# 大数据计算及应用(二)

# Association Rules and Frequent Pattern Mining

Slides adapted from http://www.mmds.org

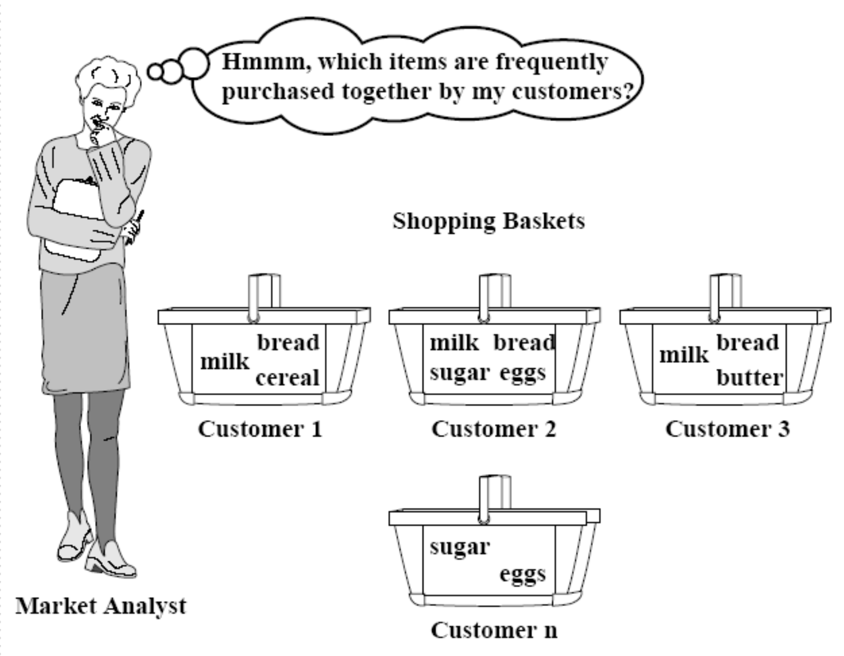
# Agenda

| High dim. data | Graph data | Infinite data | Machine learning | Apps |
|---|---|---|---|---|
| Locality sensitive hashing | PageRank, SimRank | Filtering data streams | SVM | Recommen der systems |
| Clustering | Community Detection | Web advertising | Decision Trees | Association Rules |
| Dimensiona lity reduction | Spam Detection | Queries on streams | Perceptron, kNN | Duplicate document detection |

# Association Rule

- Items frequently purchased together:

beer → diaper


- Uses:
  - Placement
  - Advertising
  - Sales
  - Coupons
- Objective: increase sales and reduce costs

# The Market-Basket Model

- A large set of *items*, e.g., things sold in a supermarket
- A large set of *baskets*, each of which is a small set of the items, e.g., the things one customer buys on one day

| ***TID*** | ***Items*** |
|---|---|
| **1** | **Beer, Diaper, Milk** |
| **2** | **Coke, Diaper, Eggs** |
| **3** | **Beer, Coke, Diaper, Eggs** |
| **4** | **Coke, Eggs** |

# The Market-Basket Model

- A general many-many mapping (association) between two kinds of things
  - But we ask about connections among "items" not "baskets"
- The technology focuses on common events, not rare events ("long tail")

# Applications – (1)

- Items = products; baskets = sets of products someone bought in one trip to the store
- Example application: given that many people buy beer and diapers together
  - Run a sale on diapers; raise price of beer
- Only useful if many buy diapers & beer

# Applications – (2)

- Items = words; Baskets = Web pages;
- Unusual words appearing together in a large number of documents, e.g., "Brad" and "Angelina" may indicate an interesting relationship

# Applications – (3)

- Items = sentences; baskets = documents containing those sentences
- Items that appear together too often could represent plagiarism

# Association Rule Mining Applications

- Basket Data Analysis
- Genomic Data
- Telecommunication
- Credit Cards/ Banking Services
- Medical Treatments
- Web Personalization
- etc.

# Scale of the Problem

- WalMart sells 100,000 items and can store billions of baskets
- The Web has  billions of words and many billions of pages

# Some Definition - Support

An itemset is supported by a basket (transaction) if it is included in the basket

**Market-Basket transactions**

| *TID* | *Items* |
|---|---|
| 1 | Beer, Diaper, Milk |
| 2 | Coke, Diaper, Eggs |
| 3 | Beer, Coke, Diaper, Eggs |
| 4 | Coke, Eggs |

<Beer, Diaper> is supported by basket 1, and 3, and its support is 2/4=50%.

# Some Definition – Frequent Itemset

If the support of an itemset exceeds user specified *min_support* (threshold), this itemset is called a frequent itemset (pattern).

**Market-Basket transactions**

| *TID* | *Items* |
|---|---|
| 1 | Beer, Diaper, Milk |
| 2 | Coke, Diaper, Eggs |
| 3 | Beer, Coke, Diaper, Eggs |
| 4 | Coke, Eggs |

min_support=50%

<Beer, Diaper> is a frequent itemset

<Beer, Milk> is not a frequent itemset

# Association Rules

- **Association Rules:**
  If-then rules about the contents of baskets
- $\{i_1, i_2, \ldots, i_k\} \rightarrow j$ means: "if a basket contains all of $i_1, \ldots, i_k$ then it is ***likely*** to contain $j$"
- **In practice there are many rules, want to find significant/interesting ones!**
- ***Confidence*** of this association rule is the probability of $j$ given $I = \{i_1, \ldots, i_k\}$

$$\mathrm{conf}(I \rightarrow j) = \frac{\mathrm{support}(I \cup j)}{\mathrm{support}(I)}$$

# Example: Confidence

$T_1 = \{m, c, b\}$ $T_2 = \{m, p, j\}$

$T_3 = \{m, b\}$ $T_4 = \{c, j\}$

$T_5 = \{m, p, b\}$ $T_6 = \{m, c, b, j\}$

$T_7 = \{c, b, j\}$ $T_8 = \{b, c\}$

- Association rule: $\{m, b\} \rightarrow c$
  - Support(m,b)=4/8, Support(m,b,c)=2/8
  - Confidence = 2/4 = 0.5

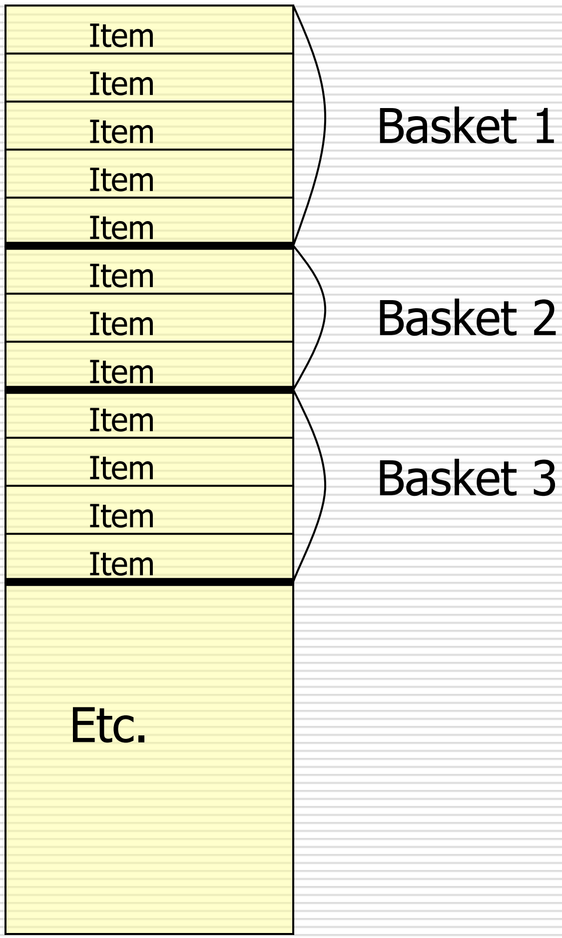
# Association Rules Mining

- Question: "find all association rules with support $\geq s$ and confidence $\geq c$"
- Hard part: finding the frequent itemsets

# Computation Model

- Typically, data is kept in flat files rather than in a database system
  - Stored on disk
  - Stored basket-by-basket
  - Expand baskets into pairs, triples, etc. as you read baskets

# File Organization




Example: items are positive integers, and boundaries between baskets are –1

# Computation Model – (2)

- The true cost of mining disk-resident data is usually the number of disk I/O's
- In practice, association-rule algorithms read the data in *passes* – all baskets read in turn
- Thus, we measure the cost by the number of passes an algorithm takes

# Main-Memory Bottleneck

- For many frequent-itemset algorithms, main memory is the critical resource
  - As we read baskets, we need to count something, e.g., occurrences of pairs
  - The number of different things we can count is limited by main memory
  - Swapping counts in/out is a disaster

# Finding Frequent Pairs

- The hardest problem often turns out to be finding the frequent pairs
  - Why? Often frequent pairs are common, frequent triples are rare
    - Why? Probability of being frequent drops exponentially with size; number of sets grows more slowly with size
- We'll concentrate on pairs, then extend to larger sets

# Naïve Algorithm

- Read file once, counting in main memory the occurrences of each pair
  - From each basket of $n$ items, generate its $n(n-1)/2$ pairs by two nested loops
- Fails if $(\#\text{items})^2$ exceeds main memory
  - Remember: #items can be 100K (Wal-Mart) or 10B (Web pages)

# Example: Counting Pairs

- Suppose $10^5$ items
- Suppose counts are 4-byte integers
- Number of pairs of items: $10^5(10^5-1)/2 = 5*10^9$ (approximately)
- Therefore, $2*10^{10}$ (20 gigabytes) of main memory needed

# Details of Main-Memory Counting

- Two approaches:

  (1) Count all pairs, using a triangular matrix

  - requires only 4 bytes/pair

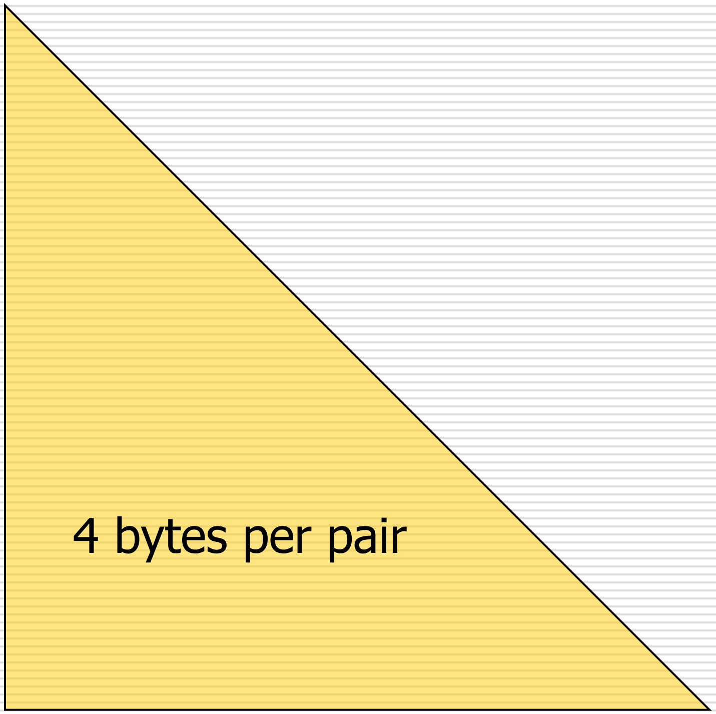
    always assume integers are 4 bytes

  (2) Keep a table of triples [*i*, *j*, *c*] = "the count of the pair of items {*i*, *j* } is *c*"

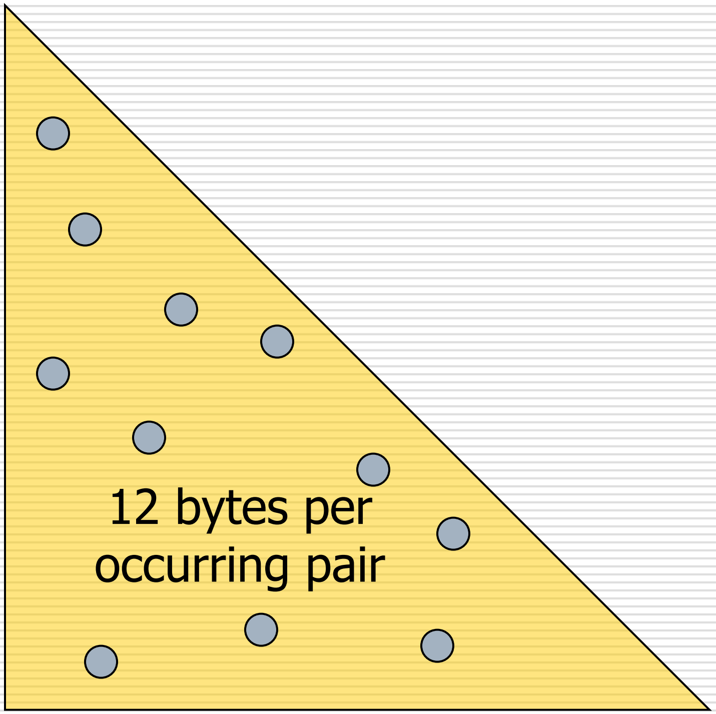
  - requires 12 bytes

    but only for those pairs with count > 0

# Details of Main-Memory Counting




Method (1)




Method (2)

# Comparing the Two Approaches

- **Approach 1: Triangular Matrix**
  - **n** = total number of items
  - Count pair of items $\{i, j\}$ only if $i<j$
  - Keep pair counts in lexicographic order:
    - {1,2}, {1,3},…, {1,$n$}, {2,3}, {2,4},…,{2,$n$}, {3,4},…{n-1,n}
  - Pair $\{i, j\}$ is at position $(i-1)(n-i/2)+j-i$
  - Total number of pairs $\boldsymbol{n(n-1)/2}$; total bytes= $\boldsymbol{2n^2}$
  - **Triangular Matrix** requires 4 bytes per pair
- **Approach 2** uses **12 *bytes*** per occurring pair *(but only for pairs with count > 0)*
  - Beats Approach 1 if less than **1/3** of possible pairs actually occur

# Comparing the Two Approaches

- **Approach 1: Triangular Matrix**
  - **n** = total number items
  - Count pair of items $\{i, j\}$ only if $i<j$
  - ..
  - s= $\boldsymbol{2n^2}$
- A pair
  (b

**Problem is if we have too many items so the pairs do not fit into memory.**

**Can we do better?**

possible pairs actually occur

# Outline

- Association Rules
- Frequent Itemset Mining Algorithms
  - Apriori
  - FP-growth
- Sequential Pattern Mining Algorithms

# Apriori Algorithm

- Proposed by Rakesh Agrawal [*VLDB'94*]
- Key idea:
  - Candidate generation-and-test
  - Anti-monotone property

http://www.vldb.org › conf PDF

Fast Algorithms for Mining Association Rules - VLDB ...

by R Agrawal · Cited by 28692 — We consider the problem of discovering **association rules** between items in a large database of sales transactions. We present two new **algorithms** for...

13 pages

# Apriori Algorithm – (1)

- A two-pass approach called *Apriori* limits the need for main memory

- *Monotonicity* : if a set of items appears at least *s* times, so does every subset
  - Contrapositive for pairs: if item *i* does not appear in *s* baskets, then no pair including *i* can appear in *s* baskets

# Apriori Algorithm – (2)

- Pass 1: Read baskets and count in main memory the occurrences of each item
  - Requires only memory proportional to #items
- Items that appear at least *s* times are the *frequent items*

# Apriori Algorithm – (3)

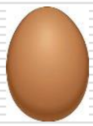
- Pass 2: Read baskets again and count in main memory only those pairs both of which were found in Pass 1 to be frequent
  - Requires memory proportional to square of *frequent* items only (for counts), plus a list of the frequent items (so you know what must be counted)

# Apriori Algorithm

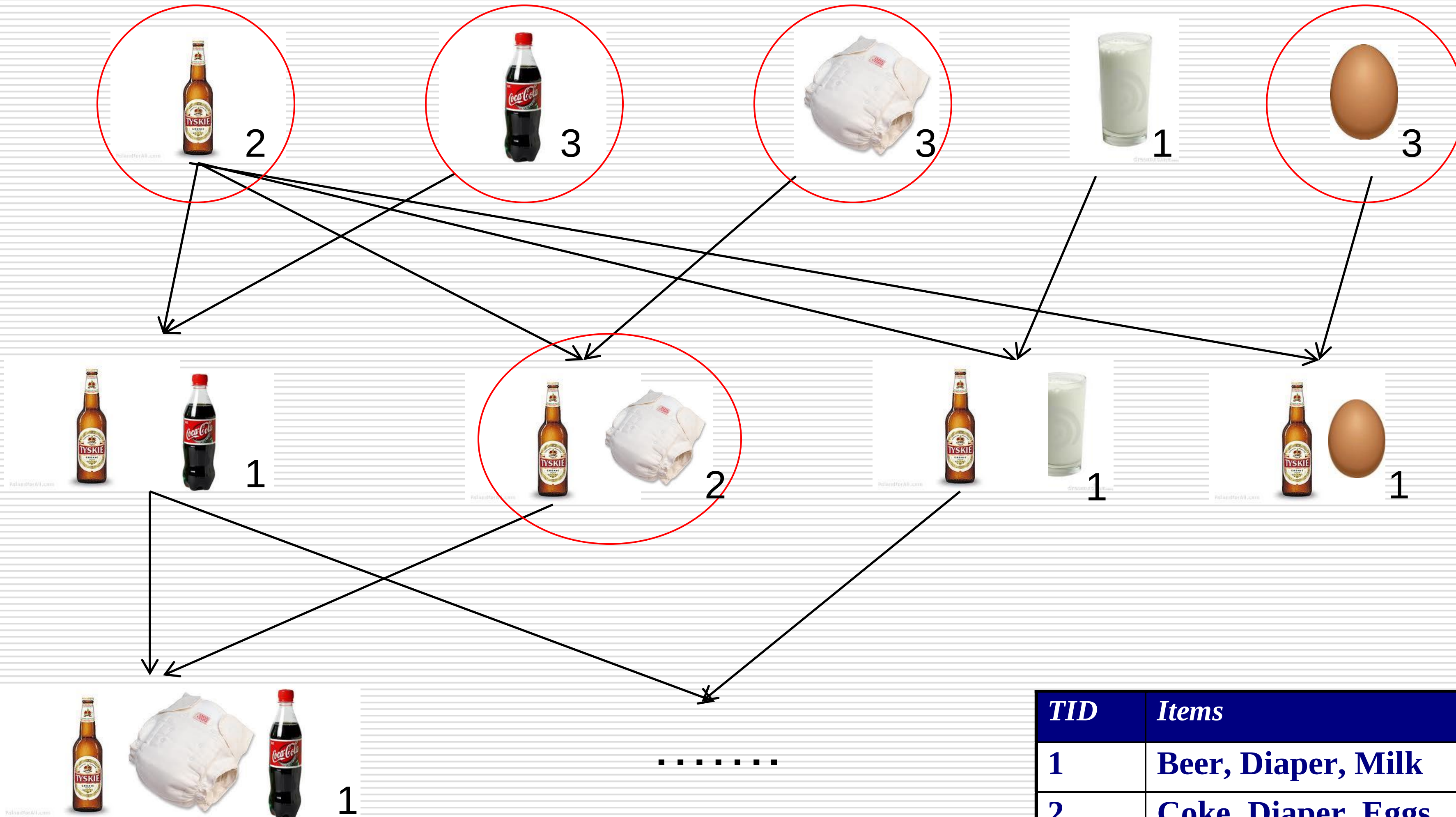
## Market-Basket transactions

| *TID* | *Items* |
|---|---|
| **1** | **Beer, Diaper, Milk** |
| **2** | **Coke, Diaper, Eggs** |
| **3** | **Beer, Coke, Diaper, Eggs** |
| **4** | **Coke, Eggs** |





# Naive Algorithm

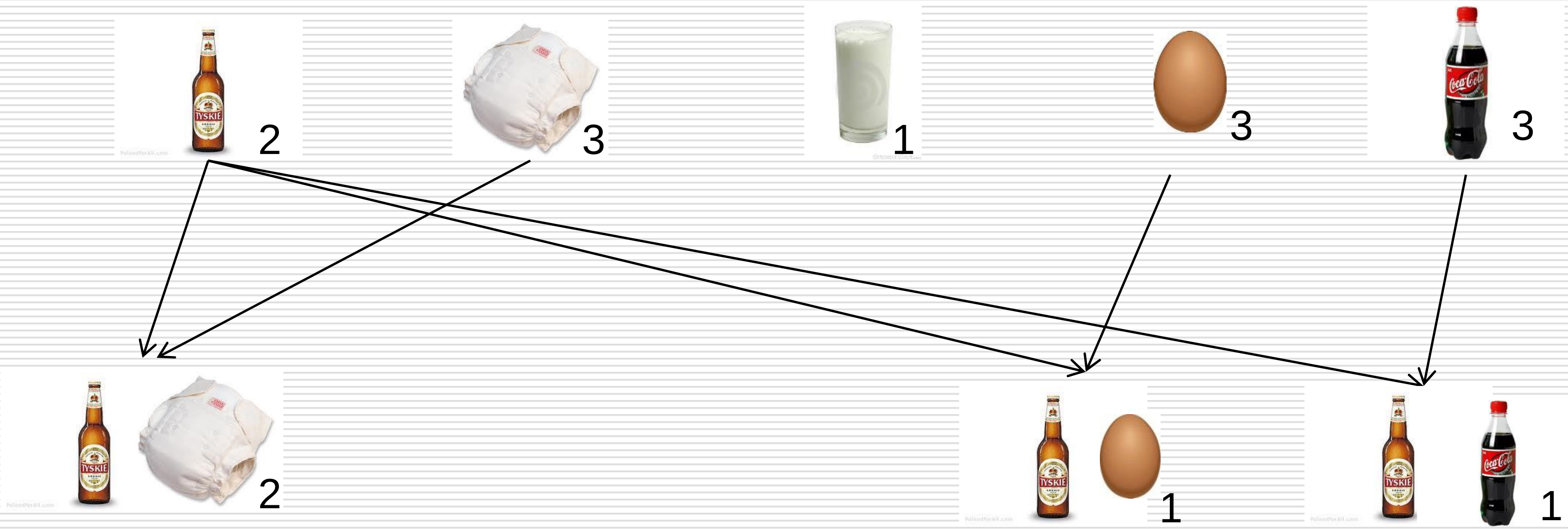



| TID | Items |
|---|---|
| 1 | Beer, Diaper, Milk |
| 2 | Coke, Diaper, Eggs |
| 3 | Beer, Coke, Diaper, Eggs |
| 4 | Coke, Eggs |

$Sup_{min}=2$

# Apriori Algorithm

- Anti-monotone property: If an itemset is not frequent, then any of its superset is not frequent




Sup$_{min}$=2

| TID | Items |
|---|---|
| 1 | Beer, Diaper, Milk |
| 2 | Coke, Diaper, Eggs |
| 3 | Beer, Coke, Diaper, Eggs |
| 4 | Coke, Eggs |

# Apriori Algorithm

$Sup_{min} = 2$

| Tid | Items |
|---|---|
| 10 | A, C, D |
| 20 | B, C, E |
| 30 | A, B, C, E |
| 40 | B, E |

1st scan → $C_1$

| Itemset | sup |
|---|---|
| {A} | 2 |
| {B} | 3 |
| {C} | 3 |
| {D} | 1 |
| {E} | 3 |

→ $L_1$

| Itemset | sup |
|---|---|
| {A} | 2 |
| {B} | 3 |
| {C} | 3 |
| {E} | 3 |

$C_2$

| Itemset |
|---|
| {A, B} |
| {A, C} |
| {A, E} |
| {B, C} |
| {B, E} |
| {C, E} |

2nd scan → $C_2$

| Itemset | sup |
|---|---|
| {A, B} | 1 |
| {A, C} | 2 |
| {A, E} | 1 |
| {B, C} | 2 |
| {B, E} | 3 |
| {C, E} | 2 |

→ $L_2$

| Itemset | sup |
|---|---|
| {A, C} | 2 |
| {B, C} | 2 |
| {B, E} | 3 |
| {C, E} | 2 |

$C_3$

| Itemset |
|---|
| {B, C, E} |

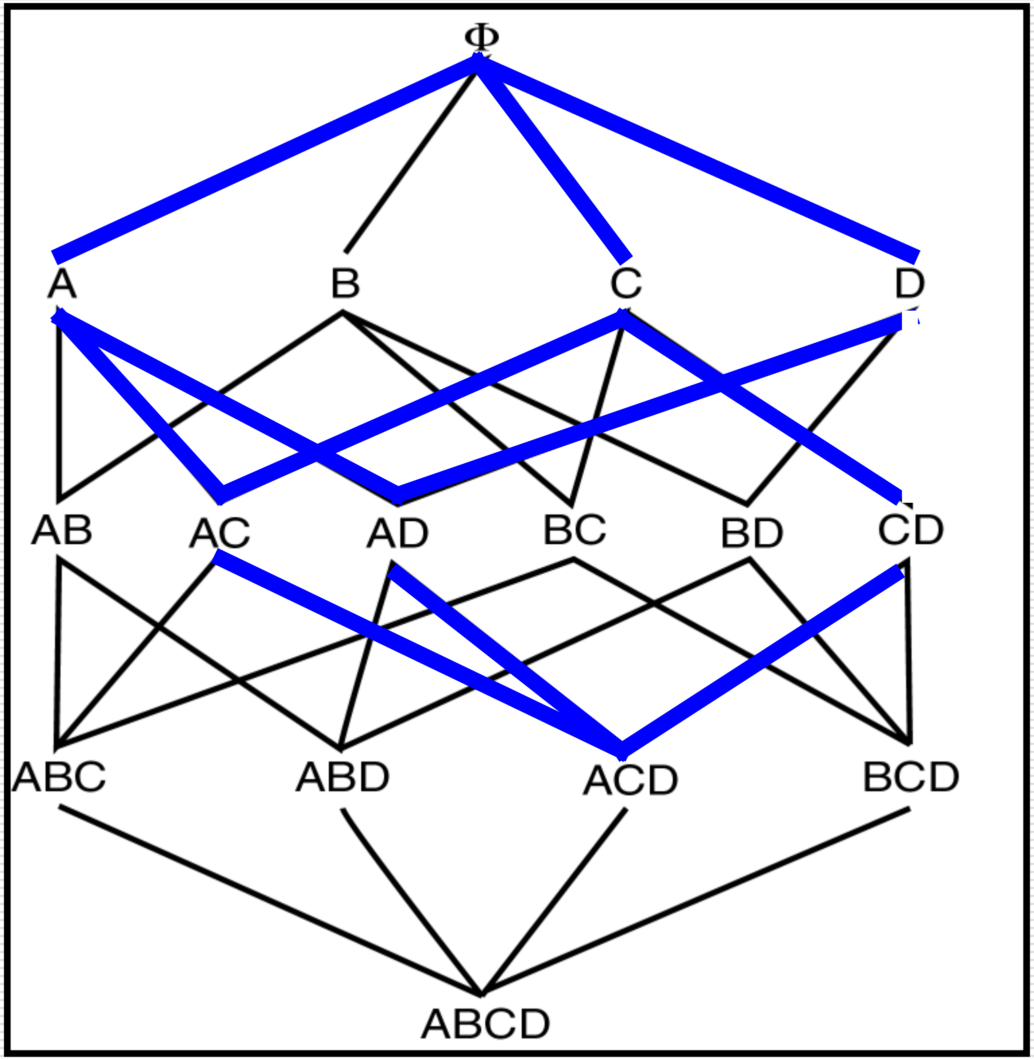
3rd scan → $L_3$

| Itemset | sup |
|---|---|
| {B, C, E} | 2 |

# Apriori Algorithm

1. $C_1$ = Itemsets of size one in I;
2. Determine all large itemsets of size 1, $L_{1;}$
3. i = 1;
4. Repeat
5.     i = i + 1;
6.     $C_i$ = Apriori-Gen($L_{i-1}$);
7.     Count $C_i$ to determine $L_{i;}$
8. until no more large itemsets found;

# Frequent Itemset Property



# Drawbacks of Apriori

- Multiple scans of transaction database
  - Multiple database scans are costly
- Huge number of candidates
  - To find frequent itemset $i_1 i_2 \ldots i_{100}$
    - # of scans: 100
    - # of Candidates: $2^{100}-1 = 1.27*10^{30}$

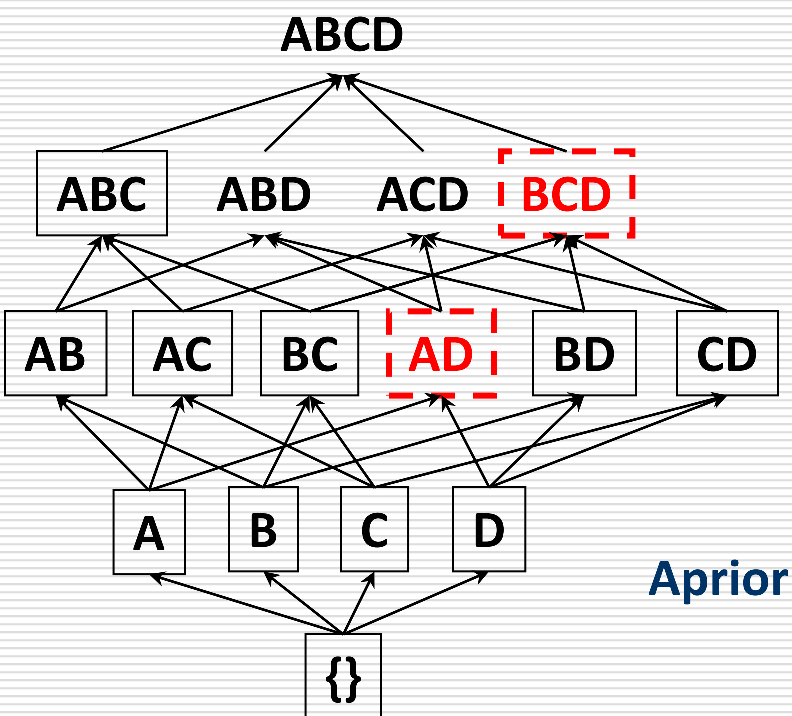
# Improving Apriori: General Ideas

- Reduce passes of transaction database scans
- Shrink number of candidates
- Facilitate support counting of candidates

# Improving Apriori's Efficiency

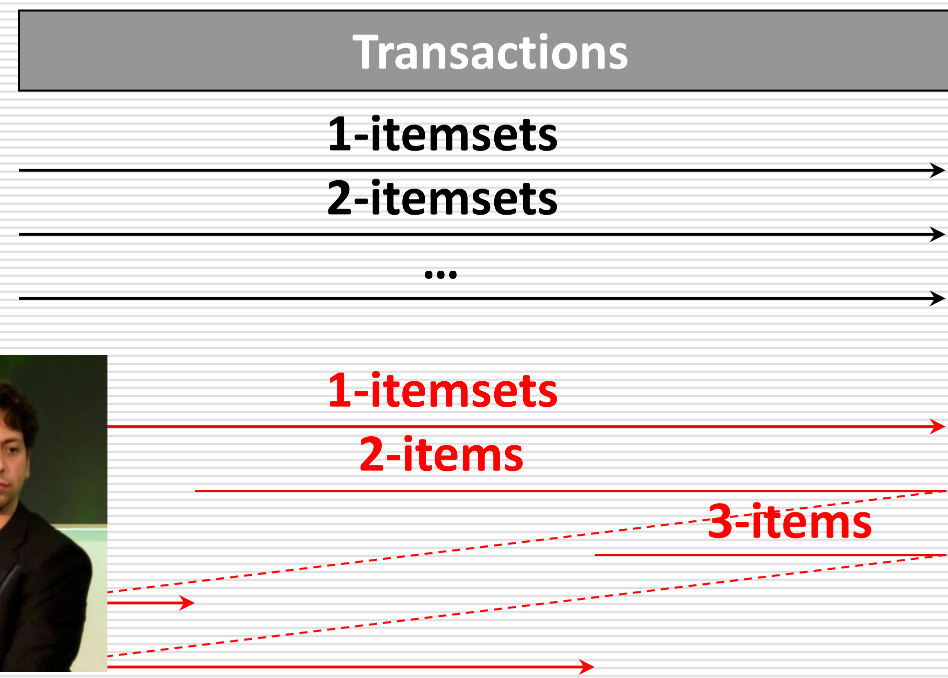
- Hash-based itemset counting: A *k*-itemset whose corresponding hashing bucket count is below the threshold cannot be frequent
- Transaction reduction: A transaction that does not contain any frequent k-itemset is useless in subsequent scans
- Partitioning: Any itemset that is potentially frequent in DB must be frequent in at least one of the partitions of DB
- Sampling: mining on a subset of given data, need a lower support threshold + a method to determine the completeness
- Dynamic itemset counting: add new candidate itemsets immediately (unlike Apriori) when all of their subsets are estimated to be frequent

# DIC: Reduce Number of Scans




Itemset lattice

- Once both A and D are determined frequent, the counting of AD begins
- Once all length-2 subsets of BCD are determined frequent, the counting of BCD begins




S. Brin , R. Motwani, J. Ullman, and S. Tsur. Dynamic itemset counting and implication rules for market basket data. In *SIGMOD'97*

# FP-growth Algorithm

# FP-Growth

- Proposed by Jiawei Han [*SIGMOD'00*]
- Uses the Apriori pruning principle
- Scan DB only twice
  - Once to find frequent 1-itemset (single item pattern)
  - Once to construct FP-tree (prefix tree, Trie), the data structure of FP-growth

# Mining Frequent Patterns without Candidate Generation

- Compress a large database into a compact, Frequent-Pattern tree (FP-tree) structure
  - highly condensed, but complete for frequent pattern mining
  - avoid costly database scans
- Develop an efficient, FP-tree-based frequent pattern mining method
  - A divide-and-conquer methodology: decompose mining tasks into smaller ones
  - Avoid candidate generation: sub-database test only!

# FP-Growth

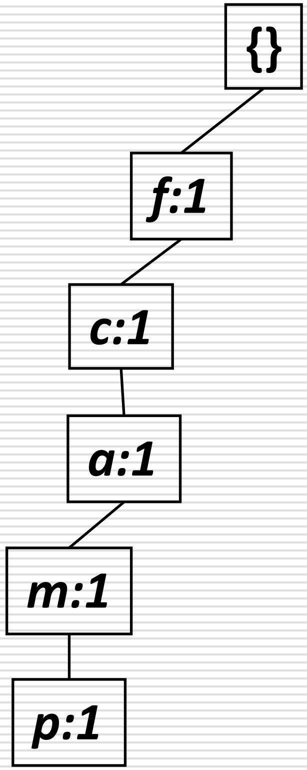
$Sup_{min} = 2$

| *TID* | *Items bought* |
|---|---|
| 10 | *{f, a, c, d, g, i, m, p}* |
| 20 | *{a, b, c, f, l, m, o}* |
| 30 | *{b, f, h, j, o, w}* |
| 40 | *{b, c, k, s, p}* |
| 50 | *{a, f, c, e, l, p, m, n}* |

**Header Table**

| *Item* | *frequency* |
|---|---|
| *f* | *4* |
| *c* | *4* |
| *a* | *3* |
| *b* | *3* |
| *m* | *3* |
| *p* | *3* |

| *TID* | *(ordered) frequent items* |
|---|---|
| 10 | *{f, c, a, m, p}* |
| 20 | *{f, c, a, b, m}* |
| 30 | *{f, b}* |
| 40 | *{c, b, p}* |
| 50 | *{f, c, a, m, p}* |



# FP-Growth

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|---|---|
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| *c* | *4* |
| *a* | *3* |
| *b* | *3* |
| *m* | *3* |
| *p* | *3* |

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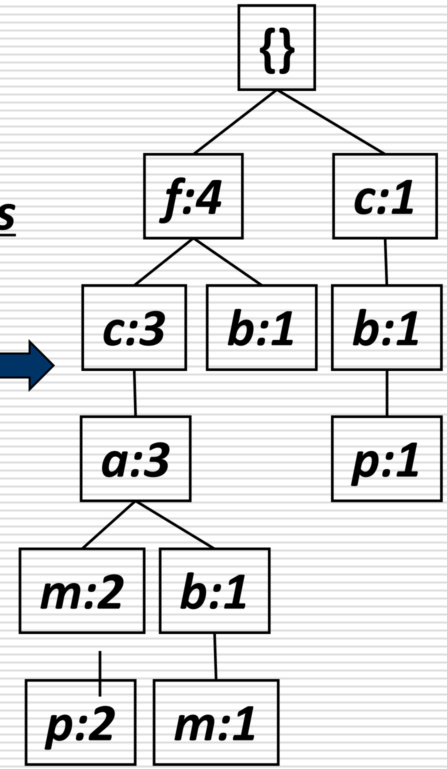


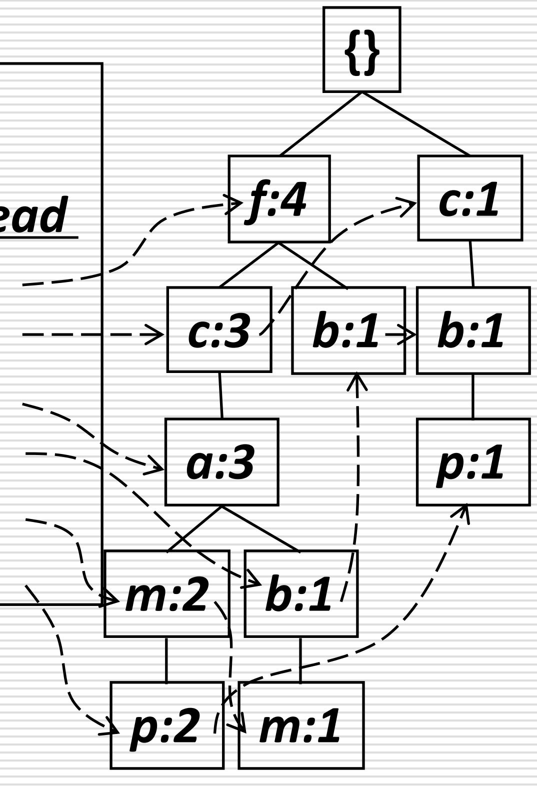
# FP-Growth

$Sup_{min} = 2$

| *TID* | *(ordered) frequent items* |
|---|---|
| 10 | {*f, c, a, m, p*} |
| 20 | {*f, c, a, b, m*} |
| 30 | {*f, b*} |
| 40 | {*c, b, p*} |
| 50 | {*f, c, a, m, p*} |

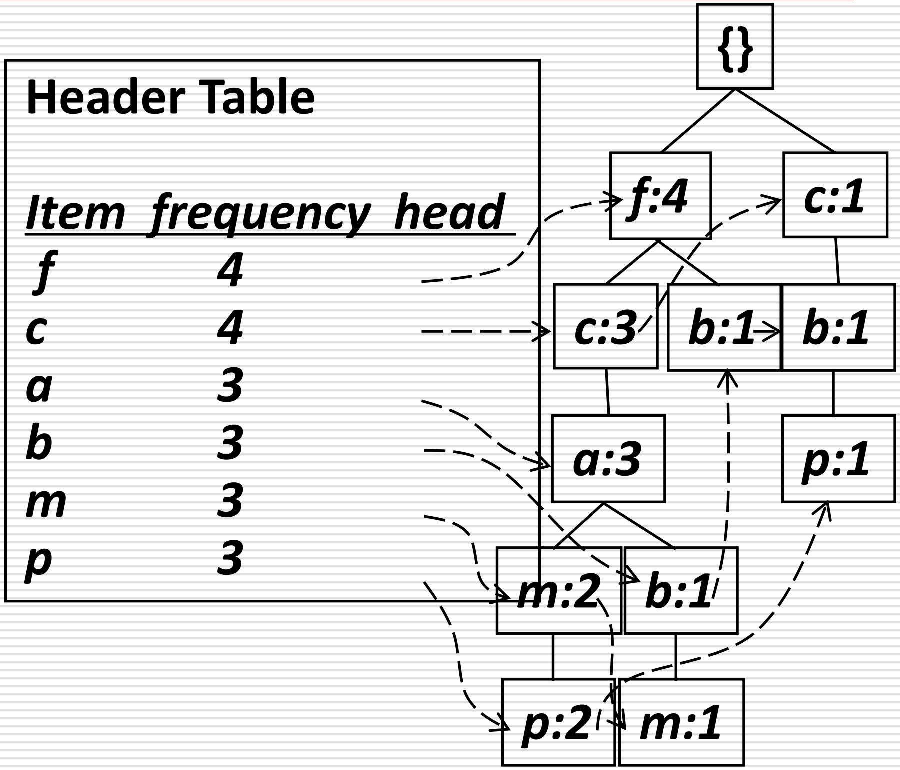
**Header Table**

| *Item* | *frequency* | *head* |
|---|---|---|
| *f* | *4* | |
| *c* | *4* | |
| *a* | *3* | |
| *b* | *3* | |
| *m* | *3* | |
| *p* | *3* | |



# FP-Growth

$Sup_{min} = 2$




***Conditional*** **pattern bases**

| *Item* | *cond. pattern base* | *freq. itemset* |
|---|---|---|
| *p* | *fcam:2, cb:1* | *fp, cp, ap, mp, fcp, fap, fmp, cap, cmp, amp, camp, facp, fcmp, famp, fcamp* |
| *m* | *fca:2, fcab:1* | *fm, cm, am, fcm, fam, cam, fcam* |
| *b* | *fca:1, f:1, c:1* | *…* |
| *a* | *fc:3* | *…* |
| *c* | *f:3* | *…* |

# Why Is Frequent Pattern Growth Fast?

- The performance study shows
  - FP-growth is faster than Apriori (in most cases), and is also faster than tree-projection (an order of magnitude on some datasets)
- Reasoning
  - No candidate generation (claimed by the authors)
  - Use compact data structure
  - Eliminate repeated database scan
  - Basic operation is counting and FP-tree building

# Extension of Association Rule Mining

- Association rule mining has been extensively studied in the data mining community.
- There are many efficient algorithms and model variations.
- Other related work includes
  - Multi-level or generalized rule mining
  - Sequential pattern mining
  - Constrained rule mining
  - Incremental rule mining
  - Maximal and closed frequent itemset mining
  - Numeric association rule mining
  - Rule interestingness and visualization
  - Parallel algorithms
  - …

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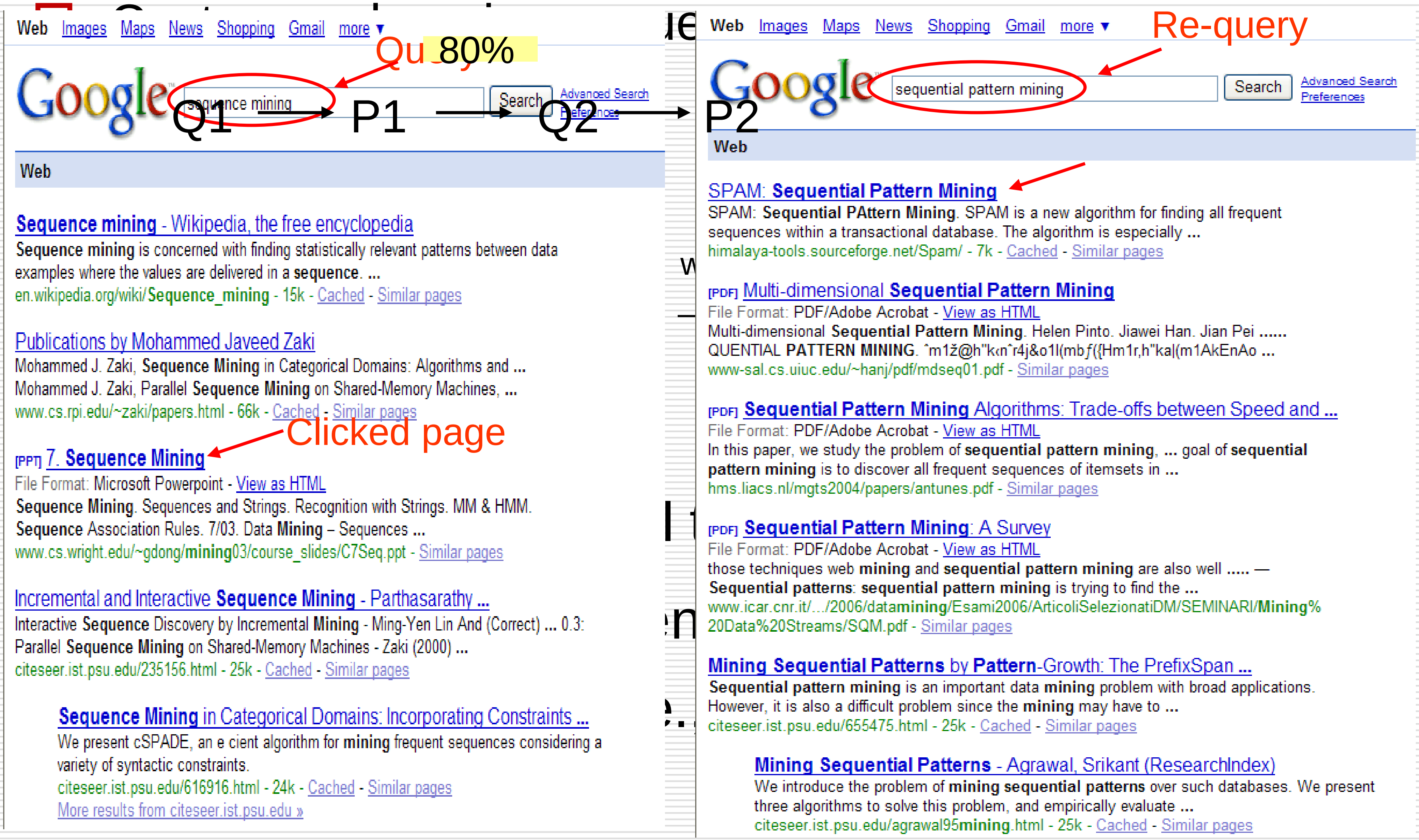
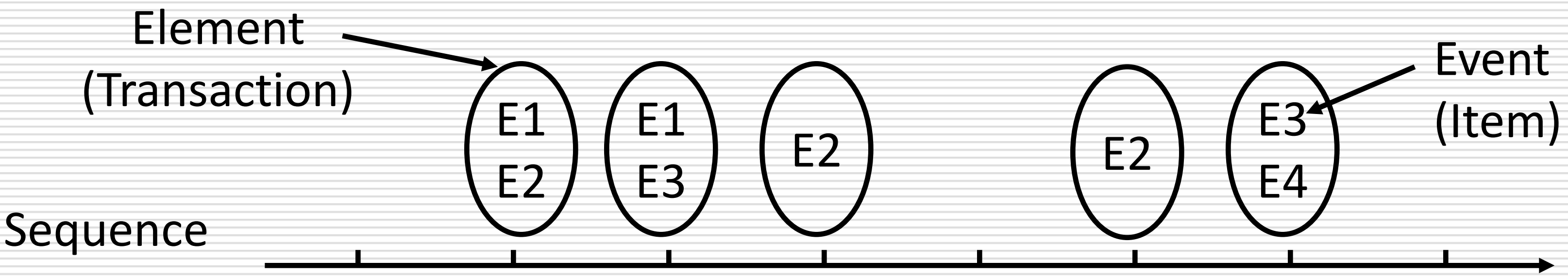
# Applications



# Examples of Sequence Data

| Sequence Database | Sequence | Element (Transaction) | Event (Item) |
|---|---|---|---|
| Customer | Purchase history of a given customer | A set of items bought by a customer at time t | Books, diary products, CDs, etc |
| Web Data | Browsing activity of a particular Web visitor | A collection of files viewed by a Web visitor after a single mouse click | Home page, index page, contact info, etc |
| Event data | History of events generated by a given sensor | Events triggered by a sensor at time t | Types of alarms generated by sensors |
| Genome sequences | DNA sequence of a particular species | An element of the DNA sequence | Bases A,T,G,C |



# Formal Definition of a Sequence

- A sequence is an ordered list of elements (transactions)

$$s = < e_1\, e_2\, e_3 \ldots >$$

  - Each element contains a collection of items

$$e_i = \{i_1, i_2, \ldots, i_k\}$$

  - Each element is attributed to a specific time

- A k-sequence is a sequence that contains k items

# Formal Definition of a Subsequence

- A sequence $<a_1\, a_2 \ldots a_n>$ is contained in another sequence $<b_1\, b_2 \ldots b_m>$ ($m \geq n$) if there exist integers $i_1 < i_2 < \ldots < i_n$ such that $a_1 \subseteq b_{i1}$ , $a_2 \subseteq b_{i1}$, ..., $a_n \subseteq b_{in}$

| Data sequence | Subsequence | Contain? |
|---|---|---|
| < {2,4} {3,5,6} {8} > | < {2} {3,5} > | Yes |
| < {1,2} {3,4} > | < {1} {2} > | No |
| < {2,4} {2,4} {2,5} > | < {2} {4} > | Yes |

- The support of a subsequence w is defined as the fraction of data sequences that contain w
- A *sequential pattern* is a frequent subsequence (i.e., a subsequence whose support is ≥ *minsup*)

# Sequential Pattern Mining: Definition

- Given:
  - a database of sequences
  - a user-specified minimum support threshold, *minsup*
- Task:
  - Find all subsequences with support ≥ *minsup*

# Sequential Pattern Mining: Challenge

- How many k-subsequences can be extracted from a given n-sequence?

<{a b} { c d e} {f} {g h i}> n = 9

k=4: Y _ _ Y Y _ _ _ Y

<{a} {d e} {i}>

Answer :

$$\binom{n}{k} = \binom{9}{4} = 126$$

# Outline

- Association Rules
- Frequent Itemset Mining Algorithms
- Sequential Pattern Mining Algorithms
  - GSP
  - SPADE
  - SPAM

# GSP (Generalized Sequential Pattern Mining)

- Proposed by Srikant and Agrawal [*EDBT'96*]
- Uses the Apriori pruning principle

# Finding Length-1 Sequential Patterns

- Initial candidates:
  - <a>, <b>, <c>, <d>, <e>, <f>, <g>, <h>
- Scan database once, count support for candidates

*min_sup* =2

| Seq. ID | Sequence |
|---|---|
| 10 | <(bd)cb(ac)> |
| 20 | <(bf)(ce)b(fg)> |
| 30 | <(ah)(bf)abf> |
| 40 | <(be)(ce)d> |
| 50 | <a(bd)bcb(ade)> |

| Cand | Sup |
|---|---|
| **<a>** | **3** |
| **<b>** | **5** |
| **<c>** | **4** |
| **<d>** | **3** |
| **<e>** | **3** |
| **<f>** | **2** |
| ~~<g>~~ | 1 |
| ~~<h>~~ | 1 |

# Generating Length-2 Candidates

51 length-2 Candidates

| | <a> | <b> | <c> | <d> | <e> | <f> |
|---|---|---|---|---|---|---|
| <a> | <aa> | <ab> | <ac> | <ad> | <ae> | <af> |
| <b> | <ba> | <bb> | <bc> | <bd> | <be> | <bf> |
| <c> | <ca> | <cb> | <cc> | <cd> | <ce> | <cf> |
| <d> | <da> | <db> | <dc> | <dd> | <de> | <df> |
| <e> | <ea> | <eb> | <ec> | <ed> | <ee> | <ef> |
| <f> | <fa> | <fb> | <fc> | <fd> | <fe> | <ff> |

| | <a> | <b> | <c> | <d> | <e> | <f> |
|---|---|---|---|---|---|---|
| <a> | | <(ab)> | <(ac)> | <(ad)> | <(ae)> | <(af)> |
| <b> | | | <(bc)> | <(bd)> | <(be)> | <(bf)> |
| <c> | | | | <(cd)> | <(ce)> | <(cf)> |
| <d> | | | | | <(de)> | <(df)> |
| <e> | | | | | | <(ef)> |
| <f> | | | | | | |

Without Apriori property, 8*8+8*7/2=92 candidates

Apriori prunes 44.57% candidates

# GSP Mining Process

5th scan: 1 cand. 1 length-5 seq. pat. <(bd)cba>

Cand. cannot pass sup. threshold

4th scan: 8 cand. 6 length-4 seq. pat. <abba> <(bd)bc> …

Cand. not in DB at all

3rd scan: 46 cand. 19 length-3 seq. pat. 20 cand. not in DB at all <abb> <aab> <aba> <baa> <bab> …

2nd scan: 51 cand. 19 length-2 seq. pat. 10 cand. not in DB at all <aa> <ab> … <af> <ba> <bb> … <ff> <(ab)> … <(ef)>

1st scan: 8 cand. 6 length-1 seq. pat. <a> <b> <c> <d> <e> <f> <g> <h>

*min_sup* =2

| Seq. ID | Sequence |
|---|---|
| 10 | <(bd)cb(ac)> |
| 20 | <(bf)(ce)b(fg)> |
| 30 | <(ah)(bf)abf> |
| 40 | <(be)(ce)d> |
| 50 | <a(bd)bcb(ade)> |

# GSP Algorithm

- Take sequences in form of <x> as length-1 candidates
- Scan database once, find $F_1$, the set of length-1 sequential patterns
- Let k=1; while $F_k$ is not empty do
  - Form $C_{k+1}$, the set of length-(k+1) candidates from $F_k$;
  - If $C_{k+1}$ is not empty, scan database once, find $F_{k+1}$, the set of length-(k+1) sequential patterns
  - Let k=k+1;

# GSP Algorithm

- Benefits from the Apriori pruning
  - Reduces search space
- Bottlenecks
  - Scans the database multiple times
  - Generates a huge set of candidate sequences

# SPADE Algorithm

# SPADE Algorithm

- Proposed by Zaki *et al.* [*MLJ'01*]
- Candidate generation-and-test
- Vertical ID-list data representation based on Lattice-theory
- Counting support through temporal joins
- Reduced I/O costs (three DB scans)

# SPADE Algorithm

| ID | Data Sequence |
|---|---|
| 1 | < a c ( b c ) d ( a b c ) a d > |
| 2 | < b ( c d ) a c ( b d ) > |
| 3 | < d ( b c ) ( a c ) ( c d ) > |

ID-List DB

| a | | b | | c | | d | |
|---|---|---|---|---|---|---|---|
| SID | Pos | SID | Pos | SID | Pos | SID | Pos |
| 1 | 1 | 1 | 3 | 1 | 2 | 1 | 4 |
| 1 | 5 | 1 | 5 | 1 | 3 | 1 | 7 |
| 1 | 6 | 2 | 1 | 1 | 5 | 2 | 2 |
| 2 | 3 | 2 | 5 | 2 | 2 | 2 | 5 |
| 3 | 3 | 3 | 2 | 2 | 4 | 3 | 1 |
| | | | | 3 | 2 | 3 | 4 |
| | | | | 3 | 3 | | |
| | | | | 3 | 4 | | |

# Temporal Joins

| {a} | |
|---|---|
| SID | Pos |
| 1 | 1 |
| 1 | 5 |
| 1 | 6 |
| 2 | 3 |
| 3 | 3 |

+

| {b} | |
|---|---|
| SID | Pos |
| 1 | 3 |
| 1 | 5 |
| 2 | 1 |
| 2 | 5 |
| 3 | 2 |

| {a, b} | |
|---|---|
| SID | Pos |
| 1 | 3 |
| 1 | 5 |
| 2 | 5 |

Supp{ab}=2

| {b, a} | |
|---|---|
| SID | Pos |
| 1 | 5 |
| 1 | 6 |
| 3 | 3 |

Supp{ba}=2

| {(ab)} | |
|---|---|
| SID | Pos |
| 1 | 5 |

Supp{(ab)}=1

min_support=2

# SPAM Algorithm

# SPAM Algorithm

- Proposed by Ayres *et al.* [*KDD'02*]
- Key idea based on SPADE
- Using bitmap data representation
- Faster than SPADE yet space consuming

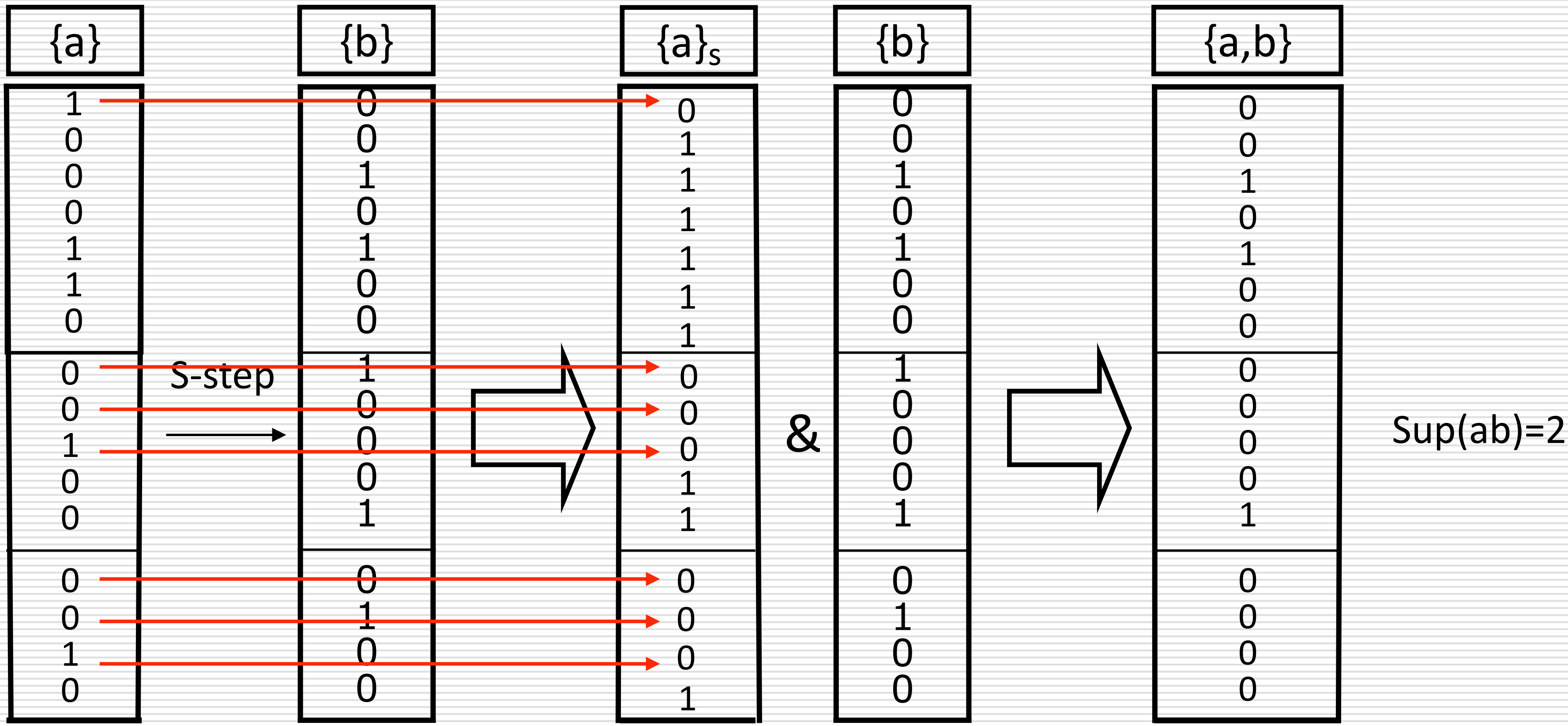
# SPAM Algorithm

| ID | Data Sequence |
|---|---|
| 10 | < a c ( b c ) d ( a b c ) a d > |
| 20 | < b ( c d ) a c ( b d ) > |
| 30 | < d ( b c ) ( a c ) ( c d ) > |

| SID | EID | {a} | {b} | {c} | {d} |
|---|---|---|---|---|---|
| 10 | 1 | 1 | 0 | 0 | 0 |
| 10 | 2 | 0 | 0 | 1 | 0 |
| 10 | 3 | 0 | 1 | 1 | 0 |
| 10 | 4 | 0 | 0 | 0 | 1 |
| 10 | 5 | 1 | 1 | 1 | 0 |
| 10 | 6 | 1 | 0 | 0 | 0 |
| 10 | 7 | 0 | 0 | 0 | 1 |
| 20 | 1 | 0 | 1 | 0 | 0 |
| 20 | 2 | 0 | 0 | 1 | 1 |
| 20 | 3 | 1 | 0 | 0 | 0 |
| 20 | 4 | 0 | 0 | 1 | 0 |
| 20 | 5 | 0 | 1 | 0 | 1 |
| 30 | 1 | 0 | 0 | 0 | 1 |
| 30 | 2 | 0 | 1 | 1 | 0 |
| 30 | 3 | 1 | 0 | 1 | 0 |
| 30 | 4 | 0 | 0 | 1 | 1 |

# SPAM Temporal Joins

Sequence extended step:




min_support=2

# Problem of SPAM

- Bitmap representation is space consuming i.e., data is commonly very sparse

# Acknowledgement

- Slides are adapted from:
  - Prof. Jeffrey D. Ullman
  - Dr. Jure Leskovec
  - Dr. Wujun Li

# Quiz

| TID | Items |
|---|---|
| 10 | {a, d, e} |
| 20 | {a, b, c, e} |
| 30 | {a, b, d, e} |
| 40 | {a, c, d, e} |
| 50 | {b, c, e} |
| 60 | {b, d, e} |
| 70 | {c, d} |
| 80 | {a, b, c} |
| 90 | {a, d, e} |
| 100 | {a, b, e} |

Confidence({bd} → {e}) = ?

Confidence({e} → {bd}) = ?

答案请发送到邮箱： bigdatacomputing@163.com

截至时间：今天(2023年2月24日）晚上24点

需要注明：(1)姓名；(2)学号;(3)专业