Data Wrangling and Data Analysis
Data Preparation (2)

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Topics for Today

- Data transformation
- Data Integration
- Data reduction
- Data discretization

Data Transformation

Data Transformation

- 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 for data transformation
  - Smoothing: Remove noise from data
  - Attribute/feature construction
    - New attributes constructed from the given ones
  - Aggregation: Summarization, data cube construction

Data Transformation (Cont.)

- Methods for data transformation
  - Normalization: Scaled to fall within a smaller, specified range
    - Min-max normalization
    - Z-score normalization
    - Normalization by decimal scaling
  - Data reformatting:
    - E.g. Jack Wilsher → Wilsher, J.
  - Use the same unit:
    - Records in inches and cm
    - Records with prices in Euros and Dollars

Data Normalization (Standardization)

The goal of standardization or normalization is to make an entire set of values have a particular property.

Data Normalization – Min-Max Normalization

- Transform the data from a given range with $[min_A, max_A]$ to a new interval $[new\_min_F, new\_max_F]$ for a given attribute A :

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

where v is the current value of attribute A.

Data Normalization – Min-Max Normalization

- Example:

  Suppose that the minimum and the maximum in the attribute income are €12,000 and €98,000, respectively

  We would like to map the income into the interval $[0,1]$

  Using min-max normalization, a value of €73,600 for income is transformed into:

$$\frac{73{,}600 - 12{,}000}{98{,}000 - 12{,}000}(1.0 - 0.0) + 0.0 = 0.716$$

Data Normalization – Z-Score Normalization

- Transform the data by converting the values to a common scale with an average of zero and a standard deviation of one.
- A value, v, of attribute A is normalized to v' by computing:

$$v' = \frac{v - \bar{A}}{\sigma_A}$$

where $\bar{A}$ and σ_A are the mean and standard deviation of attribute A, respectively.

Data Normalization – Z-Score Normalization

- Example:
  - Suppose that the mean and standard deviation of the values for the feature income are 54,000 and 16,000, respectively. With z-score normalization, a value of €73,600 for income is transformed to:

$$\frac{73{,}600 - 54{,}000}{16{,}000} = 1.225$$

Data Normalization – Decimal Scaling Normalization

- Transform the data by moving the decimal points of values of attribute A.
- The number of decimal points moved depends on the maximum absolute value of A.
- A value v of A is normalized to v' by computing: $v' = \frac{v}{10^j}$

  where j is the smallest integer such that $\max(|v'|) < 1$

Data Normalization – Decimal Scaling Normalization

- Example:
  - Suppose that the recorded values of A range from -986 to 917.
  - The maximum absolute value of A is 986.
  - To normalize by decimal scaling, we divide each value by 1,000 (i.e., $j = 3$) so that -986 normalizes to -0.986 and 917 normalizes to 0.917

Data Transformation (Cont.)

- Demo
  - Use data transformation tools – Example: flash fill of Microsoft Excel, Trifacta Wrangler
  - Transforming data in Python

Data Integration (Revisited)

Data Integration (Revisited)

- 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

Handling Redundancy when Integrating Data

- Handling data redundancy is an important task of the data integration
- Redundant data occur often when integration of multiple datasets
  - *Object identification*: The same attribute or object may have different names in different datasets
  - *Derivable data:* One attribute may be a “derived” attribute in another table, e.g., annual revenue
- Redundant attributes can be detected by correlation and covariance analysis
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining quality

Data Reduction

Data Reduction

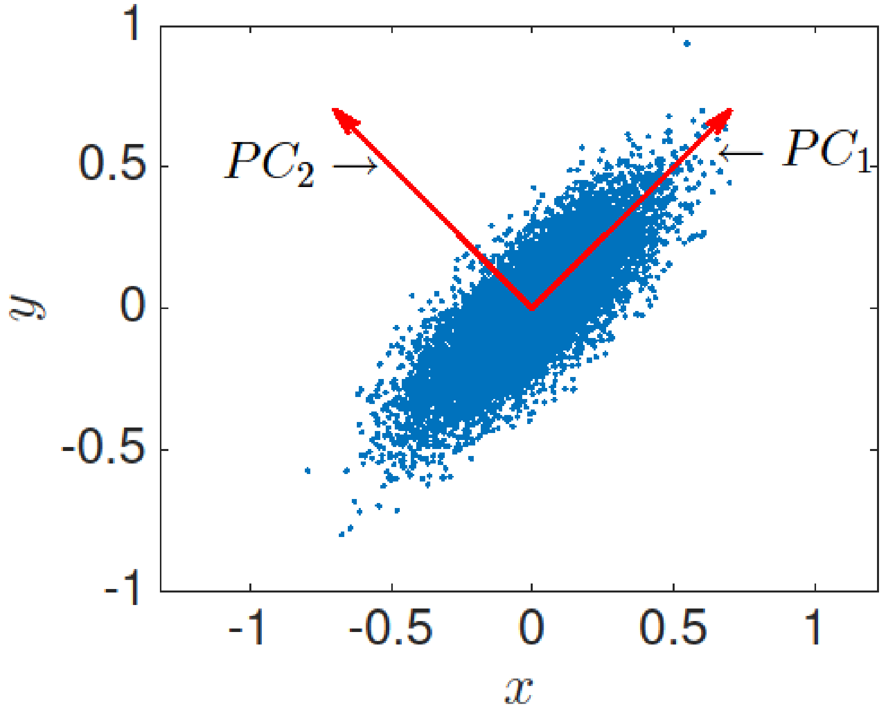
- **Data reduction**: obtain a reduced representation of the dataset
  - Much smaller in volume but yet produces the same (or almost the same) analytical results
- Why data reduction?
  - A dataset could be extremely large – Complex data analysis may take a very long time to run on the complete dataset.
- Data reduction strategies
  - Dimensionality reduction, e.g., remove unimportant attributes
    - Principal Components Analysis (PCA)
    - Singular Value Decomposition (SVD)
    - Feature subset selection, feature creation

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
- 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

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

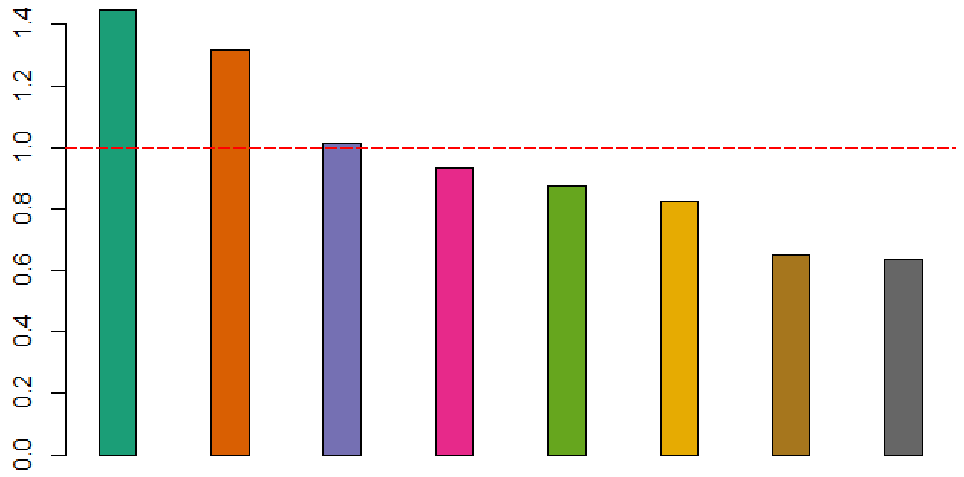


Principal Component Analysis (Steps)

- Given N data vectors from d-dimensions, find $k \leq d$ 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

PCA for Dimensionality Reduction

- Can ignore the components of lesser significance.



- You lose some information, but if the eigenvalues are small, it is not much
  - d dimensions in original data
  - calculate d eigenvectors and eigenvalues
  - choose only the first k eigenvectors, based on their eigenvalues (eigenvectors with eigenvalues greater than 1 are considered important)
  - final data set has only k dimensions

Attribute Subset Selection for Data Reduction

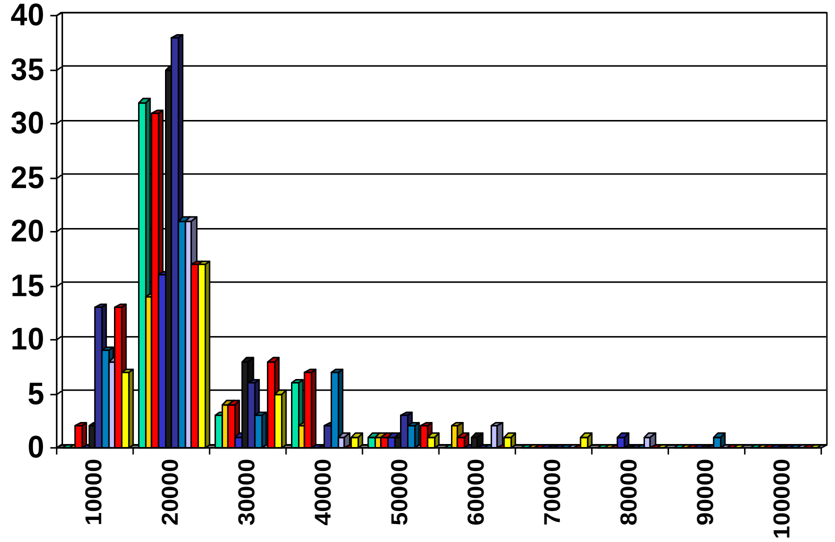
- Another way to reduce dimensionality of data
- Redundant attributes
  - Duplicate much or all of the information contained in one or more other attributes
  - E.g., purchase price of a product and the amount of sales tax paid
- Irrelevant attributes
  - Contain no information that is useful for the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

Model-Based Data Reduction

- 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
  - Approximate data by a function whose logarithm is linear

Histograms for Data Reduction

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



Clustering-Based Data Reduction

- 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
- Clustering will be studied in more details later during the course

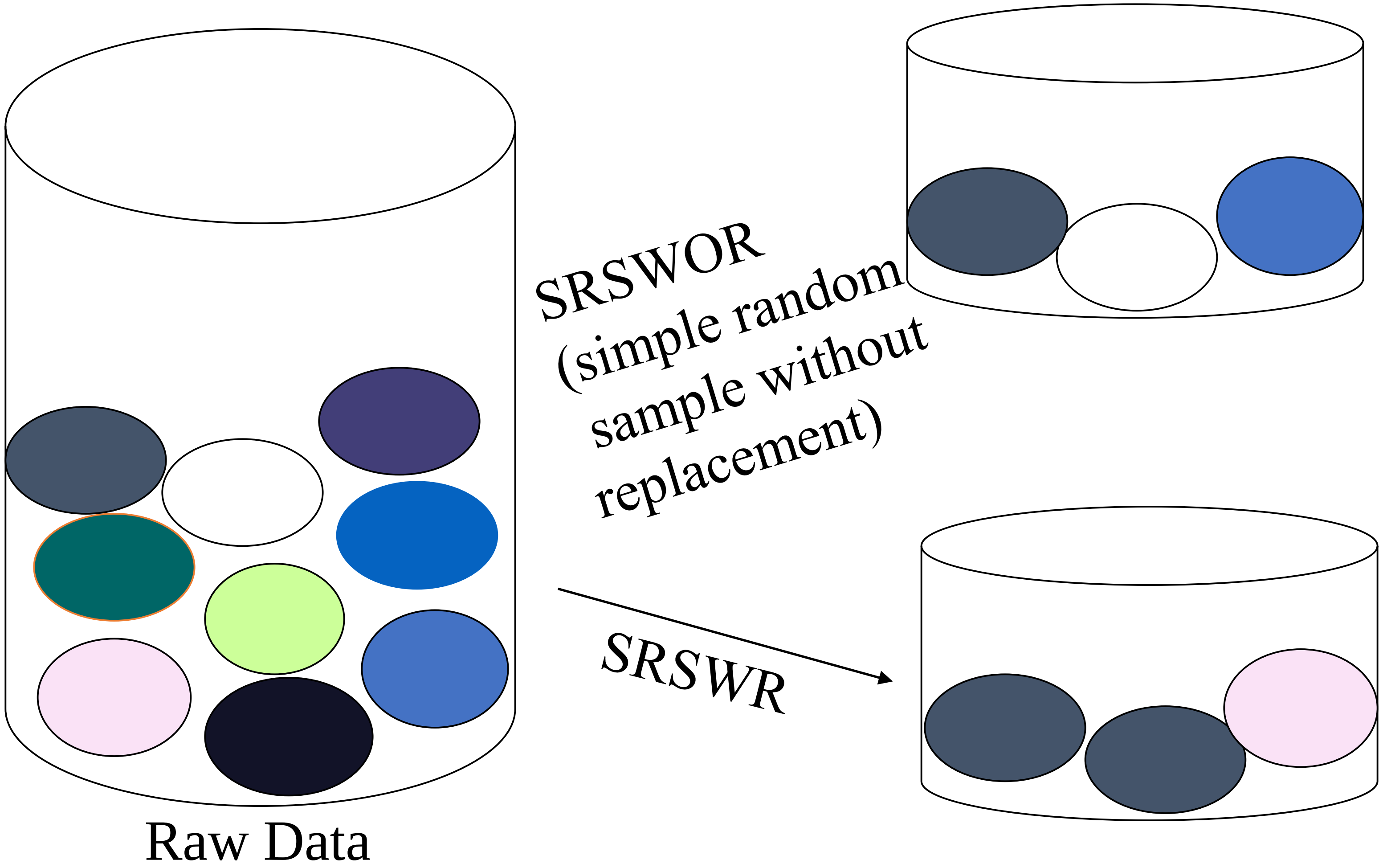
Sampling-Based Data Reduction

- 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)

Types of Sampling

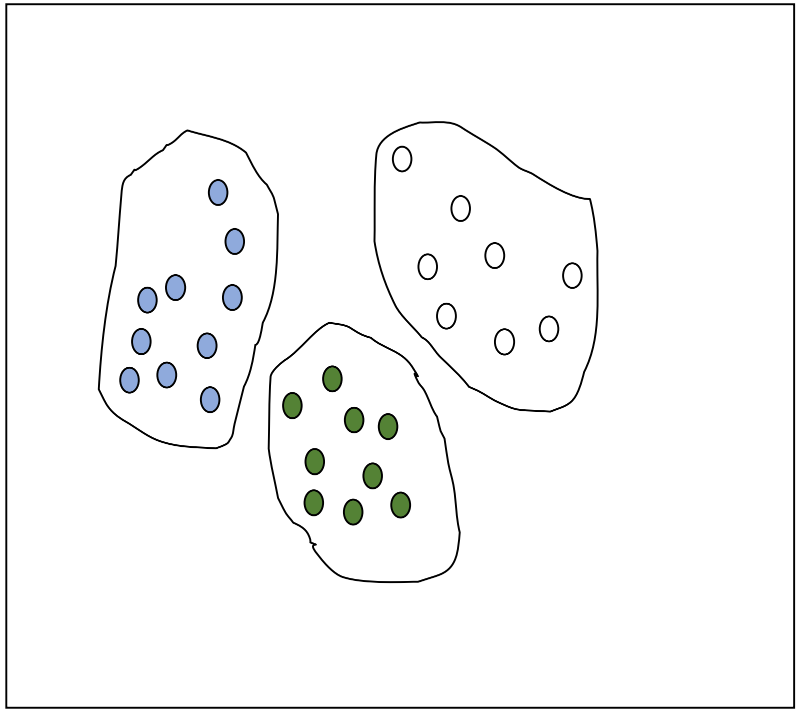
- Simple random sampling
  - There is an equal probability of selecting any particular item
- Sampling without replacement
  - Once an object is selected, it is removed from the population
- Sampling with replacement
  - A selected object is not removed from the population
- Stratified sampling:
  - Partition the data set, and draw samples from each partition (proportionally, i.e., approximately the same percentage of the data)
  - Used in conjunction with skewed data

Sampling – with or without Replacement

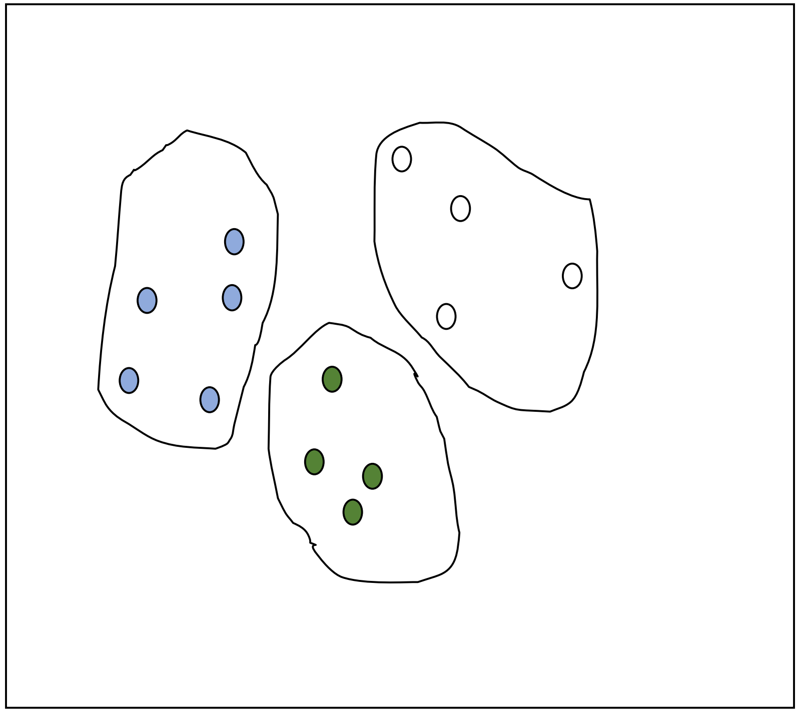


Sampling – Cluster or Stratified Sampling

Raw Data



Cluster/Stratified Sample



Data Cube Aggregation

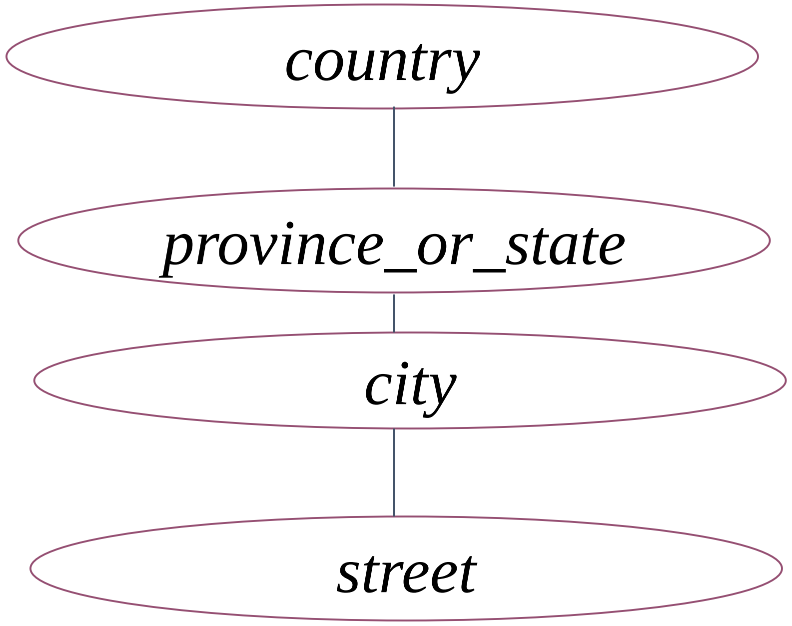
- The lowest level of a data cube (base cuboid)
  - The aggregated data for an individual entity of interest
  - E.g., a customer in a phone calling data warehouse
- Multiple levels of aggregation in data cubes
  - Further reduce the size of data to deal with
- Reference appropriate levels
  - Use the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

Data Compression

- String compression
  - There are extensive theories and well-tuned algorithms
  - 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
- Dimensionality and numerosity reduction may also be considered as forms of data compression

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



15 distinct values

365 distinct values

3567 distinct values

674,339 distinct values

Data Discretization

Data 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
  - Numeric: real numbers, e.g., integer or real numbers
- Discretization: Divide the range of a continuous attribute into intervals
  - Interval labels can be used to replace actual data values
  - Supervised vs. unsupervised
  - Split (top-down) vs. merge (bottom-up)

Discretization Methods

- Typical methods: All the methods can be applied recursively
  - Binning – Histograms
  - Clustering
  - Classification (e.g. Decision-trees)
  - Correlation

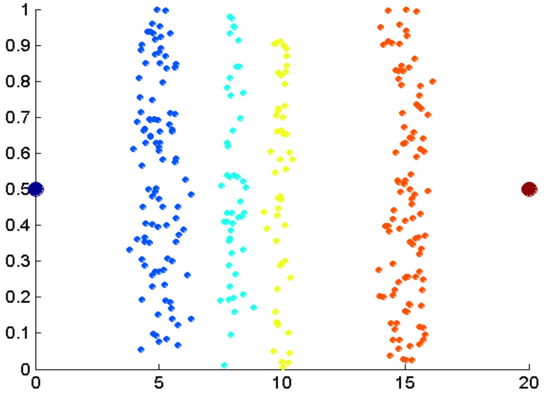
Discretization Methods – Binning

- Equal-width (distance) partitioning
  - Divides the range into N intervals of equal size: uniform grid
  - If A and B are the smallest and largest 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

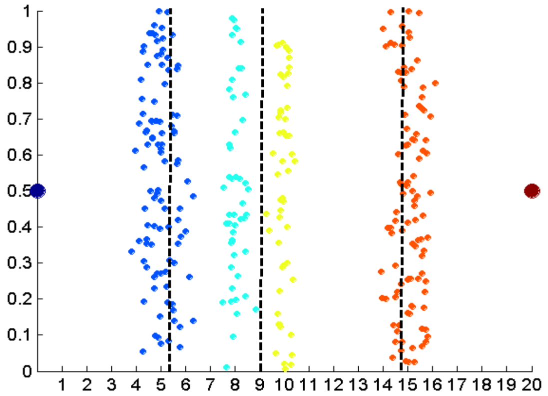
Discretization Methods – Binning (Cont.)

- 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

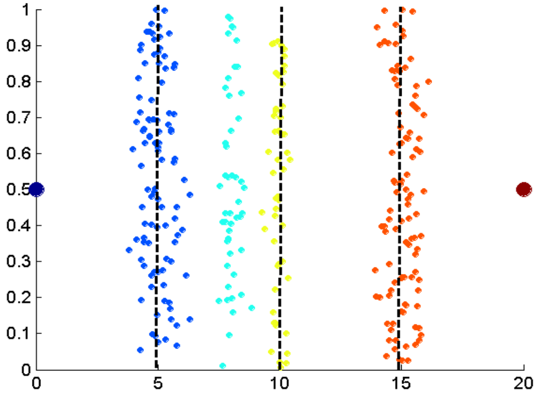
Discretization Methods – Binning (Cont.)



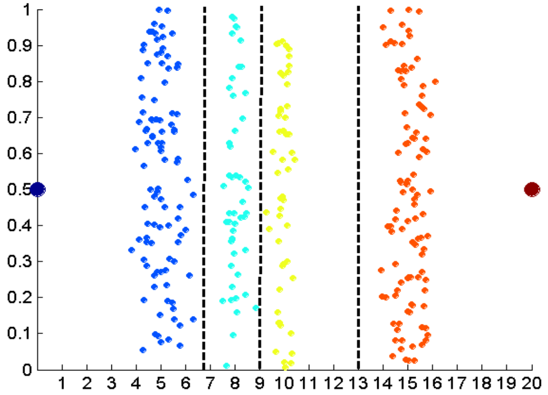
Data



Equal frequency (binning)



Equal width (binning)



Clustering-based discretization leads to better results (for this dataset)

Discretization Methods – Classification & Correlation

- 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 later during the course
- Correlation analysis (e.g., Chi-merge: χ^2-based discretization)
  - Supervised: use class information
  - Bottom-up merge: find the best neighboring intervals (those having similar distributions of classes, i.e., low χ^2 values) to merge
  - Merge performed recursively, until a predefined stopping condition is satisfied

Summary

- 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

Reading Material & Exercises

- Chapter 3 of the Data Mining: Concepts and Techniques Book