

# Unit-2-part-2.4

## Association

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# **Mining Various Kinds of Association Rules**

# **Mining Multilevel Association**

# Multilevel Association Rules

- Strong association discovered at high levels of abstraction may represent commonsense knowledge.
- In next slide example show items purchased as concept hierarchy is shown in other next slide.
- Data can be generalized by replacing low-level concepts within the data by their higher-level concepts , or ancestors, from a concept hierarchy.
- Concept hierarchies for categorical attributes are often implicit within the database schema, in which case they may be automatically generated using preprocessing methods.
- Concept hierarchies for numerical attributes can be generated using discretization techniques.

# Multilevel Association Rules

Association rules generated from mining data at multiple levels of abstraction are called multiple-level or multilevel association rules.

Table 5.6

<i>TID</i>	<i>items purchased</i>
T100	IBM-ThinkPad-T40/2373, HP-Photosmart-7660
T200	Microsoft-Office-Professional-2003, Microsoft-Plus!-Digital-Media
T300	Logitech-MX700-Cordless-Mouse, Fellowes-Wrist-Rest
T400	Dell-Dimension-XPS, Canon-PowerShot-S400
T500	IBM-ThinkPad-R40/P4M, Symantec-Norton-Antivirus-2003
...	...

# Multilevel Association Rules

It is easier to find strong association rules between generalized abstractions.

Fig. Concept hierarchy for all Electronics computer items

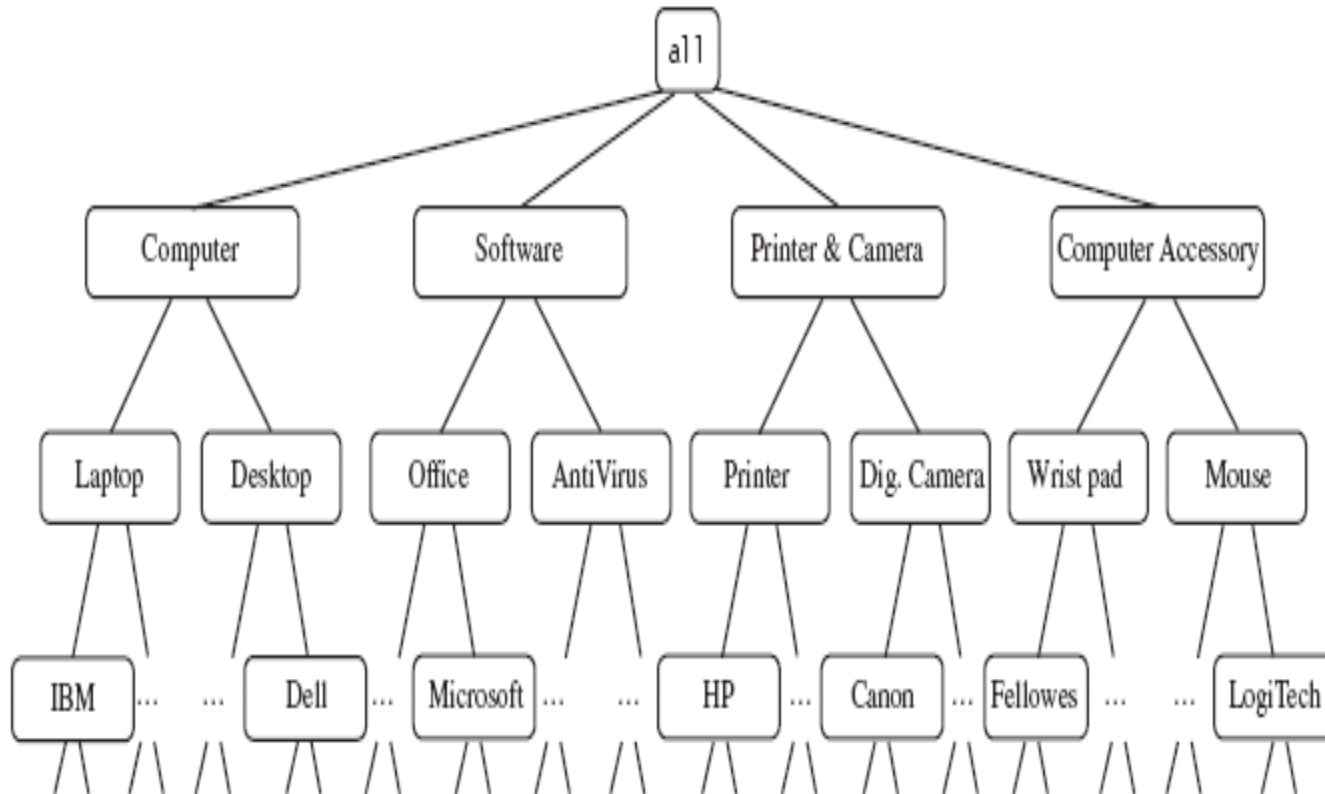


Fig 5.10

# **Multilevel Association: Uniform vs Reduced Support**

Uniform support: same minimum support threshold is used when mining at each level of abstraction.

- Reduced support: each level of abstraction has its own minimum support threshold. The deeper the level of abstraction, the smaller the corresponding threshold is.

# Multilevel Association:

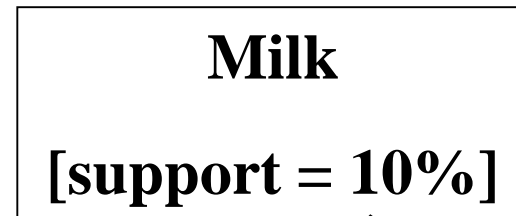
Group-based support: because users or experts often have insight as to which groups are more important than others, it is sometimes more desirable to set up user-specific ,item, or group-based minimal support thresholds when mining multilevel rules.



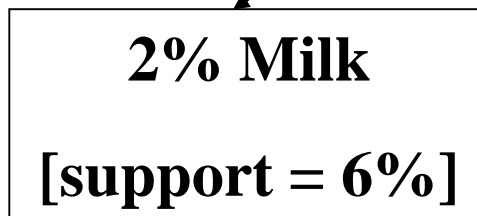
# Uniform Support

- Same minimum support threshold for all levels

**Level 1**  
**min support = 5%**



**Level 2**  
**min support = 5%**



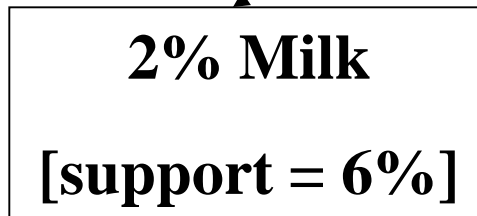
# Reduced Support

- Reduced minimum support threshold at lower levels

**Level 1**  
min support = 5%



**Level 2**  
min support = 3%



# Mining Multilevel: Top-Down Progressive Deepening

- Find multilevel frequent itemsets
  - High-level frequent itemsets  
*milk (15%), bread (10%)*
  - Lower-level “weaker” frequent itemsets  
*2% milk (5%), wheat bread (4%)*
- Generate multilevel association rules
  - High-level strong rules  
*milk  $\rightarrow$  bread [8%, 70%]*
  - Lower-level “weaker” rules:  
*2% milk  $\rightarrow$  wheat bread [2%, 72%]*

# Multi-level Association: Redundancy Filtering

- Some rules may be redundant due to “ancestor” relationships between items.
- Example
  - milk  $\Rightarrow$  wheat bread [support = 8%, confidence = 70%]
  - 2% milk  $\Rightarrow$  wheat bread [support = 2%, confidence = 72%]
- We say the first rule is an ancestor of the second rule.
- A rule is redundant if its support is close to the “expected” value, based on the rule’s ancestor.

# **Mining Multidimensional Association Rules**

# Multidimensional Association Rules

Association rules that involve two or more dimensions or predicates can be referred to as multidimensional association rules.

- Single-dimensional rules

$$\text{buys}(X, \text{“milk”}) \rightarrow \text{buys}(X, \text{“bread”})$$

- Multidimensional rules ( $\geq 2$  dimensions/predicates)

- Inter-dimension assoc. rules (no repeated predicates)

- $\text{age}(X, \text{“19-25”}) \wedge \text{occupation}(X, \text{“student”}) \rightarrow$

$$\text{buys}(X, \text{“coke”})$$

- Hybrid-dimension assoc. rules (repeated predicates)

- $\text{age}(X, \text{“19-25”}) \wedge \text{buys}(X, \text{“popcorn”}) \rightarrow$

$$\text{buys}(X, \text{“coke”})$$

# Multidimensional Association Rules

- Multidimensional association rules with no repeated predicates are called interdimensional association rules.
- Multidimensional association rules with repeated predicates, which contain multiple occurrences of some predicates. These rules are called hybrid-dimensional association rules.

# Multi-Dimensional Association : Concepts

- Single-dimensional rules:

$\text{buys}(X, \text{"milk"}) \Rightarrow \text{buys}(X, \text{"bread"})$

- Multi-dimensional rules: ○ 2 dimensions or predicates

- Inter-dimension association rules (*no repeated predicates*)

$\text{age}(X, \text{"19-25"}) \wedge \text{occupation}(X, \text{"student"}) \Rightarrow \text{buys}(X, \text{"coke"})$

- hybrid-dimension association rules (*repeated predicates*)

$\text{age}(X, \text{"19-25"}) \wedge \text{buys}(X, \text{"popcorn"}) \Rightarrow \text{buys}(X, \text{"coke"})$

- Categorical Attributes

- finite number of possible values, no ordering among values

- Quantitative Attributes

- numeric, implicit ordering among values

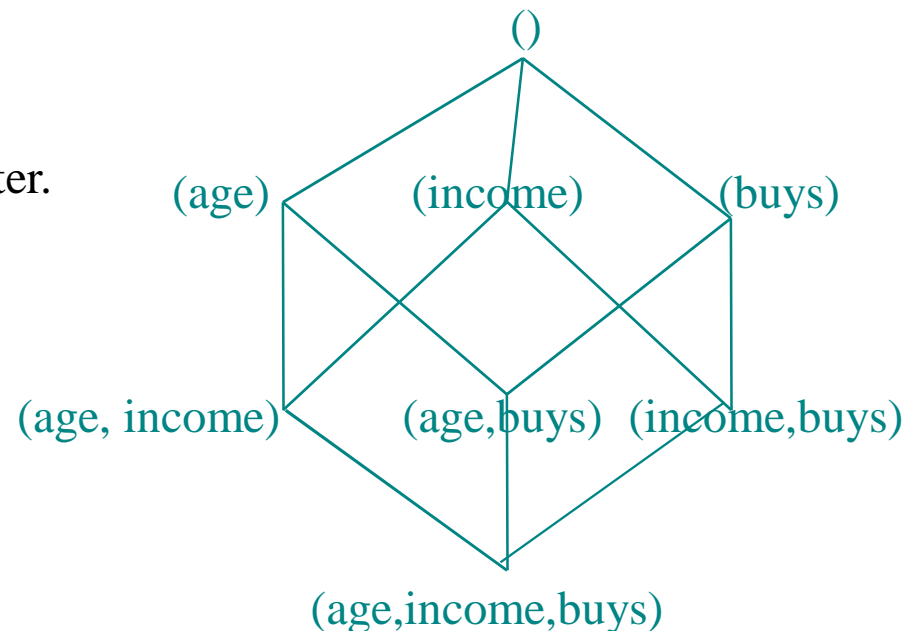


# Techniques for Mining MD Associations

- Search for frequent  $k$ -predicate set:
  - Example: {age, occupation, buys} is a 3-predicate set.
  - Techniques can be categorized by how age are treated.
- 1. Using static discretization of quantitative attributes
  - Quantitative attributes are statically discretized by using predefined concept hierarchies.
- 2. Quantitative association rules
  - Quantitative attributes are dynamically discretized into “bins” based on the distribution of the data.
- 3. Distance-based association rules
  - This is a dynamic discretization process that considers the distance between data points.

# Static Discretization of Quantitative Attributes

- Discretized prior to mining using concept hierarchy.
- Numeric values are replaced by ranges.
- In relational database, finding all frequent  $k$ -predicate sets will require  $k$  or  $k+1$  table scans.
- Data cube is well suited for mining.
- The cells of an  $n$ -dimensional
- cuboids correspond to the predicate sets.
- Mining from data cubes can be much faster.



# Quantitative Association Rules

- Numeric attributes are *dynamically* discretized
  - Such that the confidence or compactness of the rules mined is maximized.
- 2-D quantitative association rules:  $A_{\text{quan1}} \wedge A_{\text{quan2}} \Rightarrow A_{\text{cat}}$
- Cluster “adjacent” association rules to form general rules using a 2-D grid.

- Example:

$\text{age}(X, "30-34") \wedge \text{income}(X, "24K - 48K")$   
 $\Rightarrow \text{buys}(X, "high\ resolution\ TV")$

income

70-80K

60-70K

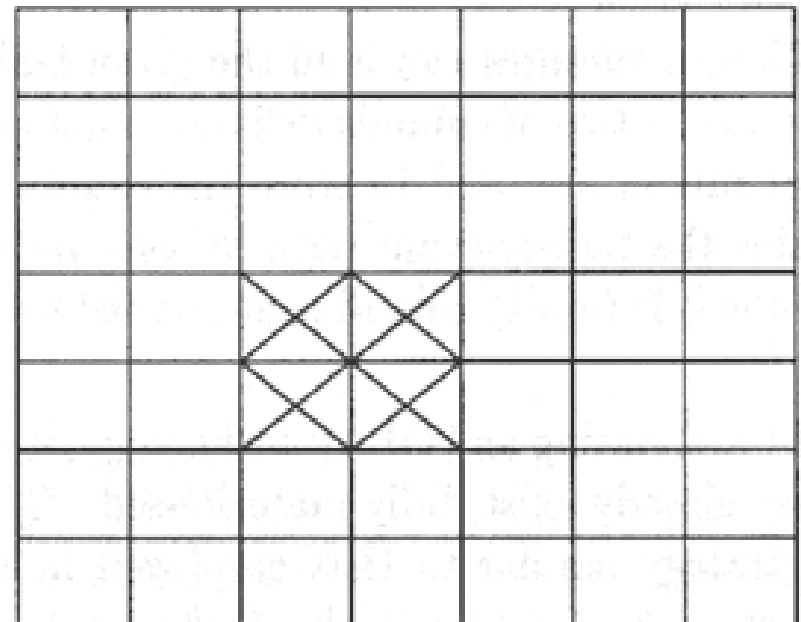
50-60K

40-50K

30-40K

20-30K

<20K



32

33

34

35

36

37

38

age

End of Unit-II part-2