COMP3420: Advanced Databases and Data Mining

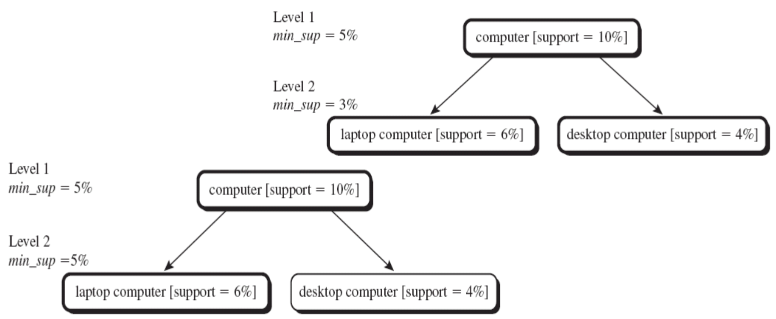
Advanced association mining

Lecture outline

- Mining various kinds of association rules
  - Multi-level association
  - Multi-dimensional association
  - Quantitative association
  - Interesting correlation patterns
- Constraints based mining
- Interestingness measure: Correlation (Lift)
  - More interestingness measures
- Visualisation of association rules

Multi-level association mining

- Items often form hierarchies
- Items at lower levels are expected to have lower support
  - Flexible *support* setting (uniform, reduced, or group-based (user specific))



Source: Han and Kamber, DM Book, 2nd Ed. (Copyright © 2006 Elsevier Inc.)

Multi-level association mining (2)

- Some rules may be redundant due to *ancestor* relationships between items
- For example:

  buys(X, `milk') ⇒ buys(X, `bread')   [s=8%, c=70%]

  buys(X, `skim milk') ⇒ buys(X, `bread')   [s=2%, c=72%]
  - The first rule is said to be 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
  - For example, if around 25% of all milk purchased is `skim milk', then the second rule above is redundant, as it has a ¼ of the support of the first, more general rule (and similar confidence)

Multi-dimensional association mining

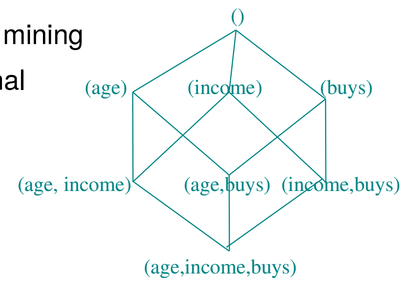
- Single-dimensional rules: *buys(X, `milk') ⇒ buys(X, `bread')*
- Multi-dimensional rules: Two or more dimensions or predicates (or attributes)
  - Inter-dimension association rules (*no repeated predicates*):
    age(X, `19-25')* and *occupation(X, `student') ⇒ buys(X, `coke')
  - Hybrid-dimension association rules (*repeated predicates*):
    age(X, `19-25')* and *buys(X, `popcorn') ⇒ buys(X, `coke')
- Categorical Attributes: finite number of possible values, no ordering among values (data cube approach)
- Quantitative Attributes: numeric, implicit ordering among values (discretisation, clustering, etc.)

Quantitative association mining

- Techniques can be categorised by how numerical attributes, such as *age* or *income,* are treated
- Static discretisation based on predefined concept hierarchies (data cube methods)
- Dynamic discretisation based on data distribution
  - A_{quant1} and $A_{quant2} \Rightarrow A_{cat}$
  - Example: *age(X, `19-25')* and *income(X, `40K-60K') ⇒ buys(X, `HDTV')*
- For quantitative rules, do discretisation such that (for example) the confidence of the rules mined is maximised

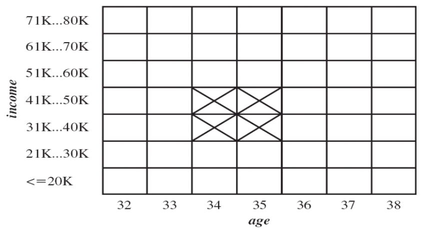
Static discretisation of quantitative attributes

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



Dynamic discretisation of quantitative attributes

- Mapping of pairs of quantitative attributes into a 2-dimensional grid, such that categorical attribute conditions are satisfied
- The grid is then searched for clusters of points from which association rules are generated
- For example:
  age(X, `34-35') and
  income(X, '31K-50K')
  ⇒ buys(X, `HDTV')



Mining interesting correlation patterns

- Flexible support
  - Some items might be very rare but are valuable (like diamonds)
  - Customise $support_{min}$ specification and application
- Top-*k* frequent patterns
  - It can be hard to specify $support_{min}$, but top-*k* rules with $length_{min}$ are more desirable
  - Achievable using special data structures, like Frequent-Pattern (FP) tree
  - Dynamically raise $support_{min}$ during FP-tree construction phase, and select most promising to mine
- Many different algorithms and data structures have been developed to allow efficient mining of associations and rules (more in the text book)

Constraint based mining

- Finding *all* the frequent rules or patterns in a database autonomously is unrealistic
  - The rules / patterns could be too many and not focussed
- Data mining should be an *interactive* process
- The user directs what should be mined using a data mining query language or a graphical user interface
- Constraint-based mining
  - User flexibility: provides constraints on what to be mined (and what not)
  - System optimisation: explores such constraints for efficient mining

Constraints in data mining

- Knowledge type constraint
  - Correlation, association, etc.
- Data constraint (use SQL like queries)
  - For example: *Find product pairs sold frequently in both stores in Sydney and Melbourne*
- Dimension / level constraint
  - In relevance to region, price, brand, customer category, etc.
- Rule or pattern constraint
  - Small sales (price < $10) trigger big sales (sum > $200)
- Interestingness constraint
  - Strong rules only: $support_{min}$ > 3%, $confidence_{min}$ > 75%

Interestingness measure: Correlation (lift)

- Example: *Play basketball* ⇒ *Eat cereal [40%, 66.67%]* is misleading
  - If overall 75 % of all students eat cereal
  - *Play basketball* ⇒ *Not eat cereal [20%, 33.3%]* is more accurate, although with lower support and confidence
- Measure of dependent / correlated events: *Lift*

$$lift = \frac{P(A \cup B)}{P(A)P(B)}$$

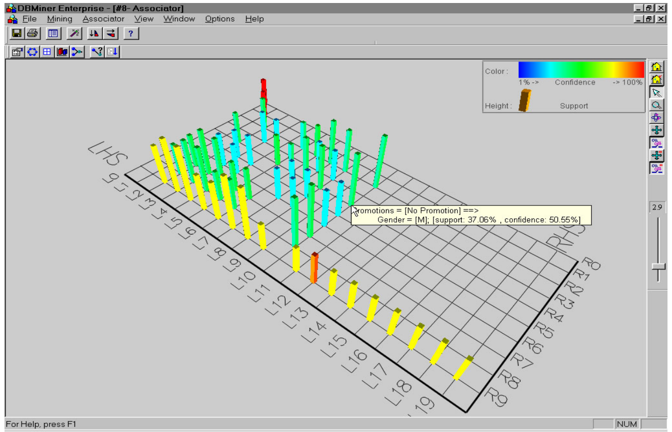
	Basketball	Not basketball	Sum (row)
Cereal	2000	1750	3750
Not cereal	1000	250	1250
Sum(col.)	3000	2000	5000

$$lift(B,C) = \frac{2000/5000}{3000/5000 * 3750/5000} = 0.89 \qquad lift(B,\neg C) = \frac{1000/5000}{3000/5000 * 1250/5000} = 1.33$$

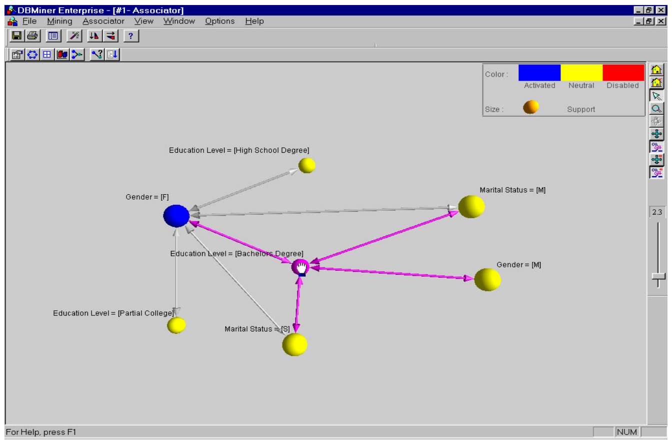
More interestingness measures (Tan et al. 2002)

symbol	measure	range	formula
ϕ	ϕ-coefficient	-1…1	$\frac{P(A,B)-P(A)P(B)}{\sqrt{P(A)P(B)(1-P(A))(1-P(B))}}$
Q	Yule's Q	-1 … 1	$\frac{P(A,B)P(\overline{A},\overline{B})-P(A,\overline{B})P(\overline{A},B)}{P(A,B)P(\overline{A},\overline{B})+P(A,\overline{B})P(\overline{A},B)}$
Y	Yule's Y	-1 … 1	$\frac{\sqrt{P(A,B)P(\overline{A},\overline{B})}-\sqrt{P(A,\overline{B})P(\overline{A},B)}}{\sqrt{P(A,B)P(\overline{A},\overline{B})}+\sqrt{P(A,\overline{B})P(\overline{A},B)}}$
k	Cohen's	-1 … 1	$\frac{P(A,B)+P(\overline{A},\overline{B})-P(A)P(B)-P(\overline{A})P(\overline{B})}{1-P(A)P(B)-P(\overline{A})P(\overline{B})}$
PS	Piatetsky-Shapiro's	-0.25 … 0.25	$P(A,B)-P(A)P(B)$
F	Certainty factor	-1 … 1	$\max(\frac{P(B\|A)-P(B)}{1-P(B)}, \frac{P(A\|B)-P(A)}{1-P(A)})$
AV	added value	-0.5 … 1	$\max(P(B\|A)-P(B), P(A\|B)-P(A))$
K	Klosgen's Q	-0.33 … 0.38	$\sqrt{P(A,B)}\max(P(B\|A)-P(B), P(A\|B)-P(A))$
g	Goodman-kruskal's	0 … 1	$\frac{\Sigma_j \max_k P(A_j,B_k)+\Sigma_k \max_j P(A_j,B_k)-\max_j P(A_j)-\max_k P(B_k)}{2-\max_j P(A_j)-max_k P(B_k)}$
M	Mutual Information	0 … 1	$\frac{\Sigma_i \Sigma_j P(A_i,B_j) \log \frac{P(A_i,B_j)}{P(A_i)P(B_J)}}{\min(-\Sigma_i P(A_i)\log P(A_i)\log P(A_i), -\Sigma_i P(B_i)\log P(B_i)\log P(B_i))}$
J	J-Measure	0 … 1	$\max(P(A,B)\log(\frac{P(B\|A)}{P(B)}) + P(A\overline{B})\log(\frac{P(\overline{B}\|A)}{P(\overline{B})}))$ $P(A,B)\log(\frac{P(A\|B)}{P(A)}) + P(\overline{A}B)\log(\frac{P(\overline{A}\|B)}{P(\overline{A})})$
G	Gini index	0 … 1	$\max(P(A)[P(B\|A)^2 + P(\overline{B}\|A)^2] + P(\overline{A}[P(B\|\overline{A})^2 + P(\overline{B}\|\overline{A})^2] - P(B)^2 - P(\overline{B})^2,$ $P(B)[P(A\|B)^2 + P(\overline{A}\|B)^2] + P(\overline{B}[P(A\|\overline{B})^2 + P(\overline{A}\|\overline{B})^2] - P(A)^2 - P(\overline{A})^2)$
s	support	0 … 1	$P(A,B)$
c	confidence	0 … 1	$max(P(B\|A), P(A\|B))$
L	Laplace	0 … 1	$\max(\frac{NP(A,B)+1}{NP(A)+2}, \frac{NP(A,B)+1}{NP(B)+2})$
IS	Cosine	0 … 1	$\frac{P(A,B)}{\sqrt{P(A)P(B)}}$
γ	coherence(Jaccard)	0 … 1	$\frac{P(A,B)}{P(A)+P(B)-P(A,B)}$
α	all_confidence	0 … 1	$\frac{P(A,B)}{\max(P(A),P(B))}$
o	odds ratio	0 … ∞	$\frac{P(A,B)P(\overline{A},\overline{B})}{P(\overline{A},B)P(A,\overline{B})}$
V	Conviction	0.5 … ∞	$\max(\frac{P(A)P(\overline{B})}{P(A\overline{B})}, \frac{P(B)P(\overline{A})}{P(B\overline{A})})$
λ	lift	0 … ∞	$\frac{P(A,B)}{P(A)P(B)}$
S	Collective strength	0 … ∞	$\frac{P(A,B)+P(\overline{AB})}{P(A)P(B)+P(\overline{A})P(\overline{B})} \times \frac{1-P(A)P(B)-P(\overline{A})P(\overline{B})}{1-P(A,B)-P(\overline{AB})}$
χ^2	χ^2	0 … ∞	$\Sigma_i \frac{(P(A_i)-E_i)^2}{E_i}$

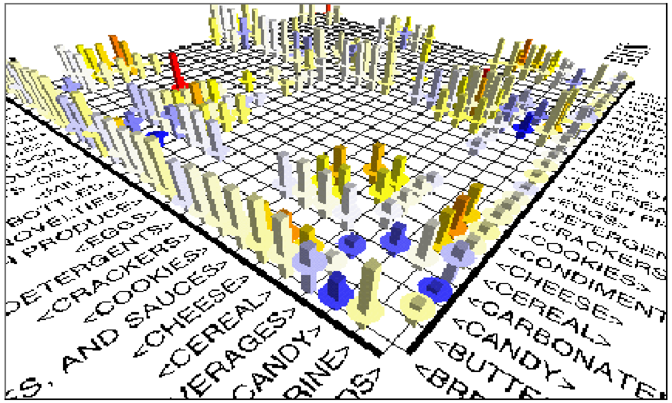
Visualisation of association rules



Visualisation of association rules (2)



Visualisation of association rules (3)



Review question

- Association rule mining allows us to predict what items customers will buy frequently together in a supermarket.

Yes or No?

- The rule: {'beer','chips'} → {'sausages'} [s=20%,c=40%] tells us that 40% of customers bought beer, chips and sausages.

Yes or No?

What now.. things to do

- Read Chapter 6 and Sections 7.1-7.3 in text book
- Lab 2 next week: Read before you go into lab!
  Topic: Association mining - theoretical and in Rattle