CS 412 Intro. to Data Mining

Chapter 3. Data Preprocessing

Jiawei Han, Computer Science, Univ. Illinois at Urbana-Champaign, 2017

Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview
- Data Cleaning
- Data Integration
- Data Reduction and Transformation
- Dimensionality Reduction
- Summary

What is Data Preprocessing? — Major Tasks

- **Data cleaning**
  - Handle missing data, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- **Data integration**
  - Integration of multiple databases, data cubes, or files
- **Data reduction**
  - Dimensionality reduction
  - Numerosity reduction
  - Data compression
- **Data transformation and data discretization**
  - Normalization
  - Concept hierarchy generation

ทำไมต้อง Preprocess ข้อมูล?

ก่อนจะนำข้อมูลไปทำ Data Mining / Machine Learning เราต้อง **"ทำความสะอาดและจัดระเบียบ"** เพราะข้อมูลจริงมีปัญหาเยอะ เช่น

ข้อมูลหาย

ค่าผิด

ไม่สอดคล้องกัน

มีค่าแปลก ๆ (Outliers)

มาจากหลายแหล่งแล้ว Format ไม่เหมือนกัน

การ Preprocess จะช่วยให้ข้อมูล **สะอาด มีคุณภาพ และนำไปวิเคราะห์ได้แม่นยำขึ้น**

Why Preprocess the Data? — Data Quality Issues

- Measures for data quality: A multidimensional view
  - Accuracy: correct or wrong, accurate or not
  - Completeness: not recorded, unavailable, …
  - Consistency: some modified but some not, dangling, …
  - Timeliness: timely update?
  - Believability: how trustable the data are correct?
  - Interpretability: how easily the data can be understood?

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Data Cleaning

- Data in the Real World Is Dirty: Lots of potentially incorrect data, e.g., instrument faulty, human or computer error, and transmission error
  - Incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
    - e.g., *Occupation* = “ ” (missing data)
  - Noisy: containing noise, errors, or outliers
    - e.g., *Salary* = “−10” (an error)
  - Inconsistent: containing discrepancies in codes or names, e.g.,
    - *Age* = “42”, *Birthday* = “03/07/2010”
    - Was rating “1, 2, 3”, now rating “A, B, C”
    - discrepancy between duplicate records
  - Intentional (e.g., *disguised missing* data)
    - Jan. 1 as everyone’s birthday?

1) Data Cleaning – การทำความสะอาดข้อมูล

◆ ปัญหาข้อมูลจริง

Missing data – ค่าหาย เช่น อายุ = “ ”

Noisy data – ค่ามั่ว ค่าผิด เช่น salary = –10

Inconsistent data – ไม่สอดคล้อง เช่น
อายุ 42 แต่วันเกิด 2010

◆ วิธีแก้ Missing Data

ลบทิ้งทั้งแถว (ใช้กรณี label หาย)

กรอกเอง (ช้า)

ใช้ค่ากลาง เช่น ค่าเฉลี่ย

ใช้ค่าเฉลี่ยเฉพาะ class

ใช้วิธีทำนาย เช่น Bayesian, Decision Tree

◆ วิธีแก้ Noisy Data

Binning – แบ่งกลุ่มแล้วแทนด้วย mean/median

Regression – ลองฟิตเส้นแนวโน้ม

Clustering – หา outliers เพื่อเอาออก

Human + Computer ตรวจร่วมกัน

Incomplete (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 were not entered due to misunderstanding
  - Certain data may not be considered important at the time of entry
  - Did not register history or changes of the data
- Missing data may need to be inferred

How to Handle Missing Data?

- Ignore the tuple: usually done when class label is missing (when doing classification)—not effective when the % 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**

Noisy Data

- **Noise:** random error or variance in a measured variable
- **Incorrect attribute values** may be due to
  - Faulty data collection instruments
  - Data entry problems
  - Data transmission problems
  - Technology limitation
  - Inconsistency in naming convention
- **Other data problems**
  - Duplicate records
  - Incomplete data
  - Inconsistent data

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
- Semi-supervised: Combined computer and human inspection
  - Detect suspicious values and check by human (e.g., deal with possible outliers)

Data Cleaning as a Process

- **Data discrepancy detection**
  - Use metadata (e.g., domain, range, dependency, distribution)
  - Check field overloading
  - 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)
- **Data migration and integration**
  - Data migration tools: allow transformations to be specified
  - ETL (Extraction/Transformation/Loading) tools: allow users to specify transformations through a graphical user interface
- Integration of the two processes
  - Iterative and interactive (e.g., Potter’s Wheels)

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Data Integration

- Data integration
  - Combining data from multiple sources into a coherent store
- Schema integration: e.g., A.cust-id ≡ B.cust-#
  - Integrate metadata from different sources
- **Entity identification:**
  - 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

2) Data Integration — รวมข้อมูลจากหลายแหล่ง

ใช้เมื่อข้อมูลมาจากหลายตาราง หลายระบบ และต้องรวมให้ "พูดภาษาเดียวกัน"

ปัญหาหลัก

ชื่อตัวแปรไม่เหมือนกัน เช่น cust-id ≡ cust-#

คนเดียวกัน แต่สะกดต่างกัน เช่น Bill Clinton = William Clinton

หน่วยต่างกัน เช่น kg vs pound

ข้อมูลซ้ำซ้อน

การทำ Integration ช่วยลด redundancy และเพิ่มความเร็วในการวิเคราะห์

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* and *covariance analysis***
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

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**
  - Reducing the number of random variables under consideration, via obtaining a set of principal variables
- **Advantages of 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

3) Data Reduction — ลดปริมาณข้อมูล

ทำให้ข้อมูลเล็กลง แต่ยังคงความสำคัญเหมือนเดิม เพื่อ

ประมวลผลเร็วขึ้น

ใช้พื้นที่น้อยลง

ลด noise

ทำ visualization ง่ายขึ้น

ประเภท:

✓ ***Dimensionality reduction***

ลดจำนวนตัวแปร เช่น PCA, Feature selection

✓ ***Numerosity reduction***

ลดจำนวนข้อมูล เช่น sampling, aggregation

✓ ***Data compression***

Dimensionality Reduction Techniques

- Dimensionality reduction methodologies
  - **Feature selection**: Find a subset of the original variables (or features, attributes)
  - **Feature extraction**: Transform the data in the high-dimensional space to a space of fewer dimensions
- Some typical dimensionality methods
  - Principal Component Analysis
  - Supervised and nonlinear techniques
    - Feature subset selection
    - Feature creation

4) Dimensionality Reduction — ลดจำนวนมิติ

ปัญหา: Curse of Dimensionality

ยิ่งตัวแปรเยอะ ข้อมูลยิ่งกระจาย → การหาความเหมือน, clustering จะยากขึ้นมาก

วิธีลดมิติ

- **Feature Selection**

เลือกแค่ตัวแปรสำคัญ เช่นใช้ Stepwise, Correlation

- **Feature Extraction**

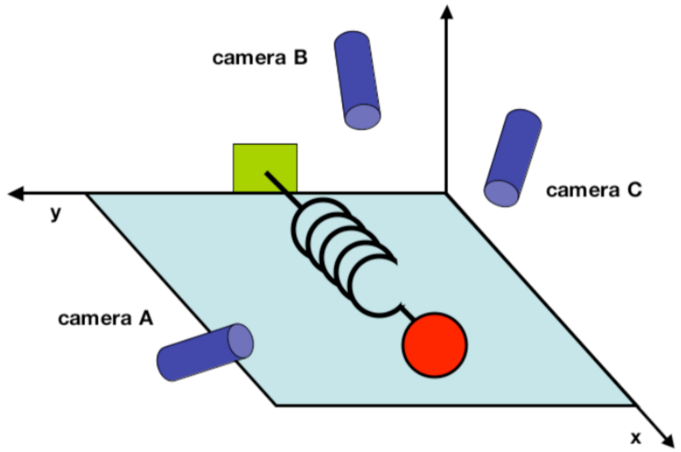
สร้างมิติใหม่ เช่น

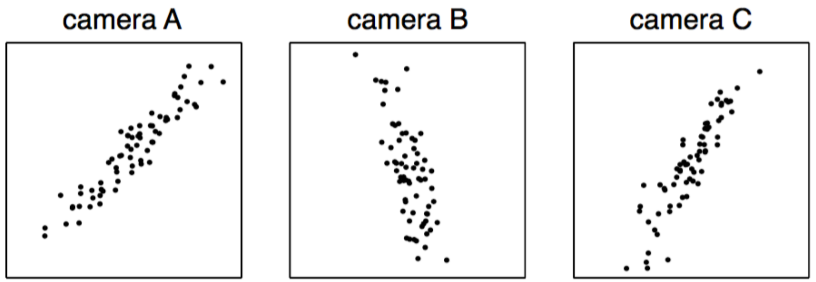
PCA

Nonlinear transformation

Principal Component Analysis (PCA)

- PCA: A statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called ***principal components***
- The original data are projected onto a much smaller space, resulting in dimensionality reduction
- Method: Find the eigenvectors of the covariance matrix, and these eigenvectors define the new space

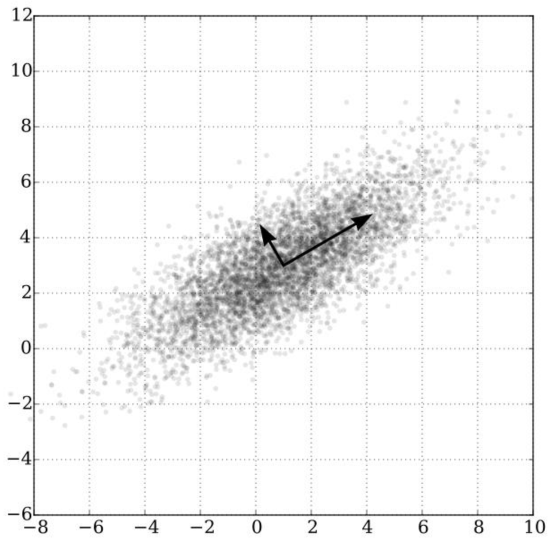




Ball travels in a straight line. Data from three cameras contain much redundancy

Principal Component Analysis (Method)

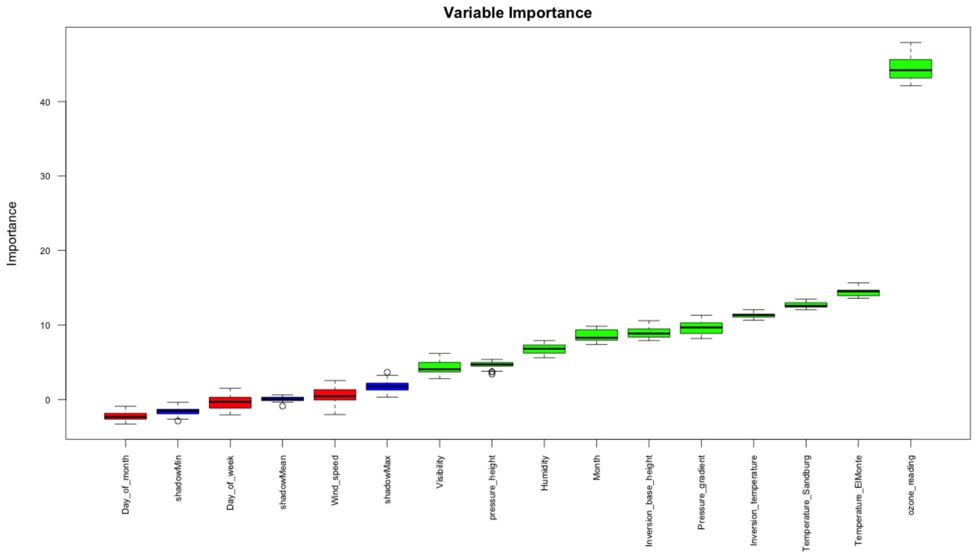
- Given N data vectors from n-dimensions, find $k \leq n$ orthogonal vectors (*principal components*) best used to represent data
  - Normalize input data: Each attribute falls within the same range
  - Compute k orthonormal (unit) vectors, i.e., *principal components*
  - Each input data (vector) is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



Ack. Wikipedia: Principal Component Analysis

Attribute Subset Selection

- 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
    - Ex. A student’s ID is often irrelevant to the task of predicting his/her GPA



PCA (Principal Component Analysis) แบบจำง่าย

ใช้กับข้อมูลตัวเลข

สร้างตัวแปรใหม่ที่เรียกว่า “Principal Components”

เป็นตัวแปรที่ไม่สัมพันธ์กัน (Orthogonal)

เอาเฉพาะตัวที่อธิบาย variance ได้มาก → ลดมิติ

ขั้นตอน:

Normalize ข้อมูล

สร้าง Covariance Matrix

หา Eigenvectors → คือแกนใหม่

เลือกแกนที่มี eigenvalue สูงที่สุด

Project ข้อมูลไปบนแกนใหม่

Heuristic Search in Attribute Selection

- 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

5) Attribute Subset Selection — เลือกตัวแปร

ลดมิติด้วยการ "เลือก" ไม่ได้สร้างตัวแปรใหม่

ตัวแปรที่ควรตัดออก:

Redundant – ซ้ำ เช่น ราคาสินค้า + VAT

Irrelevant – ไม่เกี่ยว เช่น Student ID ทำนาย GPA

6) Attribute Creation — สร้างตัวแปรใหม่

ทำเมื่อข้อมูลเดิมจับ pattern ไม่ได้ดี

วิธี:

Attribute extraction (domain knowledge)

Mapping เช่น Fourier, wavelet

Attribute construction (สร้างตัวแปรจากตัวเดิม)

Data discretization (แบ่งช่วงค่า)

Attribute Creation (Feature Generation)

- 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, manifold approaches (not covered)
  - Attribute construction
    - Combining features (see: discriminative frequent patterns in Chapter on “Advanced Classification”)
    - Data discretization

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, data transformation and data discretization**
  - Numerosity reduction; Data compression
  - Normalization; Concept hierarchy generation
- **Dimensionality reduction**

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