DATA MINING - 1DL105, 1DI111

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An introductory class in data mining

http://www.it.uu.se/edu/course/homepage/infoutv/ht06

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Course contents (preliminary)

- Course intro - introduction to data mining
- Overview of data mining techniques
- Classification
- Clustering
- Association rules
- Mining sequential patterns
- Web content mining
- Search engines
- Data mining and privacy
Course contents continued ...

- **Tutorials:**
  - Introduction to MATLAB
  - Tutorial on assignment 1
  - Tutorial on assignment 2
  - Tutorial on assignment 3 and 4

- **Assignments**
  - Assignment 1 - Classification using K Nearest Neighbours (KNN)
  - Assignment 2 - Clustering using K-Means vs. DBSCAN
  - Assignment 3 - Association Rule Mining
  - Assignment 4 - Web Searching using the HITS algorithm
Introduction to Data Mining

(Tan, Steinbach, Kumar ch. 1)

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Data Mining

• The process of extracting valid, previously unknown, comprehensible, and actionable information from large databases and using it to make crucial business decisions, (Simoudis, 1996).

• Involves the analysis of data and the use of software techniques for finding hidden and unexpected patterns and relationships in sets of data.

• Reveals information that is hidden and unexpected, as little value in finding patterns and relationships that are already intuitive.

• Patterns and relationships are identified by examining the underlying rules and features in the data.
Data Mining continued ...

• Tends to work from the data up and most accurate results normally require large volumes of data to deliver reliable conclusions.

• Starts by developing an optimal representation of structure of sample data, during which time knowledge is acquired and extended to larger sets of data.

• Data mining can provide huge paybacks for companies who have made a significant investment in data warehousing.

• Relatively new technology, however already used in a number of industries.
Why Data Mining?

• The Explosive Growth of Data: from terabytes to petabytes
  – Data collection and data availability
    • Automated data collection tools, database systems, Web, computerized society
  – Major sources of abundant data
    • Business: Web, e-commerce, transactions, stocks, …
    • Science: Remote sensing, bioinformatics, scientific simulation, …
    • Society and everyone: news, digital cameras,

• We are drowning in data, but starving for knowledge!
Evolution of Database Technology

• 1960s:
  – Data collection, database creation, IMS and network DBMS
• 1970s:
  – Relational data model, relational DBMS implementation
• 1980s:
  – RDBMS, advanced data models (extended-relational, OO, deductive, etc.)
  – Application-oriented DBMS (spatial, scientific, engineering, etc.)
• 1990s:
  – Data mining, data warehousing, multimedia databases, and Web databases
• 2000s
  – Stream data management and mining
  – Data mining and its applications
  – Web technology (XML, data integration) and global information systems
What Is Data Mining?

• Data mining (knowledge discovery from data)
  – Extraction of interesting (non-trivial, implicit, previously unknown and potentially useful) patterns or knowledge from huge amount of data
  – Exploration & analysis, by automatic or semi-automatic means, of large quantities of data in order to discover meaningful patterns
What is data mining - continued …

• Data mining: a misnomer?

• Alternative names
  – Knowledge discovery (mining) in databases (KDD), knowledge extraction, data/pattern analysis, data archeology, data dredging, information harvesting, business intelligence, etc.

• Watch out: Is everything “data mining”?
  – Simple search and query processing
  – (Deductive) expert systems
Data Mining Overview

Data-mining tools use advanced techniques from knowledge discovery, artificial intelligence, and other fields to obtain “knowledge” and apply it to business needs. Knowledge is then used to make predictions of events or forecasts of values such as sales returns. Several OLAP tools have integrated at least some of these data-mining features in their products.

Data Mining and Business Intelligence (Han & Kamber 2006)

Increasing potential to support business decisions

End User

Decision Making

Business Analyst

Data Presentation

Visualization Techniques

Data Analyst

Data Mining

Information Discovery

Data Exploration

Statistical Summary, Querying, and Reporting

DBA

Data Preprocessing/Integration, Data Warehouses

Data Sources

Paper, Files, Web documents, Scientific experiments, Database Systems
Data Mining Phases

FIGURE 13.23  Data mining phases

Operational database → Data preparation phase
- Identify data set
- Clean data set
- Integrate data set

Data warehouse → Data analysis and classification phase
- Classification analysis
- Clustering and sequence analysis
- Link analysis
- Trend and deviation analysis

Knowledge acquisition phase
- Select and apply algorithms
  - Neural nets
  - Inductive logic
  - Decision trees
  - Classification and regression tree
  - Nearest neighbor
  - Visualization, etc.

Prognosis phase
- Prediction
- Forecasting
- Modeling
Query Examples

• Database query
  – Find all credit applicants with last name of Smith.
  – Identify customers who have purchased more than $10,000 in the last month.
  – Find all customers who have purchased milk

• Data mining
  – Find all credit applicants who are poor credit risks. (classification)
  – Identify customers with similar buying habits. (clustering)
  – Find all items which are frequently purchased with milk. (association rules)
Data mining - a mix of multiple disciplines

- Database Technology
- Statistics
- Machine Learning
- Pattern Recognition
- Algorithm
- Visualization
- Other Disciplines
Data mining and related areas (Dunham, 2003)

- Similarity Measures
- Hierarchical Clustering
- IR Systems
- Imprecise Queries
- Textual Data
- Web Search Engines

- Bayes Theorem
- Regression Analysis
- EM Algorithm
- K-Means Clustering
- Time Series Analysis

- Neural Networks
- Decision Tree Algorithms

- Relational Data Model
- SQL
- Association Rule Algorithms
- Data Warehousing
- Scalability Techniques

- Algorithm Design Techniques
- Algorithm Analysis
- Data Structures

- Databases
- Information Retrieval
- DATA MINING
- Statistics
- Machine Learning
Why Not Traditional Data Analysis?

• Tremendous amount of data
  – Algorithms must be highly scalable to handle such as tera-bytes of data

• High-dimensionality of data
  – Micro-array may have tens of thousands of dimensions

• High complexity of data
  – Data streams and sensor data
  – Time-series data, temporal data, sequence data
  – Structure data, graphs, social networks and multi-linked data
  – Heterogeneous databases and legacy databases
  – Spatial, spatiotemporal, multimedia, text and Web data
  – Software programs, scientific simulations

• New and sophisticated applications
Why Mine Data? Commercial Viewpoint

• Lots of data is being collected and warehoused
  – Web data, e-commerce
  – purchases at department/grocery stores
  – Bank/Credit Card transactions

• Computers have become cheaper and more powerful

• Competitive Pressure is Strong
  – Provide better, customized services for an edge (e.g. in Customer Relationship Management)
Why Mine Data? Scientific Viewpoint

- Data collected and stored at enormous speeds (GB/hour)
  - remote sensors on a satellite
  - telescopes scanning the skies
  - microarrays generating gene expression data
  - scientific simulations generating terabytes of data
- Traditional techniques infeasible for raw data
- Data mining may help scientists
  - in classifying and segmenting data
  - in Hypothesis Formation
Mining Large Data Sets - Motivation

- There is often information “hidden” in the data that is not readily evident
- Human analysts may take weeks to discover useful information
- Much of the data is never analyzed at all

From: R. Grossman, C. Kamath, V. Kumar, “Data Mining for Scientific and Engineering Applications”
Why Data Mining?—Potential Applications

• Data analysis and decision support
  – Market analysis and management
    • Target marketing, customer relationship management (CRM), market basket analysis, cross selling, market segmentation
  – Risk analysis and management
    • Forecasting, customer retention, improved underwriting, quality control, competitive analysis
  – Fraud detection and detection of unusual patterns (outliers)

• Other Applications
  – Text mining (news group, email, documents) and Web mining
  – Stream data mining
  – Bioinformatics and bio-data analysis
Examples of applications of Data Mining

• Retail / Marketing
  – Identifying buying patterns of customers
  – Finding associations among customer demographic characteristics
  – Predicting response to mailing campaigns
  – Market basket analysis
Examples of applications of Data Mining

• Banking
  – Detecting patterns of fraudulent credit card use
  – Identifying loyal customers
  – Predicting customers likely to change their credit card affiliation
  – Determining credit card spending by customer groups
Examples of applications of Data Mining

• **Insurance**
  – Claims analysis
  – Predicting which customers will buy new policies

• **Medicine**
  – Characterizing patient behavior to predict surgery visits
  – Identifying successful medical therapies for different illnesses
Market Analysis and Management

• Where does the data come from?—Credit card transactions, loyalty cards, discount coupons, customer complaint calls, plus (public) lifestyle studies

• Target marketing
  – Find clusters of “model” customers who share the same characteristics: interest, income level, spending habits, etc.,
  – Determine customer purchasing patterns over time

• Cross-market analysis—Find associations/co-relations between product sales, & predict based on such association

• Customer profiling—What types of customers buy what products (clustering or classification)

• Customer requirement analysis
  – Identify the best products for different customers
  – Predict what factors will attract new customers

• Provision of summary information
  – Multidimensional summary reports
  – Statistical summary information (data central tendency and variation)
Corporate Analysis & Risk Management

• Finance planning and asset evaluation
  – cash flow analysis and prediction
  – contingent claim analysis to evaluate assets
  – cross-sectional and time series analysis (financial-ratio, trend analysis, etc.)

• Resource planning
  – summarize and compare the resources and spending

• Competition
  – monitor competitors and market directions
  – group customers into classes and a class-based pricing procedure
  – set pricing strategy in a highly competitive market
Fraud Detection & Mining Unusual Patterns

- Approaches: Clustering & model construction for frauds, outlier analysis
- Applications: Health care, retail, credit card service, telecomm.
  - Auto insurance: ring of collisions
  - Money laundering: suspicious monetary transactions
  - Medical insurance
    - Professional patients, ring of doctors, and ring of references
    - Unnecessary or correlated screening tests
  - Telecommunications: phone-call fraud
    - Phone call model: destination of the call, duration, time of day or week. Analyze patterns that deviate from an expected norm
  - Retail industry
    - Analysts estimate that 38% of retail shrink is due to dishonest employees
  - Anti-terrorism
Data Mining Tasks

• Prediction Methods
  – Use some variables to predict unknown or future values of other variables.

• Description Methods
  – Find human-interpretable patterns that describe the data.

From [Fayyad, et.al.] Advances in Knowledge Discovery and Data Mining, 1996
Data Mining Tasks...

- Classification [Predictive]
- Clustering [Descriptive]
- Association Rule Discovery [Descriptive]
- Sequential Pattern Discovery [Descriptive]
- Regression [Predictive]
- Deviation Detection [Predictive]
Data Mining Models and Tasks

Data Mining

Predictive
- Classification
- Regression
- Time Series Analysis
- Prediction

Descriptive
- Clustering
- Summarization
- Association Rules
- Sequence Discovery
Classification: Definition

• Given a collection of records (training set)
  – Each record contains a set of attributes, one of the attributes is the class.
• Find a model for class attribute as a function of the values of other attributes.
• Goal: previously unseen records should be assigned a class as accurately as possible.
  – A test set is used to determine the accuracy of the model. Usually, the given data set is divided into training and test sets, with training set used to build the model and test set used to validate it.
## Classification example

<table>
<thead>
<tr>
<th>Tid</th>
<th>Refund</th>
<th>Marital Status</th>
<th>Taxable Income</th>
<th>Cheat</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Yes</td>
<td>Single</td>
<td>125K</td>
<td>No</td>
</tr>
<tr>
<td>2</td>
<td>No</td>
<td>Married</td>
<td>100K</td>
<td>No</td>
</tr>
<tr>
<td>3</td>
<td>No</td>
<td>Single</td>
<td>70K</td>
<td>No</td>
</tr>
<tr>
<td>4</td>
<td>Yes</td>
<td>Married</td>
<td>120K</td>
<td>No</td>
</tr>
<tr>
<td>5</td>
<td>No</td>
<td>Divorced</td>
<td>95K</td>
<td>Yes</td>
</tr>
<tr>
<td>6</td>
<td>No</td>
<td>Married</td>
<td>60K</td>
<td>No</td>
</tr>
<tr>
<td>7</td>
<td>Yes</td>
<td>Divorced</td>
<td>220K</td>
<td>No</td>
</tr>
<tr>
<td>8</td>
<td>No</td>
<td>Single</td>
<td>85K</td>
<td>Yes</td>
</tr>
<tr>
<td>9</td>
<td>No</td>
<td>Married</td>
<td>75K</td>
<td>No</td>
</tr>
<tr>
<td>10</td>
<td>No</td>
<td>Single</td>
<td>90K</td>
<td>Yes</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Refund</th>
<th>Marital Status</th>
<th>Taxable Income</th>
<th>Cheat</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>Single</td>
<td>75K</td>
<td>?</td>
</tr>
<tr>
<td>Yes</td>
<td>Married</td>
<td>50K</td>
<td>?</td>
</tr>
<tr>
<td>No</td>
<td>Married</td>
<td>150K</td>
<td>?</td>
</tr>
<tr>
<td>Yes</td>
<td>Divorced</td>
<td>90K</td>
<td>?</td>
</tr>
<tr>
<td>No</td>
<td>Single</td>
<td>40K</td>
<td>?</td>
</tr>
<tr>
<td>No</td>
<td>Married</td>
<td>80K</td>
<td>?</td>
</tr>
</tbody>
</table>

- **Tid**: Tid
- **Refund**: Refund
- **Marital Status**: Marital Status
- **Taxable Income**: Taxable Income
- **Cheat**: Cheat

**Diagram:**
- Training Set → Learn Classifier → Model
- Test Set → Model
Classification: application 1

- **Direct Marketing**
  - **Goal:** Reduce cost of mailing by targeting a set of consumers likely to buy a new cell-phone product.
  - **Approach:**
    - Use the data for a similar product introduced before.
    - We know which customers decided to buy and which decided otherwise. This \{buy, don’t buy\} decision forms the class attribute.
    - Collect various demographic, lifestyle, and company-interaction related information about all such customers.
      - Type of business, where they stay, how much they earn, etc.
    - Use this information as input attributes to learn a classifier model.

From [Berry & Linoff] Data Mining Techniques, 1997
Classification: application 2

• **Fraud Detection**
  – **Goal:** Predict fraudulent cases in credit card transactions.
  – **Approach:**
    • Use credit card transactions and the information on its account-holder as attributes.
      – When does a customer buy, what does he buy, how often he pays on time, etc
    • Label past transactions as fraud or fair transactions. This forms the class attribute.
    • Learn a model for the class of the transactions.
    • Use this model to detect fraud by observing credit card transactions on an account.
Classification: application 3

- **Customer Attrition/Churn:**
  - **Goal:** To predict whether a customer is likely to be lost to a competitor.
  - **Approach:**
    - Use detailed record of transactions with each of the past and present customers, to find attributes.
      - How often the customer calls, where he calls, what time-of-the day he calls most, his financial status, marital status, etc.
    - Label the customers as loyal or disloyal.
    - Find a model for loyalty.

From [Berry & Linoff] Data Mining Techniques, 1997
Classification: application 4

• Sky Survey Cataloging
  – Goal: To predict class (star or galaxy) of sky objects, especially visually faint ones, based on the telescopic survey images (from Palomar Observatory).
    – 3000 images with 23,040 x 23,040 pixels per image.
  – Approach:
    • Segment the image.
    • Measure image attributes (features) - 40 of them per object.
    • Model the class based on these features.
    • Success Story: Could find 16 new high red-shift quasars, some of the farthest objects that are difficult to find!

From [Fayyad, et.al.] Advances in Knowledge Discovery and Data Mining, 1996
Classifying Galaxies

Early

Class:
• Stages of Formation

Intermediate

Attributes:
• Image features,
• Characteristics of light waves received, etc.

Late

Data Size:
• 72 million stars, 20 million galaxies
• Object Catalog: 9 GB
• Image Database: 150 GB

Courtesy: http://aps.umn.edu
Clustering Definition

- Given a set of data points, each having a set of attributes, and a similarity measure among them, find clusters such that
  - Data points in one cluster are more similar to one another.
  - Data points in separate clusters are less similar to one another.

- Similarity Measures:
  - Euclidean Distance if attributes are continuous.
  - Other Problem-specific Measures.
Illustrating Clustering

Euclidean Distance Based Clustering in 3-D space

Intracluster distances are minimized

Intercluster distances are maximized
Clustering: application 1

• **Market Segmentation:**
  - **Goal:** subdivide a market into distinct subsets of customers where any subset may conceivably be selected as a market target to be reached with a distinct marketing mix.
  - **Approach:**
    • Collect different attributes of customers based on their geographical and lifestyle related information.
    • Find clusters of similar customers.
    • Measure the clustering quality by observing buying patterns of customers in same cluster vs. those from different clusters.
Clustering: application 2

• **Document Clustering:**
  – **Goal:** To find groups of documents that are similar to each other based on the important terms appearing in them.
  – **Approach:** To identify frequently occurring terms in each document. Form a similarity measure based on the frequencies of different terms. Use it to cluster.
  – **Gain:** Information Retrieval can utilize the clusters to relate a new document or search term to clustered documents.
Illustrating Document Clustering

- Clustering Points: 3204 Articles of Los Angeles Times.
- Similarity Measure: How many words are common in these documents (after some word filtering).

<table>
<thead>
<tr>
<th>Category</th>
<th>Total Articles</th>
<th>Correctly Placed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Financial</td>
<td>555</td>
<td>364</td>
</tr>
<tr>
<td>Foreign</td>
<td>341</td>
<td>260</td>
</tr>
<tr>
<td>National</td>
<td>273</td>
<td>36</td>
</tr>
<tr>
<td>Metro</td>
<td>943</td>
<td>746</td>
</tr>
<tr>
<td>Sports</td>
<td>738</td>
<td>573</td>
</tr>
<tr>
<td>Entertainment</td>
<td>354</td>
<td>278</td>
</tr>
</tbody>
</table>
Clustering of S&P 500 Stock Data

- Observe Stock Movements every day.
- Clustering points: Stock-{UP/DOWN}
- Similarity Measure: Two points are more similar if the events described by them frequently happen together on the same day.
  - We used association rules to quantify a similarity measure.

<table>
<thead>
<tr>
<th>Discovered Clusters</th>
<th>Industry Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Applied-Matl-DOW N, Bay-Network-Down, 3-COM-DOWN,</td>
<td>Technology1-DOWN</td>
</tr>
<tr>
<td>Cabletron-Sys-DOWN, CISCO-DOWN, HP-DOWN, DSC-Comm-DOWN,</td>
<td></td>
</tr>
<tr>
<td>INTEL-DOWN, LSI-Logic-DOWN, Micron-Tech-DOWN, Texas-Inst-Down, Tellabs-Inc-Down,</td>
<td></td>
</tr>
<tr>
<td>Natl-Semiconduct-DOWN, Oracle-DOWN, SGI-DOWN, Sun-DOWN</td>
<td></td>
</tr>
<tr>
<td>2. Apple-Comp-DOWN N, Autodesk-DOWN, DEC-DOWN, ADV-Micro-Device-DOWN, Andrew-Corp-DOWN,</td>
<td></td>
</tr>
<tr>
<td>Computer-Assoc-DOWN, Circuit-City-DOWN, Compaq-DOWN, EM-Corp-DOWN, Gen-Inst-DOWN,</td>
<td></td>
</tr>
<tr>
<td>Motorola-DOWN, Microsoft-DOWN, Scientific-Atl-DOWN</td>
<td></td>
</tr>
<tr>
<td>4. Baker-Hughes-UP, Dresser-Inds-UP, Halliburton-HLD-UP,</td>
<td></td>
</tr>
<tr>
<td>Louisiana-Land-UP, Phillips-Petro-UP, Unocal-UP, Schlumberger-UP</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Association Rule Discovery: Definition

• Given a set of records each of which contain some number of items from a given collection;
  – Produce dependency rules which will predict occurrence of an item based on occurrences of other items.

<table>
<thead>
<tr>
<th>TID</th>
<th>Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Bread, Coke, Milk</td>
</tr>
<tr>
<td>2</td>
<td>Beer, Bread</td>
</tr>
<tr>
<td>3</td>
<td>Beer, Coke, Diaper, Milk</td>
</tr>
<tr>
<td>4</td>
<td>Beer, Bread, Diaper, Milk</td>
</tr>
<tr>
<td>5</td>
<td>Coke, Diaper, Milk</td>
</tr>
</tbody>
</table>

Rules Discovered:

\{\text{Milk}\} \rightarrow \{\text{Coke}\}
\{\text{Diaper, Milk}\} \rightarrow \{\text{Beer}\}
Association Rule Discovery: application 1

• Marketing and Sales Promotion:
  – Let the rule discovered be
    \{\text{Bagels, ...} \} \rightarrow \{\text{Potato Chips}\}
  – Potato Chips as consequent => Can be used to determine what should be done to boost its sales.
  – Bagels in the antecedent => Can be used to see which products would be affected if the store discontinues selling bagels.
  – Bagels in antecedent and Potato chips in consequent => Can be used to see what products should be sold with Bagels to promote sale of Potato chips!
Association Rule Discovery: application 2

• Supermarket shelf management.
  – Goal: To identify items that are bought together by sufficiently many customers.
  – Approach: Process the point-of-sale data collected with barcode scanners to find dependencies among items.
  – A classic rule --
    • If a customer buys diaper and milk, then he is very likely to buy beer.
    • So, don’t be surprised if you find six-packs stacked next to diapers!
• **Inventory Management:**
  – **Goal:** A consumer appliance repair company wants to anticipate the nature of repairs on its consumer products and keep the service vehicles equipped with right parts to reduce on number of visits to consumer households.
  – **Approach:** Process the data on tools and parts required in previous repairs at different consumer locations and discover the co-occurrence patterns.
Sequential Pattern Discovery: Definition

• Given is a set of objects, with each object associated with its own timeline of events, find rules that predict strong sequential dependencies among different events.

\[(A \quad B) \quad (C) \rightarrow (D \quad E)\]

• Rules are formed by first discovering patterns. Event occurrences in the patterns are governed by timing constraints.

\[(A \quad B) \quad (C) \quad (D) \quad (E)\]

\[\leq \text{xg} \quad >\text{ng} \quad \leq \text{ws} \quad \leq \text{ms}\]
Sequential Pattern Discovery: examples

• In telecommunications alarm logs,
  – (Inverter_Problem Excessive_Line_Current)
  – (Rectifier_Alarm) --> (Fire_Alarm)

• In point-of-sale transaction sequences,
  – Computer Bookstore:
    • (Intro_To_Visual_C) (C++_Primer) --> (Perl_for_dummies,Tcl_Tk)
  – Athletic Apparel Store:
    • (Shoes) (Racket, Racketball) --> (Sports_Jacket)
Regression

- Predict a value of a given continuous valued variable based on the values of other variables, assuming a linear or nonlinear model of dependency.
- Greatly studied in statistics, neural network fields.
- Examples:
  - Predicting sales amounts of new product based on advertising expenditure.
  - Predicting wind velocities as a function of temperature, humidity, air pressure, etc.
  - Time series prediction of stock market indices.
Deviation/Anomaly Detection

- Detect significant deviations from normal behavior
- Applications:
  - Credit Card Fraud Detection
  - Network Intrusion Detection

Typical network traffic at University level may reach over 100 million connections per day
Challenges of Data Mining

- Scalability
- Dimensionality
- Complex and heterogeneous data
- Data quality
- Data ownership and distribution
- Privacy preservation
- Streaming data