ANU MLSS 2010: Data Mining

Part 3: Application techniques and privacy aspects of data mining

Lecture outline

- Mining data streams
  - Characteristics of data streams
  - Stream data applications
  - Data stream management system
  - Challenges and methodologies of data stream processing
  - Stream data mining versus stream querying
- Link mining
  - Common link mining tasks
  - Link based object ranking and object classification
  - Link prediction
- Privacy aspects of data mining
  - Privacy and confidentiality
  - Some scenarios
  - Privacy-preserving data mining
- References and resources

Characteristics of data streams

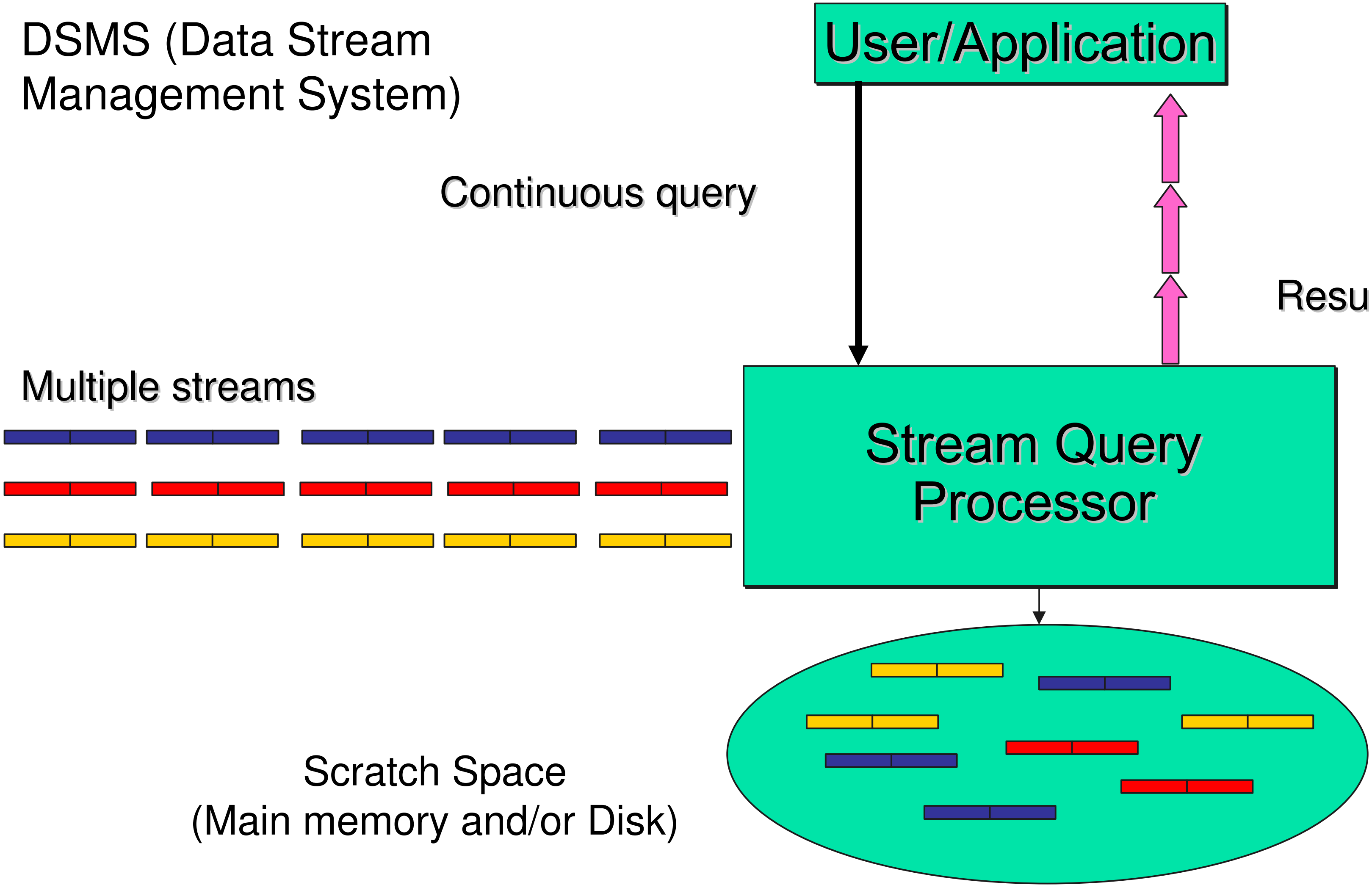
- Data streams
  - Continuous, ordered, changing, fast, huge amount
  - In a traditional DBMS, data is stored in finite, well-defined and persistent tables
- Characteristics
  - Huge volumes of continuous data, possibly infinite
  - Fast changing and requires fast, real-time response
  - Data stream captures nicely our data processing needs of today
  - Random access is expensive — single scan algorithm are required (*can only have one look at each record!*)
  - Store only the summary of the data seen thus far
  - Most stream data are at pretty low-level or multi-dimensional in nature, needs multi-level (ML) and multi-dimensional (MD) processing

Stream data applications

- Telecommunication calling records
- Business: credit card transaction flows
- Network monitoring and traffic engineering
- Financial market: stock exchange
- Engineering & industrial processes: power supply and manufacturing
- Sensor, monitoring & surveillance: video streams, RFIDs (Radio Frequency IDentification)
- Security monitoring
- Web logs and Web page click streams
- Massive data sets (even saved but random access is too expensive)

Architecture: Stream query processing

DSMS (Data Stream Management System)



Source: Han and Kamber, DM Book, 2nd Ed. (Copyright © 2006 Elsevier Inc.)

Challenges of stream data processing

- Multiple, continuous, rapid, time-varying, ordered streams
- Main memory computations
- Queries are often continuous
  - Evaluated continuously as stream data arrives
  - Answer updated over time
- Queries are often complex
  - Beyond element-at-a-time processing
  - Beyond stream-at-a-time processing
  - Beyond relational queries
- Approximate query answering
  - With bounded memory, it is not always possible to produce exact answers (high quality approximate answers are desired)

Methodologies for stream data processing

- Major challenge
  - Keep track of a large universe (for example, IP address, not ages)
- Methodology
  - Synopses (trade-off between accuracy and storage)
  - Use *synopsis* data structure, much smaller ($O(\log^k N)$ space) than their base data set ($O(N)$ space), with N the number of elements in the stream data
  - Compute an *approximate answer* within a *small error range* (factor ε of the actual answer)
- Major methods
  - *Random sampling* (maintain a set of candidates in memory)
  - *Histograms* (approximate frequency distribution of values in stream)
  - *Sliding windows* (make decision based on only recent data)
  - *Multi-resolution models* (balanced trees, wavelets, micro-clusters)
  - *Sketches* (summarises data, can be done in one pass)
  - *Randomised algorithms* (Monte Carlo algorithm, bound on run time)

Stream data mining versus stream querying

- Stream mining is a more challenging task in many cases
  - It shares most of the difficulties with stream querying
  - But often requires less *precision*, for example, no join, grouping, sorting
  - Patterns are hidden and more general than querying
  - It may require exploratory analysis (not necessarily continuous queries)
  - Change in data characteristics: *Concept drift*
- Stream data mining tasks
  - Frequent patterns in data streams (approximate frequent patterns only)
  - Mining outliers and unusual patterns in stream data
  - Classification of stream data (approximate decision trees, classifier ensemble)
  - Clustering data streams

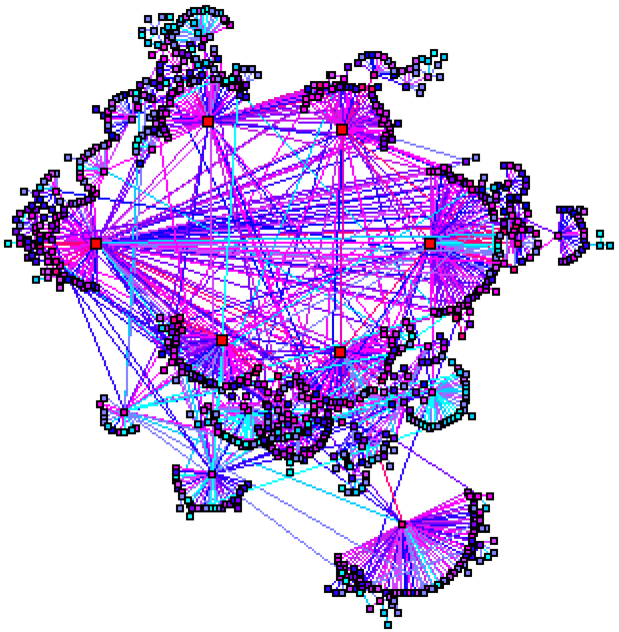
Multi-dimensional stream analysis: Examples

- Analysis of Web click streams
  - Raw data at low levels: seconds, Web page addresses, user IP addresses, IP port numbers, …
  - Analysts want: changes, trends, unusual patterns, at reasonable levels of details
  - For example: *Average clicking traffic in North America on sports in the last 15 minutes is 40% higher than that in the last 24 hours*

- Analysis of power consumption streams
  - Raw data: power consumption flow for every household, every minute
  - Patterns one may find: *average hourly power consumption surges up 30% for manufacturing companies in Chicago in the last 2 hours today than that of the same day a week ago*

Link / Network mining

- Heterogeneous, multi-relational data is represented as a graph or network
  - Nodes are objects
    - May have different kinds of objects
    - Objects have attributes
    - Objects may have labels or classes
  - Edges are links
    - May have different kinds of links
    - Links may have attributes
    - Links may be directed, are not required to be binary



- Links represent relationships and interactions between objects - rich content for data mining

What is new for link mining?

- Traditional machine learning and data mining approaches assume:
  - A random sample of homogeneous objects from a single relation
- Real world data sets:
  - Multi-relational, heterogeneous and semi-structured
- Link Mining
  - Newly emerging research area at the intersection of research in social network and link analysis, hypertext and web mining, graph mining, and relational learning

Common link mining tasks

- Object-Related Tasks
  - Link-based object ranking
  - Link-based object classification
  - Object clustering (group detection)
  - Object identification (entity resolution)
- Link-Related Tasks
  - Link prediction
- Graph-Related Tasks
  - Subgraph discovery
  - Graph classification
  - Generative model for graphs

What is a link in link mining?

- Link: relationship among data
- Two kinds of linked networks
  - Homogeneous vs. Heterogeneous
- Homogeneous networks
  - Single object type and single link type
  - Single model social networks (e.g., friends)
  - WWW: a collection of hyper-linked Web pages
- Heterogeneous networks
  - Multiple object and link types
  - Medical network: patients, doctors, disease, contacts, treatments
  - Bibliographic network: publications, authors, venues, affiliations; co-authorship relations, published in/at relations, working at relations

Link-based object ranking (LBR)

- LBR: Exploit the link structure of a graph to order or prioritize the set of objects within the graph
  - Focused on graphs with single object type and single link type
- This is a primary focus of link analysis community
- Web information analysis
  - PageRank (Google) and Hits (Hyperlink-Induced Topic Search) are typical LBR approaches
- In social network analysis (SNA), LBR is a core analysis task
  - Objective: rank individuals in terms of “centrality”
  - Rank objects relative to one or more relevant objects in the graph vs. ranks object over time in dynamic graphs

Link-based object classification (LBC)

- Predicting the category of an object based on its attributes, its links and the attributes of linked objects
- **Web**: Predict the category of a web page, based on words that occur on the page, links between pages, anchor text, HTML tags, etc.
- **Citation**: Predict the topic of a paper, based on word occurrence, citations, co-citations
- **Epidemics**: Predict disease type based on characteristics of the patients infected by the disease
- **Communication**: Predict whether a communication contact is by email, phone call or mail

Link prediction

- Predict whether a link exists between two entities, based on attributes and other observed links

- Applications
  - **Web**: predict if there will be a link between two pages
  - **Citation**: predicting if a paper will cite another paper
  - **Epidemics**: predicting who a patient's contacts are

- Methods
  - Often viewed as a binary classification problem
  - Local conditional probability model, based on structural and attribute features
  - Difficulty: sparseness of existing links
  - Collective prediction, e.g., Markov random field model

Use of labeled and unlabeled data

- In link-based domains, unlabeled data provide three sources of information:
  - Links between unlabeled data allow us to make use of attributes of linked objects
  - Links between labeled data and unlabeled data (training data and test data) help us make more accurate inferences
- Knowledge is power, but knowledge is hidden in massive links

Privacy and confidentiality

- Privacy of individuals
  - Identifying information: Names, addresses, telephone numbers, dates-of-birth, driver licenses, racial/ethnic origin, family histories, political and religious beliefs, trade union memberships, health, sexual orientation, income, ...
  - Some of this information is publicly available, other is not
  - Individuals are happy to share some information with others (to various degrees)

- Confidentiality in organisations
  - Trade secrets, corporate plans, financial status, planned collaborations, ...
  - Collect and store information about many individuals (customers, patients, employees)

- Conflict between individual privacy and information collected by organisations
  - Privacy-preserving data mining and data sharing mainly of importance when applied between organisations (businesses, government agencies)

Protect individual privacy

- Individual items (records) in a database must not be disclosed
  - Not only personal information
  - Confidential information about a corporation
  - For example, transaction records (bank account, credit card, phone call, etc.)
- Disclosing parts of a record might be possible
  - Like name or address only (but if data source is known even this can be problematic)
  - For example, a cancer register, HIV database, etc.
- Remove *identifier* so data cannot be traced to an individual
  - Otherwise data is not private anymore
  - But how can we make sure data can't be traced?

Real world scenarios

(based on slides by Chris Clifton, http://www.cs.purdue.edu/people/clifton)

- Multi-national corporation
  - Wants to mine its data from different countries to get global results
  - Some national laws may prevent sending some data to other countries
- Industry collaboration
  - Industry group wants to find best practices (some might be trade secrets)
  - A business might not be willing to participate out of fear it will be identified as conducting bad practice compared to others
- Analysis of disease outbreaks
  - Government health departments want to analyse such topics
  - Relevant data (patient backgrounds, etc.) held by private health insurers and other organisations (can/should they release such data?)

More real world scenarios (data sharing)

- Data sharing between companies
  - Two pharmaceutical companies are interested in collaborating on the expensive development of new drugs
  - Companies wish to identify how much overlap of confidential research data there is in their databases (but without having to reveal any confidential data to each other)
  - Techniques are needed that allow sharing of large amounts of data in such a way that similar data items are found (and revealed to both companies) while all other data is kept confidential

- Geocoding cancer register addresses
  - Limited resources prohibit the register to invest in an in-house geocoding system
  - Alternative: The register has to send their addresses to an external geocoding service/company (but regulatory framework might prohibit this)
  - Complete trust needed in the capabilities of the external geocoding service to conduct accurate matching, and to properly destroy the register's address data afterwards

Re-identification

- *L. Sweeney* (Computational Disclosure Control, 2001)
  - Voter registration list for Cambridge (MA, USA) with 54,805 people: 69% were unique on postal code (5-digit ZIP code) and date of birth
  - 87% in whole of population of USA (216 of 248 million) were unique on: ZIP, date of birth and gender!
  - Having these three attributes allows linking with other data sets (quasi-identifying information)

- *R. Chaytor* (Privacy Advisor, SIGIR 2006)
  - A patient living in a celebrity's neighbourhood
  - Statistical data (e.g. from ABS – Australian Bureau of Statistics) says one male, between 30 and 40, has HIV in this neighbourhood (ABS mesh block: approx. 50 households)
  - A journalist offers money in exchange of some patients medical details
  - How much can the patient reveal without disclosing the identity of his/her neighbours?

Goals of privacy-preserving data mining

- Privacy and confidentiality issues normally do not prevent data mining
  - Aim is often summary results (clusters, classes, frequent rules, etc.)
  - Results often do not violate privacy constraints (they contain no identifying information)
  - But, certain rules or classification outcomes might compromise confidentiality
  - But: Certain techniques (e.g. outlier detection) aim to find specific records (fraudulent customers, potential terrorists, etc.)
  - Also, often detailed records are required by data mining algorithms
- The problem is: How to conduct data mining without accessing the identifying data
  - Legislation and regulations might prohibit access to data (especially between organisations or countries)
- Main aim is to develop algorithms to modify the original data in some way, so that private data and private knowledge remain private even after the mining process

Privacy-preserving data mining techniques (1)

- Many approaches to preserve privacy while doing data mining
  - Distributed data: Either *horizontally* (different records reside in different locations) or *vertically* (values for different attributes reside in different locations)
- Data modifications and obfuscation
  - Perturbation (changing attribute values, e.g. by specific new values -- mean, average - or randomly)
  - Blocking (replacement of values with for example a '?')
  - Aggregation (merging several values into a coarser category, similar to concept hierarchies)
  - Swapping (interchanging values of individual records)
  - Sampling (only using a portion of the original data for mining)
- Problems: Does this really protect privacy? Still good quality data mining results?

Privacy-preserving data mining techniques (2)

- Data summarisation
  - Only the needed facts are released at a level that prohibits identification of individuals
  - Provide overall data collection statistics
  - Limit functionality of queries to underlying databases (statistical queries)
  - Possible approach: *k*-anonymity (*L. Sweeney*, 2001): any combination of values appears at least *k* times
- Problems
  - Can identifying details still be deducted from a series of such queries?
  - Is the information accessible sufficient to perform the desired data mining task?

Privacy-preserving data mining techniques (3)

- Data separation
  - Original data held by data creator or data owner
  - Private data is only given to a trusted third party
  - All communication is done using encryption
  - Only limited release of necessary data
  - Data analysis and mining done by trusted third party
- Problems
  - This approach secures the data sets, but not the potential results!
  - Mining results can still disclose identifying or confidential information
  - Can and will the trusted third party do the analysis?
  - If several parties involved, potential of collusion by two parties
- Privacy-preserving approaches for association rule mining, classification, clustering, etc. have been developed

Secure multi-party computation

- Aim: To calculate a function so that no party learns the values of the other parties, but all learn the final result
  - Assuming semi-honest behaviour: Parties follow the protocol, but they might keep intermediate results

- Example: Simple secure summation protocol (*Alan F. Karr*, 2005)
  - Consider $K > 2$ cooperating parties (businesses, hospitals, etc.)
  - Aim: to compute $v = \Sigma^{k}_{j=1} v_j$ so that no party learns other parties v_j
  - Step 1: Party 1 generates a large random number R, with $R >> v$
  - Step 2: Party 1 sends $(v_1 + R)$ to party 2
  - Step 3: Party 2 adds v_2 to $v_1 + R$ and sends $(v_1 + v_2 + R)$ to party 3 (and so on)
  - Step $K+1$: Party K sends $(v_1 + v_2 + ... + v_k + R)$ back to party 1
  - Last step: Party 1 subtracts R and gets final v, which it then sends to all other parties

References and resources (1)

- Data mining books:
  - *Data Mining: Concepts and Techniques*, J. Han and M. Kamber, 2nd Edition (2006) Morgan Kaufmann.
  - *Data Mining: Practical Machine Learning Tools and Techniques* (Weka), I. Witten and E. Frank, 2nd Edition (2005) Morgan Kaufmann.
  - *The Elements of Statistical Learning: Data Mining, Inference and Prediction*, T. Hastie, R. Tibshirani and J. Friedman, 2nd Edition (2009) Springer

- Web resources:
  - www.kdnuggets.com (Email newsletter, courses, jobs, conferences)
  - www.kmining.com (conference calendar, people)
  - www.togaware.com (Graham Williams, Australian Taxation Office)

References and resources (2)

- Open source data mining software:
  - *Rattle* (R based): www.togaware.com/rattle
    (Graham Williams, Australian Taxation Office)
  - *Weka* (Java based): http://www.cs.waikato.ac.nz/ml/weka/
    (University of Waikato, NZ and Pentaho)
  - *KNIME* (Java based): www.knime.org
    (University of Konstanz, Germany)
- Conferences and journals
  - *ACM SIGKDD:* www.sigkdd.org (also Explorations news letter)
  - *IEEE ICDM:* http://www.cs.uvm.edu/~icdm/
  - *Springer Data Mining and Knowledge Discovery:*
    http://www.springerlink.com/content/100254
  - Springer Knowledge and Information Systems:
    http://springerlink.metapress.com/content/105441/
  - IEEE Transactions on Knowledge and Data Engineering:
    http://www.computer.org/tkde