Week 4
Engineering Data (Part III)

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Source: Tan, Kumar, Steinback (2006)

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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

Techniques Used In Data Exploration

- In EDA, as originally defined by Tukey
  - The focus was on visualization
  - Clustering and anomaly detection were viewed as exploratory techniques
  - In data mining, clustering and anomaly detection are major areas of interest, and not thought of as just exploratory

- In our discussion of data exploration, we focus on
  - Summary statistics
  - Visualization
  - Online Analytical Processing (OLAP)

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://archive.ics.uci.edu/ml/
  - 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 Science Institute.

Summary Statistics

- Summary statistics are numbers that summarize properties of the data
  - Summarized properties include frequency, location and spread
    - Examples: location – mean - 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

Percentiles

- For continuous data, the notion of a percentile is more useful.

- 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 .

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

Measures of Location: Mean and Median

- 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 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.

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

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

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

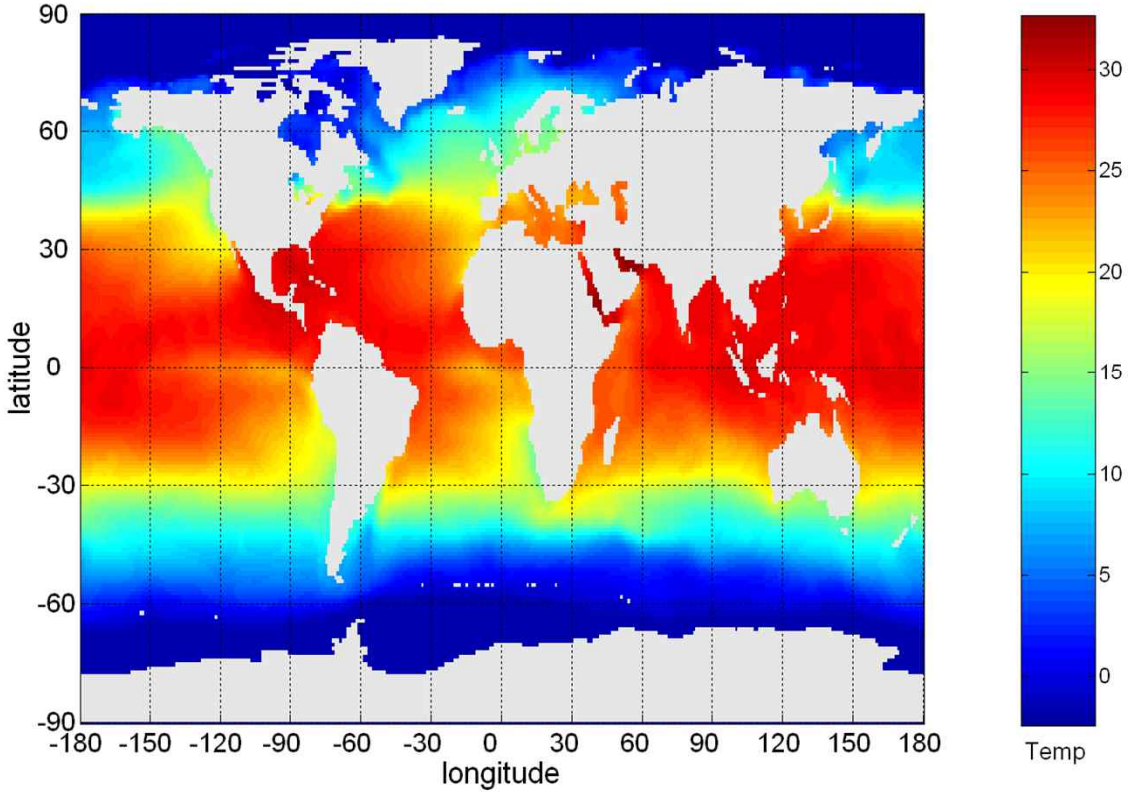
Visualization

- 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

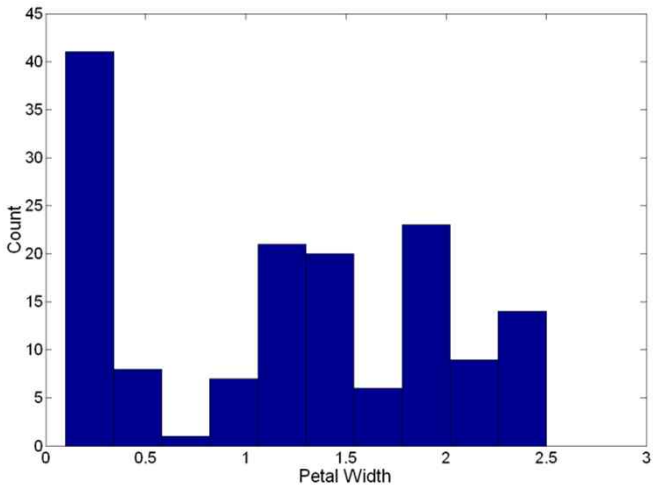
Example: Sea Surface Temperature

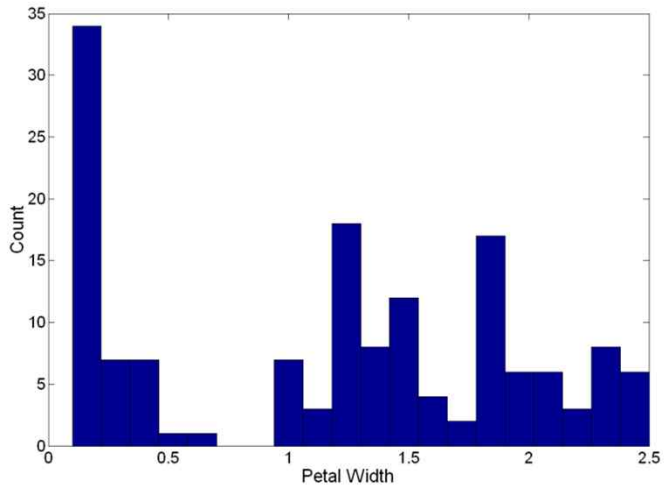
- The following shows the Sea Surface Temperature (SST) for July 1982
  - Tens of thousands of data points are summarized in a single figure



Visualization Techniques: Histograms

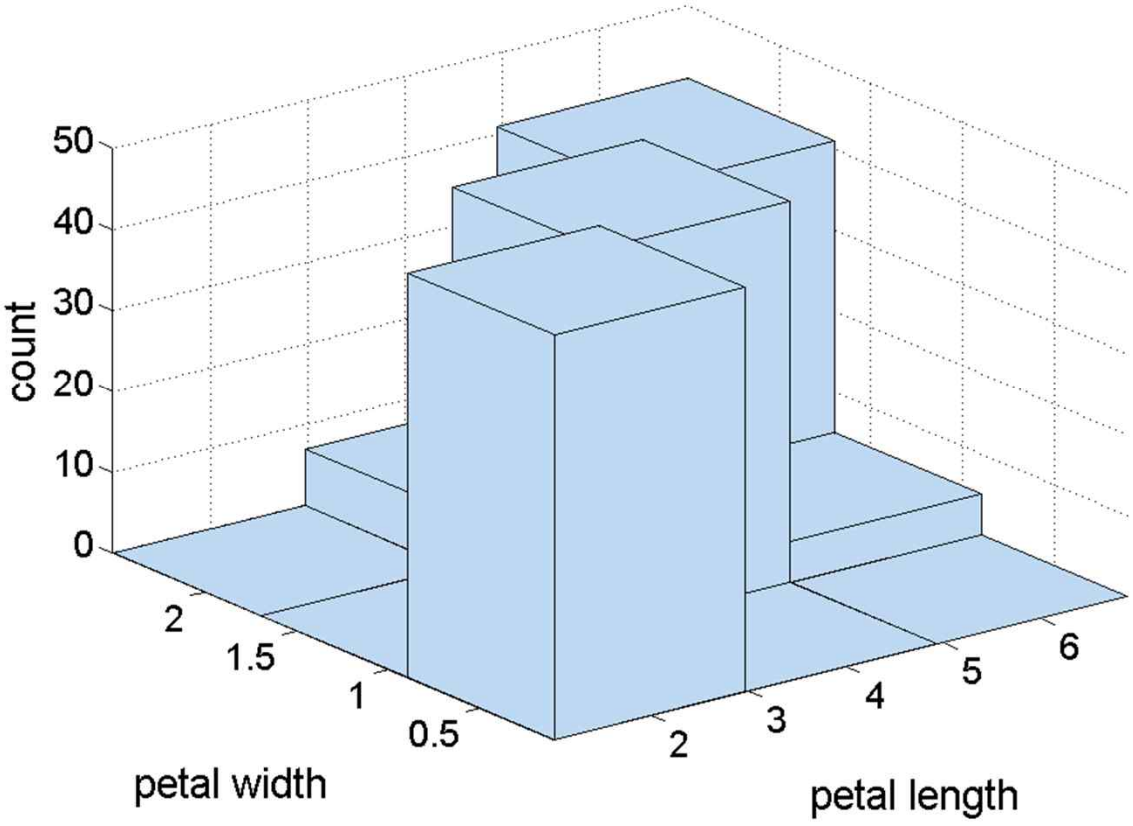
- Histogram
  - Usually shows the distribution of values of a single variable
  - Divide the values into bins and show a bar plot of the number of objects in each bin.
  - The height of each bar indicates the number of objects
  - Shape of histogram depends on the number of bins
- Example: Petal Width (10 and 20 bins, respectively)





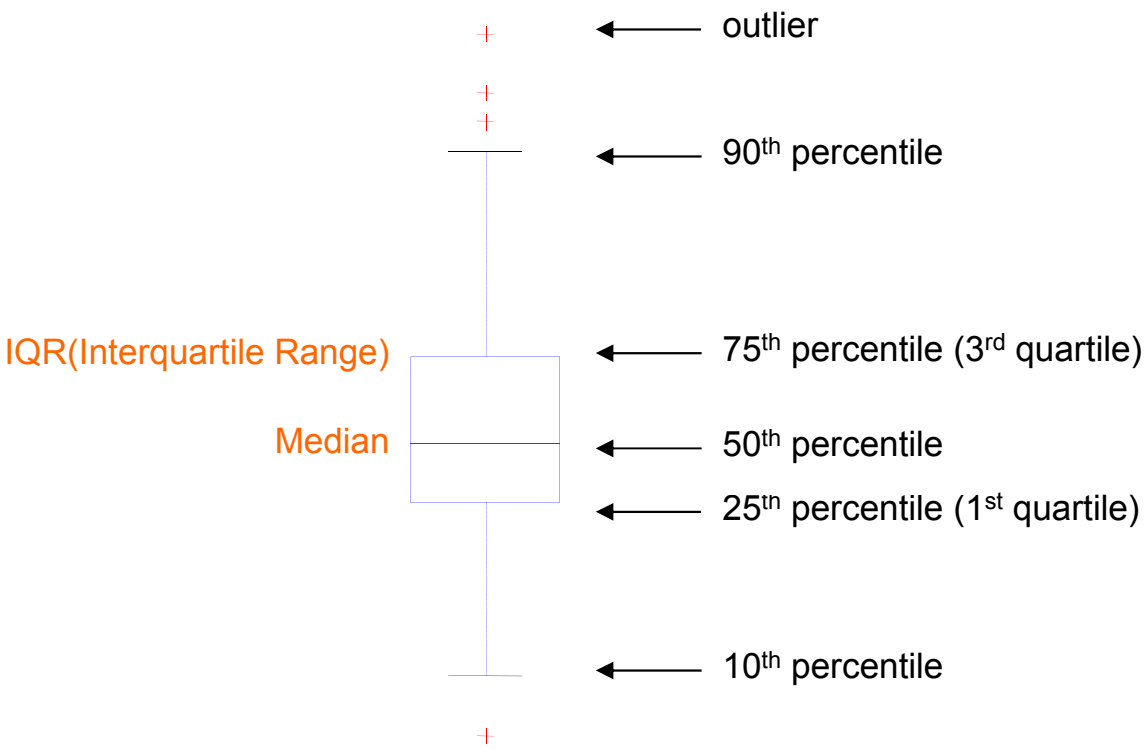
Two-Dimensional Histograms

- Show the joint distribution of the values of two attributes
- Example: petal width and petal length



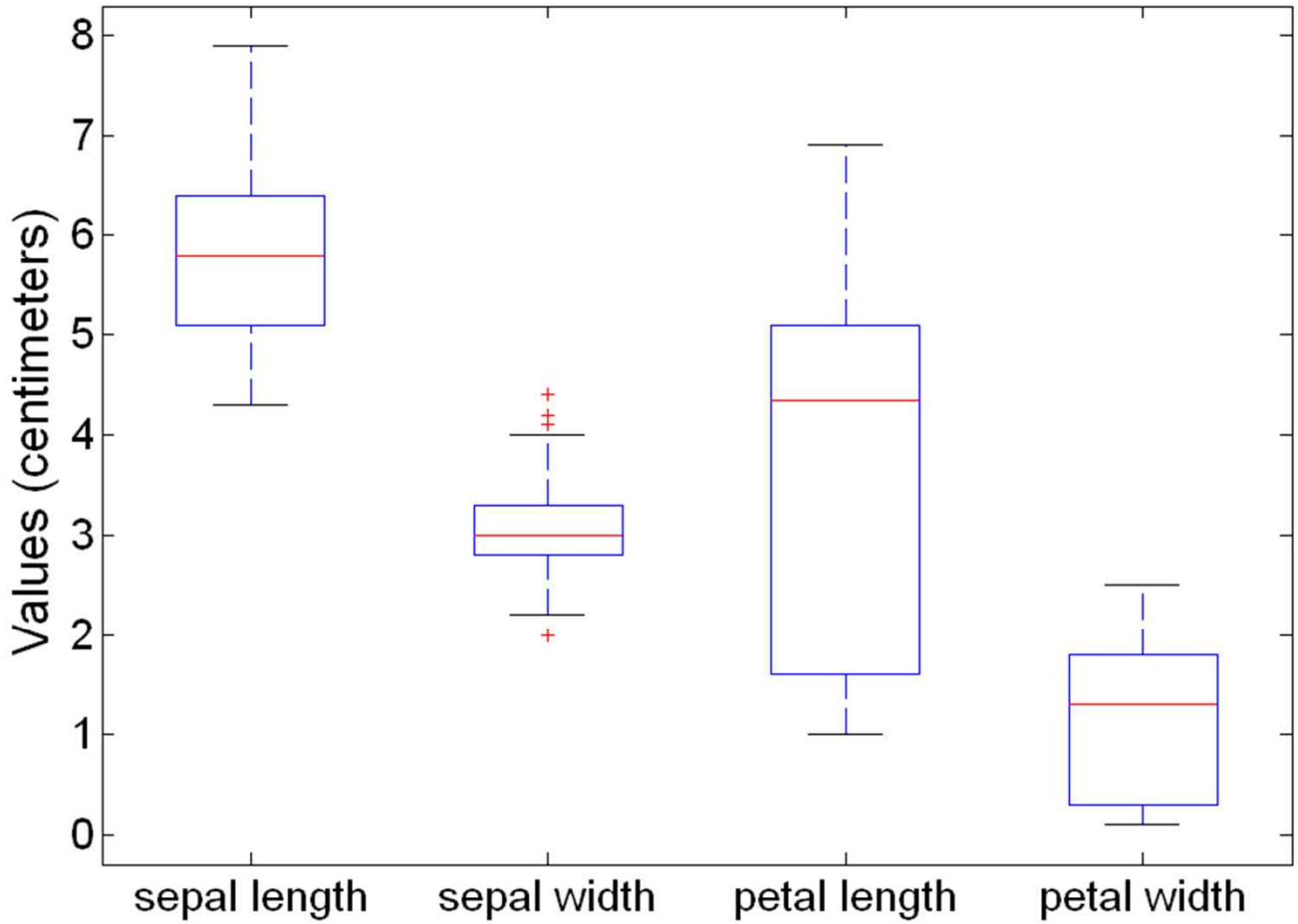
Visualization Techniques: Box Plots

- Box Plots
  - Another way of displaying the distribution of data
  - Following figure shows the basic part of a box plot



Example of Box Plots

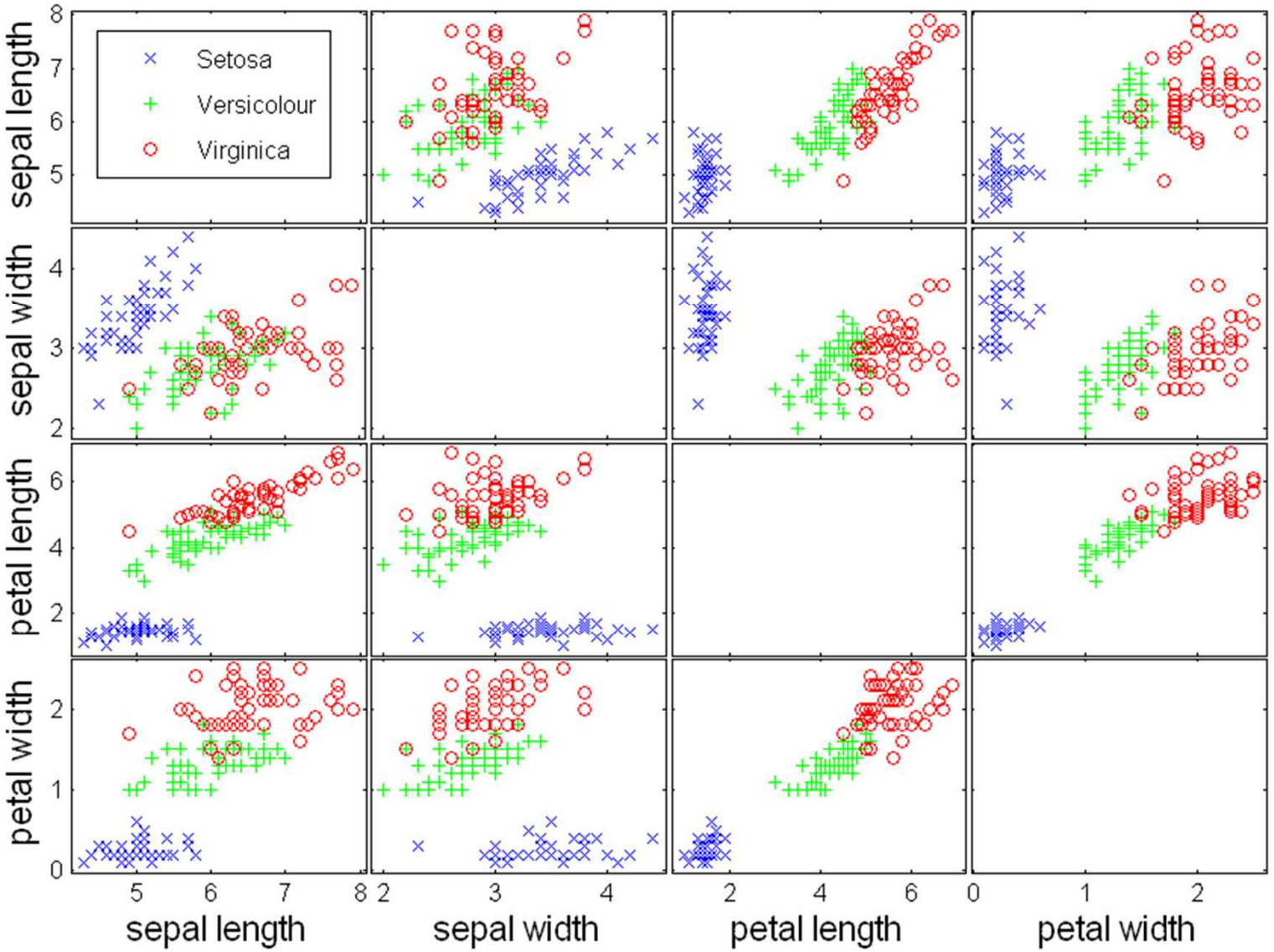
- Box plots can be used to compare attributes



Visualization Techniques: Scatter Plots

- 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
  - It is useful to have arrays of scatter plots can compactly summarize the relationships of several pairs of attributes

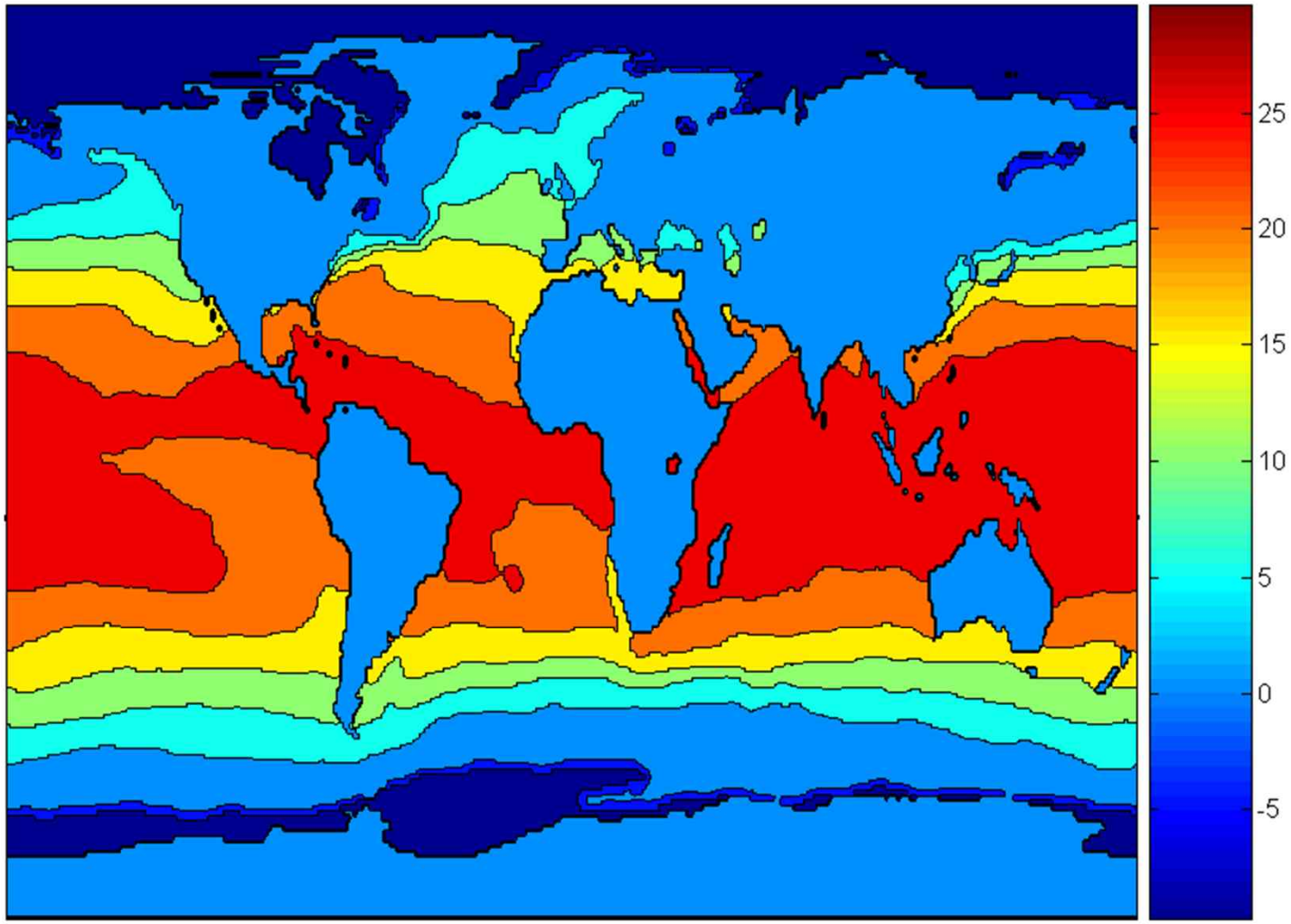
Scatter Plot Array of Iris Attributes



Visualization Techniques: Contour Plots

- 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.
    - An example for Sea Surface Temperature (SST) is provided on the next slide

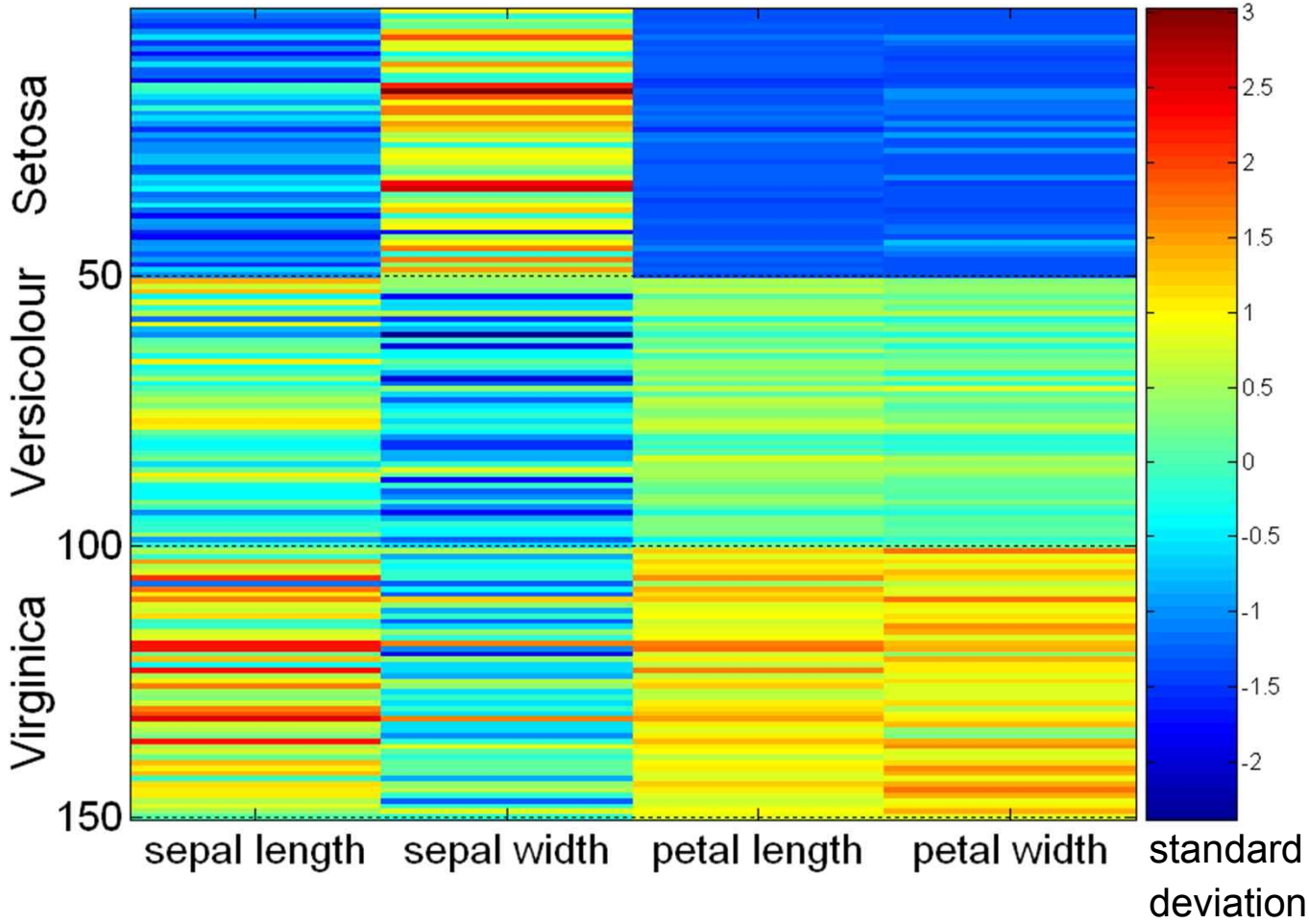
Contour Plot Example: SST Dec, 1998



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

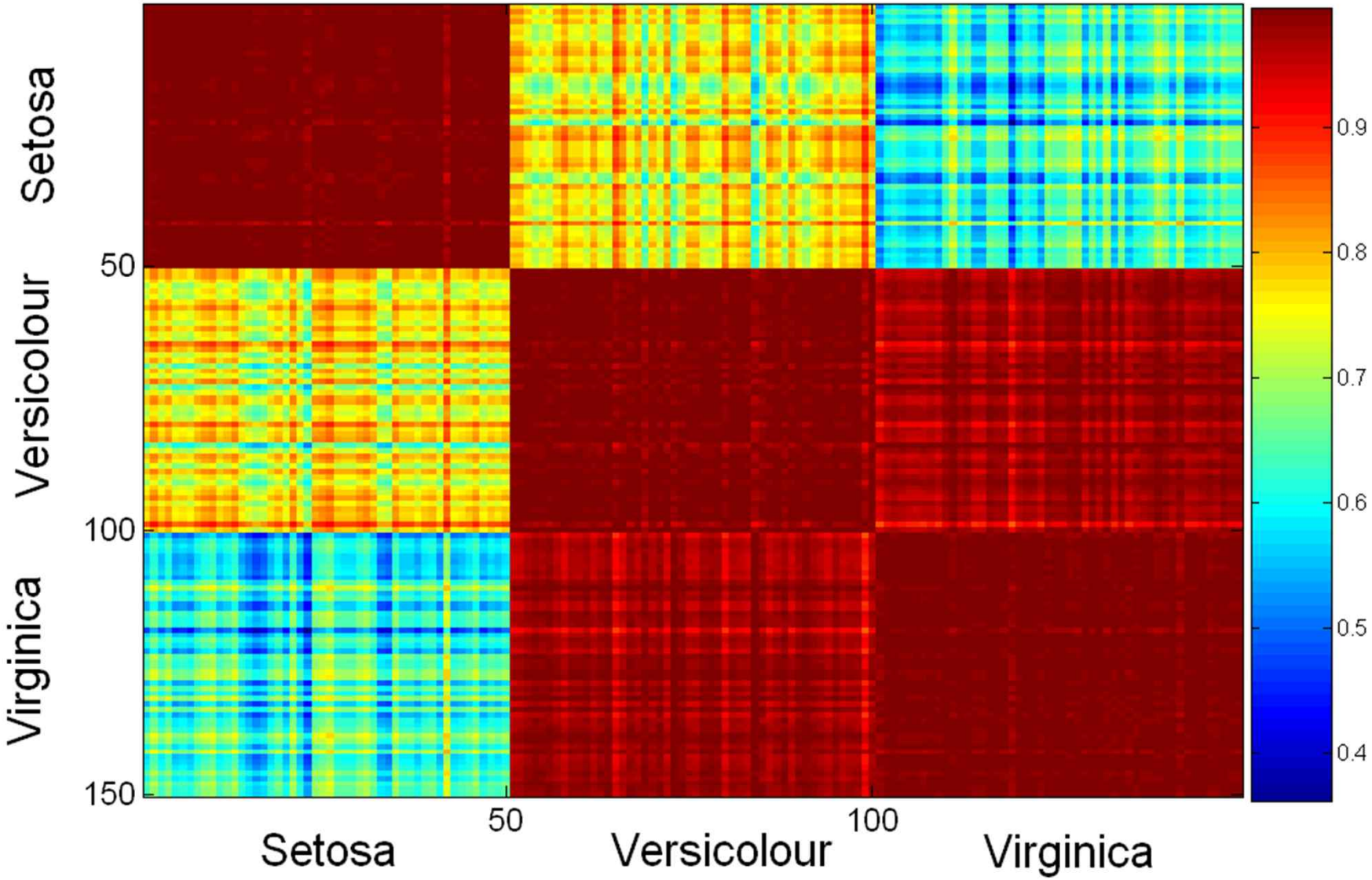
Visualization of the Iris Data Matrix



It shows the standardized data matrix for the Iris data set. The first 50 rows represent Iris flowers of the species Setosa, the next 50 Versicolour, and the last 50 Virginica.

The Setosa flowers have petal width and length well below the average, while the Versicolour flowers have petal width and length around average. The Virginica flowers have petal width and length above average.

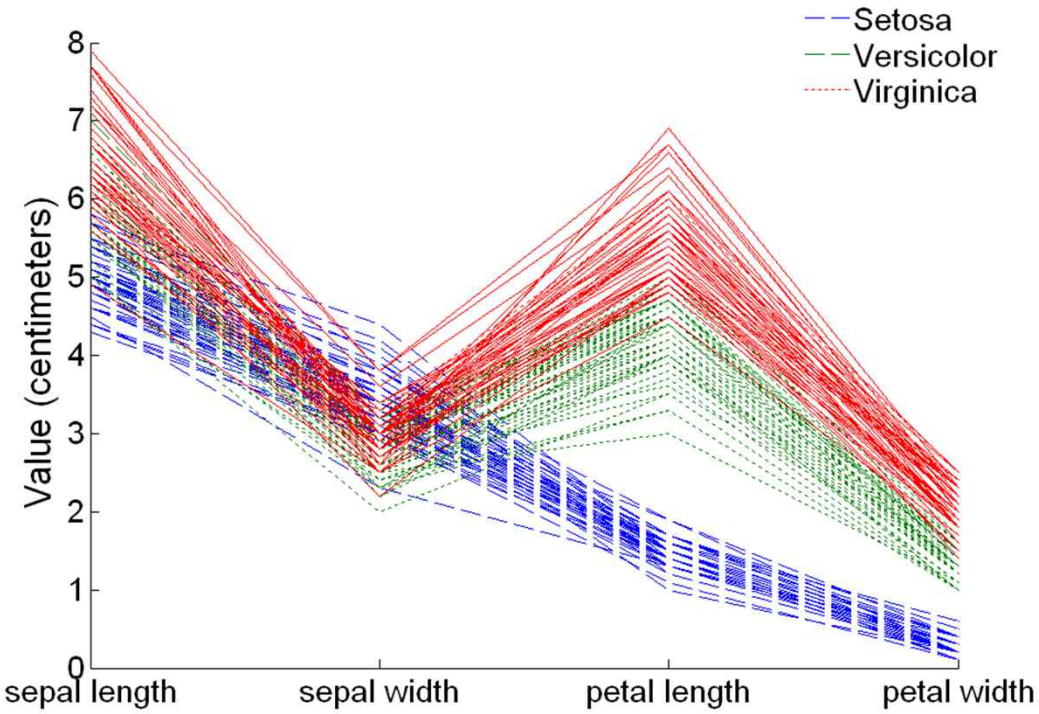
Visualization of the Iris Correlation Matrix

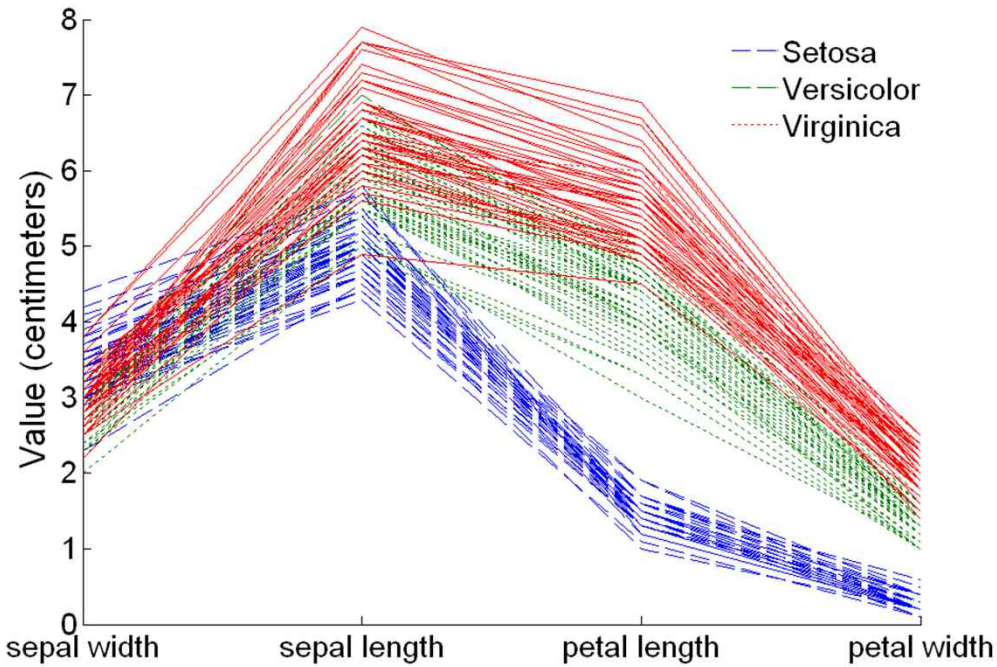


Visualization Techniques: Parallel Coordinates

- 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
  - Ordering of attributes is important in seeing such groupings

Parallel Coordinates Plots for Iris Data





If lines cross a lot, the picture can become confusion, and thus, it can be desirable to order the coordinate axes to obtain sequences of axes with less crossover in order to identify the patterns better.

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

Other Visualization Techniques

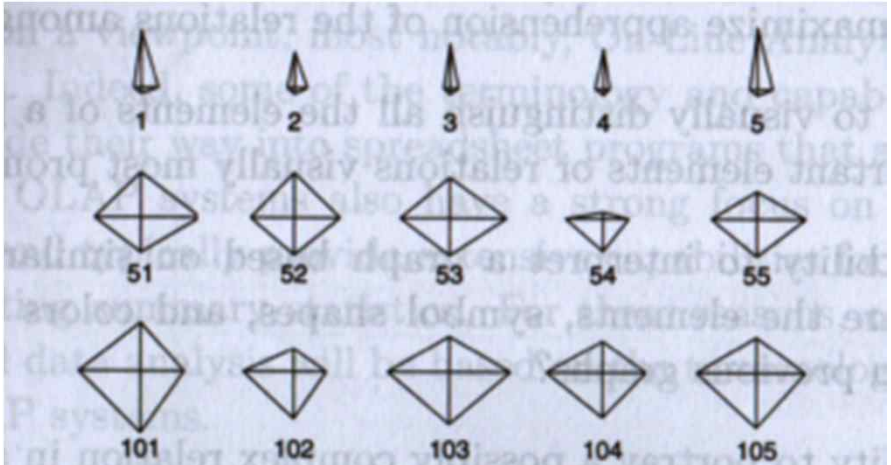


Figure 3.28. Plot of 15 Iris flowers using star coordinates.

Figure 3.29. A plot of 15 Iris flowers using Chernoff faces.

e.g., sepal length = size of face, sepal width = forehead relative arc length
petal length = shape of forehead, petal width = shape of jaw

OLAP

- On-Line Analytical Processing (OLAP) was proposed by E. F. Codd, the father of the relational database.
- Relational databases put data into tables, while OLAP typically uses a multidimensional array representation.
- There are a number of data analysis and data exploration operations that are easier with such a data representation.

Creating a Multidimensional Array

- Two key steps in converting tabular data into a multidimensional array.
  - First, identify which attributes are to be the dimensions and which attribute is to be the target attribute whose values appear as entries in the multidimensional array.
    - The attributes used as dimensions must have discrete values
    - The target value is typically a count or continuous value, e.g., the cost of an item
  - Second, find the value of each entry in the multidimensional array by summing the values (of the target attribute) or count of all objects that have the attribute values corresponding to that entry.

Example: Iris data

- We show how the attributes, petal length, petal width, and species type can be converted to a multidimensional array
  - First, we discretized the petal width and length to have categorical values: *low*, *medium*, and *high*
  - We get the following table - note the count attribute

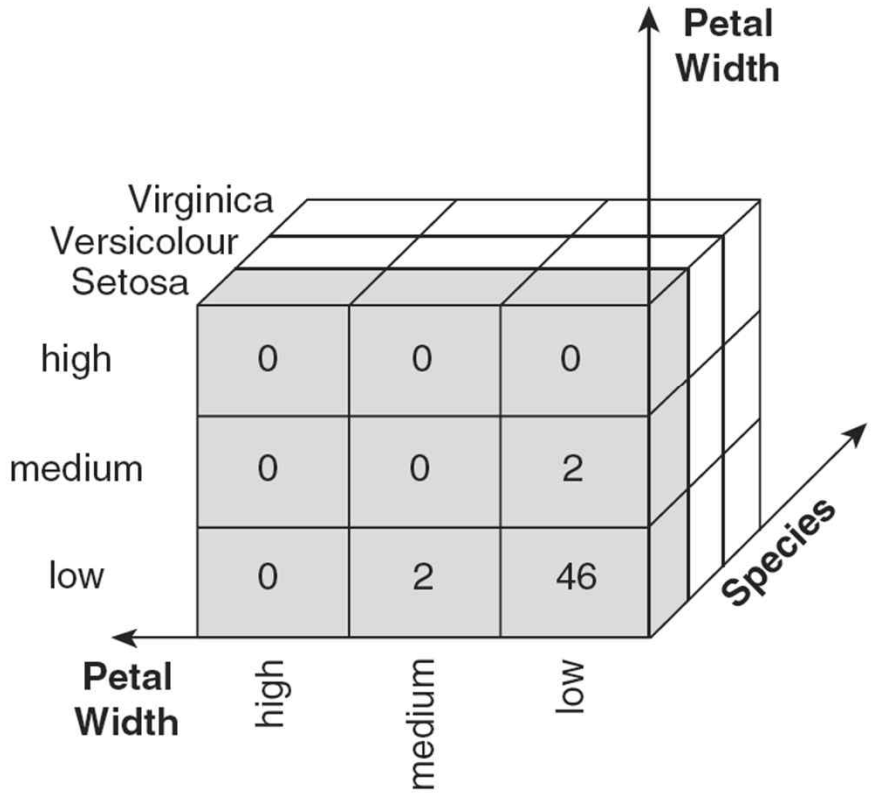
Petal Length	Petal Width	Species Type	Count
low	low	Setosa	46
low	medium	Setosa	2
medium	low	Setosa	2
medium	medium	Versicolour	43
medium	high	Versicolour	3
medium	high	Virginica	3
high	medium	Versicolour	2
high	medium	Virginica	3
high	high	Versicolour	2
high	high	Virginica	44

dimension

target

Example: Iris data (continued)

- Each unique tuple of petal width, petal length, and species type identifies one element of the array.
- This element is assigned the corresponding count value.
- The figure illustrates the result.
- All non-specified tuples are 0.



Example: Iris data (continued)

- Slices of the multidimensional array are shown by the following cross-tabulations
- What do these tables tell us?

		Width		
		low	medium	high
Length	low	46	2	0
	medium	2	0	0
	high	0	0	0

Setosa

		Width		
		low	medium	high
Length	low	0	0	0
	medium	0	43	3
	high	0	2	2

Versicolour

		Width		
		low	medium	high
Length	low	0	0	0
	medium	0	0	3
	high	0	3	44

Virginica

Table 3.11. Sales revenue of products (in dollars) for various locations and times.

Product ID	Location	Date	Revenue
⋮	⋮	⋮	⋮
1	Minneapolis	Oct. 18, 2004	$250
1	Chicago	Oct. 18, 2004	$79
⋮	⋮	⋮	
1	Paris	Oct. 18, 2004	301
⋮	⋮	⋮	⋮
27	Minneapolis	Oct. 18, 2004	$2,321
27	Chicago	Oct. 18, 2004	$3,278
⋮	⋮	⋮	
27	Paris	Oct. 18, 2004	$1,325
⋮	⋮	⋮	⋮

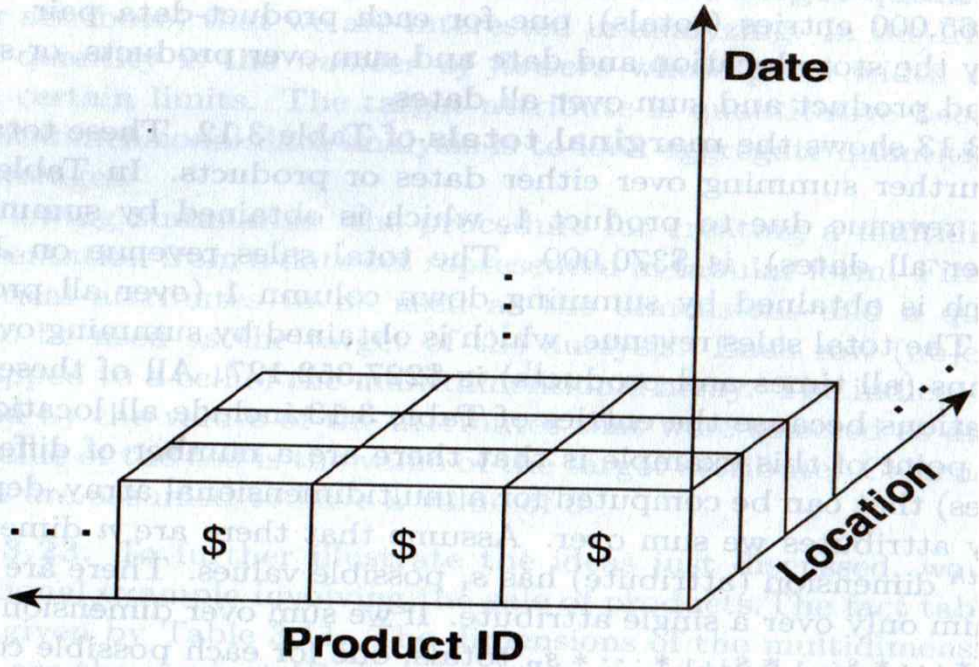


Figure 3.31. Multidimensional data representation for sales data.

Table 3.12. Totals that result from summing over all locations for a fixed time and product.

product ID \ date	Jan 1, 2004	Jan 2, 2004	...	Dec 31, 2004
1	$1,001	$987	...	$891
⋮	⋮			⋮
27	$10,265	$10,225	...	$9,325
⋮	⋮			⋮

Table 3.13. Table 3.12 with marginal totals.

product ID \ date	Jan 1, 2004	Jan 2, 2004	...	Dec 31, 2004	total
1	$1,001	$987	...	$891	$370,000
⋮	⋮			⋮	⋮
27	$10,265	$10,225	...	$9,325	$3,800,020
⋮	⋮			⋮	⋮
total	$527,362	$532,953	...	$631,221	$227,352,127