#### Association rule mining

- Association rule induction: Originally designed for market basket analysis.
- Aims at finding patterns in the shopping behavior of customers of supermarkets, mail-order companies, on-line shops etc.
- More specifically:
   Find sets of products that are frequently bought together.
- Example of an association rule:

If a customer buys bread and wine, then she/he will probably also buy cheese.

#### Association rule mining

- Possible applications of found association rules:
  - o Improve arrangement of products in shelves, on a catalog's pages.
  - Support of cross-selling (suggestion of other products), product bundling.
  - Fraud detection, technical dependence analysis.
  - o Finding business rules and detection of data quality problems.
  - o ...

#### Association rules

- Assessing the quality of association rules:
  - Support of an item set:

Fraction of transactions (shopping baskets/carts) that contain the item set.

∘ Support of an association rule  $X \rightarrow Y$ :

Either: Support of  $X \cup Y$ 

(more common: rule is correct)

Or: Support of X

(more plausible: rule is applicable)

 $\circ$  Confidence of an association rule  $X \to Y$ :

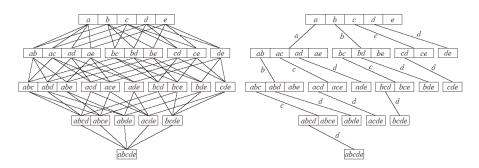
Support of  $X \cup Y$  divided by support of X (estimate of  $P(Y \mid X)$ ).

#### Association rules

- Two step implementation of the search for association rules:
  - Find the frequent item sets (also called <u>large item sets</u>),
     i.e., the item sets that have at least a user-defined minimum support.
  - Form rules using the frequent item sets found and select those that have at least a user-defined minimum confidence.

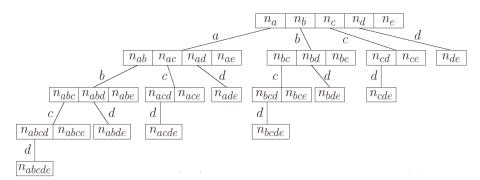
# Finding frequent item sets

Subset lattice and a prefix tree for five items:



- It is not possible to determine the support of all possible item sets, because their number grows exponentially with the number of items.
- Efficient methods to search the subset lattice are needed.

#### Item set trees



A (full) item set tree for the five items a,b,c,d, and e.

- Based on a global order of the items.
- The item sets counted in a node consist of
  - o all items labeling the edges to the node (common prefix) and
  - o one item following the last edge label.

#### Item set tree pruning

In applications item set trees tend to get very large, so pruning is needed.

#### Structural Pruning:

- o Make sure that there is only one counter for each possible item set.
- Explains the unbalanced structure of the full item set tree.

#### Size Based Pruning:

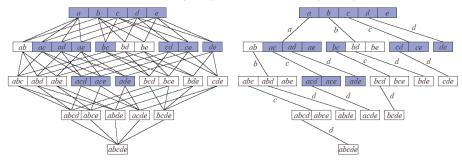
- Prune the tree if a certain depth (a certain size of the item sets) is reached.
- Idea: Rules with too many items are difficult to interpret.

#### Support Based Pruning:

- No superset of an infrequent item set can be frequent.
- No counters for item sets having an infrequent subset are needed.

## Searching the subset lattice

**Boundary** between frequent (blue) and infrequent (white) item sets:



- **Apriori**: Breadth-first search (item sets of same size).
- Eclat: Depth-first search (item sets with same prefix).

- 1:  $\{a, d, e\}$
- 2:  $\{b, c, d\}$
- 3:  $\{a, c, e\}$
- 4:  $\{a, c, d, e\}$
- 5:  $\{a, e\}$
- 6:  $\{a, c, d\}$
- 7:  $\{b, c\}$
- 8:  $\{a, c, d, e\}$
- 9:  $\{c, b, e\}$
- 10:  $\{a, d, e\}$ 
  - Example transaction database with 5 items and 10 transactions.
  - Minimum support: 30%, i.e., at least 3 transactions must contain the item set.

a: 7 | b: 3 | c: 7 | d: 6 | e: 7

• All one item sets are frequent  $\rightarrow$  full second level is needed.

2:  $\{b, c, d\}$ 3:  $\{a, c, e\}$ 4:  $\{a, c, d, e\}$ 5:  $\{a, e\}$ 

1:  $\{a, d, e\}$ 

- 6:  $\{a, c, d\}$ 7:  $\{b, c\}$
- 8:  $\{a, c, d, e\}$ 9:  $\{c, b, e\}$
- 10:  $\{a, d, e\}$ 
  - database and count the transactions that contain it (highly inefficient). Better: Traverse the tree for each transaction and find the item sets it

Determining the support of item sets: For each item set traverse the

contains (efficient: can be implemented as a simple double recursive procedure).

d: 6

c:

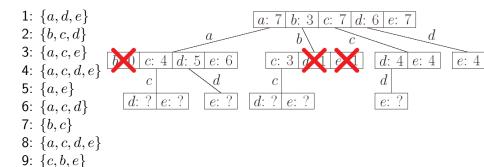
b

- 1:  $\{a, d, e\}$ 2:  $\{b, c, d\}$ 3:  $\{a, c, e\}$ 4:  $\{a, c, d, e\}$  b c c: 3 a 1 e 1 a5:  $\{a, e\}$ 6:  $\{a, c, d\}$
- 8: {a, c, d, e} 9: {c, b, e} 10: {a, d, e}

7:  $\{b, c\}$ 

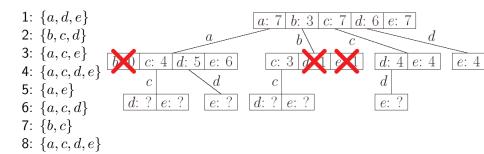
- Minimum support: 30%, i.e., at least 3 transactions must contain the item set.
- Infrequent item sets:  $\{a,b\}$ ,  $\{b,d\}$ ,  $\{b,e\}$ .
- The subtrees starting at these item sets can be pruned.

10:  $\{a, d, e\}$ 



• Generate candidate item sets with 3 items (parents must be frequent).

9:  $\{c, b, e\}$ 10:  $\{a, d, e\}$ 

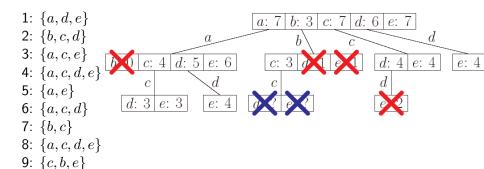


- Before counting, check whether the candidates contain an infrequent item set.
  - $\circ$  An item set with k items has k subsets of size k-1.
  - The parent is only one of these subsets.

9:  $\{c, b, e\}$ 10:  $\{a, d, e\}$ 

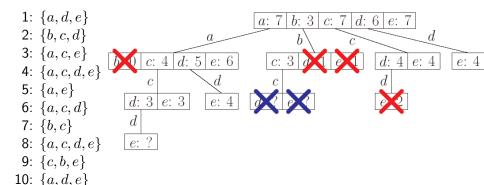
1: {a, d, e}
2: {b, c, d}
3: {a, c, e}
4: {a, c, d, e}
6: {a, e}
6: {a, c, d}
7: {b: 3 c: 7 d: 6 e: 7
d
c: 3 d e: 7
d
d: 4 e: 4
e: 4
for all contains a co

- The item sets  $\{b,c,d\}$  and  $\{b,c,e\}$  can be pruned, because
  - $\circ~\{b,c,d\}$  contains the infrequent item set  $\{b,d\}$  and
  - $\circ$   $\{b,c,e\}$  contains the infrequent item set  $\{b,e\}$ .
- Only the remaining four item sets of size 3 are evaluated.

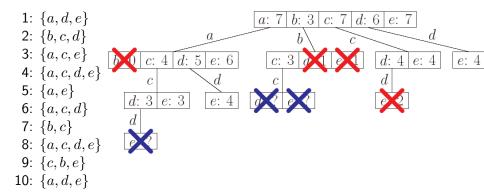


- Minimum support: 30%, i.e., at least 3 transactions must contain the item set.
- Infrequent item set:  $\{c, d, e\}$ .

10:  $\{a, d, e\}$ 



- Generate candidate item sets with 4 items (parents must be frequent).
- Before counting, check whether the candidates contain an infrequent item set.



infrequent item set  $\{c,d,e\}$ .

• The item set  $\{a, c, d, e\}$  can be pruned, because it contains the

- Consequence: No candidate item sets with four items.
- Fourth access to the transaction database is not necessary.

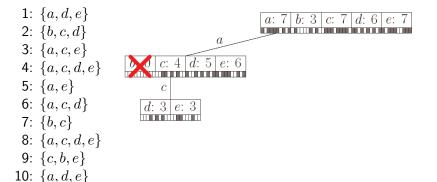
- 1:  $\{a, d, e\}$
- 2:  $\{b, c, d\}$
- 3:  $\{a, c, e\}$
- 4:  $\{a, c, d, e\}$
- 5:  $\{a, e\}$
- 6:  $\{a, c, d\}$
- 7:  $\{b, c\}$
- 8:  $\{a, c, d, e\}$
- 9:  $\{c, b, e\}$
- 10:  $\{a, d, e\}$ 
  - Form a transaction list for each item. Here: bit vector representation.

a:  $7 \mid b$ :  $3 \mid c$ :  $7 \mid d$ :  $6 \mid$ 

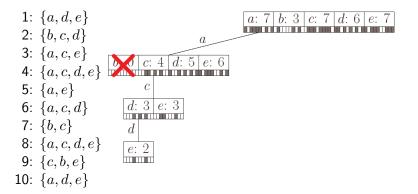
- o grey: item is contained in transaction
- o white: item is not contained in transaction
- Transaction database is needed only once (for the single item transaction lists).

10:  $\{a, d, e\}$ 

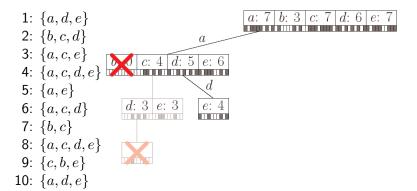
- 1: {a, d, e} 2: {b, c, d} 3: {a, c, e} 4: {a, c, d, e} 5: {a, e} 6: {a, c, d} 7: {b, c} 8: {a, c, d, e} 9: {c, b, e}
  - ullet Intersect the transaction list for item a with the transaction lists of all other items.
  - Count the number of set bits (containing transactions).
  - The item set  $\{a, b\}$  is infrequent and can be pruned.



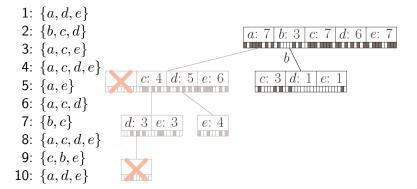
- Intersect the transaction list for  $\{a,c\}$  with the transaction lists of  $\{a,x\}$ ,  $x \in \{d,e\}$ .
- Result: Transaction lists for the item sets  $\{a, c, d\}$  and  $\{a, c, e\}$ .



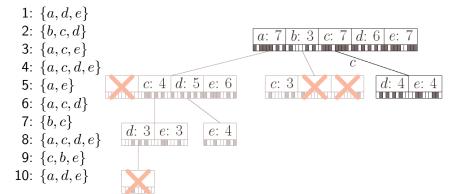
- Intersect the transaction list for  $\{a, c, d\}$  and  $\{a, c, e\}$ .
- Result: Transaction list for the item set  $\{a, c, d, e\}$ .
- With Apriori this item set could be pruned before counting, because it was known that  $\{c, d, e\}$  is infrequent.



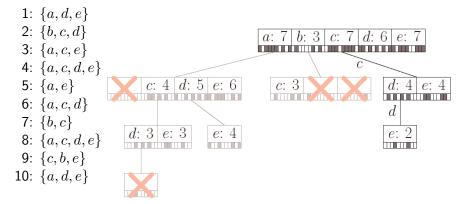
- Backtrack to the second level of the search tree and intersect the transaction list for  $\{a, d\}$  and  $\{a, e\}$ .
- Result: Transaction list for  $\{a, d, e\}$ .



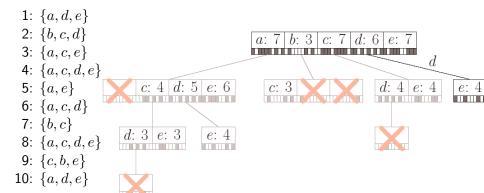
- Backtrack to the first level of the search tree and intersect the transaction list for b with the transaction lists for c, d, and e.
- Result: Transaction lists for the item sets  $\{b,c\}$ ,  $\{b,d\}$ , and  $\{b,e\}$ .
- ullet Only one item set with sufficient support o prune all subtrees.



- ullet Backtrack to the first level of the search tree and intersect the transaction list for c with the transaction lists for d and e.
- Result: Transaction lists for the item sets  $\{c, d\}$  and  $\{c, e\}$ .



- Intersect the transaction list for  $\{c, d\}$  and  $\{c, e\}$ .
- Result: Transaction list for  $\{c, d, e\}$ .
- Infrequent item set:  $\{c, d, e\}$ .



- Backtrack to the first level of the search tree and intersect the transaction list for d with the transaction list for e.
- Result: Transaction list for the item set  $\{d, e\}$ .
- With this step the search is finished.

#### Frequent item sets

| 1 item            | 2 items              |                   | 3 items                    |
|-------------------|----------------------|-------------------|----------------------------|
| $\{a\}^+$ : 70%   | $\{a,c\}^+$ : 40%    | $\{c,e\}^+$ : 40% | $\{a,c,d\}^{+*}$ : 30%     |
| { <i>b</i> }: 30% | $\{a,d\}^+$ : 50%    | $\{d, e\}$ : 40%  | $  \{a, c, e\}^{+*}$ : 30% |
| $\{c\}^+$ : 70%   | $\{a,e\}^+$ : 60%    |                   | $  \{a,d,e\}^{+*}$ : 40%   |
| ${d}^{+}$ : 60%   | $\{b,c\}^{+*}$ : 30% |                   |                            |
| $\{e\}^+$ : 70%   | $\{c,d\}^+$ : 40%    |                   |                            |

#### Types of frequent item sets

- Free Item Set: Any frequent item set (support is higher than the minimal support).
- Closed Item Set (marked with +): A frequent item set is called <u>closed</u> if no superset has the same support.
- Maximal Item Set (marked with \*): A frequent item set is called maximal if no superset is frequent.

#### Generating association rules

#### For each frequent item set S:

- Consider all pairs of sets  $X,Y\in S$  with  $X\cup Y=S$  and  $X\cap Y=\emptyset$ . Common restriction: |Y|=1, i.e. only one item in consequent (then-part).
- ullet Form the association rule  $X \to Y$  and compute its confidence.

$$\operatorname{conf}(X \to Y) = \frac{\operatorname{supp}(X \cup Y)}{\operatorname{supp}(X)} = \frac{\operatorname{supp}(S)}{\operatorname{supp}(X)}$$

• Report rules with a confidence higher than the minimum confidence.

#### Generating association rules

#### Further rule filtering can rely on:

- Require a minimum difference between rule confidence and consequent support.
- $\bullet$  Compute information gain or  $\chi^2$  for antecedent (if-part) and consequent.

## Generating association rules

**Example:** 
$$S = \{a, c, e\}, X = \{c, e\}, Y = \{a\}.$$

$${\rm conf}(c,e\to a) = \frac{{\rm supp}(\{a,c,e\})}{{\rm supp}(\{c,e\})} = \frac{30\%}{40\%} = 75\%$$

#### Minimum confidence: 80%

| association<br>rule    | support of all items | support of antecedent | confidence |
|------------------------|----------------------|-----------------------|------------|
| $b \rightarrow c$ :    | 30%                  | 30%                   | 100%       |
| $d \rightarrow a$ :    | 50%                  | 60%                   | 83.3%      |
| $e \rightarrow a$ :    | 60%                  | 70%                   | 85.7%      |
| $a \rightarrow e$ :    | 60%                  | 70%                   | 85.7%      |
| $d, e \rightarrow a$ : | 40%                  | 40%                   | 100%       |
| $a, d \rightarrow e$ : | 40%                  | 50%                   | 80%        |

#### Summary association rules

#### Association Rule Induction is a Two Step Process

- Find the frequent item sets (minimum support).
- Form the relevant association rules (minimum confidence).

#### Finding the Frequent Item Sets

- Top-down search in the subset lattice / item set tree.
- Apriori: Breadth first search; Eclat: Depth first search.
- Other algorithms: FP-growth, H-Mine, LCM, Mafia, Relim etc.
- Search Tree Pruning:
   No superset of an infrequent item set can be frequent.
   (other possible

#### Generating the Association Rules

- Form all possible association rules from the frequent item sets.
- Filter "interesting" association rules.

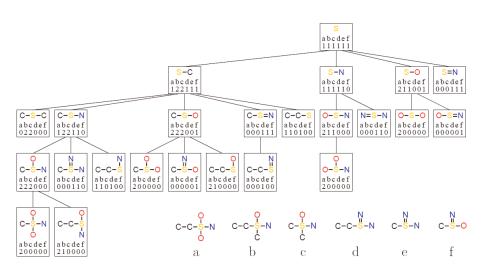
#### Structured itemsets

Sometimes, an additional structure is imposed on the "item sets".

- The "item sets" are sequences of events.
  - For instance: Customer contact (buying, complaint, questionnaire,...)
  - $\bullet$  Association rules have the form: If a and then b happens, then probably c happens next.
- Items sets are molecules: Find frequent substructures.

The additional structure leads to different tree structure, but the principal algorithm remains the same.

# Finding frequent molecule structures



## Other applications

- Finding business rules and detection of data quality problems.
  - Association rules with confidence close to 100% could be business rules.
  - Exceptions might be caused by data quality problems.
- Construction of partial classifiers.
  - Search for association rules with a given conclusion part.
  - If ..., then the customer probably buys the product.