (displaying class label)

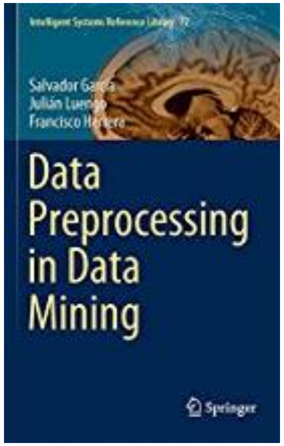
- Adding class labels helps validate whether visual patterns in Chernoff faces correspond to actual class distinctions in the data



Main References



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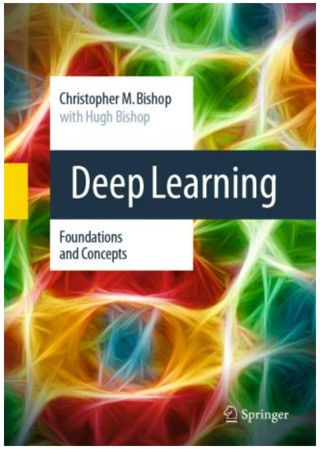

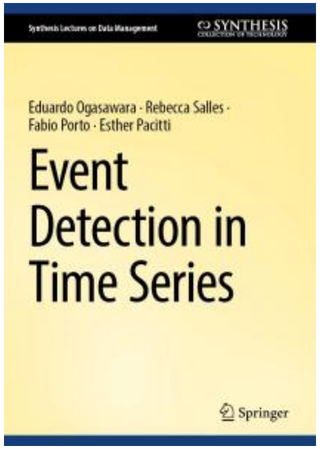
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Slides and videos at: https://eic.cefet-rj.br/~eogasawara/data-mining/