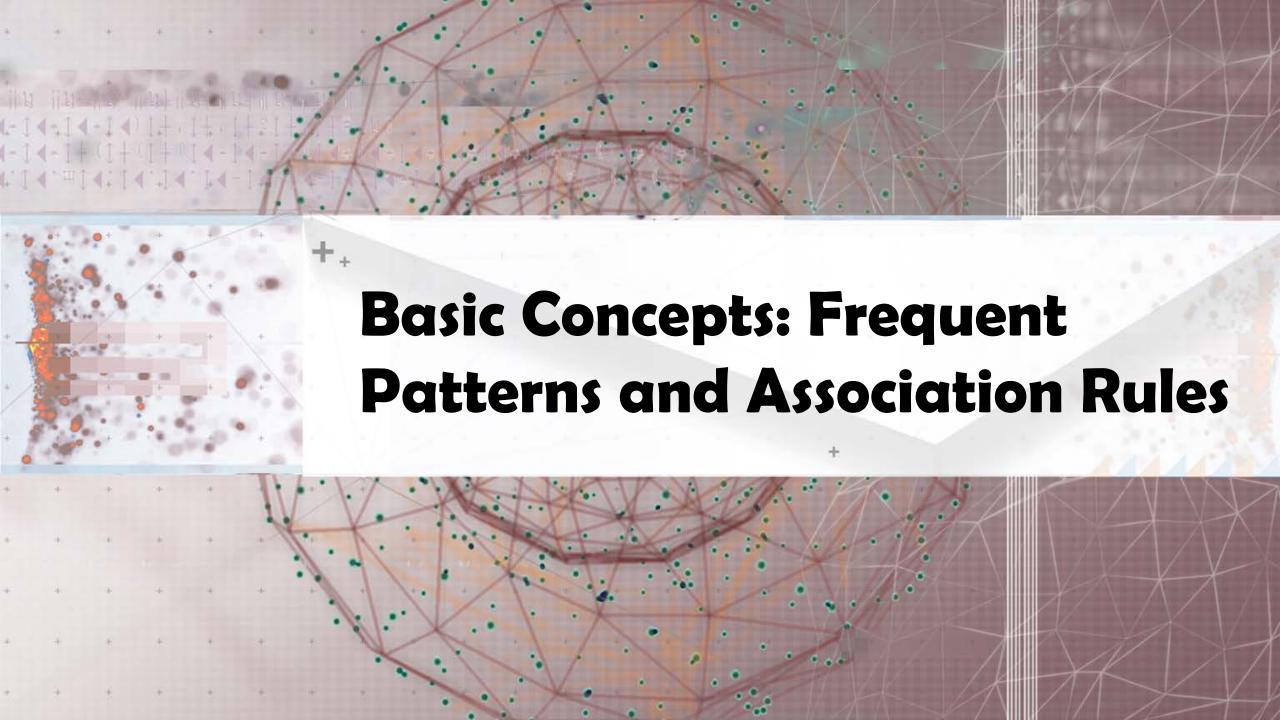


## What Is Pattern Discovery?

- What are patterns?
  - □ 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?
  - 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: Frequent Itemsets (Patterns)

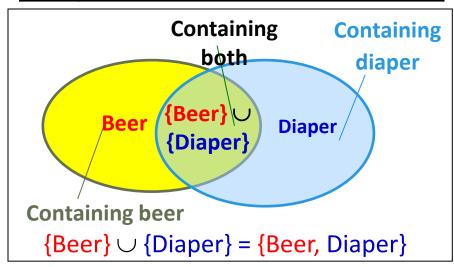
- ☐ Itemset: A set of one or more items
- $\Box$  k-itemset:  $X = \{x_1, ..., x_k\}$
- □ (absolute) support (count) of X: Frequency or the number of occurrences of an itemset X
- □ (relative) support, s: The fraction of transactions that contains X (i.e., the probability that a transaction contains X)
- □ An itemset X is *frequent* if the support of X is no less than a *minsup* threshold (denoted as σ)

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

- Let minsup = 50%
- ☐ Freq. 1-itemsets:
  - Beer: 3 (60%); Nuts: 3 (60%)
  - Diaper: 4 (80%); Eggs: 3 (60%)
- ☐ Freq. 2-itemsets:
  - □ {Beer, Diaper}: 3 (60%)

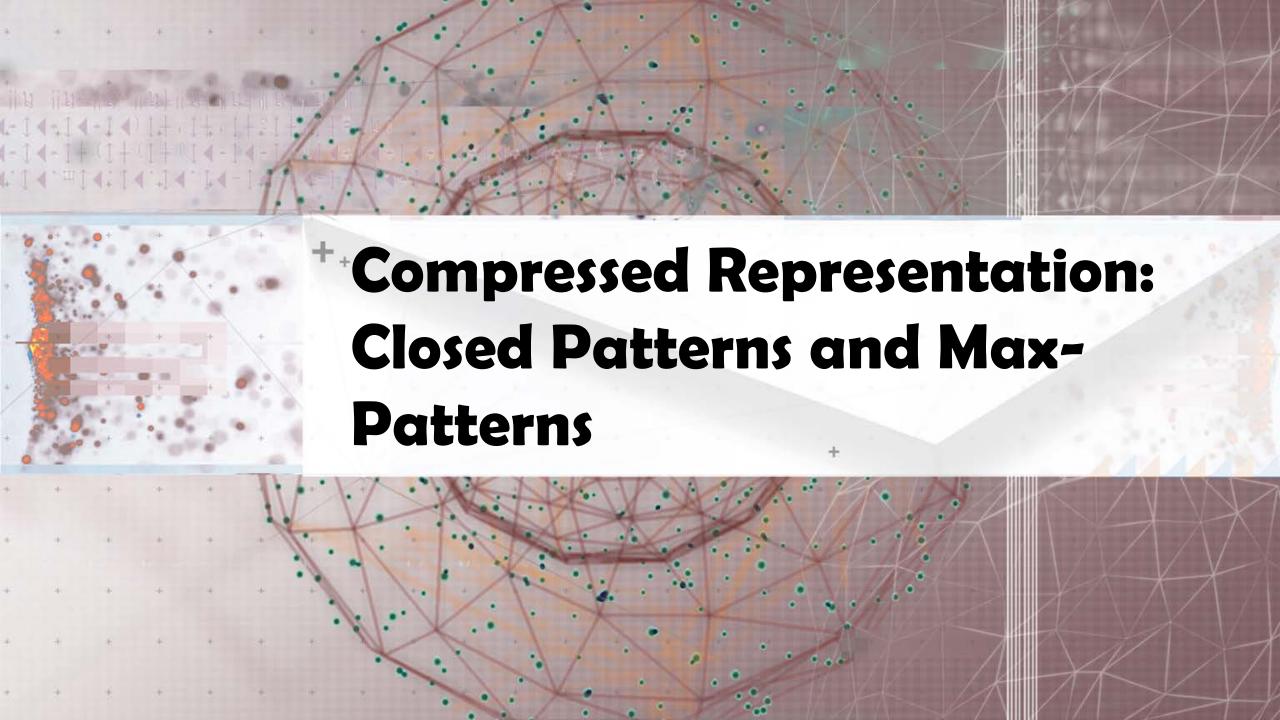
# From Frequent Itemsets to Association Rules

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



Note: Itemset:  $X \cup Y$ , a subtle notation!

- $\square$  Association rules:  $X \rightarrow Y$  (s, c)
  - Support, s: The probability that a transaction contains X ∪ Y
  - Confidence, c: The conditional probability that a transaction containing X also contains Y
  - $\Box$  c = sup(X  $\cup$  Y) / sup(X)
- □ **Association rule mining**: Find all of the rules,  $X \rightarrow Y$ , with minimum support and confidence
- ☐ Frequent itemsets: Let *minsup = 50%* 
  - ☐ Freq. 1-itemsets: Beer: 3, Nuts: 3, Diaper: 4, Eggs: 3
  - ☐ Freq. 2-itemsets: {Beer, Diaper}: 3
- ☐ Association rules: Let *minconf* = 50%
  - Beer → Diaper (60%, 100%)
    - Diaper  $\rightarrow$  Beer (60%, 75%) (Q: Are these all rules?)



## Challenge: There Are Too Many Frequent Patterns!

- □ A long pattern contains a combinatorial number of sub-patterns
- □ How many frequent itemsets does the following TDB<sub>1</sub> contain?
  - $\square$  TDB<sub>1:</sub> T<sub>1</sub>: {a<sub>1</sub>, ..., a<sub>50</sub>}; T<sub>2</sub>: {a<sub>1</sub>, ..., a<sub>100</sub>}
  - Assuming (absolute) minsup = 1
  - Let's have a try

```
1-itemsets: {a<sub>1</sub>}: 2, {a<sub>2</sub>}: 2, ..., {a<sub>50</sub>}: 2, {a<sub>51</sub>}: 1, ..., {a<sub>100</sub>}: 1, 2-itemsets: {a<sub>1</sub>, a<sub>2</sub>}: 2, ..., {a<sub>1</sub>, a<sub>50</sub>}: 2, {a<sub>1</sub>, a<sub>51</sub>}: 1 ..., ..., {a<sub>99</sub>, a<sub>100</sub>}: 1, ..., ..., ...
```

99-itemsets: {a<sub>1</sub>, a<sub>2</sub>, ..., a<sub>99</sub>}: 1, ..., {a<sub>2</sub>, a<sub>3</sub>, ..., a<sub>100</sub>}: 1

100-itemset: {a<sub>1</sub>, a<sub>2</sub>, ..., a<sub>100</sub>}: 1

□ In total:  $\binom{100}{1} + \binom{100}{2} + \dots + \binom{1}{1} \binom{0}{0} = 2^{100} - 1$  sub-patterns!

A too huge set for any computer to compute or store!

#### **Expressing Patterns in Compressed Form: Closed Patterns**

- How to handle such a challenge?
- □ Solution 1: **Closed patterns**: A pattern (itemset) X is **closed** if X is *frequent*, and there exists *no super-pattern* Y ⊃ X, *with the same* support as X
  - □ Let Transaction DB TDB<sub>1</sub>:  $T_1$ : {a<sub>1</sub>, ..., a<sub>50</sub>};  $T_2$ : {a<sub>1</sub>, ..., a<sub>100</sub>}
  - Suppose minsup = 1. How many closed patterns does TDB<sub>1</sub> contain?
    - □ Two:  $P_1$ : "{ $a_1$ , ...,  $a_{50}$ }: 2";  $P_2$ : "{ $a_1$ , ...,  $a_{100}$ }: 1"
- Closed pattern is a lossless compression of frequent patterns
  - Reduces the # of patterns but does not lose the support information!
  - □ You will still be able to say: " $\{a_2, ..., a_{40}\}$ : 2", " $\{a_5, a_{51}\}$ : 1"

#### **Expressing Patterns in Compressed Form: Max-Patterns**

- □ Solution 2: Max-patterns: A pattern X is a max-pattern if X is frequent and there exists no frequent super-pattern Y ⊃ X
- □ Difference from close-patterns?
  - Do not care the real support of the sub-patterns of a max-pattern
  - □ Let Transaction DB TDB<sub>1</sub>:  $T_1$ : {a<sub>1</sub>, ..., a<sub>50</sub>};  $T_2$ : {a<sub>1</sub>, ..., a<sub>100</sub>}
  - Suppose minsup = 1. How many max-patterns does TDB<sub>1</sub> contain?
    - □ One: P: "{a<sub>1</sub>, ..., a<sub>100</sub>}: 1"
- Max-pattern is a lossy compression!
  - $\square$  We only know  $\{a_1, ..., a_{40}\}$  is frequent
  - But we do not know the real support of  $\{a_1, ..., a_{40}\}$ , ..., any more!
- ☐ Thus in many applications, mining close-patterns is more desirable than mining max-patterns

### Recommended Readings

- □ R. Agrawal, T. Imielinski, and A. Swami, "Mining association rules between sets of items in large databases", in Proc. of SIGMOD'93
- □ R. J. Bayardo, "Efficiently mining long patterns from databases", in Proc. of SIGMOD'98
- □ N. Pasquier, Y. Bastide, R. Taouil, and L. Lakhal, "Discovering frequent closed itemsets for association rules", in Proc. of ICDT'99
- □ J. Han, H. Cheng, D. Xin, and X. Yan, "Frequent Pattern Mining: Current Status and Future Directions", Data Mining and Knowledge Discovery, 15(1): 55-86, 2007