COMP3420: Advanced Databases and Data Mining

Introduction to association mining

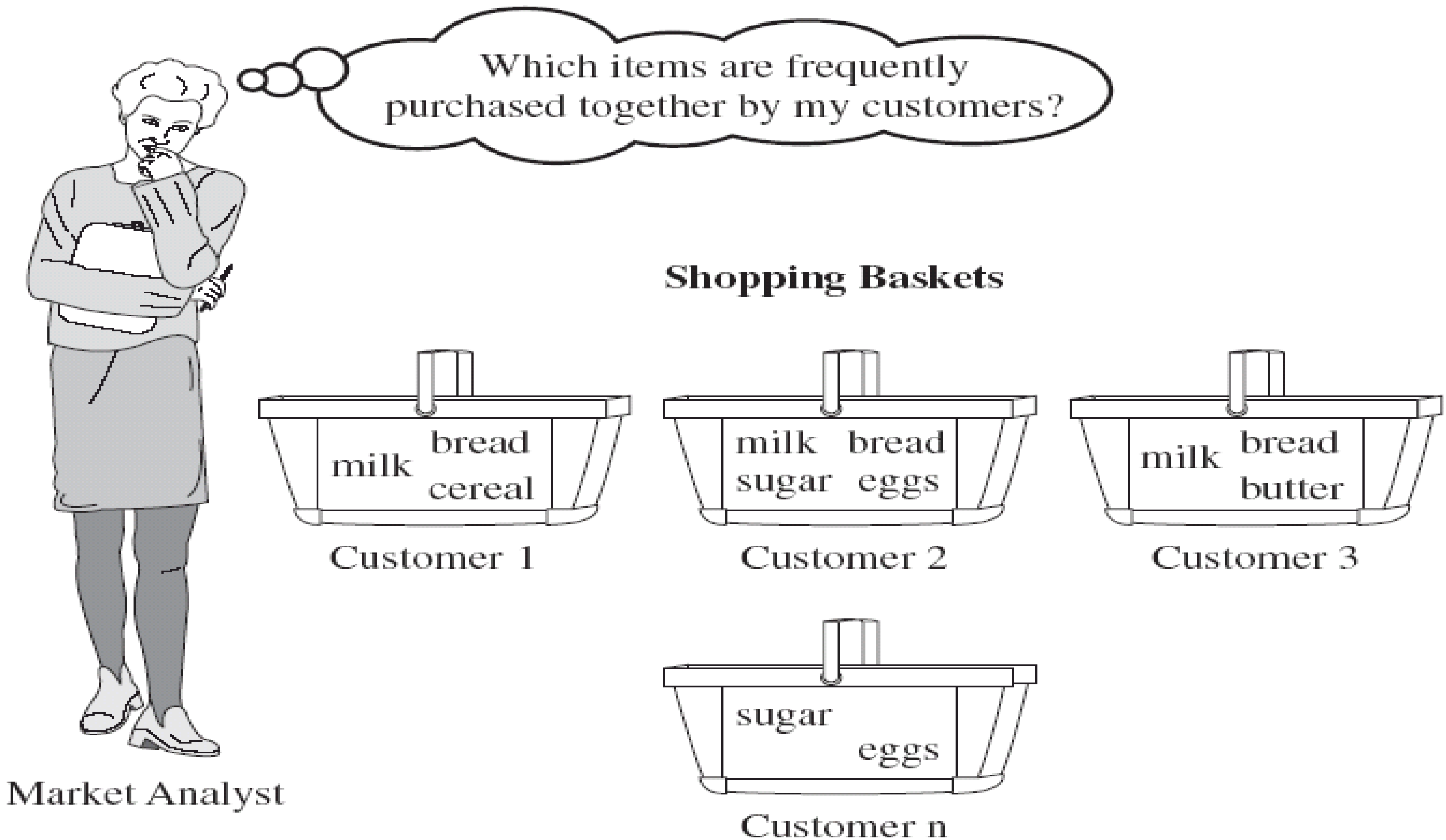
Lecture outline

- What is association mining?
- Market basket analysis and association rules examples
- Basic concepts and formalism
- Basic rule measurements
- The *Apriori* algorithm
- Performance bottlenecks in *Apriori*
- Improve *Apriori's* efficiency

What is association mining?

- Association mining is the task of finding frequent rules / associations / patterns / correlations / causal structures within (large) sets of items in transactional (relational) databases
- *Unsupervised* learning techniques (*descriptive* data mining, not *predictive* data mining)
- The main applications are
  - Market basket analysis (customers who buys X also buys Y)
  - Web log analysis (click-stream)
  - Cross-marketing
  - Sale campaign analysis
  - DNS sequence analysis

Market basket analysis



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

Association rules examples

- Rules form: *body ⇒ head [support, confidence]*
- Market basket:

  buys(X, `beer') ⇒ buys(X, `snacks')   [s=1%, c=60%]

  - If a customer X purchased `beer', in 60% she or he also purchased `snacks'
  - 1% of all transactions contain the items `beer' and `snacks'
- Student grades:

  major(X, `BIT') and takes(X, `COMP3420') ⇒

  grade(X, `D')   [s=3%, c=70%] *

  - If a student X, who's major is `BIT', took the course `COMP3420' she or he in 70% achieved a grade `D'
  - The combination `BIT', `COMP3420' and `D' appears in 3% of all transactions (records) in the database

** Disclaimer: This is only an example, it does not mean that 70% of COMP3420 students in the past achieved a 'D' grade.*

Basic concepts

- Given:
  - A (large) database of transactions
  - Each transaction contains a list of one or more items (e.g. purchased by a customer in a visit)
- Find the rules that correlate the presence of one set of items with that of another set of items
- Normally one is only interested in rules that are *frequent*
  - For example, 70% of customers who buy tires and car accessories also get their car service done
    Question: How can this be improved to 80%? Possibly offer special deals like a 15% reduction of tire costs when the service is done

Formalism

- Set of items $X = \{x_1, x_2, \ldots, x_k\}$
- Database *D* containing transactions
- Each transaction *T* is a set of items, such that *T* is a subset of *X*
- Each transaction is associated with a unique identifier, called *TID* (for example, a unique number)
- Let *A* be a set of items (a subset of *X*)
- An association rule is an implication of the form $A \Rightarrow B$, where *A* is a subset of *X* and *B* is a subset of *X*, and the intersection of *A* and *B* is empty
  - No item in *A* can be in *B*, and vice versa
  - No rule of the form: {\`beer', \`chips'} $\Longrightarrow$ {\`chips', \`peanuts'}

Basic rule measurements

- A rule $A \Rightarrow B$ holds in a database D with *support s,* with s being the percentage of transactions in D that contain A and B

$$\text{support}(A \Rightarrow B) = \text{P}(A \text{ U } B)$$

- The rule $A \Rightarrow B$ has a *confidence c* in a database D if c is the percentage of transactions in D containing A that also contain B

$$\text{confidence}(A \Rightarrow B) = \text{P}(B|A) = \text{P}(A \text{ U } B) \;/\; \text{P}(A)$$
$$\text{confidence}(A \Rightarrow B) = \text{support}(A \Rightarrow B) \;/\; \text{support}(\text{A})$$

Rule measurements example

Transaction ID	Items Bought
2000	a, b, c
1000	a, c
4000	a, d
5000	b, e, f

Itemset	Support
a	75.00%
b	50.00%
c	50.00%
a, c	50.00%

- Minimum support = 50% and confidence = 50%
- Rule $a \Rightarrow c$
  - support ($a \Rightarrow c$): 50%
  - confidence ($a \Rightarrow c$) = support($a \Rightarrow c$) / support(a) = 50% / 75% = 66.67%

Mining frequent item sets

- Key step: Find the *frequent sets of items* that have *minimum support* (appear in at least xx% of all transactions in a database)
- Basic principle (*Apriori* principle): **A sub-set of a frequent item set must also be a frequent item set**
  - For example, if {a,b} is frequent, both {a} and {b} have to be frequent (if `beer' and 'chips' are purchased frequently together, then `beer' is purchased frequently and `chips' are also purchased frequently)
- Basic approach: Iteratively find frequent item sets with cardinality from 1 to k (k-item sets), $k > 1$
- Use the frequent item sets to generate association rules
  - For example, frequent 3-item set {a,b,c} contains rules: $a \Rightarrow c$, $b \Rightarrow c$, $a \Rightarrow b$, $\{a,b\} \Rightarrow c$, $\{a,c\} \Rightarrow b$, $\{b,c\} \Rightarrow a$, etc.
- We are normally only interested in longer rules

The *Apriori* algorithm (Agrawal & Srikant, VLDB'94)

- C_k : Candidate item set of size k
  L_k : Frequent item set of size k
- Pseudo-code:

L_1 = {frequent items};
for (k = 1; L_k != { }; k++) **do begin**
  C_{k+1} = candidates generated from L_k;
  for each transaction t in database **do**
    increment the count of all candidates in C_{k+1}
      that are contained in t
  L_{k+1} = candidates in C_{k+1} with min_support
  end do
return $L = \cup_k L_k$;

The *Apriori* algorithm – An example (sup=50%)

Database D

TID	Items
100	a,c,d
200	b,c,e
300	a,b,c,e
400	b,e

Scan D

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}

Scan D

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}

Scan D

C_3

itemset	sup
{b, c, e}	2

L_3

itemset	sup
{b, c, e}	2

The *Apriori* algorithm – An example (2)

Database D

TID	Items
100	a,c,d
200	b,c,e
300	a,b,c,e
400	b,e

L_3

itemset	sup
{b, c, e}	2

- Minimum support = 50% and minimum confidence = 50%
- Rules:
  - b $\Rightarrow$ c [s=50%, c=66.67%]
  - b $\Rightarrow$ e [s=75%, c=100%]
  - c $\Rightarrow$ e [s=50%, c=66.67%]
  - {b, c} $\Rightarrow$ e [s=50%, c=100%]
  - {b, e} $\Rightarrow$ c [s=50%, c=66.67%]
  - {c, e} $\Rightarrow$ b [s=50%, c=100%]

Important details of the *Apriori* algorithm

- How to generate candidate sets?
  - Step 1: Self-joining L_k (C_k is generated by joining L_{k-1} with itself)
  - Step 2: Pruning (any *(k-1)*-item set that is not frequent cannot be a subset of a frequent *k*-item set)
- Example of candidate generation:
  - L_3 = *{{a,b,c}, {a,b,d}, {a,c,d}, {a,c,e}, {b,c,d}}*
  - Self-joining: L_3 * L_3 ({*a,b,**c,d***} from {*a,b,**c***} and {*a,b,**d***}, and {*a,c,**d,e***} from {*a,c,**d***} and {*a,c,**e***})
  - Pruning: {*a,c,d,e*} is removed because {*a,d,e*} is not in L_3
  - C_4 = {{*a,b,c,d*}}
- How to count supports for candidates?

How to generate candidate item-sets?

- Suppose the items in L_{k-1} are listed in an order (e.g. $a < b$)
- Step 1: Self-joining L_{k-1}

    insert into C_k

    select $p.item_1, p.item_2, \ldots, p.item_{k-1}, q.item_{k-1}$

    from L_{k-1} p, L_{k-1} q

    where $p.item_1 = q.item_1, \ldots, p.item_{k-2} = q.item_{k-2}, p.item_{k-1} < q.item_{k-1}$

- Step 2: Pruning

    forall item sets c **in** C_k **do**

        forall (k-1)-sub-sets s of c **do**

            if (s is not in L_{k-1}) **then** delete c from C_k

Apriori performance bottlenecks

- The core of the *Apriori* algorithm is to
  - Use frequent *(k-1)* item sets to generate candidate frequent *k* item sets
  - Use database scan and pattern matching to collect counts for candidate item sets
- Candidate generation is the main bottleneck
  - 10^4 frequent 1-item sets (sets of length 1) will generate 10^7 candidate 2-item sets!
  - To discover a frequent pattern of size 100 (for example $\{a_1, a_2, ..., a_{100}\}$) one needs to generate $2^{100} = 10^{30}$ candidates
  - Multiple scans of the database are needed (*n+1* scans if the longest pattern is *n* items long)

Methods to improve *Apriori's* efficiency

- Reduce the number of scans of the database
  - Any item set that is potentially frequent in the database must be frequent in at least one of the partitions of the database
  - Scan 1: Partition database and find local frequent patterns
  - Scan 2: Consolidate global frequent patterns
- Shrink number of candidates
  - Select a sample of the database, mine frequent patterns within sample using *Apriori*
  - Scan database once to verify frequent item sets found in sample
  - Scan database again to find missed frequent patterns
- Facilitate support of counting candidates
  - For example, use special data structures like Frequent-Pattern tree (FP-tree)