

# **Data Mining:**


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## **Chapter 3**

### **Pre-mining**

# Chapter 3: Data Preprocessing

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- Data Preprocessing: An Overview
  - Data Quality
  - Major Tasks in Data Preprocessing
- Data Cleaning
- Data Integration
- Data Reduction 
- Data Transformation and Data Discretization
- Summary

# Data Reduction Strategies

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- **Data reduction:** Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results
  - Why data reduction? — A database/data warehouse may store terabytes of data. Complex data analysis may take a very long time to run on the complete data set.
  - Data reduction strategies
    - **Dimensionality reduction**, e.g., remove unimportant attributes
      - Wavelet transforms
      - Principal Components Analysis (PCA)
      - Feature subset selection, feature creation
    - **Numerosity reduction** (some simply call it: Data Reduction)
      - Regression and Log-Linear Models
      - Histograms, clustering, sampling
      - Data cube aggregation
- SAX (covers dimensionality reduction and Numerosity reduction)**

# Data Reduction 1: Dimensionality Reduction

## ■ Curse of dimensionality

- When dimensionality increases, data becomes increasingly sparse
- Density and distance between points, which is critical to clustering, outlier analysis, becomes less meaningful
- The possible combinations of subspaces will grow exponentially

E.g. Student dataset:

ID	Age	Course	CGPA	Programming skills	Co-curricular	Exchange program	Exchange duration
1001	23	BCS	3.54	Python	Chess club	Tokyo University	6 months
1002	21	BMgmt	3.98	None	Student Council	None	None
1003	21	BCS	2.50	C++	None	None	None
1004	27	MCS	3.25	Java	None	MIT	3 months

# Data Reduction 1: Dimensionality Reduction

- **Dimensionality reduction**

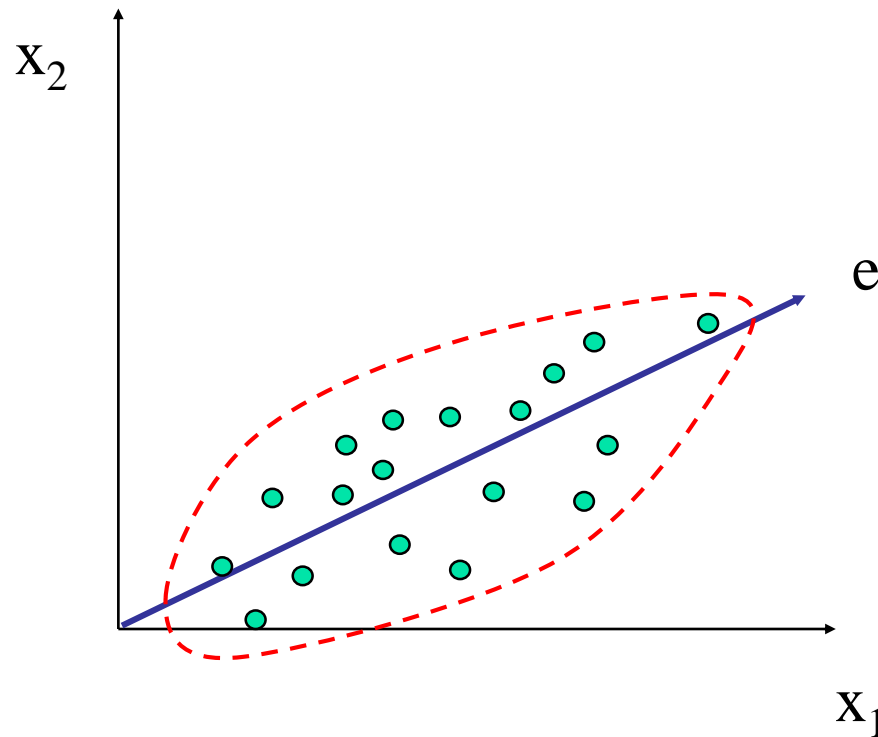
- Avoid the curse of dimensionality
- Help eliminate irrelevant features and reduce noise
- Reduce time and space required in data mining
- Allow easier visualization

- **Dimensionality reduction techniques**

- Wavelet transforms (image compression)
- Principal Component Analysis
- Supervised and nonlinear techniques (e.g., feature selection)

# Principal Component Analysis (PCA)

- Find a projection that captures the largest amount of variation in data
- The original data are projected onto a much smaller space, resulting in dimensionality reduction. We find the eigenvectors of the covariance matrix, and these eigenvectors define the new space



# Principal Component Analysis (Steps)

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- Given  $N$  data vectors from  $n$ -dimensions, find  $k \leq n$  orthogonal vectors (*principal components*) that can be best used to represent data
  - Normalize input data: Each attribute falls within the same range
  - Compute  $k$  orthonormal (unit) vectors, i.e., *principal components*
  - Each input data (vector) is a linear combination of the  $k$  principal component vectors
  - 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)
- Works for numeric data only

# Attribute Subset Selection

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- Another way to reduce dimensionality of data
- Redundant attributes
  - Duplicate much or all of the information contained in one or more other attributes
  - E.g., purchase price of a product and the amount of sales tax paid
- Irrelevant attributes
  - Contain no information that is useful for the data mining task at hand
  - E.g., students' ID is often irrelevant to the task of predicting students' GPA



# Heuristic Search in Attribute Selection

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

# Attribute Creation (Feature Generation)

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- Create new attributes (features) that can capture the important information in a data set more effectively than the original ones
- Three general methodologies
  - Attribute extraction
    - Domain-specific
  - Mapping data to new space (see: data reduction)
    - E.g., Fourier transformation, wavelet transformation
  - Attribute construction
    - Combining features
    - Data discretization

# Data Reduction 2: Numerosity Reduction

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- Reduce data volume by choosing alternative, *smaller forms* of data representation
- **Parametric methods** (e.g., regression)
  - Assume the data fits some model, estimate model parameters, store only the parameters, and discard the data (except possible outliers)
  - Ex.: Log-linear models—obtain value at a point in  $m$ -D space as the product on appropriate marginal subspaces
- **Non-parametric** methods
  - Do not assume models
  - Major families: histograms, clustering, sampling, ...

# Parametric Data Reduction: Regression and Log-Linear Models

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- **Linear regression**

- Data modeled to fit a straight line
- Often uses the least-square method to fit the line

- **Multiple regression**

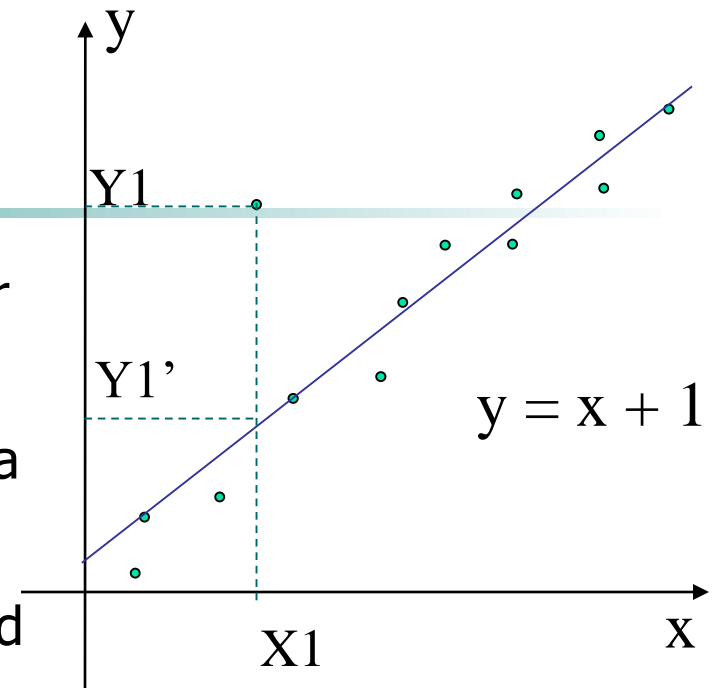
- Allows a response variable  $Y$  to be modeled as a linear function of multidimensional feature vector

- **Log-linear model**

- Approximates discrete multidimensional probability distributions

# Regression Analysis

- Regression analysis: A collective name for techniques for the modeling and analysis of numerical data consisting of values of a ***dependent variable*** (also called ***response variable*** or *measurement*) and of one or more *independent variables* (aka. ***explanatory variables*** or ***predictors***)
- The parameters are estimated so as to give a "**best fit**" of the data
- Most commonly the best fit is evaluated by using the ***least squares method***, but other criteria have also been used
- Used for prediction (including forecasting of time-series data), inference, hypothesis testing, and modeling of causal relationships



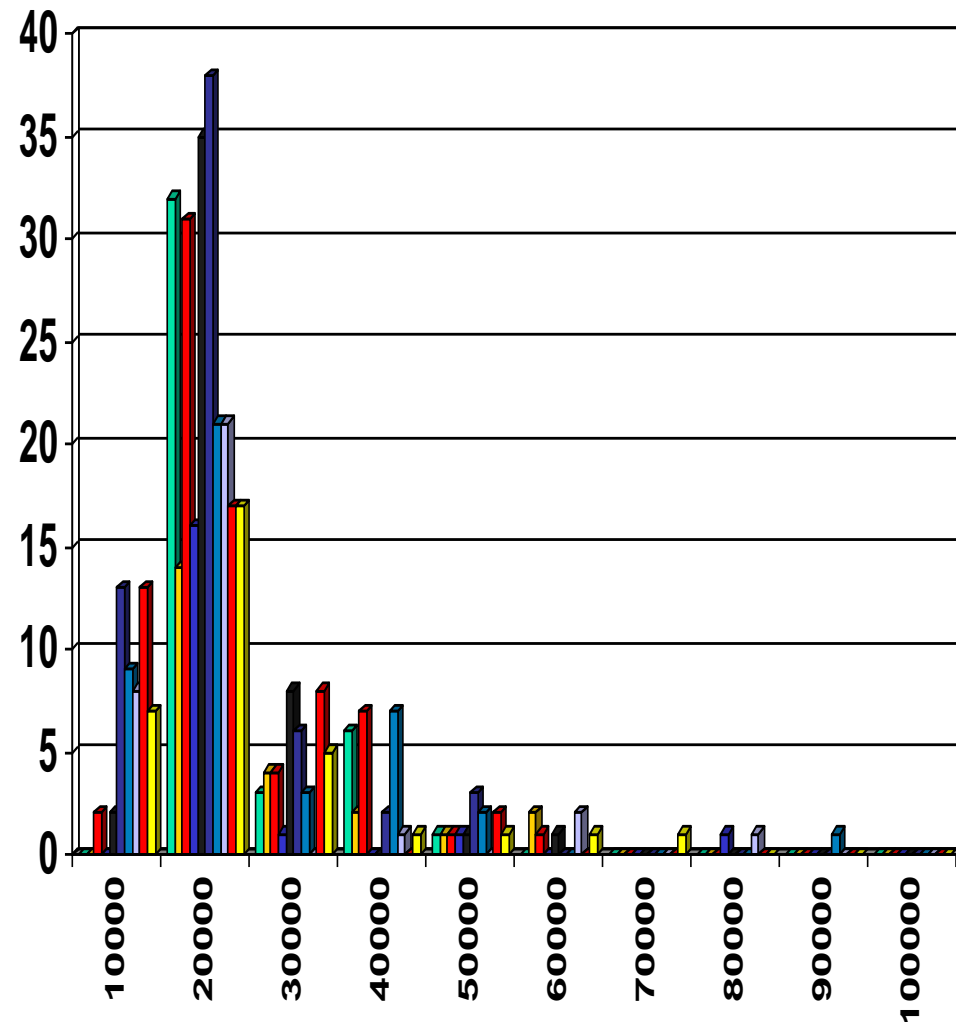
# Regress Analysis and Log-Linear Models

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- Linear regression:  $Y = wX + b$ 
  - 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  $Y_1, Y_2, \dots, X_1, X_2, \dots$
- Multiple regression:  $Y = b_0 + b_1 X_1 + b_2 X_2$ 
  - Many nonlinear functions can be transformed into the above
- Log-linear models:
  - Approximate discrete multidimensional probability distributions
  - Estimate the probability of each point (tuple) in a multi-dimensional space for a set of discretized attributes, based on a smaller subset of dimensional combinations
  - Useful for dimensionality reduction and data smoothing

# Histogram Analysis

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



# Clustering

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- 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”
- Can have hierarchical clustering and be stored in multi-dimensional index tree structures
- There are many choices of clustering definitions and clustering algorithms
- Cluster analysis will be studied in depth in Chapter 10



# Sampling

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- 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
- Key principle: Choose a **representative** subset of the data
  - Simple random sampling may have very poor performance in the presence of skew
  - Develop adaptive sampling methods, e.g., stratified sampling
- Note: Sampling may not reduce database I/Os (page at a time)

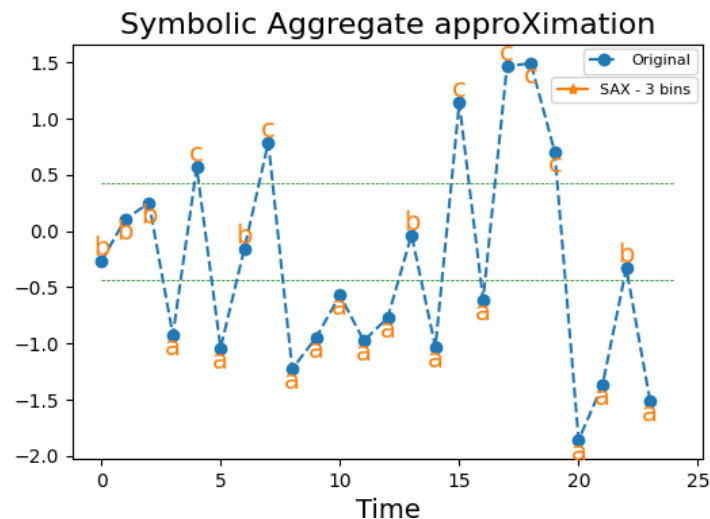
# Data Cube Aggregation

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- The lowest level of a data cube (base cuboid)
  - The aggregated data for an **individual entity of interest**
  - E.g., a customer in a phone calling data warehouse
- Multiple levels of aggregation in data cubes
  - Further reduce the size of data to deal with
- Reference appropriate levels
  - Use the smallest representation which is enough to solve the task
- Queries regarding aggregated information should be answered using data cube, when possible

# Symbolic Aggregate approXimation (SAX)

- A method for symbolic representation of time series data [1,2]
  - Allows dimensionality (and also numerosity) reduction and indexing with lower-bounding distance measure
- As good as DWT and DFT but requires less storage space
- Applied in bioinformatics and text mining
- Approach: bin continuous/time series data into intervals (approximation) and transform into sequence of symbols (letters)



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# Data Transformation

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- A function that maps the entire set of values of a given attribute to a new set of replacement values s.t. each old value can be identified with one of the new values
- Methods
  - Smoothing: Remove noise from data
  - Attribute/feature construction
    - New attributes constructed from the given ones
  - Aggregation: Summarization, data cube construction
  - Normalization: Scaled to fall within a smaller, specified range
    - min-max normalization
    - z-score normalization
    - normalization by decimal scaling
  - Discretization: Concept hierarchy climbing

# Normalization

- **Min-max normalization:** to  $[\text{new\_min}_A, \text{new\_max}_A]$

$$v' = \frac{v - \min_A}{\max_A - \min_A} (\text{new\_max}_A - \text{new\_min}_A) + \text{new\_min}_A$$

- 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** ( $\mu$ : mean,  $\sigma$ : standard deviation):

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

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

# Discretization

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- 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
  - Numeric—real numbers, e.g., integer or real numbers
- Discretization: Divide the range of a continuous attribute into intervals
  - Interval labels can then be used to replace actual data values
  - Reduce data size by discretization
  - Supervised vs. unsupervised
  - Split (top-down) vs. merge (bottom-up)
  - Discretization can be performed recursively on an attribute
  - Prepare for further analysis, e.g., classification

# Data Discretization Methods

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- Typical methods: All the methods can be applied recursively
  - Binning
    - Top-down split, unsupervised
  - Histogram analysis
    - Top-down split, unsupervised
  - Clustering analysis (unsupervised, top-down split or bottom-up merge)
  - Decision-tree analysis (supervised, top-down split)
  - Correlation (e.g.,  $\chi^2$ ) analysis (unsupervised, bottom-up merge)



# Simple Discretization: Binning

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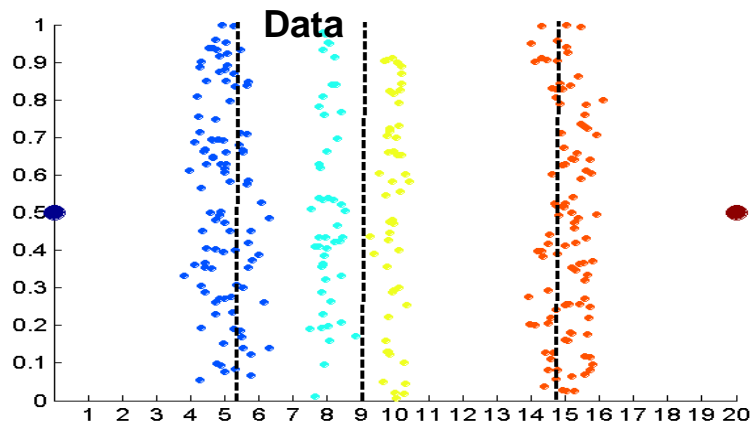
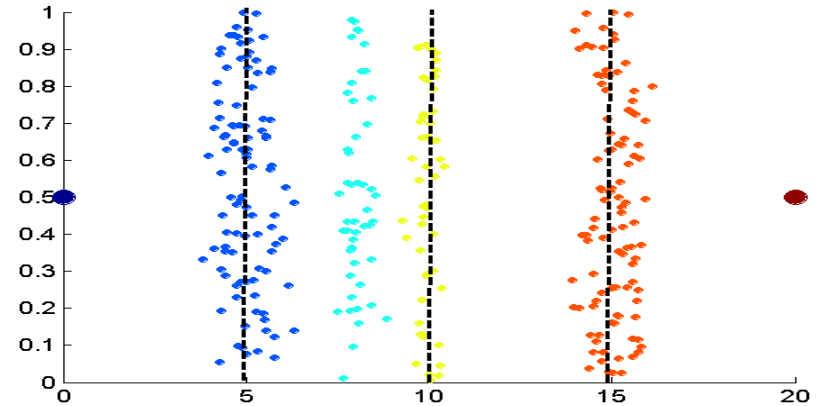
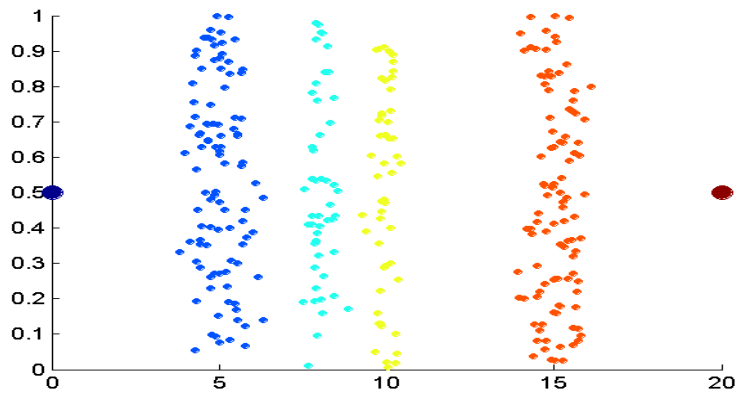
- **Equal-width** (distance) partitioning
  - Divides the range into  $N$  intervals of equal size: uniform grid
  - if  $A$  and  $B$  are the lowest and highest values of the attribute, the width of intervals will be:  $W = (B - A) / N$ .
  - The most straightforward, but outliers may dominate presentation
  - 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
  - Managing categorical attributes can be tricky

# Binning Methods for Data Smoothing

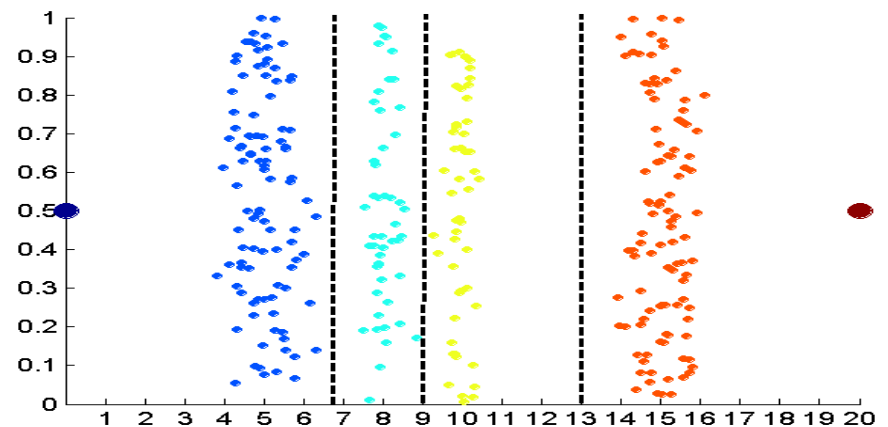
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- ❑ Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34
- \* Partition into equal-frequency (**equi-depth**) bins:
  - Bin 1: 4, 8, 9, 15
  - Bin 2: 21, 21, 24, 25
  - Bin 3: 26, 28, 29, 34
- \* Smoothing by **bin means**:
  - 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

# Discretization Without Using Class Labels (Binning vs. Clustering)



Equal frequency (binning)



K-means clustering leads to better results

# Discretization by Classification & Correlation Analysis

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- Classification (e.g., decision tree analysis)
  - Supervised: Given class labels, e.g., cancerous vs. benign
  - Using *entropy* to determine split point (discretization point)
  - Top-down, recursive split
  - Details to be covered in Chapter 7
- Correlation analysis (e.g., Chi-merge:  $\chi^2$ -based discretization)
  - Supervised: use class information
  - Bottom-up merge: find the best neighboring intervals (those having similar distributions of classes, i.e., low  $\chi^2$  values) to merge
  - Merge performed recursively, until a predefined stopping condition

# Concept Hierarchy Generation

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- **Concept hierarchy** organizes concepts (i.e., attribute values) hierarchically and is usually associated with each dimension in a data warehouse
- Concept hierarchies facilitate drilling and rolling in data warehouses to view data in multiple granularity
- 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 *youth*, *adult*, or *senior*)
- Concept hierarchies can be explicitly specified by domain experts and/or data warehouse designers
- Concept hierarchy can be automatically formed for both numeric and nominal data. For numeric data, use discretization methods shown.

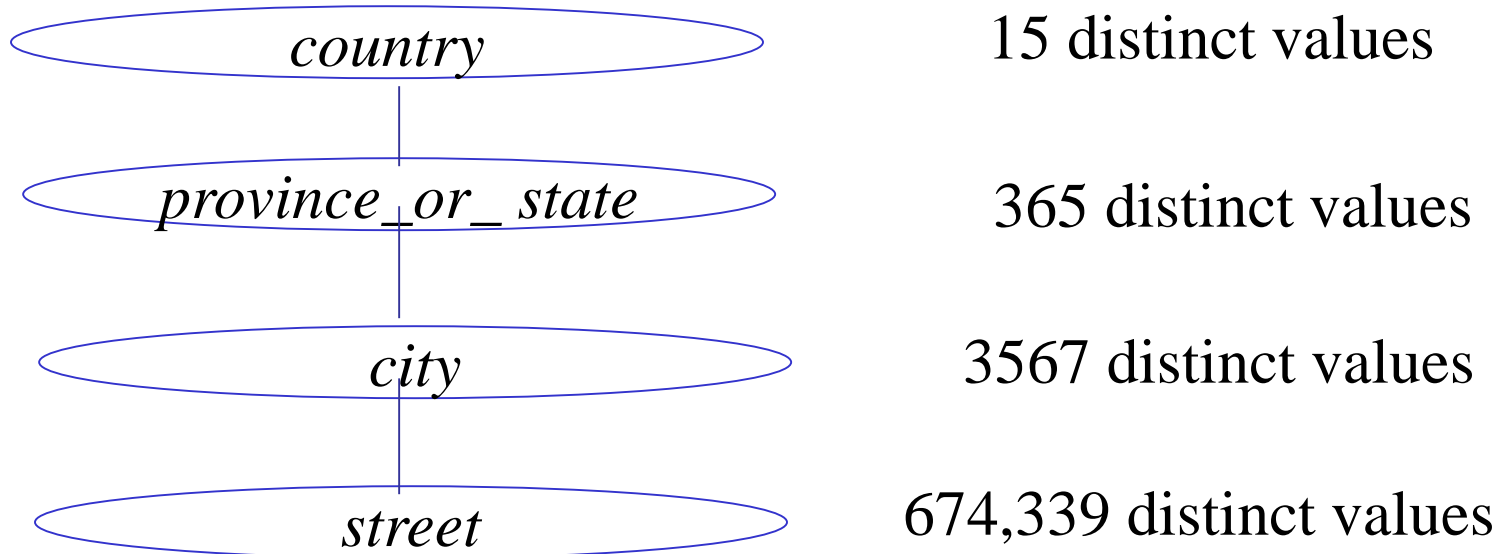
# Concept Hierarchy Generation for Nominal Data

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- 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
- Specification of only a partial set of attributes
  - E.g., only *street* < *city*, not others
- 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

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- **Data quality:** accuracy, completeness, consistency, timeliness, believability, interpretability
- **Data cleaning:** e.g. missing/noisy values, outliers
- **Data integration** from multiple sources:
  - Entity identification problem
  - Remove redundancies
  - Detect inconsistencies
- **Data reduction**
  - Dimensionality reduction
  - Numerosity reduction
  - Data compression
- **Data transformation and data discretization**
  - Normalization
  - Concept hierarchy generation

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