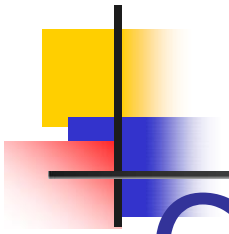


Data Mining: Concepts and Techniques

— Slides for Textbook —
— Chapter 6 & 7 —

©Jiawei Han and Micheline Kamber

Intelligent Database Systems Research Lab

School of Computing Science

Simon Fraser University, Canada

http://www.cs.sfu.ca

Chapter 6: Mining Association Rules in Large Databases

- Association rule mining
- Mining single-dimensional Boolean association rules from transactional databases
- Summary

Chapter 6: Mining Association Rules in Large Databases

- Association rule mining
  - Basic Concepts
  - Frequent Patterns
  - Association Rules
  - Support and Confidence
  - Road map

What Is Association Mining?

- Association rule mining:
  - Finding frequent patterns, among sets of items or objects in transaction databases, relational databases, and other information repositories.
  - associations, correlations, or causal structures
  - Classification: discriminative, frequent pattern analysis
  - Cluster analysis: frequent pattern-based clustering
- Frequent pattern:
  - a pattern (a set of items, subsequences, substructures, etc.) that occurs frequently in a data set
  - an intrinsic and important property of datasets
  - Foundation for many essential data mining tasks

What Is Association Mining?

- Motivation: Finding inherent regularities in data
  - What products were often purchased together?
  - What are the subsequent purchases after buying a PC?
  - What kinds of DNA are sensitive to this new drug?
  - Can we automatically classify web documents?
- Applications:
  - Basket data analysis: understanding customer purchasing patterns
  - Cross-marketing: business collaborations to increase target audience and sales
  - Loss-leader analysis: pricing producer lower than production cost to sell other more expensive products
  - catalog design, clustering, classification, etc.

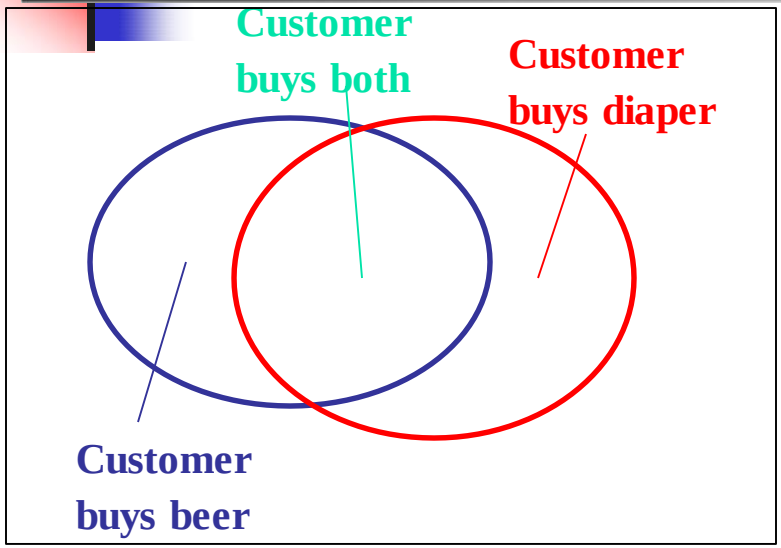
What Is Association Mining?

- Examples.
  - Rule form: "Body $\rightarrow$ Head [support, confidence]".
    - Body and head are dimensions (predicates)
    - Support and Confidence are interestingness measures
  - buys(x, "diapers") $\rightarrow$ buys(x, "beers") [0.5%, 60%]
    - Customer who buys diapers also tends to buy beer
    - Support: 0.5% of transaction under analysis shows diapers and beer are purchased together
    - Confidence: 60% of customers who purchased diapers also bought beer
  - major(x, "CS") ^ takes(x, "DB") $\rightarrow$ grade(x, "A") [1%, 75%]
    - Multidimensional association rule

Association Rule: Basic Concepts

- Given: (1) database of transactions, (2) each transaction is a list of items (purchased by a customer in a visit)
- Find: all rules that correlate the presence of one set of items with that of another set of items
  - E.g., *98% of people who purchase tires and auto accessories also get automotive services done*
- Applications
  - $* \Rightarrow$ *Maintenance Agreement* (What the store should do to boost Maintenance Agreement sales)
  - *Home Electronics* $\Rightarrow *$ (What other products should the store stocks up?)
  - Attached mailing in direct marketing
  - Detecting "ping-pong"ing of patients, faulty "collisions"

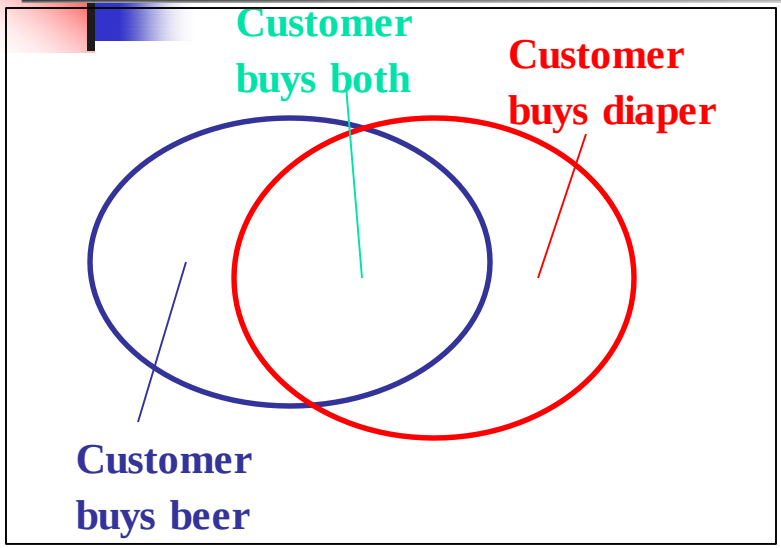
Basic Concepts: Frequent Patterns



Tid	Items bought
10	Beer, Nuts, Diaper
20	Beer, Coffee, Diaper
30	Beer, Diaper, Eggs
40	Nuts, Eggs, Milk
50	Nuts, Coffee, Diaper, Eggs, Milk

- itemset: A set of one or more items
- k-itemset $X = \{x_1, \ldots, x_k\}$
- *(absolute) support*, or, *support count* of X: Frequency or occurrence of an itemset X
- *(relative) support*, *s*, is the fraction of transactions that contains X (i.e., the probability that a transaction contains X)
- An itemset X is *frequent* if X's support is no less than a *minsup* threshold

Basic Concepts: Association Rules



Tid	Items bought
10	Beer, Nuts, Diaper
20	Beer, Coffee, Diaper
30	Beer, Diaper, Eggs
40	Nuts, Eggs, Milk
50	Nuts, Coffee, Diaper, Eggs, Milk

- Find all the rules $X \rightarrow Y$ with minimum support and confidence
  - support, *s*, probability that a transaction contains $X \cup Y$
  - confidence, *c*, conditional probability that a transaction having X also contains *Y*

Let minsup = 50%, minconf = 50%

Freq. Pat.: Beer:3, Nuts:3, Diaper:4, Eggs:3, {Beer, Diaper}:3

Association rules: (many more!)

- *Beer* → *Diaper* (60%, 100%)
- *Diaper* → *Beer* (60%, 75%)

Rule Measures: Support and Confidence

- Find all the rules $X \& Y \Rightarrow Z$ with minimum confidence and support
  - support, *s*, probability that a transaction contains {X Y Z}
  - confidence, *c*, conditional probability that a transaction having {X Y} also contains *Z*

Let minimum support 50%, and minimum confidence 50%, we have

Transaction ID	Items Bought
2000	X,Y, Z
1000	W,X,Y
4000	X,Z
5000	W,X,Z

X ^ Y => Z [25%,50%]

Z => X ^ Y [25%, 33%]

Rule Measures: Support and Confidence

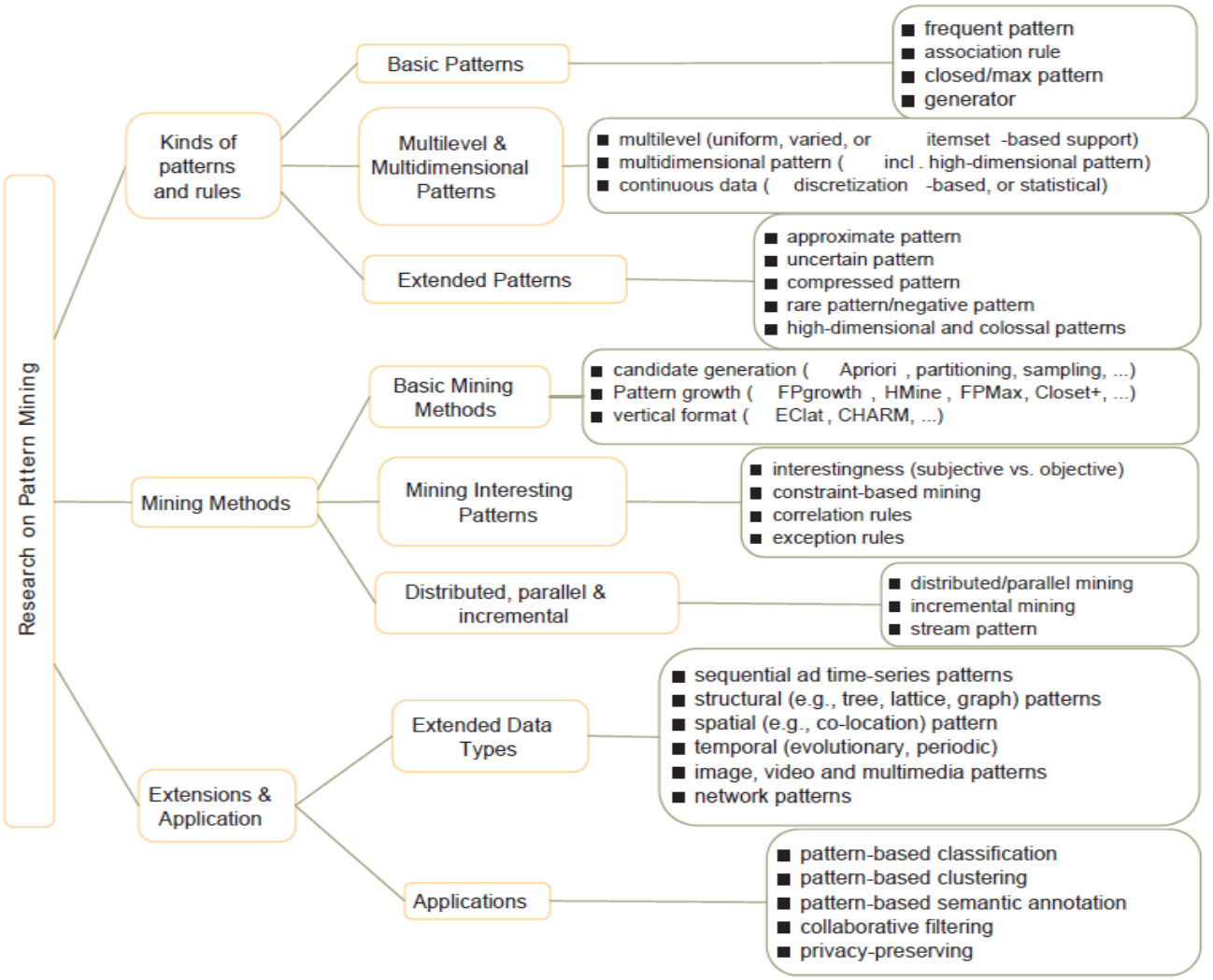
- Find all the rules $A \Rightarrow C$ with minimum confidence and support
  - support, *s*, probability that a transaction contains {A ^ C}
  - confidence, *c*, conditional probability that a transaction having A also contains *C*

Let minimum support 50%, and minimum confidence 50%, we have

Transaction ID	Items Bought
2000	A,B,C
1000	A,C
4000	A,D
5000	B,E,F

- $A \Rightarrow C$ (50%, 66.6%)
- $C \Rightarrow A$ (50%, 100%)

Association Rule Mining: A Road Map



Association Rule Mining: A Road Map

- Boolean vs. quantitative associations (Based on the types of values handled)
  - buys(x, "SQLServer") ^ buys(x, "DMBook") → buys(x, "DBMiner") [0.2%, 60%]
  - age(x, "30..39") ^ income(x, "42..48K") → buys(x, "PC") [1%, 75%]
- Quantitative associations
  - Techniques can be categorized by how numerical attributes, such as age or salary are treated
    - **Static discretization** based on predefined concept hierarchies (data cube methods)
    - **Dynamic discretization** based on data distribution (quantitative rules)
    - Clustering: Distance-based
      - One dimensional clustering then association
    - Deviation:

      Sex = female => Wage: mean=$7/hr (overall mean = $9)

Association Rule Mining: A Road Map

- Single dimension vs. multiple dimensional associations (see ex. Above)
  - Single-dimensional rules:

    buys(X, "milk") $\Rightarrow$ buys(X, "bread")
  - Multi-dimensional rules: $\geq$ 2 dimensions or predicates
    - Inter-dimension assoc. rules (*no repeated predicates*)

      age(X,"19-25") $\wedge$ occupation(X,"student") $\Rightarrow$ buys(X, "coke")
    - hybrid-dimension assoc. rules (*repeated predicates*)

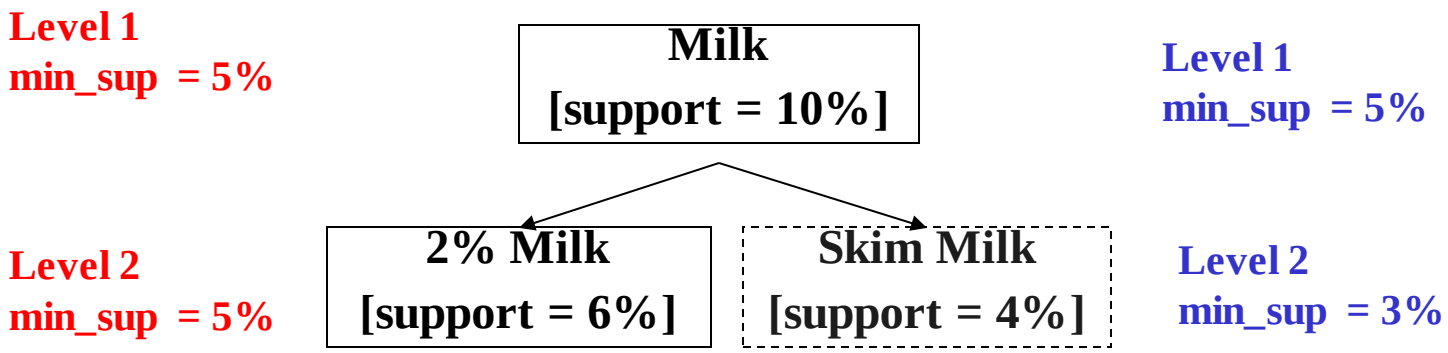
      age(X,"19-25") $\wedge$ buys(X, "popcorn") $\Rightarrow$ buys(X, "coke")

Association Rule Mining: A Road Map

- Single level vs. multiple-level analysis
  - What brands of beers are associated with what brands of diapers?
  - Items often form hierarchies
  - Flexible support settings
    - Items at the lower level are expected to have lower support

uniform support

reduced support



Association Rule Mining: A Road Map

- Various extensions
  - Correlation, causality analysis
    - Association does not necessarily imply correlation or causality
  - Maxpatterns and closed itemsets: handles long patterns containing combinatorial number of sub-patterns
    - An itemset X is **closed** if X is frequent and there exists no super-pattern Y ⊃X, with the same support as X
    - An itemset X is a **max-pattern** if X is frequent and there exists no frequent super-pattern Y ⊃X
    - Closed pattern is a lossless compression of freq. patterns
    - Reducing the # of patterns and rules

Association Rule Mining: A Road Map

- Various extensions
  - Constraints enforced
    - E.g., small sales (sum < 100) trigger big buys (sum > 1,000)?
    - Finding all the patterns in a database autonomously? — unrealistic!
      - The patterns could be too many but not focused!
    - Data mining should be an interactive process
      - User directs what to be mined using a data mining query language (or a graphical user interface)
  - Constraint-based mining
    - User flexibility: provides constraints on what to be mined
    - Optimization: explores such constraints for efficient mining — constraint-based mining: constraint-pushing, similar to push selection first in DB query processing
    - Note: still find all the answers satisfying constraints, not finding some answers in "heuristic search"

Chapter 6: Mining Association Rules in Large Databases

- Association rule mining
- Mining single-dimensional Boolean association rules from transactional databases
- Summary

References

- R. Agarwal, C. Aggarwal, and V. V. V. Prasad. A tree projection algorithm for generation of frequent itemsets. In Journal of Parallel and Distributed Computing (Special Issue on High Performance Data Mining), 2000.
- R. Agrawal, T. Imielinski, and A. Swami. Mining association rules between sets of items in large databases. SIGMOD'93, 207-216, Washington, D.C.
- R. Agrawal and R. Srikant. Fast algorithms for mining association rules. VLDB'94 487-499, Santiago, Chile.
- R. Agrawal and R. Srikant. Mining sequential patterns. ICDE'95, 3-14, Taipei, Taiwan.
- R. J. Bayardo. Efficiently mining long patterns from databases. SIGMOD'98, 85-93, Seattle, Washington.
- S. Brin, R. Motwani, and C. Silverstein. Beyond market basket: Generalizing association rules to correlations. SIGMOD'97, 265-276, Tucson, Arizona.
- S. Brin, R. Motwani, J. D. Ullman, and S. Tsur. Dynamic itemset counting and implication rules for market basket analysis. SIGMOD'97, 255-264, Tucson, Arizona, May 1997.
- K. Beyer and R. Ramakrishnan. Bottom-up computation of sparse and iceberg cubes. SIGMOD'99, 359-370, Philadelphia, PA, June 1999.
- D.W. Cheung, J. Han, V. Ng, and C.Y. Wong. Maintenance of discovered association rules in large databases: An incremental updating technique. ICDE'96, 106-114, New Orleans, LA.
- M. Fang, N. Shivakumar, H. Garcia-Molina, R. Motwani, and J. D. Ullman. Computing iceberg queries efficiently. VLDB'98, 299-310, New York, NY, Aug. 1998.

References (2)

- G. Grahne, L. Lakshmanan, and X. Wang. Efficient mining of constrained correlated sets. ICDE'00, 512-521, San Diego, CA, Feb. 2000.
- Y. Fu and J. Han. Meta-rule-guided mining of association rules in relational databases. KDOOD'95, 39-46, Singapore, Dec. 1995.
- T. Fukuda, Y. Morimoto, S. Morishita, and T. Tokuyama. Data mining using two-dimensional optimized association rules: Scheme, algorithms, and visualization. SIGMOD'96, 13-23, Montreal, Canada.
- E.-H. Han, G. Karypis, and V. Kumar. Scalable parallel data mining for association rules. SIGMOD'97, 277-288, Tucson, Arizona.
- J. Han, G. Dong, and Y. Yin. Efficient mining of partial periodic patterns in time series database. ICDE'99, Sydney, Australia.
- J. Han and Y. Fu. Discovery of multiple-level association rules from large databases. VLDB'95, 420-431, Zurich, Switzerland.
- J. Han, J. Pei, and Y. Yin. Mining frequent patterns without candidate generation. SIGMOD'00, 1-12, Dallas, TX, May 2000.
- T. Imielinski and H. Mannila. A database perspective on knowledge discovery. Communications of ACM, 39:58-64, 1996.
- M. Kamber, J. Han, and J. Y. Chiang. Metarule-guided mining of multi-dimensional association rules using data cubes. KDD'97, 207-210, Newport Beach, California.
- M. Klemettinen, H. Mannila, P. Ronkainen, H. Toivonen, and A.I. Verkamo. Finding interesting rules from large sets of discovered association rules. CIKM'94, 401-408, Gaithersburg, Maryland.

References (3)

- F. Korn, A. Labrinidis, Y. Kotidis, and C. Faloutsos. Ratio rules: A new paradigm for fast, quantifiable data mining. VLDB'98, 582-593, New York, NY.
- B. Lent, A. Swami, and J. Widom. Clustering association rules. ICDE'97, 220-231, Birmingham, England.
- H. Lu, J. Han, and L. Feng. Stock movement and n-dimensional inter-transaction association rules. SIGMOD Workshop on Research Issues on Data Mining and Knowledge Discovery (DMKD'98), 12:1-12:7, Seattle, Washington.
- H. Mannila, H. Toivonen, and A. I. Verkamo. Efficient algorithms for discovering association rules. KDD'94, 181-192, Seattle, WA, July 1994.
- H. Mannila, H Toivonen, and A. I. Verkamo. Discovery of frequent episodes in event sequences. Data Mining and Knowledge Discovery, 1:259-289, 1997.
- R. Meo, G. Psaila, and S. Ceri. A new SQL-like operator for mining association rules. VLDB'96, 122-133, Bombay, India.
- R.J. Miller and Y. Yang. Association rules over interval data. SIGMOD'97, 452-461, Tucson, Arizona.
- R. Ng, L. V. S. Lakshmanan, J. Han, and A. Pang. Exploratory mining and pruning optimizations of constrained associations rules. SIGMOD'98, 13-24, Seattle, Washington.
- N. Pasquier, Y. Bastide, R. Taouil, and L. Lakhal. Discovering frequent closed itemsets for association rules. ICDT'99, 398-416, Jerusalem, Israel, Jan. 1999.

References (4)

- J.S. Park, M.S. Chen, and P.S. Yu. An effective hash-based algorithm for mining association rules. SIGMOD'95, 175-186, San Jose, CA, May 1995.
- J. Pei, J. Han, and R. Mao. CLOSET: An Efficient Algorithm for Mining Frequent Closed Itemsets. DMKD'00, Dallas, TX, 11-20, May 2000.
- J. Pei and J. Han. Can We Push More Constraints into Frequent Pattern Mining? KDD'00. Boston, MA. Aug. 2000.
- G. Piatetsky-Shapiro. Discovery, analysis, and presentation of strong rules. In G. Piatetsky-Shapiro and W. J. Frawley, editors, Knowledge Discovery in Databases, 229-238. AAAI/MIT Press, 1991.
- B. Ozden, S. Ramaswamy, and A. Silberschatz. Cyclic association rules. ICDE'98, 412-421, Orlando, FL.
- J.S. Park, M.S. Chen, and P.S. Yu. An effective hash-based algorithm for mining association rules. SIGMOD'95, 175-186, San Jose, CA.
- S. Ramaswamy, S. Mahajan, and A. Silberschatz. On the discovery of interesting patterns in association rules. VLDB'98, 368-379, New York, NY..
- S. Sarawagi, S. Thomas, and R. Agrawal. Integrating association rule mining with relational database systems: Alternatives and implications. SIGMOD'98, 343-354, Seattle, WA.
- A. Savasere, E. Omiecinski, and S. Navathe. An efficient algorithm for mining association rules in large databases. VLDB'95, 432-443, Zurich, Switzerland.
- A. Savasere, E. Omiecinski, and S. Navathe. Mining for strong negative associations in a large database of customer transactions. ICDE'98, 494-502, Orlando, FL, Feb. 1998.

References (5)

- C. Silverstein, S. Brin, R. Motwani, and J. Ullman. Scalable techniques for mining causal structures. VLDB'98, 594-605, New York, NY.
- R. Srikant and R. Agrawal. Mining generalized association rules. VLDB'95, 407-419, Zurich, Switzerland, Sept. 1995.
- R. Srikant and R. Agrawal. Mining quantitative association rules in large relational tables. SIGMOD'96, 1-12, Montreal, Canada.
- R. Srikant, Q. Vu, and R. Agrawal. Mining association rules with item constraints. KDD'97, 67-73, Newport Beach, California.
- H. Toivonen. Sampling large databases for association rules. VLDB'96, 134-145, Bombay, India, Sept. 1996.
- D. Tsur, J. D. Ullman, S. Abitboul, C. Clifton, R. Motwani, and S. Nestorov. Query flocks: A generalization of association-rule mining. SIGMOD'98, 1-12, Seattle, Washington.
- K. Yoda, T. Fukuda, Y. Morimoto, S. Morishita, and T. Tokuyama. Computing optimized rectilinear regions for association rules. KDD'97, 96-103, Newport Beach, CA, Aug. 1997.
- M. J. Zaki, S. Parthasarathy, M. Ogihara, and W. Li. Parallel algorithm for discovery of association rules. Data Mining and Knowledge Discovery, 1:343-374, 1997.
- M. Zaki. Generating Non-Redundant Association Rules. KDD'00. Boston, MA. Aug. 2000.
- O. R. Zaiane, J. Han, and H. Zhu. Mining Recurrent Items in Multimedia with Progressive Resolution Refinement. ICDE'00, 461-470, San Diego, CA, Feb. 2000.

http://www.cs.sfu.ca/~han/dmbook

Thank you !!!