

CS 412 Intro. to Data Mining

Chapter 6. Mining Frequent Patterns, Association and Correlations: Basic Concepts and Methods

Jiawei Han, Computer Science, Univ. Illinois at Urbana-Champaign, 2017

Chapter 6: Mining Frequent Patterns, Association and Correlations: Basic Concepts and Methods

Basic Concepts



- Efficient Pattern Mining Methods
- Pattern Evaluation
- Summary

What Is Pattern Discovery?

- □ What are patterns? กรลับนา อุลุปชากร ก็รับนุมยู่ใน Data
 - Patterns: A set of items, subsequences, or substructures that occur frequently together (or strongly correlated) in a data set
 - Patterns represent intrinsic and important properties of datasets
- Pattern discovery: Uncovering patterns from massive data sets
- Motivation examples:
 - □ What products were often purchased together? 🗎 คัวร่างกับกับเนื่อ
 - □ What are the subsequent purchases after buying an iPad?
 - What code segments likely contain copy-and-paste bugs?
 - What word sequences likely form phrases in this corpus?

Pattern Discovery: Why Is It Important?

- Finding inherent regularities in a data set
- Foundation for many essential data mining tasks
 - Association, correlation, and causality analysis
 - Mining sequential, structural (e.g., sub-graph) patterns
 - Pattern analysis in spatiotemporal, multimedia, time-series, and stream data
 - Classification: Discriminative pattern-based analysis
 - Cluster analysis: Pattern-based subspace clustering
- Broad applications
 - Market basket analysis, cross-marketing, catalog design, sale campaign analysis, Web log analysis, biological sequence analysis



Basic Concepts: k-Itemsets and Their Supports

- gows items in man to isany
- Itemset: A set of one or more items 3 Kmz
- k-itemset: $X = \{x_1, ..., x_k\}$
 - Ex. {Beer, Nuts, Diaper} is a 3-itemset (absolute) support (count) of X, sup{X}:
- Frequency or the number of occurrences of an itemset X
 - Ex. $sup\{Beer\} = 3$
 - Ex. sup{Diaper} = 4
 - Ex. sup{Beer, Diaper} = 3
 - Ex. sup{Beer, Eggs} = 1

ช mint > เรียง อะมีก็อนที่มา Support ก็ก็งมีรู

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		

- \Box (*relative*) *support*, $s\{X\}$: The fraction of transactions that contains X (i.e., the probability that a transaction contains X)
 - Ex. $s\{Beer\} = 3/5 = 60\%$
 - Ex. $s\{Diaper\} = 4/5 = 80\%$
 - Ex. s{Beer, Eggs} = 1/5 = 20%

aira support us Beer 7-156 60%. UD transaction mucha

Basic Concepts: Frequent Itemsets (Patterns)

- An itemset (or a pattern) X is *frequent* if the support of X is no less than a minsup threshold σ
- Let $\sigma = 50\%$ (σ : minsup threshold) For the given 5-transaction dataset
 - All the frequent 1-itemsets:
 - □ Beer: 3/5 (60%); Nuts: 3/5 (60%)
 - □ Diaper: 4/5 (80%); Eggs: 3/5 (60%)
 - All the frequent 2-itemsets:
 - □ {Beer, Diaper}: 3/5 (60%)
 - All the frequent 3-itemsets?
 - None

Coffee	:	25	(40	7.)
--------	---	----	---	----	----	---

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	

- Why do these itemsets (shown on the left) form the complete set of frequent k-itemsets (patterns) for any k?
- Observation: We may need an efficient method to mine a complete set of frequent patterns

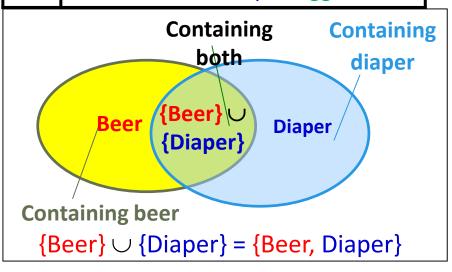
From Frequent Itemsets to Association Rules

- Comparing with itemsets, rules can be more telling
 - Ex. Diaper → Beer OLATO Ruper ANIMAL METS Beer ME
 - Buying diapers may likely lead to buying beers
- How strong is this rule? (support, confidence)
 - \square Measuring association rules: $X \rightarrow Y$ (s, c)
 - Both X and Y are itemsets



- Support, s: The probability that a transaction contains $X \cup Y$ Support $X \cup Y$
 - \Box Ex. s{Diaper, Beer} = 3/5 = 0.6 (i.e., 60%)
- Confidence, c: The conditional probability that a transaction containing X also contains Y
 - $\Box \quad \text{Calculation: } c = \sup(X \cup Y) / \sup(X)$
 - \Box Ex. $c = \sup{\text{Diaper, Beer}/\sup{\text{Diaper}}} = \frac{3}{4} = 0.75$

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



Note: $X \cup Y$: the union of two itemsets

■ The set contains both X and Y

Mining Frequent Itemsets and Association Rules

- Association rule mining
- אטנאיער היישוינית
- Given two thresholds: minsup, minconf
- \Box Find all of the rules, $X \rightarrow Y$ (s, c)
 - \square such that, $s \ge minsup$ and $c \ge minconf$
- Let minsup = 50%
 - Freq. 1-itemsets: Beer: 3, Nuts: 3,Diaper: 4, Eggs: 3
 - ☐ Freq. 2-itemsets: {Beer, Diaper}: 3
- Let minconf = 50% ($c = sup(X \cup Y) / sup(X)$)
 - \Box Beer \rightarrow Diaper (60%, 100%)
 - \square Diaper \rightarrow Beer (60%, 75%)

(Q: Are these all 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	

Observations:

- Mining association rules and mining frequent patterns are very close problems
- Scalable methods are needed for mining large datasets

Efficient Pattern Mining Methods

- ☐ The Downward Closure Property of Frequent Patterns
 - 80
- The Apriori Algorithm
- Extensions or Improvements of Apriori
- Mining Frequent Patterns by Exploring Vertical Data Format
- ☐ FPGrowth: A Frequent Pattern-Growth Approach
- Mining Closed Patterns

Apriori Pruning and Scalable Mining Methods

- Apriori pruning principle: If there is any itemset which is infrequent, its superset should not even be generated! (Agrawal & Srikant @VLDB'94, Mannila, et al. @ KDD' 94)
- Scalable mining Methods: Three major approaches

WILLIAM

- Level-wise, join-based approach: Apriori (Agrawal & Srikant@VLDB'94)
- Vertical data format approach: Eclat (Zaki, Parthasarathy, Ogihara, Li @KDD'97)
- Frequent pattern projection and growth: FPgrowth (Han, Pei, Yin @SIGMOD'00)

Apriori: A Candidate Generation & Test Approach

- Outline of Apriori (level-wise, candidate generation and test)
 - Initially, scan DB once to get frequent 1-itemset
 - □ Repeat הצאין
 - Generate length-(k+1) candidate itemsets from length-k frequent itemsets
 - ☐ Test the candidates against DB to find frequent (k+1)-itemsets
 - Set k := k +1
 - Until no frequent or candidate set can be generated
 - Return all the frequent itemsets derived

The Apriori Algorithm (Pseudo-Code)

```
C_k: Candidate itemset of size k
F_k: Frequent itemset of size k
                   K := 1;
F_k := \{ \text{frequent items} \}; // \text{frequent 1-itemset} 
While (F_k != \emptyset) do \{ // when F_k is non-empty
  C_{k+1} := candidates generated from F_k; // candidate generation
  Derive F_{k+1} by counting candidates in C_{k+1} with respect to TDB at minsup;
  k := k + 1
                    // return F_k generated at each level
return \bigcup_k F_k
```

The Apriori Algorithm—An Example U MONG JEM SUPPORT WIS INCLUSED. N SUPPORT WIS INCLUSED.

Database TDB

Items

A, C, D

B, C, E

A, B, C, E

Tid

10

20

30

 F_2

minsup = 2

1st scan

Itemset	sup
{A}	2
{B}	3
{C}	3
{D}	
{E}	3
2001	

מואוזה 1:622

Itemset	sup
√ {A}	2
{B}	3
{C}	3
{E}	3

B, E 40

Itemset	sup	
{A, C}	2	
{B, C}	2	←
{B, E}	3	
{C, E}	2	

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

2nd scan

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

เกษาจับก่

visions item set

Itemset {B, C, E}

3rd scan

Itemset	sup
{B, C, E}	2