Big Data:
From Theory to Practice

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Data Preprocessing

- **Why preprocess the data?**
- **Descriptive data summarization**
- **Data cleaning**
- **Data integration and transformation**
- **Data reduction**
- **Discretization and concept hierarchy generation**
- **Summary**

Why Data Preprocessing?

- **Data in the real world is dirty**
  - **incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data**
    - **e.g., occupation=“ ”**
  - **noisy: containing errors or outliers**
    - **e.g., Salary=“-10”**
  - **inconsistent: containing discrepancies in codes or names**
    - **e.g., Age=“42” Birthday=“03/07/1997”**
    - **e.g., Was rating “1,2,3”, now rating “A, B, C”**
    - **e.g., discrepancy between duplicate records**

Why Is Data Dirty?

- **Incomplete data may come from**
  - **"Not applicable" data value when collected**
  - **Different considerations between the time when the data was collected and when it is analyzed.**
  - **Human/hardware/software problems**
- **Noisy data (incorrect values) may come from**
  - **Faulty data collection instruments**
  - **Human or computer error at data entry**
  - **Errors in data transmission**
- **Inconsistent data may come from**
  - **Different data sources**
  - **Functional dependency violation (e.g., modify some linked data)**
- **Duplicate records also need data cleaning**

Why Is Data Preprocessing Important?

- **No quality data, no quality mining results!**
  - **Quality decisions must be based on quality data**
    - **e.g., duplicate or missing data may cause incorrect or even misleading statistics.**
  - **Data warehouse needs consistent integration of quality data**
- **Data extraction, cleaning, and transformation comprises the majority of the work of building a data warehouse**

Multi-Dimensional Measure of Data Quality

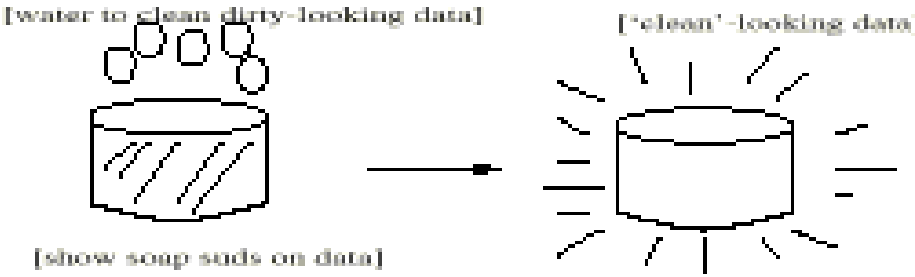
- **A well-accepted multidimensional view:**
  - **Accuracy**
  - **Completeness**
  - **Consistency**
  - **Timeliness**
  - **Believability**
  - **Value added**
  - **Interpretability**
  - **Accessibility**

Major Tasks in Data Preprocessing

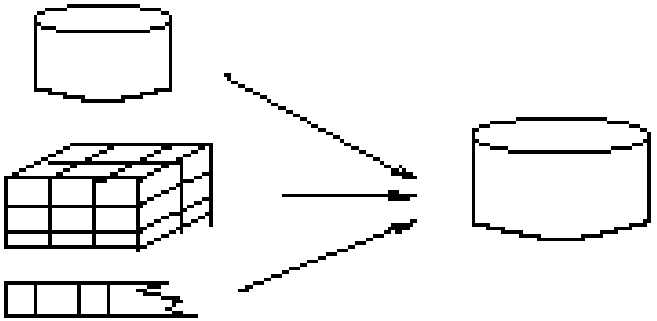
- **Data cleaning**
  - **Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies**
- **Data integration**
  - **Integration of multiple databases, data cubes, or files**
- **Data transformation**
  - **Normalization and aggregation**
- **Data reduction**
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

Forms of Data Preprocessing

Data Cleaning



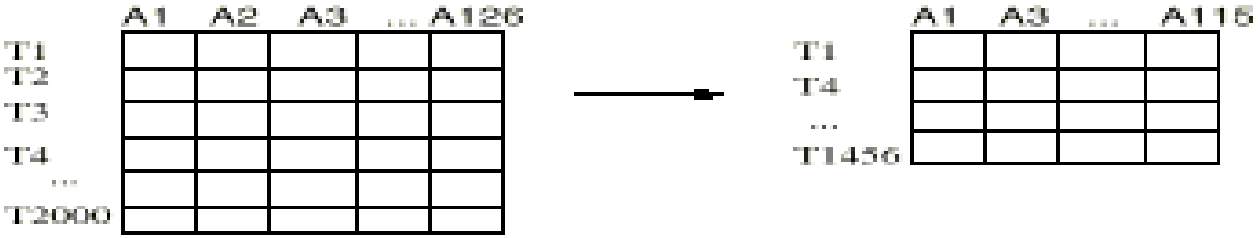
Data Integration



Data Transformation

-2, 32, 100, 59, 48 → -0.02, 0.32, 1.00, 0.59, 0.48

Data Reduction



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Mining Data Descriptive Characteristics

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

Measuring the Central Tendency

Comparison of common **averages** of **values** { 1, 2, 2, 3, 4, 7, 9 }

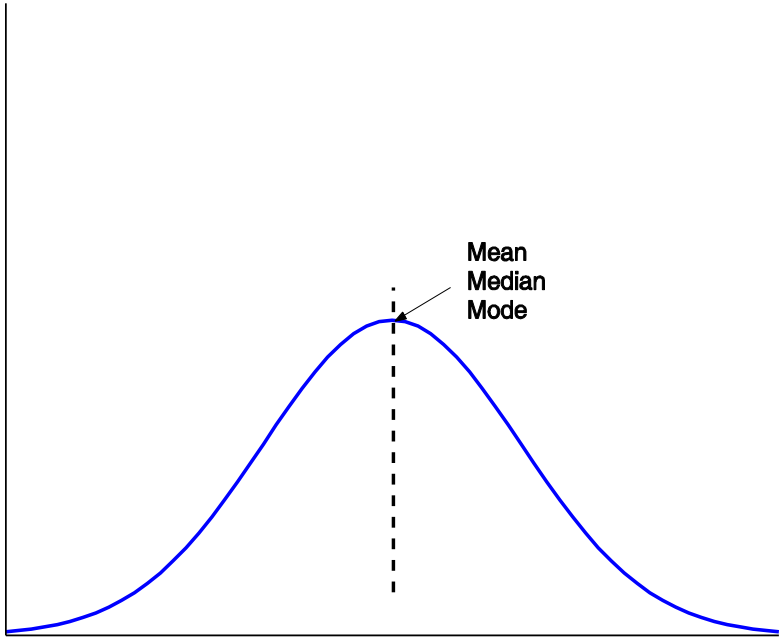
Type	Description	Example	Result
Arithmetic mean	**Sum of values of a data set divided by number of values**	**(1+2+2+3+4+7+9) / 7**	**4**
Median	**Middle value separating the greater and lesser halves of a data set**	**1, 2, 2, 3, 4, 7, 9**	**3**
Mode	**Most frequent value in a data set**	**1, 2, 2, 3, 4, 7, 9**	**2**

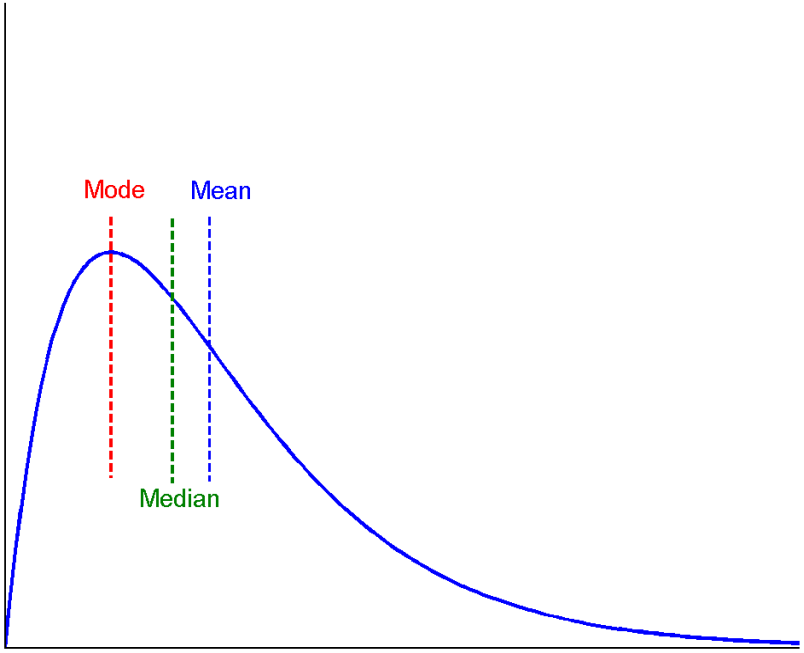
Measuring the Central Tendency

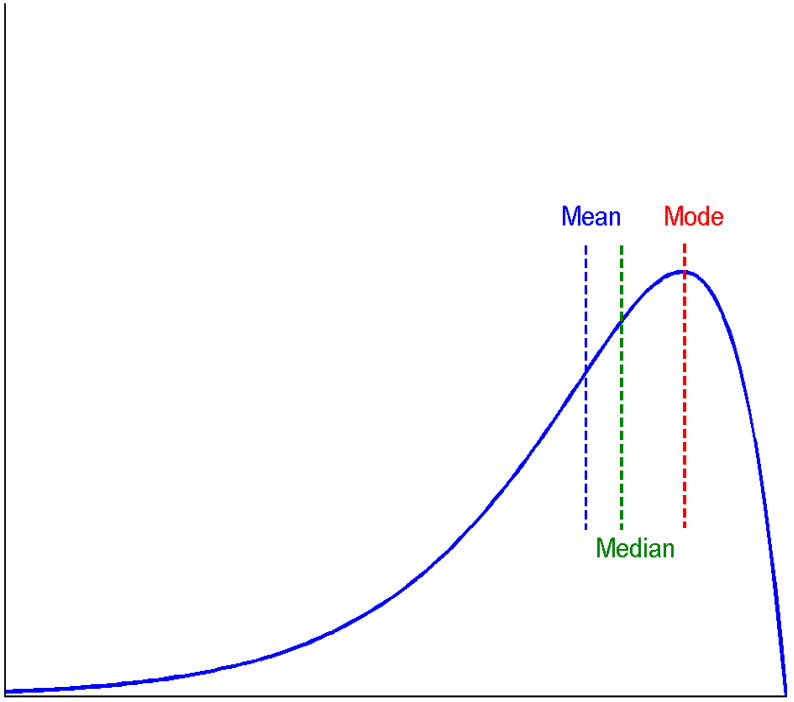
- **Mean (algebraic measure) (sample vs. population):** $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \quad \mu = \frac{\sum x}{N}$
  - **Weighted arithmetic mean:** $\bar{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}$
  - **Trimmed mean: chopping extreme values**
- **Median: A holistic measure（中位数）**
  - **Middle value if odd number of values, or average of the middle two values otherwise**
- **Mode**
  - **Value that occurs most frequently in the data**
  - **Unimodal, bimodal, trimodal**
  - **Empirical formula:** $mean - mode = 3 \times (mean - median)$

Symmetric vs. Skewed Dat

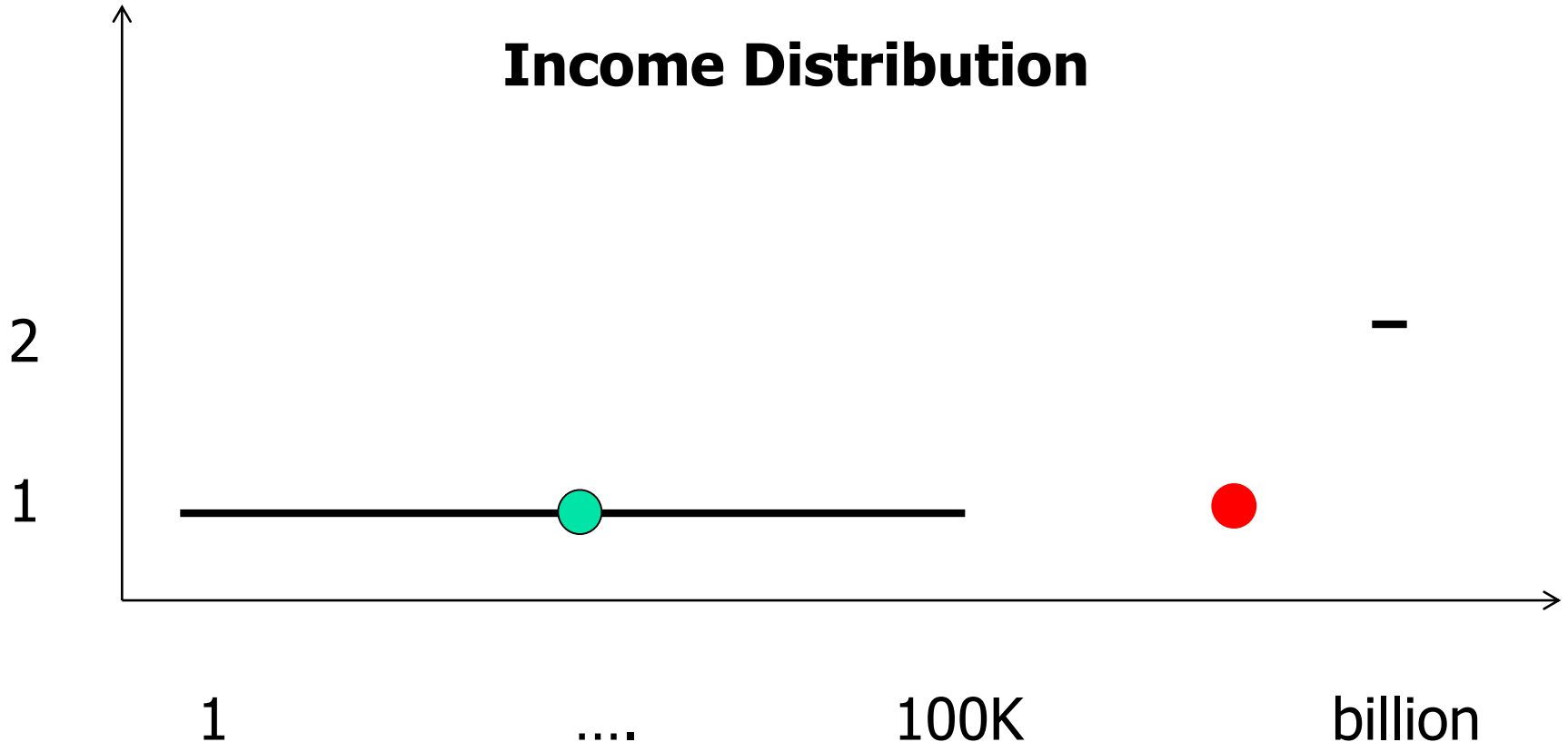
- Median, mean and mode of symmetric, positively and negatively skewed data







Question: can mean be in the middle of median and mode?



Measuring the Dispersion of Data

- **Quartiles, outliers and boxplots**
  - **Quartiles四分位数: Q_1 (25th percentile), Q_3 (75th percentile)**
  - **Inter-quartile range: IQR = $Q_3 - Q_1$**

数列	参数	四分差
1	102	
2	104	
3	105	Q1
4	107	
5	108	
6	109	Q2 (Median)
7	110	
8	112	
9	115	Q3
10	118	
11	118	

四分位数（Quartile）是统计学中分位数的一种，即把所有数值由小到大排列并分成四等份，处于三个分割点位置的数值就是四分位数。

Measuring the Dispersion of Data

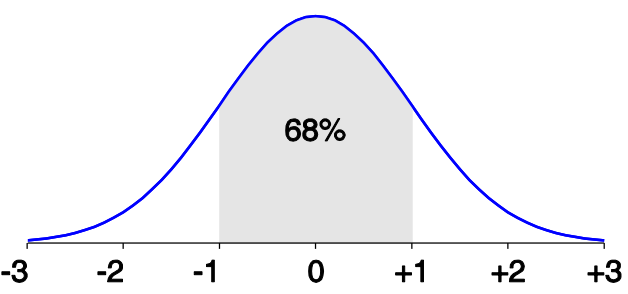
- **Quartiles, outliers and boxplots**
  - **Five number summary: min, Q_1, M, Q_3, max**
  - **Boxplot: ends of the box are the quartiles, median is marked, whiskers (min / max), and plot outlier individually**
  - **Outlier: usually, a value higher/lower than 1.5 x IQR**
- **Variance and standard deviation (*sample: s, population: σ*)**
  - **Variance: (algebraic, scalable computation)**

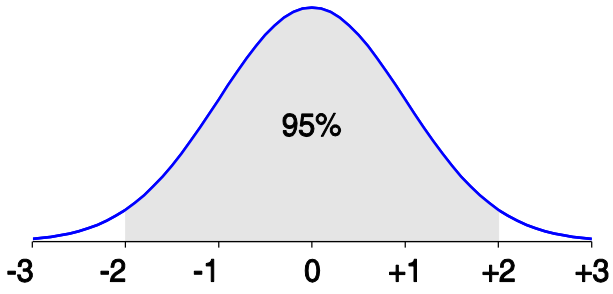
$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 = \frac{1}{n-1}[\sum_{i=1}^{n} x_i^2 - \frac{1}{n}(\sum_{i=1}^{n} x_i)^2] \qquad \sigma^2 = \frac{1}{N}\sum_{i=1}^{n}(x_i - \mu)^2 = \frac{1}{N}\sum_{i=1}^{n} x_i^2 - \mu^2$$

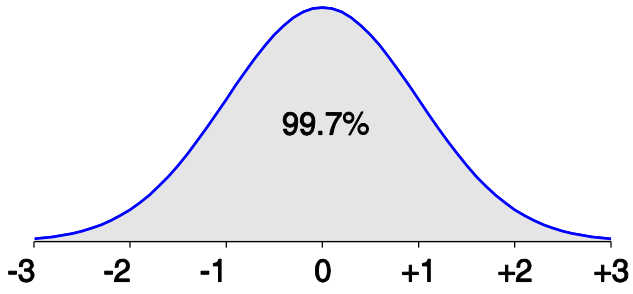
  - **Standard deviation *s (or σ)* is the square root of variance *s^2 (or σ^2)***

Properties of Normal Distribution Curve

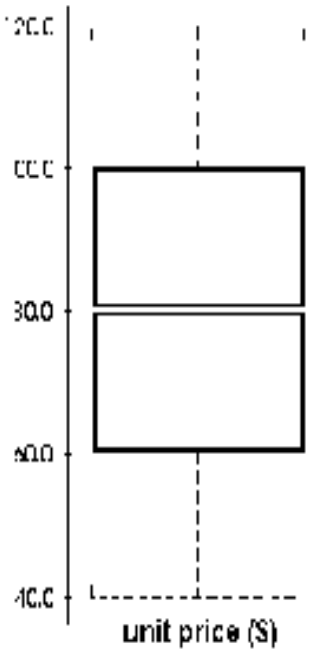
- **The normal (distribution) curve**
  - **From μ–σ to μ+σ: contains about 68% of the measurements (μ: mean, σ: standard deviation)**
  - **From μ–2σ to μ+2σ: contains about 95% of it**
  - **From μ–3σ to μ+3σ: contains about 99.7% of it**







Boxplot Analysis

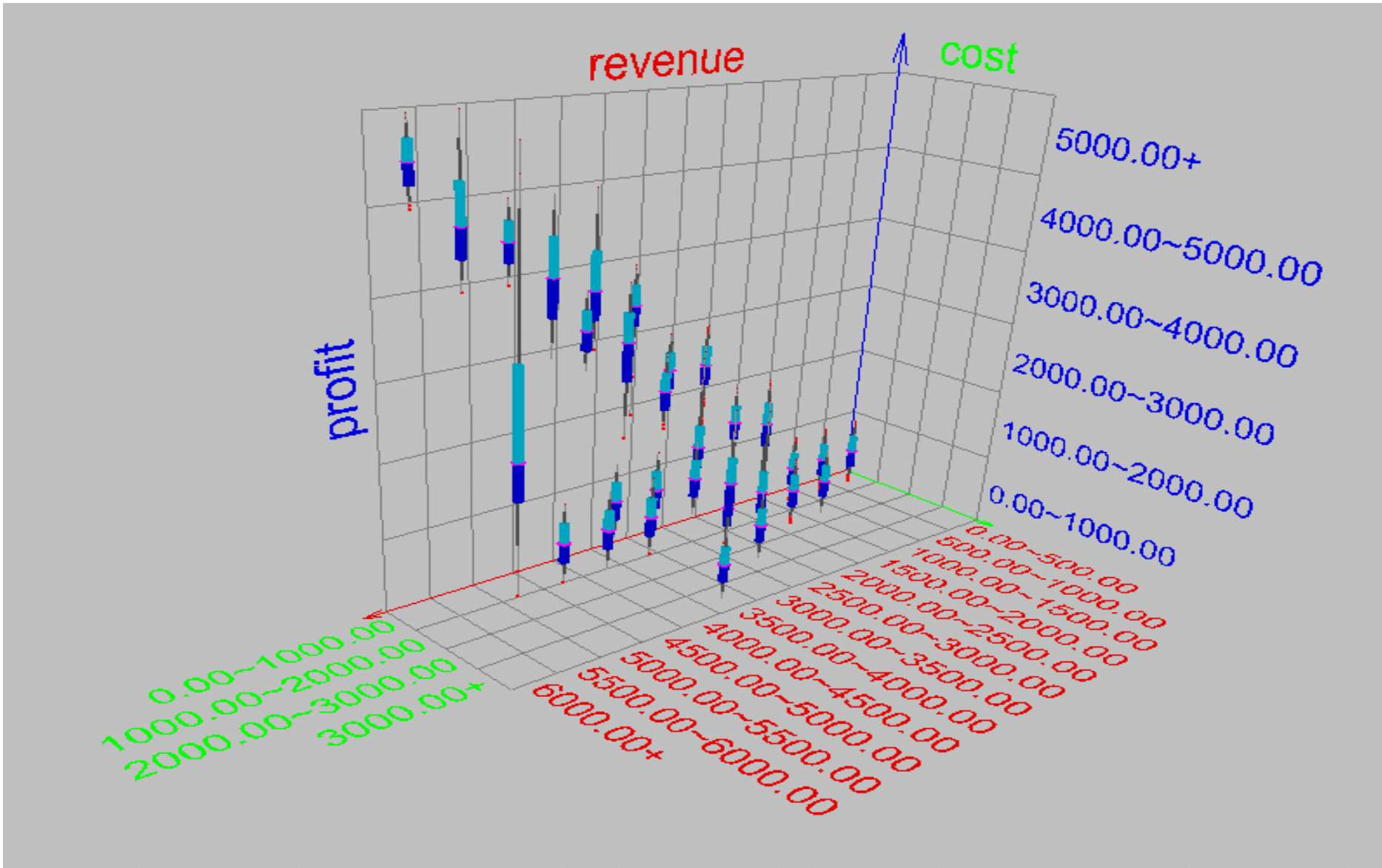


- Five-number summary of a distribution:

  Minimum, Q1, M, Q3, Maximum

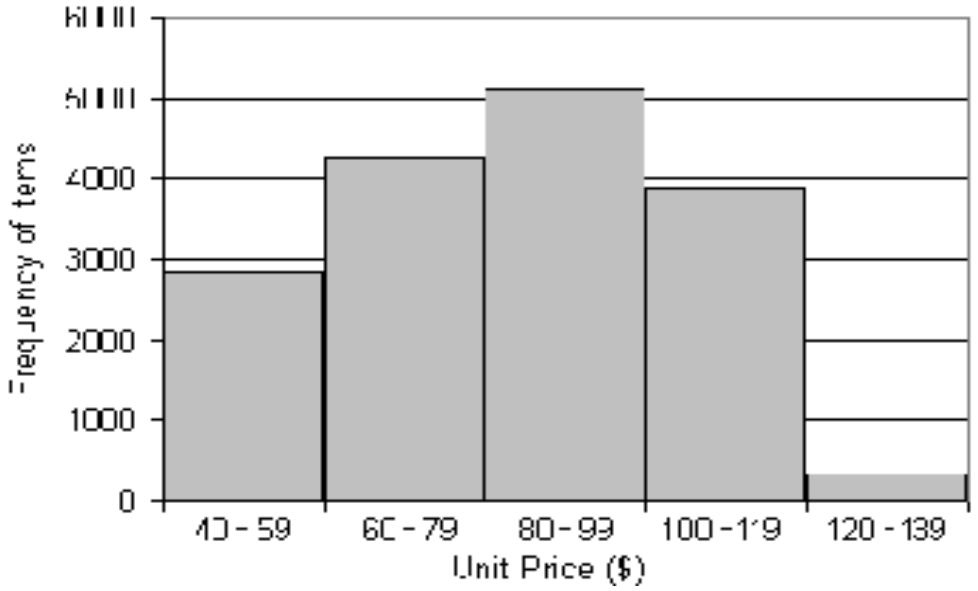
- Boxplot
  - Data is represented with a box
  - The ends of the box are at the first and third quartiles, i.e., the height of the box is IRQ
  - The median is marked by a line within the box
  - Whiskers: two lines outside the box extend to Minimum and Maximum

Visualization of Data Dispersion: Boxplot Analysis



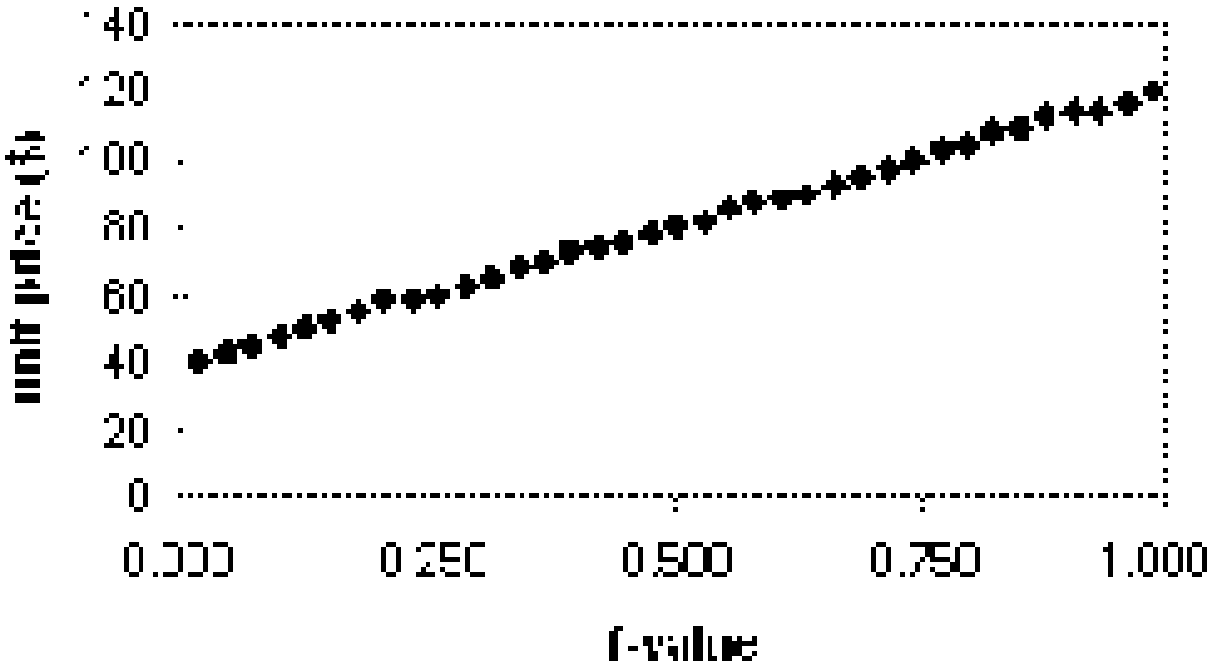
Histogram Analysis

- Graph displays of basic statistical class descriptions
  - Frequency histograms
    - A univariate graphical method
    - Consists of a set of rectangles that reflect the counts or frequencies of the classes present in the given data



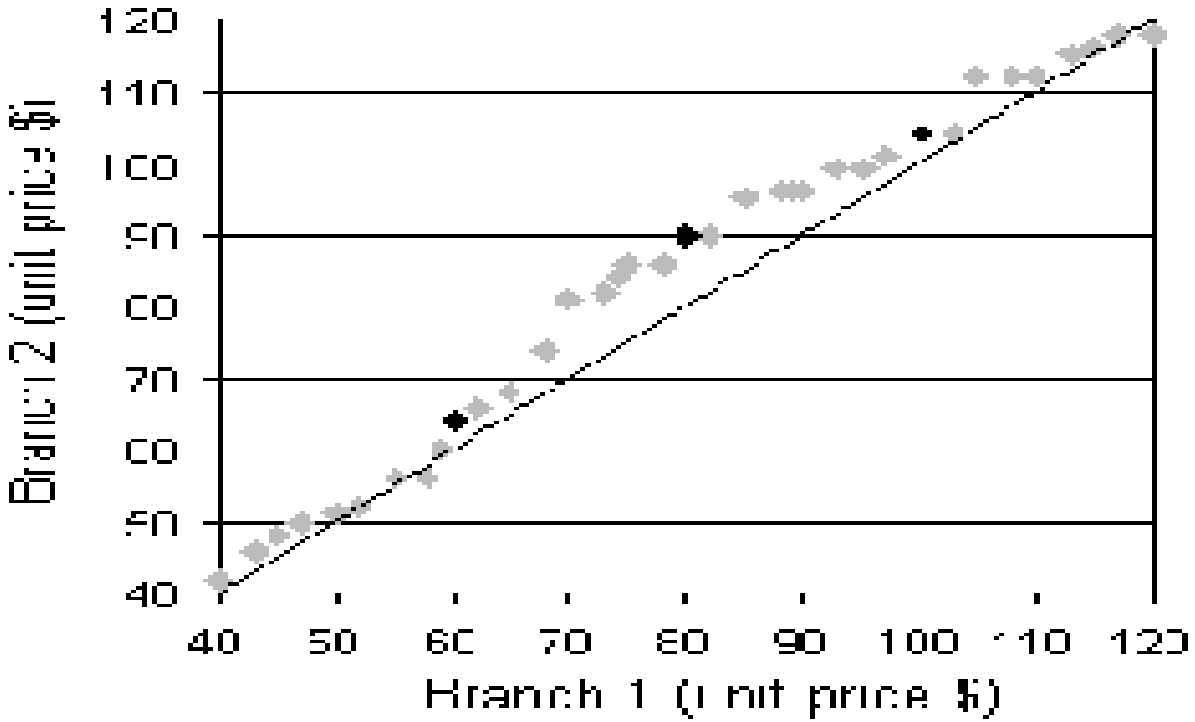
Quantile Plot

- 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 in range [0, 1] indicates that approximately 100 f_i% of the data are below or equal to the value x_i



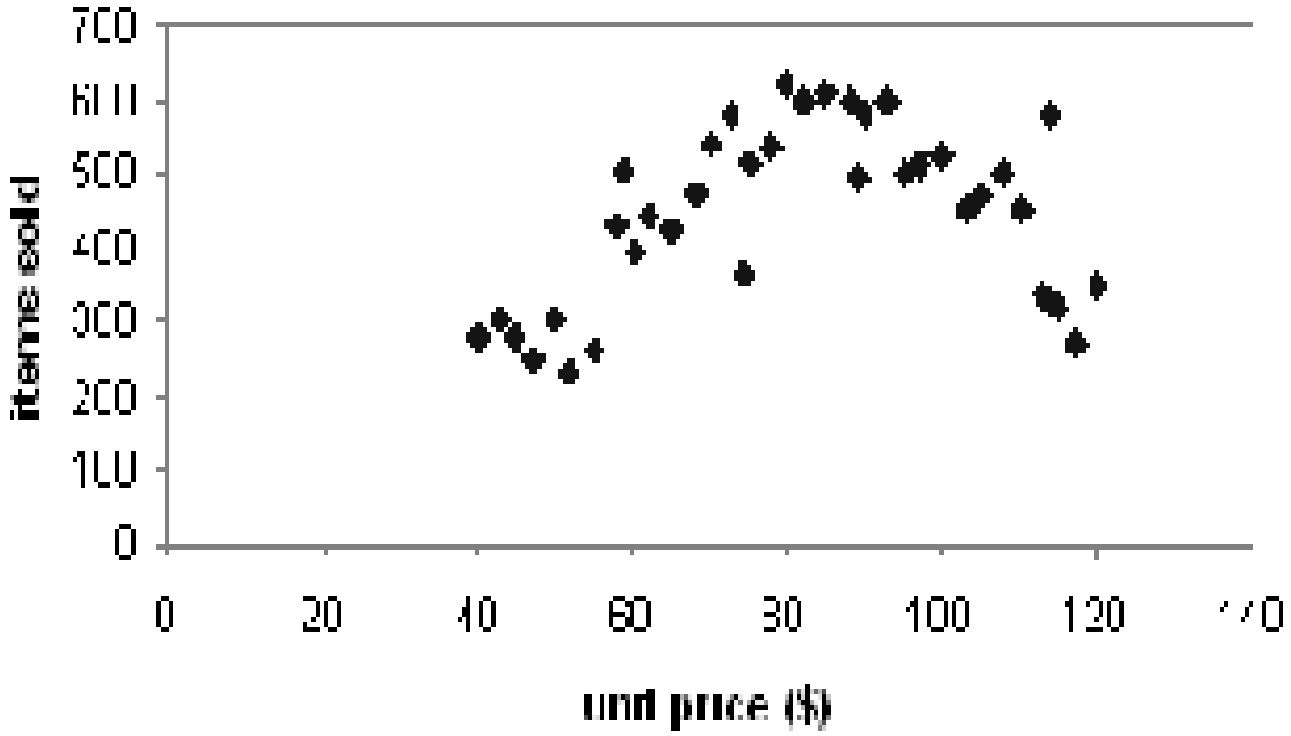
Quantile-Quantile (Q-Q) Plot

- Graphs the quantiles of one univariate distribution against the corresponding quantiles of another
- Allows the user to view whether there is a shift in going from one distribution to another



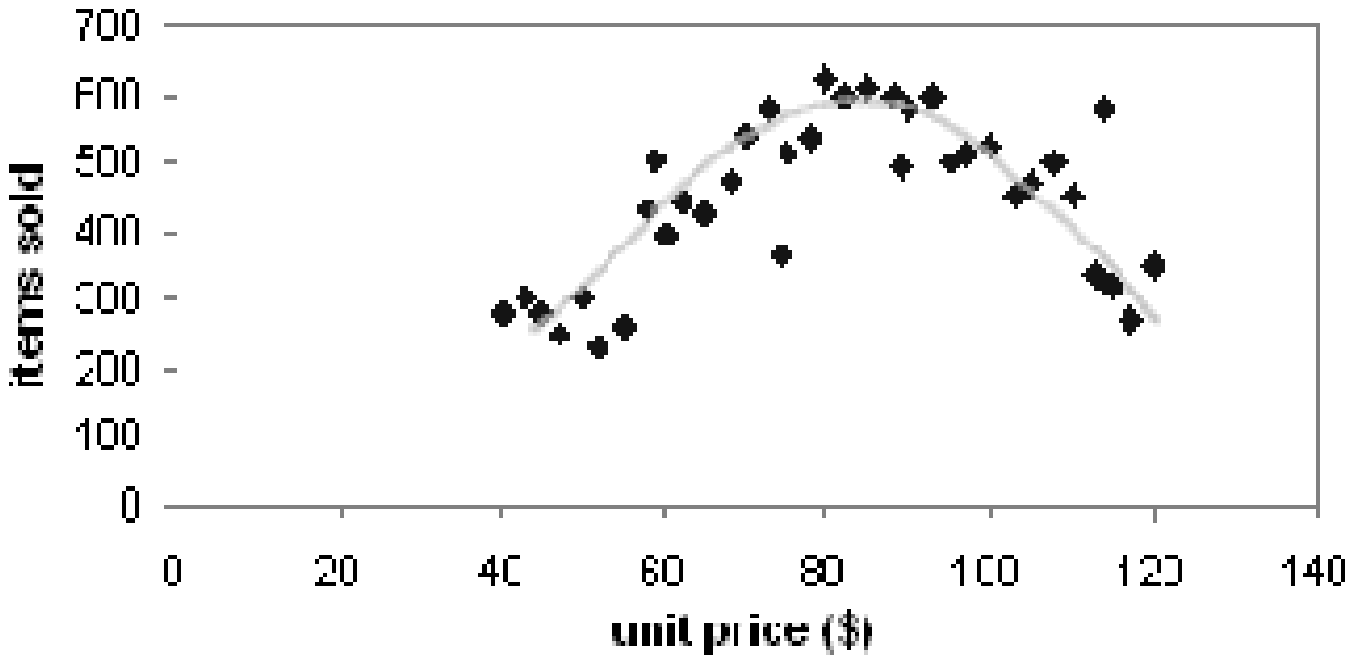
Scatter plot

- 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

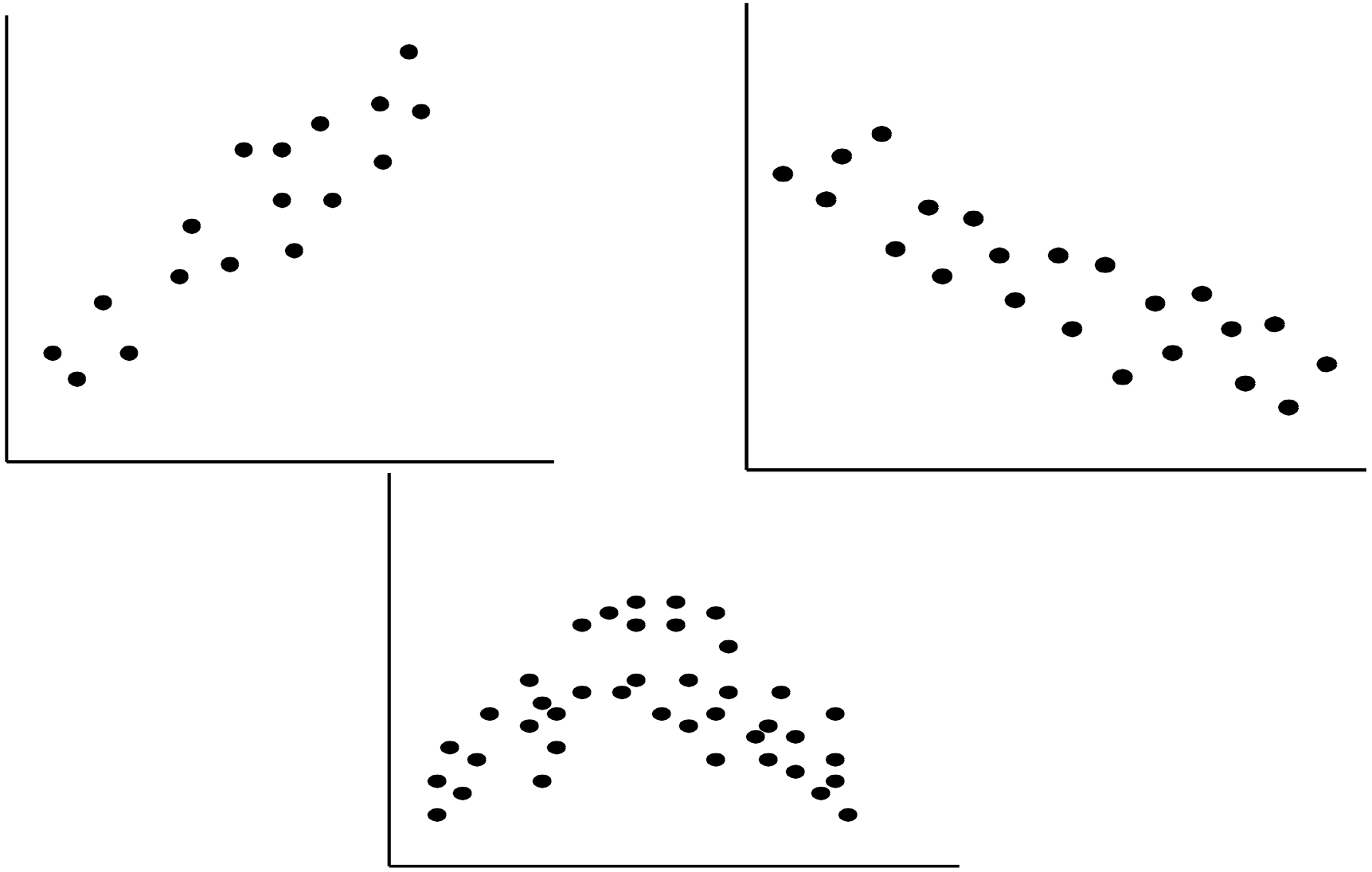


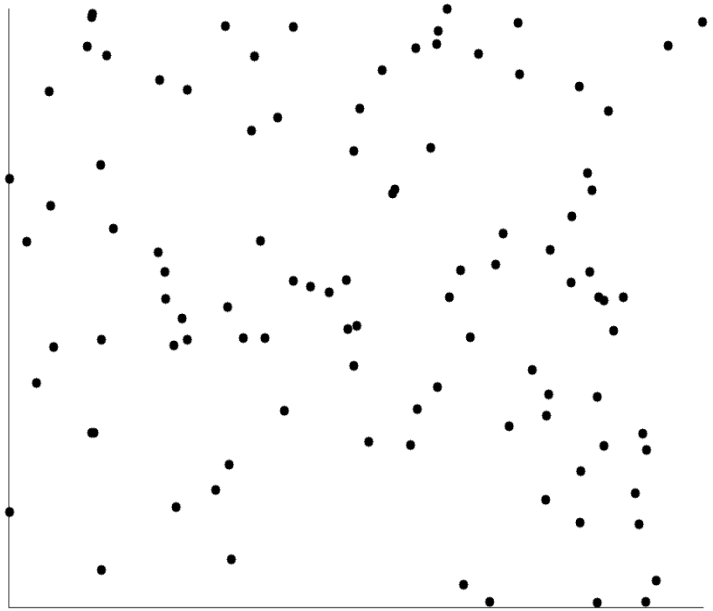
Loess Curve

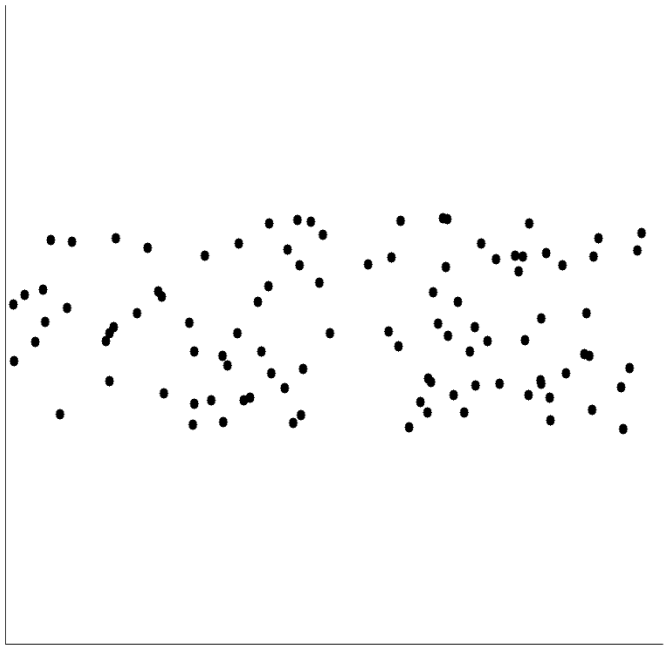
- Adds a smooth curve to a scatter plot in order to provide better perception of the pattern of dependence
- Loess curve is fitted by setting two parameters: a smoothing parameter, and the degree of the polynomials that are fitted by the regression

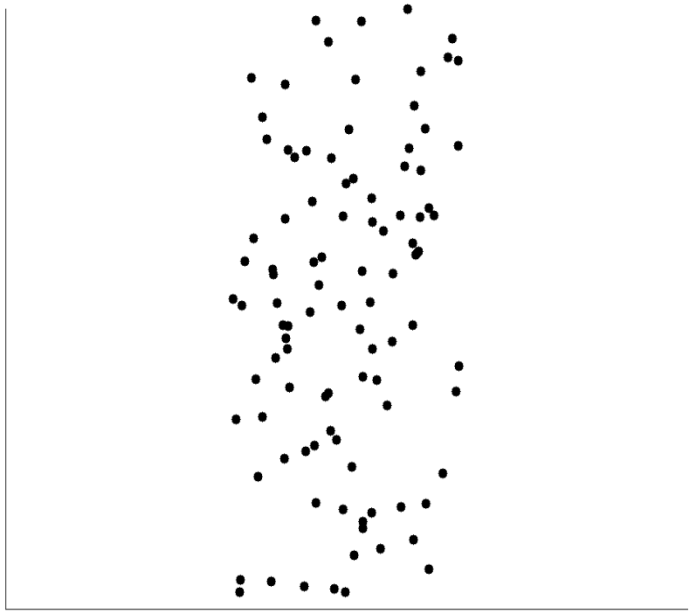


Positively and Negatively Correlated Data

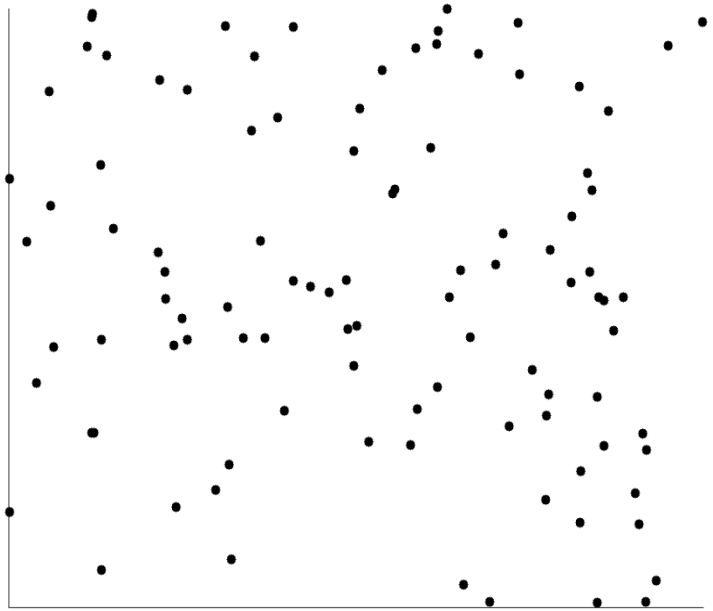


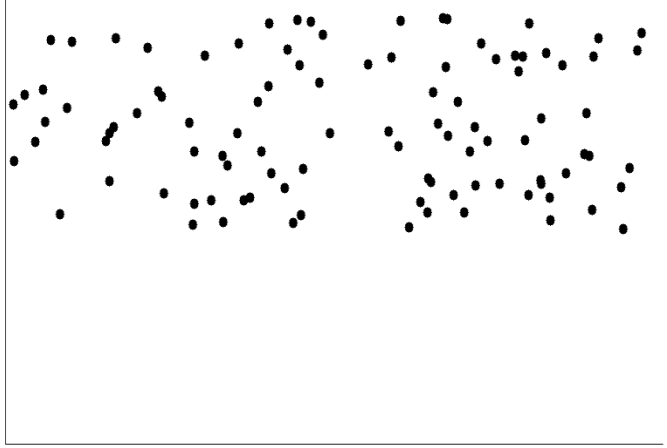


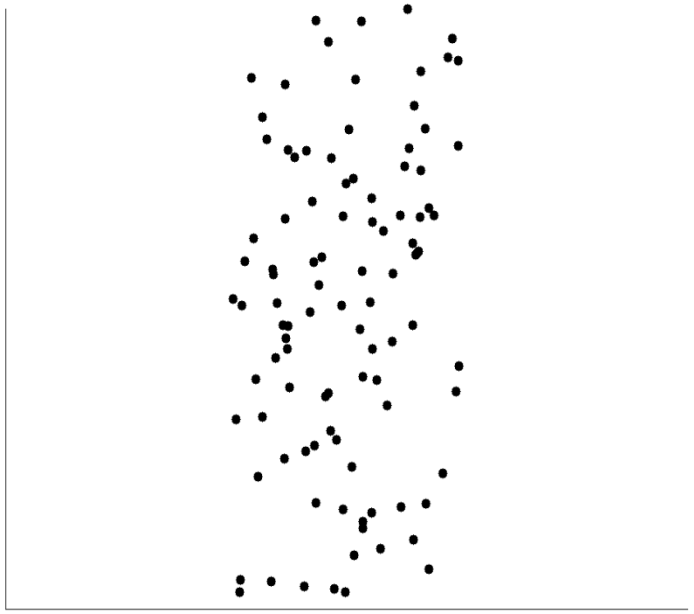




Not Correlated Data







Graphic Displays of Basic Statistical Descriptions

- Histogram
- Boxplot
- Quantile plot: each value x_i is paired with f_i indicating that approximately 100 f_i% of data are $\leq x_i$
- Quantile-quantile (q-q) plot: graphs the quantiles of one univariant distribution against the corresponding quantiles of another
- Scatter plot: each pair of values is a pair of coordinates and plotted as points in the plane
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Data Preprocessing

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Data Cleaning

- Importance
  - “Data cleaning is one of the three biggest problems in data warehousing”—Ralph Kimball
  - “Data cleaning is the number one problem in data warehousing”—DCI survey
- Data cleaning tasks
  - Fill in missing values
  - Identify outliers and smooth out noisy data
  - Correct inconsistent data
  - Resolve redundancy caused by data integration

Missing Data

- Data is not always available
  - E.g., many tuples have no recorded value for several attributes, such as customer income in sales data
- Missing data may be due to
  - equipment malfunction
  - inconsistent with other recorded data and thus deleted
  - data not entered due to misunderstanding
  - certain data may not be considered important at the time of entry
- Missing data may need to be inferred.

Customer Data

Name	Age	Sex	Income	Class
Mike	40	Male	150k	Big spender
Jenny	20	Female	?	Regular
…				

How to Handle Missing Data?

- **Ignore the tuple**: usually done when class label is missing (assuming the tasks in classification—not effective when the percentage of missing values per attribute varies considerably.
- **Fill in the missing value manually**: tedious + infeasible?
- **Fill in it automatically** with
  - a global constant : e.g., “unknown”, a new class?!
  - the attribute mean
  - the attribute mean for all samples belonging to the same class: smarter
  - the most probable value: inference-based such as Bayesian formula or decision tree (e.g., predict my age based on the info at my web site?)

Noisy Data

- Noise: random error or variance in a measured variable
- Incorrect attribute values may due to
  - faulty data collection instruments
  - data entry problems
  - data transmission problems
  - technology limitation
  - inconsistency in naming convention

How to Handle Noisy Data?

- Binning
  - first sort data and partition into (equal-frequency) bins
  - then one can smooth by bin means, smooth by bin median, smooth by bin boundaries, etc.
- Regression
  - smooth by fitting the data into regression functions
- Clustering
  - detect and remove outliers
- Combined computer and human inspection
  - detect suspicious values and check by human (e.g., deal with possible outliers)

Simple Discretization Methods: Binning

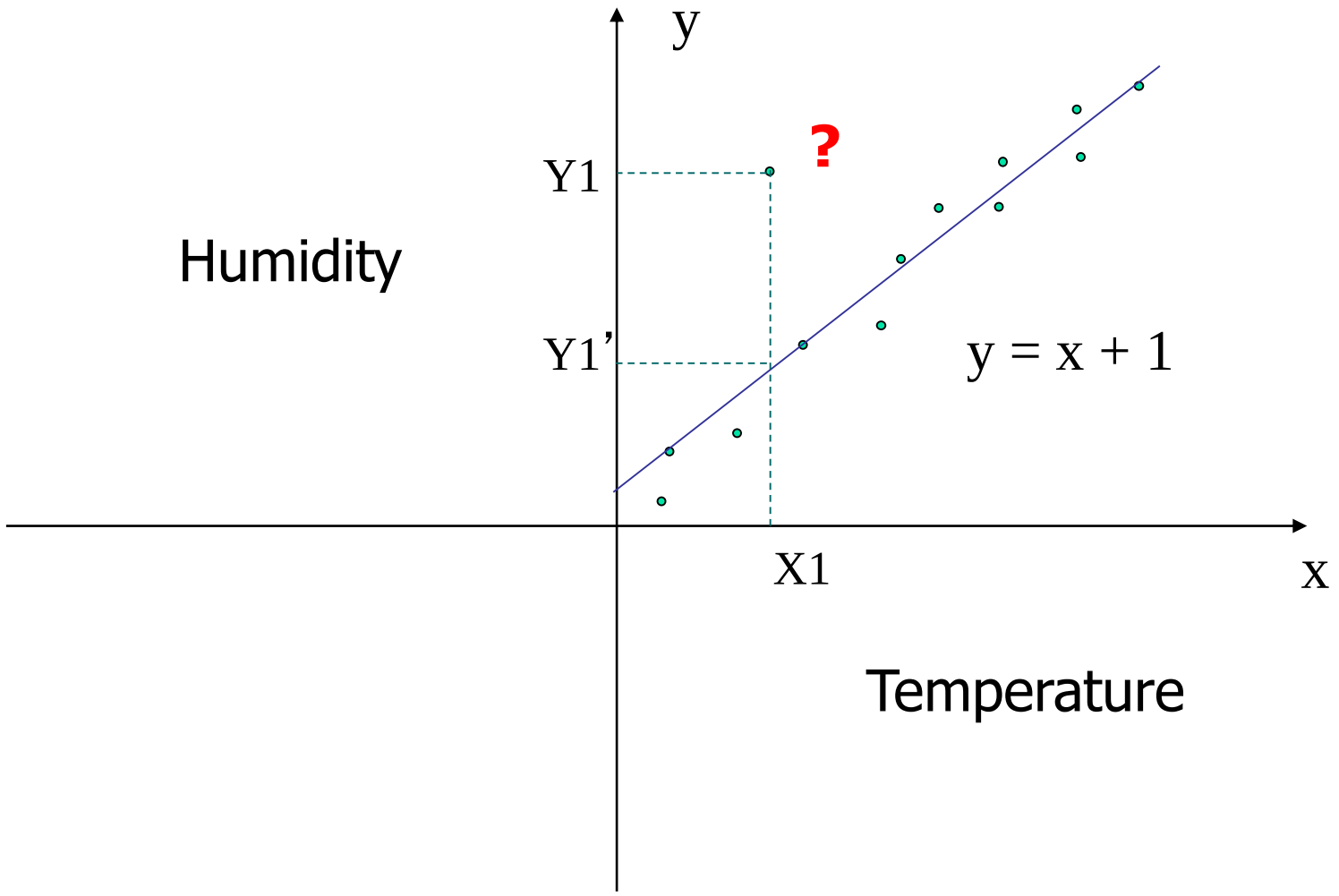
- Equal-width (distance) partitioning
  - Divides the range into *N* intervals of equal size: uniform grid
  - if *A* and *B* are the lowest and highest values of the attribute, the width of intervals will be: $W = (B - A)/N$.
  - The most straightforward, but outliers may dominate presentation
  - Skewed data is not handled well
- Equal-depth (frequency) partitioning
  - Divides the range into *N* intervals, each containing approximately same number of samples
  - Good data scaling

Binning Methods for Data Smoothing

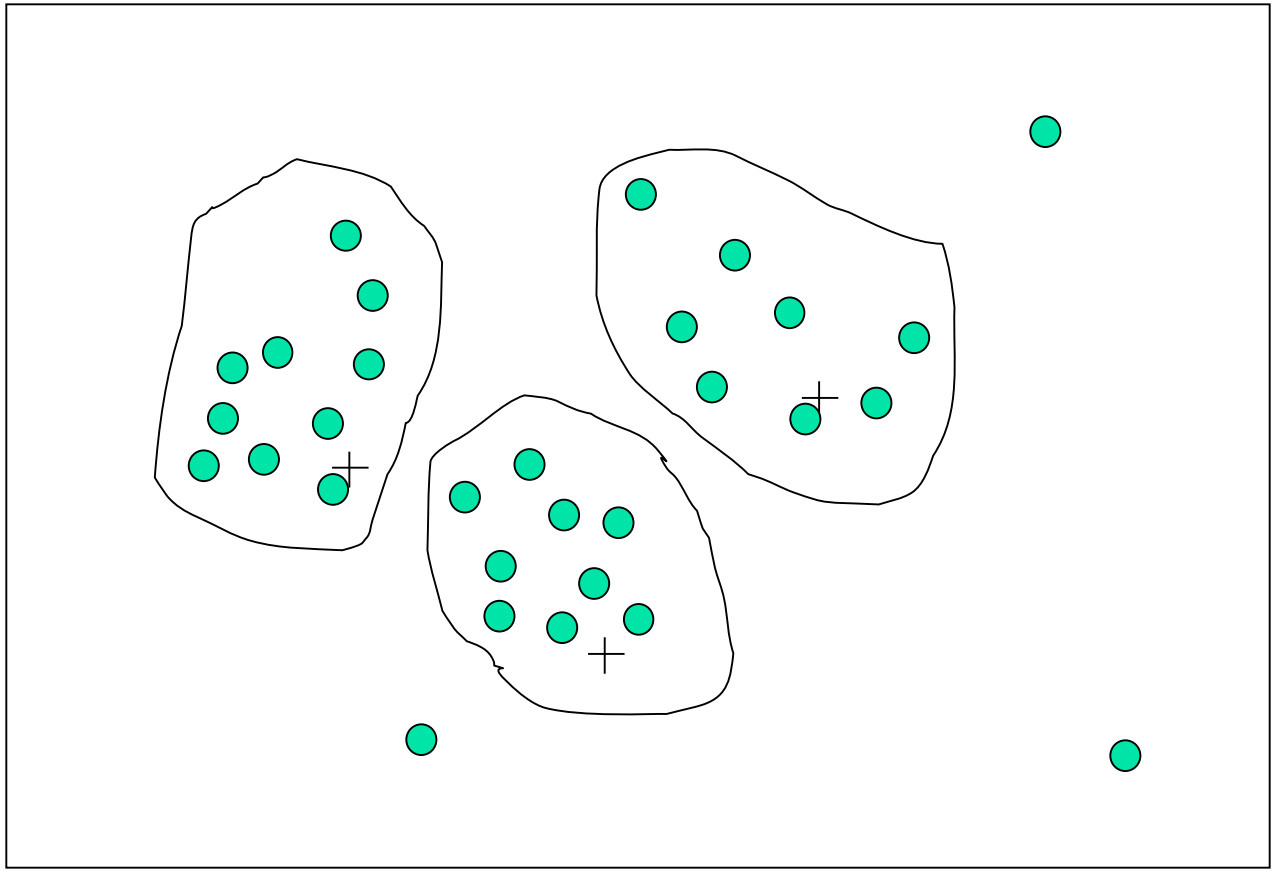
- Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34

* Partition into equal-frequency (equi-depth) bins:
  - Bin 1: 4, 8, 9, 15
  - Bin 2: 21, 21, 24, 25
  - Bin 3: 26, 28, 29, 34
* Smoothing by bin means:
  - Bin 1: 9, 9, 9, 9
  - Bin 2: 23, 23, 23, 23
  - Bin 3: 29, 29, 29, 29
* Smoothing by bin boundaries:
  - Bin 1: 4, 4, 4, 15
  - Bin 2: 21, 21, 25, 25
  - Bin 3: 26, 26, 26, 34

Regression



Cluster Analysis



Data Cleaning as a Process

- **Data discrepancy detection**
  - Use metadata (e.g., domain, range, dependency, distribution)

    (How many people are there in Nebraska?)
  - Check uniqueness rule, consecutive rule and null rule
  - Use commercial tools
    - Data scrubbing: use simple domain knowledge (e.g., postal code, spell-check) to detect errors and make corrections
    - Data auditing: by analyzing data to discover rules and relationship to detect violators (e.g., correlation and clustering to find outliers)

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Data Integration

- Data integration:
  - Combines data from multiple sources into a coherent store
- Schema integration: e.g., A.cust-id ≡ B.cust-#
  - Integrate metadata from different sources
- Entity identification problem:
  - Identify real world entities from multiple data sources, e.g., Bill Clinton = William Clinton
- Detecting and resolving data value conflicts
  - For the same real world entity, attribute values from different sources are different
  - Possible reasons: different representations, different scales, e.g., metric vs. British units (e.g., GPA in US and China)

Handling Redundancy in Data Integration

- Redundant data occur often when integration of multiple databases
  - *Object identification*: The same attribute or object may have different names in different databases
  - *Derivable data:* One attribute may be a "derived" attribute in another table, e.g., annual revenue
- Redundant attributes may be able to be detected by *correlation analysis*
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

Correlation Analysis (Numerical Data)

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

$$r_{A,B} = \frac{\sum (A - \bar{A})(B - \bar{B})}{(n-1)\sigma_A \sigma_B} = \frac{\sum (AB) - n\bar{A}\bar{B}}{(n-1)\sigma_A \sigma_B}$$

where n is the number of tuples, $\bar{A}$ and $\bar{B}$ are the respective means of A and B, σ_A and σ_B are the respective standard deviation of A and B, and $\Sigma(AB)$ 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; $r_{A,B} < 0$: negatively correlated

Correlation Analysis (Categorical Data)

- X^2 (chi-square) test (Example: Grade and Sex)

$$\chi^2 = \sum \frac{(Observed - Expected)^2}{Expected}$$

- The larger the X^2 value, the more likely the variables are related
- The cells that contribute the most to the X^2 value are those whose actual count is very different from the expected count
- Correlation does not imply causality
  - # of hospitals and # of car-theft in a city are correlated
  - Both are causally linked to the third variable: population

Chi-Square Calculation: An Example

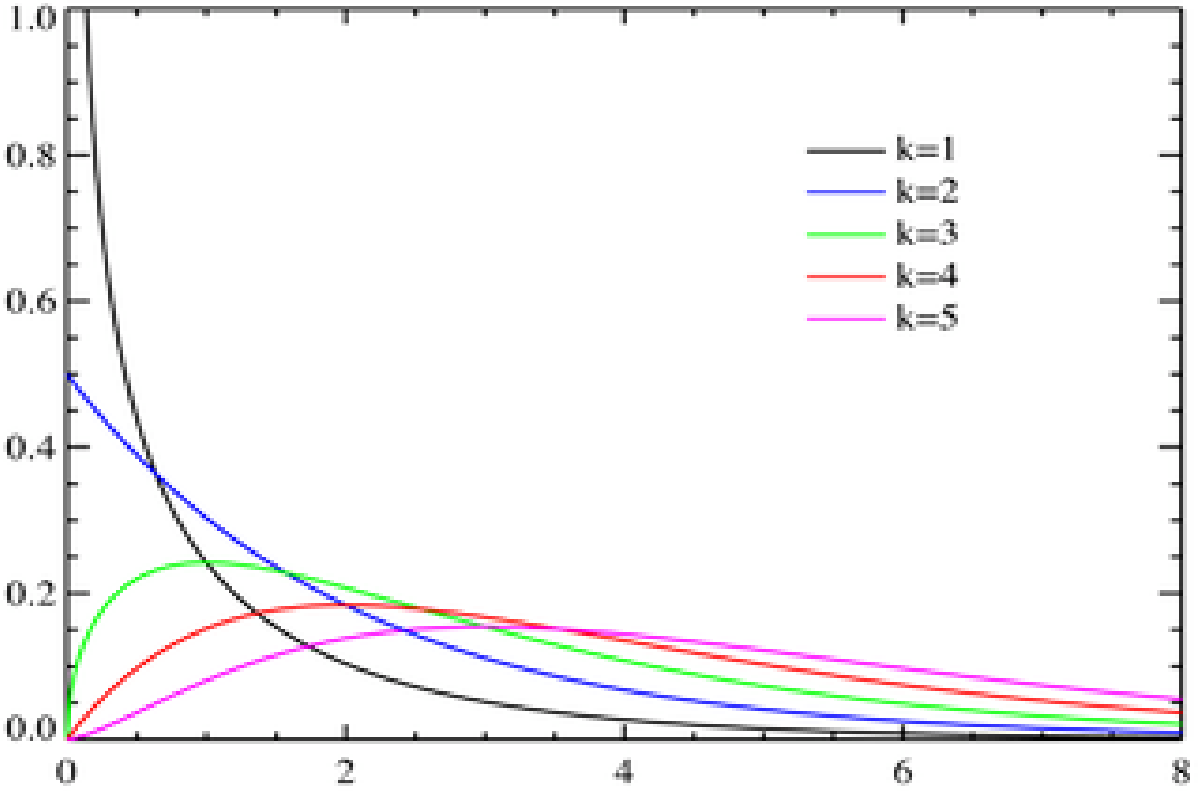
	Play chess	Not play chess	Sum (row)
Like science fiction	250(90)	200(360)	450
Not like science fiction	50(210)	1000(840)	1050
Sum(col.)	300	1200	1500

- X^2 (chi-square) calculation (numbers in parenthesis are expected counts calculated based on the data distribution in the two categories)

$$\chi^2 = \frac{(250-90)^2}{90} + \frac{(50-210)^2}{210} + \frac{(200-360)^2}{360} + \frac{(1000-840)^2}{840} = 507.93$$

- It shows that like_science_fiction and play_chess are correlated in the group

Chi Square Distribution



Degree of freedom = 1 (e.g., $(r-1)(c-1)$)

For 0.001 significance, threshold = 10.828

http://en.wikipedia.org/wiki/Pearson's_chi-squared_test

Data Transformation

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

Data Transformation: Normalization

- Min-max normalization: to [new_min$_A$, new_max$_A$]

$$v' = \frac{v - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A$$

  - Ex. Let income range \$12,000 to \$98,000 normalized to [0.0, 1.0]. Then \$73,000 is mapped to $\frac{73{,}600 - 12{,}000}{98{,}000 - 12{,}000}(1.0 - 0) + 0 = 0.716$

- Z-score normalization (μ: mean, σ: standard deviation):

$$v' = \frac{v - \mu_A}{\sigma_A}$$

  - Ex. Let μ = 54,000, σ = 16,000. Then $\frac{73{,}600 - 54{,}000}{16{,}000} = 1.225$

- Normalization by decimal scaling

$$v' = \frac{v}{10^j} \quad \text{Where } j \text{ is the smallest integer such that Max}(|v'|) < 1$$

Data Preprocessing

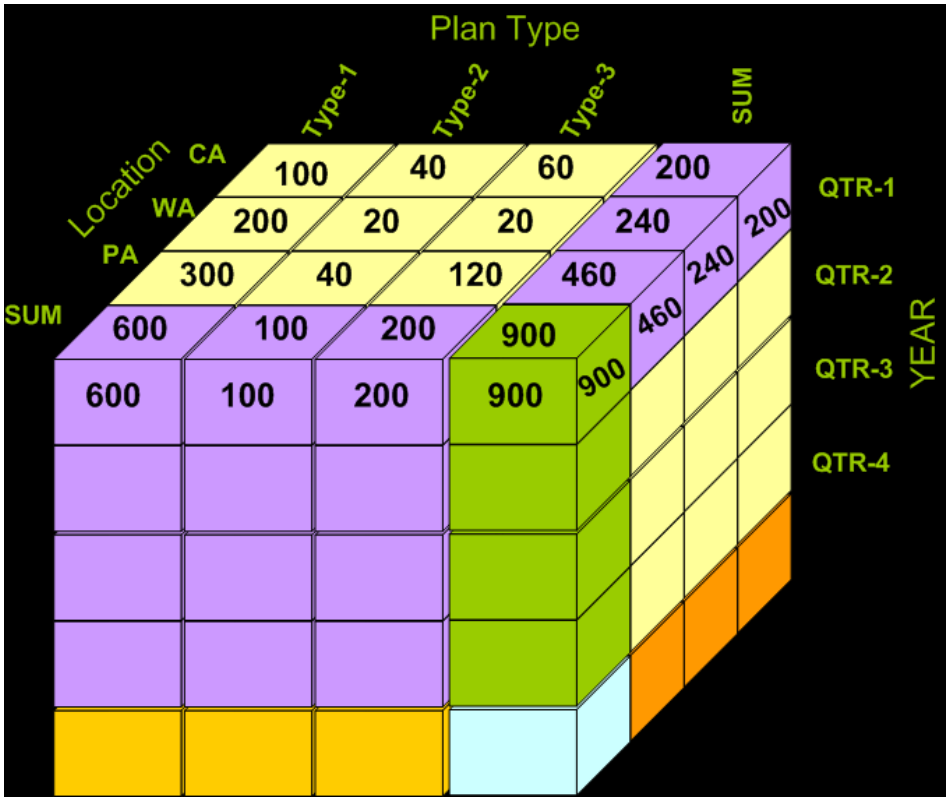
- Why preprocess the data?
- Data cleaning
- Data integration and transformation
- Data reduction
- Discretization and concept hierarchy generation
- Summary

Data Reduction Strategies

- Why data reduction?
  - A database/data warehouse may store terabytes of data
  - Complex data analysis/mining may take a very long time to run on the complete data set
- Data reduction
  - Obtain a reduced representation of the data set that is much smaller in volume but yet produce the same (or almost the same) analytical results
- Data reduction strategies
  - Data cube aggregation:
  - Dimensionality reduction — e.g., remove unimportant attributes
  - Data Compression
  - Numerosity reduction — e.g., fit data into models

Data Cube Aggregation

- The lowest level of a data cube (base cuboid)
  - The aggregated data for an individual entity of interest
- Multiple levels of aggregation in data cubes
  - Further reduce the size of data to deal with

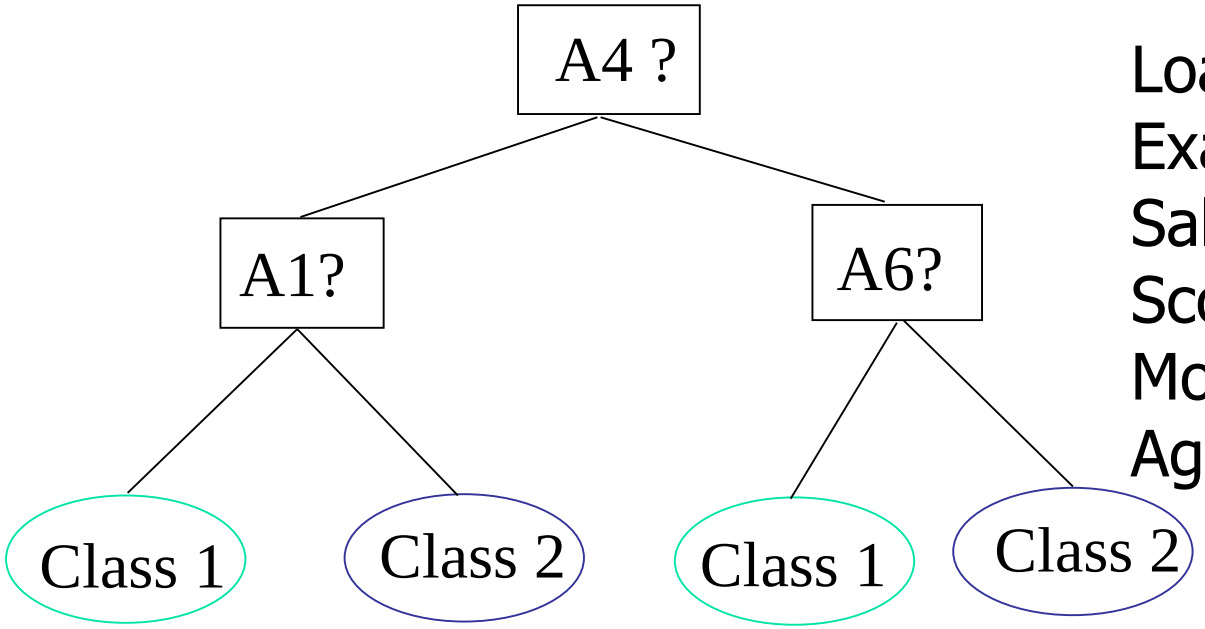


Attribute Subset Selection

- Feature selection (i.e., attribute subset selection):
  - Select a minimum set of features such that the probability distribution of different classes given the values for those features is as close as possible to the original distribution given the values of all features
  - reduce # of patterns in the patterns, easier to understand
- Heuristic methods (due to exponential # of choices):
  - Step-wise forward selection
  - Step-wise backward elimination
  - Combining forward selection and backward elimination
  - Decision-tree induction

Example of Decision Tree Induction

Initial attribute set:
{A1, A2, A3, A4, A5, A6}

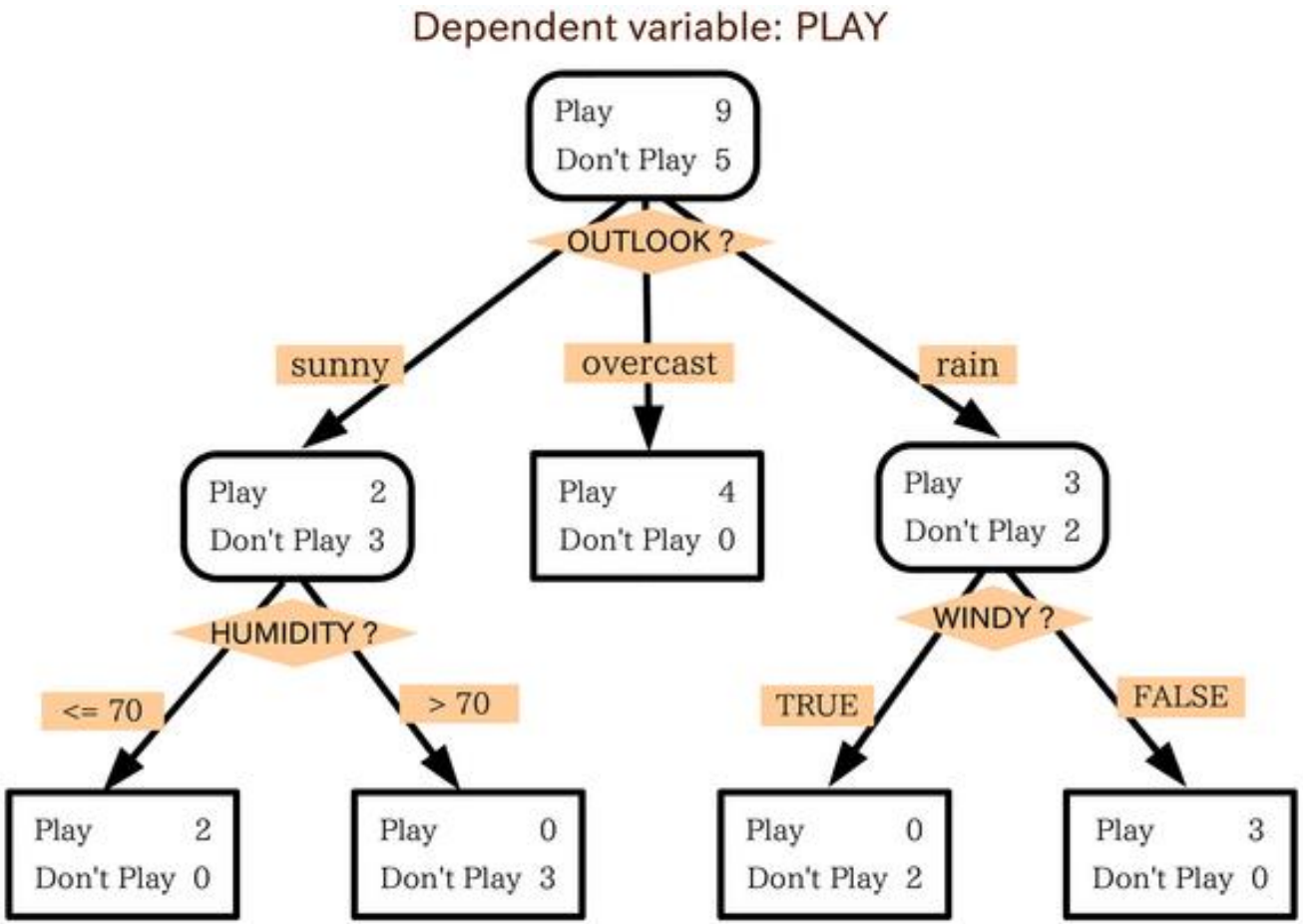


Loan Approval Example: Salary, Credit Score, House, Monthly payment, Age

-------> Reduced attribute set: {A1, A4, A6}

The weather data example.

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes
Sunny	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Rainy	Mild	High	True	No



http://gautam.lis.illinois.edu/monkmiddleware/public/analytics/decisiontree.html

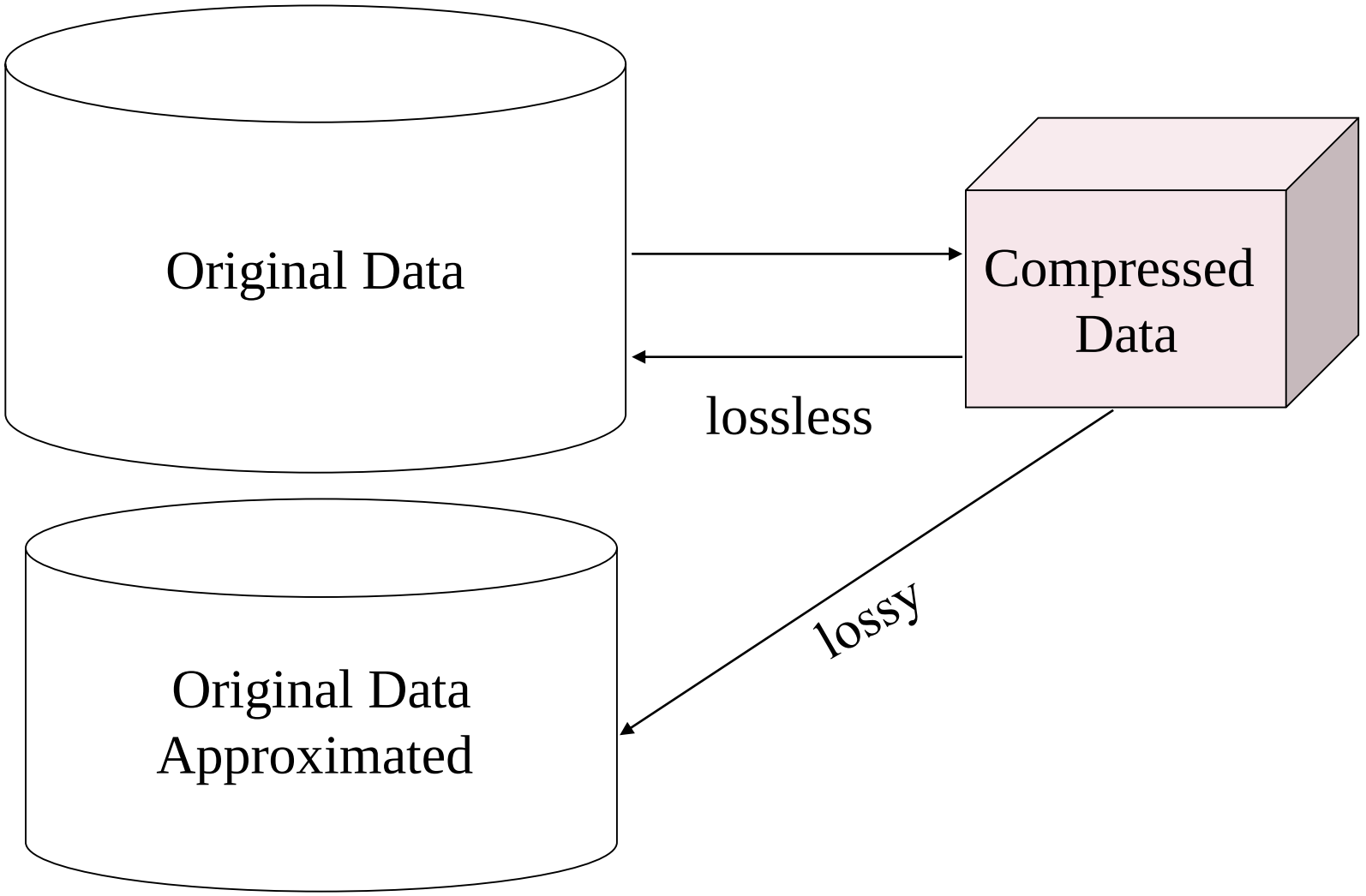
Heuristic Feature Selection Methods

- There are 2^d possible sub-features of d features
- Several heuristic feature selection methods:
  - Best single features under the feature independence assumption: choose by significance tests (how?)
  - Best step-wise feature selection:
    - The best single-feature is picked first
    - Then next best feature condition to the first, ...
  - Step-wise feature elimination:
    - Repeatedly eliminate the worst feature
  - Best combined feature selection and elimination
  - Optimal branch and bound:
    - Use feature elimination and backtracking

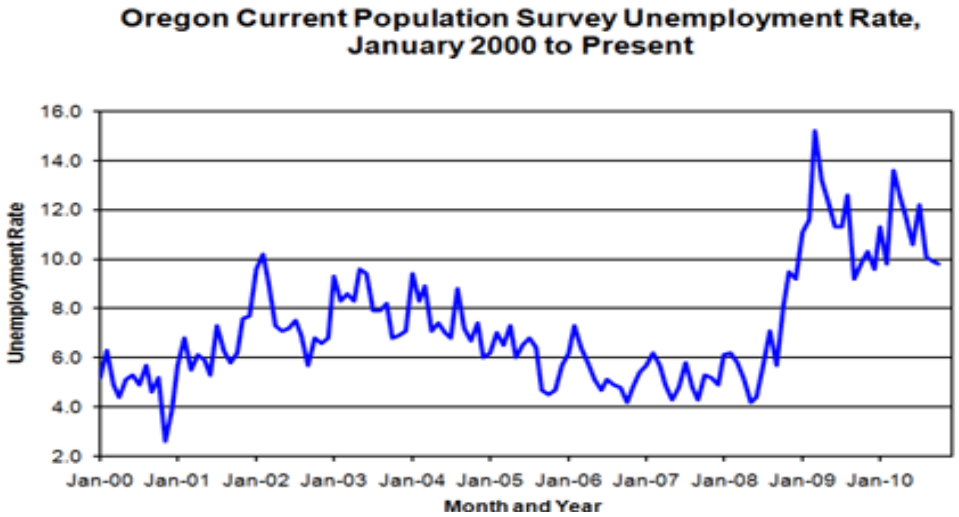
Data Compression

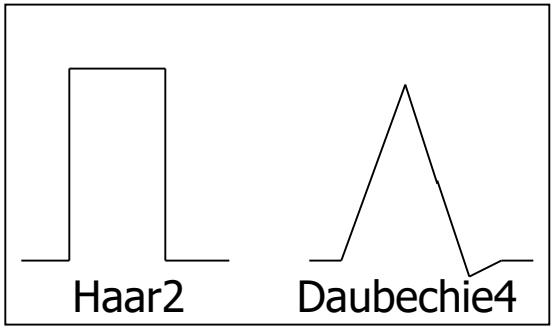
- String compression
  - There are extensive theories and well-tuned algorithms (e.g., Huffman encoding algorithm)
  - Typically lossless
  - But only limited manipulation is possible without expansion
- Audio/video compression
  - Typically lossy compression, with progressive refinement
  - Sometimes small fragments of signal can be reconstructed without reconstructing the whole
- Time sequence is not audio
  - Typically short and vary slowly with time

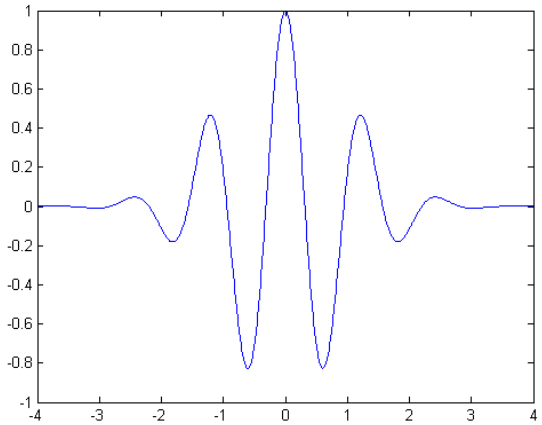
Data Compression



Sequence Data and Wavelet Function

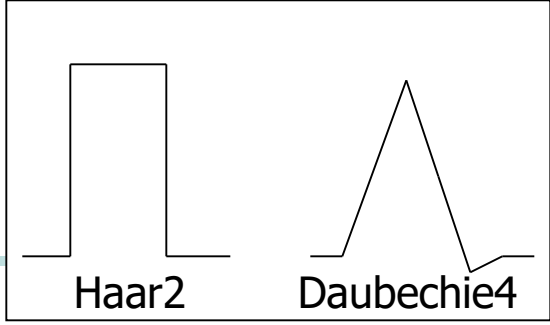






A continuous wavelet function

Dimensionality Reduction: Wavelet Transformation



- Discrete wavelet transform (DWT): linear signal processing, multi-resolutional analysis
- Similar to discrete Fourier transform (DFT), but better lossy compression, localized in space
- Method:
  - Length, L, must be an integer power of 2 (padding with 0's, when necessary)
  - Each transform has 2 functions: sum, difference
  - Applies to pairs of data, resulting in two set of data of length L/2
  - Applies two functions recursively, until reaches the desired length
- Compressed approximation: store only a small fraction of the strongest of the wavelet coefficients

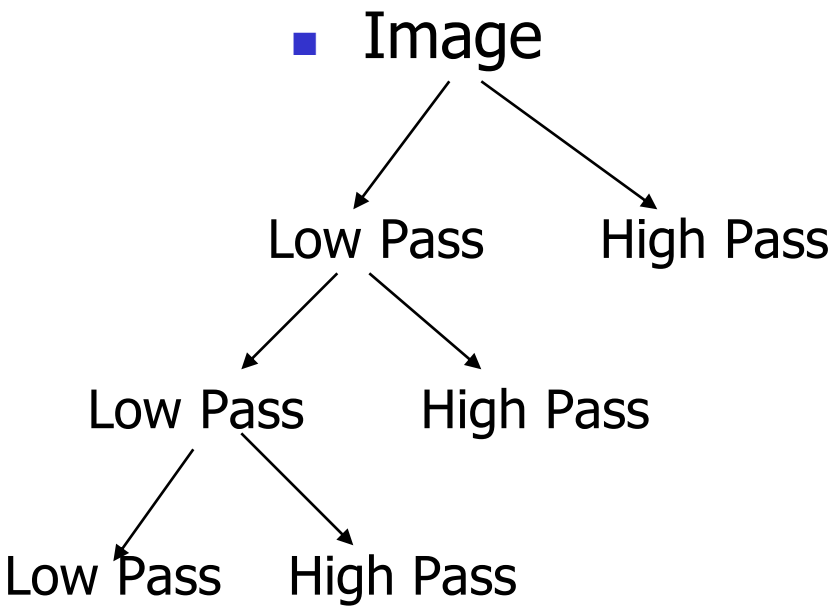
An example

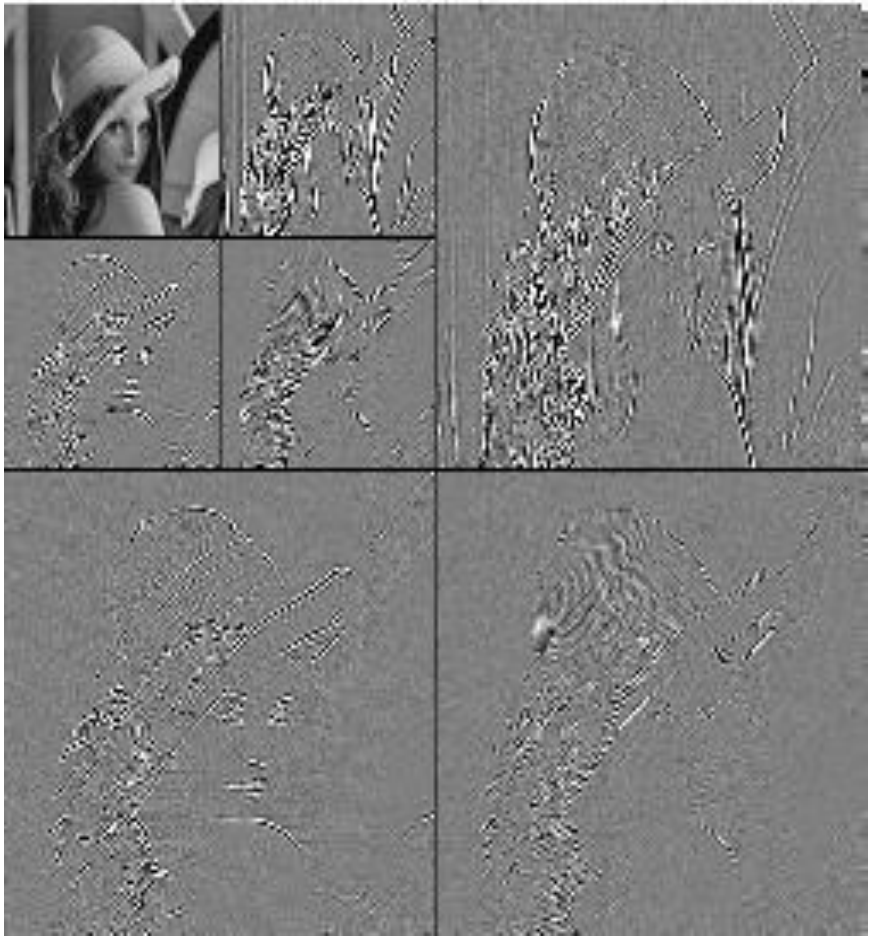
	0	1	2	3	4	3	2	1
1	1	-1	-1		1	5	7	3
0	0	2	-2		4	-4	6	10
0	**0**	**-4**	**0**		**-8**	**0**	**4**	**16**

History of Lena Image

- Alexander Sawchuk estimates that it was in June or July of 1973 when he, then an assistant professor of electrical engineering at the University of Southern California Signal and Image Processing Institute (SIPI), was hurriedly searching the lab for a good image to scan for a colleague's conference paper. They wanted something glossy to ensure good output dynamic range, and they wanted a human face. Just then, somebody happened to walk in with a recent issue of *Playboy*.

DWT for Image Compression



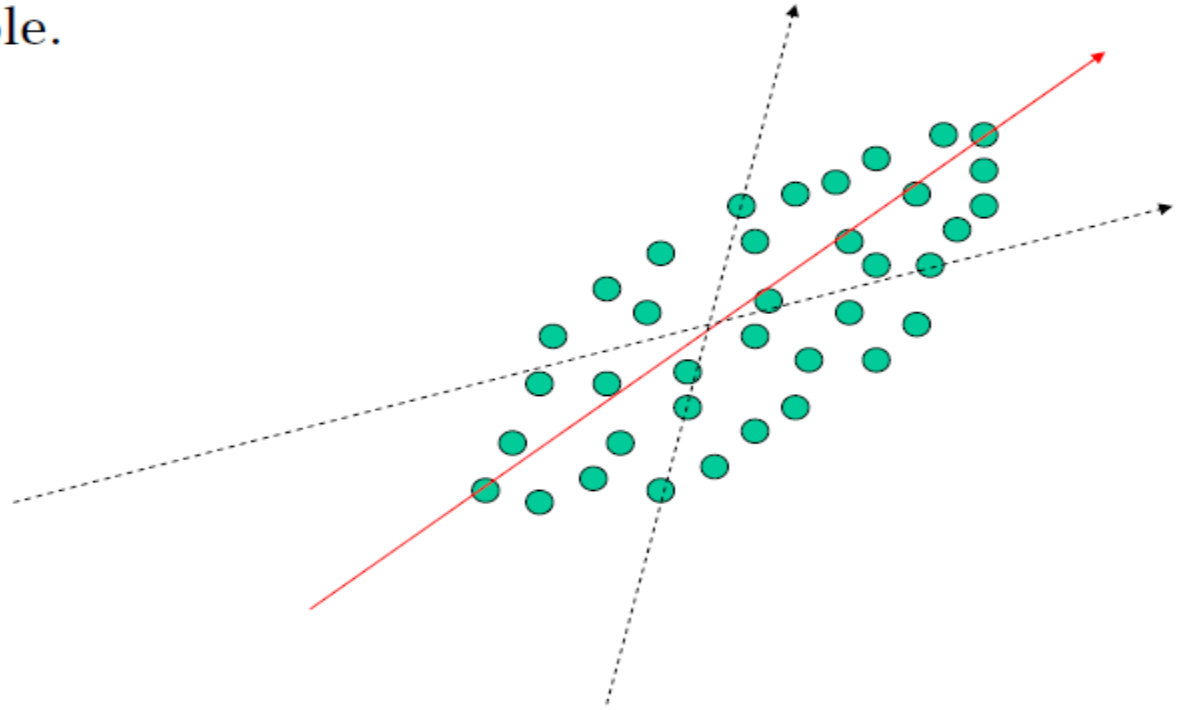


Dimensionality Reduction: Principal Component Analysis (PCA)

- Given *N* data vectors from *d*-dimensions, find $k \leq d$ orthogonal vectors (*principal components*) that can be best used to represent data
- Steps
  - Normalize input data
  - Compute *k* orthonormal (unit) vectors, i.e., *principal components*
  - The principal components are sorted in order of decreasing "significance" or strength
  - Since the components are sorted, the size of the data can be reduced by eliminating the weak components, i.e., those with low variance. (i.e., using the strongest principal components, it is possible to reconstruct a good approximation of the original data)
- Used when the number of dimensions is large

Basic Idea of PCA

Goal: Map data points into a few dimension while trying to preserve the variance of data as much as possible.



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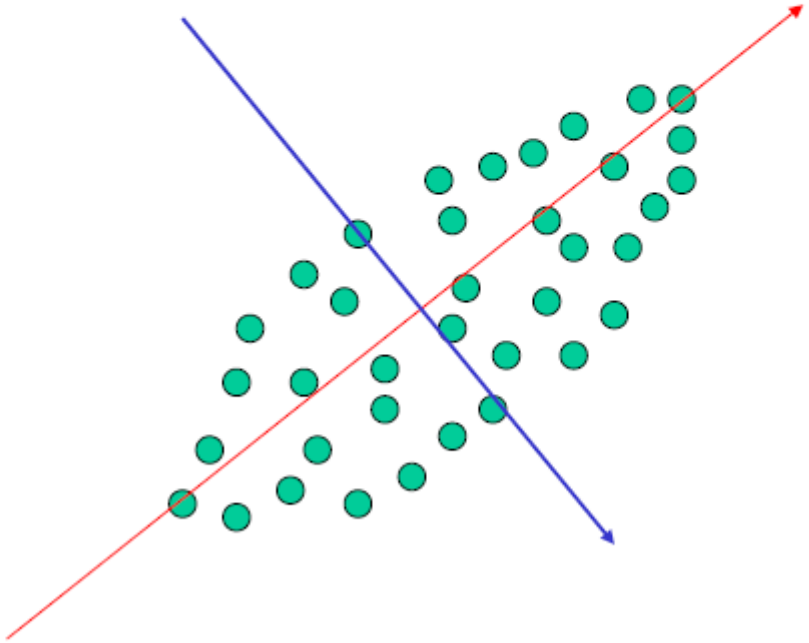
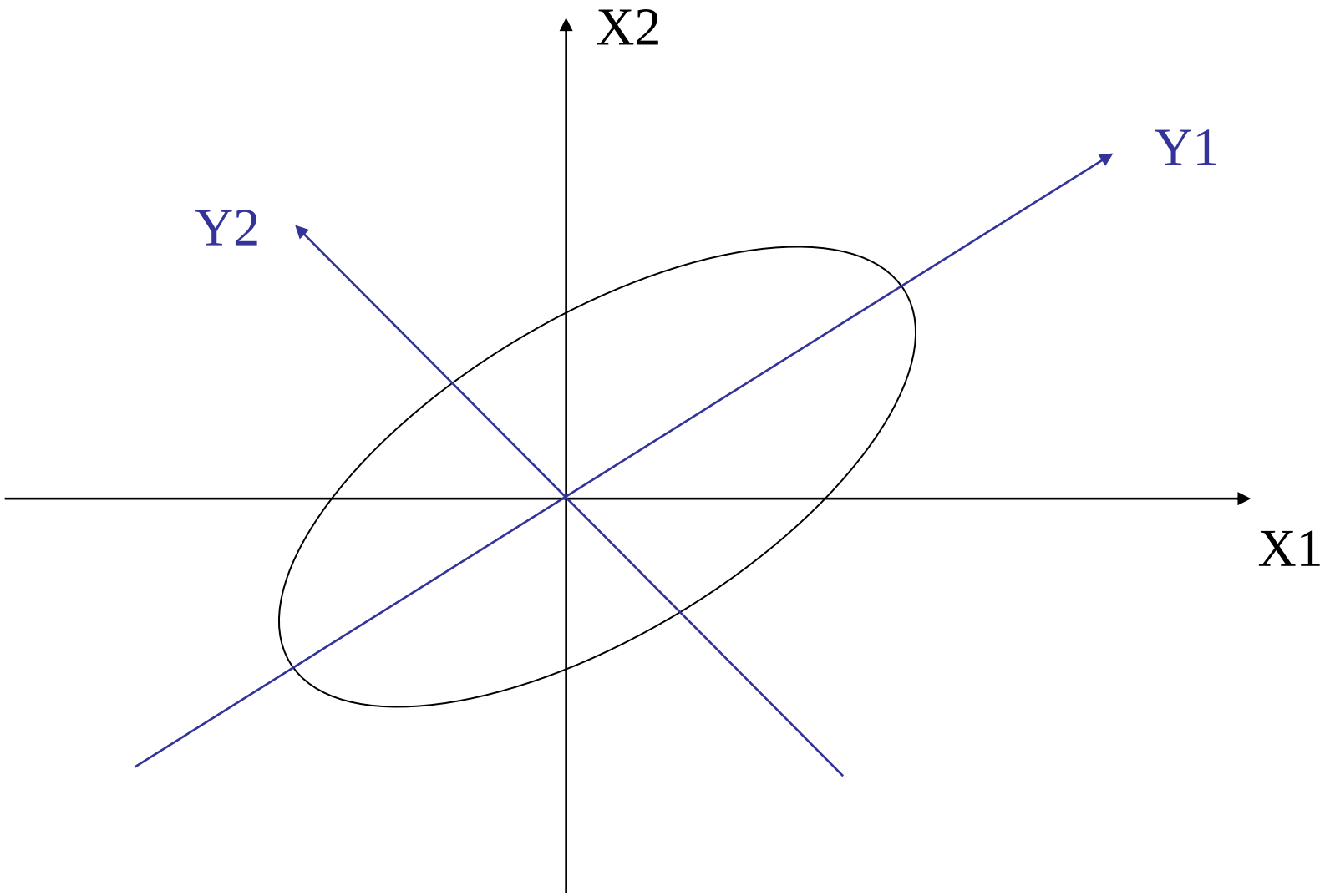


PCA Method

- Given a data matrix X ($n \times d$, n data points, d dimension).
- Normalize X by subtracting mean from each data point
- Construct a covariance matrix $C=X^TX/(n-1)(d \times d)$
- Calculate the eigenvectors and eigenvalues of the covariance matrix C. ($C\ v = v\ \lambda$).
- Sort eigenvectors by eigenvalues in decreasing order
- Map data point *x* to the direction *v* by computing the dot product.
- A well studied problem. Implementation in many software such as MatLab.

Principal Component Analysis



Numerosity Reduction

- Reduce data volume by choosing alternative, smaller forms of data representation
- Parametric methods
  - Assume the data fits some model, estimate model parameters, store only the parameters, and discard the data (except possible outliers)

- Non-parametric methods
  - Do not assume models
  - Major families: histograms, clustering, sampling

Data Reduction Method (1): Regression Models

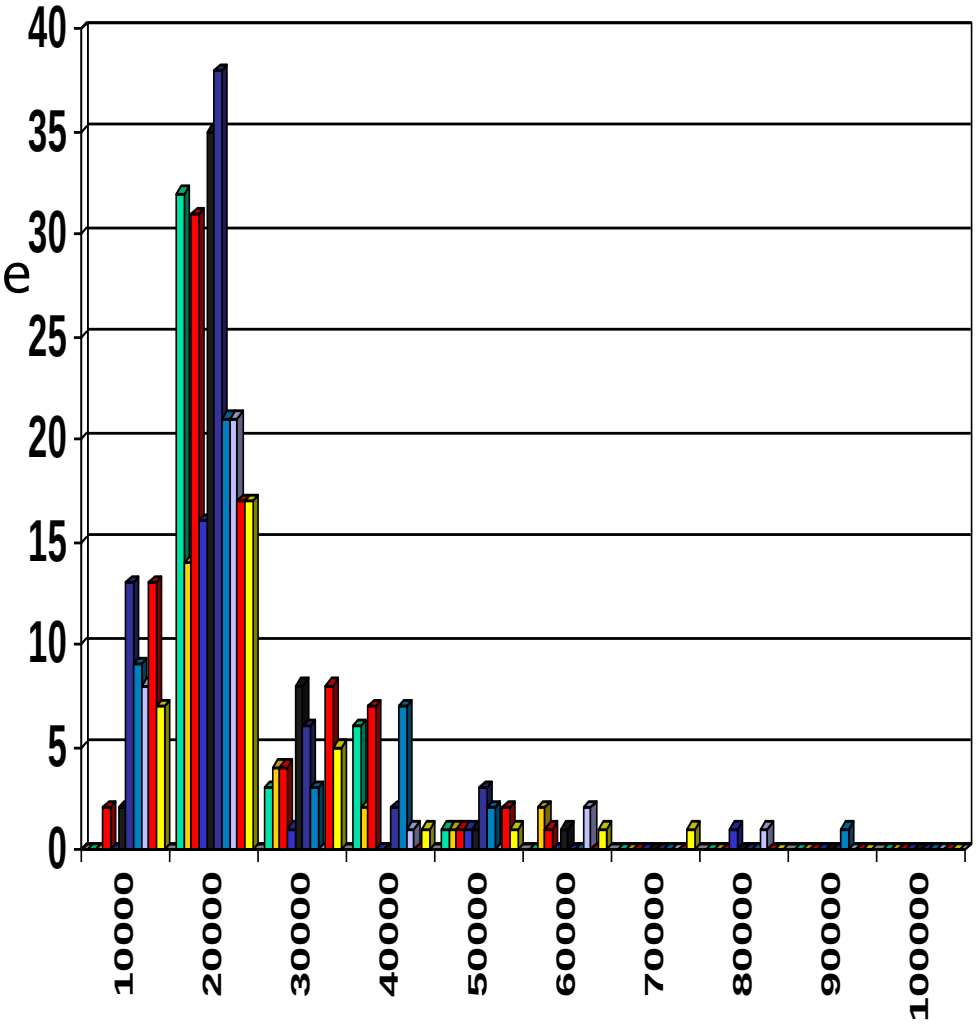
- Linear regression: Data are modeled to fit a straight line
  - Often uses the least-square method to fit the line
- Multiple regression: allows a response variable Y to be modeled as a linear function of multidimensional feature vector

Regress Analysis and Log-Linear Models

- Linear regression: $Y = w X + b$
  - Two regression coefficients, w and b, specify the line and are to be estimated by using the data at hand
  - Using the least squares criterion to the known values of $Y_1, Y_2, \ldots, X_1, X_2, \ldots$.
- Multiple regression: $Y = b0 + b1\ X1 + b2\ X2.$
  - Many nonlinear functions can be transformed into the above

Data Reduction Method (2): Histograms

- Divide data into buckets and store average (sum) for each bucket
- Partitioning rules:
  - Equal-width: equal bucket range
  - Equal-frequency (or equal-depth)



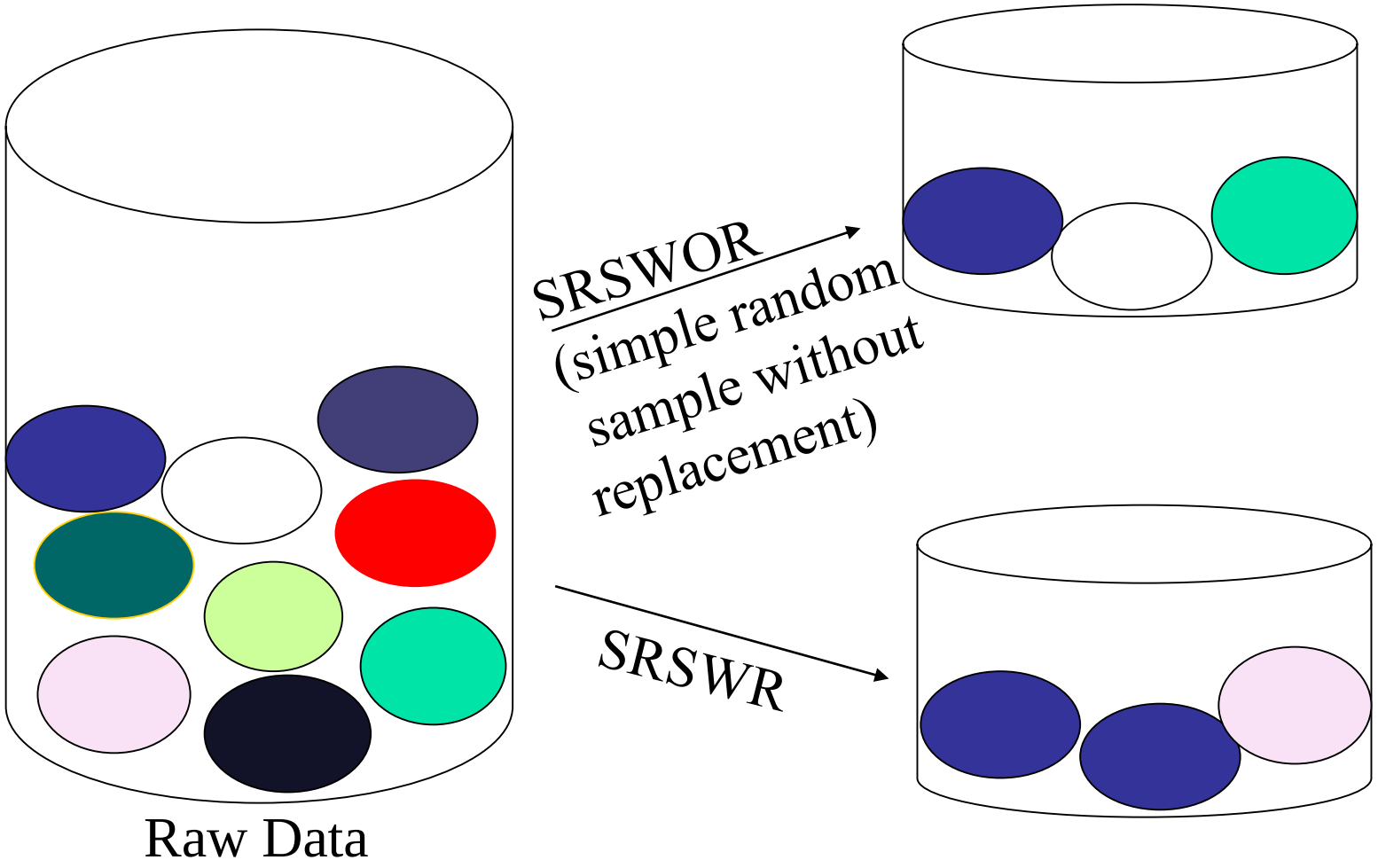
Data Reduction Method (3): Clustering

- Partition data set into clusters based on similarity, and store cluster representation (e.g., centroid and diameter) only
- Can be very effective if data is clustered but not if data is "smeared"
- There are many choices of clustering definitions and clustering algorithms
- Cluster analysis will be studied in depth

Data Reduction Method (4): Sampling

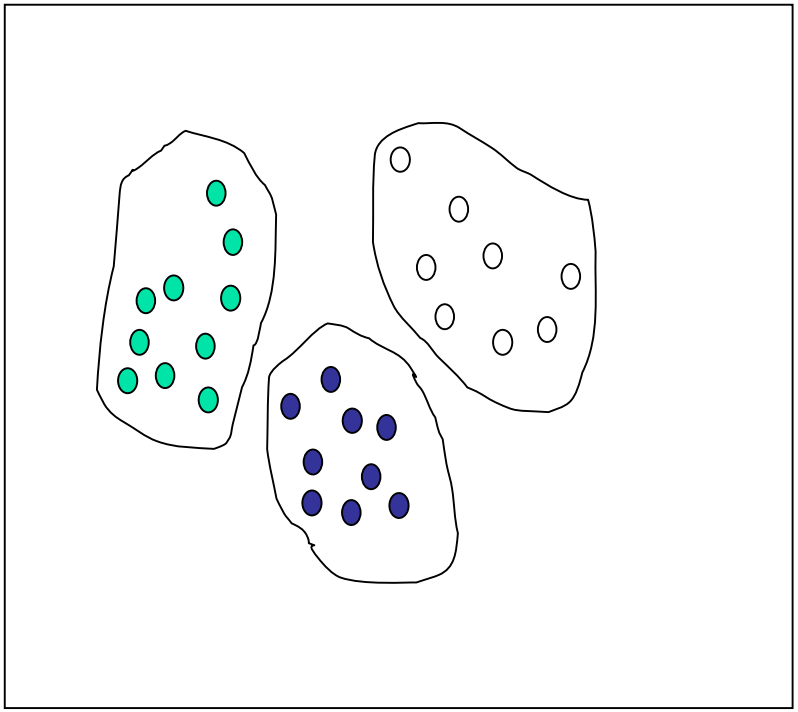
- Sampling: obtaining a small sample *s* to represent the whole data set *N*
- Allow a mining algorithm to run in complexity that is potentially sub-linear to the size of the data
- Choose a representative subset of the data
  - Simple random sampling may have very poor performance in the presence of skew
- Develop adaptive sampling methods
  - Stratified sampling:
    - Approximate the percentage of each class (or subpopulation of interest) in the overall database
    - Used in conjunction with skewed data

Sampling: with or without Replacement

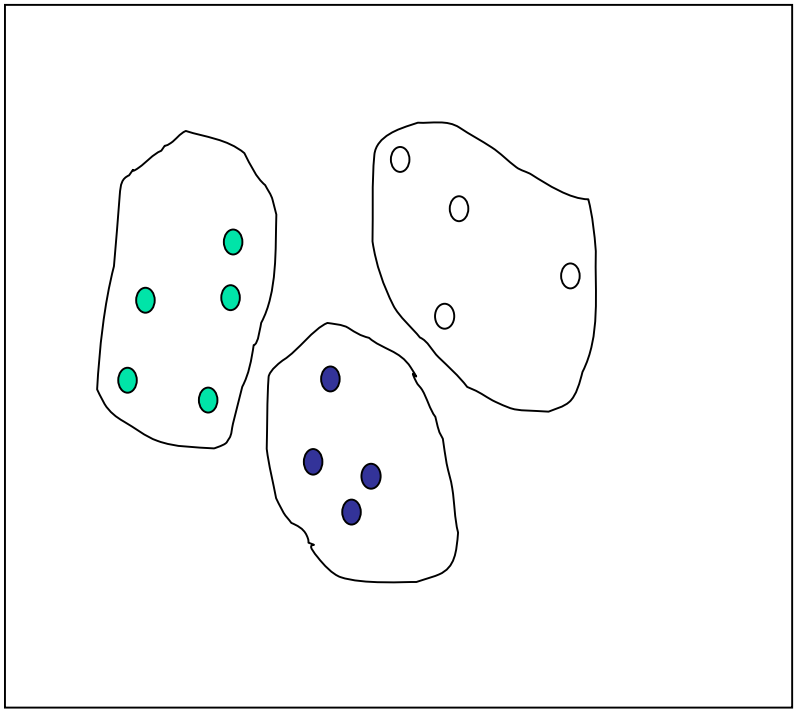


Sampling: Cluster or Stratified Sampling

Raw Data



Cluster/Stratified Sample



Data Preprocessing

- Why preprocess the data?
- Data cleaning
- Data integration and transformation
- Data reduction
- Discretization and concept hierarchy generation
- Summary

Discretization

- Three types of attributes:
  - Nominal — values from an unordered set, e.g., color, profession
  - Ordinal — values from an ordered set, e.g., military or academic rank
  - Continuous — real numbers, e.g., integer or real numbers
- Discretization:
  - Divide the range of a continuous attribute into intervals
  - Some classification algorithms only accept categorical attributes.
  - Reduce data size by discretization

Discretization and Concept Hierarchy

- Discretization
  - Reduce the number of values for a given continuous attribute by dividing the range of the attribute into intervals
  - Interval labels can then be used to replace actual data values
  - Supervised vs. unsupervised
  - Split (top-down) vs. merge (bottom-up)
  - Discretization can be performed recursively on an attribute
- Concept hierarchy formation
  - Recursively reduce the data by collecting and replacing low level concepts (such as numeric values for age) by higher level concepts (such as young, middle-aged, or senior)

Discretization and Concept Hierarchy Generation for Numeric Data

- Typical methods: All the methods can be applied recursively
  - Binning
    - Top-down split, unsupervised,
  - Histogram analysis
    - Top-down split, unsupervised
  - Clustering analysis
    - Either top-down split or bottom-up merge, unsupervised
  - Entropy-based discretization: supervised, top-down split
  - Interval merging by χ^2 Analysis: supervised, bottom-up merge

Entropy-Based Discretization

- Entropy is calculated based on class distribution of the samples in the set. Given *m* classes, the entropy of S_1 is

$$Entropy(S_1) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

where p_i is the probability of class *i* in S_1

- Given a set of samples S, if S is partitioned into two intervals S_1 and S_2 using boundary T, the information gain after partitioning is

$$I(S,T) = Entropy(S) - (\frac{|S_1|}{|S|} Entropy(S_1) + \frac{|S_2|}{|S|} Entropy(S_2))$$

- The boundary that minimizes the entropy function over all possible boundaries (i.e. maximize information is selected as a binary discretization)
- The process is recursively applied to partitions obtained until some stopping criterion is met
- Such a boundary may reduce data size and improve classification accuracy

Interval Merge by χ^2 Analysis

- Merging-based (bottom-up) vs. splitting-based methods
- Merge: Find the best neighboring intervals and merge them to form larger intervals recursively
- ChiMerge [Kerber AAAI 1992, See also Liu et al. DMKD 2002]
  - Initially, each distinct value of a numerical attr. A is considered to be one interval
  - χ^2 tests are performed for every pair of adjacent intervals
  - Adjacent intervals with the least χ^2 values are merged together, since low χ^2 values for a pair indicate similar class distributions
  - This merge process proceeds recursively until a predefined stopping criterion is met (such as significance level, max-interval, max inconsistency, etc.)

Examples

	Interval 1	Interval 2	Sum
Class 1	100	100	200
Class 2	200	200	400
Sum	300	300	

	Interval 1	Interval 2	Sum
Class 1	200	0	200
Class 2	200	200	400
Sum	400	200	

Examples

	Interval 1	Interval 2	Sum
Class 1	100 (100)	100 (100)	200
Class 2	200 (200)	200 (200)	400
Sum	300	300	

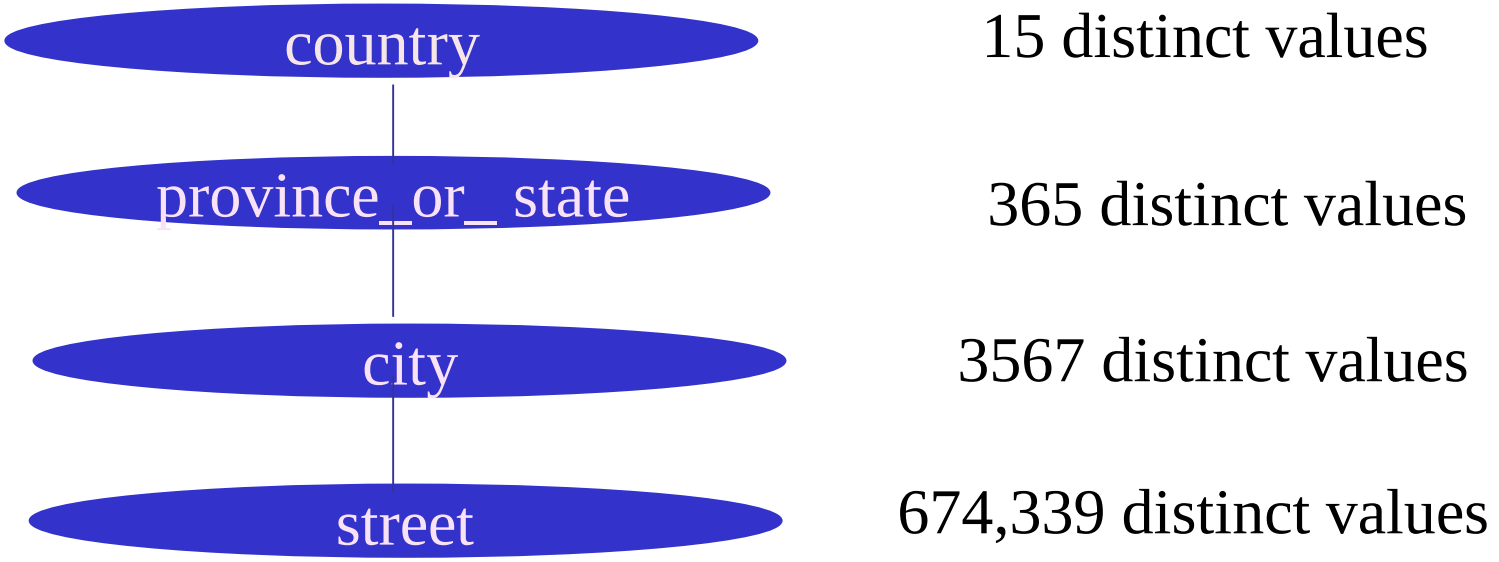
	Interval 1	Interval 2	Sum
Class 1	200 (133)	0 (67)	200
Class 2	200 (267)	200 (133)	400
Sum	400	200	

Concept Hierarchy Generation for Categorical Data

- Specification of a partial/total ordering of attributes explicitly at the schema level by users or experts
  - street < city < state < country
- Specification of a hierarchy for a set of values by explicit data grouping
  - {Urbana, Champaign, Chicago} < Illinois
- Automatic generation of hierarchies (or attribute levels) by the analysis of the number of distinct values
  - E.g., for a set of attributes: {street, city, state, country}

Automatic Concept Hierarchy Generation

- Some hierarchies can be automatically generated based on the analysis of the number of distinct values per attribute in the data set
  - The attribute with the most distinct values is placed at the lowest level of the hierarchy
  - Exceptions, e.g., weekday, month, quarter, year



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Summary

- Data preparation or preprocessing is a big issue for both data warehousing and data mining
- Descriptive data summarization is needed for quality data preprocessing
- Data preparation includes
  - Data cleaning and data integration
  - Data reduction and feature selection
  - Discretization
- A lot a methods have been developed but data preprocessing still an active area of research

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