Data Preprocessing Techniques/Methods Use for Weka, Python

Why Data Preprocessing?

- Data in the real world is imperfect
  - incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
  - noisy: containing errors or outliers
  - inconsistent: containing discrepancies in codes or names
- No quality data, no quality mining results!
  - Quality decisions must be based on quality data
  - Data warehouse needs consistent integration of quality data

Types of Data Sets

- Relational records

NAME	AGE	INCOME	CREDIT RATING
Mike	<= 30	low	fair
Mary	<= 30	low	poor
Bill	31..40	high	excellent
Jim	>40	med	fair
Dave	>40	med	fair
Anne	31..40	high	excellent

- Transaction data

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

- Data matrix, e.g., numerical matrix
- Document data:
  - text documents: term-frequency vector

Data Objects

- Data sets are made up of data objects.
- A **data object** represents an entity.
- Examples:
  - sales database: customers, store items, sales
  - medical database: patients, treatments
  - university database: students, professors, courses
- Also called *samples , examples, instances, data points, objects, tuples*.
- Data objects are described by **attributes**.
- Database rows -> data objects; columns ->attributes.

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
    - special kind of nominal – binary, ordinal
  - Numeric
    - Quantitative
    - Interval-scaled

Nominal Attributes

- **Nominal:** categories, states, or “names of things”
  - *Hair_color = {auburn, black, blond, brown, grey, red, white}*
  - marital status, occupation, ID numbers, zip codes
- **Special kind of nominal:**
  - **Binary**
    - Nominal attribute with only 2 states (0 and 1)
    - <u>Symmetric binary</u>: both outcomes equally important
      - e.g., gender
    - <u>Asymmetric binary</u>: outcomes not equally important.
      - e.g., medical test (positive vs. negative)
      - Convention: assign 1 to 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

Numeric Attributes

- **Quantity** (integer or real-valued)
- **Interval**
  - Measured on a scale of **equal-sized units**
  - Values have order
    - e.g., *calendar dates*
  - No true zero-point

Discrete and Continuous Attributes

- **Discrete Attribute**
  - Has only a finite or countably infinite set of values
    - e.g., zip codes, profession, or the set of words in a collection of documents
  - Sometimes, represented as integer variables
  - Note: Binary attributes are a special case of discrete attributes
- **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

Basic Statistical Descriptions of Data

- Motivation
  - To better understand the data: central tendency, variation and spread
- Data dispersion characteristics
  - median, max, min, quantiles, outliers, variance, etc.
- Numerical dimensions correspond to sorted intervals
  - Data dispersion: analyzed with multiple granularities of precision
  - Boxplot or quantile analysis on sorted intervals

Measuring the Central Tendency

- <u>Mean (algebraic measure) (sample vs. population):</u>

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad \mu = \frac{\sum x}{N}$$

  Note: *n* is sample size and *N* is population size.

  - Weighted arithmetic mean:

$$\bar{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}$$

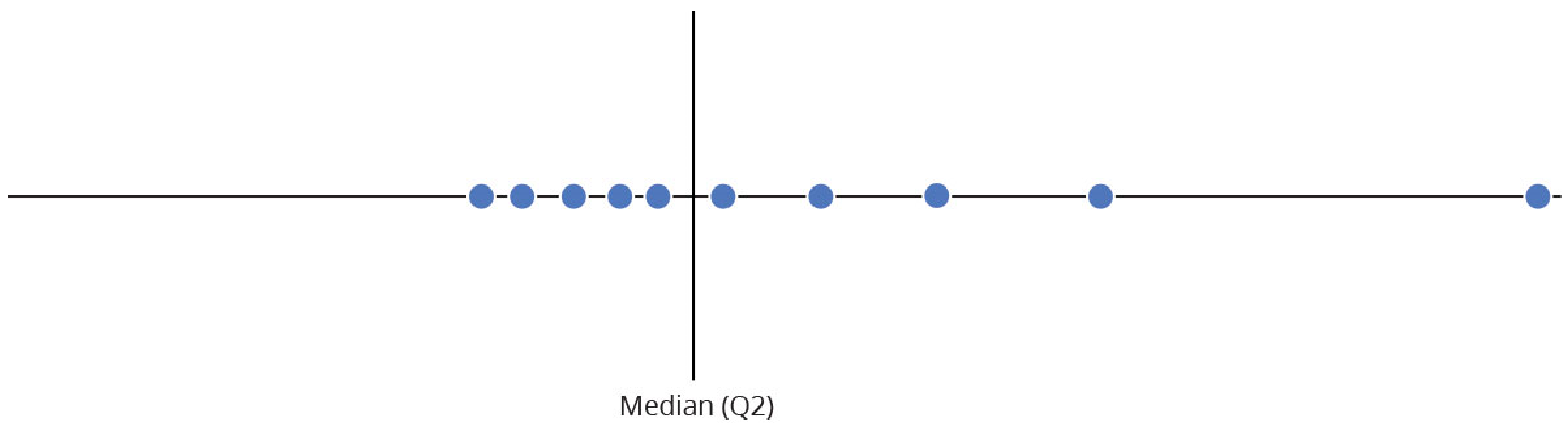
  - Trimmed mean: chopping extreme values
- <u>Median</u>:
  - Middle value if odd number of values, or average of the middle two values otherwise
  - Estimated by interpolation (for *grouped data*):

$$median = L_1 + \left(\frac{n/2 - \left(\sum freq\right)_l}{freq_{median}}\right) width$$

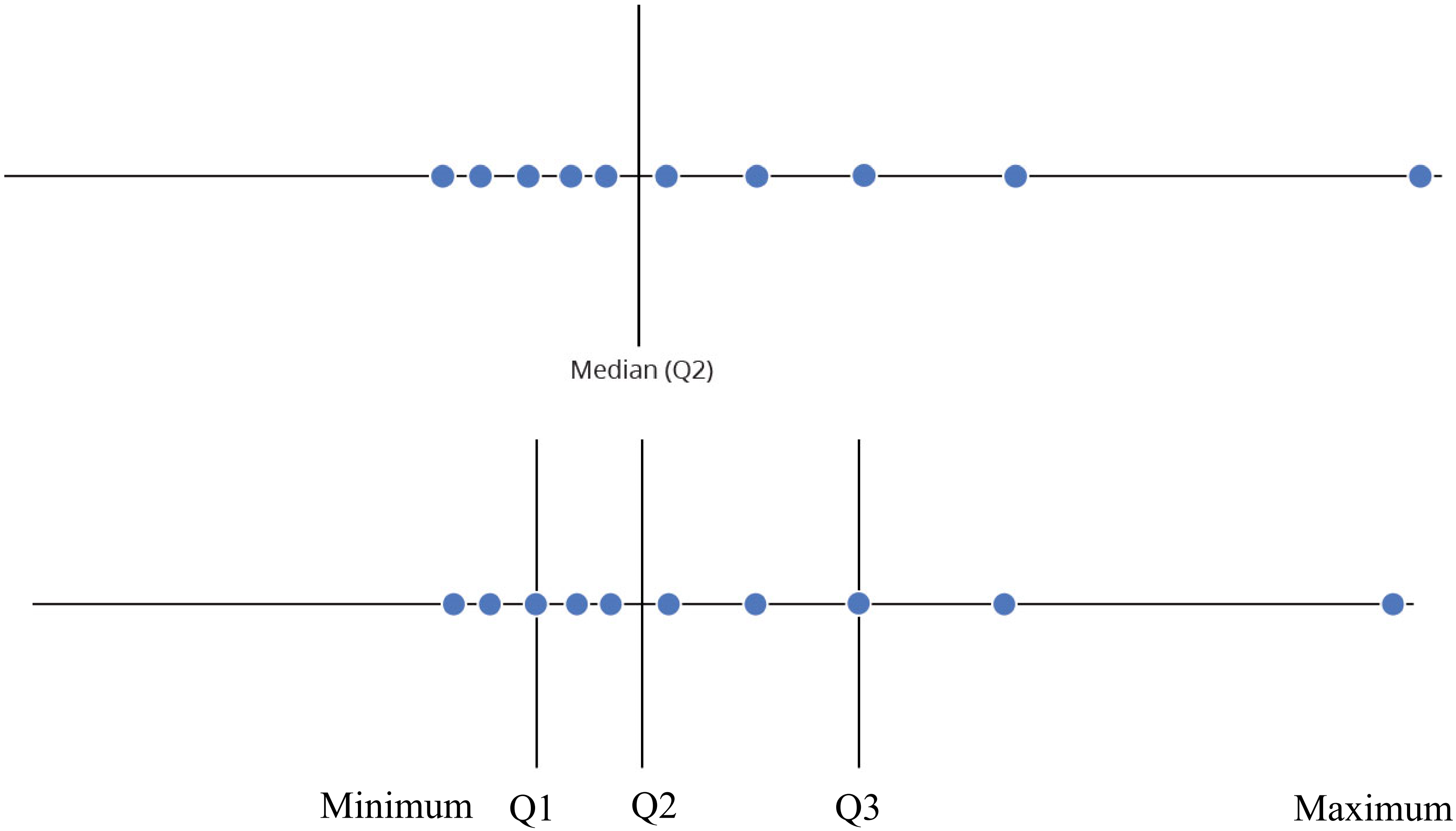
- <u>Mode</u>
  - Value that occurs most frequently in the data
  - Unimodal, bimodal, trimodal

Median - Example

Suppose that we consider the attribute:
"unit price of different products" of a company



Example of Five-number Summary



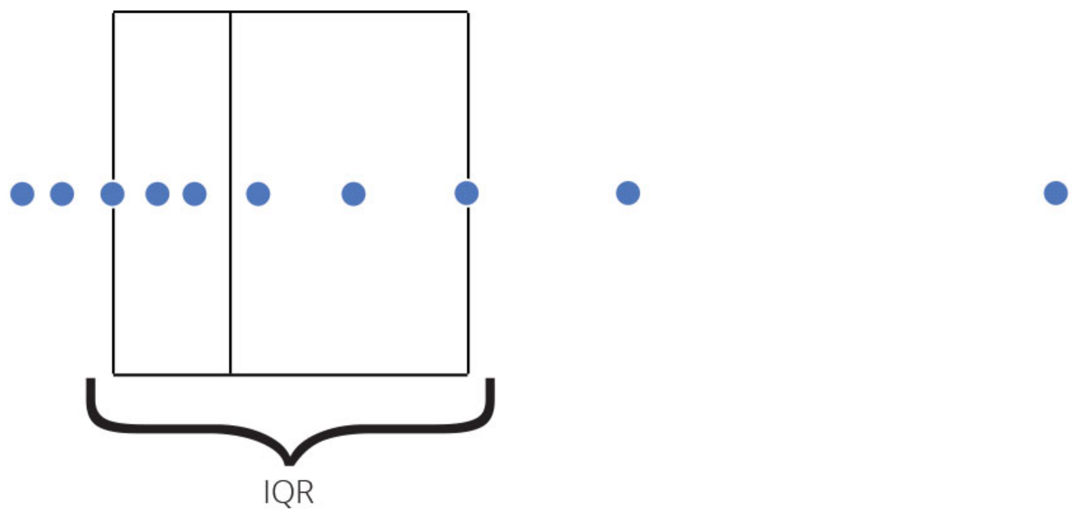
Measuring the Dispersion of Data

- Quartiles, outliers and boxplots
  - **Quartiles**: Q_1 (25th percentile), Q_3 (75th percentile)
  - **Inter-quartile range**: IQR = $Q_3 - Q_1$
  - **Five number summary**: min, Q_1, median, Q_3, max
  - **Boxplot**: ends of the box are the quartiles; median is marked; add whiskers, and plot outliers individually
- Variance and standard deviation (*sample: s, population: σ*)
  - **Variance**: (algebraic, scalable computation)

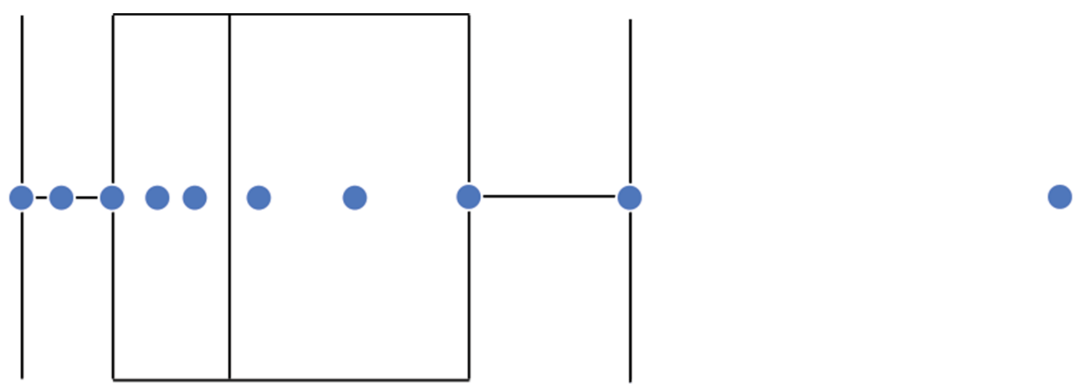
$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 = \frac{1}{n-1}\left[\sum_{i=1}^{n} x_i^{\,2} - \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)^2\right] \qquad \sigma^2 = \frac{1}{N}\sum_{i=1}^{n}(x_i - \mu)^2 = \frac{1}{N}\sum_{i=1}^{n} x_i^{\,2} - \mu^2$$

  - **Standard deviation** *s (or σ)* is the square root of variance s^2 (or σ^2)

Example of inter-quartile range (IQR)

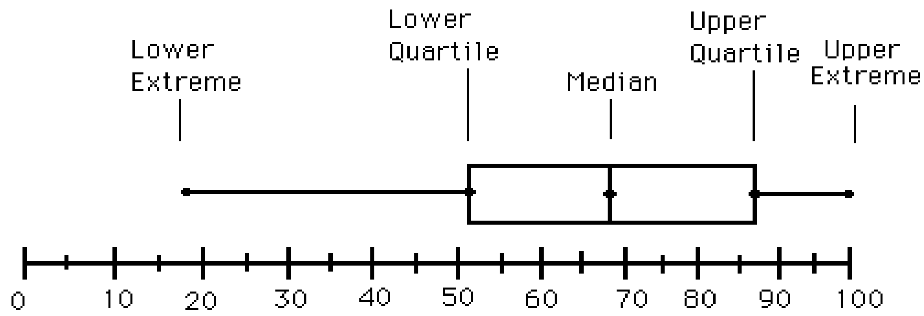


Example of Boxplot

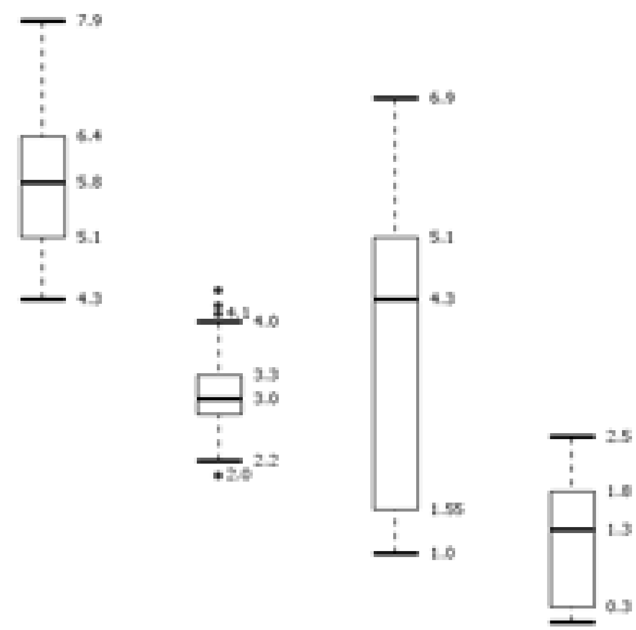


whisker and an outlier

Boxplot Analysis



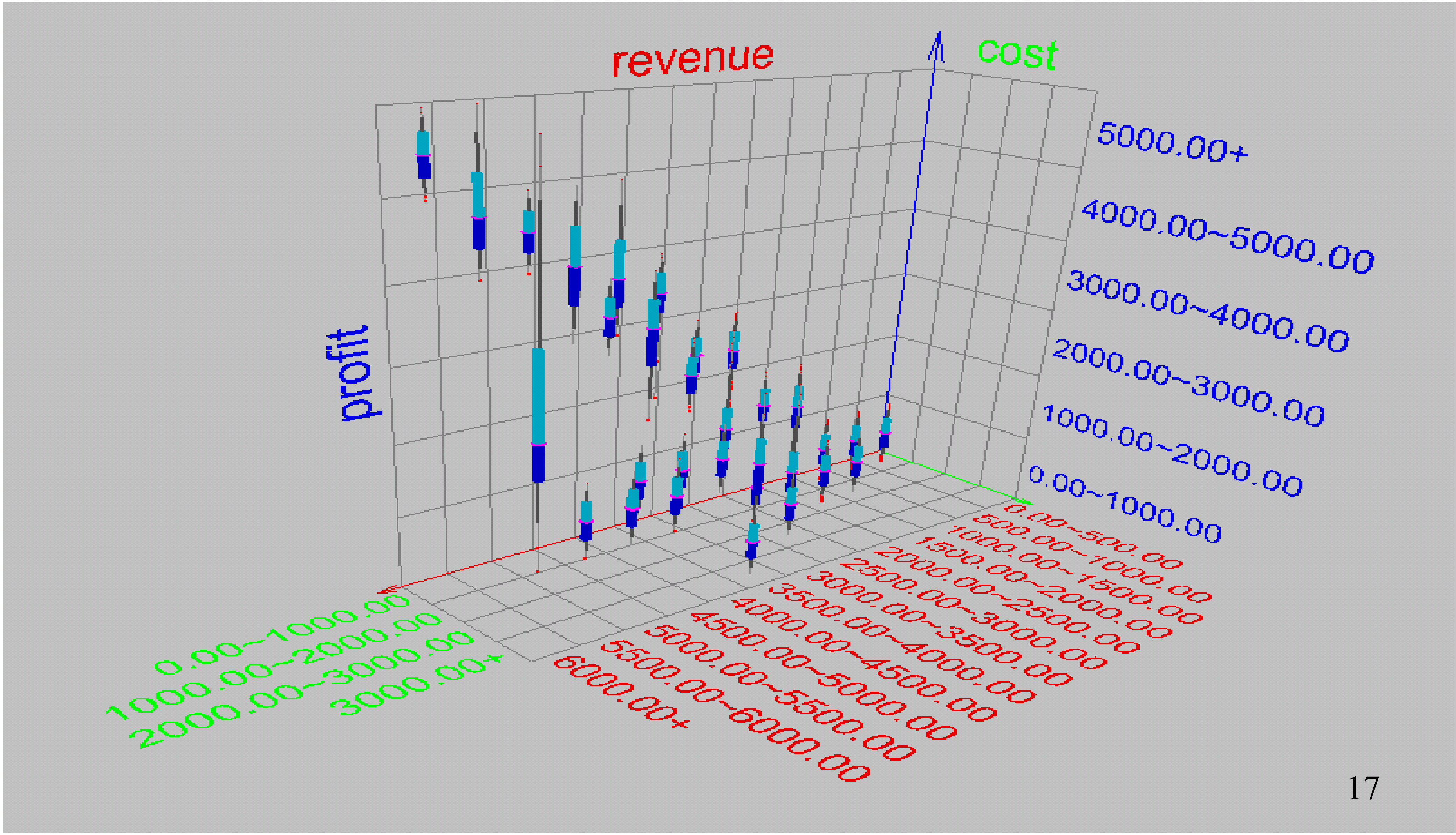
- **Five-number summary** of a distribution
  - Minimum, Q1, Median, Q3, Maximum
- **Boxplot**
  - Data is represented with a box
  - The ends of the box are at the first and third quartiles, i.e., the height of the box is IQR
  - The median is marked by a line within the box
  - Whiskers: two lines outside the box extended to Minimum and Maximum
  - Outliers: points beyond a specified outlier threshold, plotted individually



Outliers

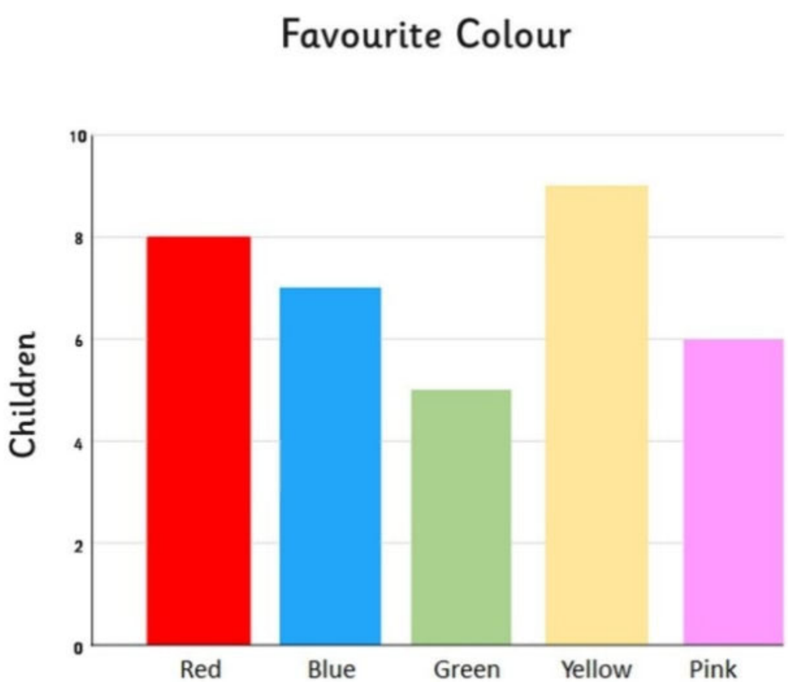
- An outlier is a data point that comes from a distribution different (in location, scale, or distributional form) from the bulk of the data
- In the real world, outliers have a range of causes, from as simple as
  - operator blunders
  - equipment failures
  - day-to-day effects
  - batch-to-batch differences
  - anomalous input conditions
  - warm-up effects

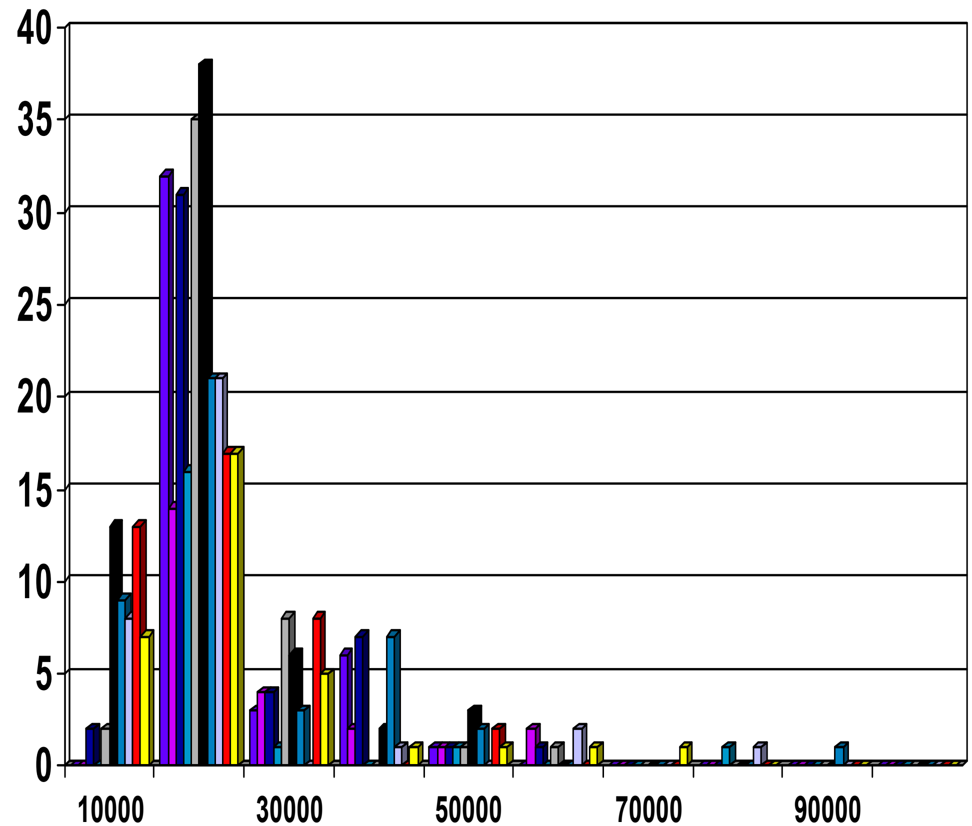
Visualization of Data Dispersion: 3-D Boxplots



Histograms

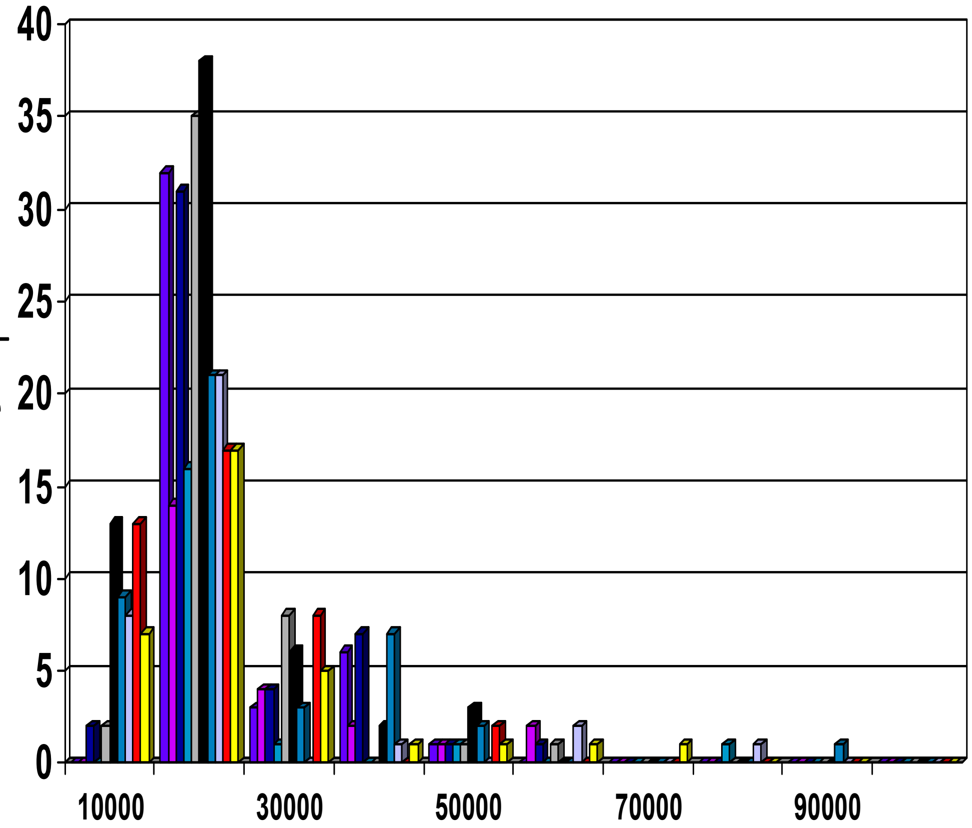
- Histogram: Graph display of tabulated frequencies, shown as bars
- x-axis are values, y-axis represent frequency
- It shows what proportion of cases fall into each of several categories
- Looks like a bar chart, e.g.





Histograms

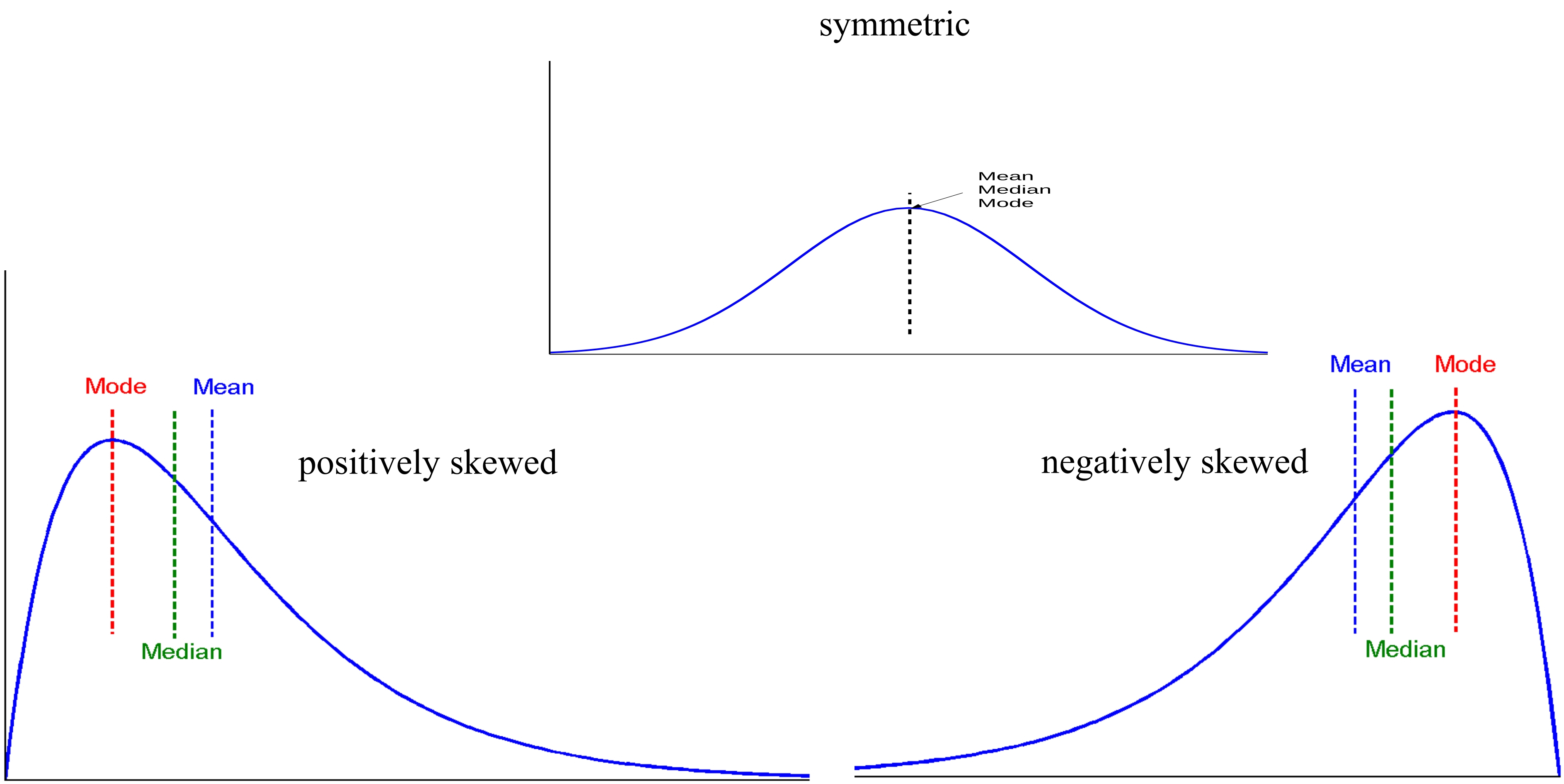
- Differs from a bar chart in that it is the *area* of the bar that denotes the value, not the height as in bar charts, a crucial distinction when the categories are not of uniform width
- The categories are usually specified as non-overlapping intervals of some variable. The categories (bars) must be adjacent



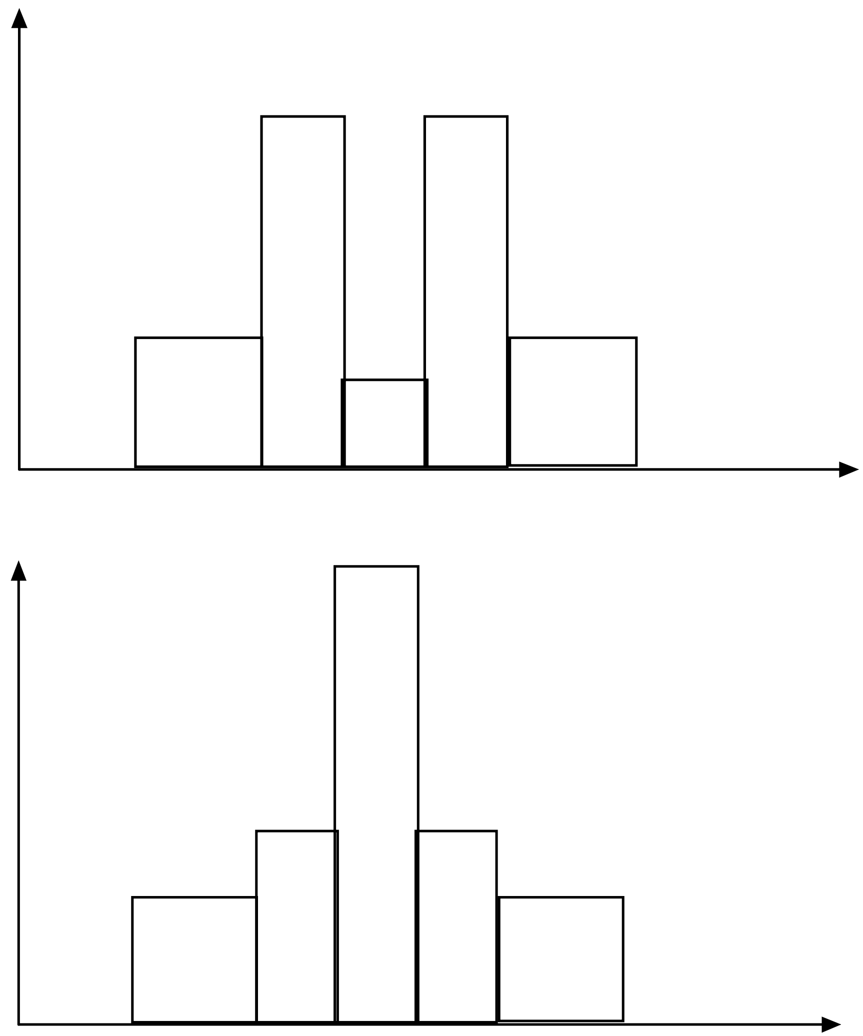
Histograms

Median, mean and mode of

symmetric, positively and negatively skewed data

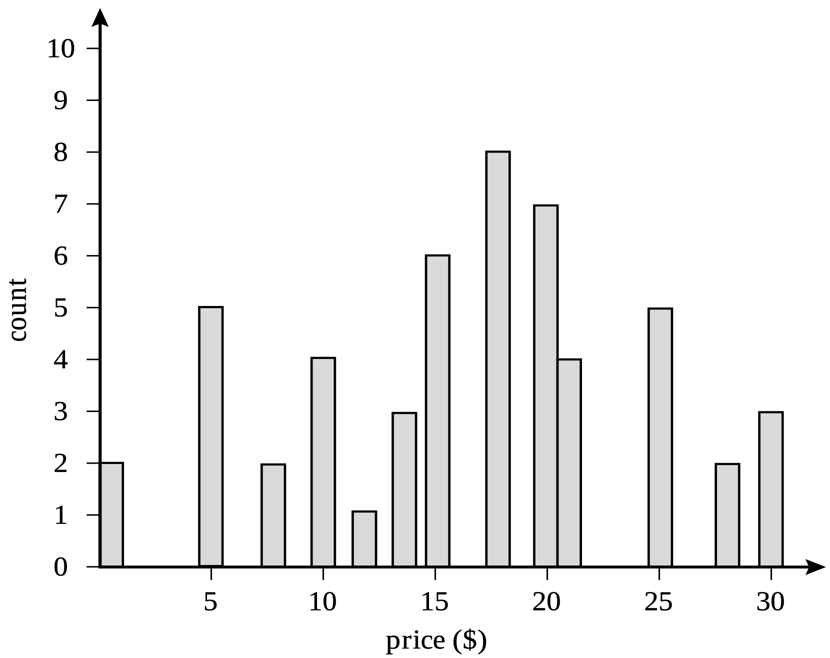


Histograms Often Tell More than Boxplots

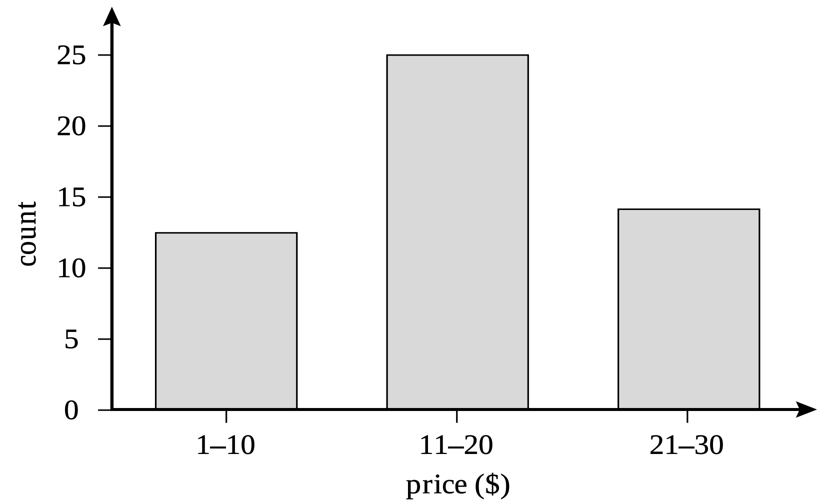


- The two histograms shown in the left may have the same boxplot representation
  - The same values for: min, Q1, median, Q3, max
- But they have rather different data distributions

Histograms



Singleton buckets



Buckets denoting a
Continuous range of values

Histograms

- How are buckets determined and the attribute values partitioned?
  - Equiwidth: The width of each bucket range is uniform
  - Equidepth: The buckets are created so that, roughly, the frequency of each bucket is constant

Histogram Examples

- Suppose that the values for the attribute *age*:

13, 15, 16, 16, 19, 20, 20, 21, 21, 22, 25, 25, 25. 25, 30, 30, 30, 30, 32, 33, 33, 37, 40, 40, 40, 42, 42

Equiwidth Histogram:

Bucket range	Frequency
13-22	10
23-32	9
33-42	8

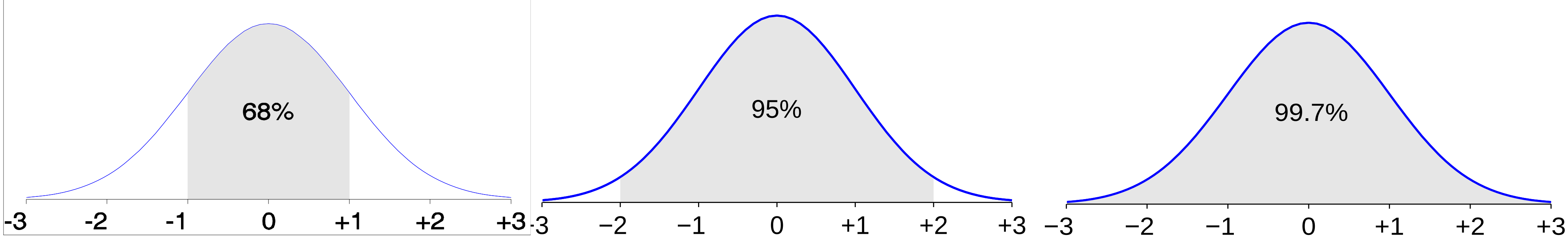
Equidepth Histogram:

Bucket range	Frequency
13-21	9
22-30	9
32-42	9

Equiwidth Histograms

Properties of Normal Distribution Curve

- 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

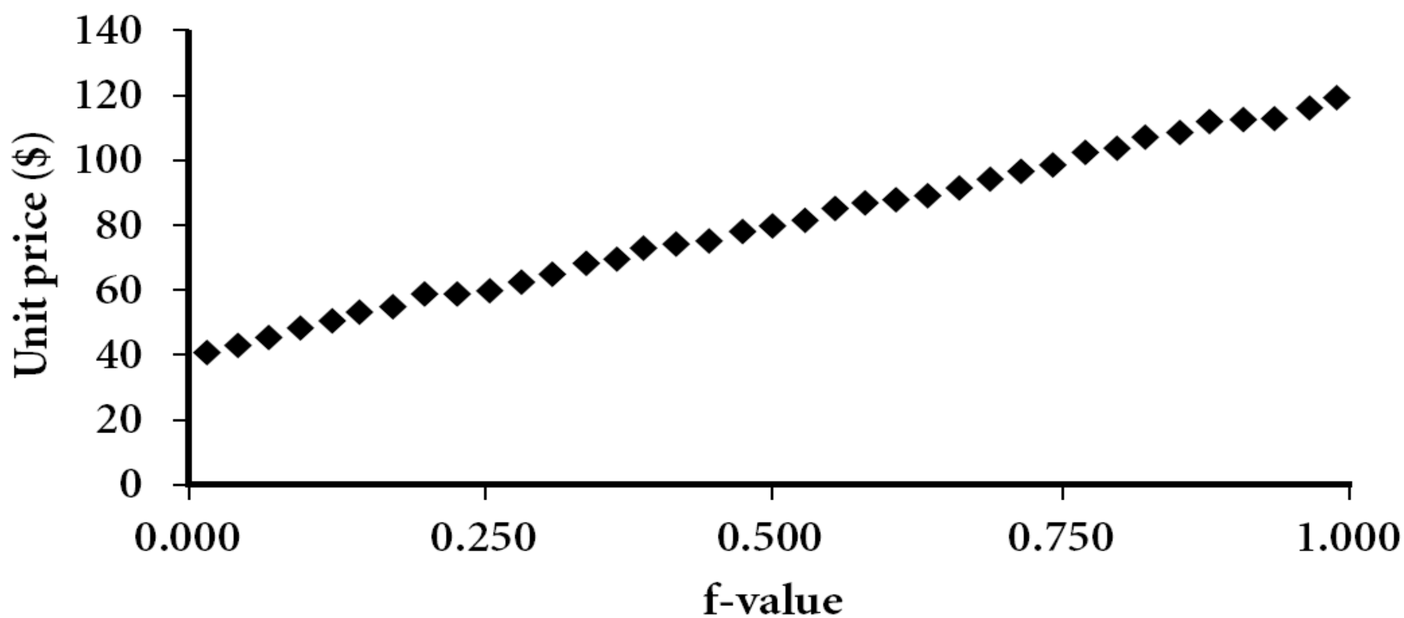


Graphic Displays of Basic Statistical Descriptions

- **Boxplot**: graphic display of five-number summary
- **Histogram**: x-axis are values, y-axis repres. frequencies
- **Quantile plot**: each value x_i is paired with f_i indicating that approximately 100 f_i % of data are $\leq x_i$
- **Scatter plot**: each pair of values is a pair of coordinates and plotted as points in the plane

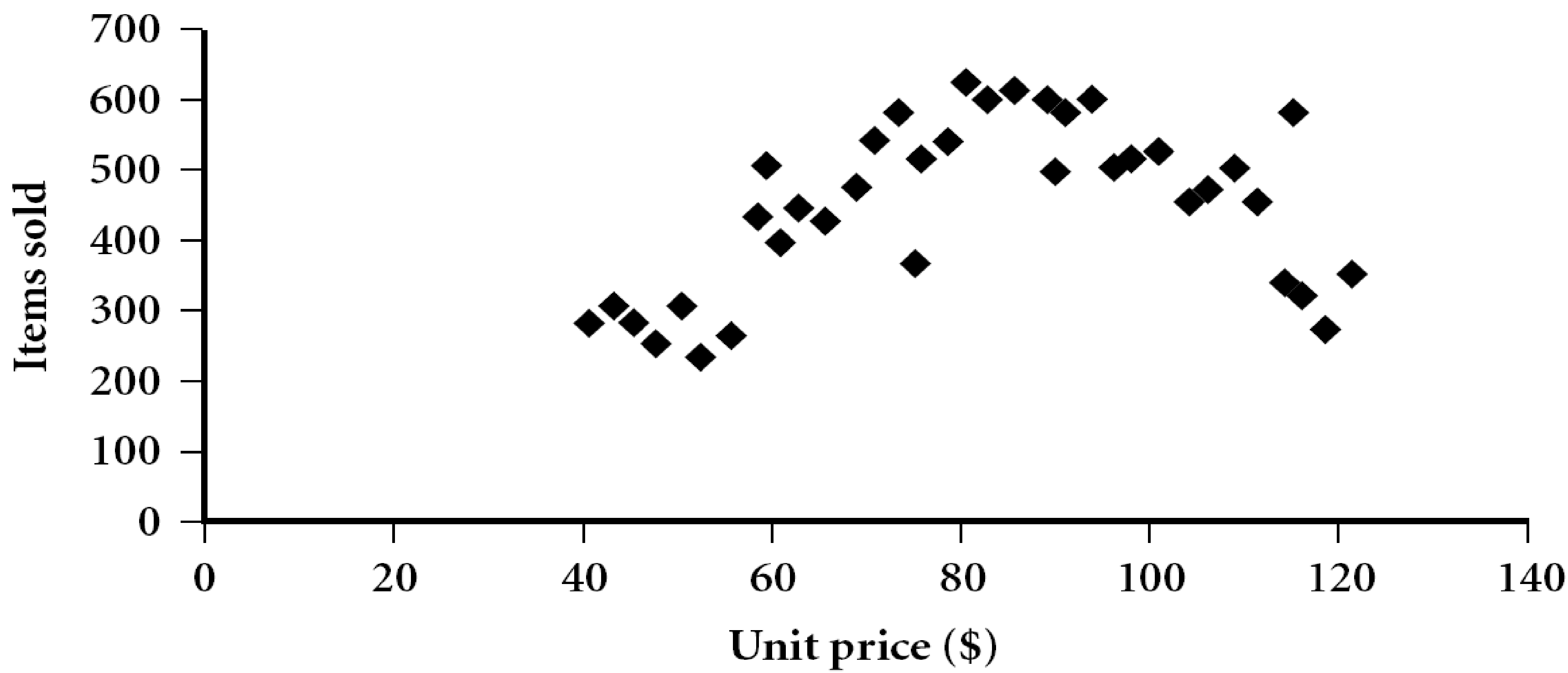
Quantile Plot

- Displays all of the data (allowing the user to assess both the overall behavior and unusual occurrences)
- Plots **quantile** information
  - For a data x_i data sorted in increasing order, f_i indicates that approximately 100 f_i% of the data are below or equal to the value x_i



Scatter Plot

- Provides a first look at bivariate data to see clusters of points, outliers, etc
- Each pair of values is treated as a pair of coordinates and plotted as points in the plane



Correlation

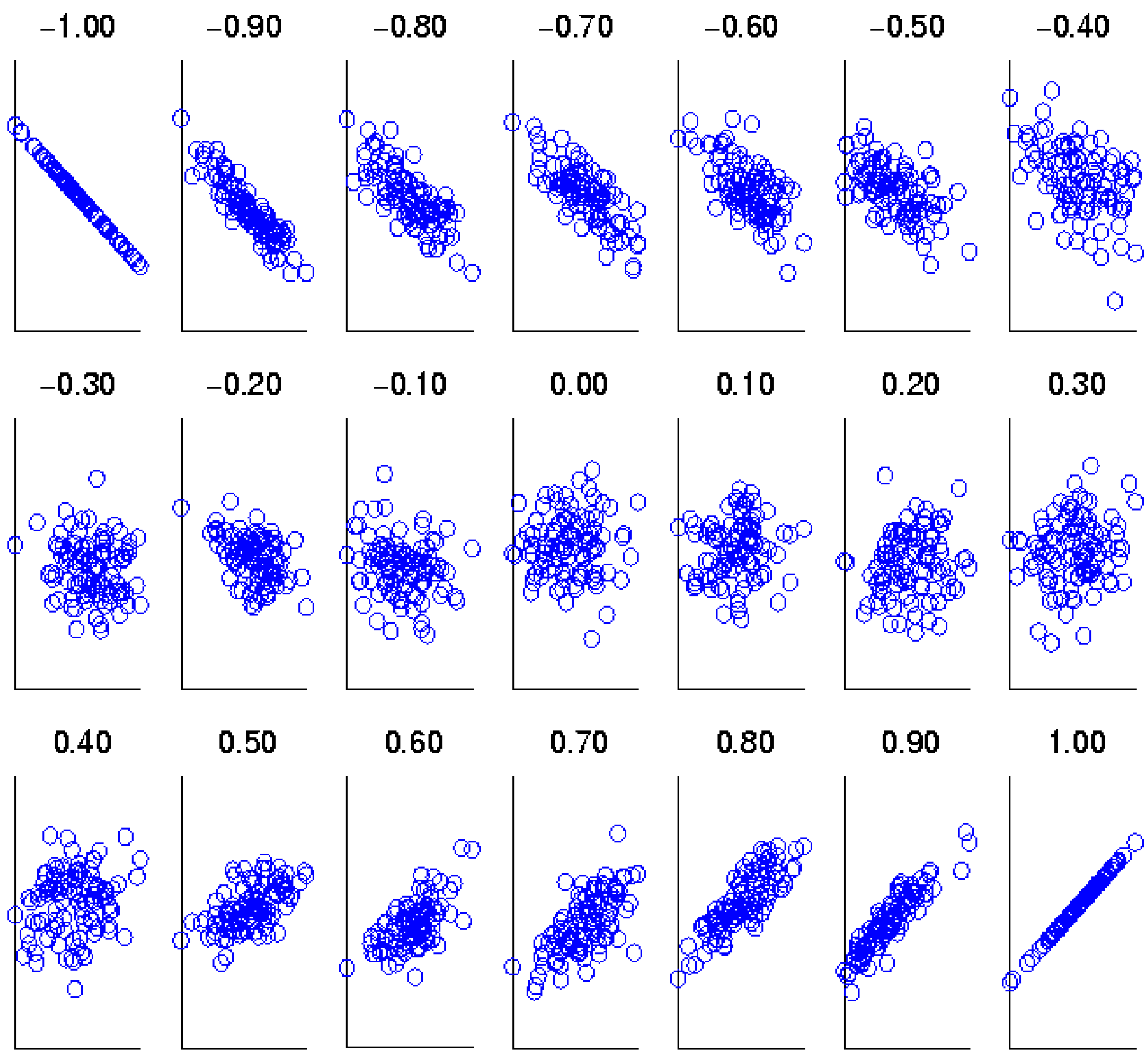
- Correlation coefficient (also called Pearson's product moment coefficient)

$$r_{A,B} = \frac{\sum_{i=1}^{n}(a_i - \overline{A})(b_i - \overline{B})}{(n-1)\sigma_A \sigma_B} = \frac{\sum_{i=1}^{n}(a_i b_i) - n\overline{A}\,\overline{B}}{(n-1)\sigma_A \sigma_B}$$

where n is the number of tuples, $\overline{A}$ and $\overline{B}$ are the respective means of A and B, σ_A and σ_B are the respective standard deviation of A and B, and $\Sigma(a_i b_i)$ is the sum of the AB cross-product.

- If $r_{A,B} > 0$, A and B are positively correlated (A's values increase as B's). The higher, the stronger correlation.
- $r_{A,B} = 0$: independent; $r_{AB} < 0$: negatively correlated

Correlation

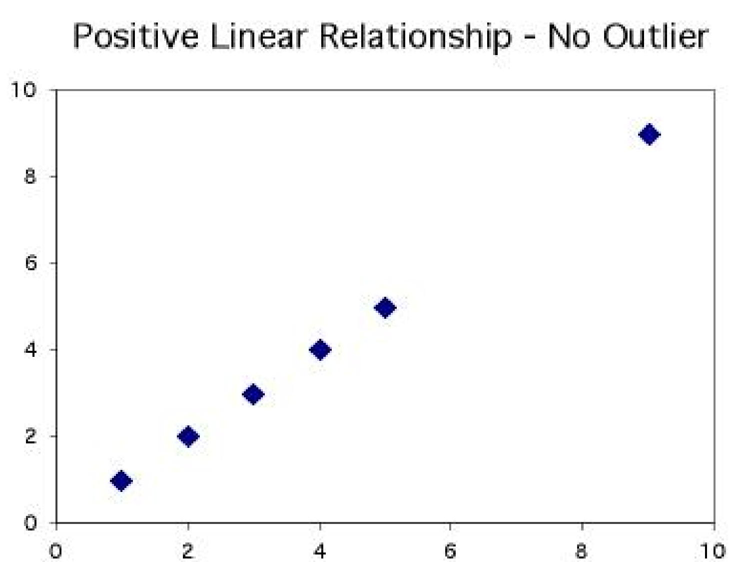


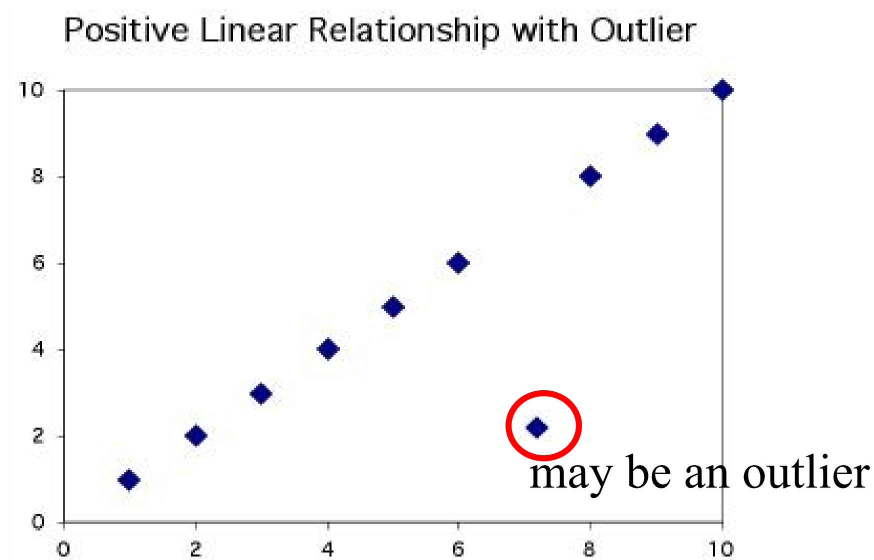
Scatter plots showing the similarity from –1 to 1

Uncorrelated Data

More on Outliers

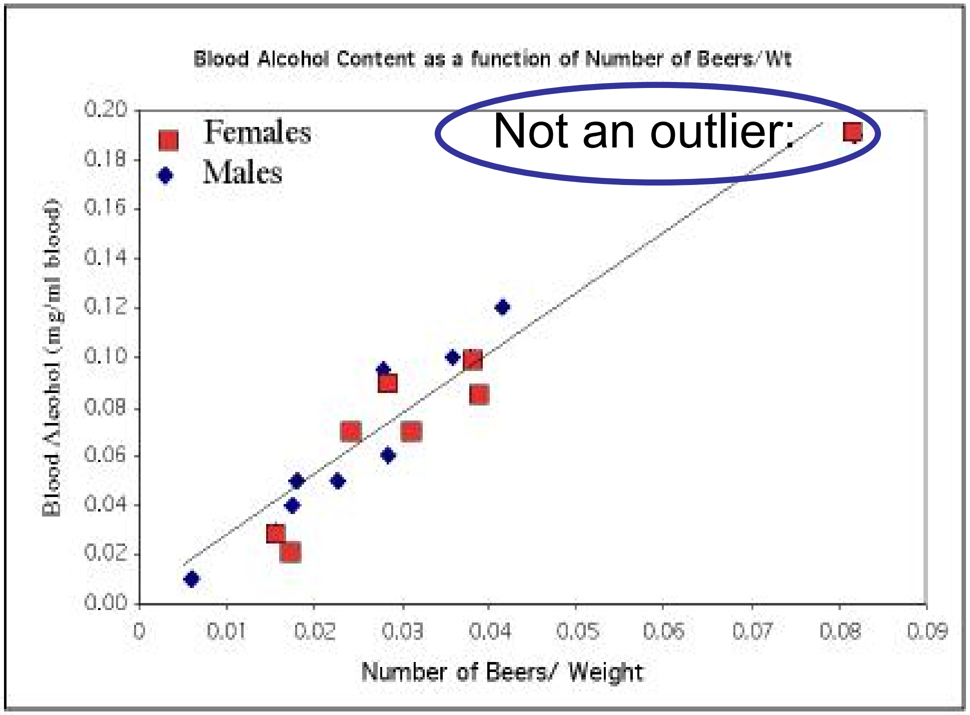
- An **outlier** is a data value that has a very low probability of occurrence (i.e., it is unusual or unexpected).



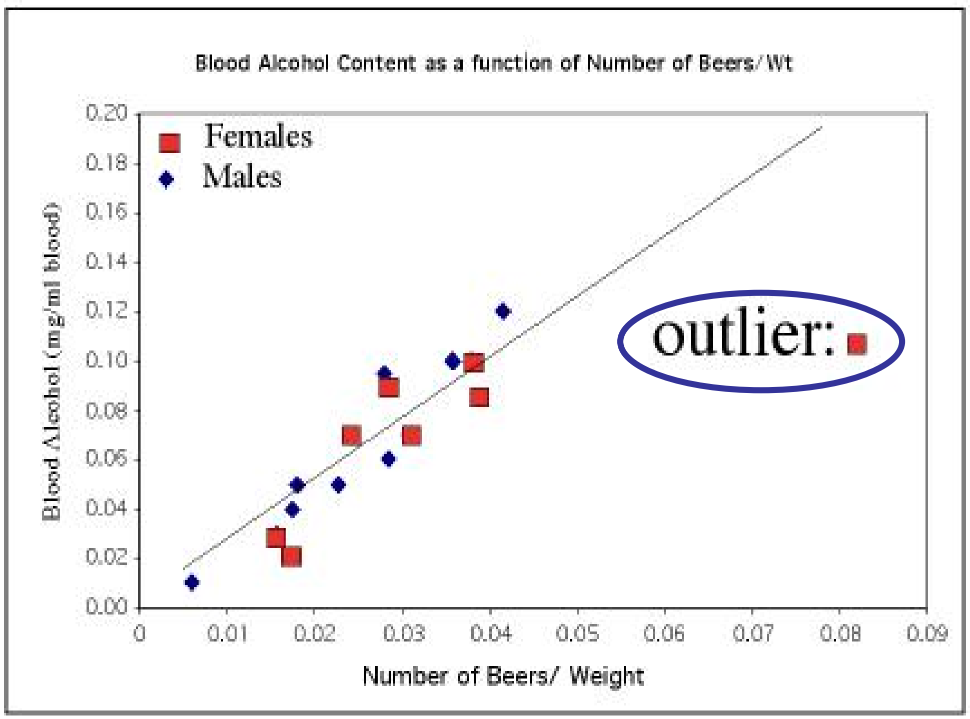


- In a scatter plot, outliers are points that fall outside of the overall pattern of the relationship.

Outliers



- The upper right-hand point here is probably <u>not</u> an outlier of the relationship
- It is what you would expect for this many beers given the linear relationship between beers/weight and blood alcohol.

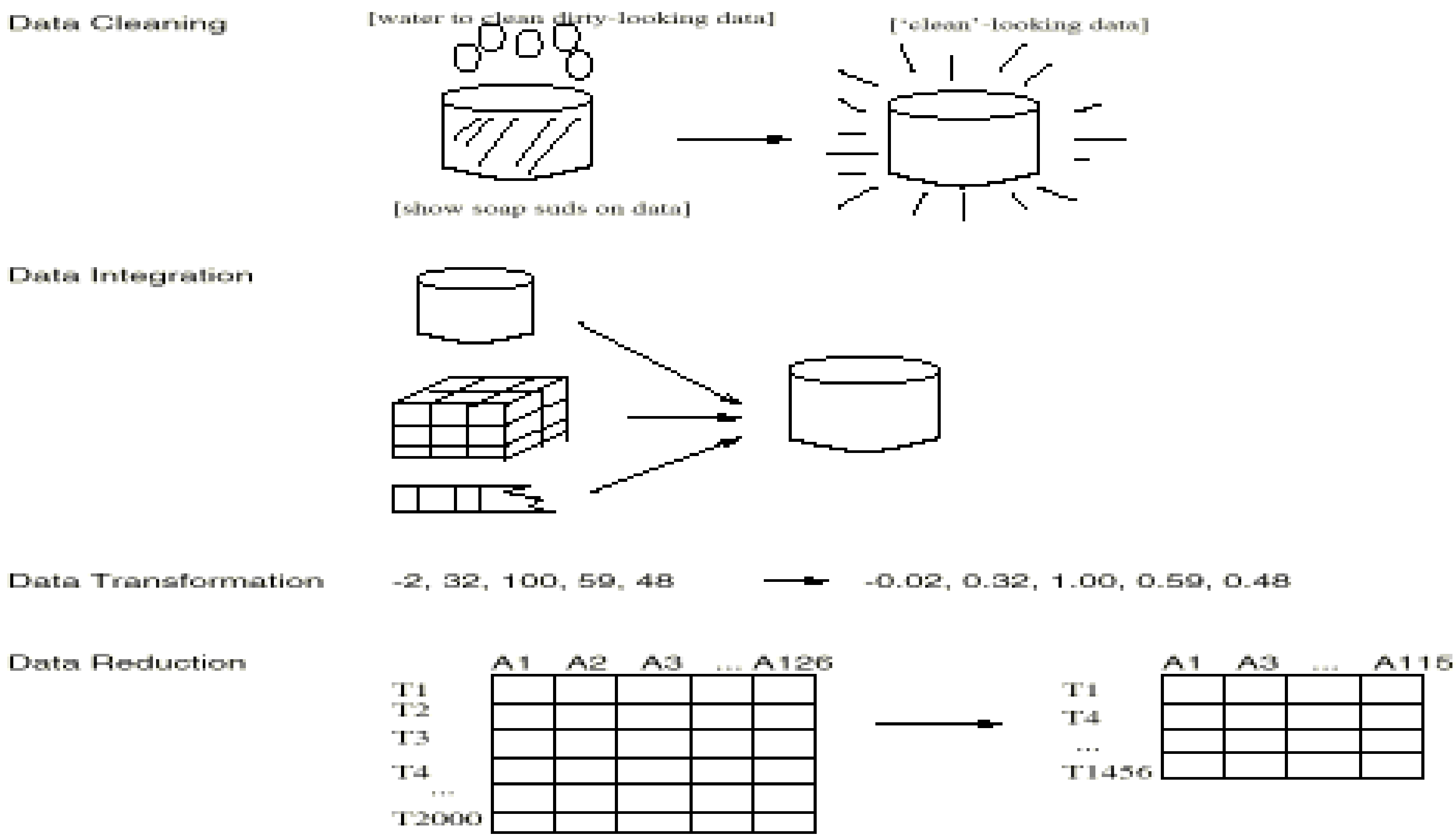


- This point is not in line with the others, so it <u>may be</u> an outlier of the relationship.

Major Tasks in Data Preprocessing

- Data cleaning
  - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- Data integration
  - Integration of multiple databases, data cubes, or files
- Data transformation
  - Normalization and aggregation
- Data reduction
  - Obtains reduced representation in volume but produces the same or similar analytical results
- Data discretization
  - Part of data reduction but with particular importance, especially for numerical data

Forms of data preprocessing



Data Cleaning

- Data cleaning tasks
  - Fill in missing values
  - Identify outliers and smooth out noisy data
  - Correct inconsistent data

Recover Missing Values
Moving Average

- A **simple moving average** is the unweighted mean of the previous *n* data points in the time series
- A **weighted moving average** is a weighted mean of the previous *n* data points in the time series
  - A weighted moving average is more responsive to recent movements than a simple moving average

Data Transformation

- Smoothing: remove noise from data
- Aggregation: summarization, data cube construction
- Normalization: scaled to fall within a small, specified range
  - min-max normalization
  - z-score normalization
- Attribute/feature construction
  - New attributes constructed from the given ones

Data Transformation: Normalization

- min-max normalization

$$v' = \frac{v - min}{max - min}(new\_max - new\_min) + new\_min$$

- z-score normalization

$$v' = \frac{v - mean}{stand\_dev}$$

Normalization - Examples

- Suppose that the minimum and maximum values for attribute income are 12,000 and 98,000 respectively. How to map an income value of 73,600 to the range of [0.0,1.0]?
- Suppose that the mean and standard deviation for the attribute income are 54,000 and 15,000. How to map an income value of 73,600 using z-score normalization?

Normalization – Examples (Answers)

1) min-max normalization

$$\frac{73600-12000}{98000-12000}(1.0-0)+0=0.716$$

2) z-score normalization

$$\frac{73600-54000}{15000}=1.307$$

Transformation to Achieve Normality

- Some data mining methods require that the variables be normally distributed.
- Note that z-score standardization cannot achieve normality, i.e. distribution may still be skewed
- Apply a transformation such as natural log, square root, and inverse square root

Transformation to Achieve Normality

distributed.

We use the following statistic to measure the *skewness* of a distribution[8]:

$$\text{Skewness} = \frac{3(\text{mean} - \text{median})}{\text{standard deviation}}$$

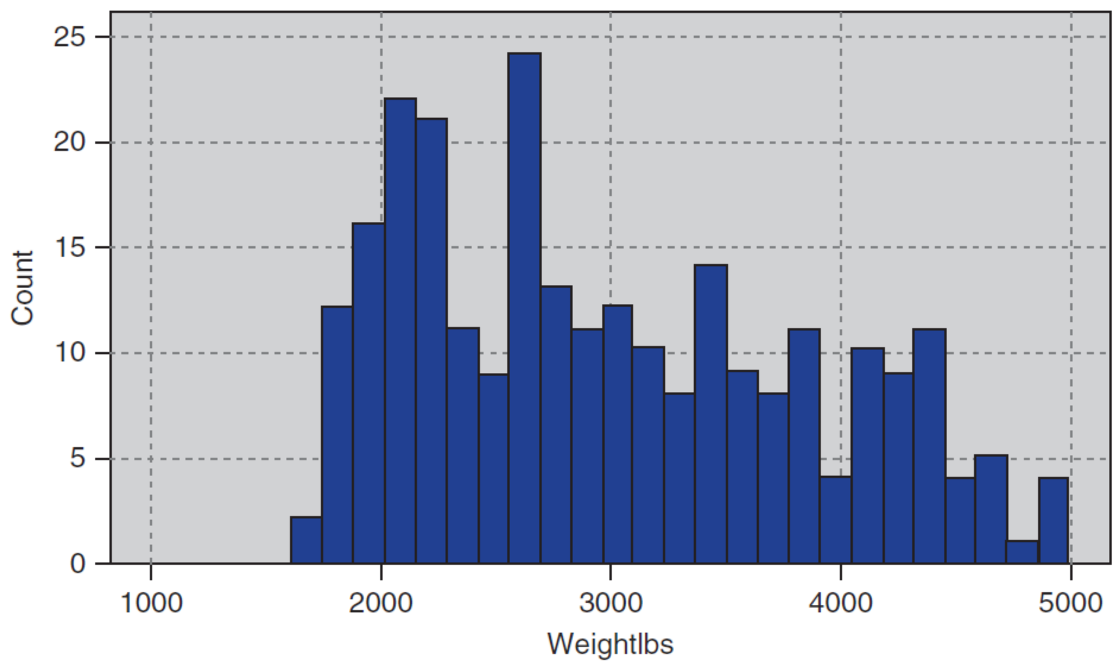
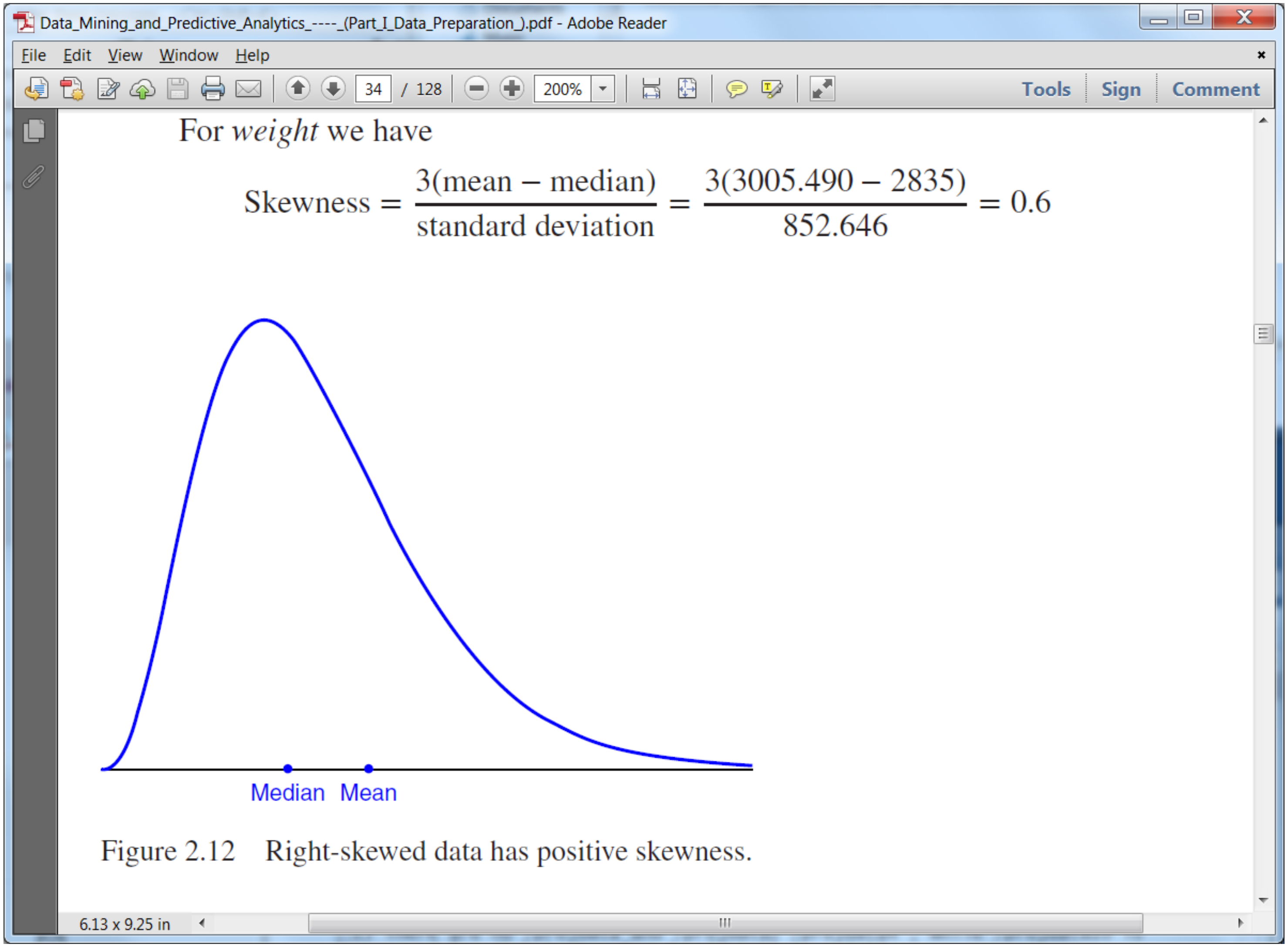


Figure 2.10 Original data.

Transformation to Achieve Normality



For *weight* we have

$$\text{Skewness} = \frac{3(\text{mean} - \text{median})}{\text{standard deviation}} = \frac{3(3005.490 - 2835)}{852.646} = 0.6$$

Figure 2.12 Right-skewed data has positive skewness.

Transformation to Achieve Normality

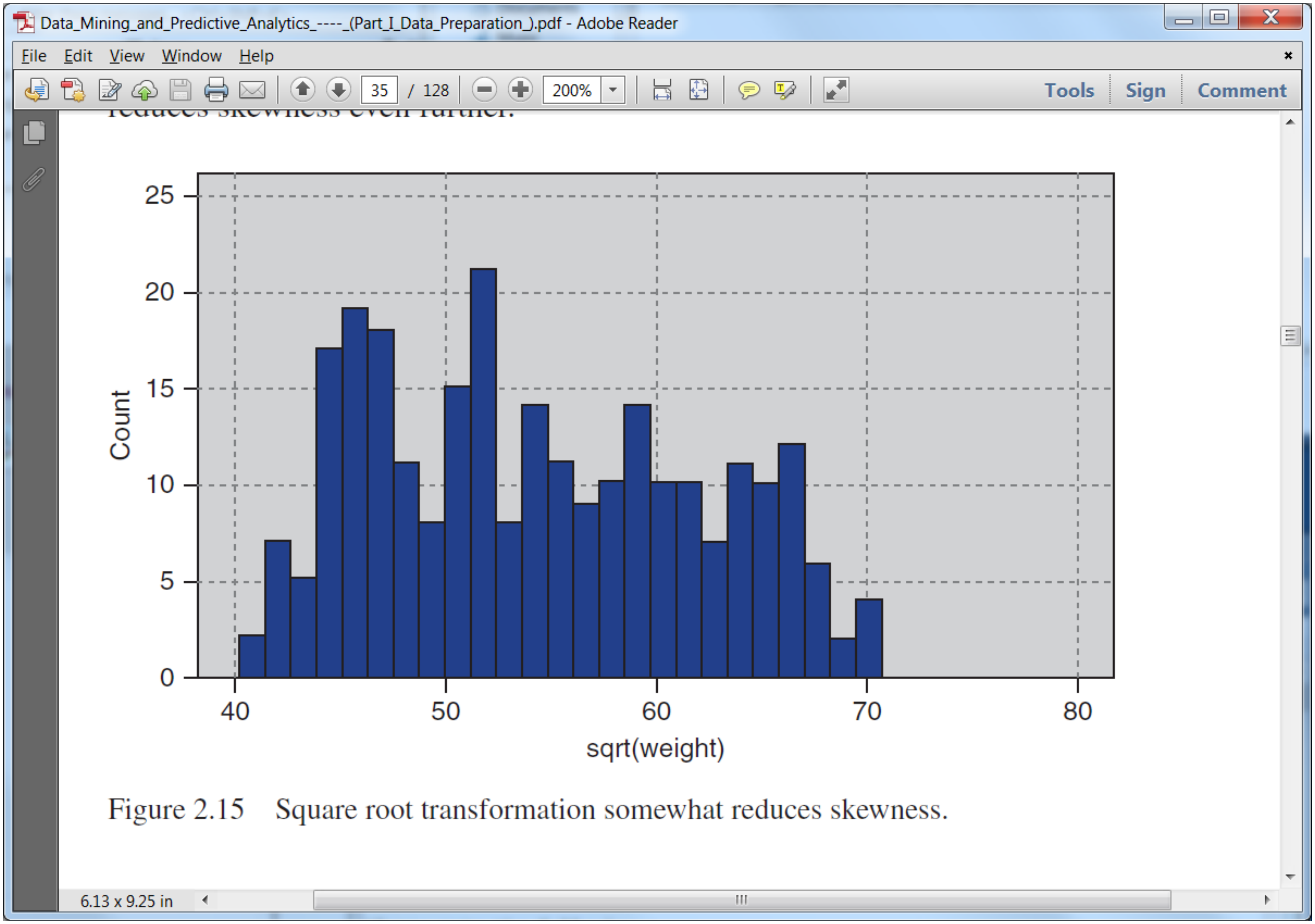


Figure 2.15 Square root transformation somewhat reduces skewness.

Transformation to Achieve Normality

The statistics in Figure 2.17 are used to calculate the reduction in skewness:

$$\text{Skewness (sqrt(weight))} = \frac{3(54.280 - 53.245)}{7.709} \approx 0.40$$

$$\text{Skewness (ln(weight))} = \frac{3(7.968 - 7.950)}{0.284} \approx 0.19$$

Finally, we try the inverse square root transformation $1/\sqrt{\text{weight}}$, which gives us the distribution in Figure 2.18. The statistics in Figure 2.19 give us

$$\text{Skewness (inverse\_sqrt(weight))} = \frac{3(0.019 - 0.019)}{0.003} = 0$$

Transformation to Achieve Normality

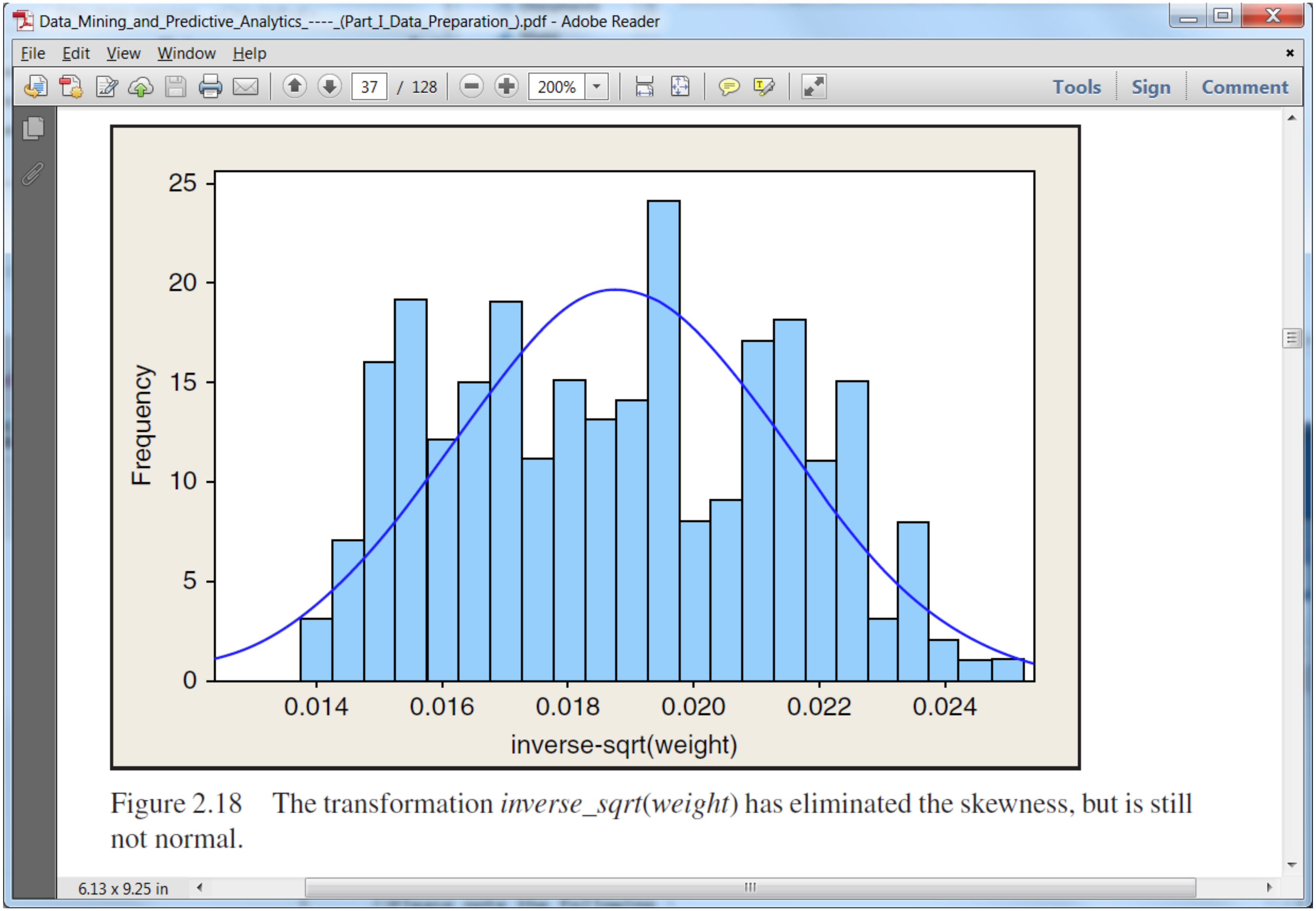


Figure 2.18 The transformation *inverse_sqrt*(*weight*) has eliminated the skewness, but is still not normal.

Transformation to Achieve Normality

Data_Mining_and_Predictive_Analytics_----_(Part_I_Data_Preparation_).pdf - Adobe Reader

Although we have achieved symmetry, we still have not arrived at normality. To check for normality, we construct a *normal probability plot,* which plots the quantiles of a particular distribution against the quantiles of the standard normal distribution. Similar to a *percentile,* the pth *quantile* of a distribution is the value x_p such that p% of the distribution values are less than or equal to x_p.

In a normal probability plot, if the distribution is normal, the bulk of the points in the plot should fall on a straight line; systematic deviations from linearity in this plot indicate nonnormality. Note from Figure 2.18 that the distribution is not a good fit for the normal distribution curve shown. Thus, we would not expect our normal probability plot to exhibit normality. As expected, the normal probability plot of *inverse_sqrt(weight)* in Figure 2.20 shows systematic deviations from linearity, indicating nonnormality. For contrast, a normal probability plot of normally distributed data is shown in Figure 2.21; this graph shows no systematic deviations from linearity.

Experimentation with further transformations (not shown) did not yield acceptable normality for *inverse_sqrt(weight)*. Fortunately, algorithms requiring normality usually do fine when supplied with data that is symmetric and unimodal.

aniel T., and Chantal D. Larose. Data Mining and Predictive Analytics, John Wiley & Sons, Incorporated, 2015.

Transformation to Achieve Normality

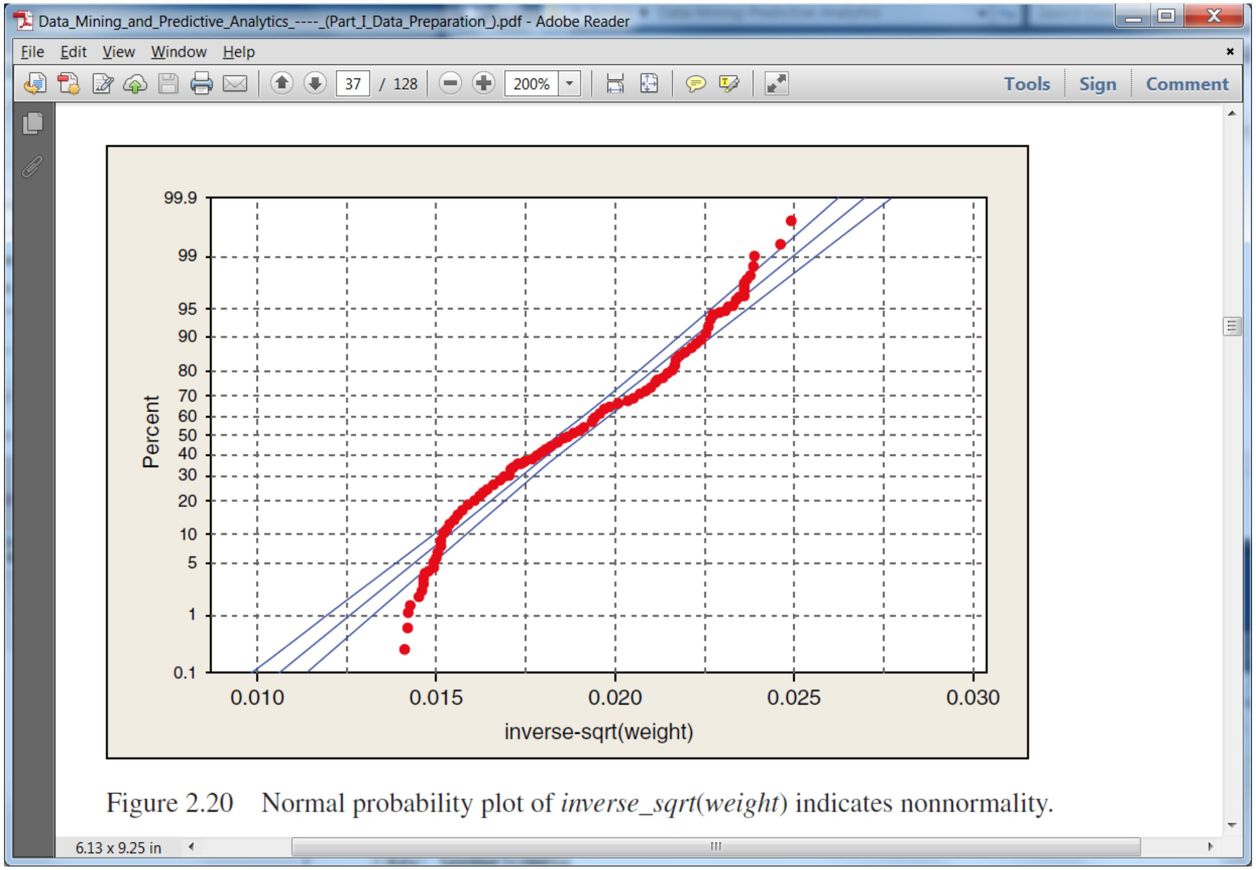


Figure 2.20 Normal probability plot of *inverse_sqrt(weight)* indicates nonnormality.

- Fortunately methods requiring normality usually do fine when supplied with data that is symmetric and unimodal.

Data Reduction Strategies

- Complex data analysis/mining may take a very long time to run on the complete data set
- Data reduction
  - Obtains a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results
- Data reduction strategies
  - Dimensionality reduction

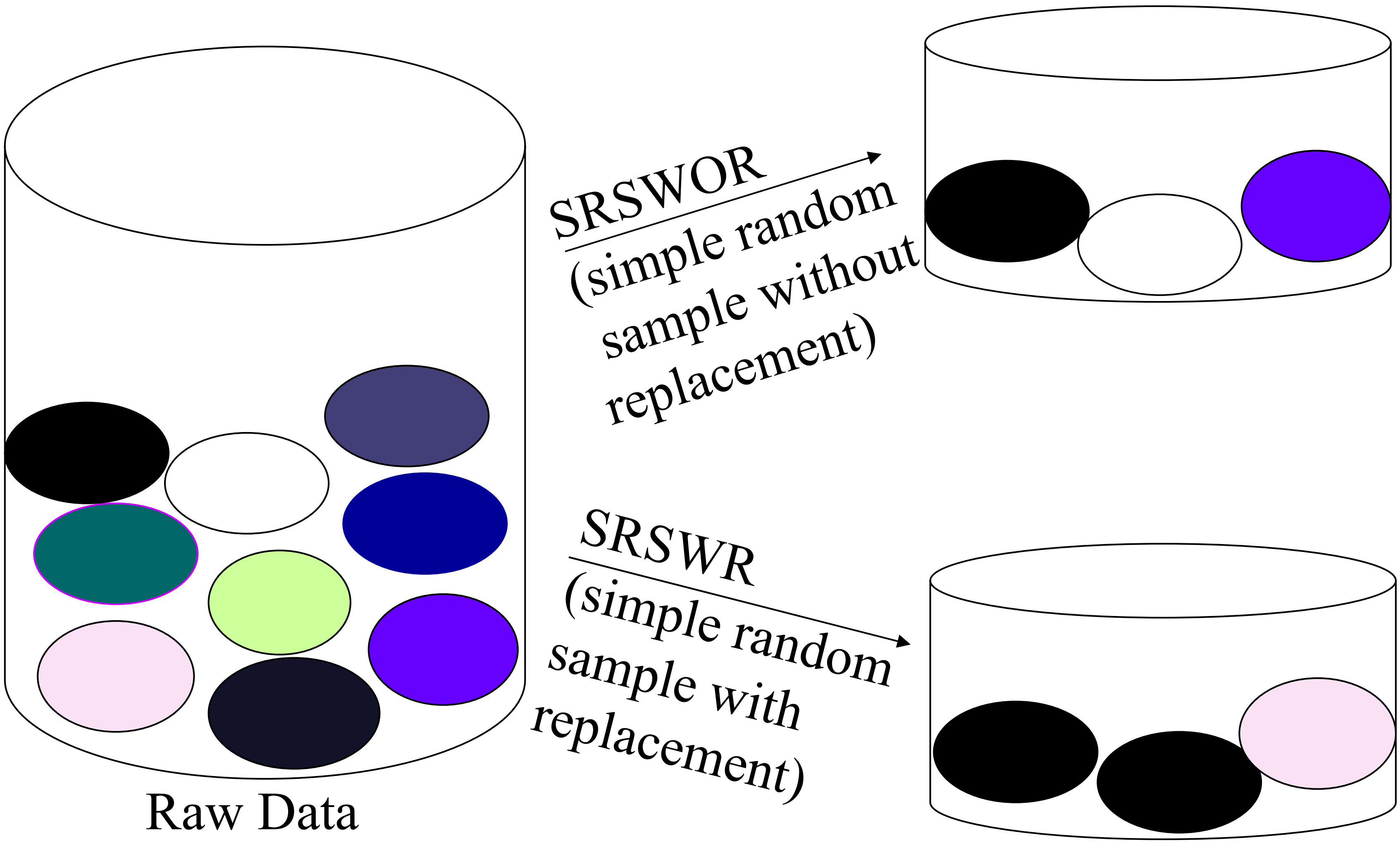
Dimensionality Reduction

- Feature selection (i.e., attribute subset selection):
  - Select a minimum set of features useful for data mining
  - reduce # of patterns in the patterns, easier to understand

Sampling

- Allow a mining algorithm to handle an extremely large amount of the data
- Choose a representative subset of the data

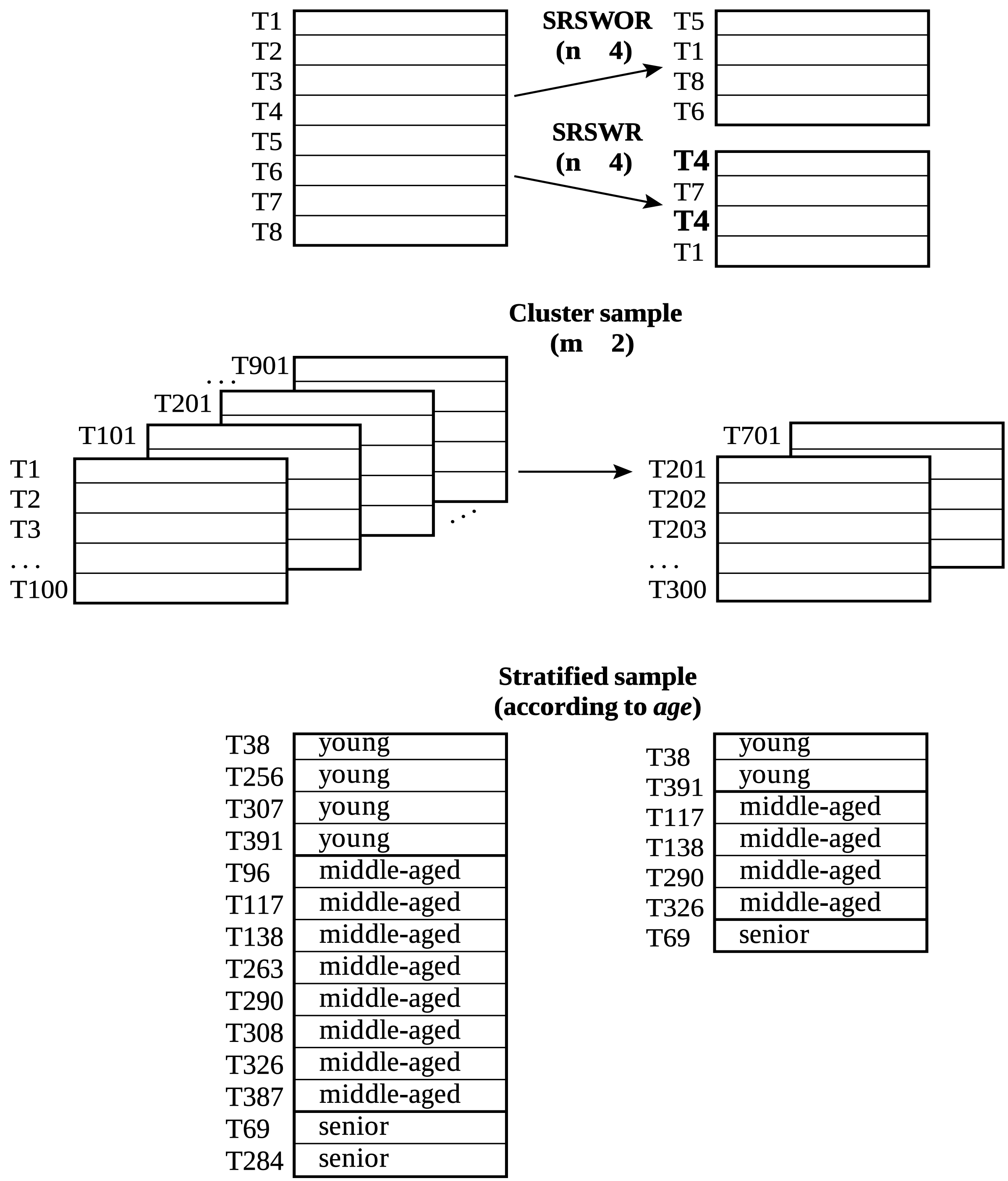
Sampling



SRSWOR
(simple random sample without replacement)
SRSWR
(simple random sample with replacement)
Raw Data

Sampling

- Simple random sampling may have very poor performance in the presence of skew
- Adaptive sampling method - Stratified sampling:
  - Approximate the percentage of each class (or subpopulation of interest) in the overall database
  - Used in conjunction with skewed data


SRSWOR
(n 4)
SRSWR
(n 4)
T1
T2
T3
T4
T5
T6
T7
T8
T5
T1
T8
T6
T4
T7
T4
T1
Cluster sample
(m 2)
T901
T201
T101
T1
T2
T3
. . .
T100
T701
T201
T202
T203
. . .
T300
Stratified sample
(according to *age*)
T38 young
T256 young
T307 young
T391 young
T96 middle-aged
T117 middle-aged
T138 middle-aged
T263 middle-aged
T290 middle-aged
T308 middle-aged
T326 middle-aged
T387 middle-aged
T69 senior
T284 senior
T38 young
T391 young
T117 middle-aged
T138 middle-aged
T290 middle-aged
T326 middle-aged
T69 senior