DATA MINING 1

Data Understanding

Dino Pedreschi, Riccardo Guidotti

Revisited slides from Lecture Notes for Chapter 2 “Introduction to Data Mining”, 2nd Edition by Tan, Steinbach, Karpatne, Kumar

UNIVERSITÀ DI PISA

Getting To Know Your Data

- For preparing data for data mining task it is essential to have an overall picture of your data
- Gain insight in your data
  - with respect to your project goals
  - and general to understand properties
- Find answers to the questions
  - What kind of attributes do we have?
  - How is the data quality?
  - Does a visualization helps?
  - Are attributes correlated?
  - What about outliers?
  - How are missing values handled?
  - Do we need to extract other attributes

Types of data sets

- Record
  - Data Matrix
  - Document Data
  - Transaction Data
- Graph
  - World Wide Web
  - Molecular Structures
- Ordered
  - Spatial Data
  - Temporal Data
  - Sequential Data
  - Genetic Sequence Data

What is Data?

- Collection of **data objects** and their **attributes**
- An **attribute** is a property or characteristic of an object
  - Examples: eye color of a person, temperature, etc.
  - Attribute is also known as variable, field, characteristic, dimension, or feature
- A collection of attributes describe an **object**
  - Object is also known as record, point, case, sample, entity, or instance

Attributes

Objects

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Data Matrix

- If data objects have the same fixed set of numeric attributes, then the data objects can be thought of as points in a multi-dimensional space, where each dimension represents a distinct attribute
- Such data set can be represented by an *m* by *n* matrix, where there are *m* rows, one for each object, and *n* columns, one for each attribute

Projection of x Load	Projection of y load	Distance	Load	Thickness
10.23	5.27	15.22	2.7	1.2
12.65	6.25	16.22	2.2	1.1

Document Data

- Each document becomes a 'term' vector
  - Each term is a component (attribute) of the vector
  - The value of each component is the number of times the corresponding term occurs in the document.

	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

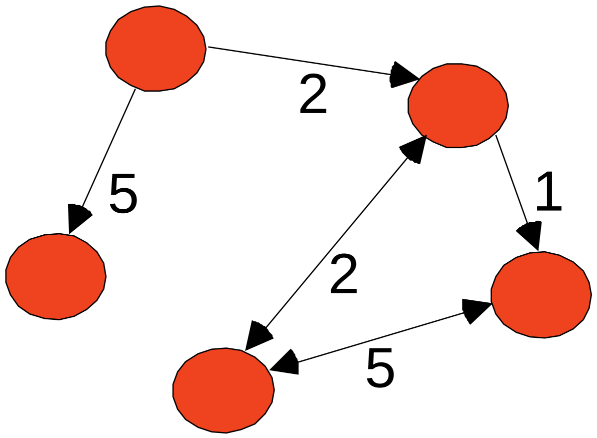
Transaction Data

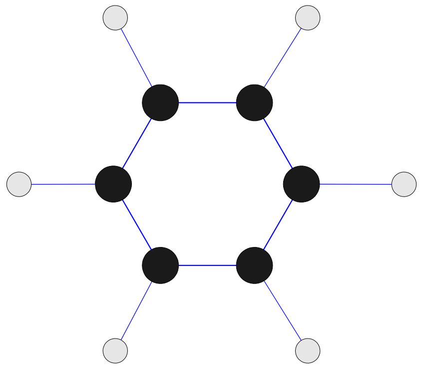
- A special type of record data, where
  - Each record (transaction) involves a set of items.
  - For example, consider a grocery store. The set of products purchased by a customer during one shopping trip constitute a transaction, while the individual products that were purchased are the items.

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

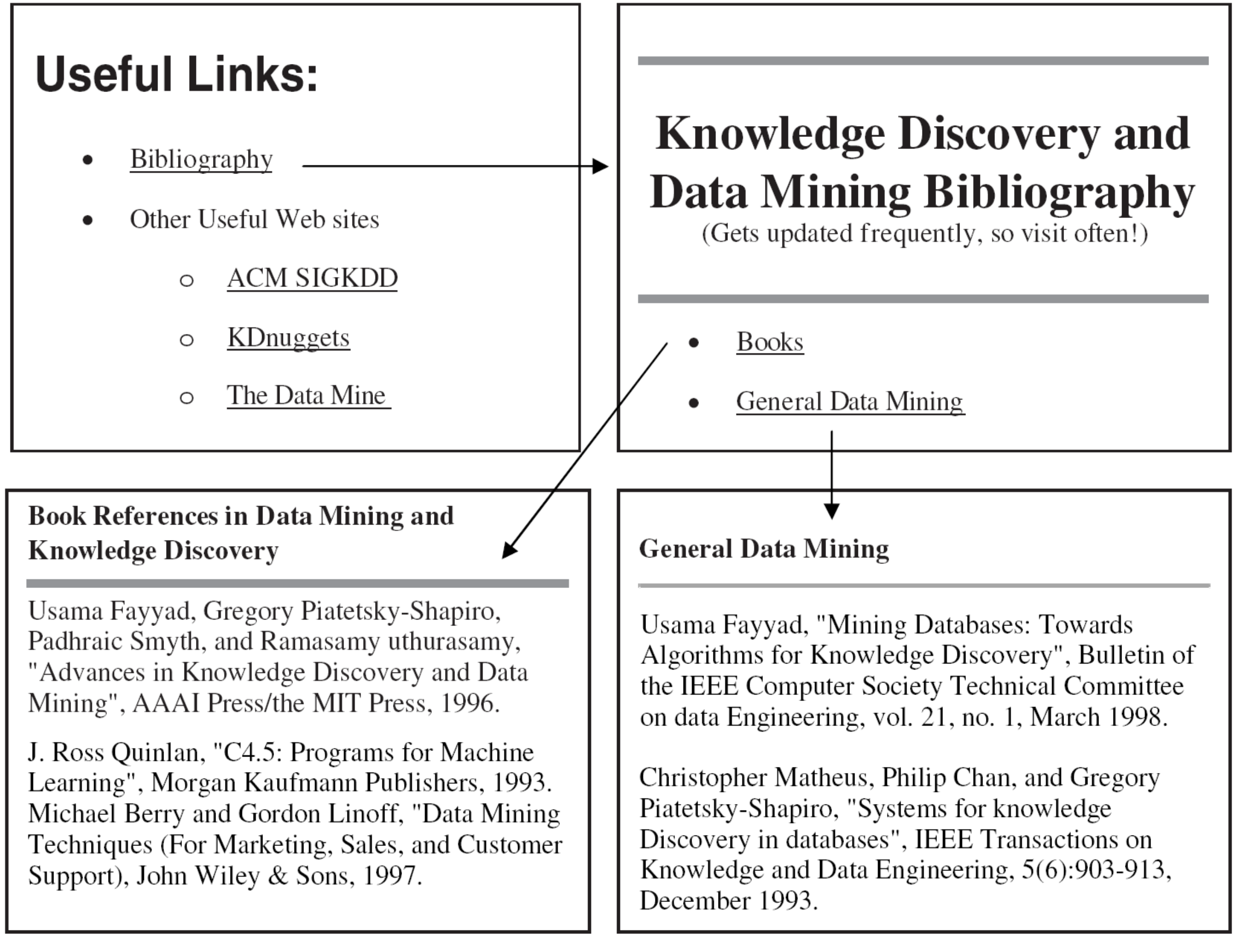
Graph Data

- Examples: Generic graph, a molecule, and webpages





Benzene Molecule: C6H6



Ordered Data

- Sequences of transactions

Items/Events

(A B) (D) (C E)
(B D) (C) (E)
(C D) (B) (A E)

An element of the sequence

Retail data

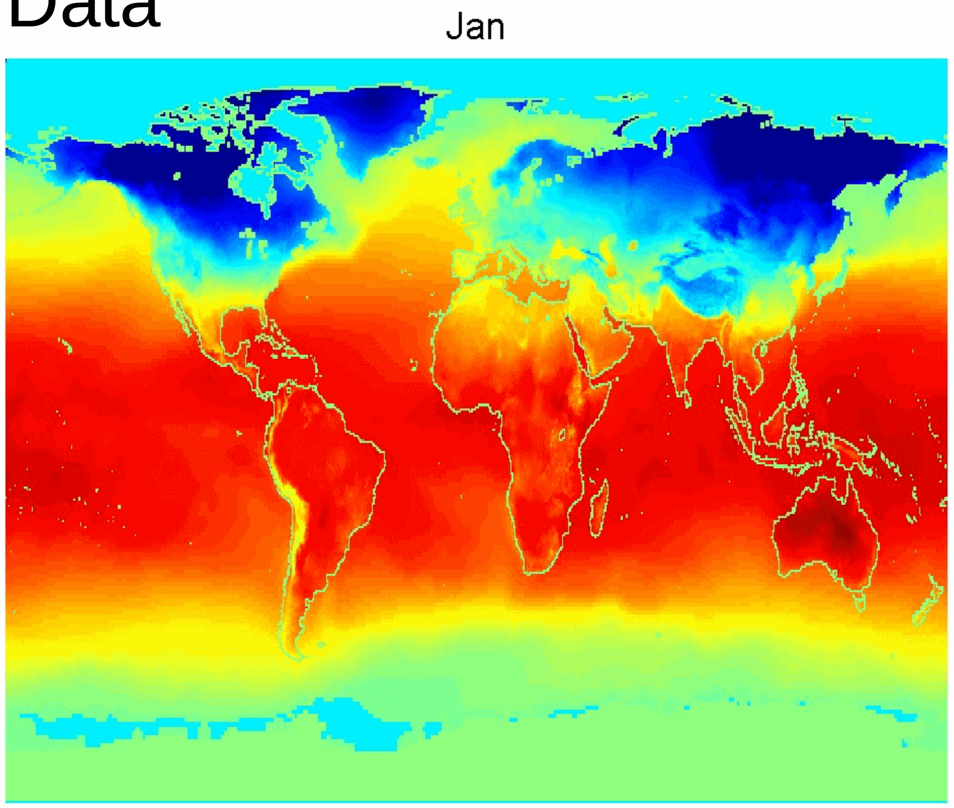
Ordered Data

- Genomic sequence data

```
GGTTCCGCCTTCAGCCCCGCGCC
CGCAGGGCCCGCCCCGCGCCGTC
GAGAAGGGCCCGCCTGGCGGGCG
GGGGGAGGCGGGGCCGCCCGAGC
CCAACCGAGTCCGACCAGGTGCC
CCCTCTGCTCGGCCTAGACCTGA
GCTCATTAGGCGGCAGCGGACAG
GCCAAGTAGAACACGCGAAGCGC
TGGCTGCCTGCTGCGACCAGGG
```

Ordered Data

- Spatio-Temporal Data



Average Monthly Temperature of land and ocean

Types of Attributes

- Five are different types of attributes
  - Nominal/Categorical: attribute values in a finite domain, categories
    - **Examples**: ID numbers, eye color, zip codes
  - Binary: Nominal attribute with only 2 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) The convention is to assign 1 to most important outcome (e.g., having cancer)
  - Ordinal: finite domain with a meaningful ordering on the domain
    - **Examples**: rankings (e.g., taste of potato chips on a scale from 1-10), grades, height {tall, medium, short}

Types of Attributes

- Numeric: quantity (integer or real-valued)
  - **Interval-Scaled**
    - Measured on a scale of equal-sized units
    - Values have order
  - **Examples**: calendar dates, temperatures in Celsius
- Ratio-Scaled: We can speak of values as being an order of magnitude larger than the unit of measurement
  - **Examples**: length, counts, elapsed time (e.g., time to run a race)
  - A baseball game lasting 3 hours is **50% longer** than a game lasting **2 hours.**

Discrete and Continuous Attributes

- Discrete Attribute
  - Has only a finite or countably infinite set of values
  - **Examples**: zip codes, counts, or the set of words in a collection of documents
  - Often represented as integer variables.
  - Note: binary attributes are a special case of discrete attributes
- Continuous Attribute
  - **Has real numbers** as attribute values
  - **Examples**: 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.

Properties of Attribute Values

The type of an attribute depends on which of the following properties/operations it possesses:

- Distinctness: $=$ $\neq$
- Order: $<$ $>$
- Differences are meaningful : $+$ $-$
- Ratios are meaningful $*$ $/$

- Nominal attribute: distinctness
- Ordinal attribute: distinctness & order
- Interval attribute: distinctness, order & meaningful differences
- Ratio attribute: all 4 properties/operations

	Attribute Type	Description	Examples	Operations
Categorical Qualitative	Nominal	Nominal attribute values only distinguish. (=, ≠)	zip codes, employee ID numbers, eye color, sex: {*male, female*}	mode, entropy, contingency correlation, $\chi 2$ test
	Ordinal	Ordinal attribute values also order objects. (<, >)	hardness of minerals, {*good, better, best*}, grades, street numbers	median, percentiles, rank correlation, run tests, sign tests
Numeric Quantitative	Interval	For interval attributes, differences between values are meaningful. (+, -)	calendar dates, temperature in Celsius or Fahrenheit	mean, standard deviation, Pearson's correlation, *t* and *F* tests
	Ratio	For ratio variables, both differences and ratios are meaningful. (*, /)	temperature in Kelvin, monetary quantities, counts, age, mass, length, current	geometric mean, harmonic mean, percent variation

Data Quality

- Poor data quality negatively affects many data processing efforts

"The most important point is that poor data quality is an unfolding disaster.

  - Poor data quality costs the typical company at least ten percent (10%) of revenue; twenty percent (20%) is probably a better estimate."

Thomas C. Redman, DM Review, August 2004

- Data mining example: a classification model for detecting people who are loan risks is built using poor data
  - Some credit-worthy candidates are denied loans
  - More loans are given to individuals that default

Data Quality …

- What kinds of data quality problems?
- How can we detect problems with the data?
- What can we do about these problems?

- Examples of data quality problems:
  - Wrong data
  - Duplicate data
  - Noise and outliers
  - Missing values

Data Quality issues …

- **Syntactic accuracy:** Entry is not in the domain.
  - **Examples**: fmale in gender, text in numerical attributes, … Can be checked quite easy.
- **Semantic accuracy:** Entry is in the domain but not correct
  - **Example**: John Smith is female
  - Needs more information to be checked (e.g. “business rules”).
- **Completeness:** is violated if an entry is not correct although it belongs to the domain of the attribute.
  - **Example**: Complete records are missing, the data is biased (A bank has rejected customers with low income.)
- **Unbalanced data:** Dataset might be extremely biased to one type of records.
  - **Example**: Defective goods are a very small fraction of all.
- **Timeliness:** Is the available data up to date?

Duplicate Data

- Data set may include data objects that are duplicates, or almost duplicates of one another
  - Major issue when merging data from heterogeneous sources

- Examples:
  - Same person with multiple email addresses

- Data cleaning
  - Process of dealing with duplicate data issues

Statistics & Visualization

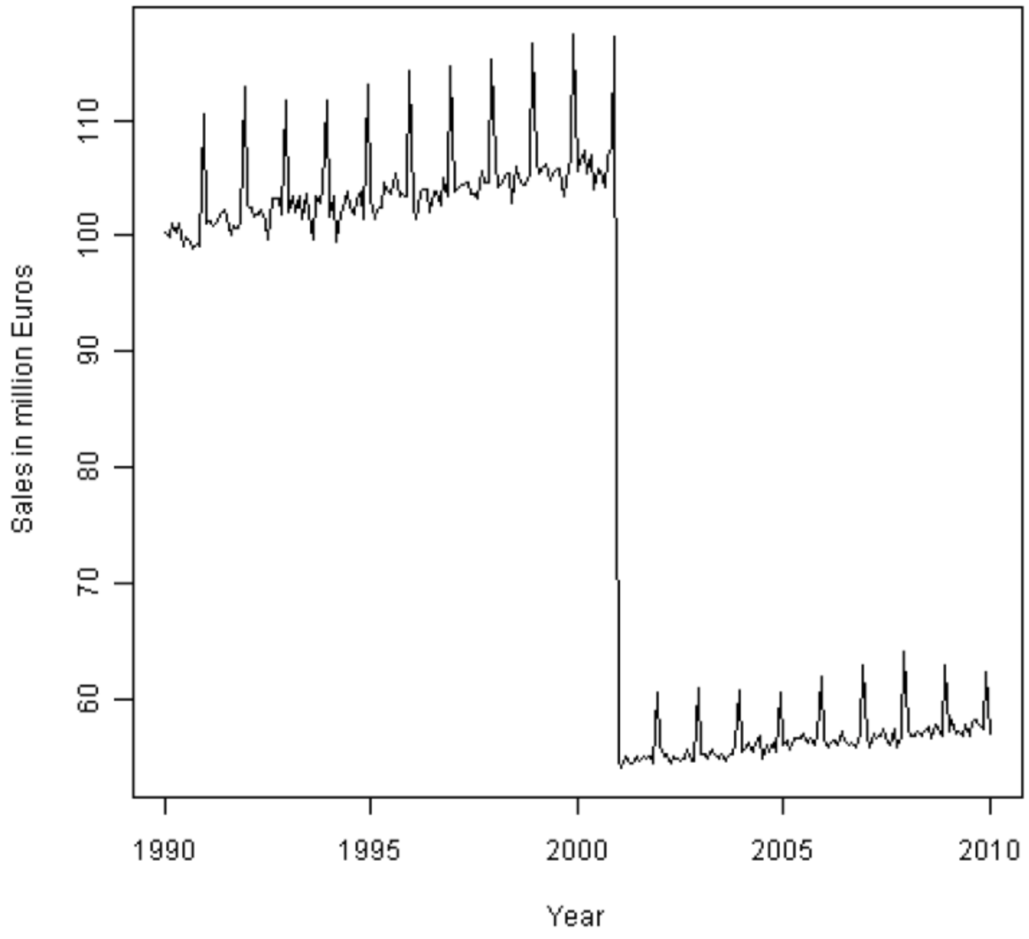
In order to know our data and discovery quality issues we need:

- Use descriptive statistics for getting a global picture and summarize properties of data

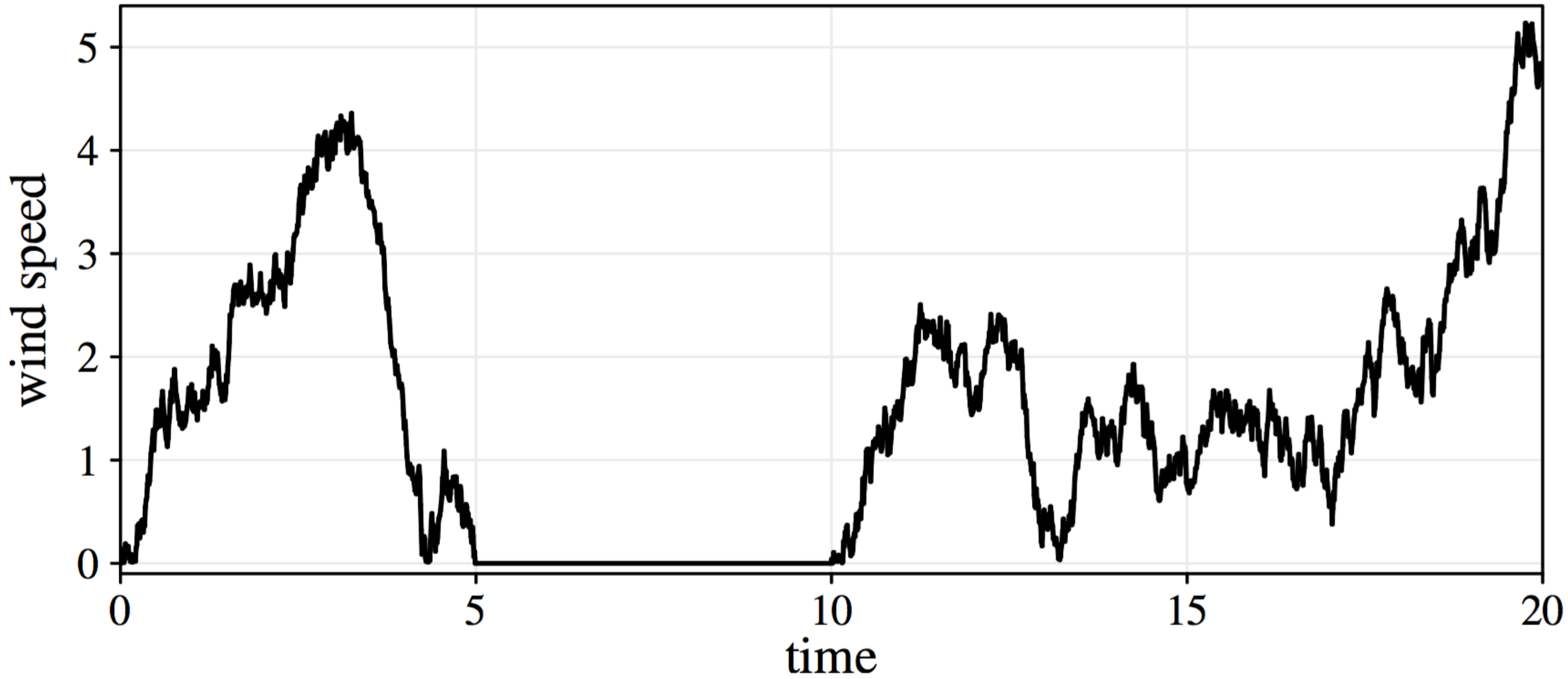
- Compare statistics with the expected behaviour

- Exploit visualization techniques that can help in detecting
  - general patterns and trends
  - outliers and unusual patterns

Data Visualization

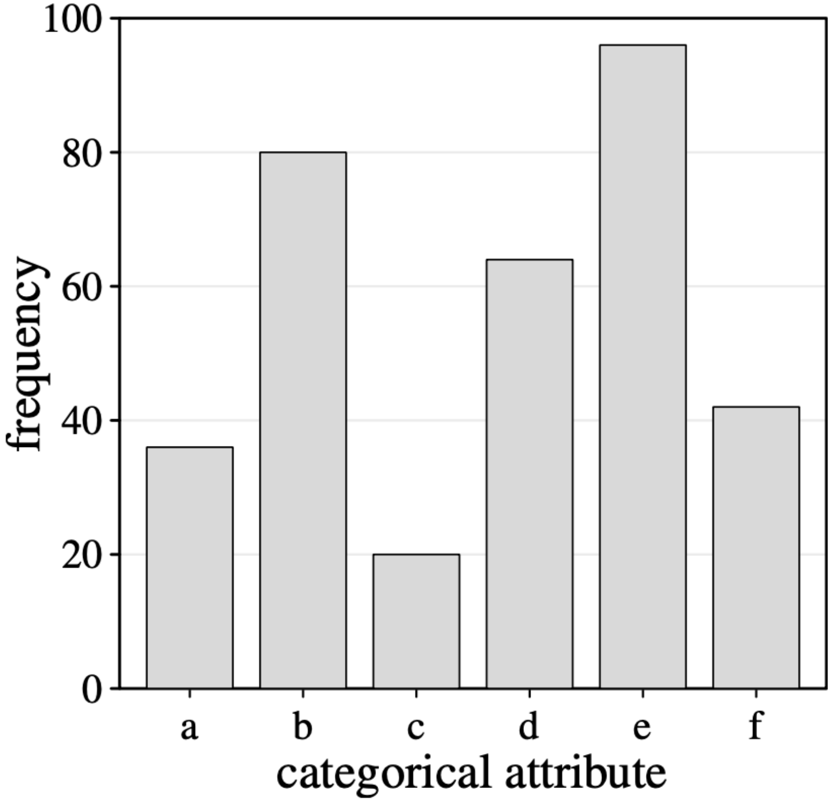


Data Visualization



The zero values might come from a broken or blocked sensor and might be consider as missing values.

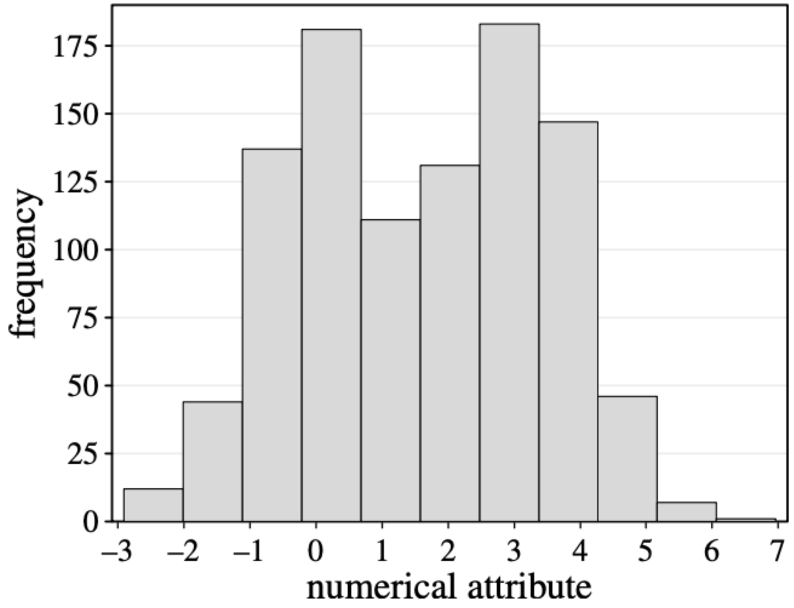
Bar Chart for Categorical Attributes



A bar chart is a simple way to depict the frequencies of the values of a categorical attribute.

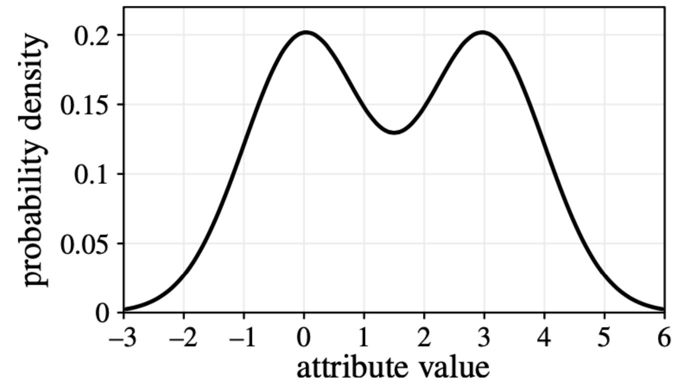
Histograms for Numerical Attributes

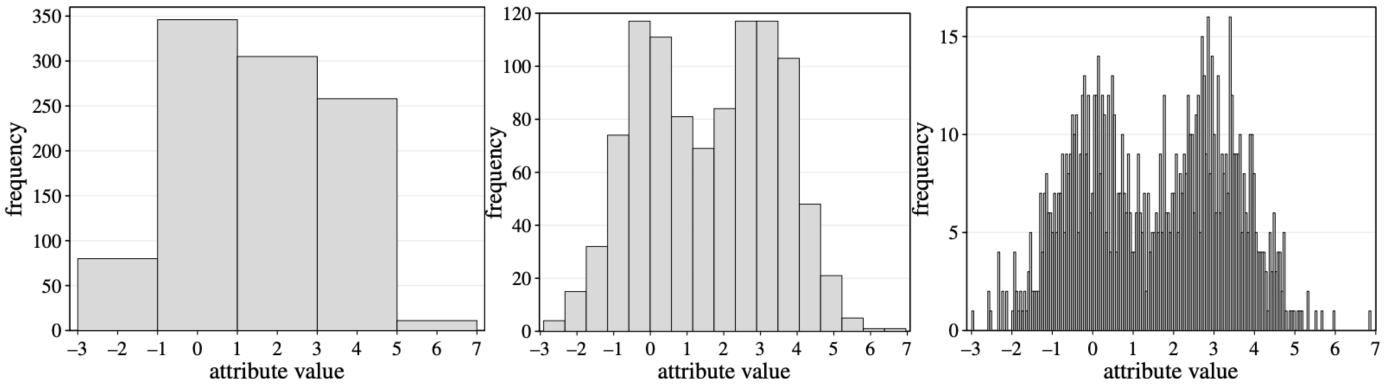
- A **histogram** shows the frequency distribution for a numerical attribute.
- The range of the numerical attribute is **discretized** into a fixed number of intervals (**bins**)
- For each interval the (absolute) **frequency** of values falling into it is indicated by the height of a bar.



Histograms: Number of bins

3 histograms with 5, 17 and 200 bins for a sample from the same bimodal distribution.





Number of bins

- Number of bins according to **Sturges' rule:**

$$k = \lceil \log_2(n) + 1 \rceil$$

where n is the sample size

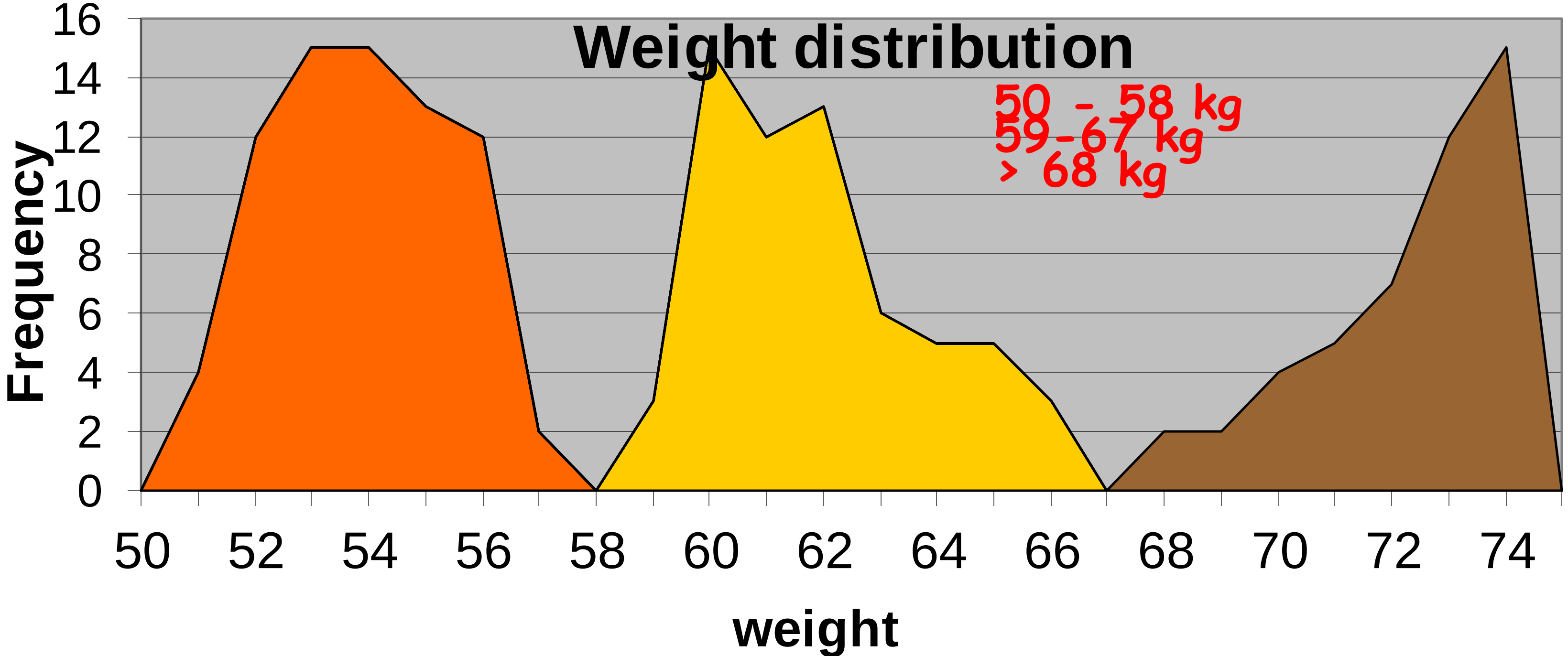
- Sturges' rule is suitable for data from normal distributions and from data sets of moderate size.

How to choose intervals?

1. Interval with a fixed “reasonable” granularity
   Ex. intervals of 10 cm for height.

2. Interval size is defined by some domain dependent criterion
   Ex.: 0-20ML, 21-22ML, 23-24ML, 25-26ML, >26ML

3. Interval size determined by analyzing data, studying the distribution and find breaks or using clustering



Natural Binning

- Simple
- Sort of values, subdivision of the range of values in *k* parts with the same size

$$\delta = \frac{x_{\max} - x_{\min}}{k}$$

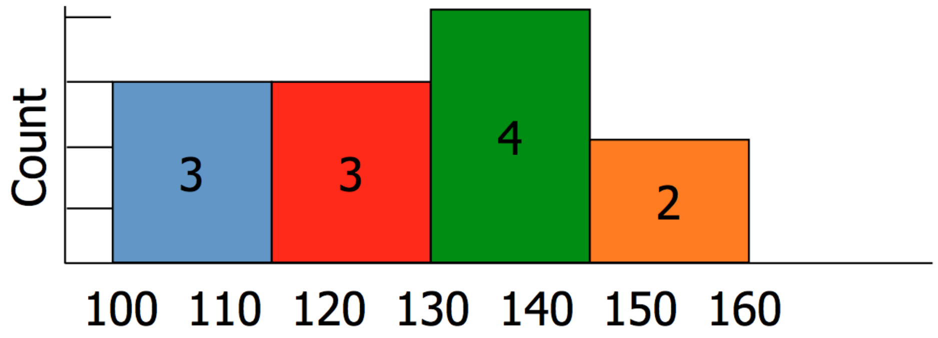
- Element x_j belongs to the class i if

$$x_j \in [x_{min} + i\delta,\ x_{min} + (i+1)\delta)$$

- It can generate distribution very unbalanced

Example

- Histogram for Price
- δ =(160-100)/4 = 15
- bin 1: [100,115)
- bin 2: [115,130)
- bin 3: [130,145)
- bin 4: [145, 160]



Bar	Beer	Price
A	Bud	100
A	Becks	120
C	Bud	110
D	Bud	130
D	Becks	150
E	Becks	140
E	Bud	120
F	Bud	110
G	Bud	130
H	Bud	125
H	Becks	160
I	Bud	135

Equal Frequency Binning

- Sort and count the elements, definition of k intervals of f, where:

$$f = \frac{N}{k}$$

(*N* = number of elements of the sample)

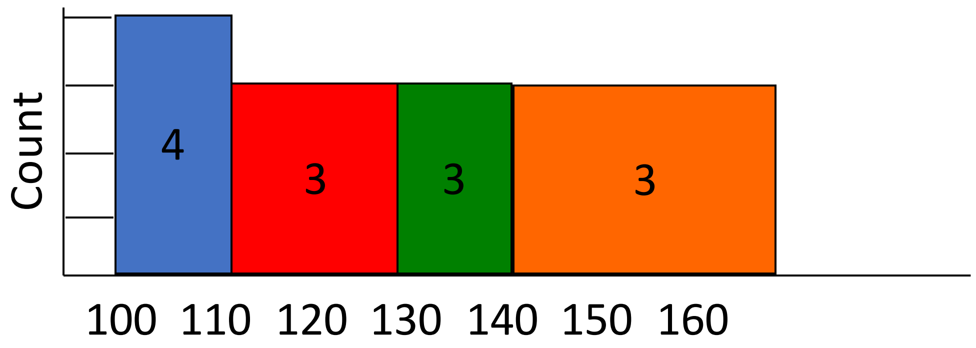
- The element x_i belongs to the class j if

$$j \times f \leq i < (j+1) \times f$$

- It is not useful for highlighting interesting distribution

Example

- Histogram for Price
- $f = 12/4 = 3$
- class 1: {100,110,110}
- class 2: {120,120,125}
- class 3: {130,130,135}
- class 4: {140,150,160}



Bar	Beer	Price
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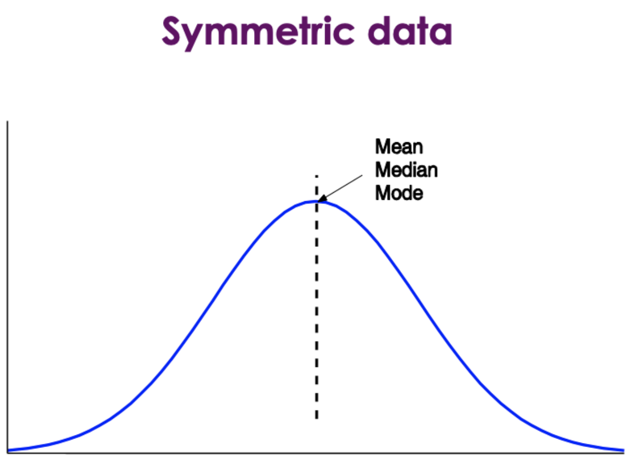
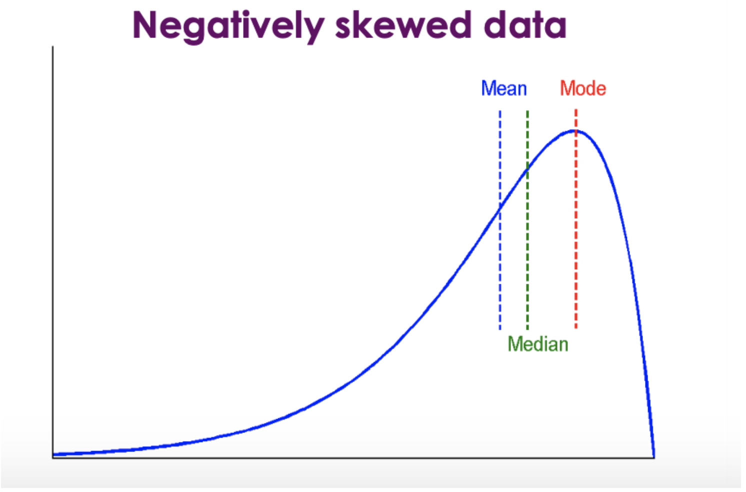
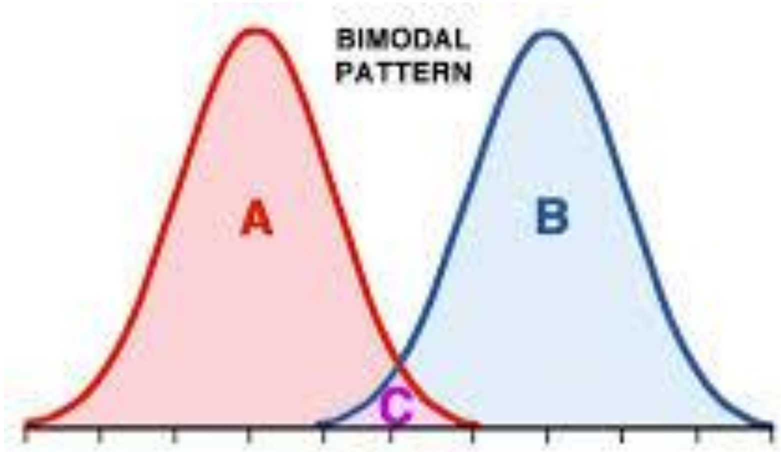
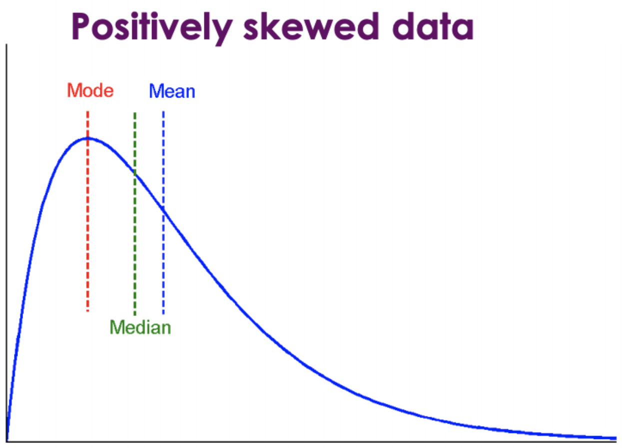
D	Bud	130
D	Becks	150
E	Becks	140
E	Bud	120
F	Bud	110
G	Bud	130
H	Bud	125
H	Becks	160
I	Bud	135

Observing Data Distribution









Example

Give an example of something having a positively skewed distribution

- **income** is a good example of a positively skewed variable: there will be a few people with extremely high incomes, but most people will have incomes bunched together below the mean.

Give an example of something having a bimodal distribution

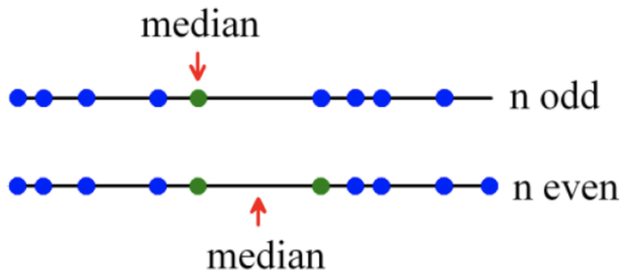
- bimodal distribution has some kind of underlying binary variable that will result in a separate mean for each value of this variable.
- One example can be **human weight** – the gender is binary and is a statistically significant indicator of how heavy a person is.

Measuring the Central Tendency

- Mean
  - *m* is the sample size
  - A distributive measure can be computed by partitioning the data into smaller subsets
  - However, the mean is very sensitive to outliers
  - The median or a trimmed mean are also commonly used

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

- Median
  - Middle value if odd number of values, or average of the middle two values otherwise



- Mode
  - Value that occurs m**ost frequently** in the data
  - It is possible that several different values have the greatest frequency: Unimodal, bimodal, trimodal, multimodal
  - If each data value occurs only once then **there is no mode**

Measuring the Dispersion of Data

- The degree in which data tend to spread is called the **dispersion**, or **variance** of the data

- The most common measures for data dispersion are **range**, **standard deviation,** the **five-number summary** (based on quartiles), and the **inter-quartile range**

- **Range**: The distance between the largest and the smallest values

Measuring the Dispersion of Data

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

- **Standard deviation** σ is the square root of variance σ^2
  - σ measures spread about the mean ands should be used only when the mean is chosen as the measure of the center
  - $\sigma=0$ only when there is no spread, that is, when all observations have the same value. Otherwise $\sigma>0$

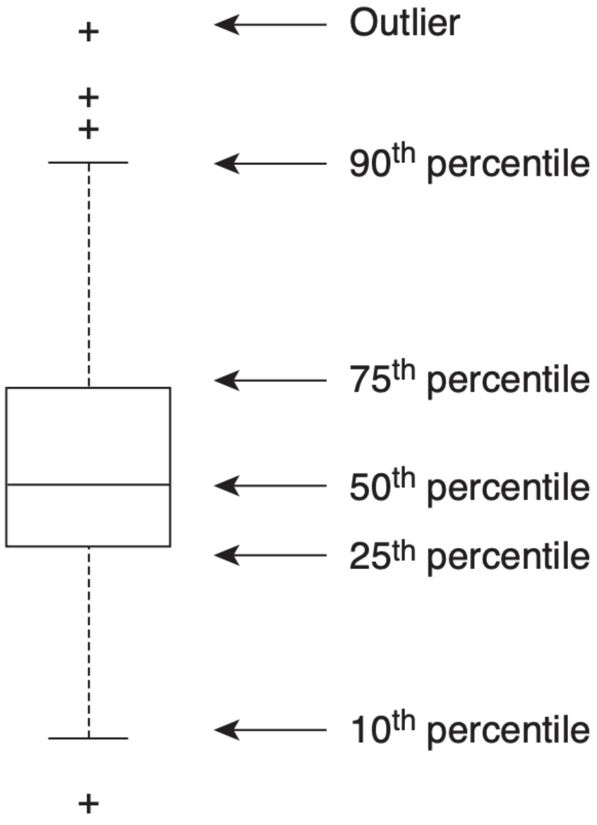
- **Because of outliers**, other measures are often used:
  - **absolute average deviation** (AAD)
  - **median average deviation** (MAD)

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

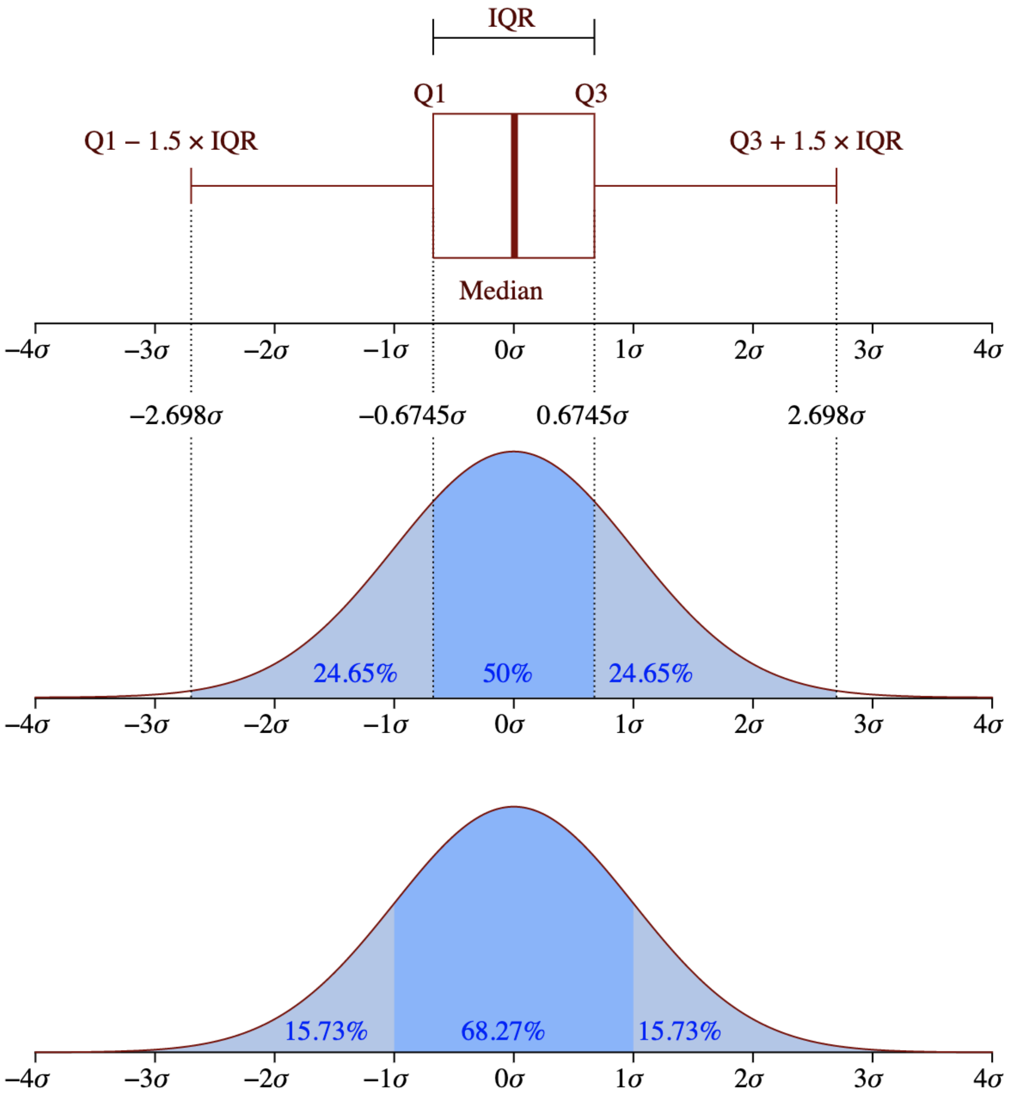
$$\text{MAD}(x) = median\Big(\{|x_1 - \overline{x}|, \ldots, |x_m - \overline{x}|\}\Big)$$

Box Plot: Five-number summary of a distribution

- Data represented with a **box**
- The ends of the box are at the
  - **Q1: 1st quartiles** (25%-quantile or 25th percentile)
  - **Q3: 3rd quartiles** (75%-quantile or 75th percentile)
- **Median**: value in the middle is the **Q2**: **2nd quartile** (50%-qua,, 50th perc.)
- The height of the box is **Interquartile range** (**IQR**): Q3 - Q1
- **Whiskers**: two lines outside the box extended from:
  - 1st, or 5th, or 10th percentile, or Q1 – *k* IQR (with k = 1.5)
  - 99th, or 95th, or 90th percentile, or Q3 + *k* IQR (with k = 1.5)
- **Outliers**: are points beyond whiskers
- In general, p%-quantile (0 < p < 100): Is the value *x* s.t. p% of the values are smaller and 100-p% are larger.



Relationship Between Box-Plot and Histogram



Example Data Set: Iris data

iris setosa

iris versicolor

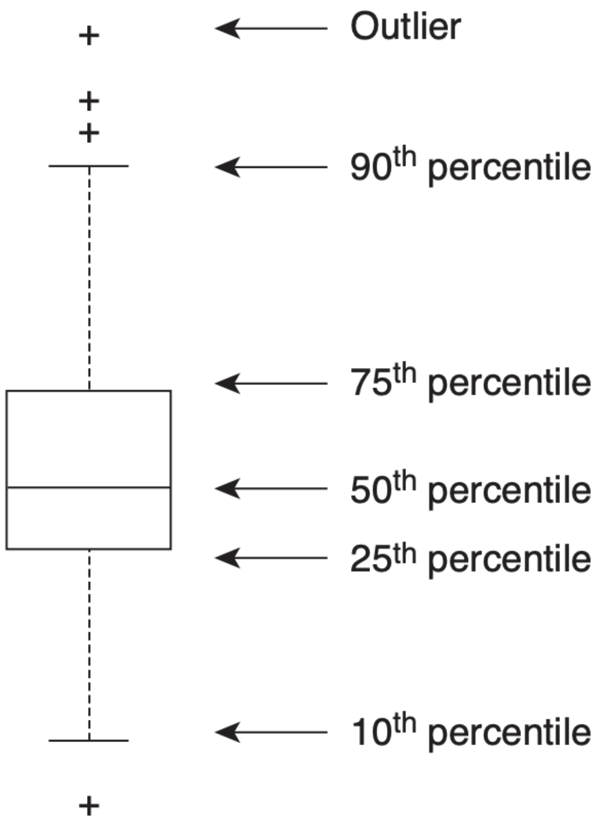
iris virginica

- collected by E. Anderson in 1935
- contains measurements of four real-valued variables:
  - sepal length, sepal widths, petal lengths and petal width of 150 iris flowers of types *Iris Setosa*, *Iris Versicolor*, *Iris Virginica* (50 each)
- The fifth attribute is the name of the flower type.

Example data set: Iris data

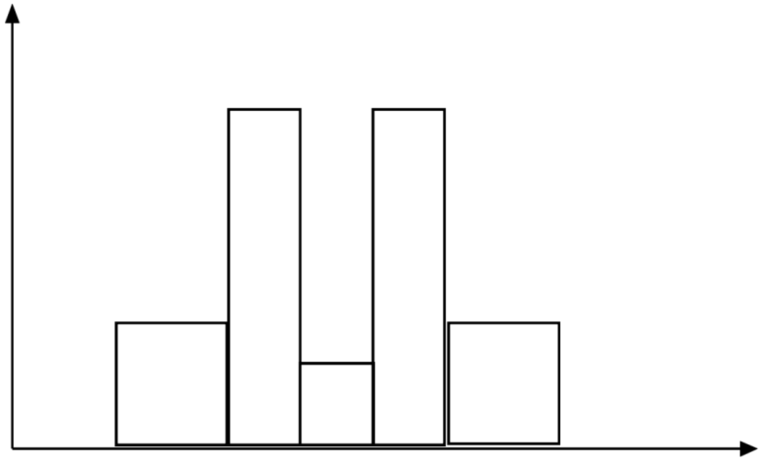
Sepal Length	Sepal Width	Petal Length	Petal Width	Species
5.1	3.5	1.4	0.2	Iris-setosa
...				
...				
5.0	3.3	1.4	0.2	Iris-setosa
7.0	3.2	4.7	1.4	Iris-versicolor
...				
...				
5.1	2.5	3.0	1.1	Iris-versicolor
5.7	2.8	4.1	1.3	Iris-versicolor
...				
...				
5.9	3.0	5.1	1.8	Iris-virginica

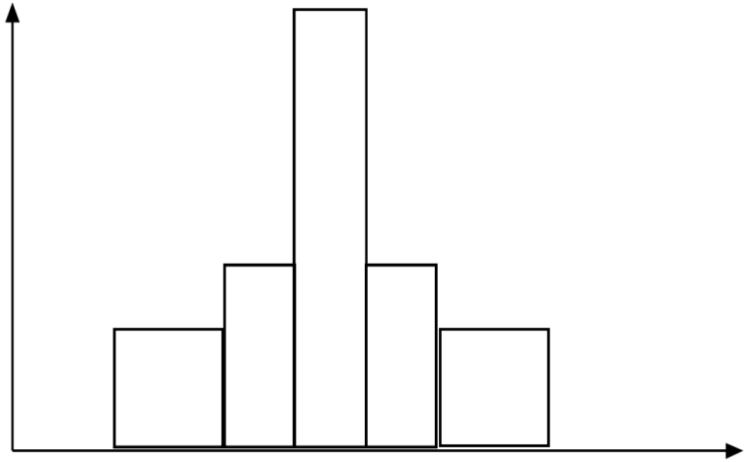
Example of Conditional Box Plot



Histograms Often Tell More than Boxplots

- The two histograms may have the same boxplot representation
  - **The same values** for: **min, Q1, median, Q3, max**
  - But they have rather **different data distributions**

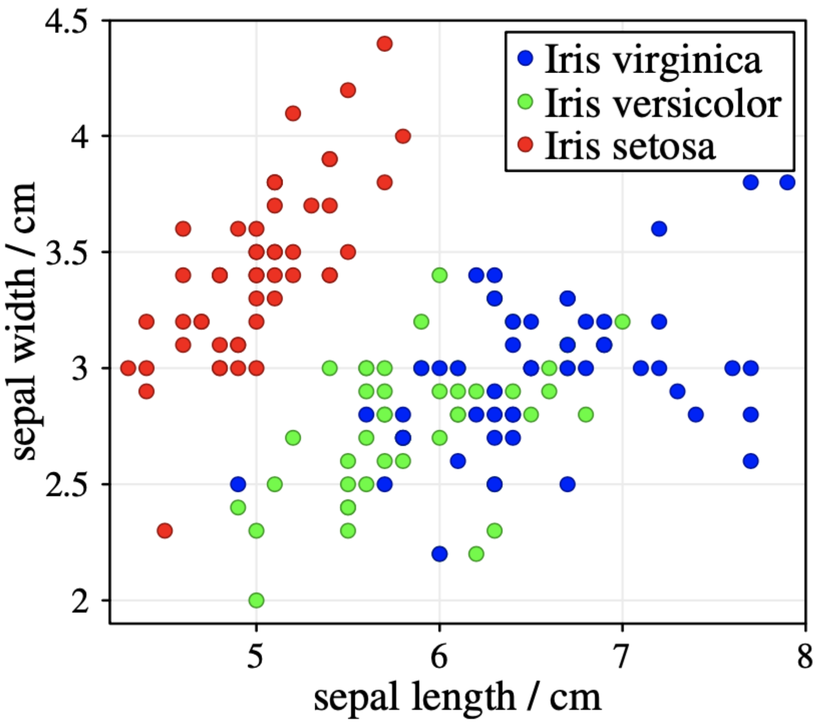




Scatter Plot

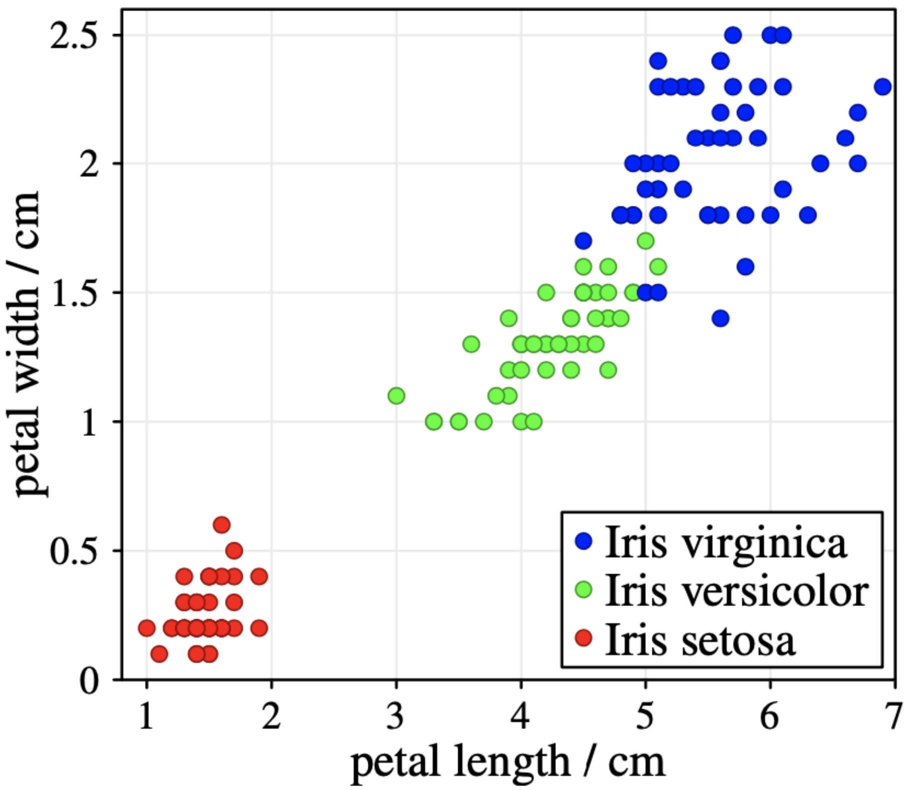
- Provides a first look at **bivariate data** to see **clusters** of points, **outliers**, **correlations**

- Each pair of values is treated as a **pair of coordinates** and plotted as points in the plane



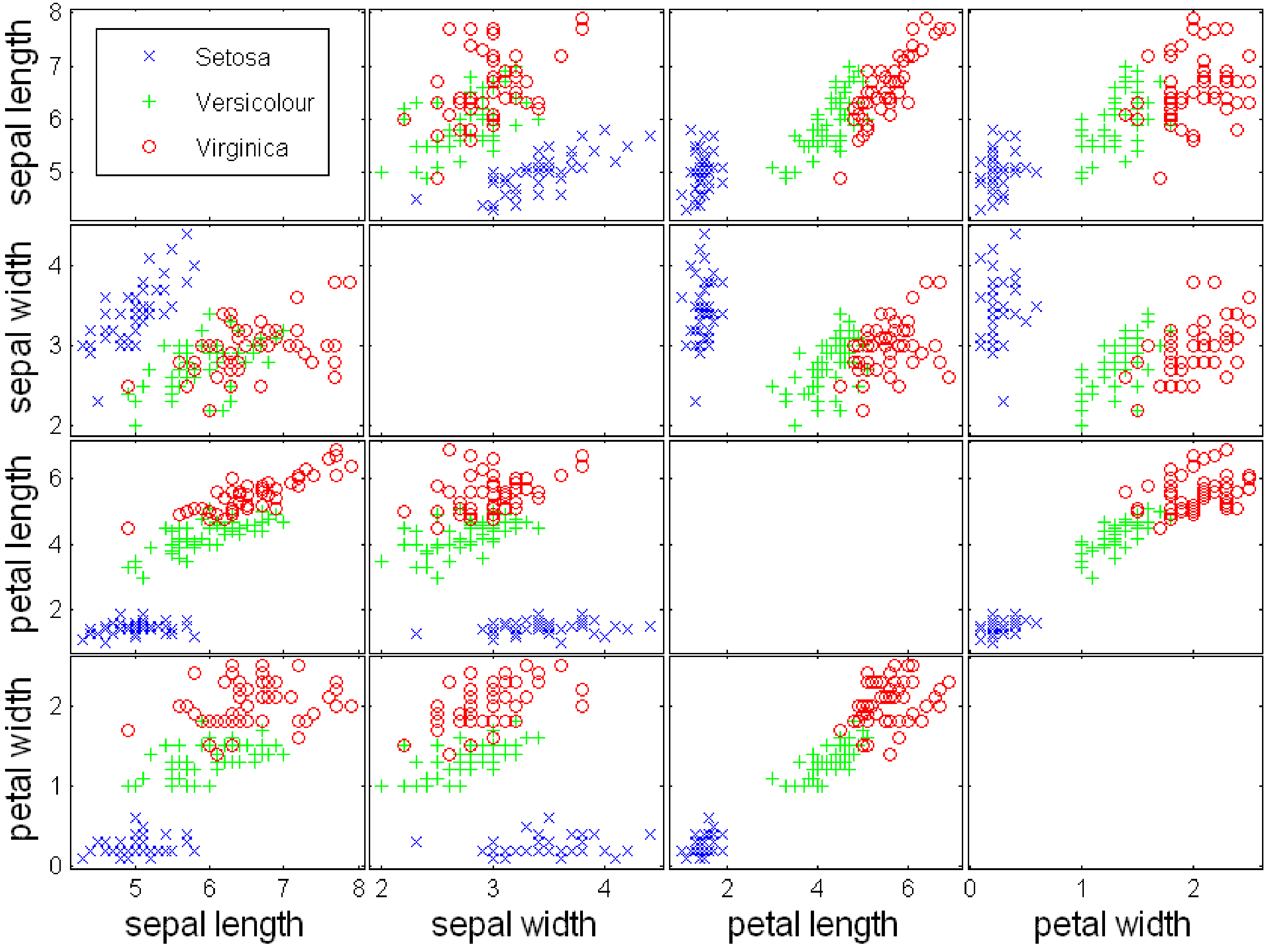
Scatter plots can be enriched with additional information: **Colour** or **different symbols** to **incorporate a third attribute** in the scatter plot.

Scatter Plot



The two attributes petal length and width provide a **better separation of the classes** Iris versicolor and Iris virginica than the sepal length and width.

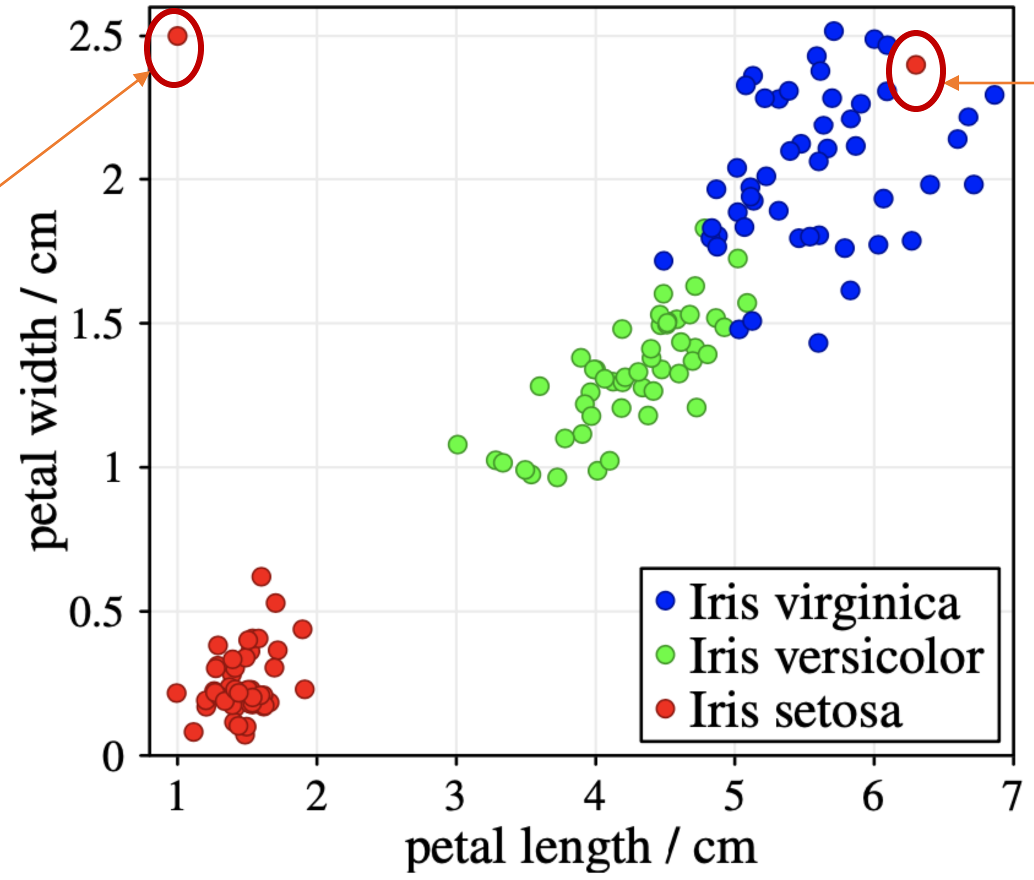
Scatter Matrix of Iris Attributes



Scatter Plot & Outliers

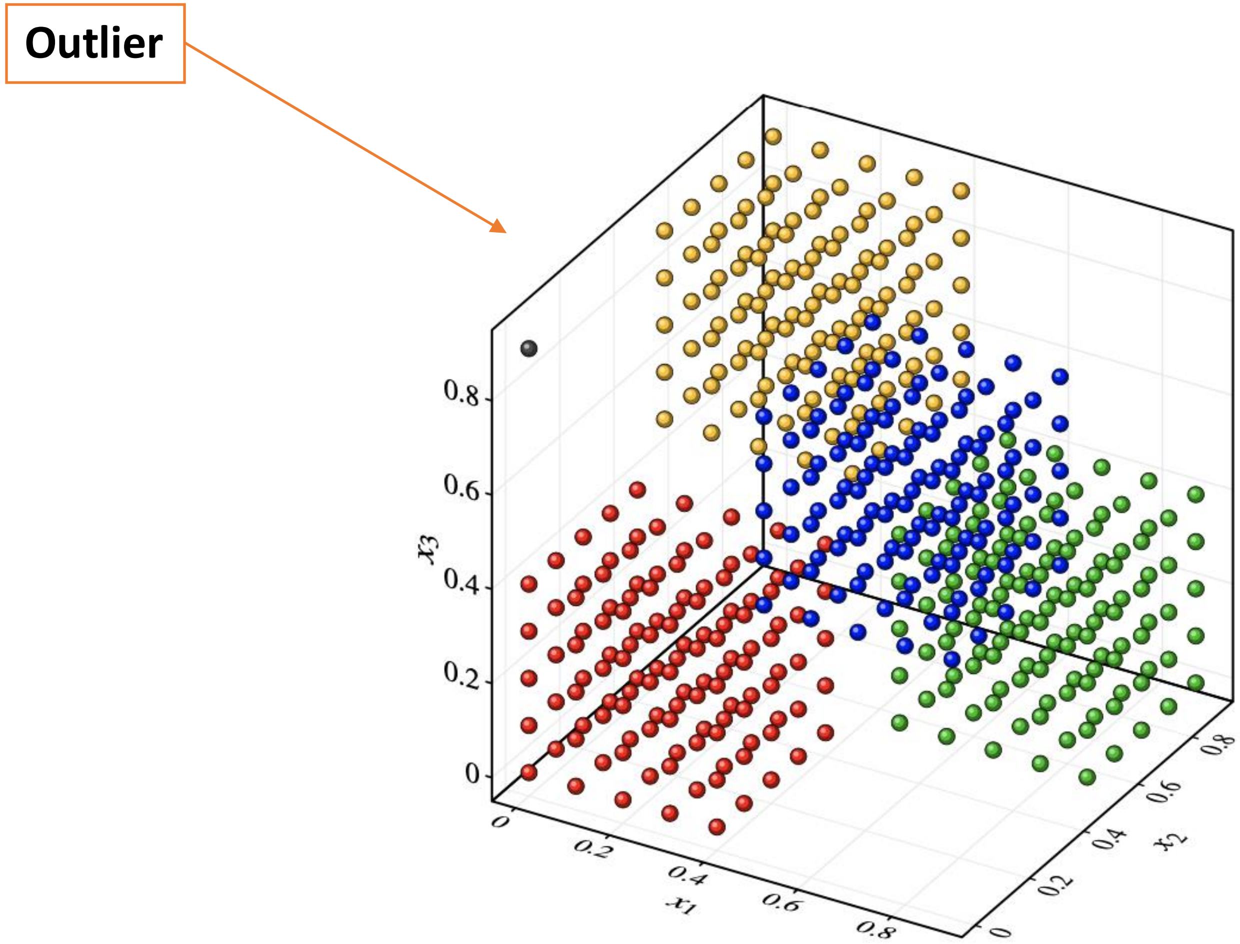
The Iris data set with two (additional artificial) outliers

outlier for the **whole dataset**



outlier for the **class Iris setosa.**

3D Scatter Plot



Visualization as a Test

- When visualisations reveal patterns or exceptions, then there is "something" in the data set.

- When visualisations do not indicate anything specific, there might still be patterns or structures in the data that cannot be revealed by the corresponding (simple) visualisation techniques.

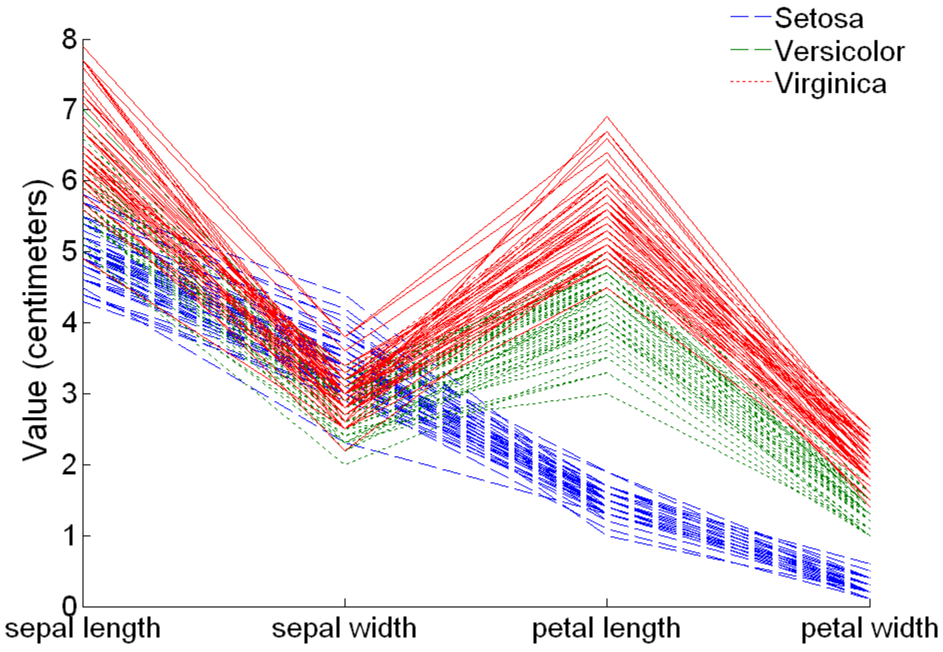
Parallel Coordinates

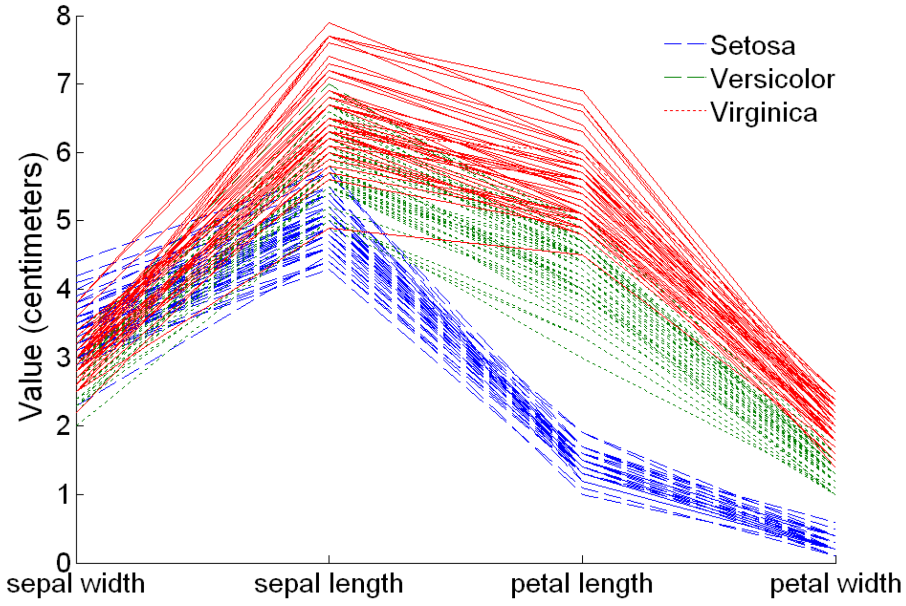
- Used to plot the attribute values of high-dimensional data
- Instead of using perpendicular axes, use a set of parallel axes

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

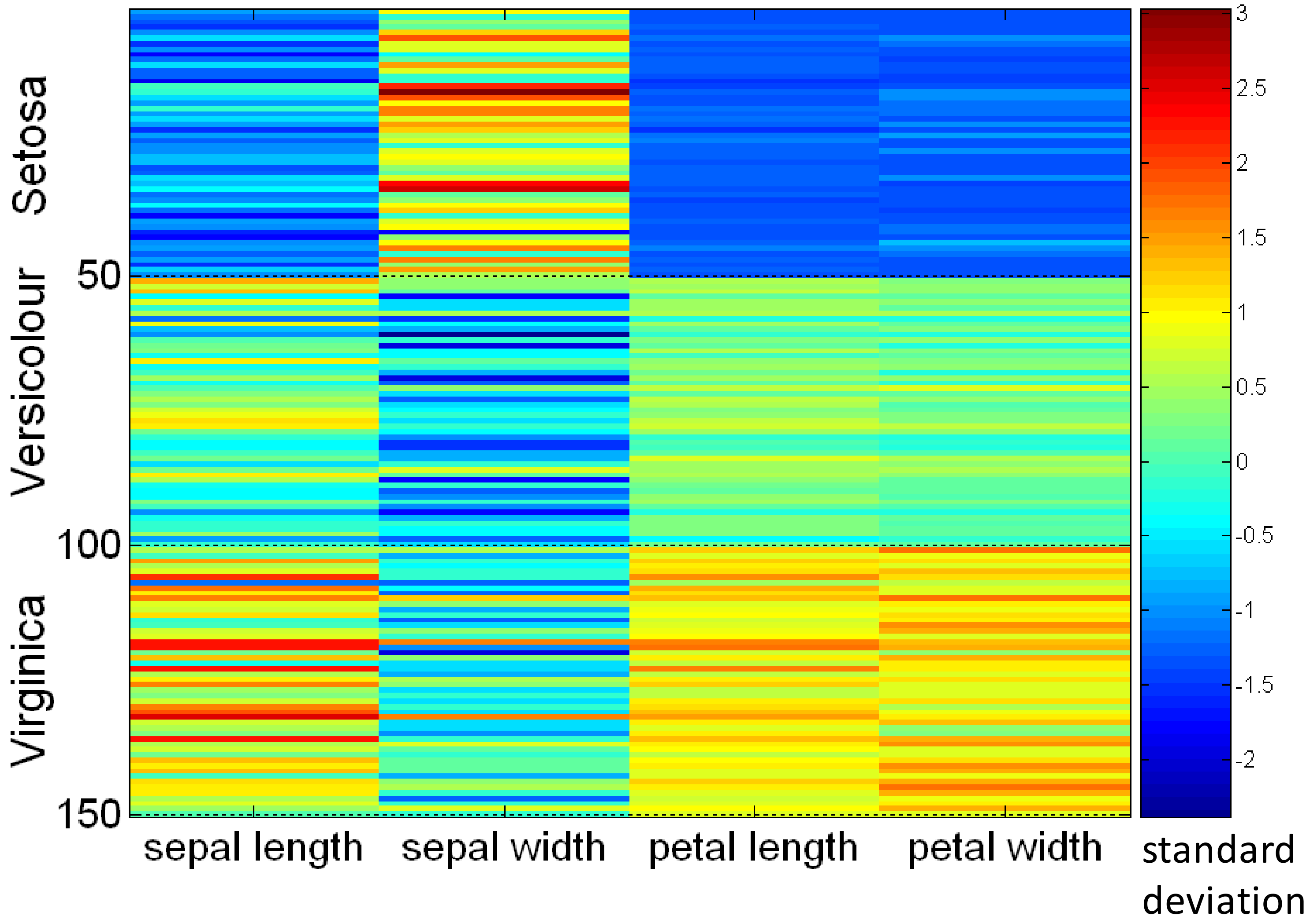




Matrix Plots

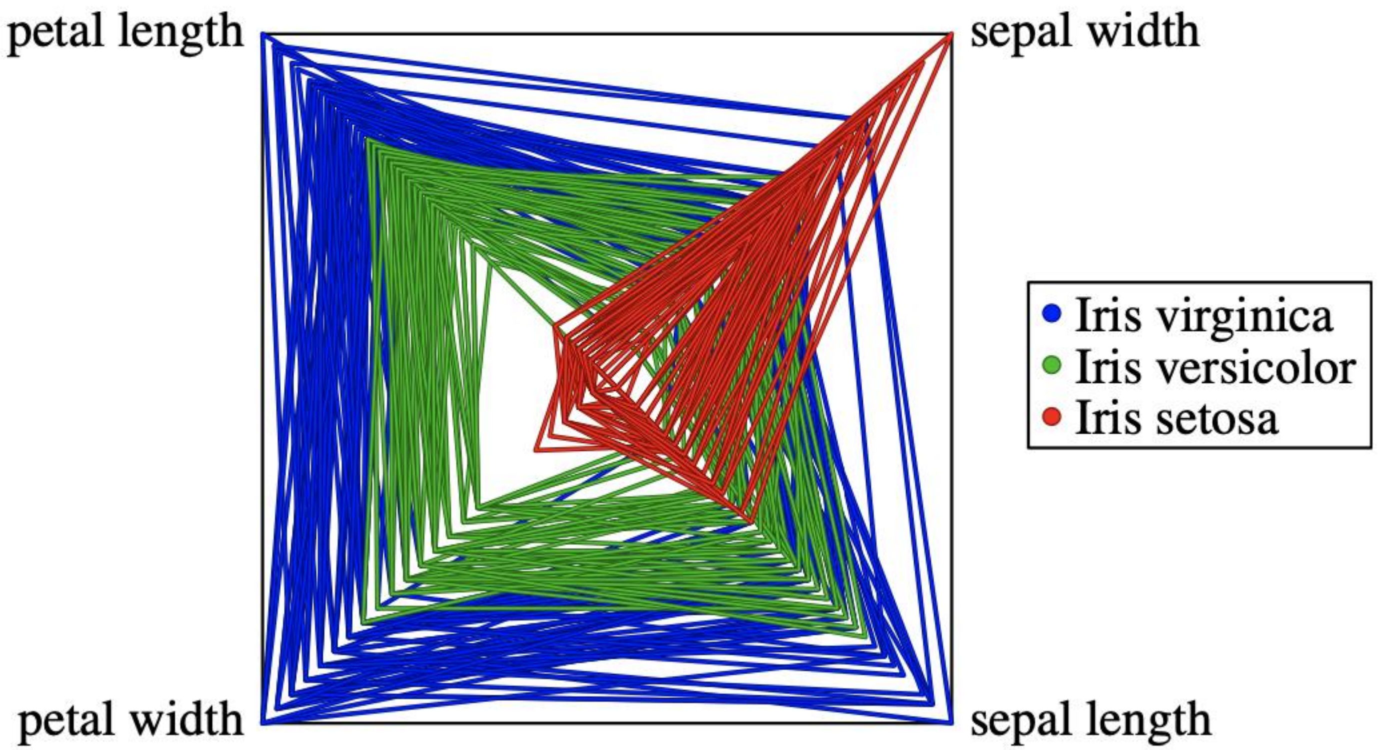
- Can plot the data matrix
- This can be useful when objects are sorted according to class
- Typically, the attributes are normalized to prevent one attribute from dominating the plot
- **Plots of similarity or distance matrices** can also be useful for visualizing the relationships between objects

Visualization of the Iris Data Matrix

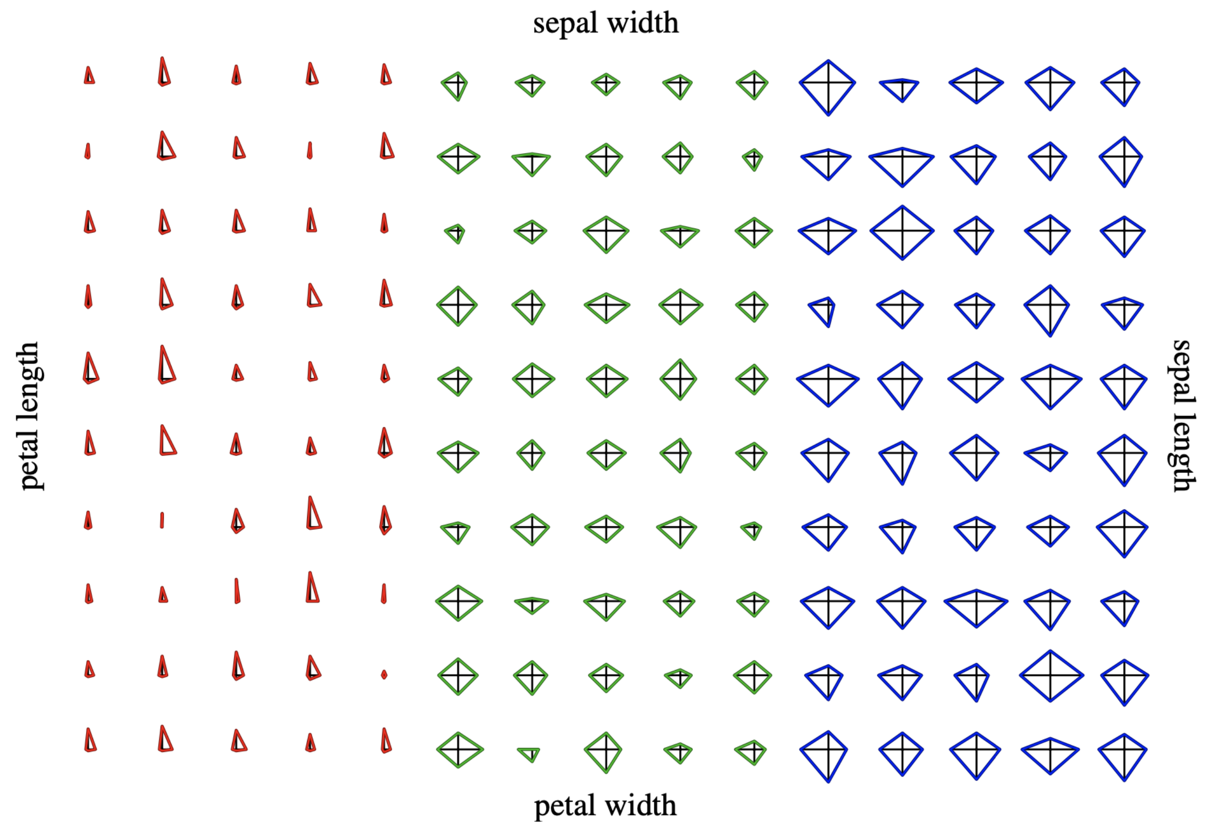


Radar Plot for Iris Data

- Similar idea as parallel coordinates
- Coordinate axes are drawn as parallel lines, but in a star-like fashion intersecting in one point
- Axes radiate from a central point
- The line connecting the values of an object is a polygon



Star Plots for Iris Data



Star plots are the same as radar plots where **each data object is drawn separately**.

Correlation Analysis

- Correlation measures the linear relationship between objects
- Captures similar behaviour of two attributes

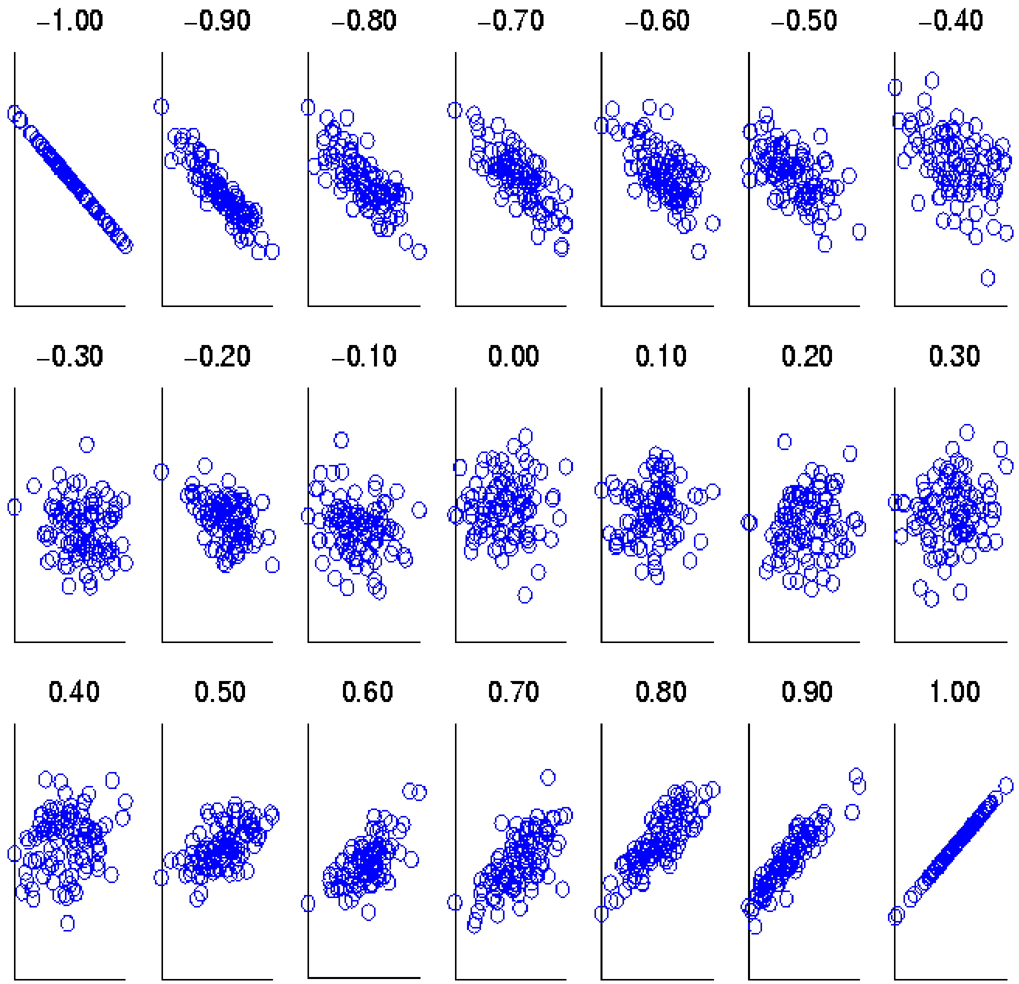
Pearson's Correlation Coefficient

The (sample) Pearson's correlation coefficient is a measure for a linear relationship between two numerical attributes X and Y and is defined as

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{(n-1)s_x s_y} \qquad -1 \leq r_{xy} \leq 1$$

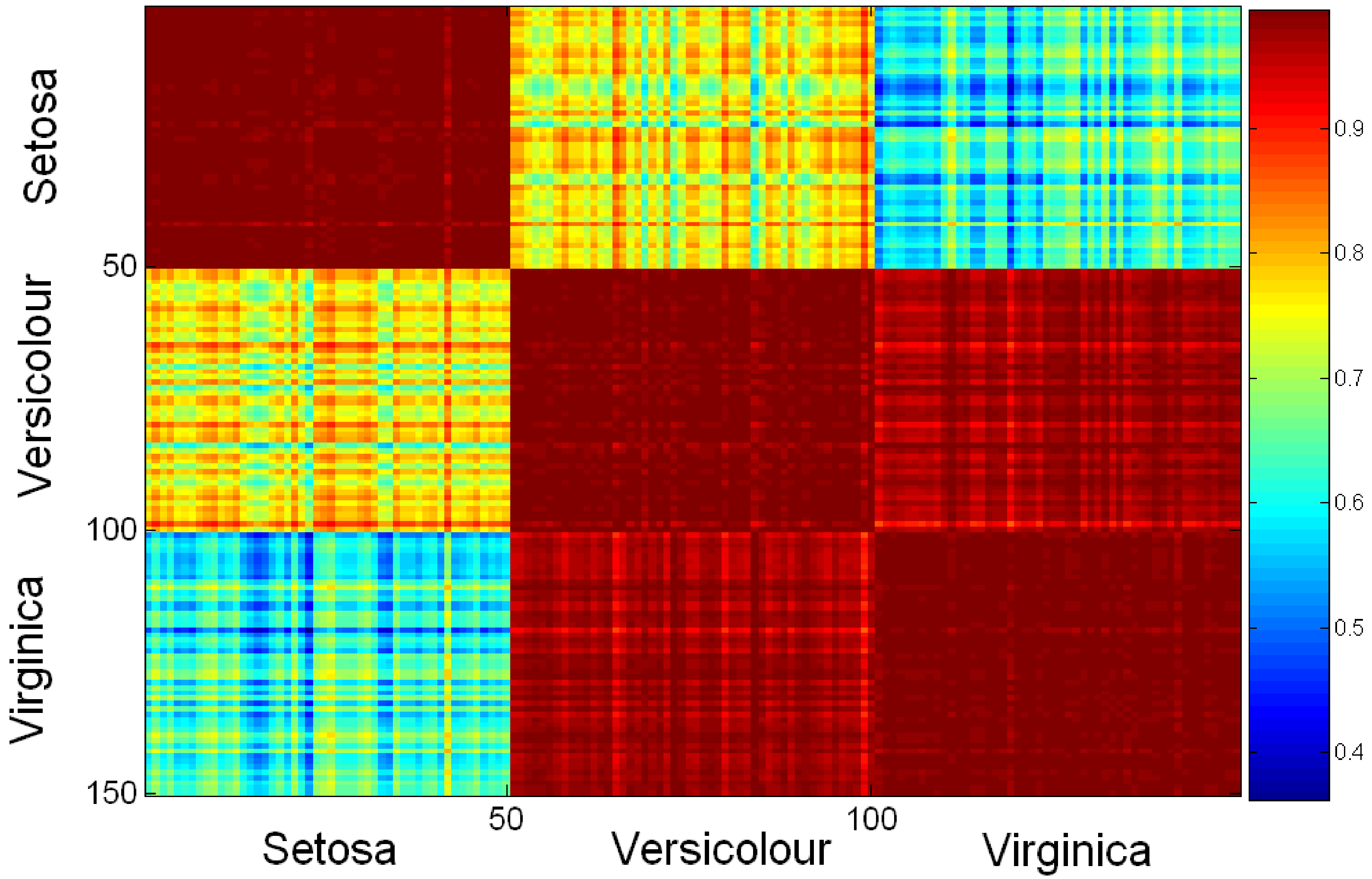
- where $\bar{x}$ and $\bar{y}$ are the mean values of the attributes X and Y, respectively. s_x and s_y are the corresponding (sample) standard deviations.
- The larger the absolute value of the Pearson correlation coefficient, the stronger the linear relationship between the two attributes.
- For $|r_{xy}| = 1$ the values of X and Y lie exactly on a line.
- Positive (negative) correlation indicates a line with positive (negative) slope.

Visually Evaluating Correlation



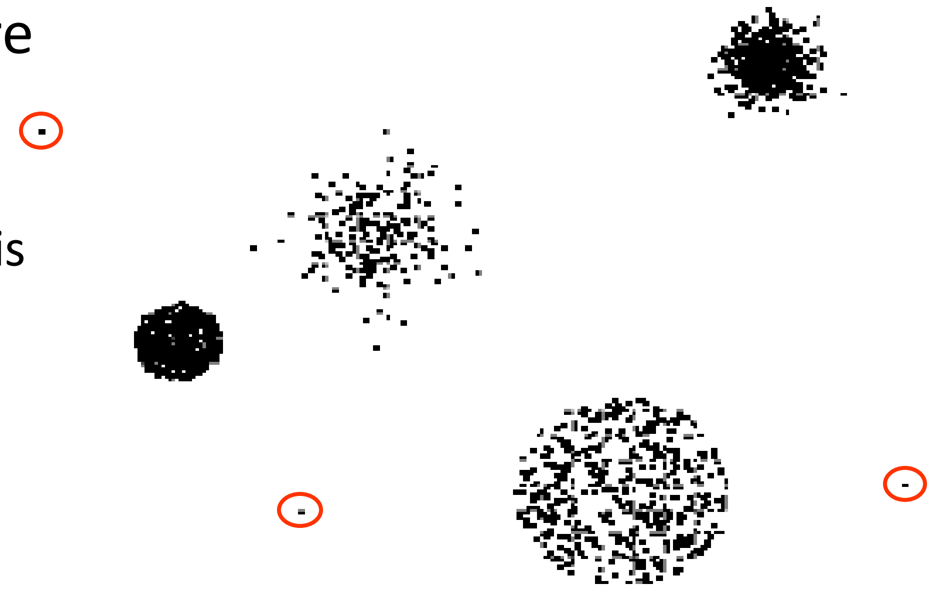
Scatter plots showing the similarity from –1 to 1.

Visualization of the Iris Correlation Matrix



Outliers

- **Outliers** are data objects with characteristics that are considerably different than most of the other data objects in the data set
  - **Case 1:** Outliers are noise that interferes with data analysis
  - **Case 2:** Outliers are the goal of our analysis
    - Credit card fraud
    - Intrusion detection
- **Causes:**
  - Data quality problems (erroneous data coming from wrong measurements or typing mistakes)
  - Exceptional or unusual situations/data objects.



Outliers as Noise

- Outliers coming from erroneous data should be excluded from the analysis
- Even if the outliers are correct (exceptional data), it is sometime useful to exclude them from the analysis.
- For example, a single extremely large outlier can lead to completely **misleading values for the mean value**.

Outlier Detection

- **Single attribute:**
  - **Categorical** attributes: An outlier is a value that occurs with a frequency extremely lower than the frequency of all other values.
  - **Numerical** attributes: box plots (points outside whiskers)
- **Multidimensional attribute:**
  - Scatter plots for (visually detecting) outliers w.r.t. two attributes
  - PCA plots for (visually detecting) outliers
  - Cluster analysis techniques: Outliers are those points which cannot be assigned to any cluster.

Missing Values

- For some instances values of single attributes might be missing
- Reasons for missing values
  - **Information is not collected**
    (e.g., people decline to give their age and weight)
  - **Attributes may not be applicable to all cases**
    (e.g., annual income is not applicable to children)
  - **Broken sensors**
  - **Refusal to answer a question**
- Missing value might not necessarily be indicated as missing (instead: zero or default values).

Checklist for Data Understanding

- Determine the quality of the data. (e.g. syntactic accuracy)
- Find outliers. (e.g. using visualization techniques)
- Detect and examine missing values. Possible hidden by default values.
- Discover new or confirm expected dependencies or correlations between attributes.
- Check specific application dependent assumptions (e.g. the attribute follows a normal distribution)
- Compare statistics with the expected behaviour.