



Exploratory Data Analysis

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Content outline

- Data objects and Attributes
- Basic statistical data descriptions
- Basic data visualization
- Data proximity measures

Data collection: Record datasets

- Relational / transactional tuples
- Term-frequency vectors, numerical matrices, crosstabs

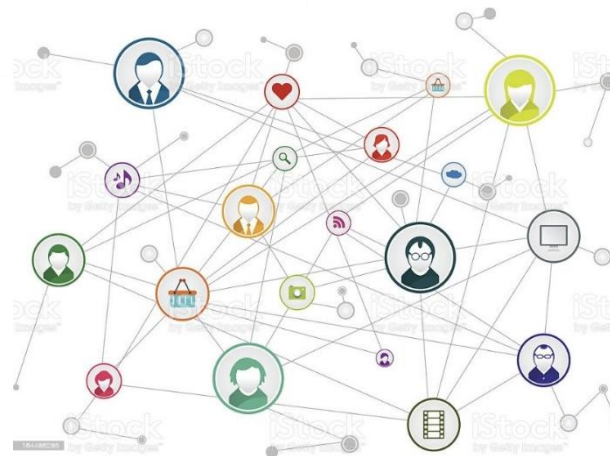
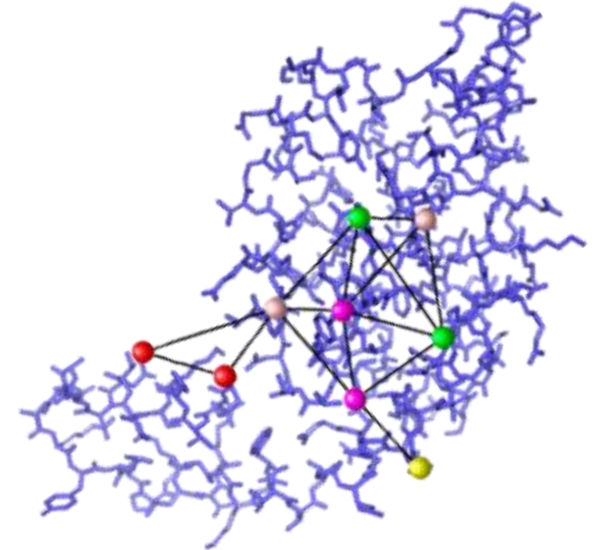
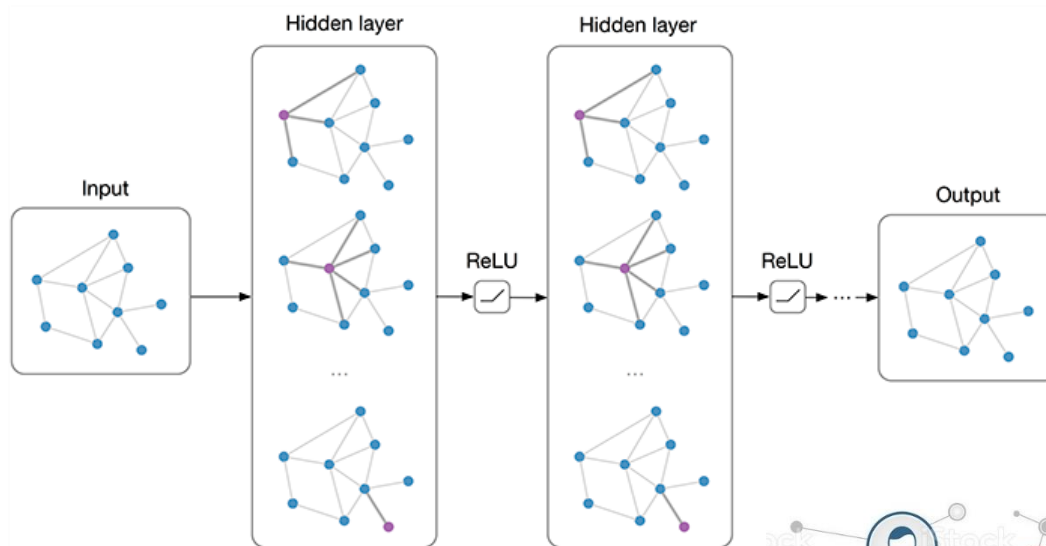
<i>TID</i>	Items
1	{Bread, Milk}
2	{Bread, Diapers, Beer, Eggs}
3	{Milk, Diapers, Beer, Cola}
4	{Bread, Milk, Diapers, Beer}
5	{Bread, Milk, Diapers, Cola}

	for	great	greatest	lasagna	life	love
sentence 1	0	0	1	0	1	1
sentence 2	0	2	0	0	0	1
sentence 3	0	0	1	0	0	1
sentence 4	1	0	0	1	0	1

		Task Performance		Total
		Fail	Success	
User Felt	Very bad	0	0	0
	Bad	2	1	3
	Neutral	1	4	5
	Good	0	15	15
	Very good	0	5	5
Total		3	25	28

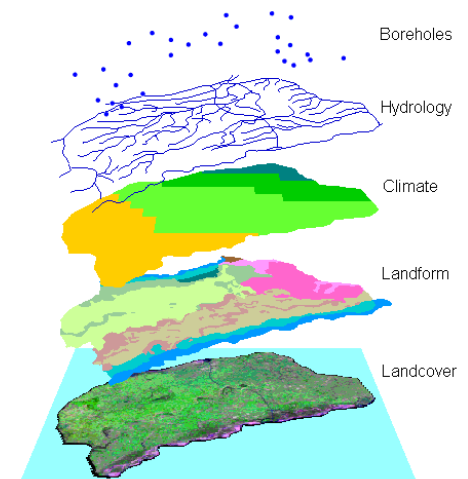
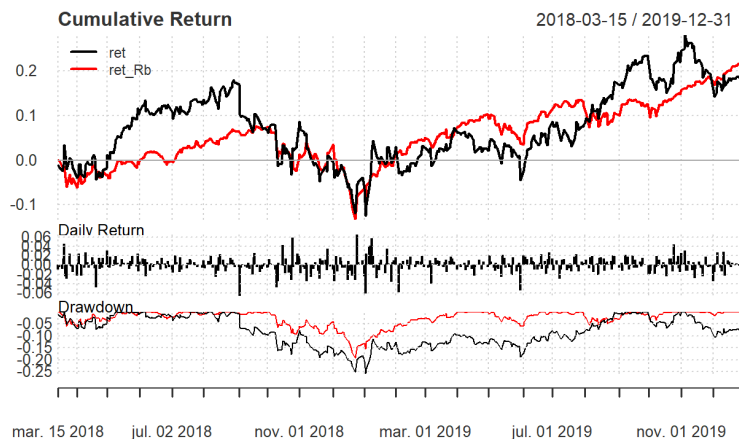
Data collection: Graph datasets

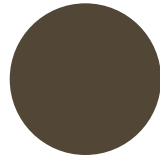
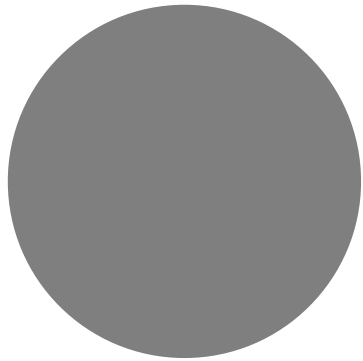
- The Internet, social networks, molecular structures



Data collection: Ordered datasets

- Sequential data: transaction sequences, genetic sequences
- Video data, temporal data, time-series data, etc.

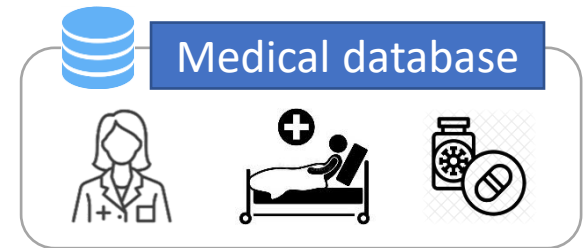




Data objects and Attributes

Data objects

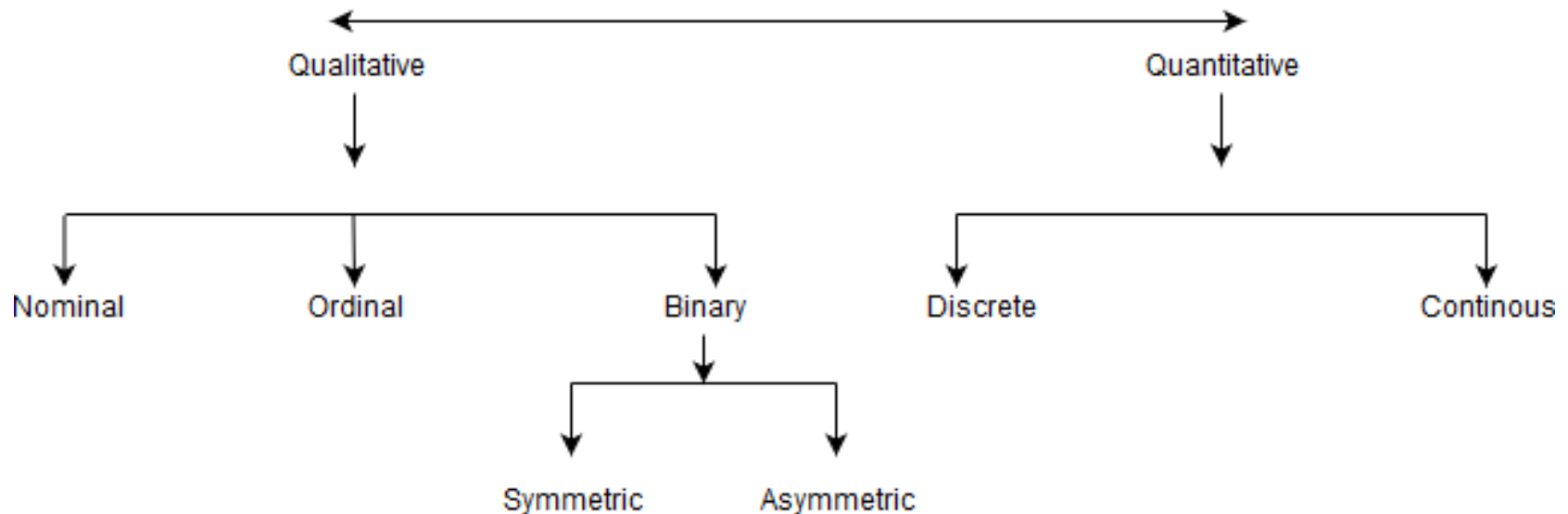
- A **data object** represents an entity, serving as the building block for a dataset.
 - Similar terms: sample, example, instance, data point, and tuple



- Data objects are described by attributes.
 - In a database: rows \rightarrow data objects, columns \rightarrow attributes

Attributes

- An **attribute** shows some characteristic of a data object.
 - Similar terms: dimension, feature, and variable
 - E.g., a Customer object has 3 attributes {id, name, address}
- **Observation**: an observed value for a given attribute
- **Feature vector**: a set of attributes used to describe an object

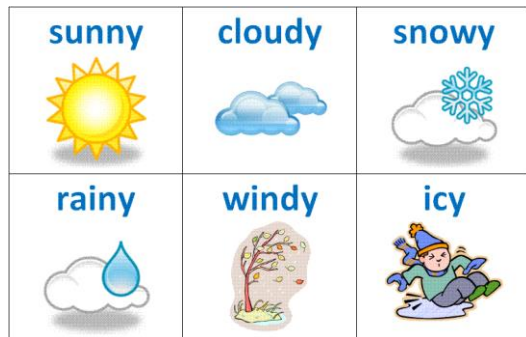


Attribute types: Nominal

- Qualitative, values do not have any meaningful order
- Enumerations: categories, states, or “names of things”



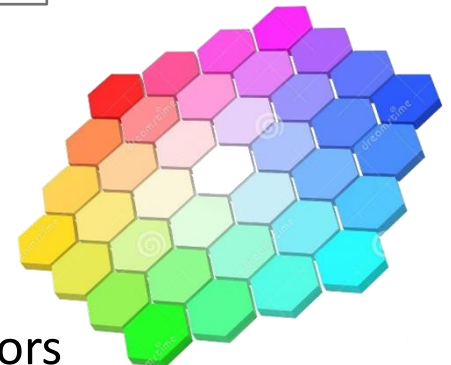
Day and Night



Weather



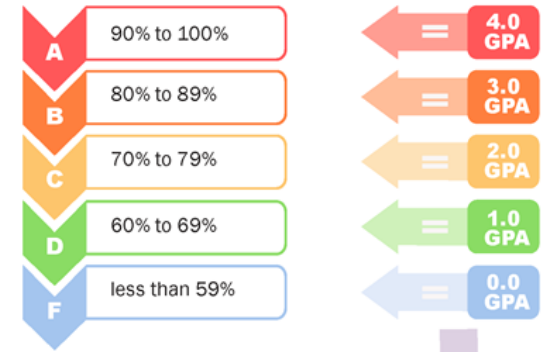
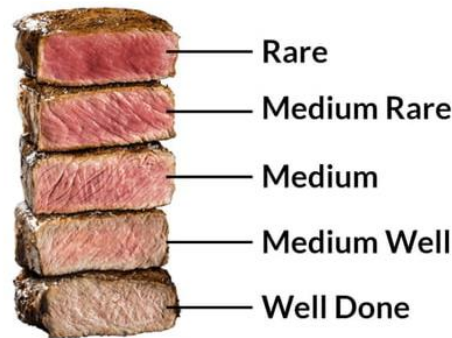
Occupation



Colors

Attribute types: Ordinal

- Qualitative, values have a meaningful order (ranking) but magnitude between successive values is not known



- Useful for subjective assessments of qualities that cannot be measured objectively
 - E.g., customer satisfaction



Attribute types: Binary

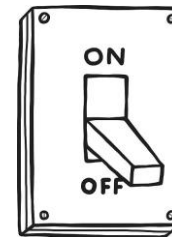
- Nominal attribute with only 2 states
- **Symmetric binary**: both outcomes **equally important**



Day and night

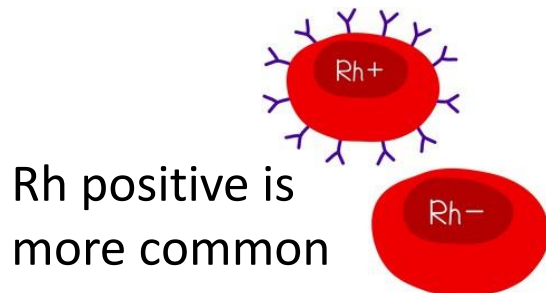


Male and Female



Switch light
On and Off

- **Asymmetric binary**: outcomes **not equally important**
 - Convention: assign 1 to the most important outcome (e.g., HIV test)



A positive result is more significant



Attribute types: Numeric

Interval numeric attribute

- Measured on a scale of **equal-sized units**
- Values have order (e.g., temperature in C° or F°, calendar dates)
- No true **zero-point**: able to compute the difference – not able to talk of one value as being a multiple of another
 - E.g., 20°C is five degrees higher than 15°C (right), 10°C is twice as warm as 5°C (wrong)

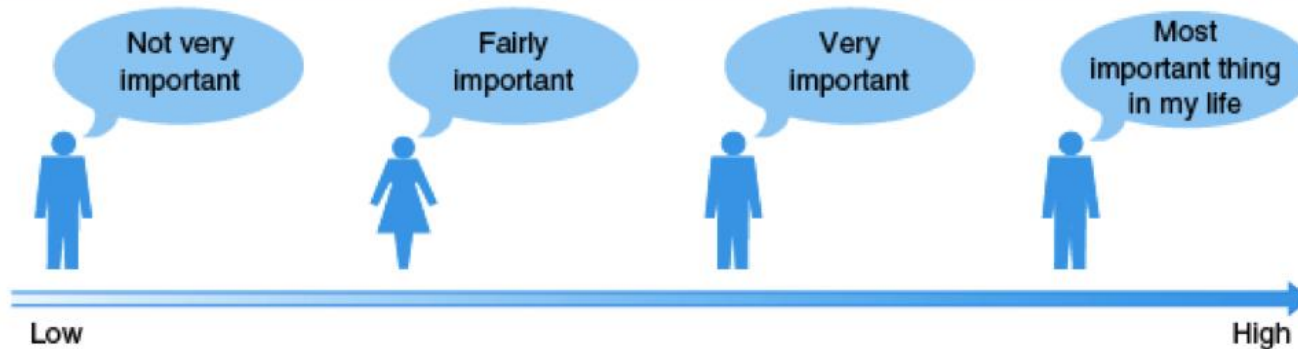
Ratio numeric attribute

- Inherent **zero-point**
- Values can be considered as being an order of magnitude larger than the unit of measurement
 - E.g., temperature (10°K is twice as high as 5°K), monetary (you are 100 times richer with \$100 than with \$1), measurements (height, weight)

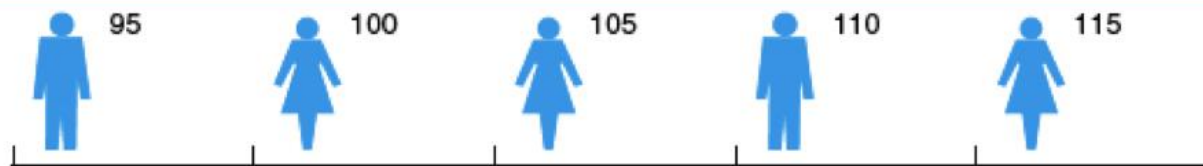
Nominal Measure Example: Gender



Ordinal Measure Example: Religiosity "How important is religion to you?"



Interval Measure Example: IQ

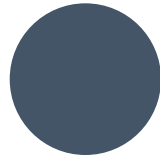
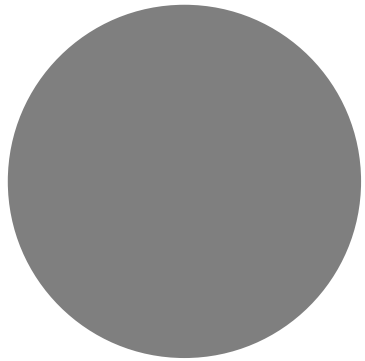


Ratio Measure Example: Income



Attributes: Discrete vs. Continuous

- There are many ways to organize attribute types, which are not mutually exclusive.
- Discrete attribute
 - Only a finite or countably infinite set of values
 - The values are sometimes represented as integers.
 - Binary attributes are a special case of discrete attributes.
- Continuous attribute
 - Real numbers of continuous domains
 - The values are usually represented using a finite number of digits
→ floating-point variables



Basic statistical data descriptions

Central tendency: Arithmetic mean

- Let x_1, x_2, \dots, x_N be a set of N values or observations for some numeric attribute X .
- The **arithmetic mean** is defined as $\mu = \frac{1}{N} \sum_{i=1}^N x_i$
- The **weighted arithmetic mean** is written as $\mu^w = \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i}$
 - where w_i is the weight value that associates with x_i .
- It is the most common and effective numeric measure

Central tendency: Arithmetic mean

- Consider the score records of John and Kelly.
- The (non-weighted) mean scores are

$$\mu_{John} = 82.6, \quad \mu_{Kelly} = 84.6$$

John's record	
Homework	92
Quiz	74
Lab	83
Test	76
Final exam	88

Kelly's record	
Homework	100
Quiz	82
Lab	95
Test	70
Final exam	76

Homework	15 %
Quiz	10 %
Lab	20 %
Test	25 %
Final exam	30 %

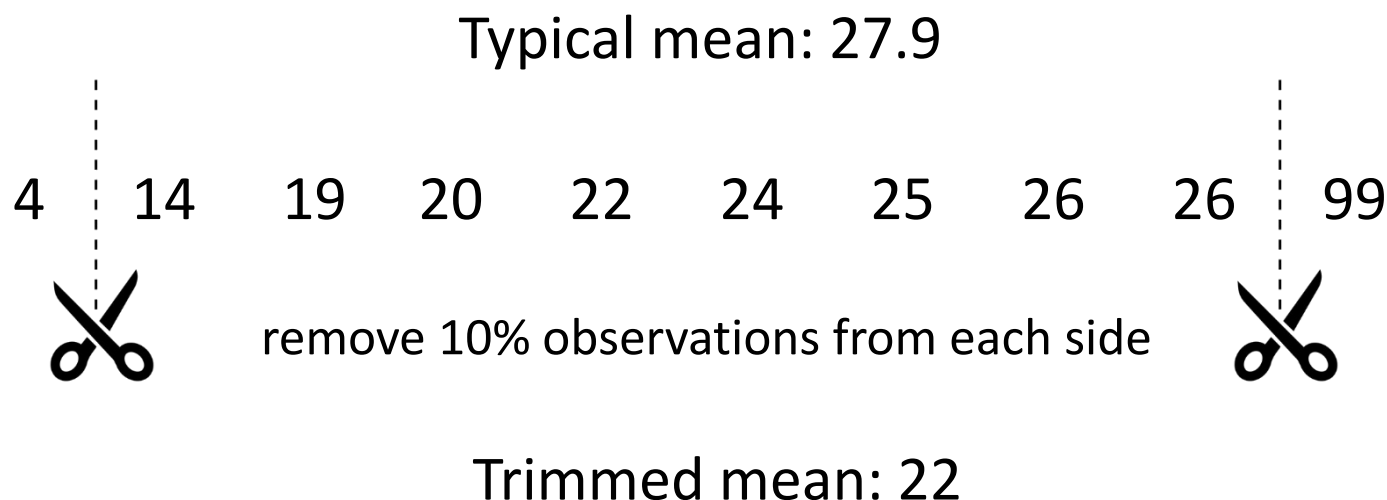
- We now have the course grade distribution
- The weighted mean scores are

$$\mu_{John}^w = 83.2, \quad \mu_{Kelly}^w = 82.5$$

$$\mu_{John}^w = \frac{0.15 \times 92 + 0.1 \times 74 + 0.2 \times 83 + 0.25 \times 76 + 0.3 \times 88}{0.15 + 0.1 + 0.2 + 0.25 + 0.3} = 83.2$$

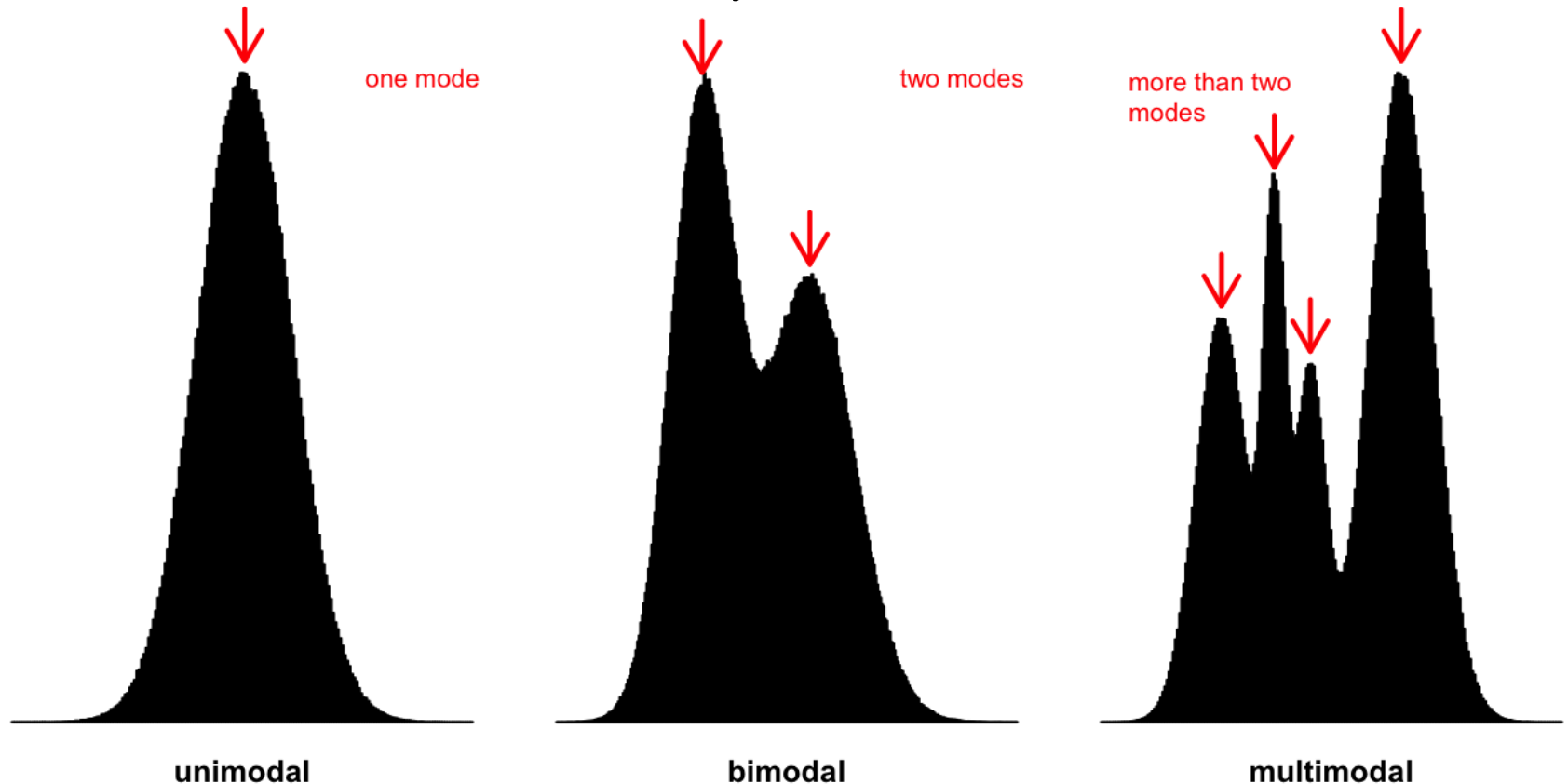
Central tendency: Arithmetic mean

- Means are highly sensitive to extreme values (e.g., outlier).
- Trimmed mean**: chop extreme values before calculating the regular mean



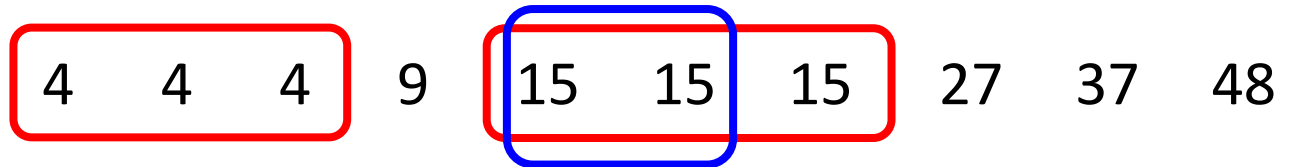
Central tendency: Mode

- **Mode** is the value that occurs most frequently in the data, defined for both qualitative and quantitative attributes.
 - If each data value occurs only once, then there is no mode

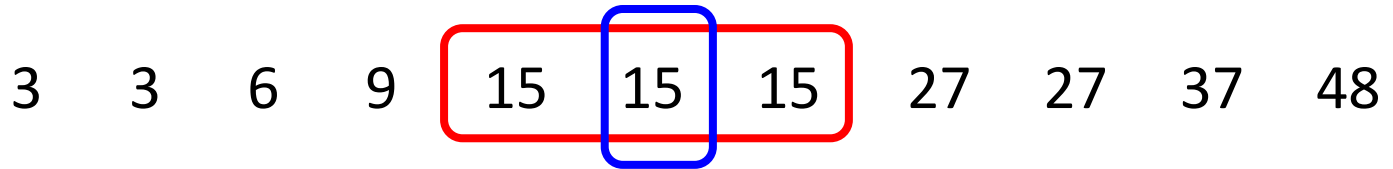


Central tendency: Median

- Suppose that the given set of N observations is sorted.
- **Median** is the middle value of the ordered set.
 - N is **odd**: pick the *exact middle value*; otherwise, take the *average of the two middlemost values*.
- **Midrange** is the average of the largest and smallest values in the set.

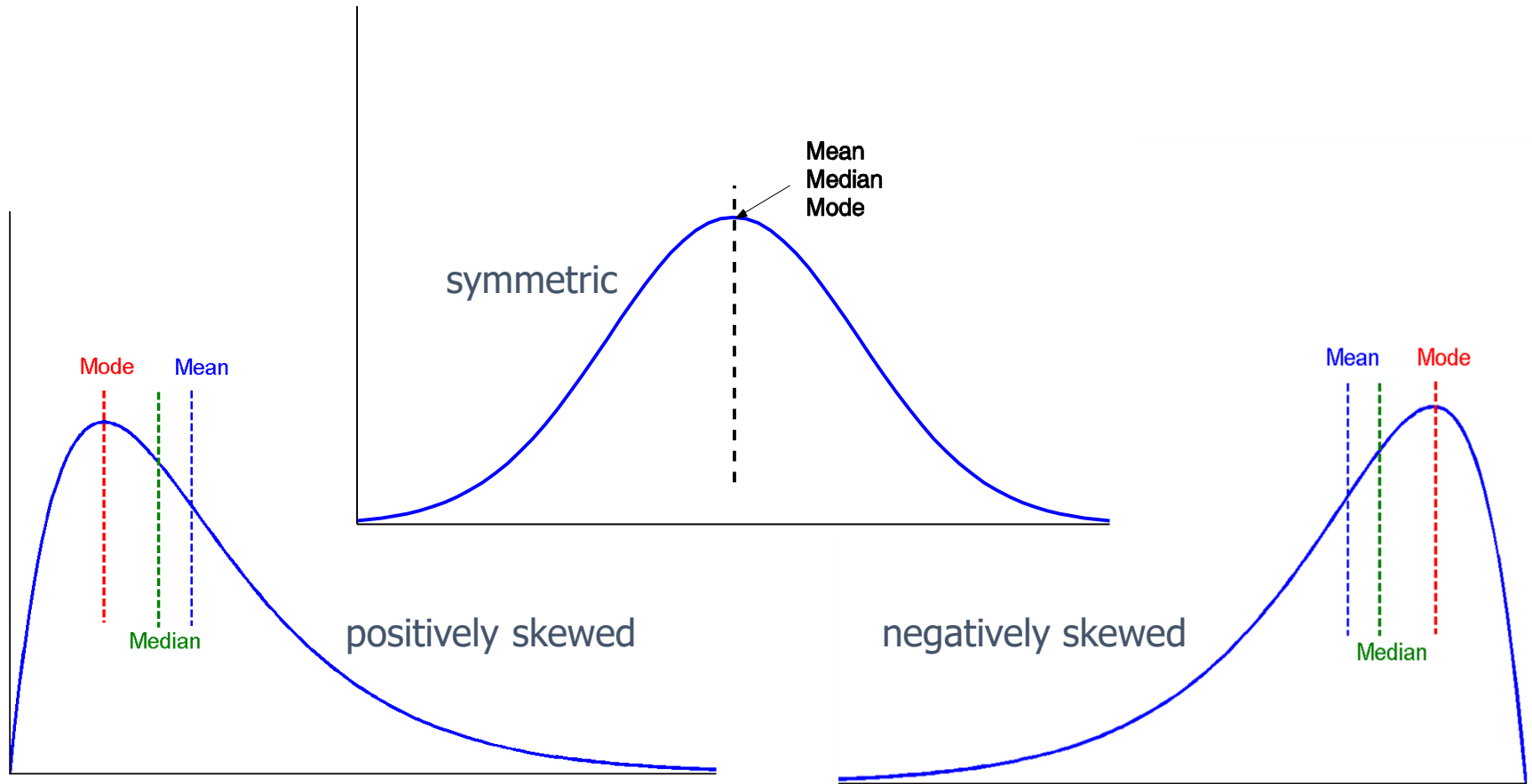


mean = 17.8 – mode: 4 and 15 – midrange = 22, median = $(15+15)/2 = 15$



mean = 18.636 – mode: 15 – midrange = 22.5, median = 15

Symmetric data vs. Skew data



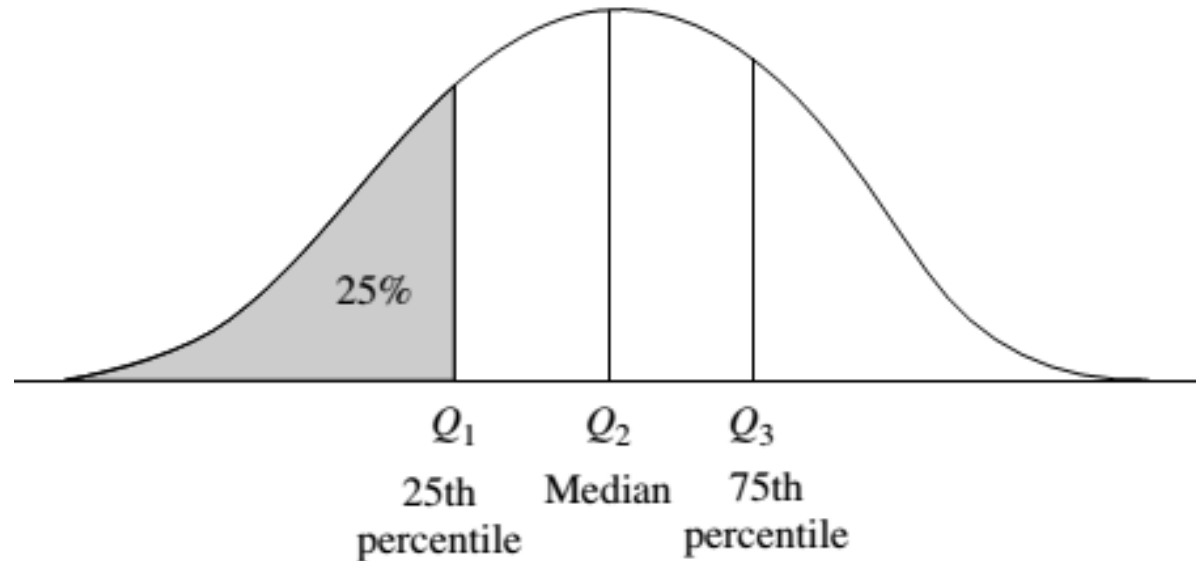
- For moderately skewed unimodal numeric data, the empirical formula is
$$mean - mode \approx 3 \times (mean - median)$$

Data dispersion: Quantiles

- Let x_1, x_2, \dots, x_N be a set of N observations sorted in increasing order for a numeric attribute X .
- **Quantiles** are points taken at regular intervals of a data distribution, dividing it into equal-sized consecutive sets.
- **k^{th} q-quantile** ($0 < k < q, k \in \mathbb{N}^*$): a value x such that at most k/q data values $< x$ and at most $(q - k)/q$ of which $> x$.
 - There are $q - 1$ q-quantiles.

Data dispersion: Quantiles

- **Quartiles** (4-quantiles) split the data distribution into four equal parts.



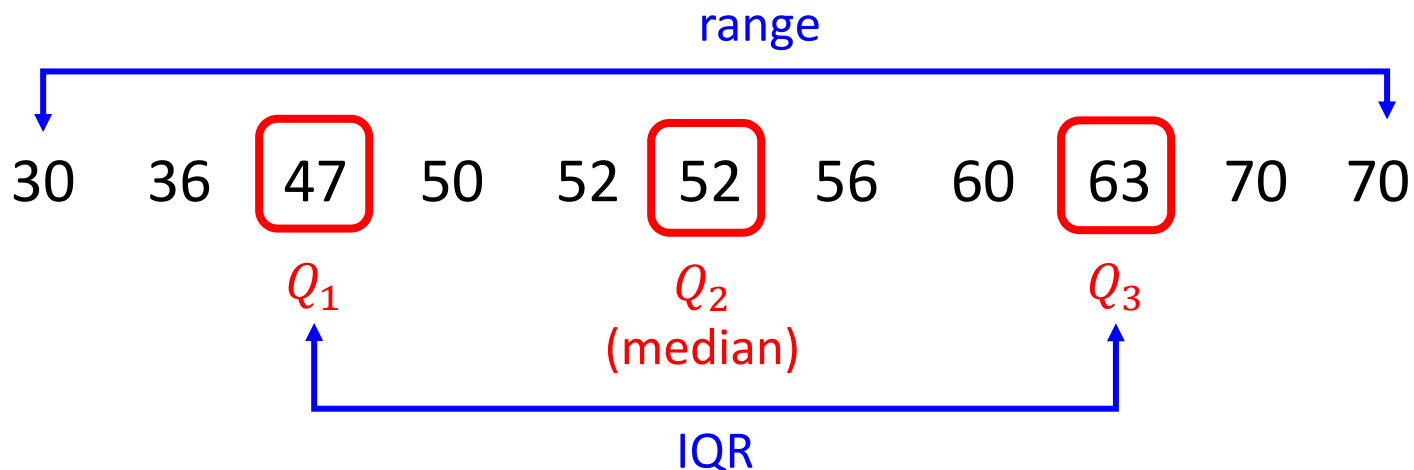
- **Percentiles** (100-quantiles): 100 equal-sized consecutive sets
- **2-quantile** is the median that splits the distribution into halves

Data dispersion: Interquartile range

- **Interquartile range** (IQR) is the distance between the first and third quartiles.

$$IQR = Q_3 - Q_1$$

- **Range** is the difference between the largest and smallest values in the set.



How to determine the quartile?

- Use the median to divide the ordered set into two halves.
 - If the original set has an even number of points, split it exactly in half
 - Otherwise, **do not include** the median in either half.
- Q_1 and Q_3 are the medians of the lower and upper halves, respectively.

6 7 15 36 39 40 41 42 43 47 49

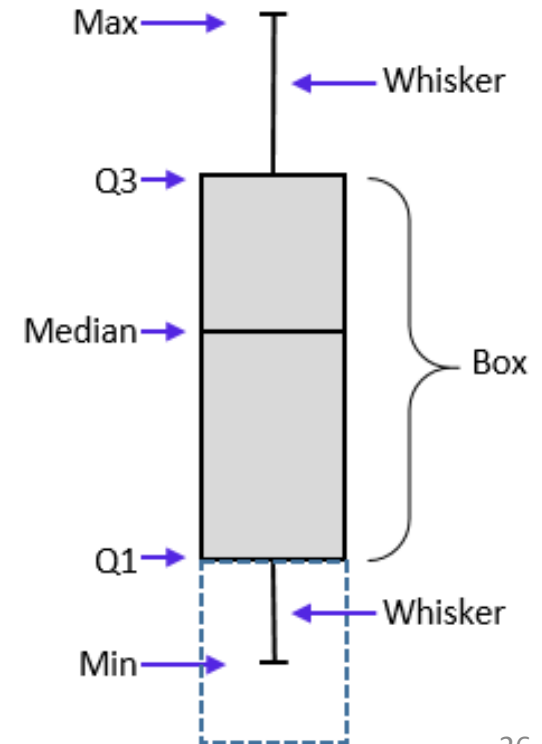
Q_1 Q_2 Q_3

7 15 36 39 40 41

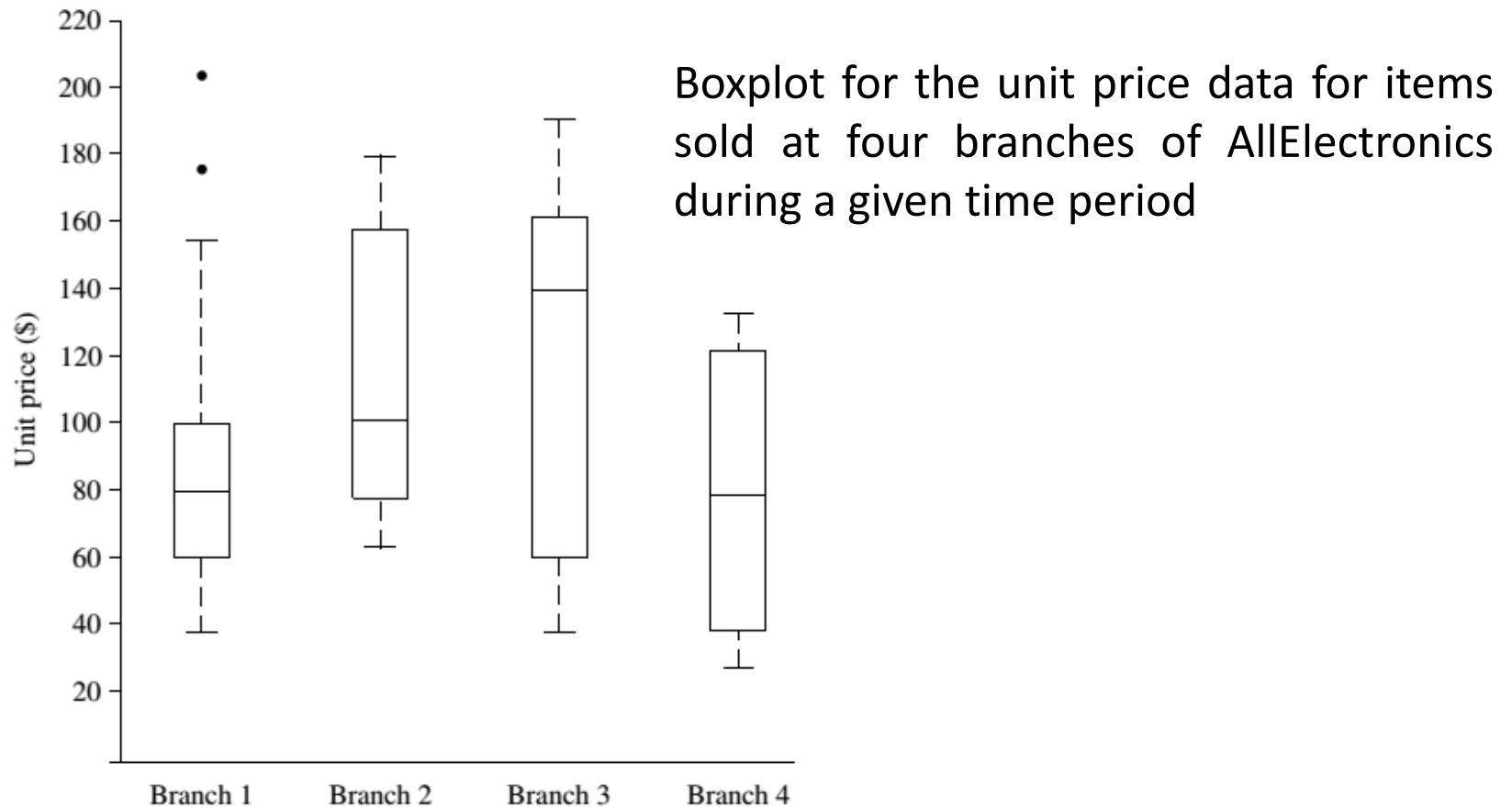
Q_1 $Q_2 = 37.5$ Q_3

Data dispersion: Boxplot

- A **five-number summary** of a distribution includes
 - The median (Q_2), the quartiles Q_1 and Q_3 ,
 - The smallest (**Min**) and largest (**Max**) individual values.
- The summary is presented by a **boxplot**.
 - Outliers: points that are out the range $[-1.5 \times IQR, 1.5 \times IQR]$, plotted individually



Data dispersion: Boxplot



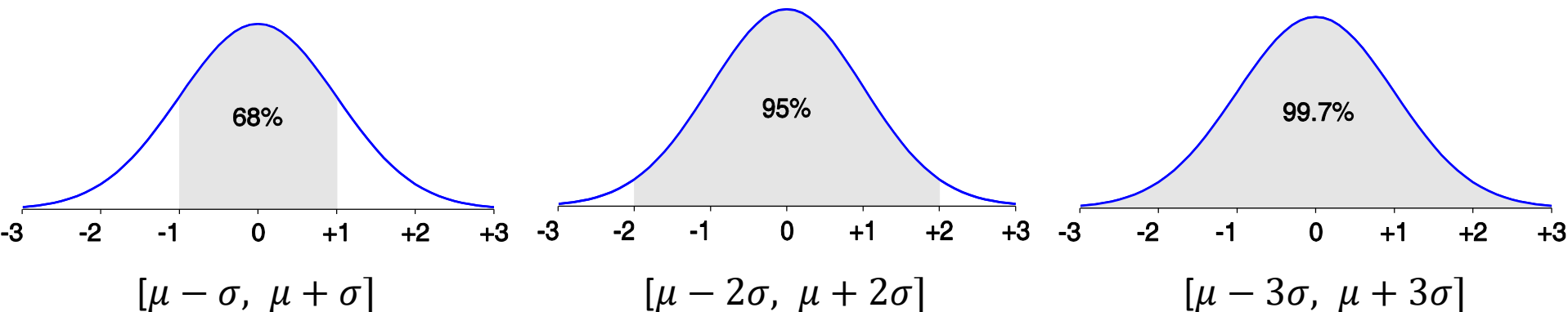
- For Branch 1, the median price of items sold is \$80, Q_1 is \$60, and Q_3 is \$100. Notice that two outlying observations, 175 and 202, were plotted individually as they are more than $1.5 \times \text{IQR}$.

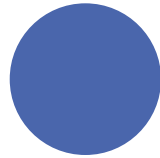
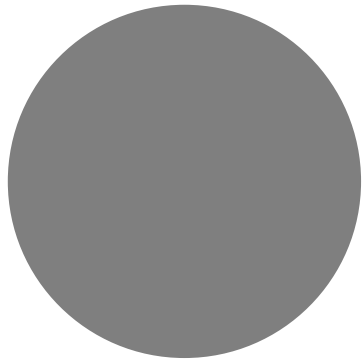
Data dispersion: Variance

- The (population) variance is defined as

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2 = \left(\frac{1}{N} \sum_{i=1}^N x_i^2 \right) - \bar{x}^2$$

- The standard deviation is the square root of the variance.
 - Low $\sigma \rightarrow$ the data tends to be very close to the mean
 - High $\sigma \rightarrow$ the data spreads out over a large range of values





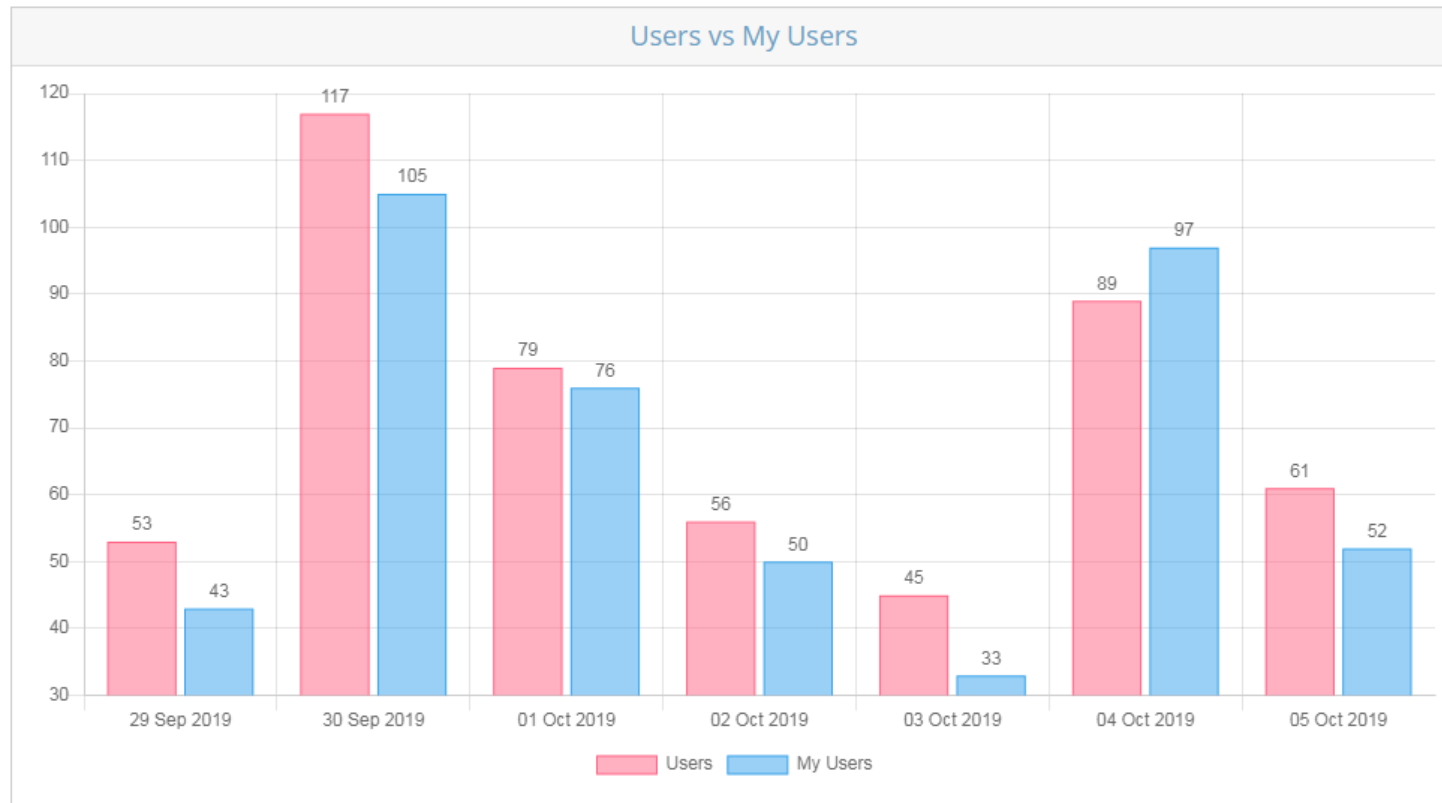
Basic data visualization

Why data visualization?

- Gain insight into an information space by mapping data onto graphical primitives
- Provide qualitative overview of large datasets
- Search for patterns, trends, irregularities, relationships among data
- Help find interesting regions and suitable parameters for further quantitative analysis
- Provide a visual proof of computer representations derived

Bar chart

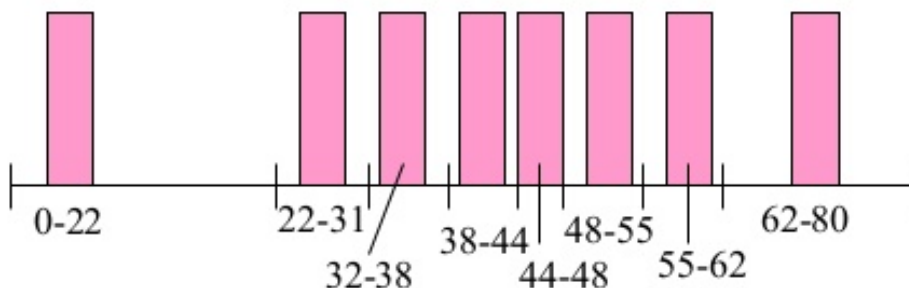
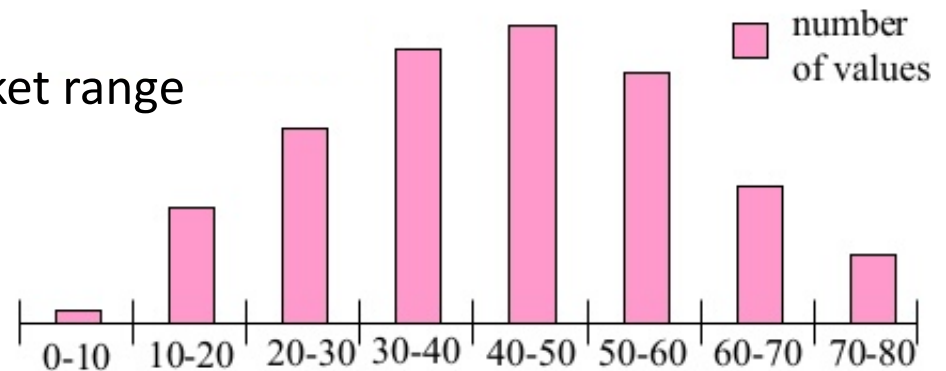
- A **bar chart** presents **nominal data** by using rectangular bars with heights proportional to the values represented.



Histogram

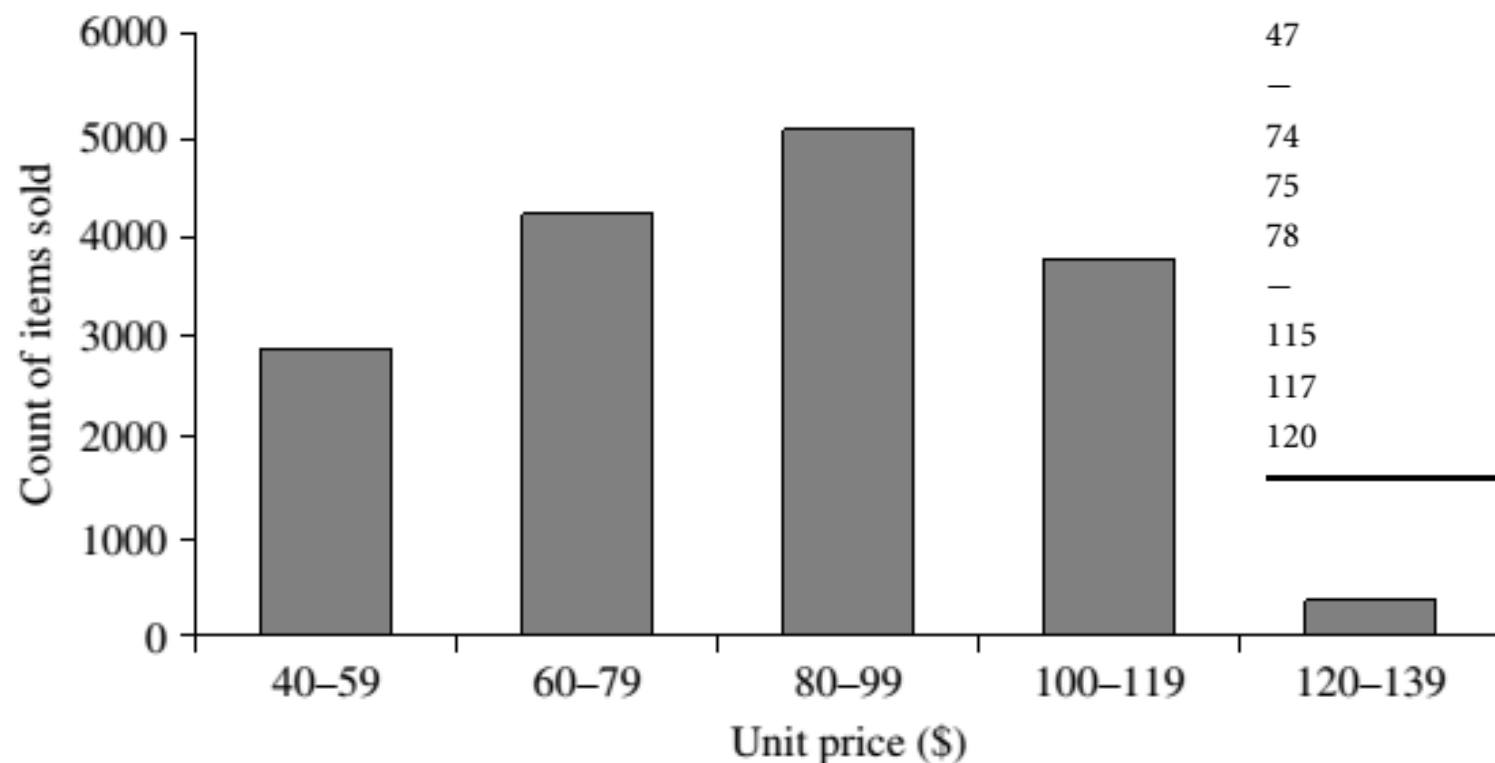
- The range of values for a numeric attribute X is partitioned into disjoint consecutive subranges, called **buckets** or **bins**.
- A bar is drawn for each subrange such that its height represents the total items within the subrange.

Equal-width: equal bucket range



Equal-frequency: equal bucket depth

Histogram: An example

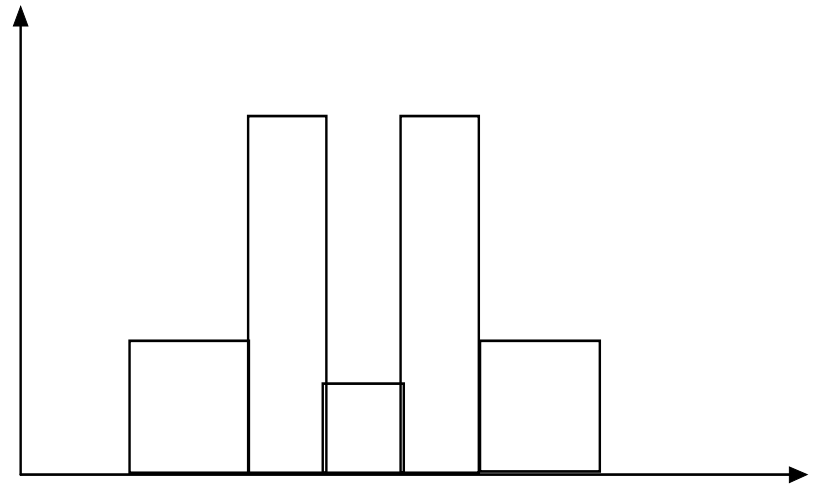
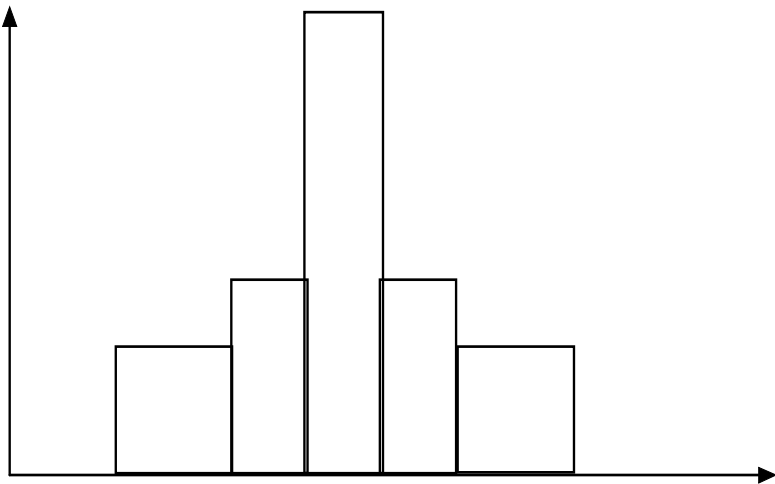


A Set of Unit Price Data for Items Sold at a Branch of *AllElectronics*

Unit price (\$)	Count of items sold
40	275
43	300
47	250
—	—
74	360
75	515
78	540
—	—
115	320
117	270
120	350

Histogram over boxplot

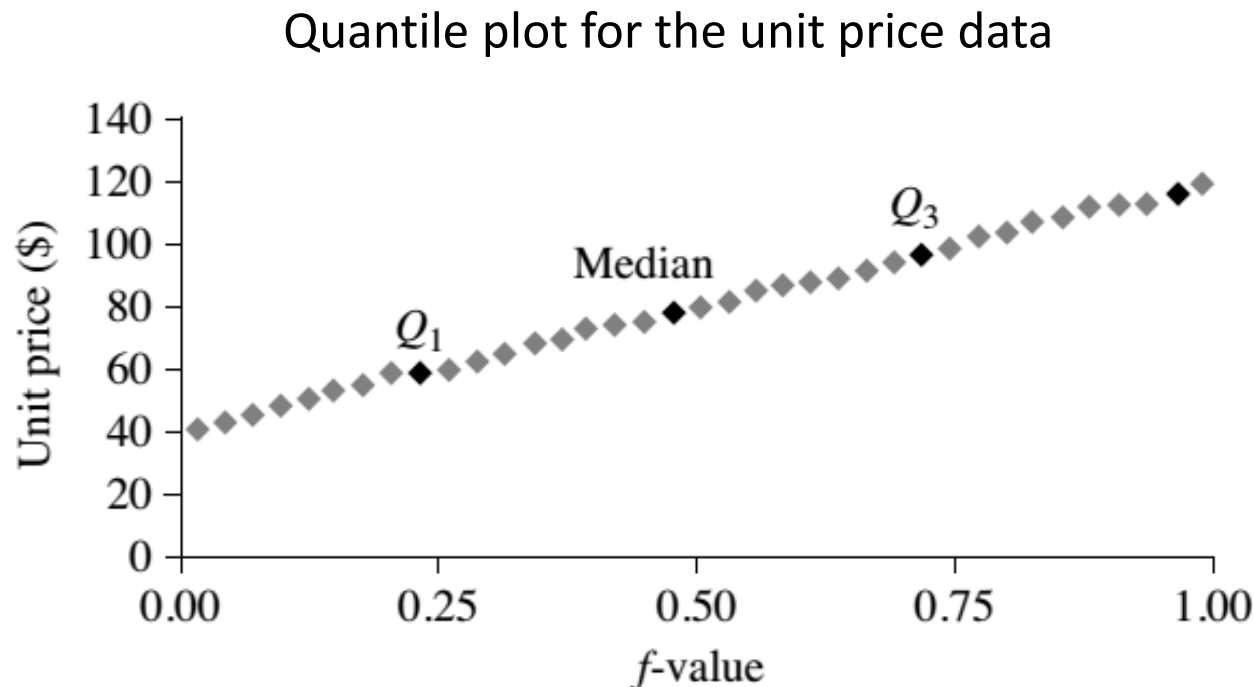
- The two following histograms may have the same boxplot.
- However, they represent rather different data distributions.



Quantile plot

- A **quantile plot** presents the plot quantile information for a univariate data distribution
 - It allows access to both overall behavior and unusual occurrences.
- Let x_1, x_2, \dots, x_N be the data observations sorted in increasing order for some ordinal or numeric attribute X .
- Each value x_i is paired with $f_i = \frac{i-0.5}{N}$, indicating that approximately $f_i \times 100\%$ of data are $\leq x_i$.

Quantile plot: An example



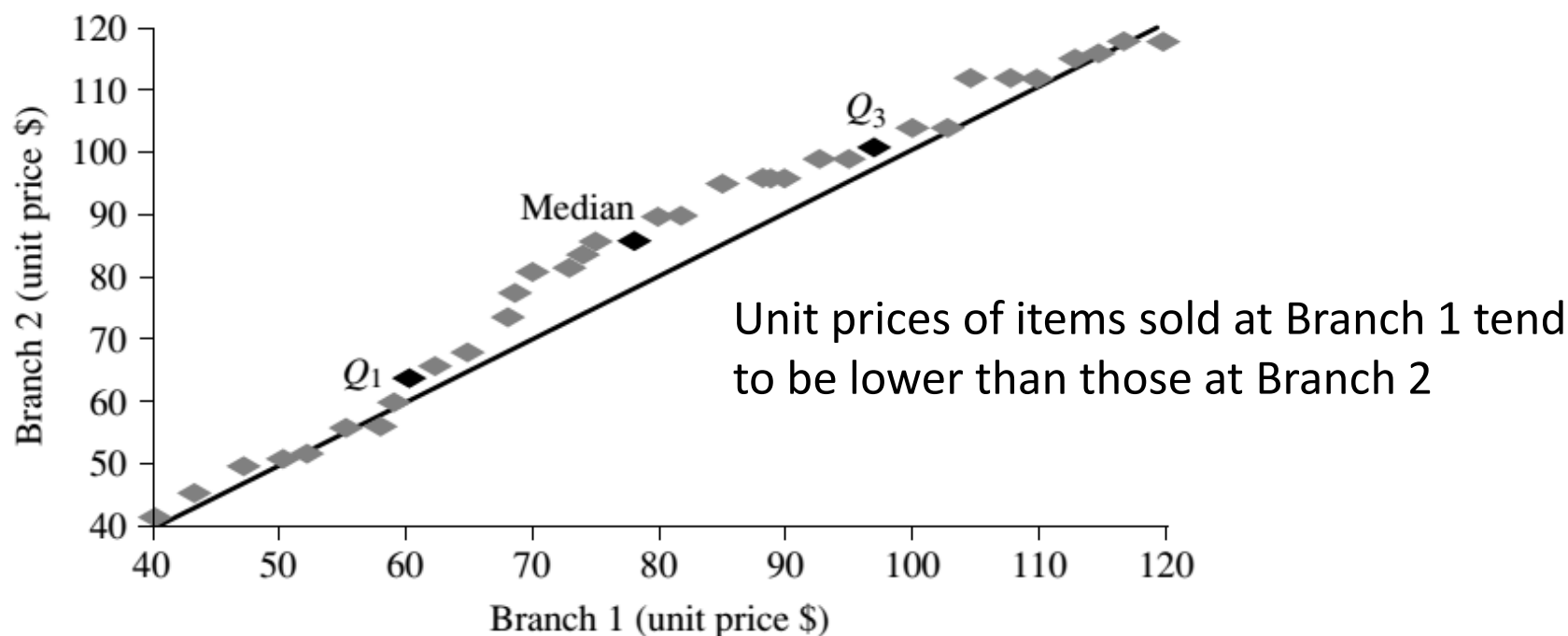
A Set of Unit Price Data for Items Sold at a Branch of *AllElectronics*

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120	350

Quantile-Quantile plot

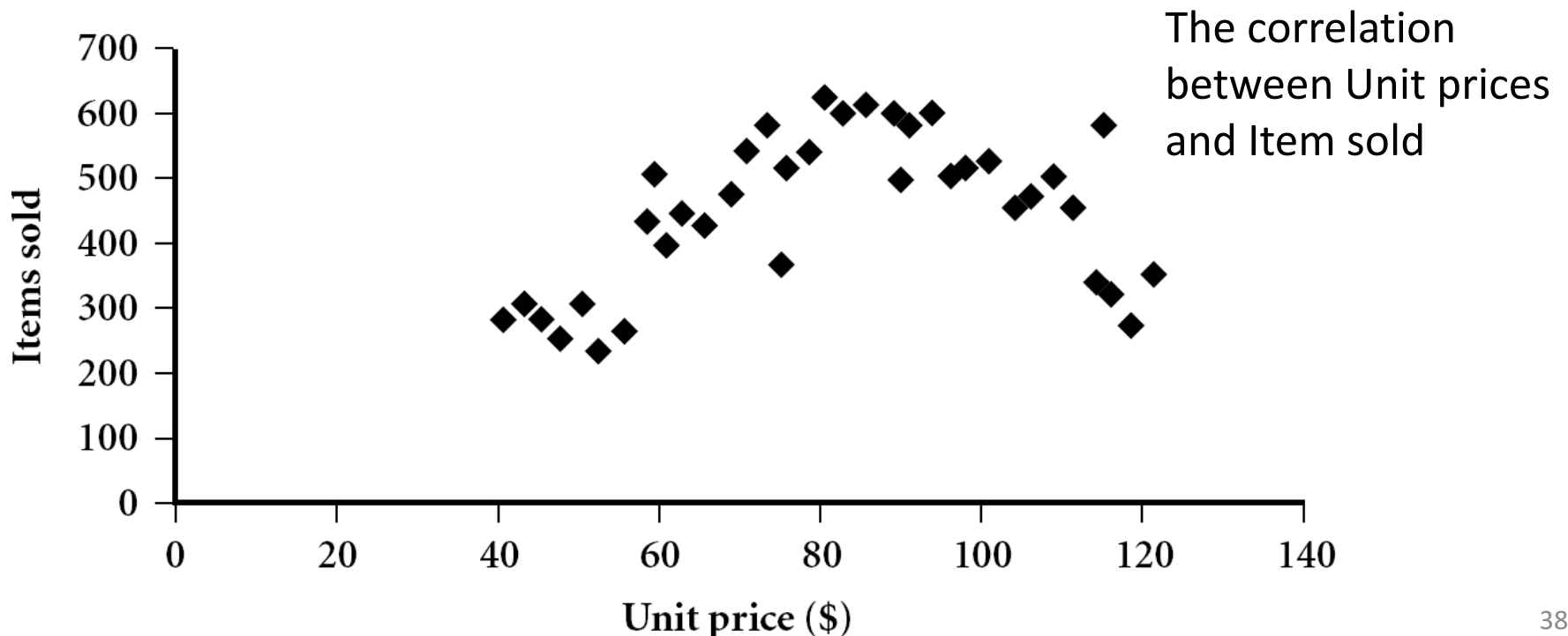
- A **quantile-quantile plot** draws the quantiles of one univariate distribution against the corresponding quantiles of another.

Is there a shift in going from one distribution to another?

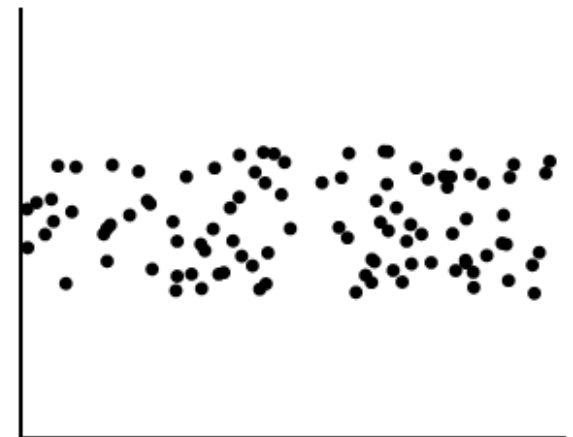
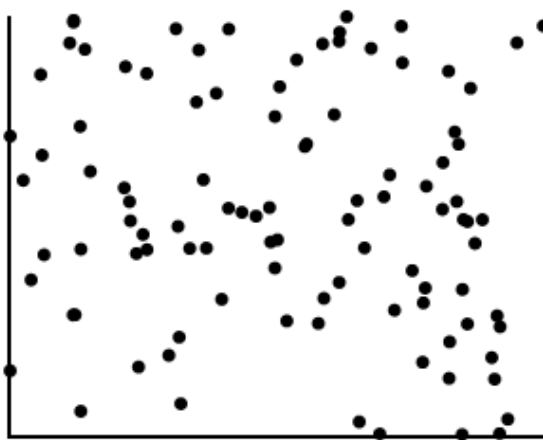
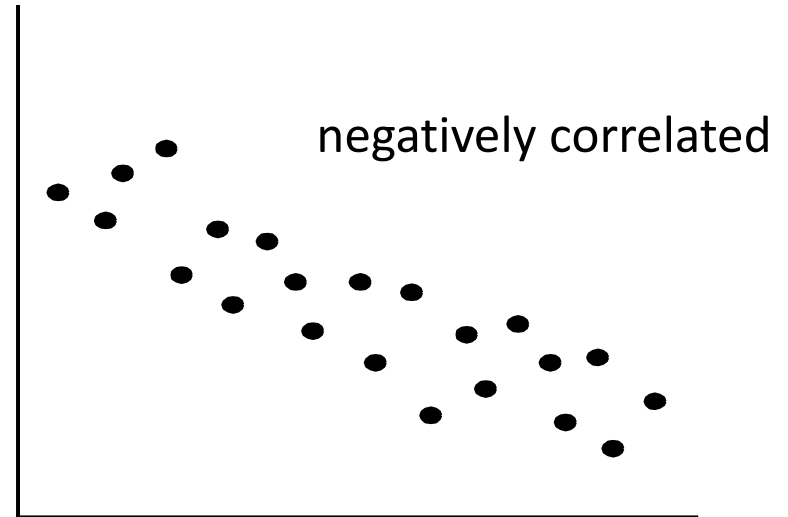
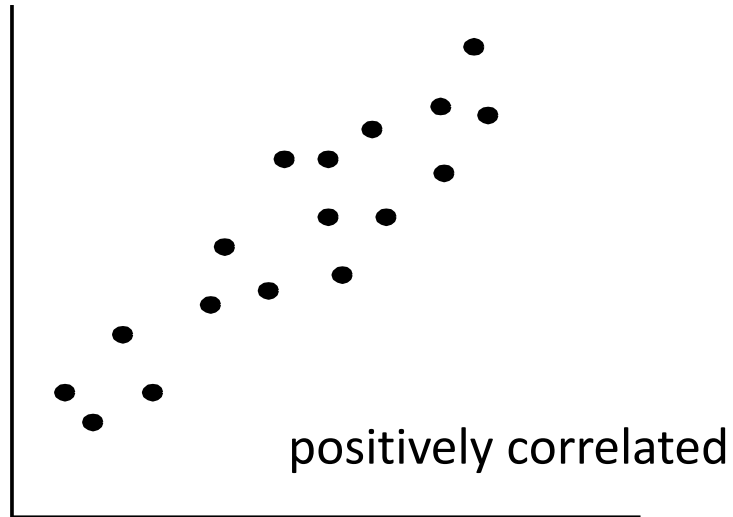


Scatter plot

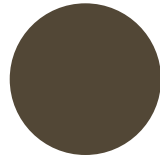
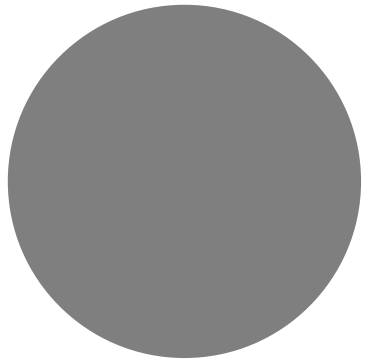
- A **scatter plot** looks at the bivariate data to see clusters of points or outliers
 - Each pair of values is treated as a pair of coordinates and plotted as points in the plane.



Scatter plot: Data correlation



uncorrelated data



Data proximity measures

Similarity and Dissimilarity

Similarity

- A numerical measure of **how alike** two data objects, i and j , are
- Values often falls in the range $[0,1]$: 0 – unlike \rightarrow 1 – identical

Dissimilarity (distance)

- A numerical measure of **how different** two data objects are
- It works in an opposite direction to some similarity measure
- The lower bound is often 0, while the upper limit varies

Proximity

- This refers to either similarity or dissimilarity

Feature matrix vs. Dissimilarity matrix

- Feature matrices are essential to most machine learning task

Feature matrix

$$\begin{bmatrix} x_{11} & \dots & x_{1f} & \dots & x_{1p} \\ \dots & \dots & \dots & \dots & \dots \\ x_{i1} & \dots & x_{if} & \dots & x_{ip} \\ \dots & \dots & \dots & \dots & \dots \\ x_{n1} & \dots & x_{nf} & \dots & x_{np} \end{bmatrix}$$

- n data points with p dimensions
- Object-by-attribute structure

Dissimilarity matrix

$$\begin{bmatrix} 0 & & & & \\ d(2,1) & 0 & & & \\ d(3,1) & d(3,2) & 0 & & \\ \vdots & \vdots & \vdots & & \\ d(n,1) & d(n,2) & \dots & \dots & 0 \end{bmatrix}$$

- A collection of distances for all pairs of n objects
- Object-by-object structure

- Many nearest-neighbor algorithms use dissimilarity matrices.

Measures for nominal attributes

- Let the number of states of a nominal attribute be M
- Method 1:** Simple matching $d(i, j) = \frac{p-m}{p}$
 - m : the number of attributes for which i and j are in the same state,
 - p : the total number of attributes describing the objects

Object Identifier	test-1 (nominal)	test-2 (ordinal)	test-3 (numeric)
1	code A	excellent	45
2	code B	fair	22
3	code C	good	64
4	code A	excellent	28

$$\begin{bmatrix} 0 & & & \\ 1 & 0 & & \\ 1 & 1 & 0 & \\ 0 & 1 & 1 & 0 \end{bmatrix}$$

$$\begin{bmatrix} d(2, 1) & & & \\ d(3, 1) & d(3, 2) & & 0 \\ d(4, 1) & d(4, 2) & d(4, 3) & 0 \end{bmatrix}$$

- Method 2:** Create a binary attribute for each of the M states
- Measures of similarity $sim(i, j) = 1 - d(i, j) = \frac{m}{p}$

Measures for binary attributes

- Contingency table

		Object j		
		1	0	sum
Object i	1	q	r	$q + r$
	0	s	t	$s + t$
	sum	$q + s$	$r + t$	p

- Symmetric binary variable

$$d(i, j) = \frac{r + s}{q + r + s + t}$$

- Asymmetric binary variable

$$d(i, j) = \frac{r + s}{q + r + s}$$

- Jaccard coefficient: $\text{sim}(i, j) = 1 - d(i, j) = \frac{q}{q + r + s}$

Measures for binary attributes

<i>name</i>	<i>gender</i>	<i>fever</i>	<i>cough</i>	<i>test-1</i>	<i>test-2</i>	<i>test-3</i>	<i>test-4</i>
Jack	M	Y	N	P	N	N	N
Jim	M	Y	Y	N	N	N	N
Mary	F	Y	N	P	N	P	N
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

- Gender is symmetric binary, the remaining attributes are asymmetric
- Let the values Y and P be 1 and the value N be 0.
- Suppose that the distance between objects (patients) is computed based only on the asymmetric attributes

$$d(\text{Jack}, \text{Jim}) = \frac{1+1}{1+1+1} = 0.67, \quad d(\text{Jack}, \text{Mary}) = \frac{0+1}{2+0+1} = 0.33$$

$$d(\text{Jim}, \text{Mary}) = \frac{1+2}{1+1+2} = 0.75$$

Measures for numeric attributes

- Consider two data points of p -dimensional

$$i = (x_{i1}, x_{i2}, \dots, x_{ip}) \text{ and } j = (x_{j1}, x_{j2}, \dots, x_{jp})$$

- Minkowski distance (L_h norm)

$$d(i, j) = \sqrt[h]{|x_{i1} - x_{j1}|^h + |x_{i2} - x_{j2}|^h + \dots + |x_{ip} - x_{jp}|^h}$$

- where h is the order

Measures for numeric attributes

- $h = 1$: Manhattan (city block, L_1 norm) distance

$$d(i, j) = |x_{i1} - x_{j1}| + |x_{i2} - x_{j2}| + \cdots + |x_{ip} - x_{jp}|$$

- $h = 2$: Euclidean (L_2 norm) distance

$$d(i, j) = \sqrt{|x_{i1} - x_{j1}|^2 + |x_{i2} - x_{j2}|^2 + \cdots + |x_{ip} - x_{jp}|^2}$$

- $h \rightarrow \infty$: “supremum” (L_{max} / L_∞ norm, Chebyshev) distance

$$d(i, j) = \lim_{h \rightarrow \infty} \left(\sum_{f=1}^p |x_{if} - x_{jf}|^h \right)^{1/h} = \max_f |x_{if} - x_{jf}|$$

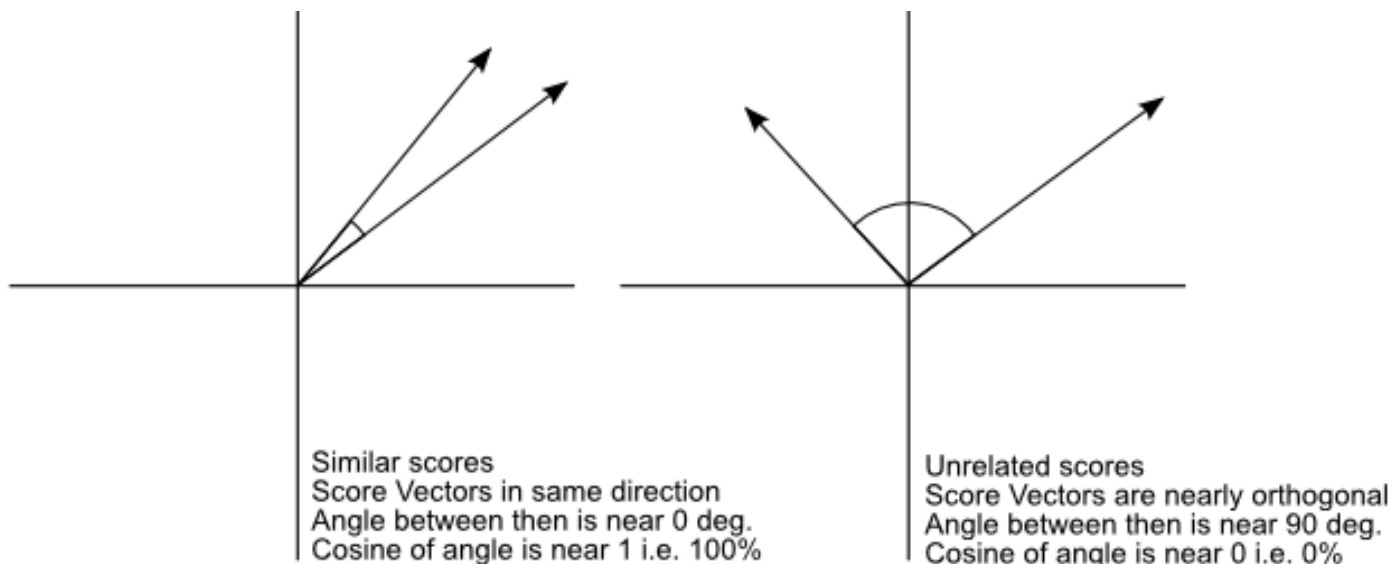
Cosine similarity

- A document can be represented by thousands of keywords in the document.

Document	team	coach	hockey	baseball	soccer	penalty	score	win	loss	season
<i>Document1</i>	5	0	3	0	2	0	0	2	0	0
<i>Document2</i>	3	0	2	0	1	1	0	1	0	1
<i>Document3</i>	0	7	0	$sim(d_1, d_2) = 0.94$			0	3	0	0
<i>Document4</i>	0	1	0				2	0	3	0

Cosine similarity

- Let d_1 and d_2 are two vectors (e.g., term-frequency vectors).
- Cosine similarity is **non-metric**: $sim(d_1, d_2) = \frac{d_1 \cdot d_2}{\|d_1\| \|d_2\|}$
 - where \cdot is vector dot product, $\|d\|$ is the length of vector d
 - $sim = 0$ means no match, while $sim = 1$ means a complete match.



Measures for ordinal attributes

- The range of a numeric attribute can be mapped to an ordinal attribute f having M_f states.
 - E.g., temperate: cold ($-30^{\circ}\text{C} - 10^{\circ}\text{C}$), moderate ($-10^{\circ}\text{C} - 10^{\circ}\text{C}$), and warm ($10^{\circ}\text{C} - 30^{\circ}\text{C}$)
- Let M represent the number of possible ordered states, which define the ranking $1, \dots, M_f$
- Replace each x_{if} by its corresponding rank, $r_{if} \in \{1, \dots, M_f\}$
- Replace rank r_{if} of i^{th} object by $z_{if} = \frac{r_{if} - 1}{M_f - 1}$
- Continue with any measure for numeric attributes

Measures for ordinal attributes

Object Identifier	test-1 (nominal)	test-2 (ordinal)	test-3 (numeric)
1	code A	excellent	45
2	code B	fair	22
3	code C	good	64
4	code A	excellent	28

- test-2 = {fair, good, excellent}, i.e., $M_f = 3$
- The ranks of four objects are 3, 1, 2, and 3, respectively
- Map the rank 1 to 0.0, rank 2 to 0.5, and rank 3 to 1.0
- Dissimilarity matrix using Euclidean distance

$$\begin{bmatrix} 0 & & & \\ 1.0 & 0 & & \\ 0.5 & 0.5 & 0 & \\ 0 & 1.0 & 0.5 & 0 \end{bmatrix}$$

Measures for attributes of mixed types

- Suppose that the dataset has p attributes of mixed type.
- The distance between objects i and j is $d(i, j) = \frac{\sum_{f=1}^p \delta_{ij}^{(f)} d_{ij}^{(f)}}{\sum_{f=1}^p \delta_{ij}^{(f)}}$
 - $\delta_{ij}^{(f)} = 0$ if (1) x_{if} or x_{jf} is missing, or (2) $x_{if} = x_{jf} = 0$ and attribute f is asymmetric binary. Otherwise, $\delta_{ij}^{(f)} = 1$
 - If f is numeric: $d_{ij}^{(f)} = \frac{|x_{if} - x_{jf}|}{\max_h x_{hf} - \min_h x_{hf}}$, where h runs over all nonmissing objects for attribute f
 - If f is nominal or binary: $d_{ij}^{(f)} = 0$ if $x_{if} = x_{jf}$; otherwise, $d_{ij}^{(f)} = 1$
 - If f is ordinal: compute r_{if} and treat $z_{if} = \frac{r_{if} - 1}{M_f - 1}$ as numeric

Measures for attributes of mixed types

Dissimilarity matrix of test-1

$$\begin{bmatrix} 0 & & & \\ 1 & 0 & & \\ 1 & 1 & 0 & \\ 0 & 1 & 1 & 0 \end{bmatrix}$$

Dissimilarity matrix of test-2

$$\begin{bmatrix} 0 & & & \\ 1.0 & 0 & & \\ 0.5 & 0.5 & 0 & \\ 0 & 1.0 & 0.5 & 0 \end{bmatrix}$$

Dissimilarity matrix of test-3

$$\begin{bmatrix} 0 & & & \\ 0.55 & 0 & & \\ 0.45 & 1.00 & 0 & \\ 0.40 & 0.14 & 0.86 & 0 \end{bmatrix}$$

Object Identifier	test-1 (nominal)	test-2 (ordinal)	test-3 (numeric)
1	code A	excellent	45
2	code B	fair	22
3	code C	good	64
4	code A	excellent	28

- $\delta_{ij}^{(f)} = 1$ for each attribute f
- $d(3,1) = \frac{1(1)+1(0.50)+1(0.45)}{3} = 0.65$
- The resulting dissimilarity matrix

$$\begin{bmatrix} 0 & & & \\ 0.85 & 0 & & \\ 0.65 & 0.83 & 0 & \\ 0.13 & 0.71 & 0.79 & 0 \end{bmatrix}$$

References

- Jiawei Han, Micheline Kamber, and Jian Pei. 2011. Data Mining: Concepts and Techniques (3rd ed.). Morgan Kaufmann Publishers Inc. Chapter 2.