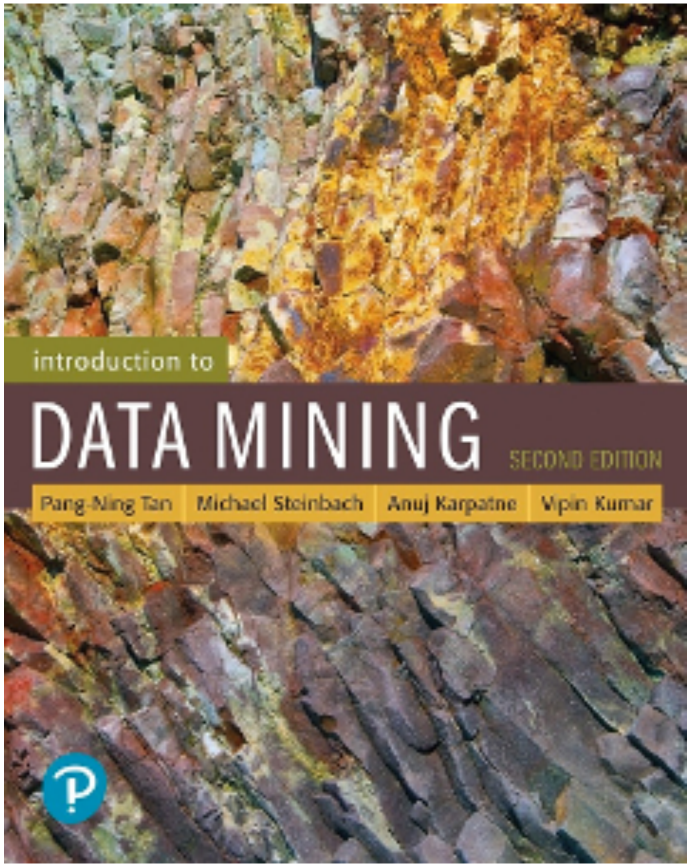
CMPSC 497: Introduction to Data Mining

- What is this course about?
  - Fundamental concepts, algorithms, and techniques for data mining and their applications to data warehouse and big data analytics.
  - Emphasis more on *algorithmic* aspects.
- What to expect?
  - Obtain broad knowledge in data mining & analytics and skills for their applications.
  - Exercise the obtained knowledge and skills to address important technical issues in realistic data mining tasks and applications

Textbook/Readings

- *Introduction to Data Mining*, 2nd Edition, by P.-N. Tan, M. Steinbach A, Karpatne and V. Kumar, Pearson.
- Supplementary materials
- Presentations extended from the slides of the textbook
- (Optional) *Data Mining: Concepts and Techniques*, by J. Han, M. Kamber, and P. Jian, Morgan Kaufmann.

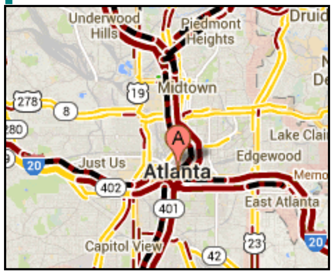


Big Data is Everywhere!

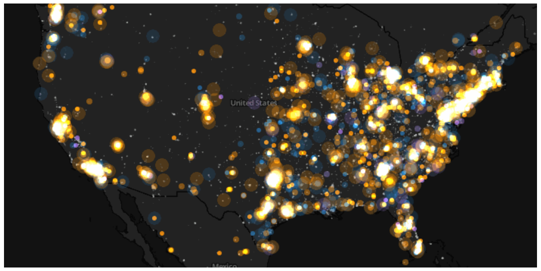
- Enormous data growth in both commercial and scientific databases due to advances in data generation and collection technologies
- New mantra: Gather whatever data you can whenever & wherever.
- Expectations: Gathered data have value either for the its purpose or for a purpose not envisioned.

Cyber Security

E-Commerce

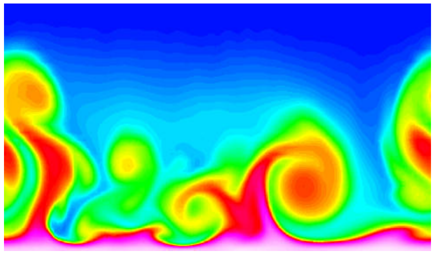


Traffic Patterns



Social Networking: Twitter

Sensor Networks



Computational Simulations

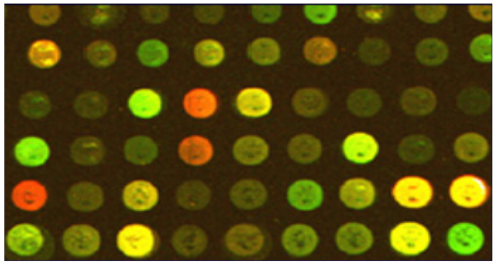
Why Mine Data? Commercial Viewpoint

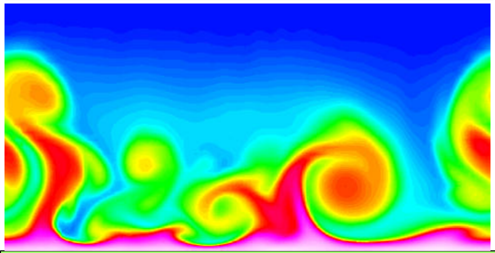
- Lots of data is being collected and warehoused
  - Web data（Peta Bytes)
  - Purchases at department/ grocery／e-commerce stores
  - Bank/Credit Card transactions

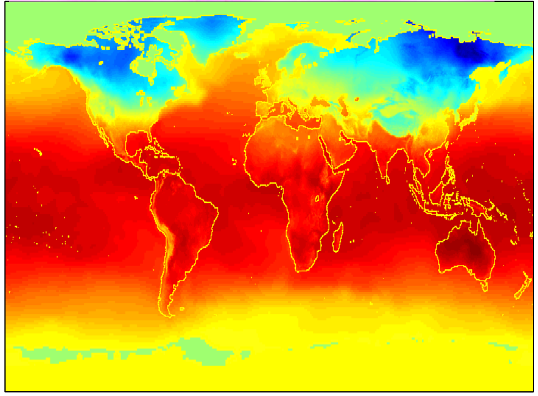
- Computers have become cheaper and more powerful
- Competitive Pressure is Strong
  - Provide better, customized services for an *edge* (e.g. in Customer Relationship Management)

Why Mine Data? Scientific Viewpoint

- Data collected at enormous speeds
  - remote sensors on a satellite
  - telescopes scanning the skies
  - microarrays generating gene expression data
  - scientific simulations
- Traditional techniques infeasible for raw data
- Data mining may help scientists
  - in classifying and segmenting data
  - in Hypothesis Formation

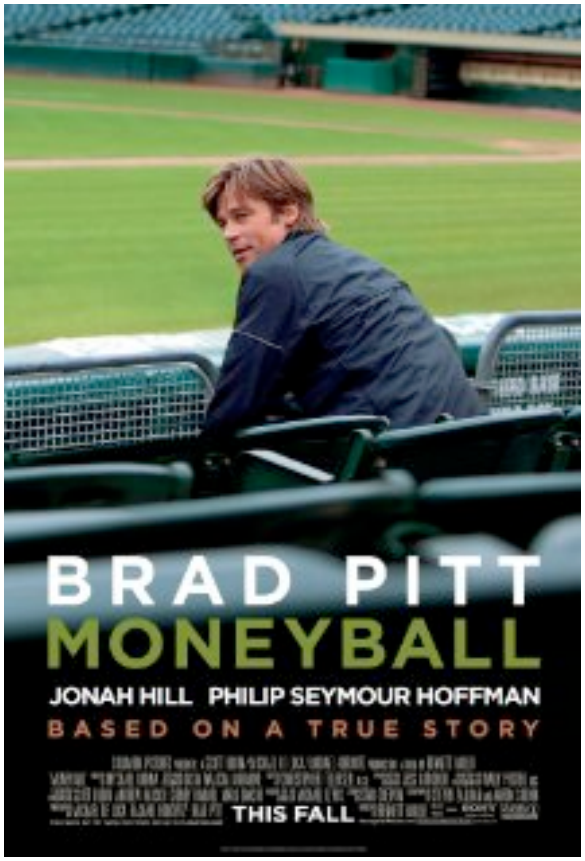






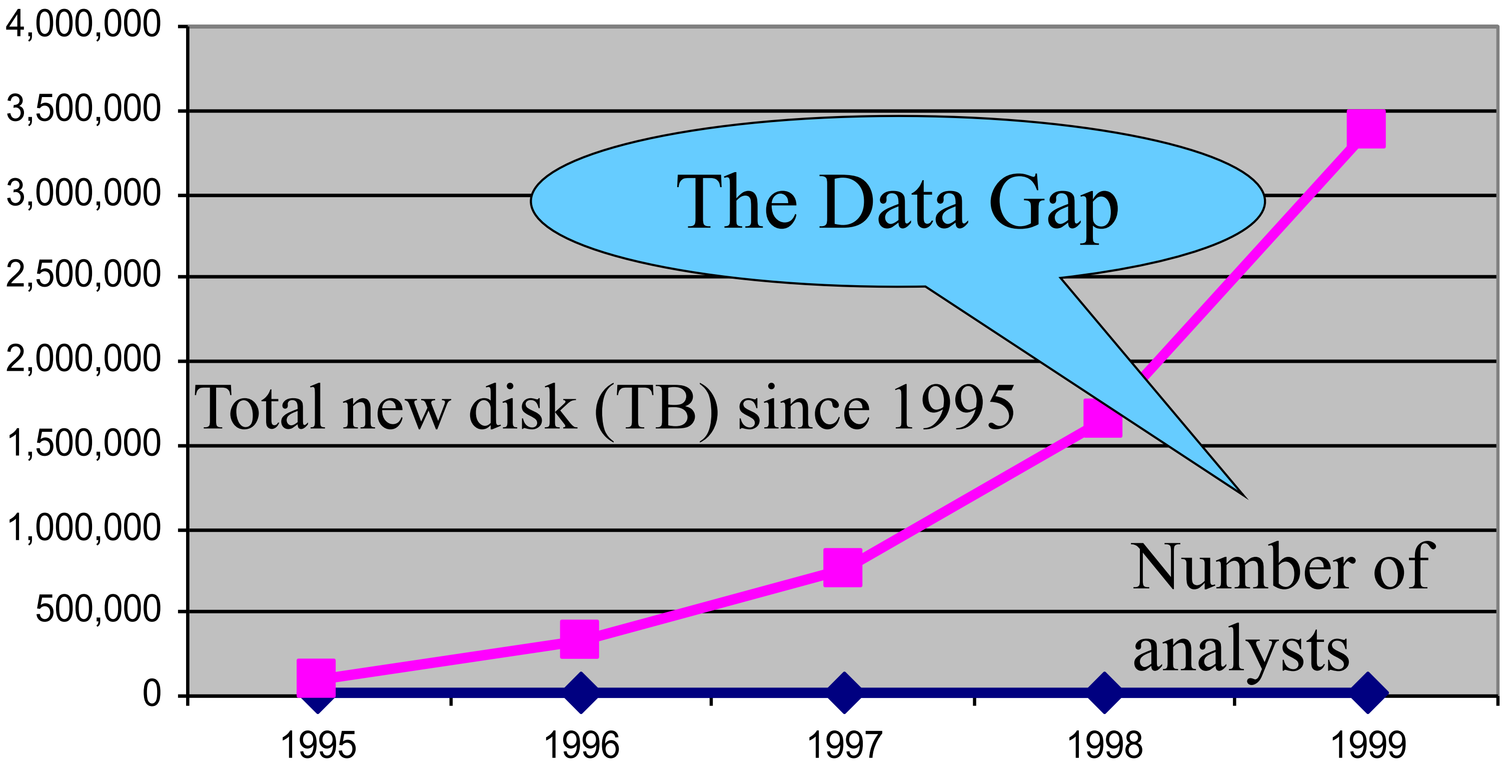
Motivation

- We are data rich but information poor
  - We are buried in data, but dying for information and knowledge.
- Data mining
  - Knowledge discovery in databases
  - Extraction of interesting knowledge (e.g., rules, regularities, patterns) from data in large databases.
- The uncovered knowledge can be used to *predict* the outcome of a future action/observation.

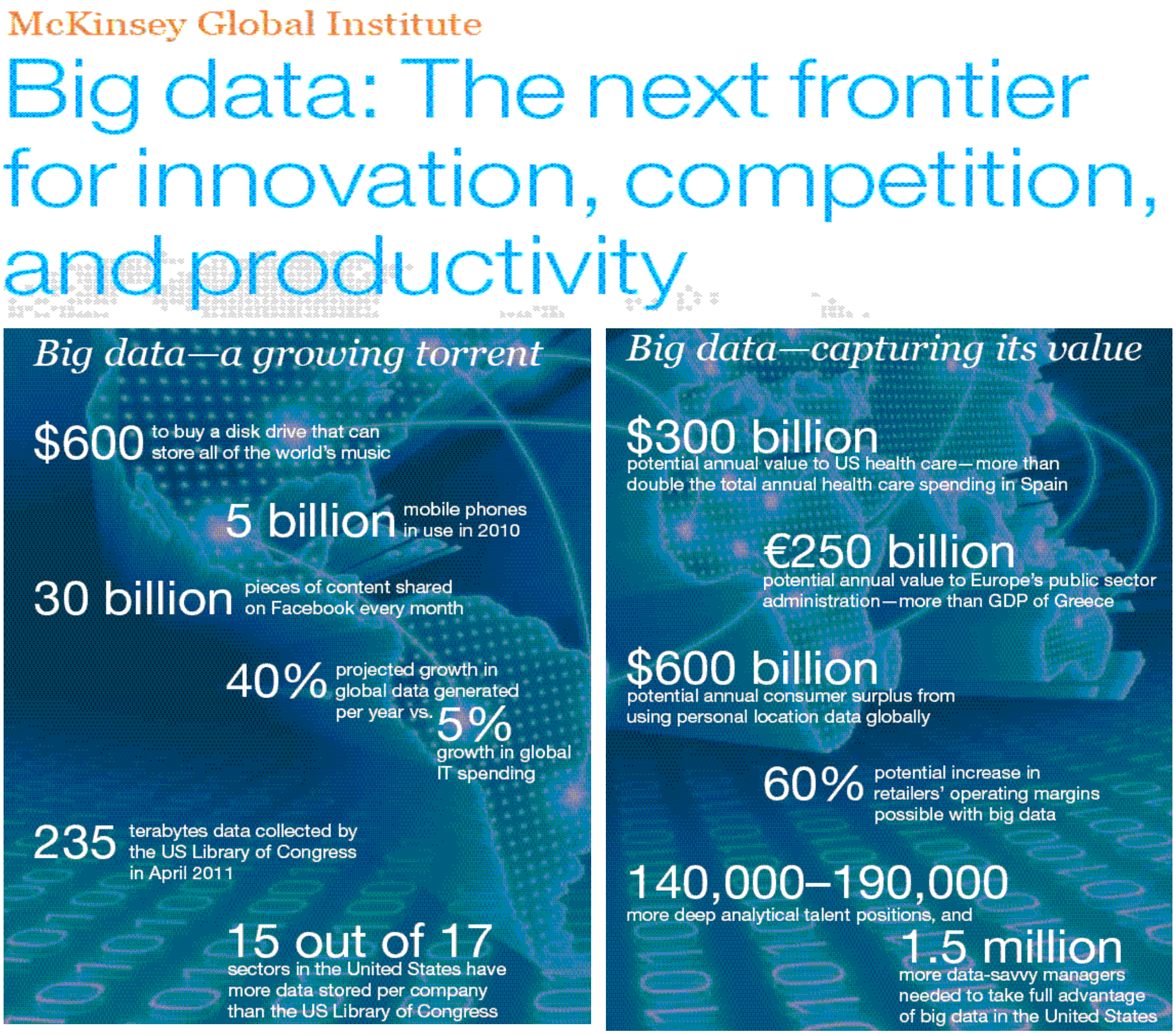


Mining Large Data Sets

- 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



Opportunities: Improve productivity



McKinsey Global Institute

Big data: The next frontier for innovation, competition, and productivity

Big data—a growing torrent

$600 to buy a disk drive that can store all of the world's music

5 billion mobile phones in use in 2010

30 billion pieces of content shared on Facebook every month

40% projected growth in global data generated per year vs. 5% growth in global IT spending

235 terabytes data collected by the US Library of Congress in April 2011

15 out of 17 sectors in the United States have more data stored per company than the US Library of Congress

Big data—capturing its value

$300 billion potential annual value to US health care—more than double the total annual health care spending in Spain

€250 billion potential annual value to Europe's public sector administration—more than GDP of Greece

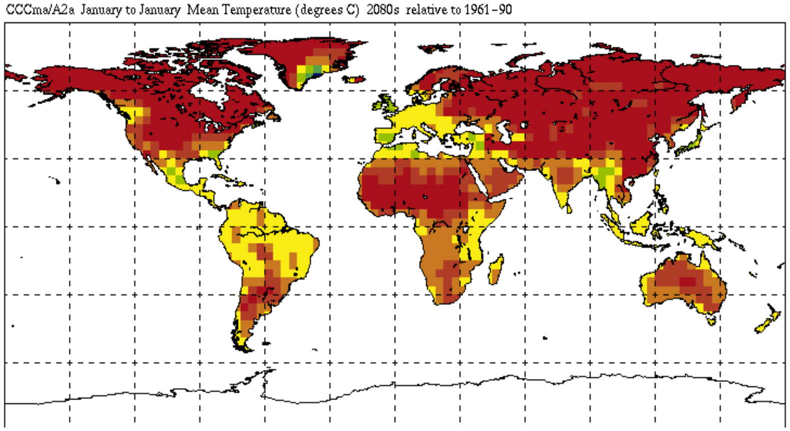
$600 billion potential annual consumer surplus from using personal location data globally

60% potential increase in retailers' operating margins possible with big data

140,000–190,000 more deep analytical talent positions, and 1.5 million more data-savvy managers needed to take full advantage of big data in the United States

Opportunities: Society Problems

Improving health care and reducing costs


CCCma/A2a January to January Mean Temperature (degrees C) 2080s relative to 1961-90

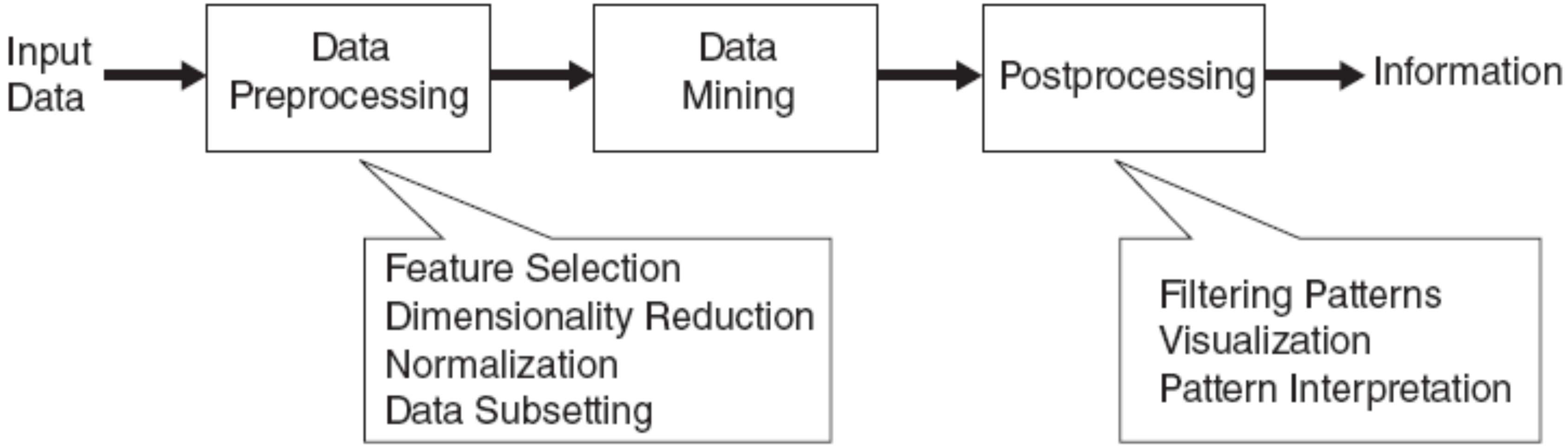
Predicting the impact of climate change

Finding alternative/ green energy sources

Reducing hunger and poverty by increasing agriculture production

What is Data Mining?

- Nontrivial extraction of implicit, previously unknown and potentially useful information from data
- Exploration & analysis, by automatic or semi-automatic means, of large quantities of data in order to discover meaningful patterns



Input Data

Data Preprocessing

Data Mining

Postprocessing

Information

Feature Selection
Dimensionality Reduction
Normalization
Data Subsetting

Filtering Patterns
Visualization
Pattern Interpretation

Figure 1.1. The process of knowledge discovery in databases (KDD).

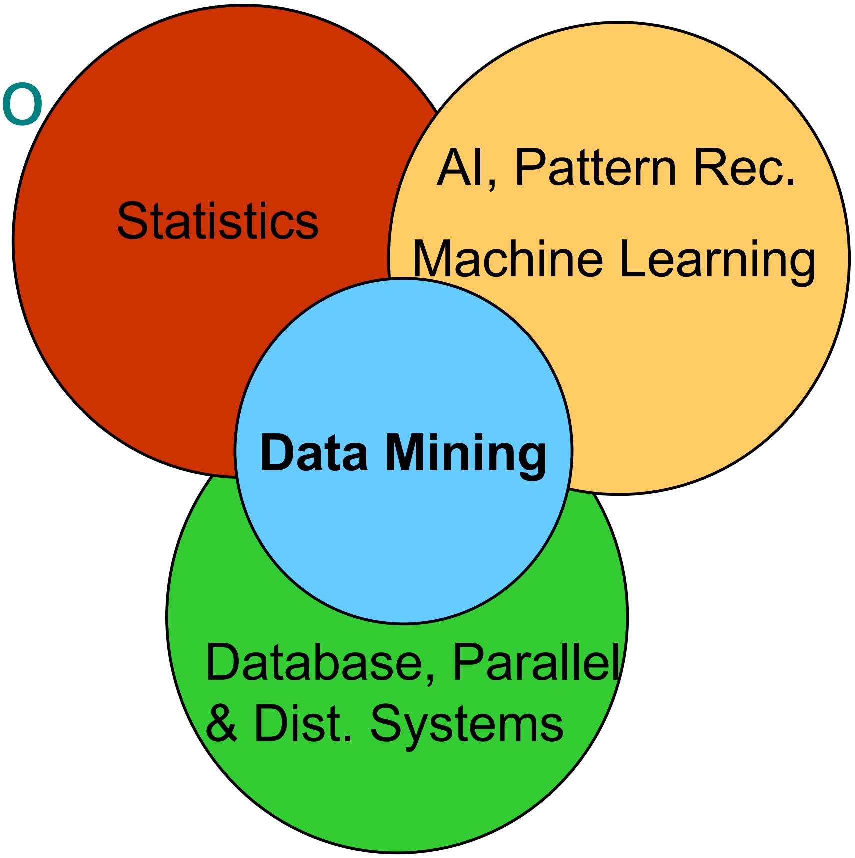
What is NOT Data Mining?

- What is not Data Mining?
  - Look up names for phone number in phone directory
  - Query a Web search engine for information about “Amazon”

- What is Data Mining?
  - Certain names are more prevalent in certain US locations (O’Brien, O’Rurke, O’Reilly… in Boston area)
  - Group together similar documents returned by search engine according to their context (e.g. Amazon rainforest, Amazon.com,)

Origins of Data Mining

- Draws ideas from machine learning/AI, pattern recognition, statistics, and database systems
- Traditional Techniques may be unsuitable due to
  - Enormity of data
  - High dimensionality of data
  - Heterogeneous, distributed nature of data



Characterization of Data Mining Tasks

- *Prediction*
  - Use some variables to predict unknown or future values of other variables.
  - Usually *building a predictive model* from observed cases.
- *Description*
  - Find human-interpretable patterns that describe the data.
  - Often *exploratory* in nature.

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

Data Mining Tasks...

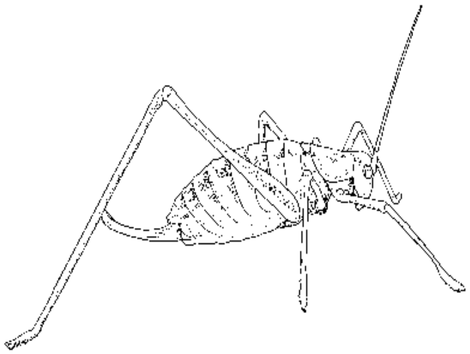
- Classification [Predictive] [Descriptive]
- Clustering [Descriptive]
- Association Rule Discovery [Descriptive]
- Sequential Pattern Discovery [Descriptive]
- Regression [Predictive]
- Anomaly Detection [Predictive]

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 the 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.

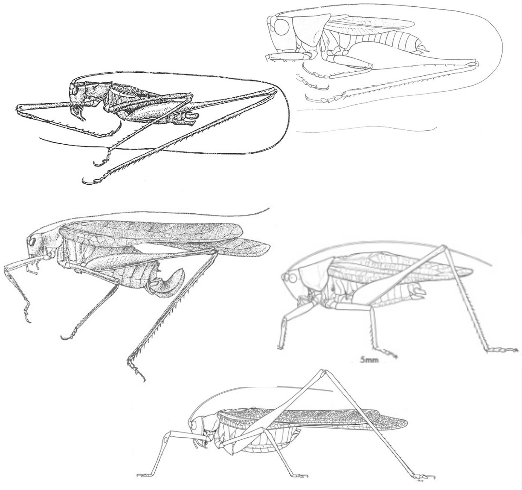
Classification Problem

- Given a collection of annotated data. In this case, 5 instances Katydids of and five of Grasshoppers, decide what type of insect the unlabeled example is.

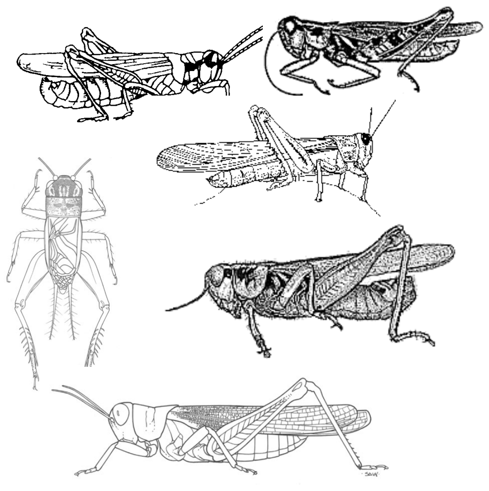


Katydid or Grasshopper?

Katydids



Grasshoppers

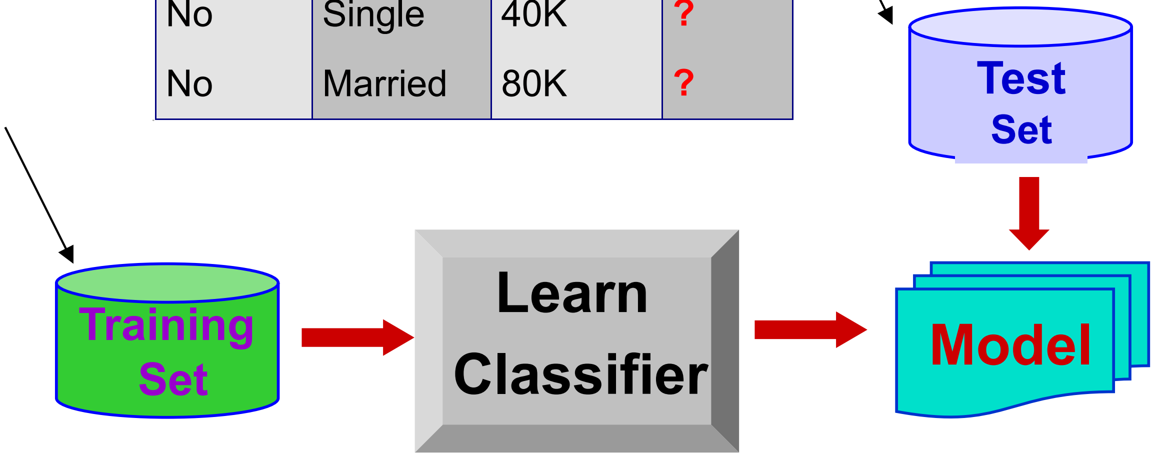


Classification Example

categorical categorical continuous class

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Refund	Marital Status	Taxable Income	Cheat
No	Single	75K	?
Yes	Married	50K	?
No	Married	150K	?
Yes	Divorced	90K	?
No	Single	40K	?
No	Married	80K	?



Classification: Application 1

- Direct Marketing
  - Goal: Reduce cost of mailing by *targeting* a set of consumers likely to buy a new product.
  - Approach:
    - Use the data for a similar product introduced before.
    - We know which customers decided to buy and which decided otherwise. This *{buy, not buy}* decision forms the *class attribute*.
    - Collect various demographic, lifestyle, and other useful 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 discriminative and informative 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

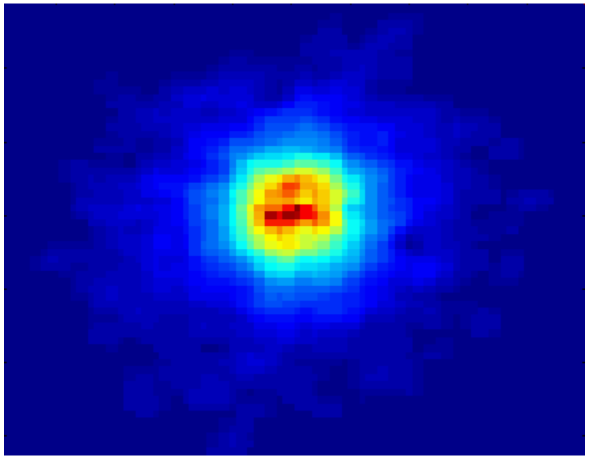
- Sky Survey Cataloging
  - Goal: To predict class (star or galaxy) of sky objects, especially visually faint ones, based on the telescopic survey images (from Palomar Observatory).
    - 3000 images with 23,040 x 23,040 pixels per image.
  - Approach:
    - Segment the image.
    - Measure image attributes (features) - 40 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

Courtesy: http://aps.umn.edu

Early



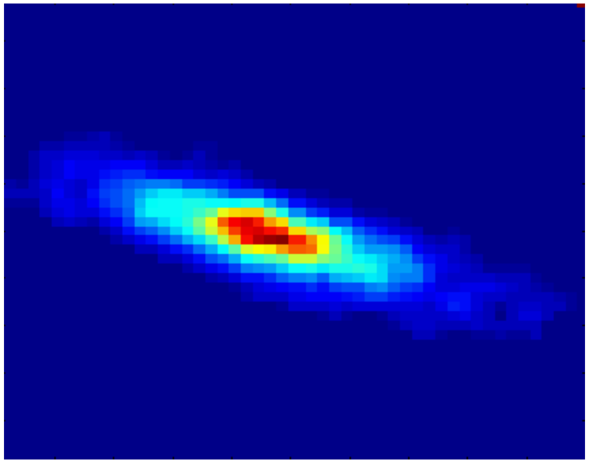
Class:

- **Stages of Formation**

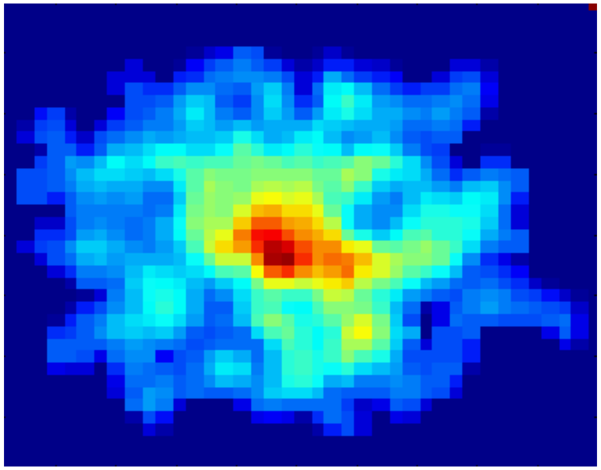
Attributes:

- **Image features,**
- **Characteristics of light waves received, etc.**

Intermediate



Late

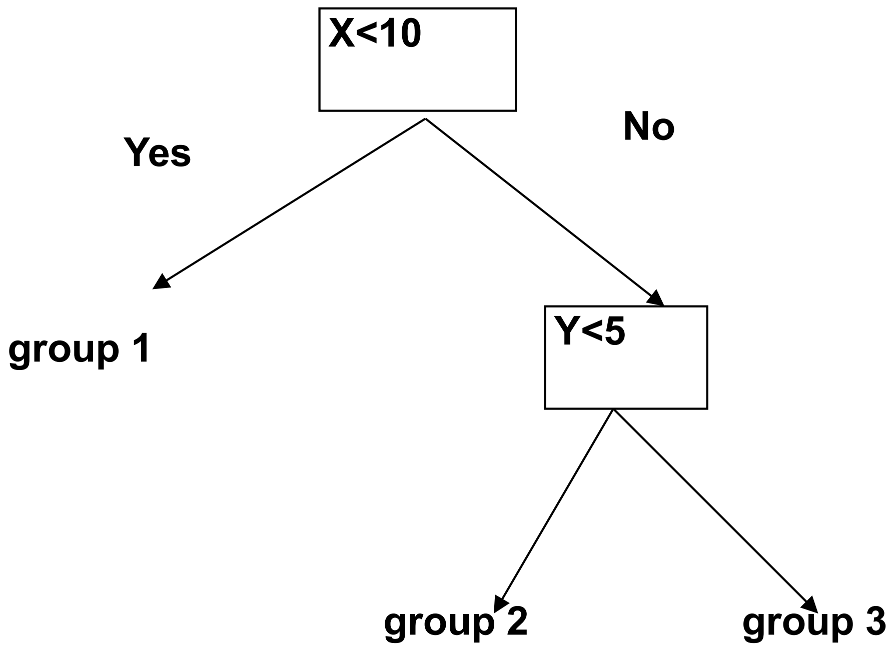


Data Size:

- **72 million stars, 20 million galaxies**
- **Object Catalog: 9 GB**
- **Image Database: 150 GB**

Classification – Descriptive Model

- By organizing data into given classes based on attribute values, certain models, e.g., decision tree, actually characterize the data set well.



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.
- Extensively 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.

Regression

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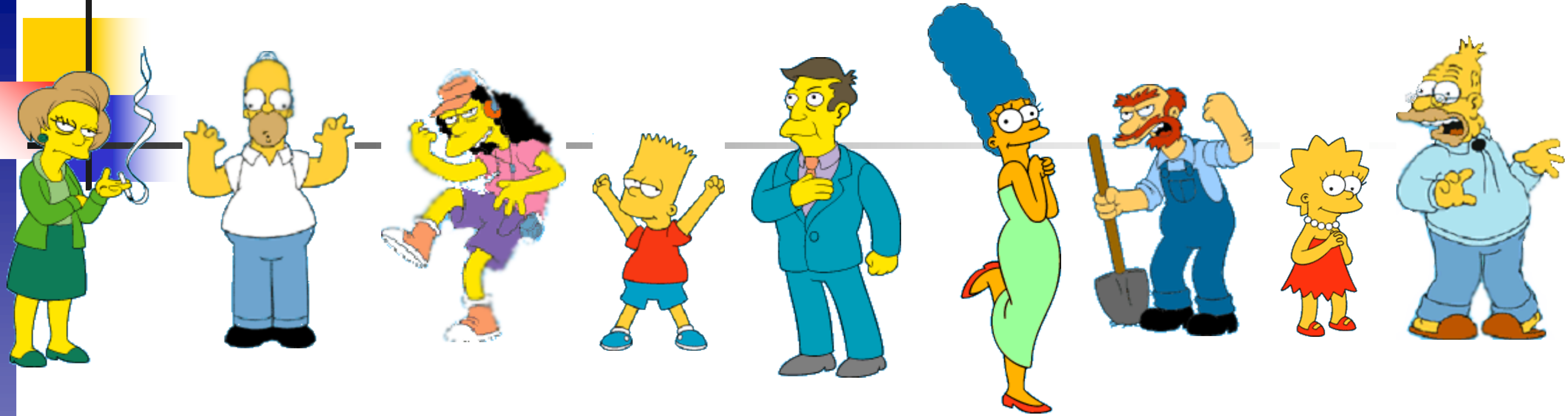
  - Time series prediction of stock market indices.

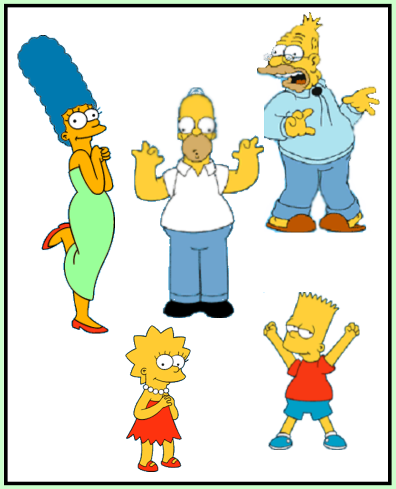
Clustering: Definition

- Given a set of data points, each with 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.

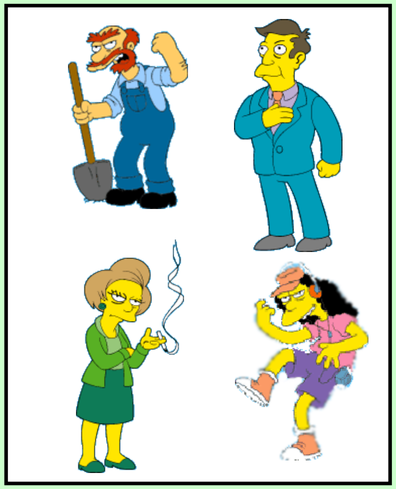
What is a natural grouping?



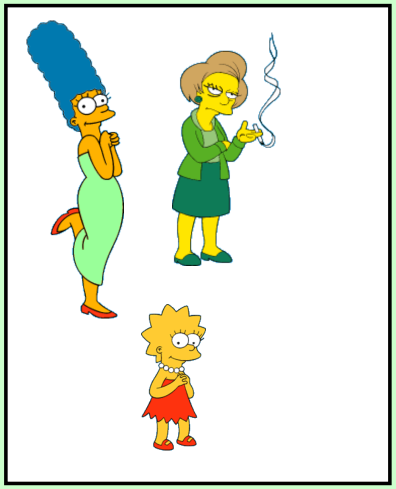
Clustering is subjective!



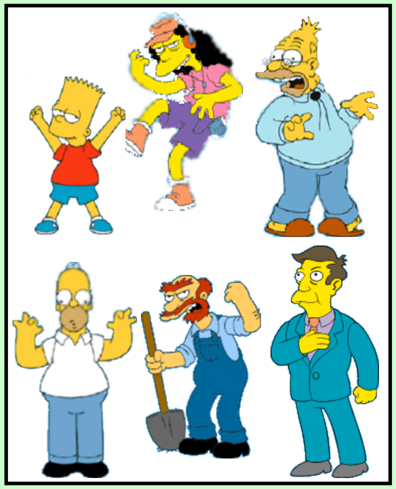
Simpson's Family



School Employees



Females



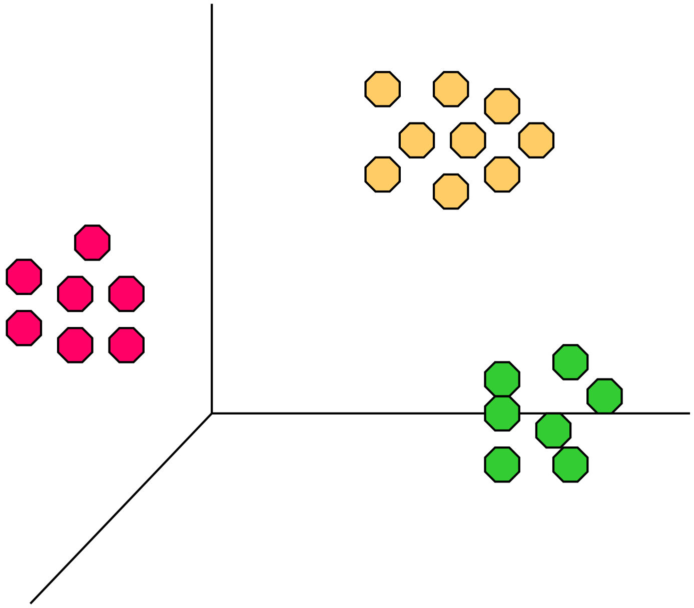
Males

Illustrating Clustering

Euclidean Distance Based Clustering in 3-D space.

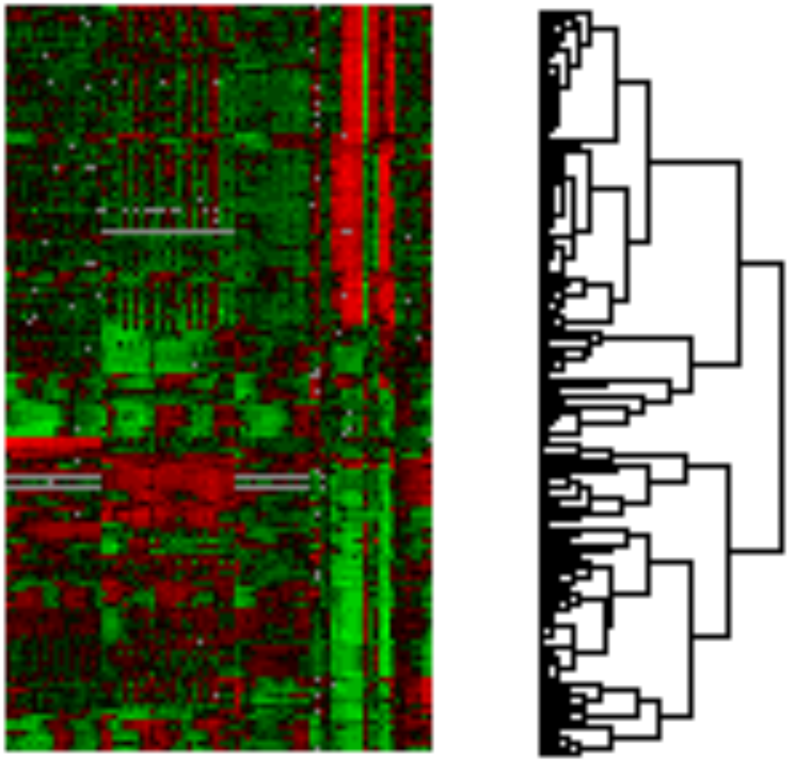
Intracluster distances are minimized

Intercluster distances are maximized

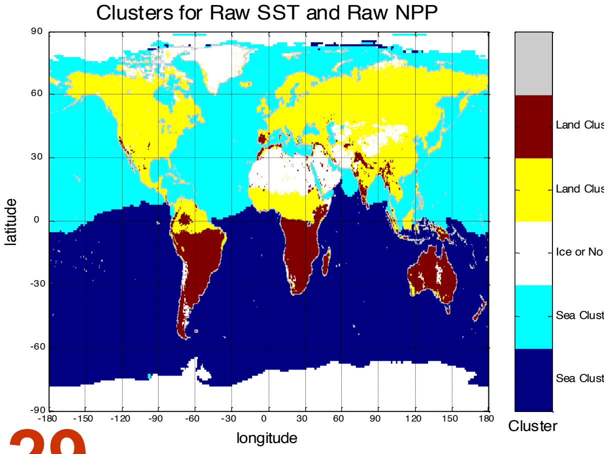


Applications of Cluster Analysis

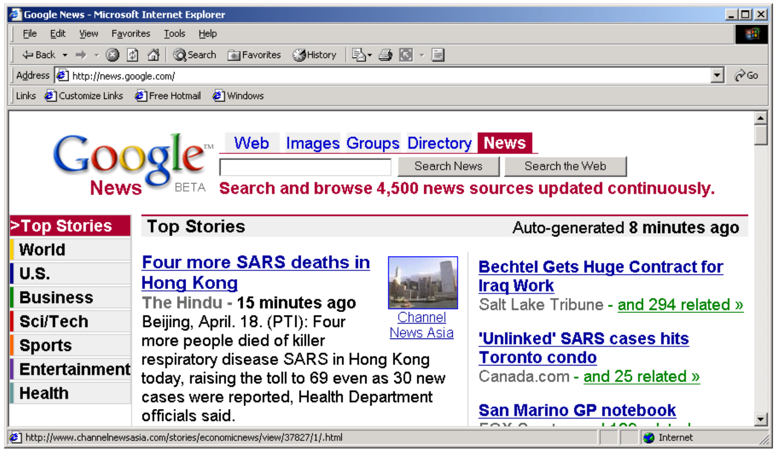
- **Understanding**
  - Custom profiling for targeted marketing
  - Group related documents for browsing
  - Group genes and proteins that have similar functionality
  - Group stocks with similar price fluctuations



- **Summarization**
  - Reduce the size of large data sets



Use of K-means to partition Sea Surface Temperature (SST) and Net Primary Production (NPP) into clusters that reflect the Northern and Southern Hemispheres.



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The Hindu - 15 minutes ago

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Channel News Asia

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Salt Lake Tribune - and 294 related »

'Unlinked' SARS cases hits Toronto condo

Canada.com - and 25 related »

San Marino GP notebook

http://www.channelnewsasia.com/stories/economicnews/view/37827/1/.html

Clustering: Application 1

- Market Segmentation (for targeted marketing)
  - Goal: divide 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.

Document Clustering

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

Category	*Total Articles*	*Correctly Placed*
Financial	555	364
Foreign	341	260
National	273	36
Metro	943	746
Sports	738	573
Entertainment	354	278

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.
- The above uses association rules to quantify a similarity measure.

	Discovered Clusters	*Industry Group*
1	Applied-Matl-DOWN,Bay-Network-Down,3-COM-DOWN, Cabletron-Sys-DOWN,CISCO-DOWN,HP-DOWN, DSC-Comm-DOWN,INTEL-DOWN,LSI-Logic-DOWN, Micron-Tech-DOWN,Texas-Inst-Down,Tellabs-Inc-Down, Natl-Semiconduct-DOWN,Oracl-DOWN,SGI-DOWN, Sun-DOWN	Technology1-DOWN
2	Apple-Comp-DOWN,Autodesk-DOWN,DEC-DOWN, ADV-Micro-Device-DOWN,Andrew-Corp-DOWN, Computer-Assoc-DOWN,Circuit-City-DOWN, Compaq-DOWN, EMC-Corp-DOWN, Gen-Inst-DOWN, Motorola-DOWN,Microsoft-DOWN,Scientific-Atl-DOWN	Technology2-DOWN
3	Fannie-Mae-DOWN,Fed-Home-Loan-DOWN, MBNA-Corp-DOWN,Morgan-Stanley-DOWN	Financial-DOWN
4	Baker-Hughes-UP,Dresser-Inds-UP,Halliburton-HLD-UP, Louisiana-Land-UP,Phillips-Petro-UP,Unocal-UP, Schlumberger-UP	Oil-UP

Association Rule Discovery: Definition

- Given a set of records each of which contains some number of items from a given collection
- Produce *dependency rules* which will predict occurrence of an item based on *occurrences* of other items.

TID	*Items*
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Rules Discovered:
{Milk} --> {Coke}
{Diaper, Milk} --> {Beer}

Association Rule Discovery: Application 1

- Marketing and Sales Promotion
  - Discovered rule:

    {Bagels, … } --> {Potato Chips}

  - Potato Chips as consequent → determine what should be done to boost its sales.
  - Bagels in the antecedent → see which products would be affected if the store discontinues selling bagels.
  - Bagels in antecedent *and* Potato chips in consequent → 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.
    - Don’t be surprised if you find six-packs stacked next to diapers!

Association Rule Discovery: Application 3

- 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 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 B) (C) → (D E)

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

Sequential Pattern Discovery: Examples

- Telecommunications alarm logs
  - (Inverter_Problem Excessive_Line_Current)

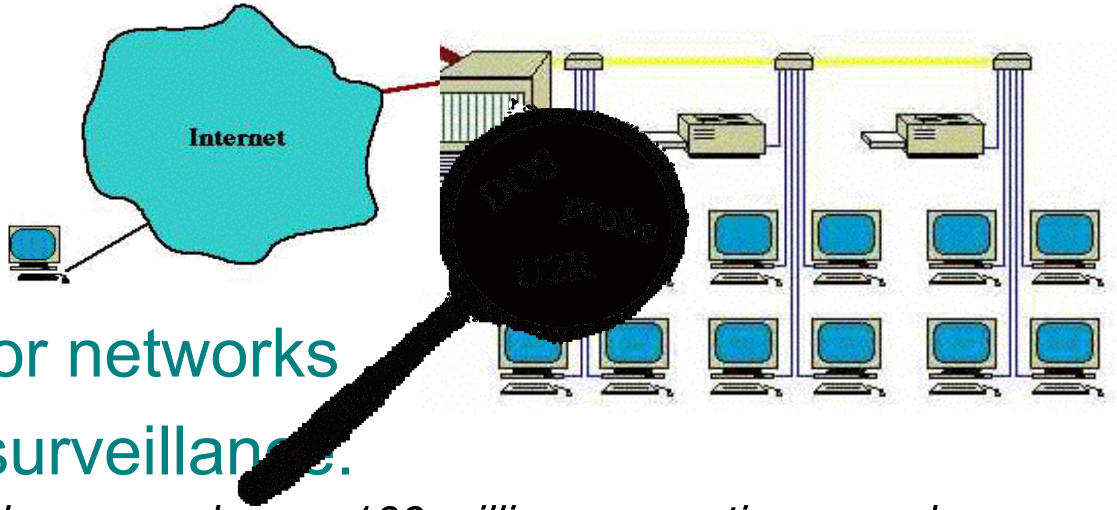
    (Rectifier_Alarm) → (Fire_Alarm)
- Point-of-sale transaction sequences
  - Computer Bookstore

    (Intro_To_Visual_C) (C++_Primer) → (Perl_for_dummies,Tcl_Tk)
  - Athletic Apparel Store

    (Shoes) (Racket, Racketball) → (Sports_Jacket)

Anomaly (Deviation) Detection

- Detect significant deviations from normal behavior
- Applications:
  - Credit Card Fraud Detection
  - Detecting changes in the global forest cover.
  - Network Intrusion Detection
  - Identify anomalous behavior from sensor networks for monitoring and surveillance.



Typical network traffic at University level may reach over 100 million connections per day

Performance Measurement

- Efficiency
- Effectiveness
  - Objective measures; based on statistics & structures of patterns
    - e.g. support, confidence
  - Subjective measures: based on user's beliefs in data
    - e.g. unexpectedness, novelty

Challenges of Data Mining

- Scalability
- High Dimensionality
- Complex and Heterogeneous Data
- Data Quality
- Data Ownership and Distribution
- Privacy Preservation
- Streaming Data