

The background of the slide is a complex, abstract composition. It features a dark, reddish-brown base with a network of thin, light-colored lines forming a web-like structure. Overlaid on this are various data visualizations: a grid of small, light-colored plus signs on the left; a series of horizontal, slightly wavy lines in shades of orange and red; and a large, irregular shape composed of many small, dark green dots. The overall aesthetic is technical and data-driven.

What Is Pattern Discovery? Why Is It Important?

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

The background features a complex, abstract design. It includes a grid of small grey plus signs on the left, a network of red lines with green dots in the center, and a dark purple geometric pattern on the right. A white banner with a grey triangle on the left contains the title text. A small inset image in the top left shows a heatmap with orange and red spots.

Basic Concepts: Frequent Patterns and Association Rules

Basic Concepts: Frequent Itemsets (Patterns)

- ❑ **Itemset**: A set of one or more items
- ❑ **k-itemset**: $X = \{x_1, \dots, x_k\}$
- ❑ **(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)

5	transaction	'Beer'가
3		60%.
- ❑ An itemset X is **frequent** if the support of X is no less than a *minsup* threshold (denoted as σ)

5 transaction.

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%

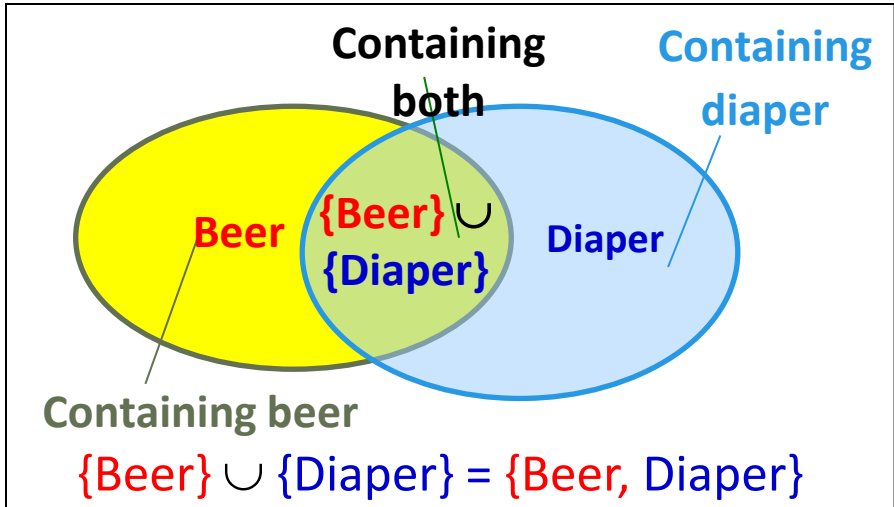
50%

- ❑ Freq. 1-itemsets:
 - ❑ Beer: 3 (60%); Nuts: 3 (60%)
 - ❑ Diaper: 4 (80%); Eggs: 3 (60%)
- ❑ Freq. 2-itemsets:
 - ❑ {Beer, Diaper}: 3 (60%)

X item	Y item	(degree of coupling)
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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!

Association rules: $X \rightarrow Y (s, c)$

X	Y	support()
confidence()		가?

Support, s : The probability that a transaction contains $X \cup Y$

item	(sequence)
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Confidence, c : The conditional probability that a transaction containing X also contains Y

X	가	!
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$c = \text{sup}(X \cup Y) / \text{sup}(X)$

Association rule mining: Find **all** of the rules, $X \rightarrow Y$, with minimum support and confidence

Frequent itemsets: Let $\text{minsup} = 50\%$

Freq. 1-itemsets: Beer: 3, Nuts: 3, Diaper: 4, Eggs: 3

Freq. 2-itemsets: $\{Beer, Diaper\}$: 3

Association rules: Let $\text{minconf} = 50\%$

(1) $X \rightarrow Y(S, C)$
(2) $Y \rightarrow X(S, C)$

$Beer \rightarrow Diaper$ (60%, 100%)

$Diaper \rightarrow Beer$ (60%, 75%)

(Q: Are these all rules?)



+ + Compressed Representation: Closed Patterns and Max- Patterns

Challenge: There Are Too Many Frequent Patterns!

- A long pattern contains a combinatorial number of sub-patterns
- How many frequent itemsets does the following TDB₁ contain?

Long pattern
frequent pattern 가 .

- TDB₁: T₁: {a₁, ..., a₅₀}; T₂: {a₁, ..., a₁₀₀}

- Assuming (absolute) *minsup* = 1

- Let's have a try

1-itemsets: {a₁}: 2, {a₂}: 2, ..., {a₅₀}: 2, {a₅₁}: 1, ..., {a₁₀₀}: 1,

2-itemsets: {a₁, a₂}: 2, ..., {a₁, a₅₀}: 2, {a₁, a₅₁}: 1 ..., ..., {a₉₉, a₁₀₀}: 1,

..., ..., ..., ...

99-itemsets: {a₁, a₂, ..., a₉₉}: 1, ..., {a₂, a₃, ..., a₁₀₀}: 1

100-itemset: {a₁, a₂, ..., a₁₀₀}: 1

- In total: $\binom{100}{1} + \binom{100}{2} + \dots + \binom{100}{100} = 2^{100} - 1$ 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* $Y \supset X$, with the same support as X
 - ❑ Let Transaction DB TDB_1 : $T_1: \{a_1, \dots, a_{50}\}$; $T_2: \{a_1, \dots, a_{100}\}$
 - ❑ Suppose $minsup = 1$. How many closed patterns does TDB_1 contain?
 - ❑ Two: $P_1: \{\{a_1, \dots, a_{50}\}: 2\}$; $P_2: \{\{a_1, \dots, a_{100}\}: 1\}$
- ❑ **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: $\{\{a_2, \dots, a_{40}\}: 2\}$, $\{\{a_5, a_{51}\}: 1\}$

Closed pattern:
parent pattern child pattern

Close patterns.

- * frequent pattern
closed pattern mining
- * huffman coding
- * core frequent pattern
- * ex) pattern_1{a}, pattern_2{abc} {a}
mining 7 {abc}(core)
- * (core) frequent pattern

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 $Y \supset X$

❑ Difference from close-patterns?

❑ Do not care the real support of the sub-patterns of a max-pattern

❑ Let Transaction DB TDB_1 : $T_1: \{a_1, \dots, a_{50}\}$; $T_2: \{a_1, \dots, a_{100}\}$

❑ Suppose $minsup = 1$. How many max-patterns does TDB_1 contain?

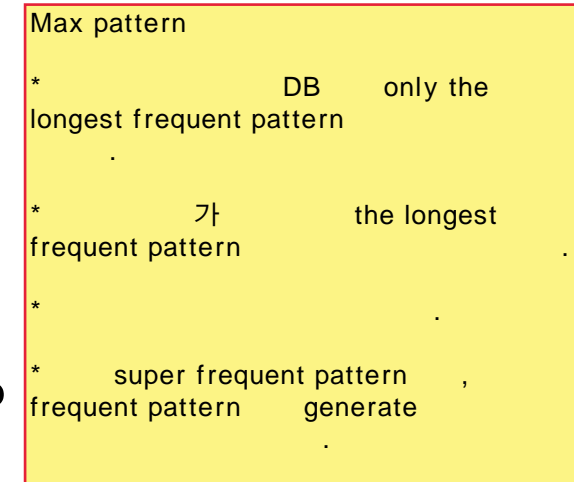
❑ One: $P: \{a_1, \dots, a_{100}\}: 1$

❑ **Max-pattern** is a **lossy compression**!

❑ We only know $\{a_1, \dots, a_{40}\}$ is frequent

❑ But we do not know the real support of $\{a_1, \dots, a_{40}\}$, ..., 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