# Introduction to Data Mining

## Web Chapter
## Exploring Data

by Michael Hahsler

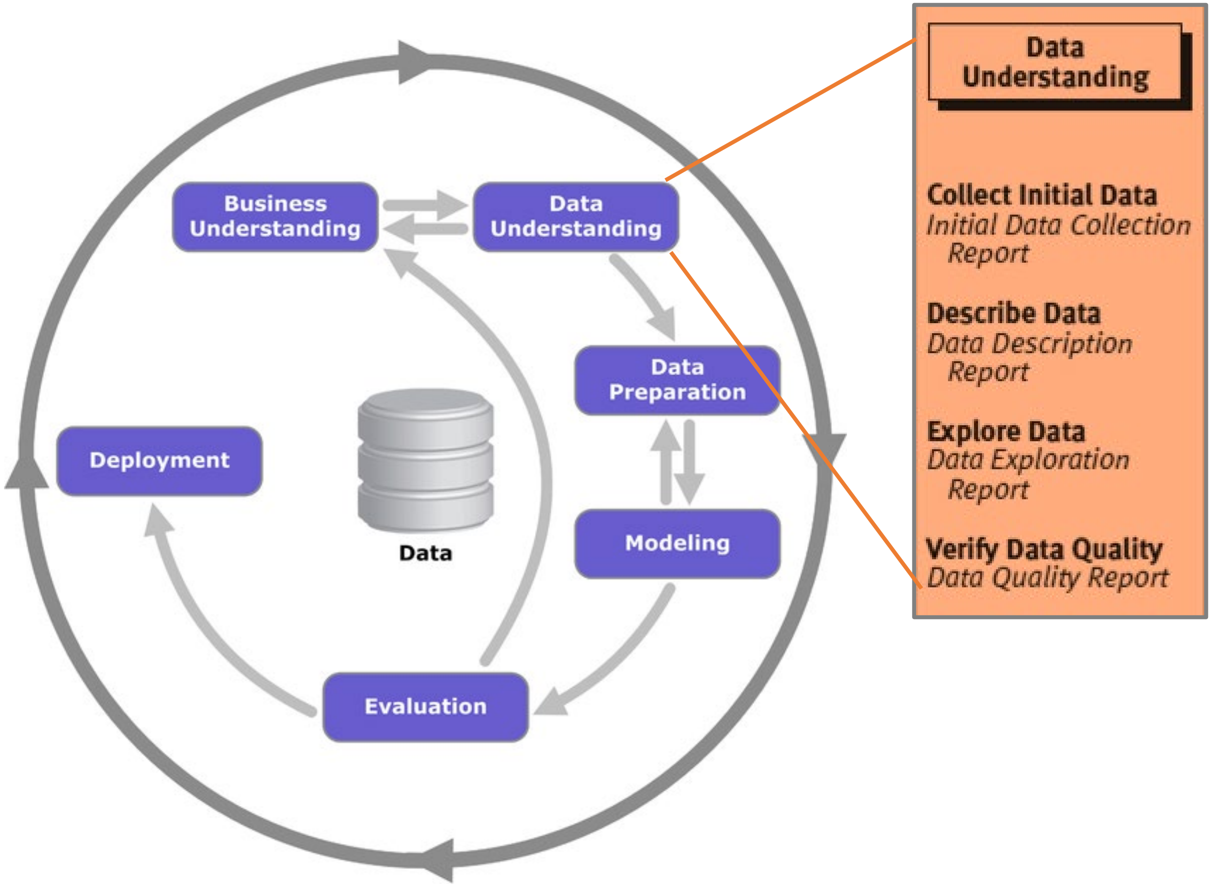
Based in Slides by Tan, Steinbach, Karpatne, Kumar

# R Code Examples

- Available R Code examples are indicated on slides by the R logo

- The Examples are available at https://mhahsler.github.io/Introduction_to_Data_Mining_R_Examples/

# Exploring Data in the Data Mining Process



**Data Understanding**

**Collect Initial Data**
*Initial Data Collection Report*

**Describe Data**
*Data Description Report*

**Explore Data**
*Data Exploration Report*

**Verify Data Quality**
*Data Quality Report*

# Topics

- **Exploratory Data Analysis**
- Summary Statistics
- Visualization

# What is Data Exploration?

**“A preliminary exploration of the data to better understand its characteristics.”**

- Key motivations of data exploration include
  - Helping to select the right tool for preprocessing or analysis
  - Making use of humans’ abilities to recognize patterns. People can recognize patterns not captured by data analysis tools

- Related to the area of Exploratory Data Analysis (EDA)
  - Created by statistician John Tukey
  - Seminal book is "Exploratory Data Analysis" by Tukey
  - A nice online introduction can be found in Chapter 1 of the NIST Engineering Statistics Handbook
  - http://www.itl.nist.gov/div898/handbook/index.htm

# Topics

- Exploratory Data Analysis
- **Summary Statistics**
- Visualization

# Summary Statistics

Summary statistics  are numbers that summarize properties of the data

- Summarized properties include location and spread for continuous data

  Examples:         location - mean
                    spread - standard deviation

- Most summary statistics can be calculated in a single pass through the data

# Frequency and Mode

- The frequency of an attribute value is the percentage of time the value occurs in the
  data set
  - For example, given the attribute ‘gender’ and a representative population of people, the gender ‘female’ occurs about 50% of the time.
- The mode of an attribute is the most frequent attribute value
- The notions of frequency and mode are typically used with **categorical data.**

# Measures of Location: Mean and Median

- For quantitative features.
- The mean is the most common measure of the location of a set of points.
- However, the mean is very sensitive to outliers.
- Thus, the median or a trimmed mean is also commonly used.

$$\text{mean}(x) = \overline{x} = \frac{1}{m}\sum_{i=1}^{m} x_i$$

$$\text{median}(x) = \begin{cases} x_{(r+1)} & \text{if } m \text{ is odd, i.e., } m = 2r+1 \\ \frac{1}{2}(x_{(r)} + x_{(r+1)}) & \text{if } m \text{ is even, i.e., } m = 2r \end{cases}$$

# Measures of Spread: Range and Variance

- Range is the difference between the max and min
- The variance or standard deviation is the most common measure of the spread of a set of points.

$$\text{variance}(x) = s_x^2 = \frac{1}{m-1}\sum_{i=1}^{m}(x_i - \overline{x})^2$$

- However, this is also sensitive to outliers, so that other measures are often used.

$$\text{AAD}(x) = \frac{1}{m}\sum_{i=1}^{m}|x_i - \overline{x}|$$

$$\text{MAD}(x) = median\Big(\{|x_1 - \overline{x}|, \ldots, |x_m - \overline{x}|\}\Big)$$

$$\text{interquartile range}(x) = x_{75\%} - x_{25\%}$$

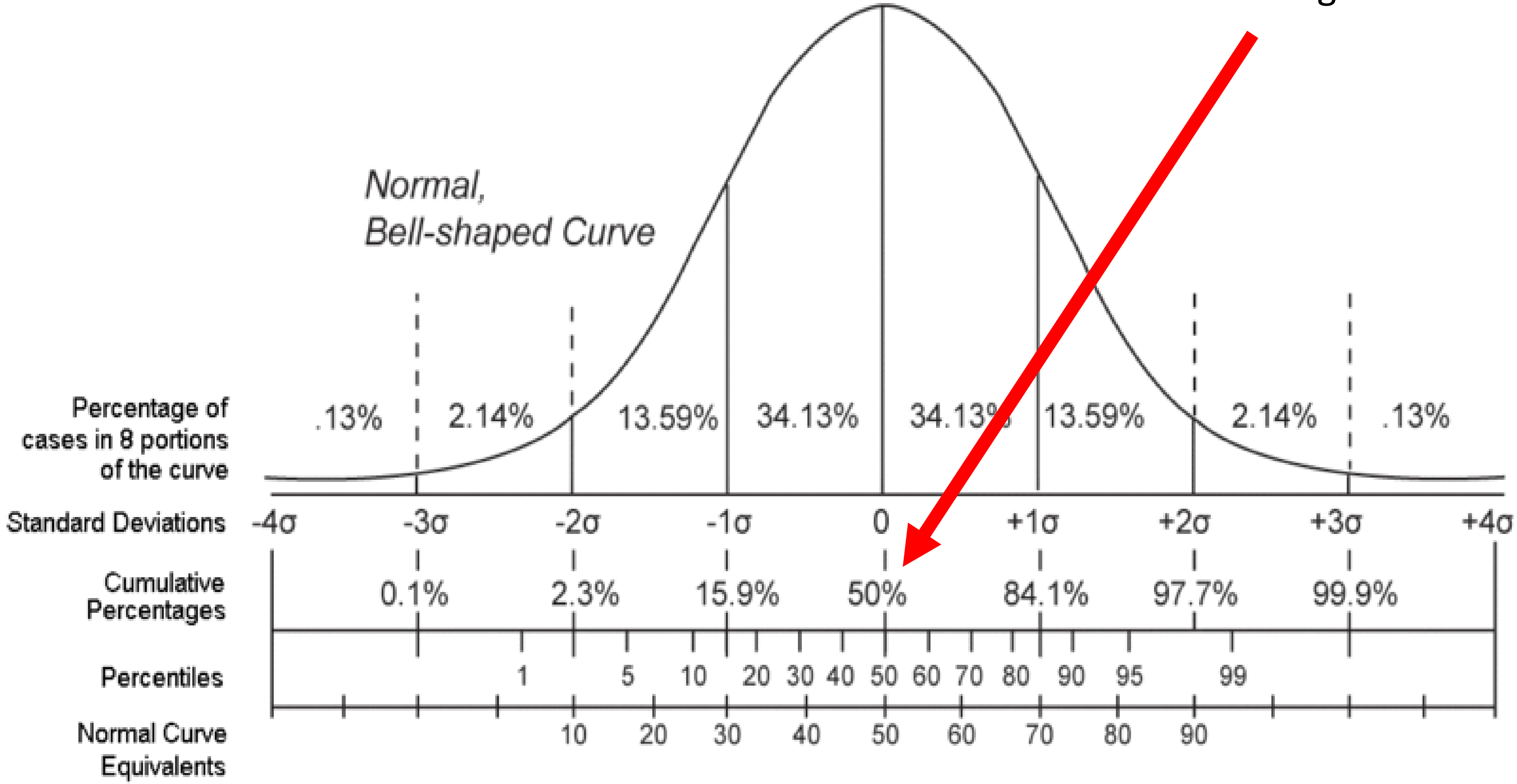
# Percentiles

- Given an ordinal or continuous attribute x and a number p between 0 and 100, the $p^{th}$percentile is a value $x_{p\%}$ of x such that p% of the observed values of x are less than $x_{p\%}$.

- Example: the 50th percentile is the value $x_{50\%}$ such that 50% of all values of x are less than $x_{50\%}$.

# Percentiles

**Median –** 50% of the cases has a smaller value & 50% are larger



# Multivariate Summary Statistics

| Object | $x_1$ | $x_2$ |
|---|---|---|
| 1 | 12 | 15 |
| 2 | 2 | 4 |
| ... | ... | ... |
| m | 18 | 4 |

- Covariance between features i and j

$$s_{ij} = \frac{1}{m-1} \sum_{k=1}^{m} (x_{ki} - \bar{x}_i)(x_{kj} - \bar{x}_j)$$

- Correlation

$$r_{ij} = \frac{s_{ij}}{s_i s_j}$$

- $s_i$ is the variance of feature i

# Topics

- Exploratory Data Analysis
- Summary Statistics
- **Visualization**

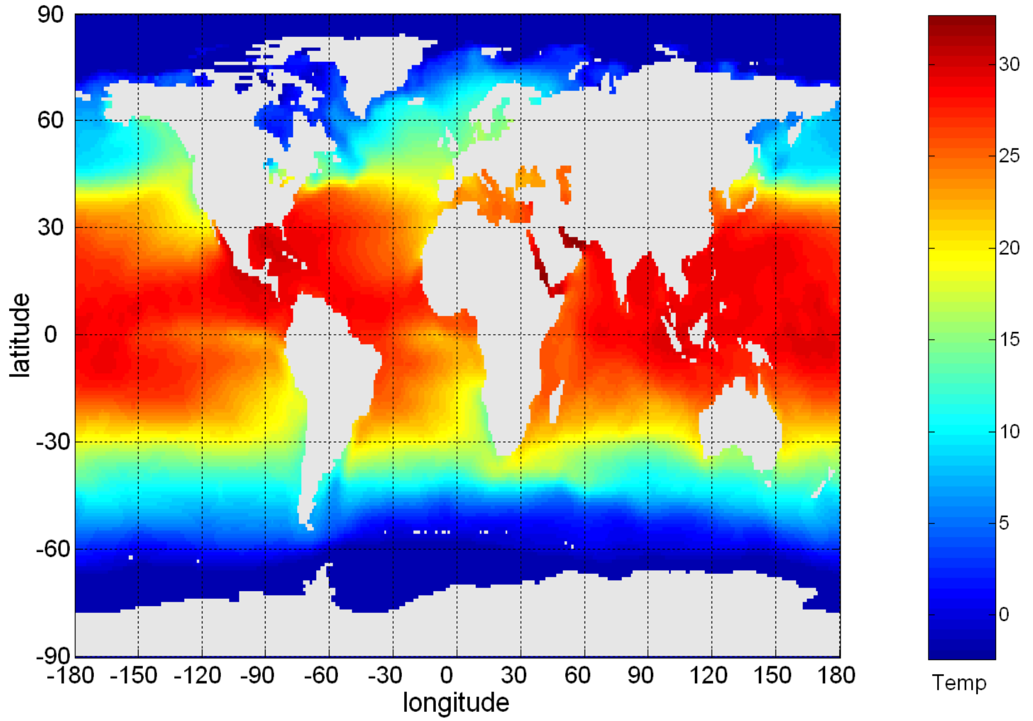
# Visualization

- Visualization is the conversion of data into a visual or tabular format so that the characteristics of the data and the **relationships among data items or attributes** can be analyzed or reported.

- Visualization of data is one of the most powerful and appealing techniques for data exploration.
  - Humans have a well-developed ability to analyze large amounts of information that is presented visually
  - Can detect general patterns and trends
  - Can detect outliers and unusual patterns

# Example: Sea Surface Temperature

- The following shows the Sea Surface Temperature (SST) for July 1982
- Tens of thousands of data points are summarized in a single figure

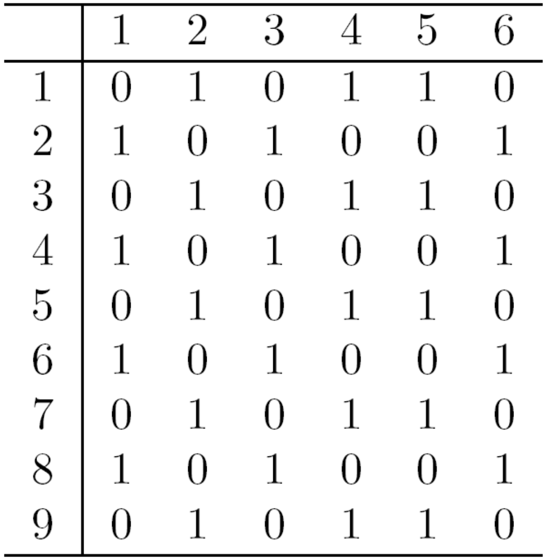


# Representation

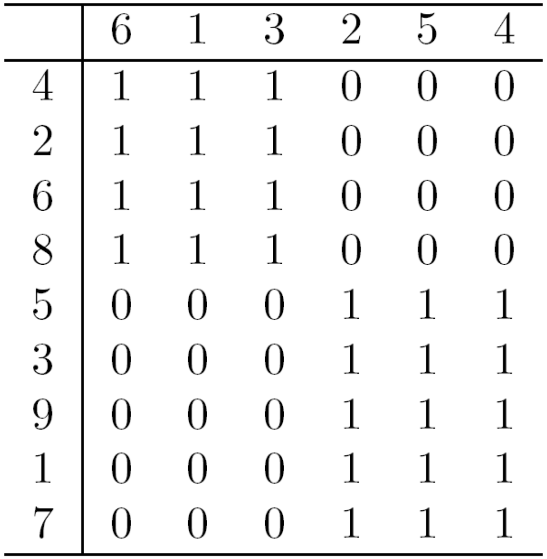
- Is the mapping of information to a visual format
- Data objects, their attributes, and the relationships among data objects are translated into graphical elements such as points, lines, shapes, and colors.
- Example:
  - Objects are often represented as points
  - Their attribute values can be represented as the position of the points or the characteristics of the points, e.g., color, size, and shape
  - If position is used, then the relationships of points, i.e., whether they form groups or a point is an outlier, is easily perceived.

# Arrangement

- Is the placement of visual elements within a display
- Can make a large difference in how easy it is to understand the data
- Example:



| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 0 | 1 | 1 | 0 |
| 2 | 1 | 0 | 1 | 0 | 0 | 1 |
| 3 | 0 | 1 | 0 | 1 | 1 | 0 |
| 4 | 1 | 0 | 1 | 0 | 0 | 1 |
| 5 | 0 | 1 | 0 | 1 | 1 | 0 |
| 6 | 1 | 0 | 1 | 0 | 0 | 1 |
| 7 | 0 | 1 | 0 | 1 | 1 | 0 |
| 8 | 1 | 0 | 1 | 0 | 0 | 1 |
| 9 | 0 | 1 | 0 | 1 | 1 | 0 |

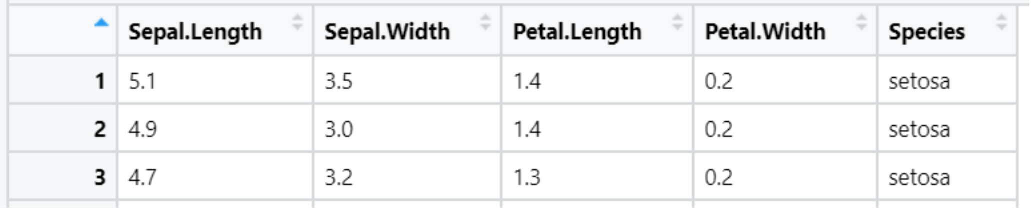


| | 6 | 1 | 3 | 2 | 5 | 4 |
|---|---|---|---|---|---|---|
| 4 | 1 | 1 | 1 | 0 | 0 | 0 |
| 2 | 1 | 1 | 1 | 0 | 0 | 0 |
| 6 | 1 | 1 | 1 | 0 | 0 | 0 |
| 8 | 1 | 1 | 1 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 1 | 1 | 1 |
| 3 | 0 | 0 | 0 | 1 | 1 | 1 |
| 9 | 0 | 0 | 0 | 1 | 1 | 1 |
| 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| 7 | 0 | 0 | 0 | 1 | 1 | 1 |

# The Iris Dataset

Many of the exploratory data techniques are illustrated with the Iris Plant data set.

- Included as a demo datasert in many tools (R, scikit-learn, Rapidminer, …).
- Can be obtained from the UCI Machine Learning Repository [http://www.ics.uci.edu/~mlearn/MLRepository.html](http://www.ics.uci.edu/~mlearn/MLRepository.html)
- From the statistician R.A. Fisher
- 150 flowers, three types (classes).
- Four (non-class) attributes



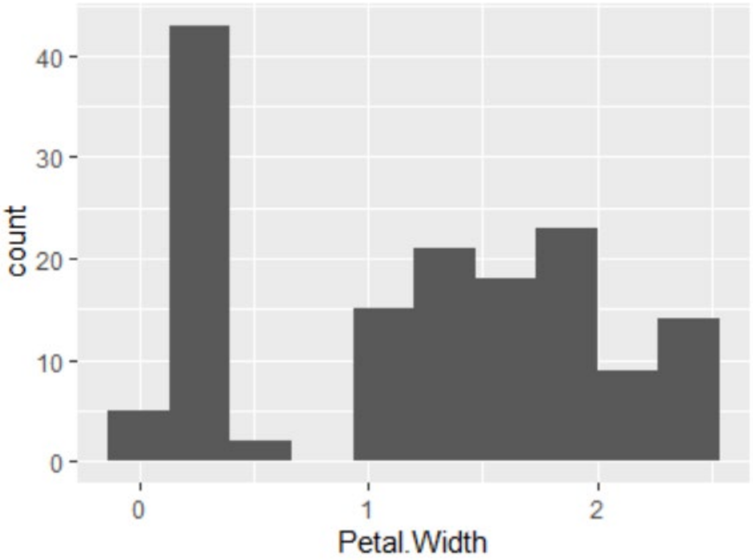
| | Sepal.Length | Sepal.Width | Petal.Length | Petal.Width | Species |
|---|---|---|---|---|---|
| 1 | 5.1 | 3.5 | 1.4 | 0.2 | setosa |
| 2 | 4.9 | 3.0 | 1.4 | 0.2 | setosa |
| 3 | 4.7 | 3.2 | 1.3 | 0.2 | setosa |

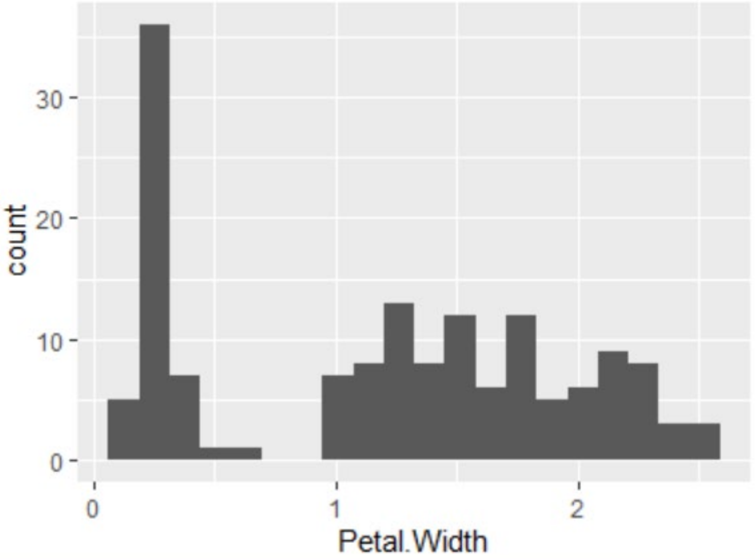
…

# Distribution: Histograms

- Usually shows the distribution of values of a single variable
- Divide the values into bins and show a bar plot of the number of objects in each bin.
- The height of each bar indicates the number of objects
- Shape of histogram depends on the number of bins

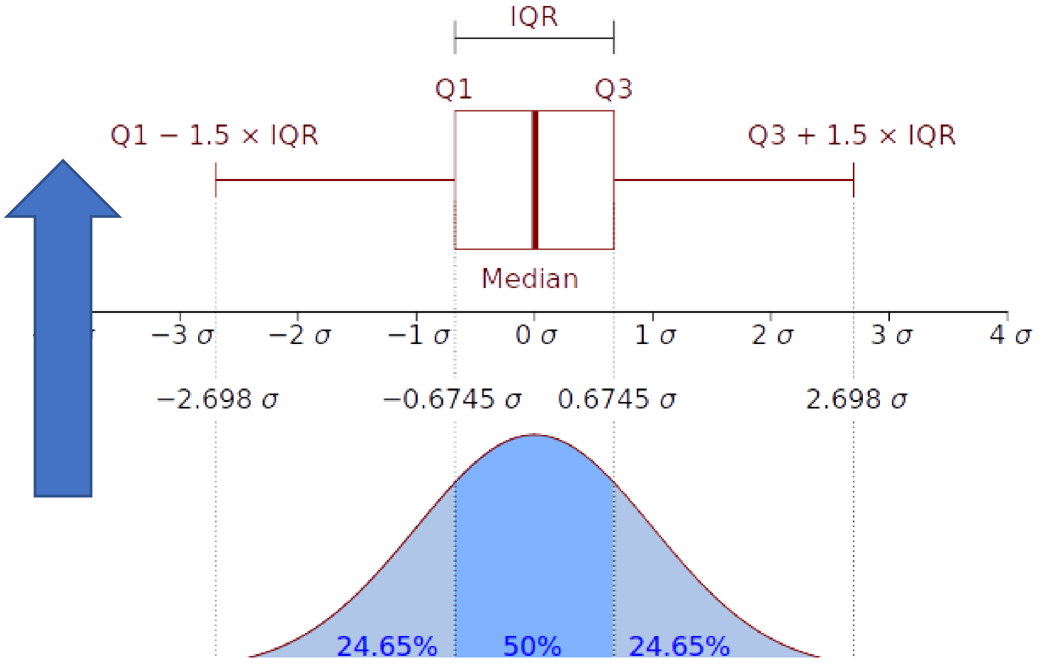
- Example: Petal Width (10 and 20 bins, respectively)



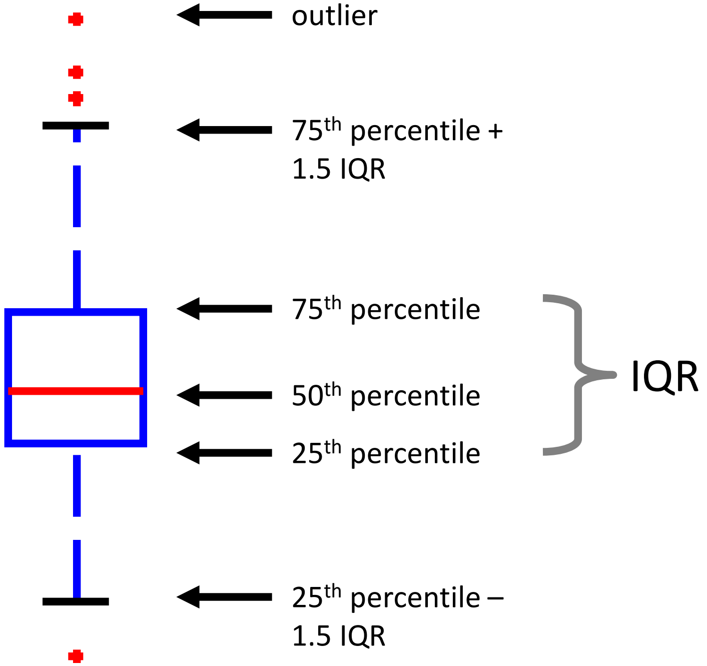


# Distribution Box Plots

- Invented by J. Tukey
- Simplified version of a PDF/histogram.



PDF or histogram



outlier

75th percentile + 1.5 IQR

75th percentile

50th percentile

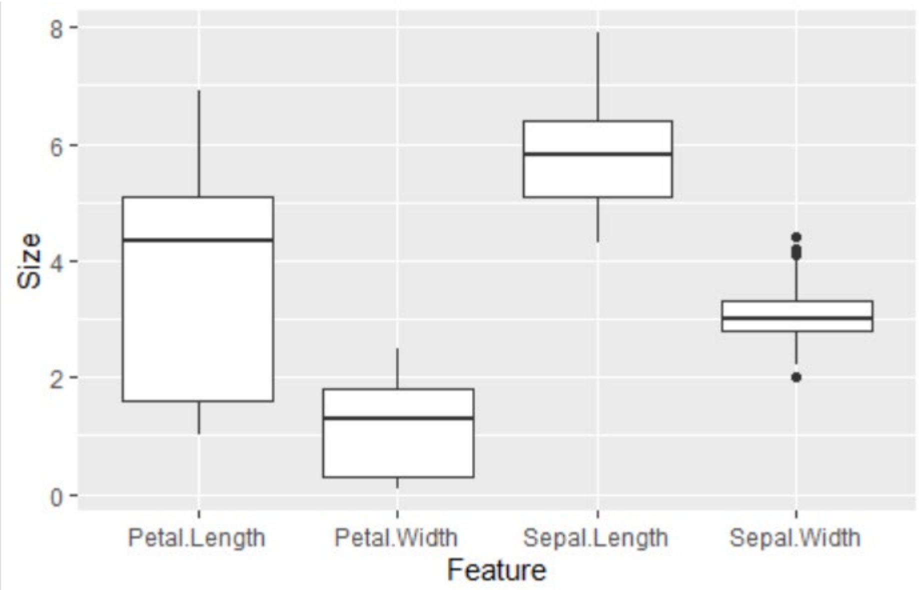
25th percentile

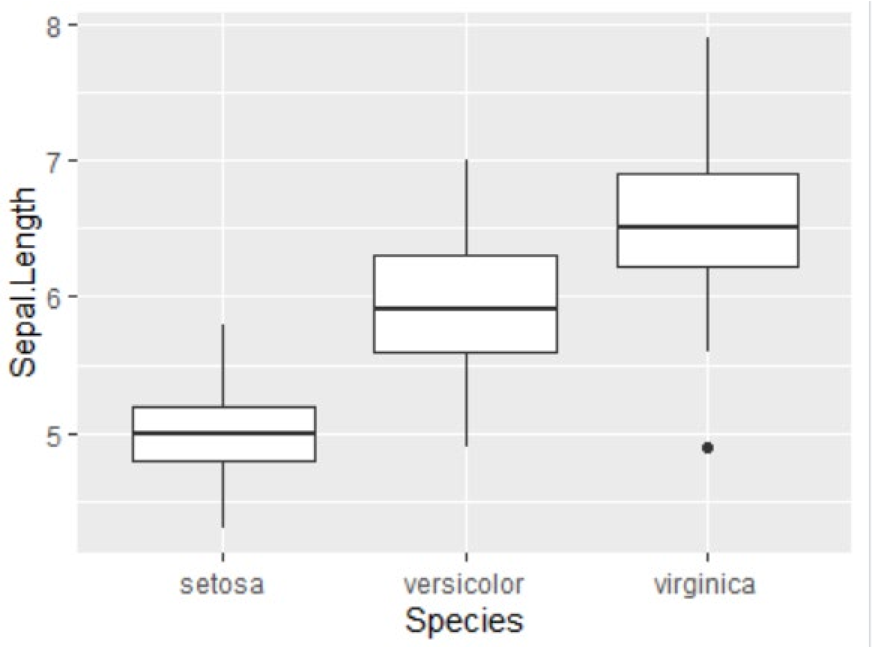
IQR

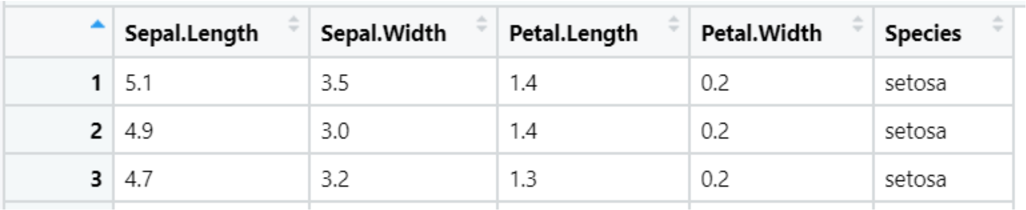
25th percentile – 1.5 IQR

# Examples of Box Plots

- Box plots can be used to compare attributes or subgroups.







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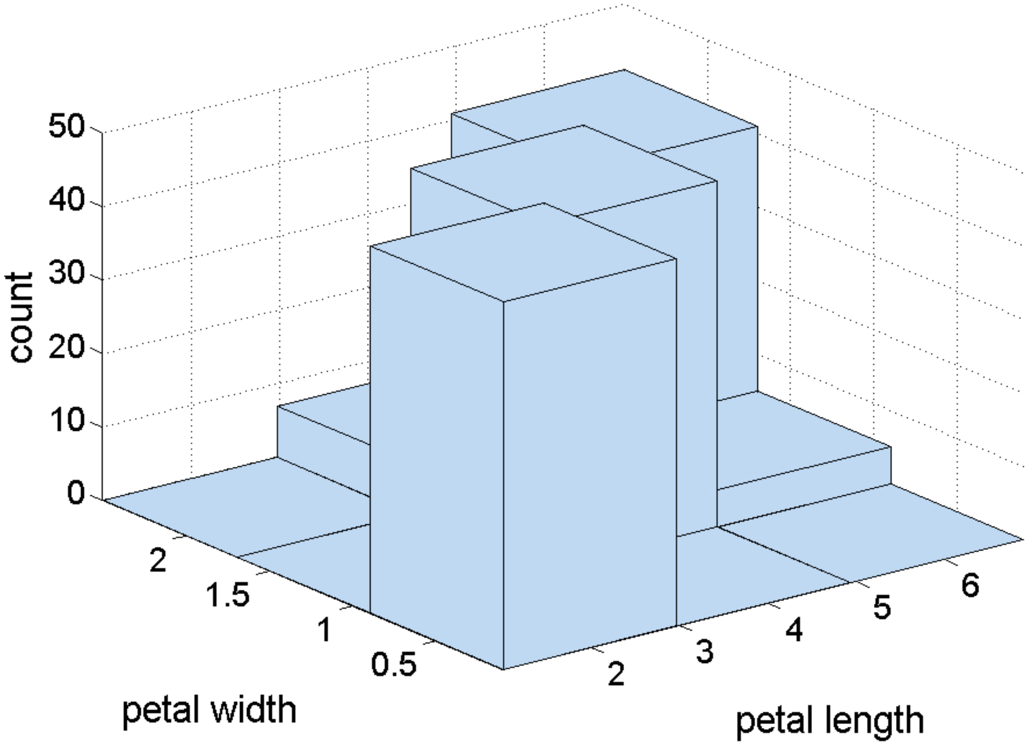
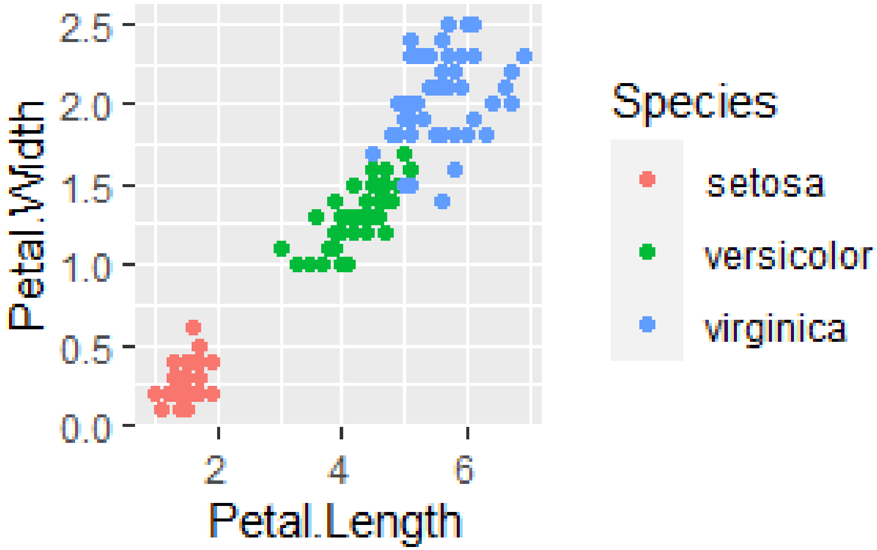
# Two-Dimensional Histograms

- Show the joint distribution of the values of two attributes
- Example: petal width and petal length
  - What does this tell us?

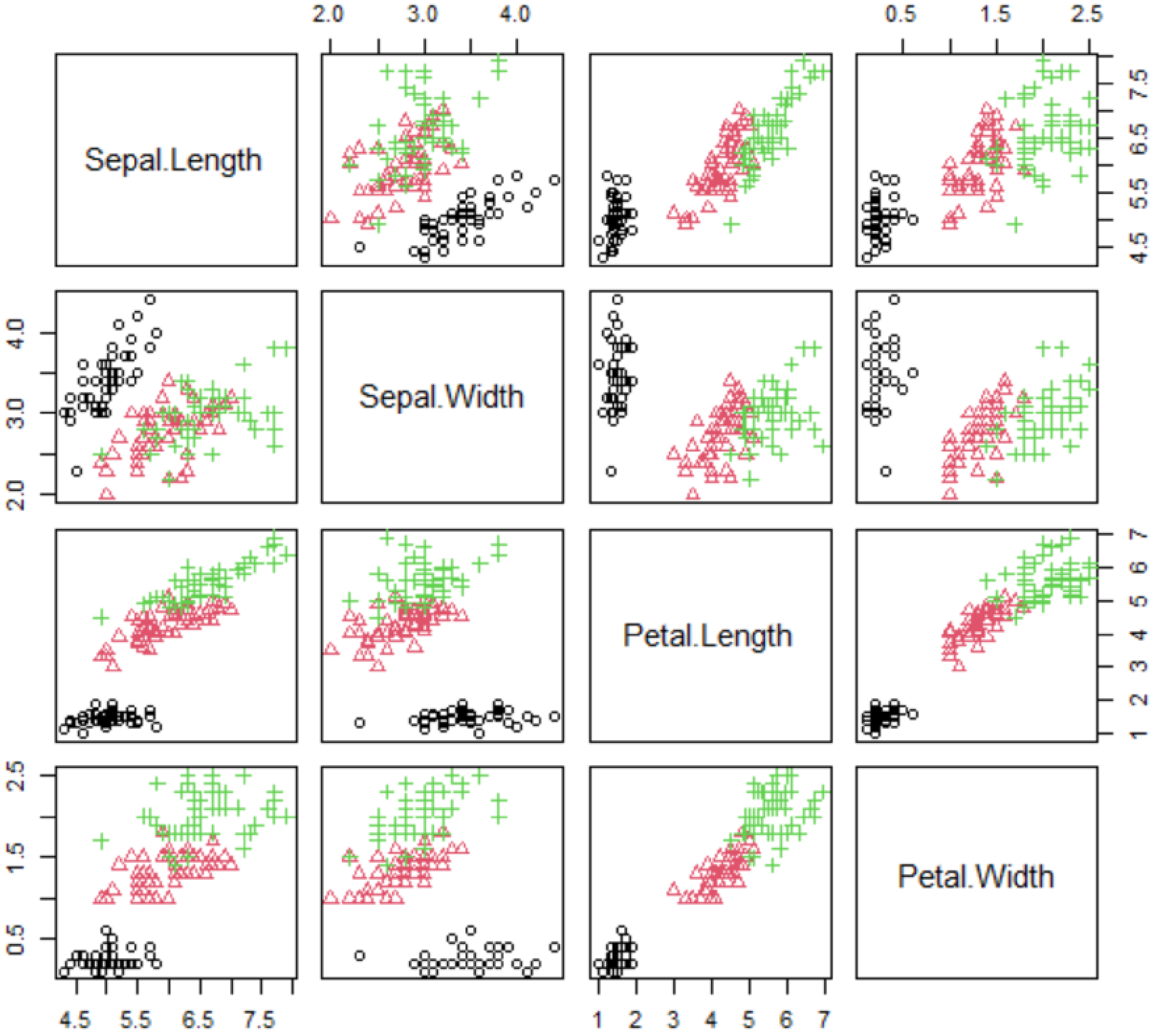


# Scatter Plots

- Attributes values determine the position
- Two-dimensional scatter plots most common, but can have three-dimensional scatter plots
- Often additional attributes can be displayed by using the size, shape, and color of the markers that represent the objects

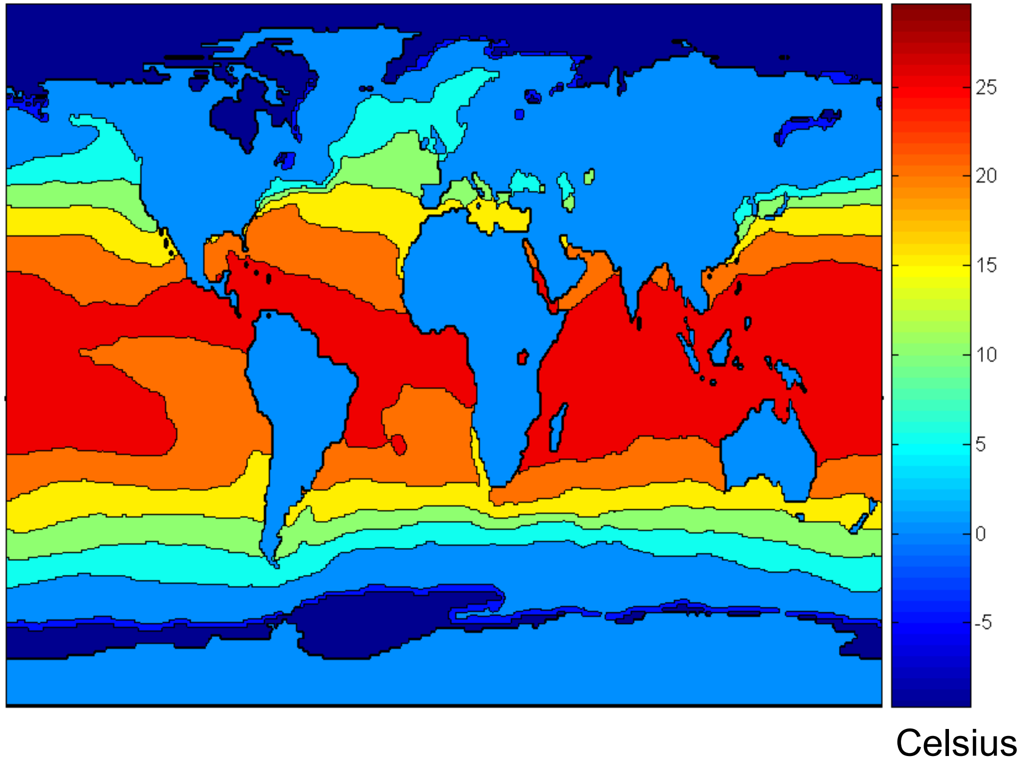


# Scatter Plot Array of Iris Attributes



# Contour Plots

- Useful when a continuous attribute is measured on a **spatial grid**
- They partition the plane into regions of similar values
- The contour lines that form the boundaries of these regions connect points with equal values
- The most common example is contour maps of elevation
- Can also display temperature, rainfall, air pressure, etc.

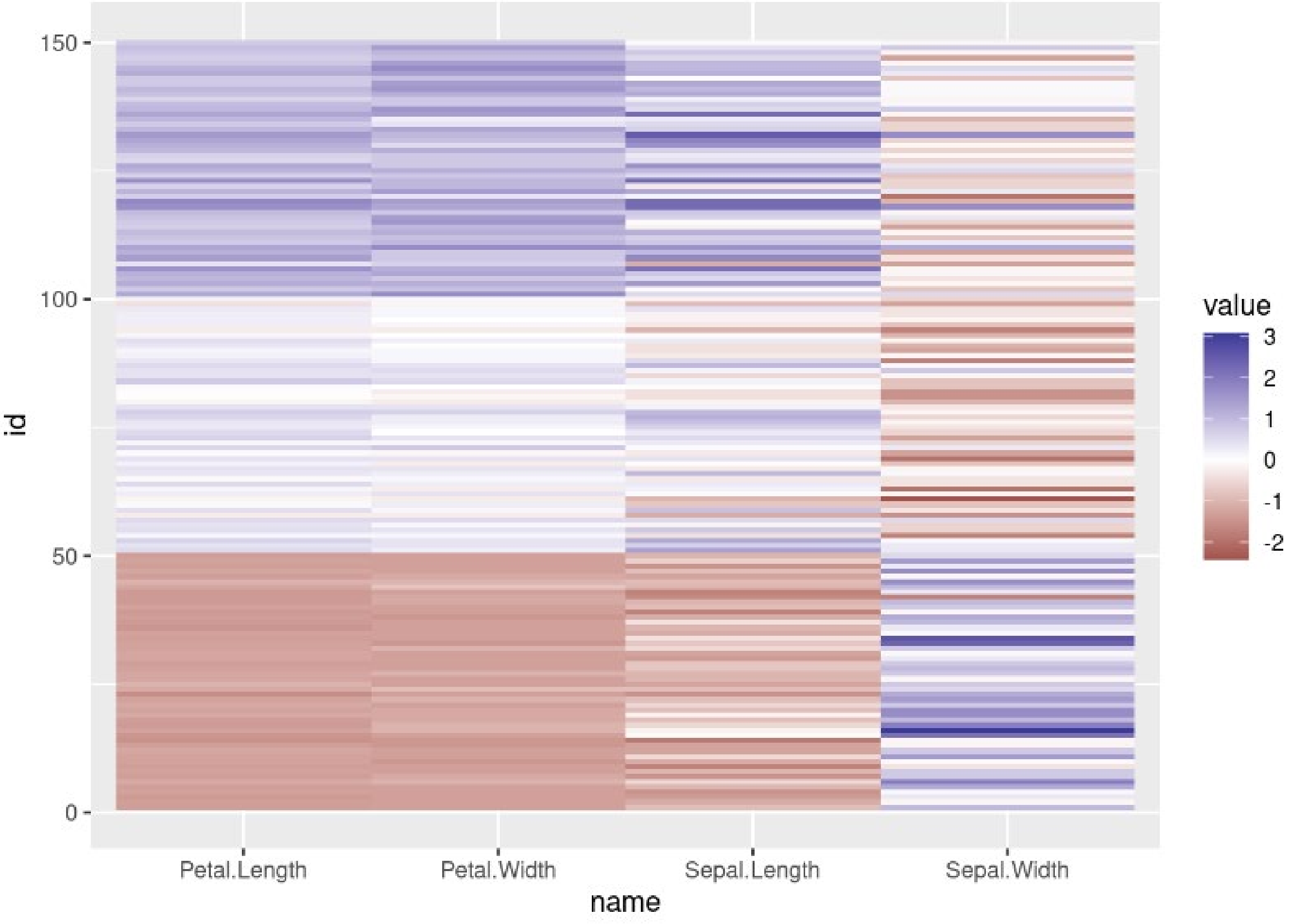


# Matrix Plots

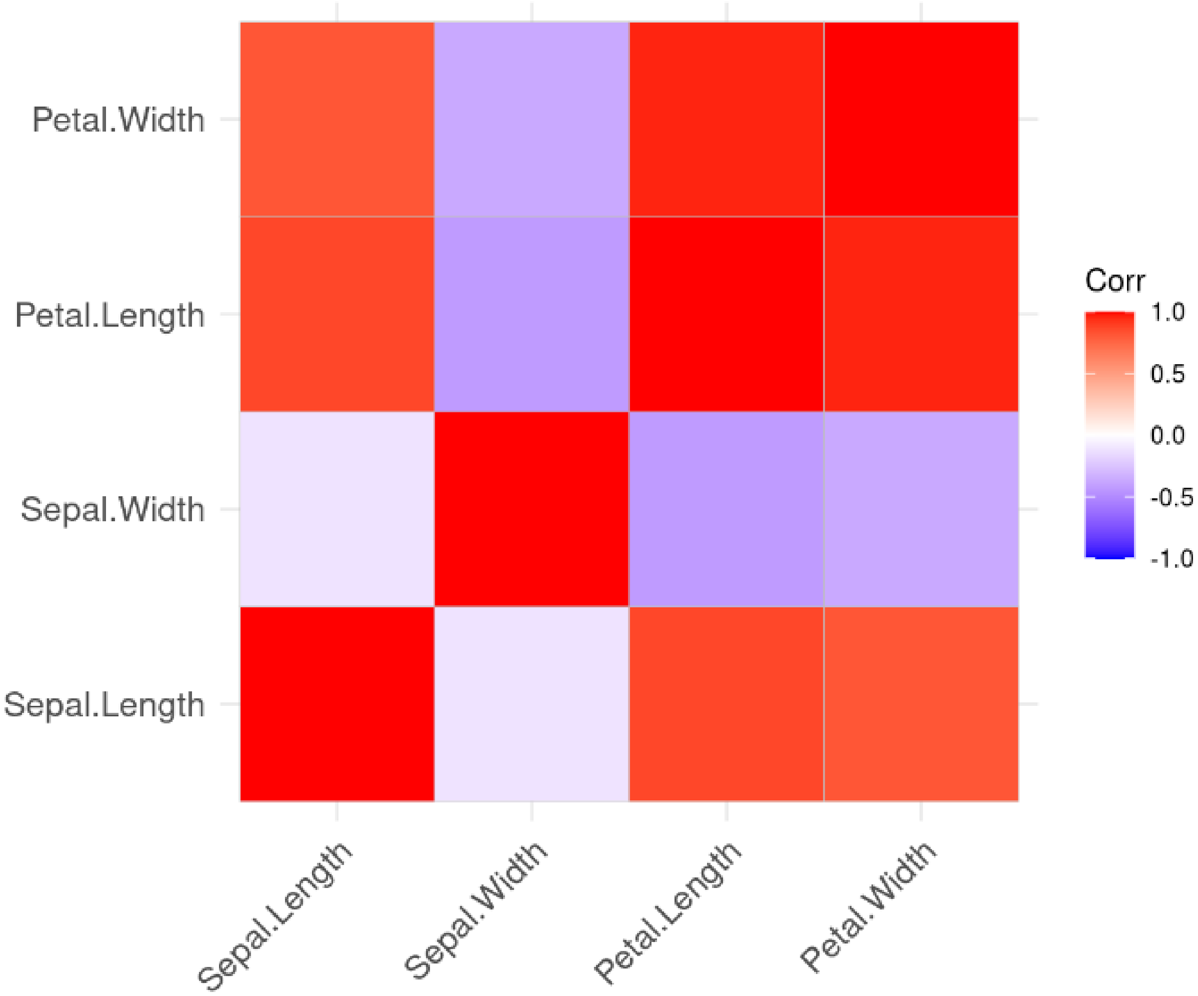
- Can plot a data matrix
- Can be useful when objects are sorted according to class
- Typically, the attributes are normalized to prevent one attribute from dominating the plot
- Plots of similarity or distance matrices can also be useful for visualizing the relationships between objects

# Visualization of the Iris Data Matrix

## Deviation form feature mean



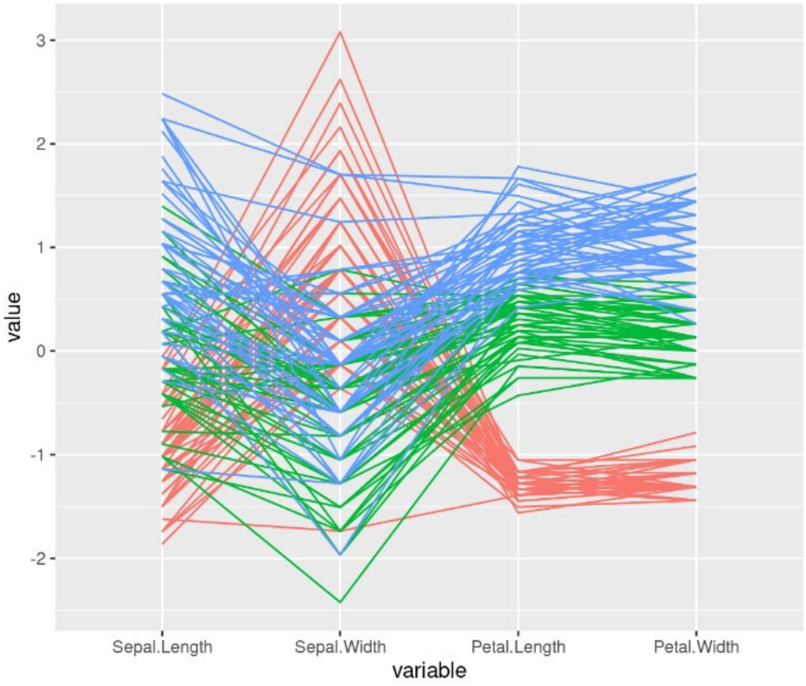
# Visualization of the Iris Correlation Matrix

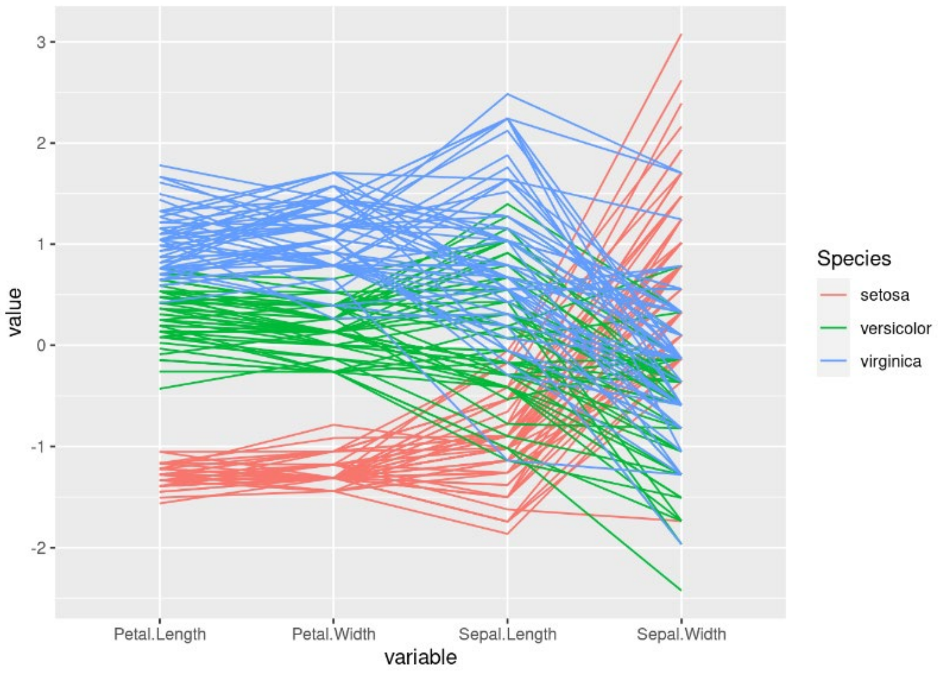


# Parallel Coordinates

- Used to plot the attribute values of high-dimensional data
- Instead of using perpendicular axes, use a set of parallel axes
- The attribute values of each object are plotted as a point on each corresponding coordinate axis and the points are connected by a line
- Thus, each object is represented as a line
- Often, the lines representing a distinct class of objects group together, at least for some attributes
- Ordering of attributes is important in seeing such groupings

# Parallel Coordinates Plots for Iris Data





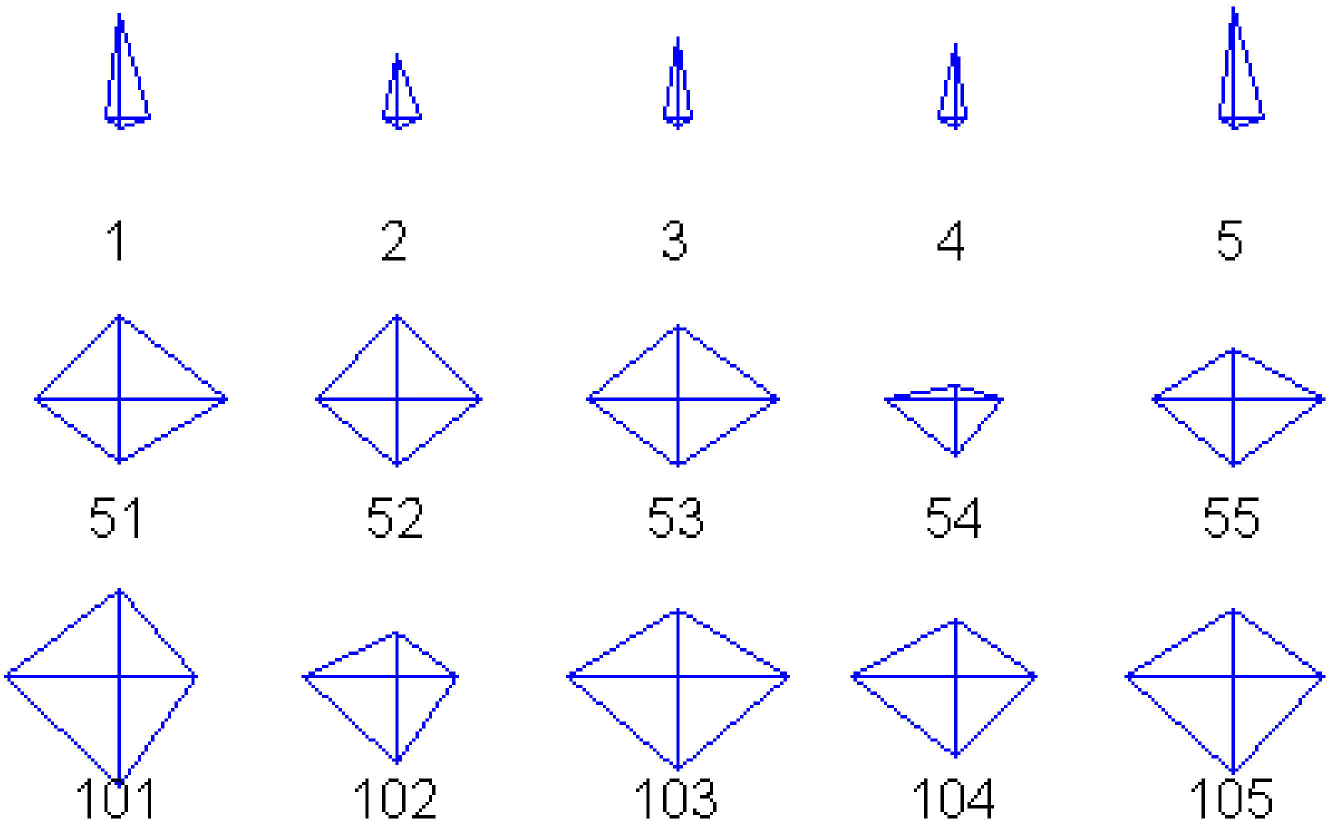
Reordered features

# Other Visualization Techniques

- Star Plots
  - Similar approach to parallel coordinates, but axes radiate from a central point
  - The line connecting the values of an object is a polygon
- Chernoff Faces
  - Approach created by Herman Chernoff
  - This approach associates each attribute with a characteristic of a face
  - The values of each attribute determine the appearance of the corresponding facial characteristic
  - Each object becomes a separate face
  - Relies on human’s ability to distinguish faces

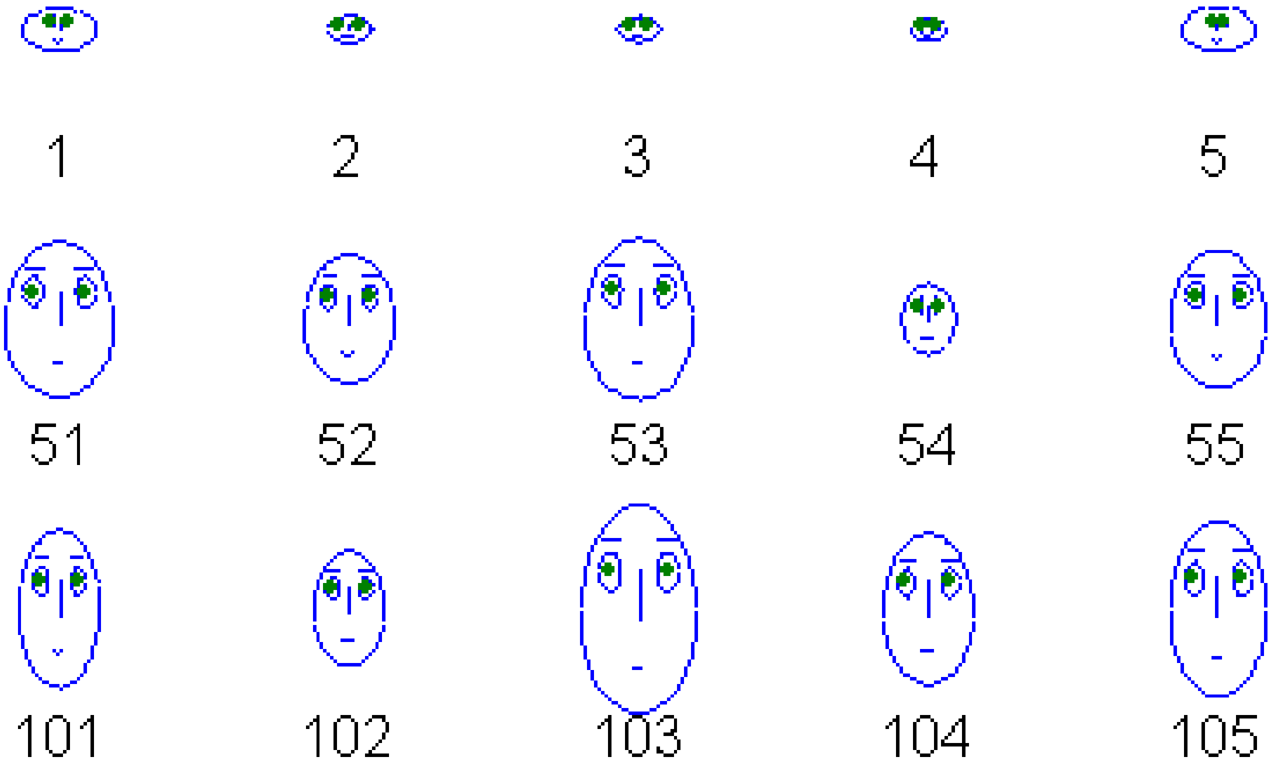
# Star Plots for Iris Data

- Setosa
- Versicolor
- Virginica



# Chernoff Faces for Iris Data

- Setosa
- Versicolor
- Virginica



# Conclusion

- Exploring data is the first step when working with data.
- The goal is to:
  1. Understand what data is available.
  2. Assess data distributions and how variables relate to each other.
  3. Assess data quality.

- Understanding the data is necessary to decide on data preparation and modeling.