Data Wrangling and Data Analysis

Data Preparation (2)

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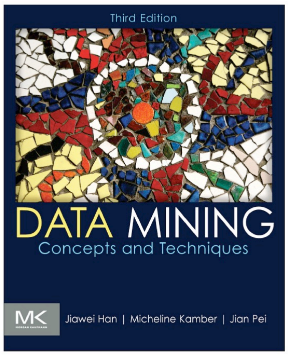
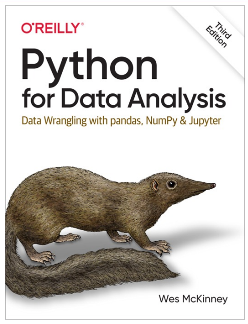
Reading Material for Today

- Data Mining: Concepts and Techniques Book

  CH 3.3 – 3.5

- Python for Data Analysis, 3E
  CH 7.2





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Topics for Today

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

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Data Transformation

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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

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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

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Data Normalization (Standardization)

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

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Data Normalization – Min-Max Normalization

- Transform the data from a given range with $[min_A, max_A]$ to a new interval $[new\_min_A, new\_max_A]$ 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.

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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:

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

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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.

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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:

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

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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 $\max(|v'|) < 1$

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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.)

- Exercise
  - Use flash fill of Microsoft Excel to convert set of names from the format Family_name, First_name middle_initial. to First_name Family_name
    - E.g. Wilsher, John K. to John Wilsher

Data Integration (Revisited)

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Data Integration

- Combines data from multiple sources into a coherent store
- Schema integration: e.g., A.cust-id ≡ B.cust-No
  - 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

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Handling Redundancy when Integrating Data

- Handling data redundancy is an important task of the data integration
- Duplicate records can be identified by applying entity resolution techniques
- 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

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Entity Resolution

Problem of identifying and linking/grouping different representations of the same real-world object.

Examples:

- Different ways of addressing (names, email addresses, FaceBook accounts) the same person in text.
- Web pages with differing descriptions of the same business.
- Different photos of the same object.
- …

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Ironically, Entity Resolution has Many Duplicate Names

Reference reconciliation

Record linkage

Duplicate detection

Fuzzy match

Object identification

Object consolidation

Deduplication

Entity clustering

Identity uncertainty

Approximate match

Household matching

Doubles

Reference matching

Hardening soft databases

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Entity Resolution – Normalization

- Schema Normalization
  - Schema matching: e.g., Contact No. vs. Phone
  - Compound attributes: e.g., address vs. (street, city, zip)
- Data Normalization
  - Capitalization, white-space normalization
  - Correcting typos, replacing abbreviations, variations, nick names
    - Usually done by employing dictionaries

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Entity Resolution – Matching Features

- Given two records, compute a vector of similarity scores for corresponding features
- E.g., to match two bibliographical references, compute:
  - First author match score
  - Title match score
  - Venue match score
  - Year match score
  - …
- Score can be Boolean (match/mismatch) or a continuous value based on specific similarity measure (distance function).

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Entity Resolution – Similarity Measures

- Atomic similarity measures
  - Difference between numerical values
  - Jaro for comparing names
  - Edit distance for typos
  - Phonetic-based
    - Soundex
- Set similarity
  - Jaccard similarity
- Vector-based
  - Cosine similarity

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Entity Resolution – Issues

- Similarity measures has different scales
  - How to combine the different values to compare the tuples
- Pairwise similarity between records is expensive
  - Takes $O(n^2)$
- Blocking to reduce the quadratic time complexity
  - Divide the records into blocks
  - Perform pairwise comparison between records within the same block only
  - When $\#blocks = k$ and block size $\approx (n/k)$, the time complexity $O(k(n/k)^2)$

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Data Reduction

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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

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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

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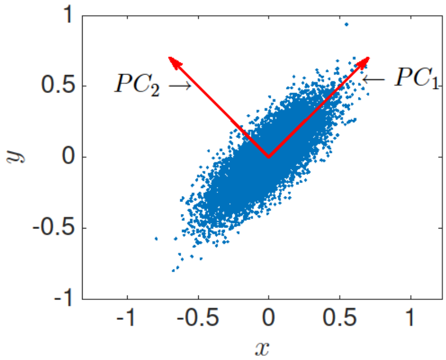
Principal Component Analysis (PCA)

- 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



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Principal Component Analysis (Steps)

- Given: N data vectors from d-dimensions, find $k \leq d$ principal components that can accurately represent the 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
  - The components are sorted
    - Reduce the data dimensionality by eliminating the weak components
    - Weak components have low variance
    - We can reconstruct a good approximation of the original data using strong components
- Works for numeric data only

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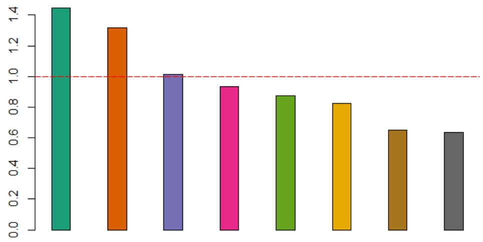
PCA for Dimensionality Reduction

- 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

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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

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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

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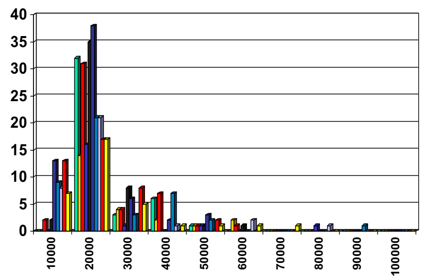
Histograms for Data Reduction

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



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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"
- There are many choices of clustering definitions and clustering algorithms
- Clustering will be studied in more details in weeks 7 & 8

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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)

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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

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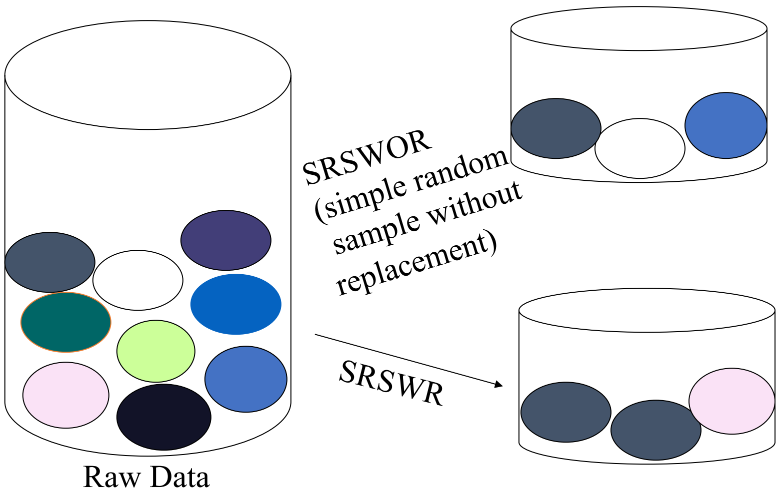
Sampling – with or without Replacement



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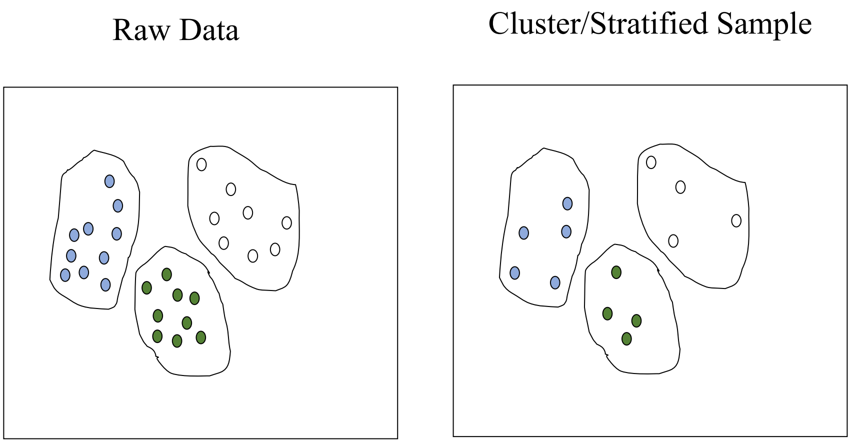
Sampling – Cluster or Stratified Sampling



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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

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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

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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

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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

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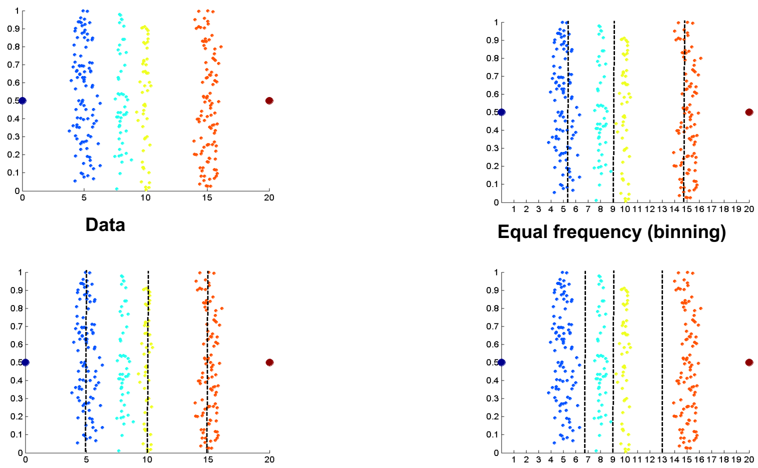
Discretization Methods – Binning (Cont.)



Data

Equal frequency (binning)

Equal width (binning)

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

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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
  - Supervised: use class information
  - Bottom-up merge: find the best neighboring intervals (those having similar distributions of classes) to merge
  - Merge performed recursively, until a predefined stopping condition is satisfied

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Other Data Preparation Techniques

Categorical feature

Color
Red
Red
Green
Blue
Yellow
Blue
Red
Blue

One-hot encoding

Red	Green	Blue	Yellow
1	0	0	0
1	0	0	0
0	1	0	0
0	0	0	0
0	0	0	1
0	0	1	0
1	0	0	0
0	0	1	0

Label encoding

Color
1
1
2
3
4
3
1
3

- Transforming categorical data into numerical data (See the Figure)
  - Label encoding
  - One-hot encoding
- Data Enrichment
  - Augmentation
  - Join & Union
- Data Validation
  - Check Permitted Characters
  - Find Type-Mismatched Data

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Wrap-Up

Summarize what you learned today in 2-minutes

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