# Chapter V: Mining frequent patterns, associations and correlations

## Knowledge Discovery in Databases

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# Chapter V: Mining frequent patterns, associations and correlations

**Basic Concepts.**

Scalable frequent-itemset-mining methods.

- Apriori: a candidate-generation-and-test approach.
- Improving the efficiency of apriori.
- FPGrowth: a frequent-pattern-growth approach.
- ECLAT: frequent-pattern mining with vertical data format.
- Mining closed itemsets and max-itemsets.

Generating association rules from frequent itemsets.

Which patterns are interesting? Pattern-evaluation methods.

Summary.

# What is frequent-pattern analysis?

**Frequent pattern:**

A pattern (a set of items, subsequences, substructures, etc.) that occurs frequently in a dataset.

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**Motivation: Finding inherent regularities in data:**

What products are often purchased together? Beer and diapers?!

What are the subsequent purchases after buying a PC?

FPGrowth: a frequent-pattern-growth approach.

"Who bought this has often also bought . . ."

What kinds of DNA are sensitive to this new drug?

Can we automatically classify Web documents?

**Applications:**

Basket-data analysis, cross-marketing, catalog design, sale-campaign analysis, Web-log (click-stream) analysis, and DNA-sequence analysis.

# Why is frequent-pattern mining important?

**A frequent pattern is an intrinsic and important property of a dataset.**

**Foundation for many essential data-mining tasks:**

- Association, correlation, and causality analysis.
- Sequential, structural (e.g., sub-graph) patterns.
- Pattern analysis in spatiotemporal, multimedia, time-series, and stream data.
- Classification: discriminative, frequent-pattern analysis.
- Cluster analysis: frequent-pattern-based clustering.
- Data warehousing: iceberg cube and cube gradient.
- Semantic data compression: fascicles (Jagadish, Madar, and Ng, VLDB'99).
- Broad applications.

# An example

**From: Martin Lindstrom: Brandwashed. Random House, 2011:**

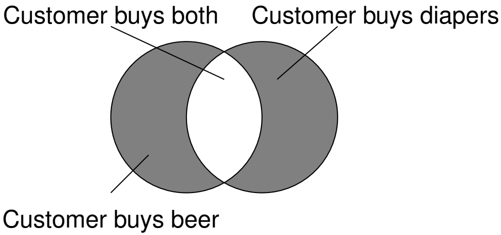
*It is by crunching these numbers that the data-mining industry has uncovered some even more surprising factoids:*

*Did you know, for example, that at Walmart a shopper who buys a Barbie doll is 60 percent more likely to purchase one of three types of candy bars? Or that toothpaste is most often bought alongside canned tuna? Or that a customer who buys a lot of meat is likely to spend more money in a health-food store than a non-meat-eater? Or what about the data revealed to one Canadian grocery chain that customers who bought coconuts also tended to buy prepaid calling cards? At first, no one in store management could figure out what was going on. What could coconuts possibly have to do with calling cards?*

*Finally it occurred to them that the store served a huge population of shoppers from the Caribbean islands and Asia, both of whose cuisines use coconuts in their cooking. Now it made perfect sense that these Caribbean and Asian shoppers were buying prepaid calling cards to check in with their extended families back home.*

## An example

| TID | Items bought |
|---|---|
| 10 | Beer, Nuts, Diapers |
| 20 | Beer, Coffee, Diapers |
| 30 | Beer, Diapers, Eggs |
| 40 | Nuts, Eggs, Milk |
| 50 | Nuts, Coffee, Diapers, Eggs, Milk |




**Itemset:**

A set of one or more items.
$k$-itemset $X = \{x_1, x_2, \ldots, x_k\}$.

**(Absolute) Support, or support count of $X$:**

Frequency or occurrence of $X$.

(Relative) Support $s$:

The fraction of the transactions that contain $X$.
I.e. the **probability** that a transaction contains $X$.

**An itemset $X$ is frequent, if $X$'s support is no less than a `min_sup` threshold.**

## An example

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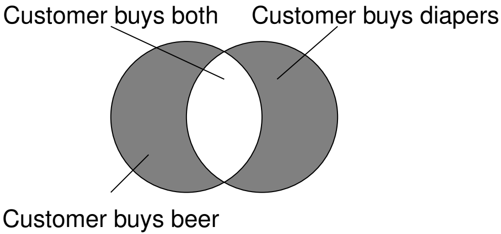


**Find all the rules $X \rightarrow Y$ with minimum support and confidence.**

**Support** $s$: probability that a transaction contains $X \cup Y$.

**Confidence** $c$: conditional probability that a transaction having $X$ also contains $Y$.

**Example:**

Let min_sup $= 50\%$ and min_conf $= 50\%$.

Frequent itemsets:

Beer: 3, Nuts: 3,
Diapers: 4, Eggs: 3,
$\{$Beer, Diapers$\}$: 3.

**Association rules:**

Beer $\rightarrow$ Diapers (60%, 100%).
Diapers $\rightarrow$ Beer (60%, 75%).

# References: Basic concepts of frequent-pattern mining


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Thank you for your attention.

**Any questions about the fifth chapter?**

Ask them now, or again, drop me a line:

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