Exploratory Data Analysis

Introduction

- Applying data mining (InfoVis as well) techniques requires gaining useful insights into the input data first
  - We saw this in the previous lecture
- Exploratory Data Analysis (EDA) helps to achieve this
- EDA offers several techniques to comprehend data
- But EDA is more than a library of data analysis techniques
- EDA is an approach to data analysis
- EDA involves inspecting data without any assumptions
  - Mostly using information graphics
  - Modern InfoVis tools use many of the EDA techniques which we study later
- Insights gained from EDA help selecting appropriate data mining (InfoVis) technique.

Descriptive Statistics

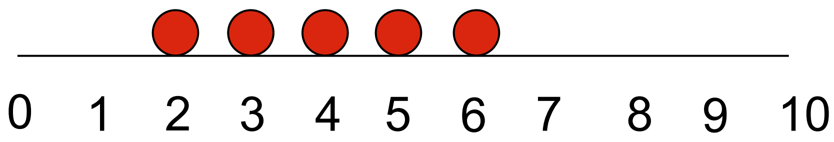
- Descriptive statistical methods quantitatively describe the main features of data
- Main data features
  - measures of central tendency – represent a ‘center’ around which measurements are distributed
    - e.g. mean and median
  - measures of variability – represent the ‘spread’ of the data from the ‘center’
    - e.g. standard deviation
  - measures of relative standing – represent the ‘relative position’ of specific measurements in the data
    - e.g quantiles

Mean

- Sum all the numbers and divide by their count

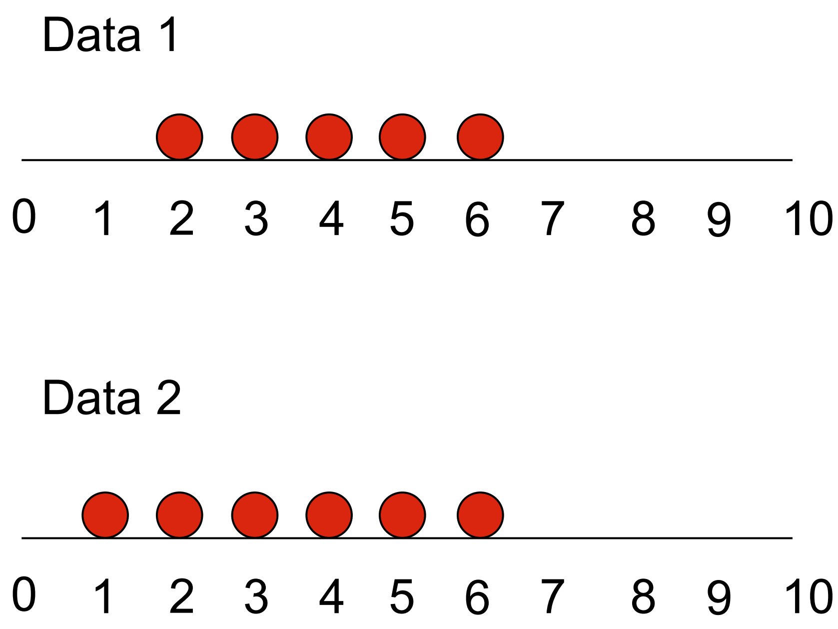
  $x = (x_1+x_2+ \ldots +x_n)/n$
- F~~o~~r the example data
  - Mean = (2+3+4+5+6)/5

  = 4
  - 4 is the 'center'
- The information graphic used here is called a dot diagram



Median

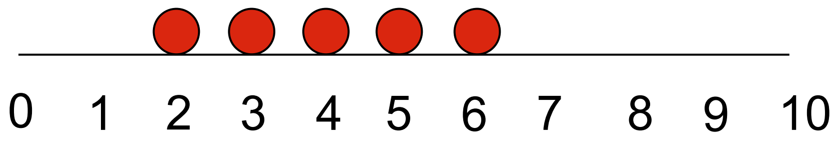
- The exact middle value
- When count is odd just find the middle value of the sorted data
- When count is even find the mean of the middle two values
- For example data 1
  - Median is 4
  - 4 is the 'center'
- For example data 2
  - Median is (3+4)/2 = 3.5
  - 3.5 is the 'center'



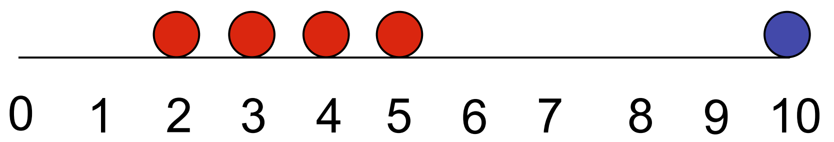
Median VS Mean

- When data has outliers median is more robust
  - The blue data point is the outlier in data 2
- When data distribution is skewed median is more meaningful
- For example data 1
  - Mean=4 and median=4
- For example data 2
  - Mean=24/5 and median=4

Data 1



Data 2

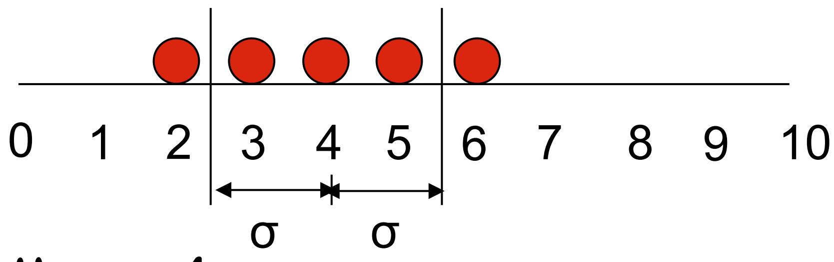


Standard Deviation

- Computation steps
  - Compute mean
  - Compute each measurement's deviations from the mean
  - Square the deviations
  - Sum the squared deviations
  - Divide by (count-1)
  - Compute the square root

$\sigma = \sqrt{}(\sum(x_i-\bar{x})^2)/(n-1)$

Data 1



Mean = 4

Deviations: -2, -1, 0, 1, 2

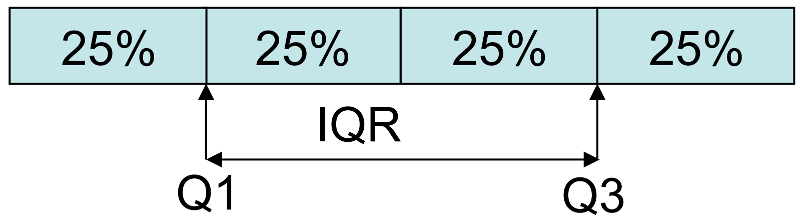
Squared deviations: 4, 1, 0, 1, 4

Sum = 10

Standard deviation = $\sqrt{(10/4)}$ = 1.58

Quartiles

- Median is the 2nd quartile
- 1st quartile is the measurement with 25% measurements smaller and 75% larger – lower quartile (Q1)
- 3rd quartile is the measurement with 75% measurements smaller and 25% larger – upper quartile (Q3)
- Inter quartile range (IQR) is the difference between Q3 and Q1
  - Q3-Q1



Stem and Leaf Plot

- This plot organizes data for easy visual inspection
  - Min and max values
  - Data distribution
- Unlike descriptive statistics, this plot shows all the data
  - No information loss
  - Individual values can be inspected
- Structure of the plot
  - Stem – the digits in the largest place (e.g. tens place)
  - Leaves – the digits in the smallest place (e.g. ones place)
  - Leaves are listed to the left of stem separated by '|'
- Possible to place leaves from another data set to the right of the stem for comparing two data distributions

Data

29, 44, 12, 53, 21, 34, 39, 25, 48, 23, 17, 24, 27, 32, 34, 15, 42, 21, 28, 37

Stem and Leaf Plot

1 | 2 7 5

2 | 9 1 5 3 4 7 1 8

3 | 4 9 2 4 7

4 | 4 8 2

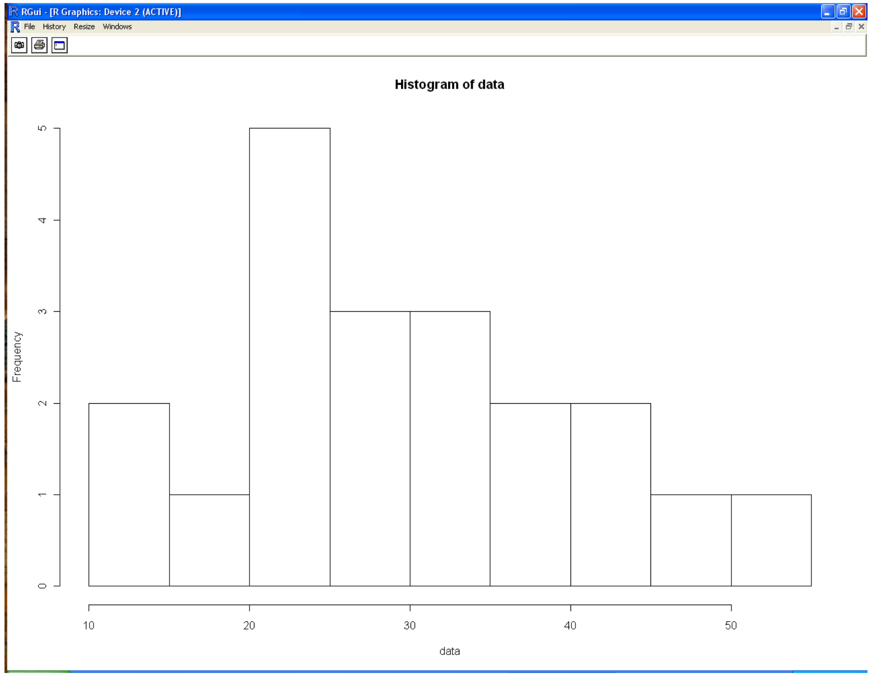
5 | 3

Histogram/Bar Chart

- Graphical display of <u>frequency distribution</u>
  - Counts of data falling in various ranges (bins)
  - Histogram for numeric data
  - Bar chart for nominal data
- Bin size selection is important
  - Too small – may show spurious patterns
  - Too large – may hide important patterns
- Several Variations possible
  - Plot relative frequencies instead of raw frequencies
  - Make the height of the histogram equal to the 'relative frequency/width'
    - Area under the histogram is 1
- When observations come from continuous scale histograms can be approximated by continuous curves

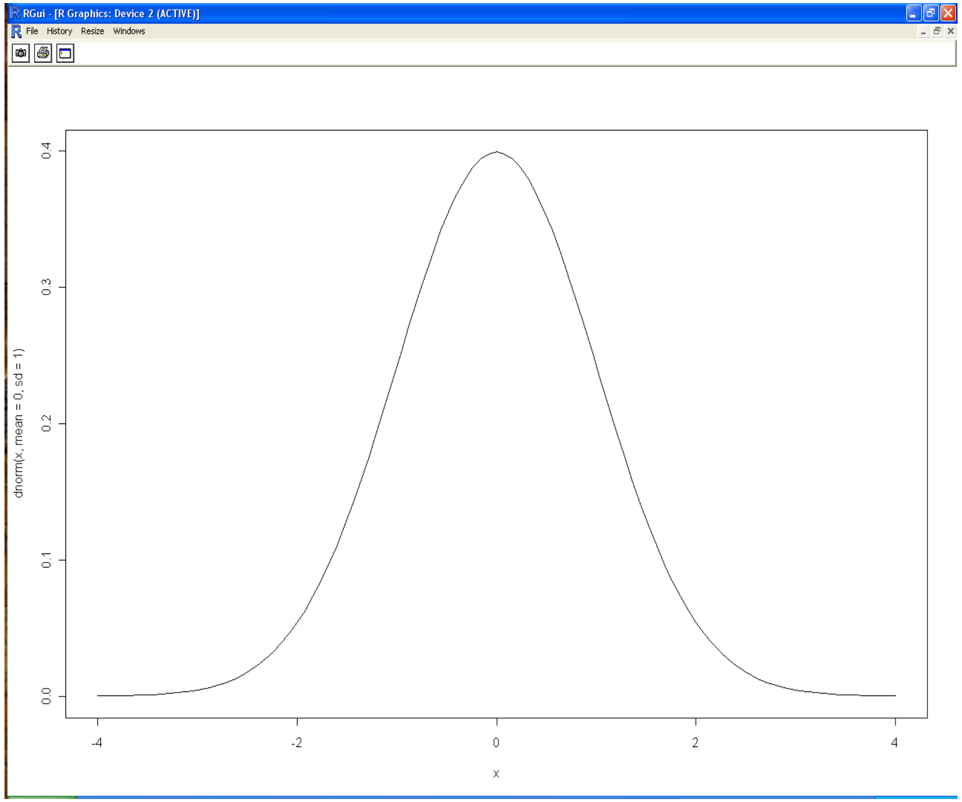
Data

29, 44, 12, 53, 21, 34, 39, 25, 48, 23, 17, 24, 27, 32, 34, 15, 42, 21, 28, 37



Normal Distribution

- Distributions of several data sets are bell shaped
  - Symmetric distribution
  - With peak of the bell at the mean, μ of the data
  - With spread (extent) of the bell defined by the standard deviation, σ of the data
- For example, height, weight and IQ scores are normally distributed
- **The 68-95-99.7% Rule**
  - 68% of measurements fall within $\mu - \sigma$ and $\mu + \sigma$
  - 95% of measurements fall within $\mu - 2\sigma$ and $\mu + 2\sigma$
  - 99.7% of observations fall within $\mu - 3\sigma$ and $\mu + 3\sigma$



Standardization

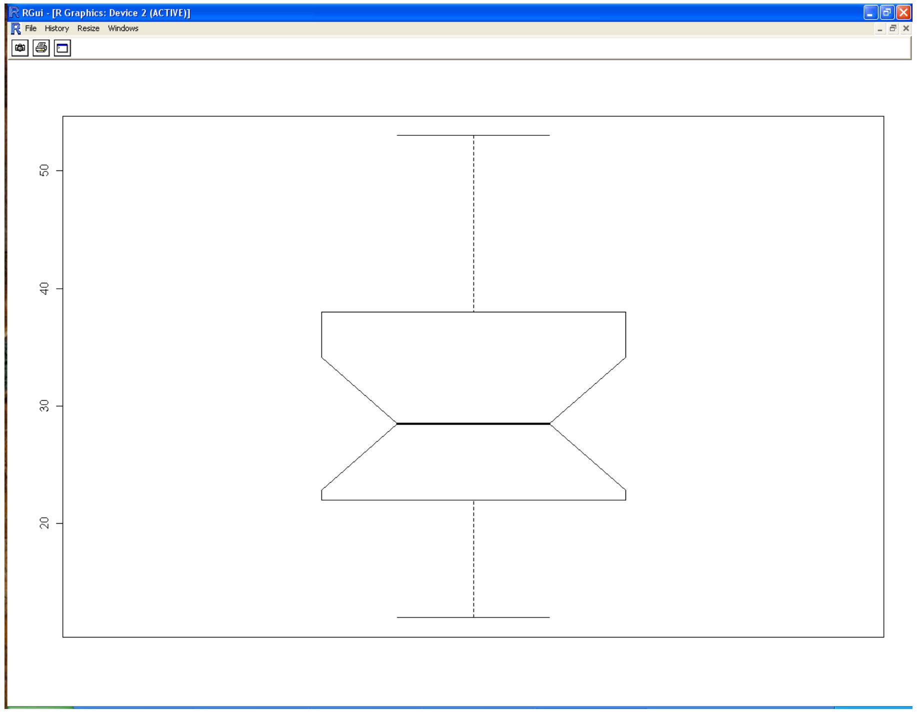
- Data sets originate from several sources and there are bound to be differences in measurements
  - Comparing data from different distributions is hard
- Standard deviation of a data set is used as a yardstick for adjusting for such distribution specific differences
- Individual measurements are converted into what are called standard measurements called z scores
- An individual measurement is expressed in terms of the number of standard deviations, σ it is away from the mean, μ
- Z score of $x = (x - \mu)/\sigma$
  - Formula for standardizing attribute values
- Z scores are more meaningful for comparison
- When different attributes use different ranges of values, we use standardization

Box Plot

- A five value summary plot of data
  - Minimum, maximum
  - Median
  - 1st and 3rd quartiles
- Often used in conjunction with a histogram in EDA
- Structure of the plot
  - Box represents the IQR (the middle 50% values)
  - The horizontal line in the box shows the median
  - Vertical lines extend above and below the box
  - Ends of vertical lines called whiskers indicate the max and min values
    - If max and min fall within 1.5*IQR
  - Shows outliers above/below the whiskers

Data

29, 44, 12, 53, 21, 34, 39, 25, 48, 23, 17, 24, 27, 32, 34, 15, 42, 21, 28, 37



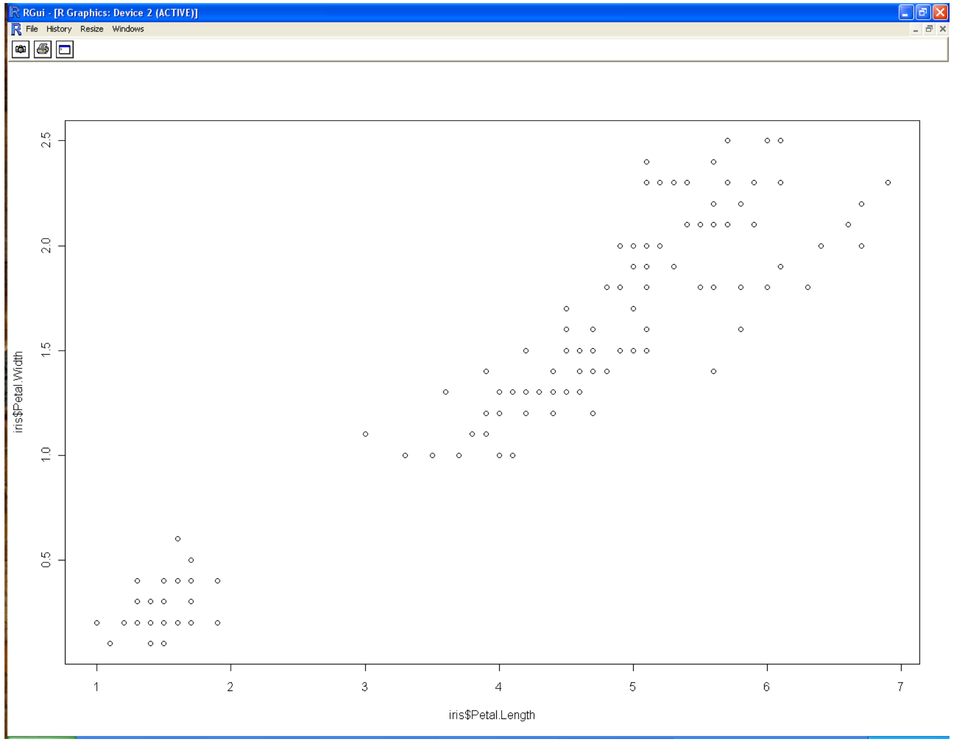
Iris Sample Data Set

- Many of the exploratory data techniques are illustrated with the Iris Plant data set.
  - Can be obtained from the UCI Machine Learning Repository http://www.ics.uci.edu/~mlearn/MLRepository.html
  - From the statistician Douglas Fisher
  - Three flower types (classes):
    - Setosa
    - Virginica
    - Versicolour
  - Four (non-class) attributes
    - Sepal width and length
    - Petal width and length

Virginica. Robert H. Mohlenbrock. USDA NRCS. 1995. Northeast wetland flora: Field office guide to plant species. Northeast National Technical Center, Chester, PA. Courtesy of USDA NRCS Wetland

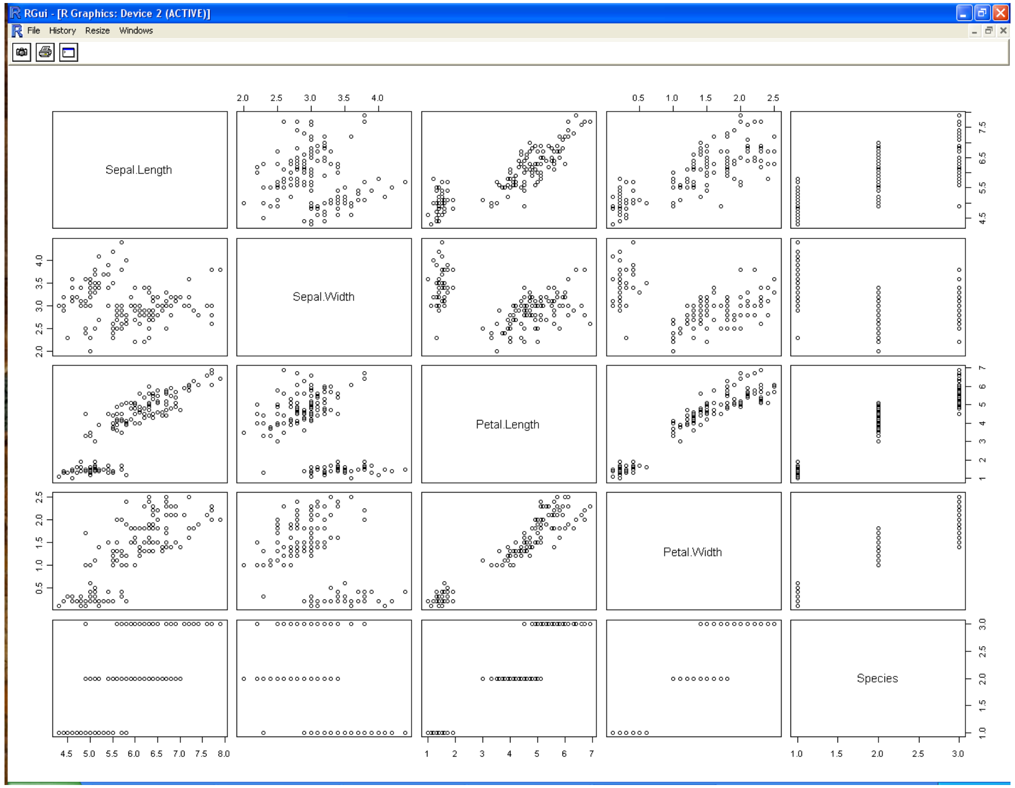
Scatter Plot

- Scatter plots are two dimensional graphs with
  - explanatory attribute plotted on the x-axis
  - Response attribute plotted on the y-axis
- Useful for understanding the relationship between two attributes
- Features of the relationship
  - strength
  - shape (linear or curve)
  - Direction
  - Outliers
- Scatter plot of iris$Petal.Width against iris$Petal.Length (refer to practical 1 about IRIS data) is shown here



Scatter Plot Matrix

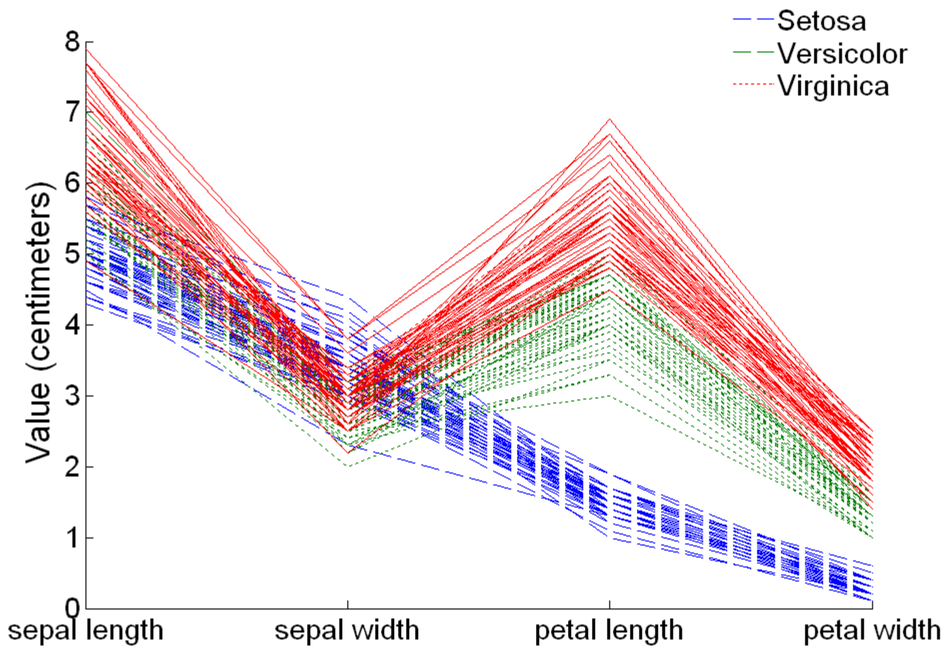
- When multiple attributes need to be visualized all at once
  - Scatter plots are drawn for every pair of attributes and arranged into a 2D matrix.
- Useful for spotting relationships among attributes
  - Similar to a scatter plot
- Scatter plot matrix of IRIS data is shown here
  - Attributes are shown on the diagonal
- Later in the course we learn to use parallel coordinates for plotting multi-attribute data

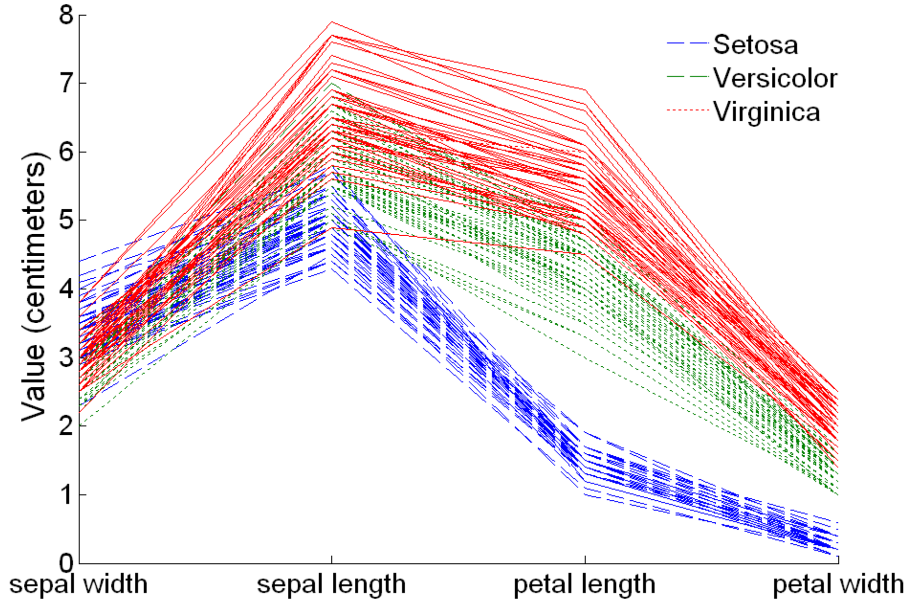


Visualization Techniques: Parallel Coordinates

- 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

Parallel Coordinates Plots for Iris Data

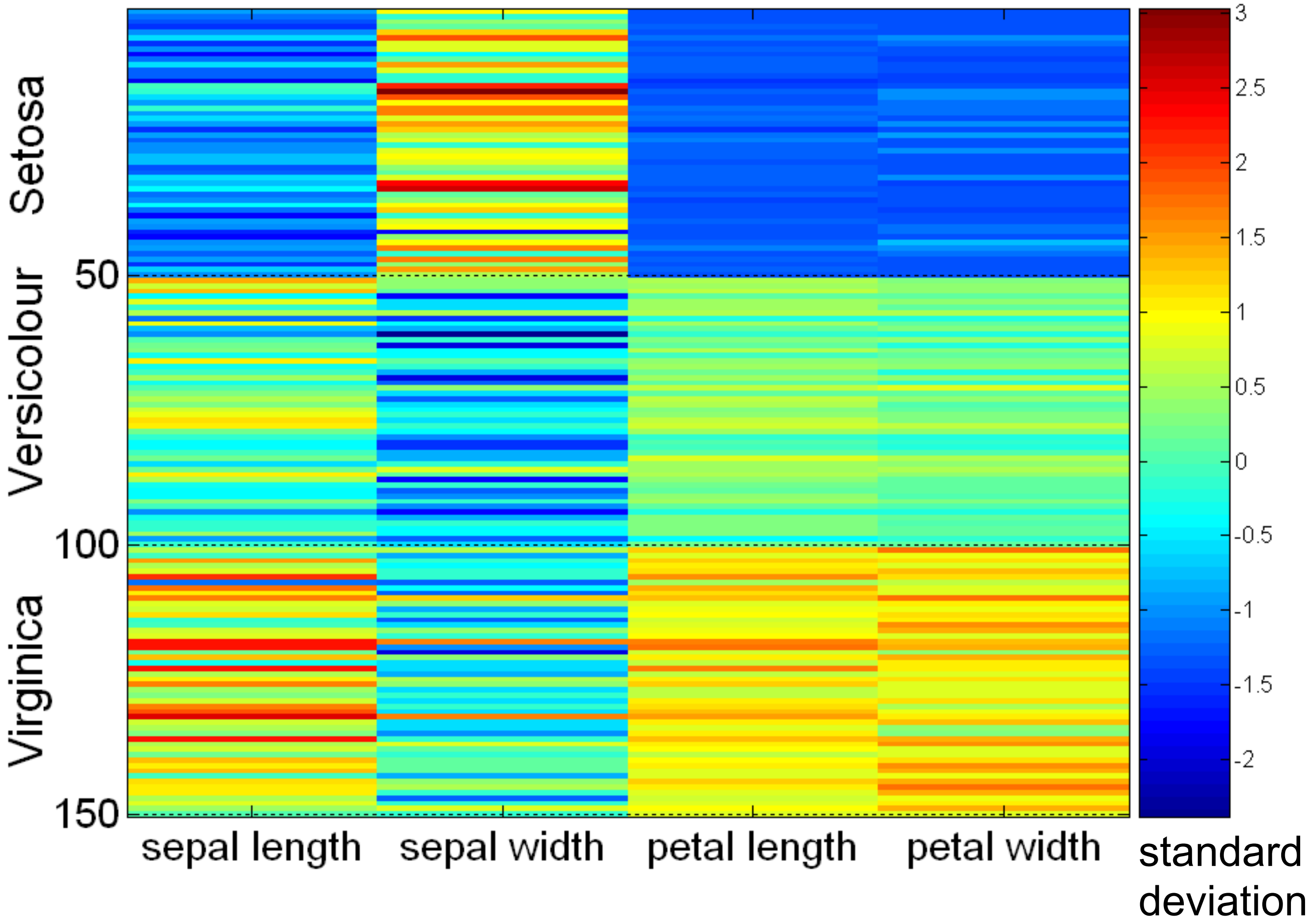




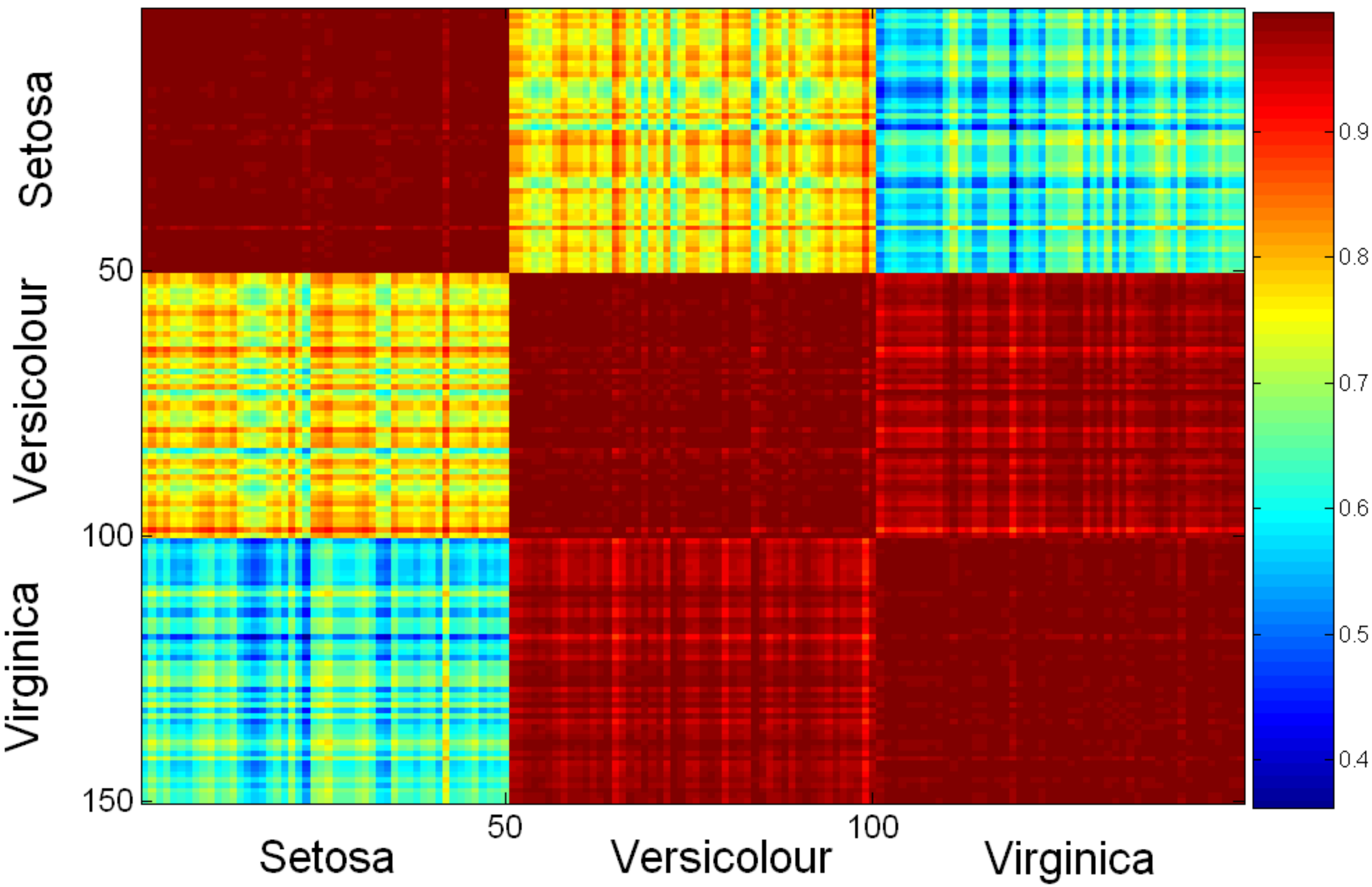
Visualization Techniques: Matrix Plots

- 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
  - Examples of matrix plots are presented on the next two slides

Visualization of the Iris Data Matrix



Visualization of the Iris Correlation Matrix



EDA Answers Questions

- All the techniques presented so far are the tools useful for EDA
- But without an understanding built from the EDA, effective use of tools is not possible
  - A detective investigating a crime scene needs tools for obtaining finger prints.
  - Also needs an understanding (common sense) to know where to look for finger prints
    - Door knobs better places than door hinges?
- EDA helps to answer a lot of questions
  - What is a typical value?
  - What is the uncertainty of a typical value?
  - What is a good distributional fit for the data?
  - What are the relationships between two attributes?
  - etc

Next Three Lectures

- Classification
- Dr. Chenghua Lin

Acknowledgement

- Some of the slides are based on the course slides provided by
  - Tan, Steinbach and Kumar (Introduction to Data Mining)

- Some pictures are taken from various online resources.