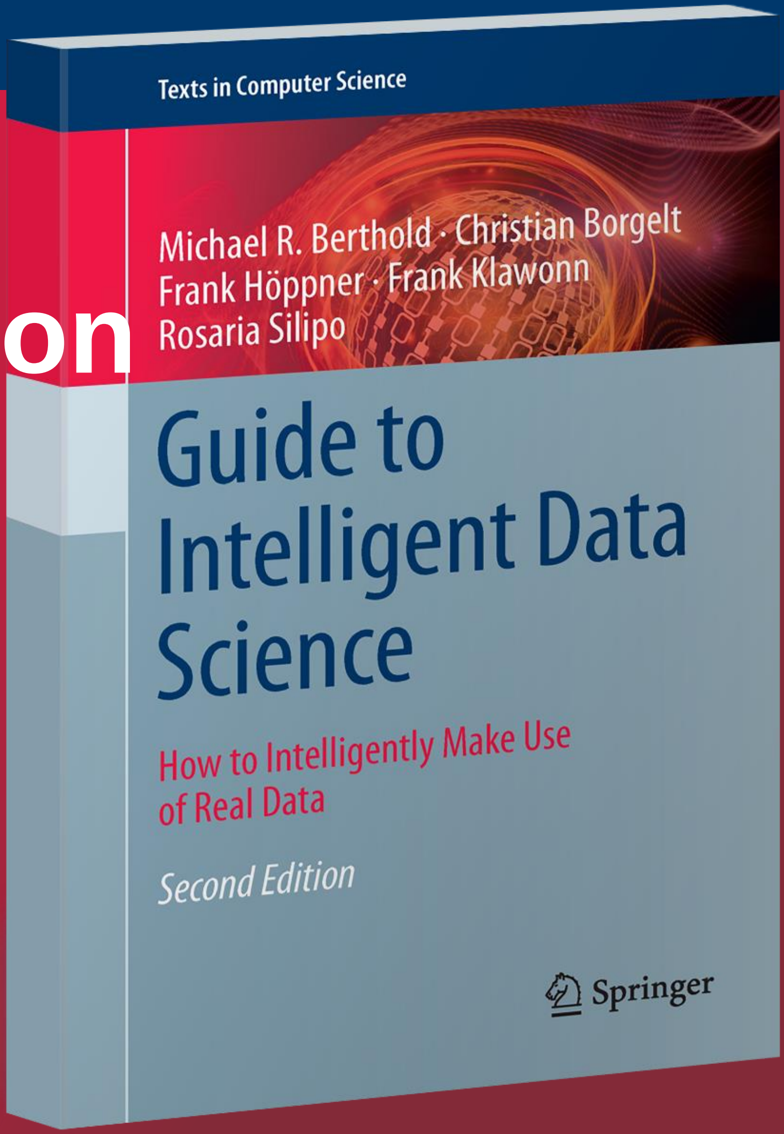
Recommendation Engines



Summary of this lesson

“We all make choices, but in the end our choices make us”
-Ken Levine

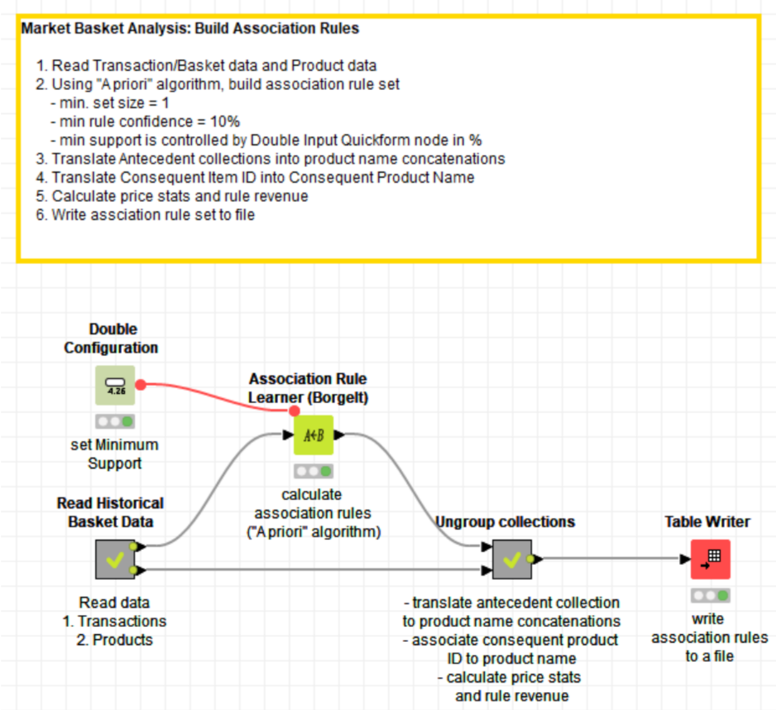
Are there events that always happen together?

**This lesson refers to chapter 7 of the GIDS book*

What you will learn

- Associaition Rules
- Itemset Mining
- Generating Associaition Rules
- Collaborative Filtering

- Datasets used : transaction data & products data
- Example Workflow:
  - „Association_Rules_for_MarketBasketAnalysis“ https://kni.me/w/fQ9yZLztzEUmAsQ0



Association Rules

Overview

- Association Rules: Motivation
- Item Set Mining
  - Breadth First Searching: The Apriori Algorithm
  - Depth First Searches: The Eclat Algorithm
  - (Compact) Representation of Itemsets
- Finding Association Rules

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: Example

IF 

+ 

THEN 

Antecedent

Consequent

From the analysis of many shopping baskets ...

A-priori algorithm

Recommendation

IF

+

THEN

Possible applications of found association rules:

- 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.
- Finding business rules and detection of data quality problems.
- . . .

- Two step implementation:

- Find the **frequent item sets** (also called large item sets), 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**.

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)

Confidence of an association rule $X \rightarrow Y$:

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

Itemset Mining

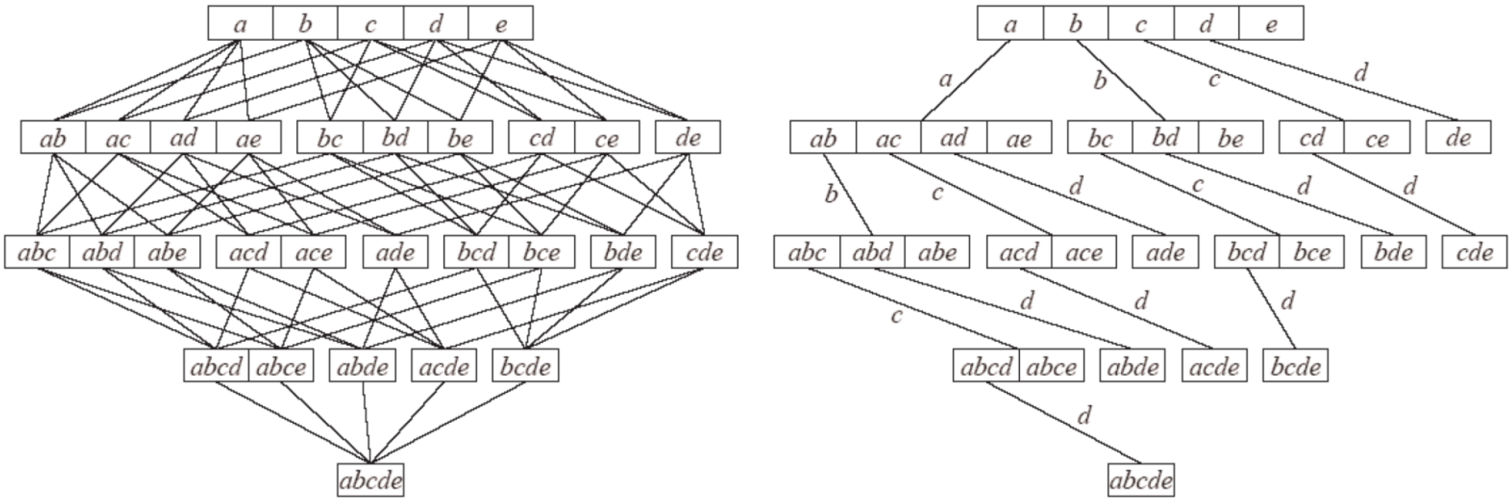
N shopping baskets

Search for

frequent itemsets

{A, B, F, H}
{A, B, C}
{B, C, H}
{D, E , F}
{D, E}
{A, B}
{A, C}
{H, F}
…

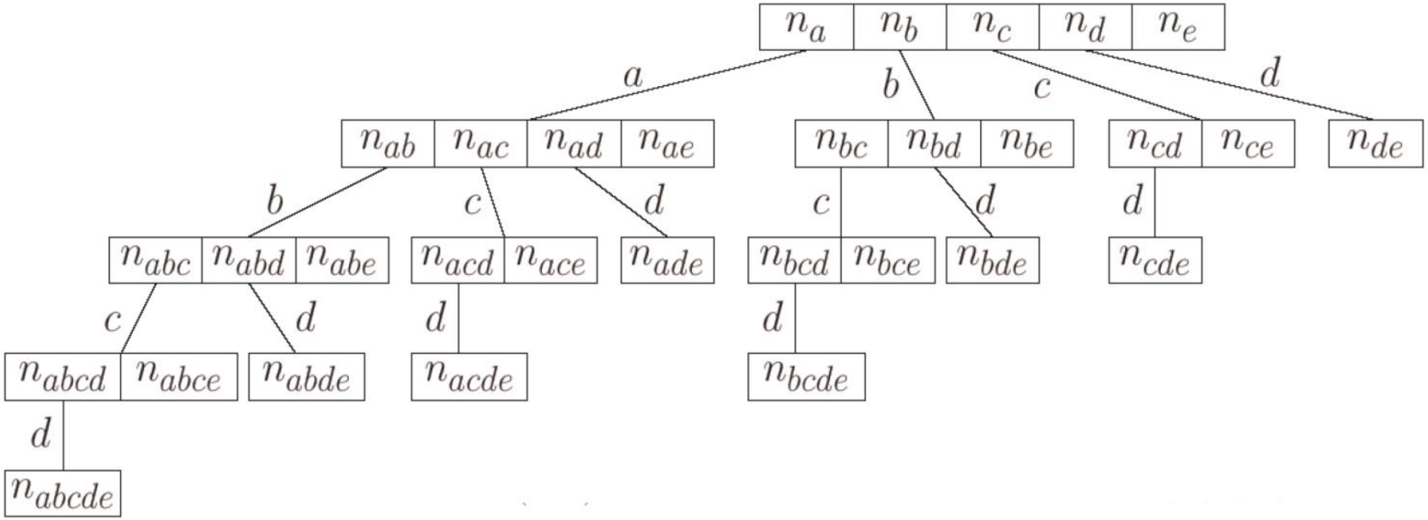
– Subset lattice and a prefix tree for five items:



– 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

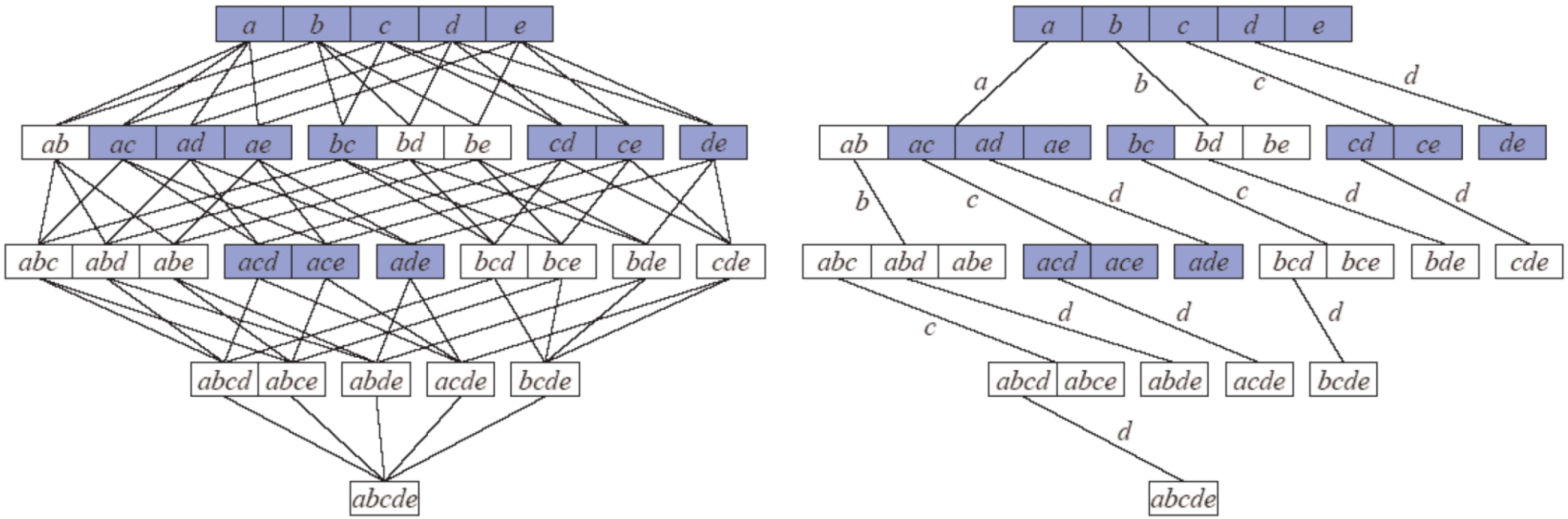


- A (full) item set tree for the five items *a, b, c, d,* and *e*.
- Based on a global order of the items.
- The item sets counted in a node consist of all items labeling the edges to the node (common prefix) and one item following the last edge label.

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

- **Structural Pruning:**
  - 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

– **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).

Apriori Breadth first Search

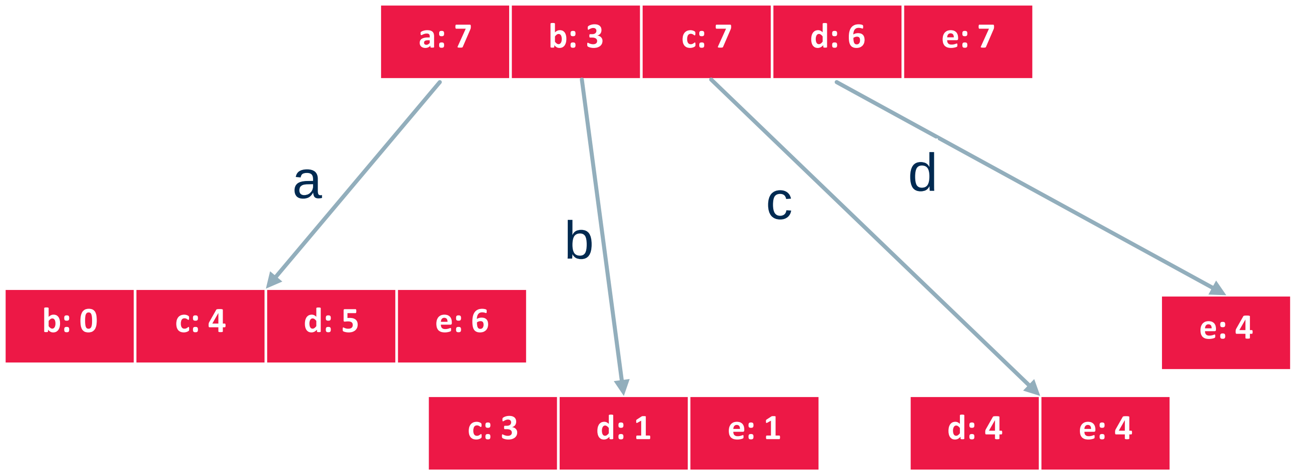
1. {*a*, *d*, *e*}
2. {*b*, *c*, *d*}
3. {*a*, *c*, *e*}
4. {*a*, *c*, *d*, *e*}
5. {*a*, *e*}
6. {*a*, *c*, *d*}
7. {*b*, *c*}
8. {*a*, *c*, *d*, *e*}
9. {*c*, *b*, *e*}
10. {*a*, *d*, *e*}

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

- Example transaction database with 5 items { a,b,c,d,e } and 10 transactions.
- Minimum support: 30%, i.e., at least 3 transactions must contain the item set.
- All one item sets are frequent -> full second level is needed.

Apriori Breadth first Search

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*}

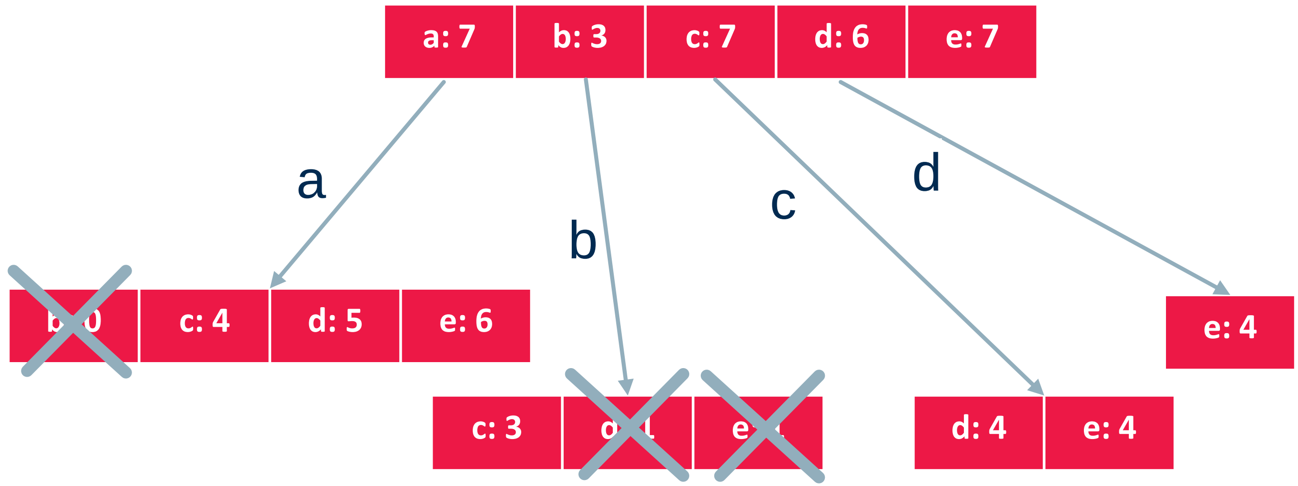


– Determining the support of item sets: For each item set traverse the database and count the transactions that contain it (highly inefficient).

– Better: Traverse the tree for each transaction and find the item sets it contains (efficient: can be implemented as a simple double recursive procedure).

Apriori Breadth first Search

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*}



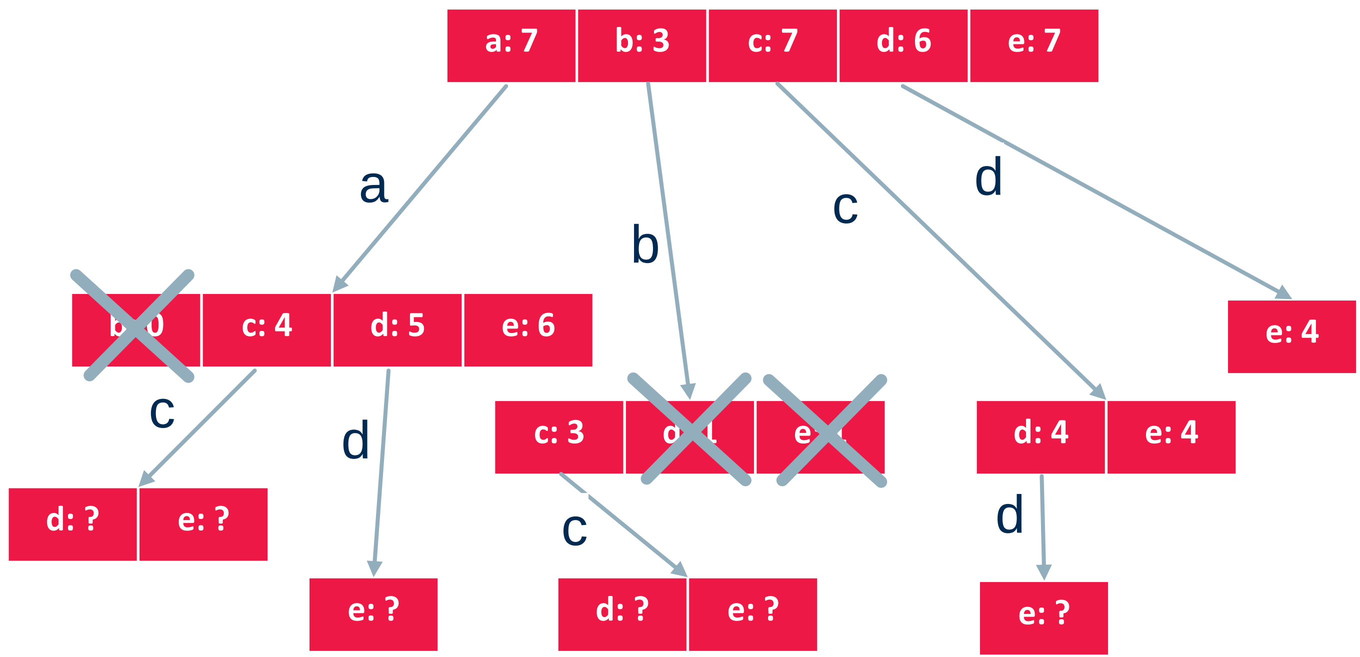
– Minimum support: 30%, i.e., at least 3 transactions must contain the item set.

– Infrequent item sets: {*a*, *b*}, {*b*, *d*}, {*b*, *e*}.

– The subtrees starting at these item sets can be pruned.

Apriori Breadth first Search

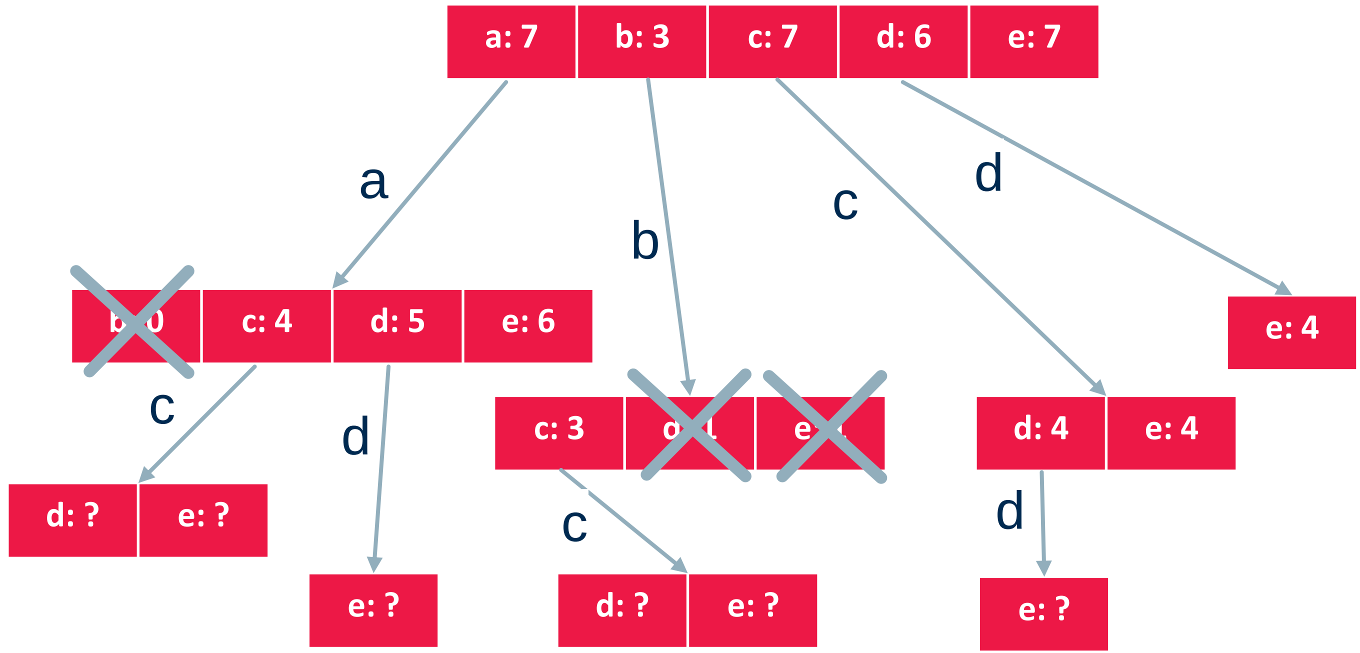
1. {*a*, *d*, *e*}
2. {*b*, *c*, *d*}
3. {*a*, *c*, *e*}
4. {*a*, *c*, *d*, *e*}
5. {*a*, *e*}
6. {*a*, *c*, *d*}
7. {*b*, *c*}
8. {*a*, *c*, *d*, *e*}
9. {*c*, *b*, *e*}
10. {*a*, *d*, *e*}



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

Apriori Breadth first Search

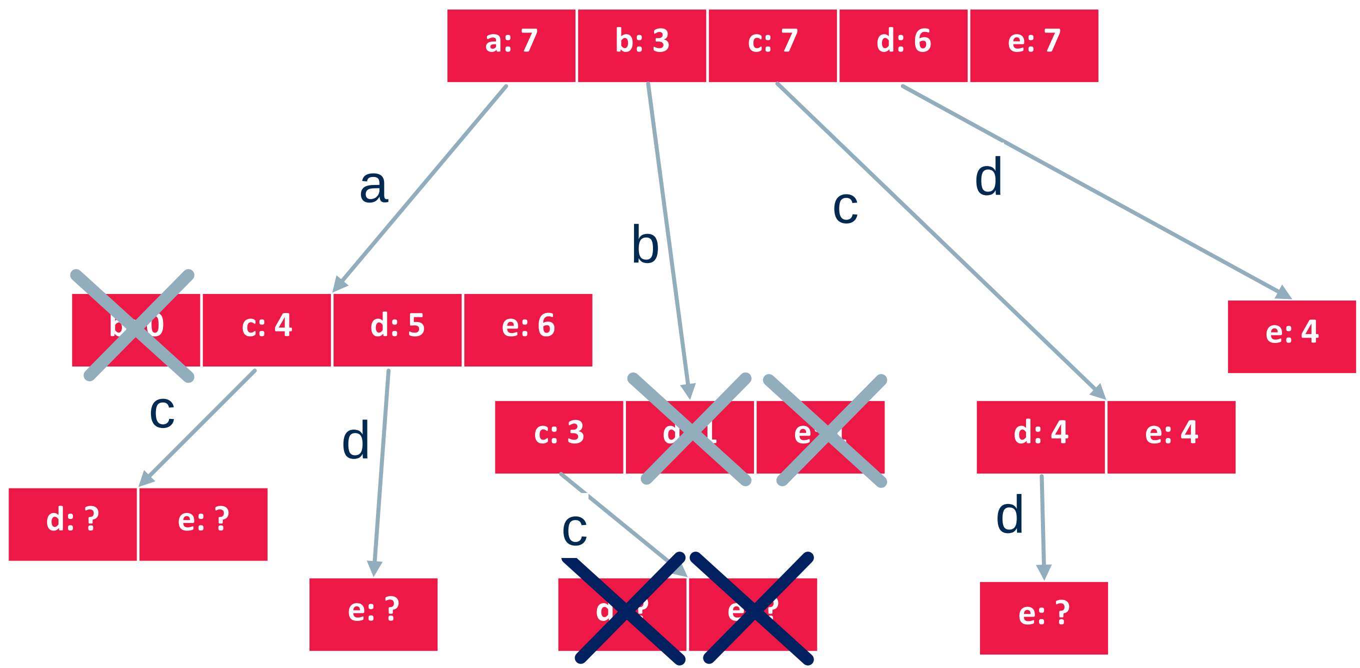
1. {*a*, *d*, *e*}
2. {*b*, *c*, *d*}
3. {*a*, *c*, *e*}
4. {*a*, *c*, *d*, *e*}
5. {*a*, *e*}
6. {*a*, *c*, *d*}
7. {*b*, *c*}
8. {*a*, *c*, *d*, *e*}
9. {*c*, *b*, *e*}
10. {*a*, *d*, *e*}



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

Apriori Breadth first Search

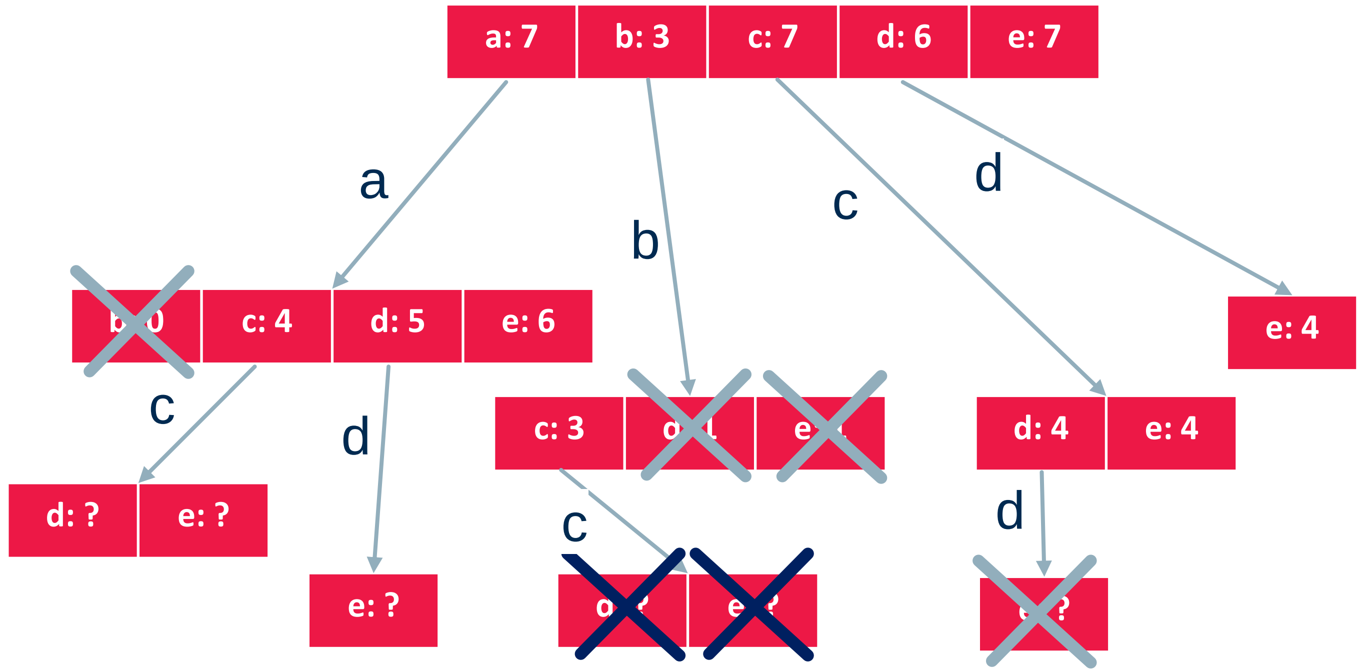
1. {*a*, *d*, *e*}
2. {*b*, *c*, *d*}
3. {*a*, *c*, *e*}
4. {*a*, *c*, *d*, *e*}
5. {*a*, *e*}
6. {*a*, *c*, *d*}
7. {*b*, *c*}
8. {*a*, *c*, *d*, *e*}
9. {*c*, *b*, *e*}
10. {*a*, *d*, *e*}



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

Apriori Breadth first Search

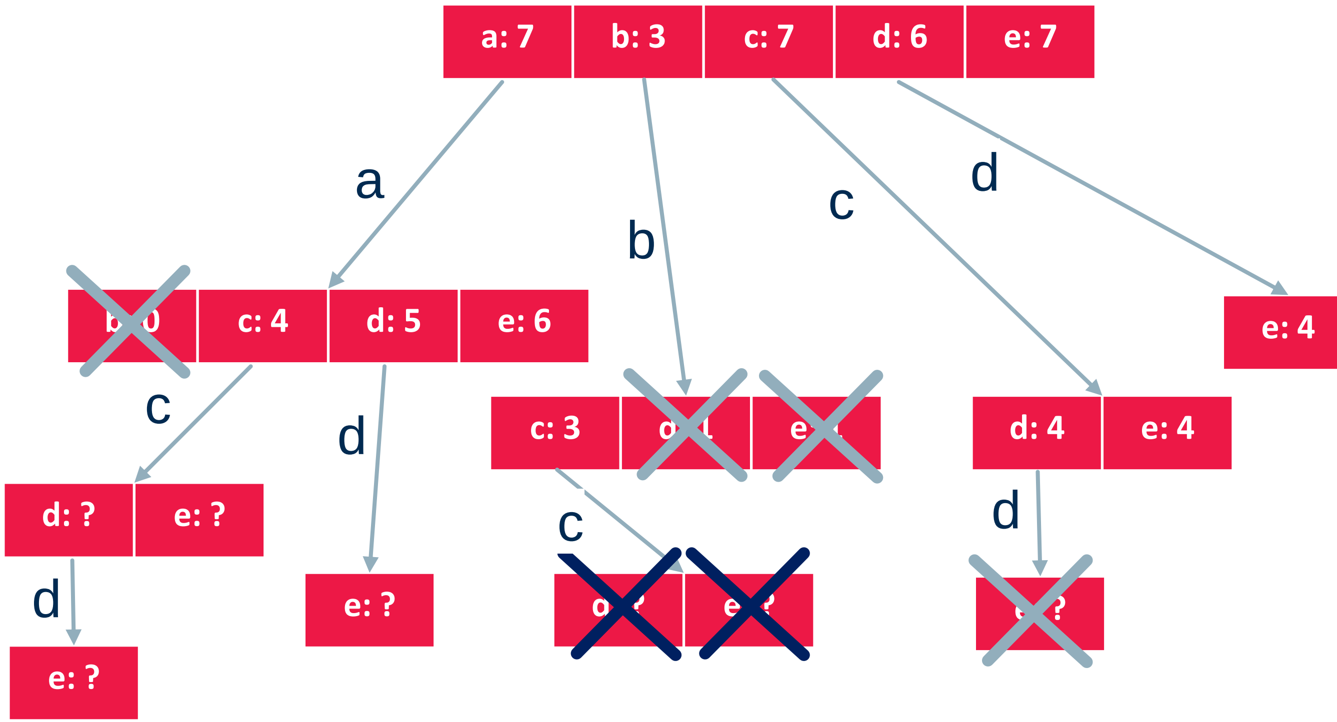
1. {*a*, *d*, *e*}
2. {*b*, *c*, *d*}
3. {*a*, *c*, *e*}
4. {*a*, *c*, *d*, *e*}
5. {*a*, *e*}
6. {*a*, *c*, *d*}
7. {*b*, *c*}
8. {*a*, *c*, *d*, *e*}
9. {*c*, *b*, *e*}
10. {*a*, *d*, *e*}



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

Apriori Breadth first Search

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*}

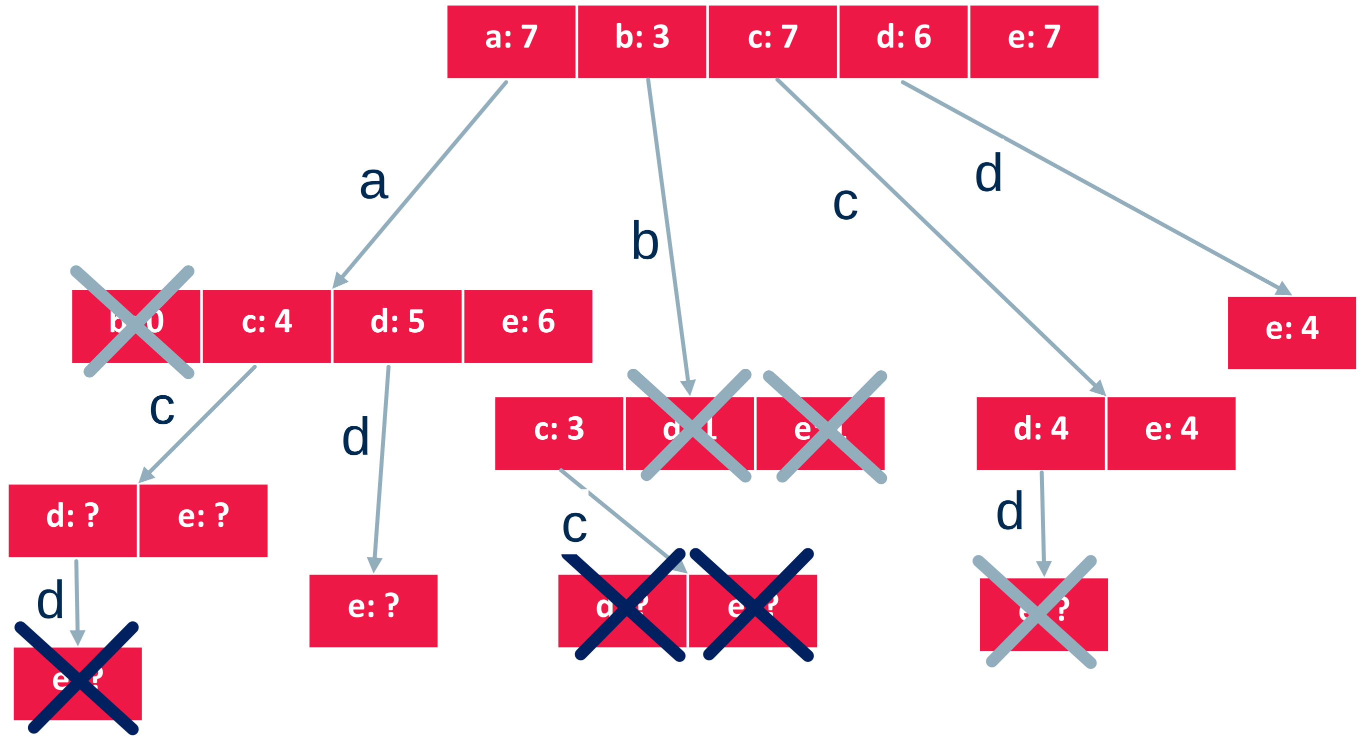


– Generate candidate item sets with 4 items (parents must be frequent).

– Before counting, check whether the candidates contain an infrequent item set.

Apriori Breadth first Search

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*}



– The item set {*a*,*c*,*d*,*e*} can be pruned, because it contains the infrequent item set {*c*, *d*, *e*}.

– Consequence: No candidate item sets with four items. Stop.

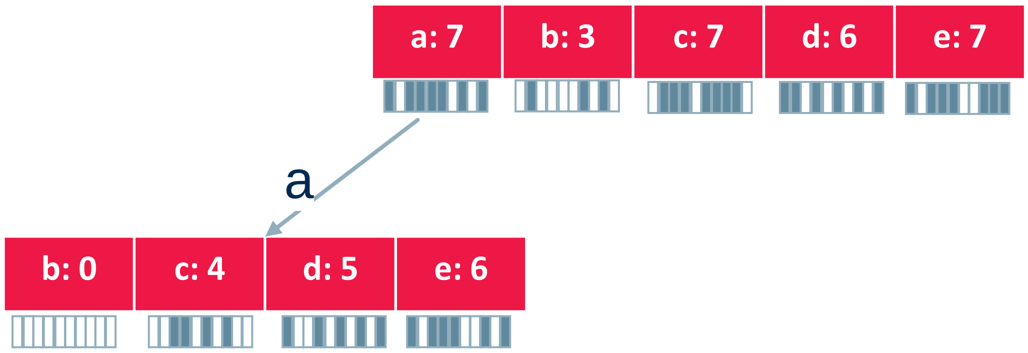
Eclat Depth first Search

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

Eclat Depth first Search

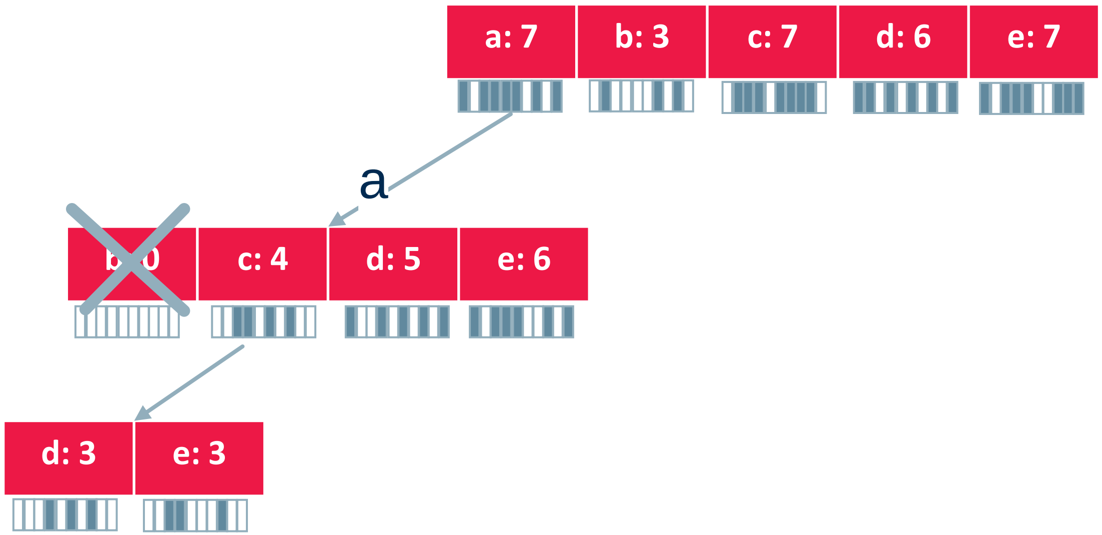
1. {*a*, *d*, *e*}
2. {*b*, *c*, *d*}
3. {*a*, *c*, *e*}
4. {*a*, *c*, *d*, *e*}
5. {*a*, *e*}
6. {*a*, *c*, *d*}
7. {*b*, *c*}
8. {*a*, *c*, *d*, *e*}
9. {*c*, *b*, *e*}
10. {*a*, *d*, *e*}



– 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.

Eclat Depth first Search

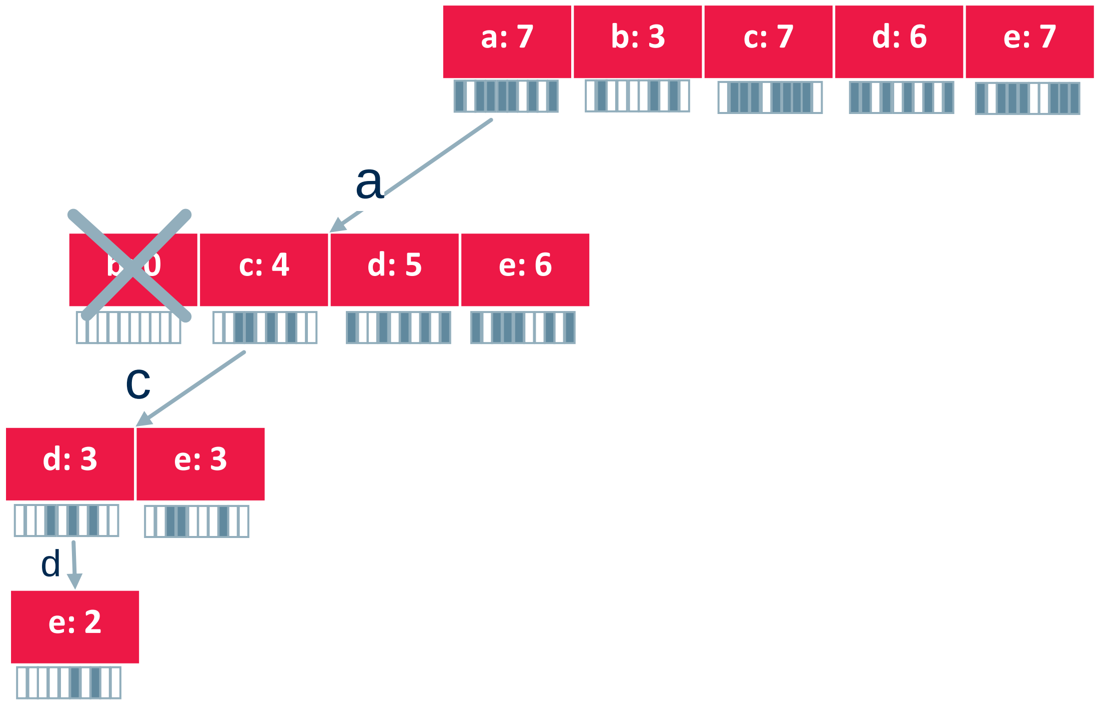
1. {*a, d, e*}
2. {*b, c, d*}
3. {*a, c, e*}
4. {*a, c, d, e*}
5. {*a, e*}
6. {*a, c, d*}
7. {*b, c*}
8. {*a, c, d, e*}
9. {*c, b, e*}
10. {*a, d, e*}



– 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*}.

Eclat Depth first Search

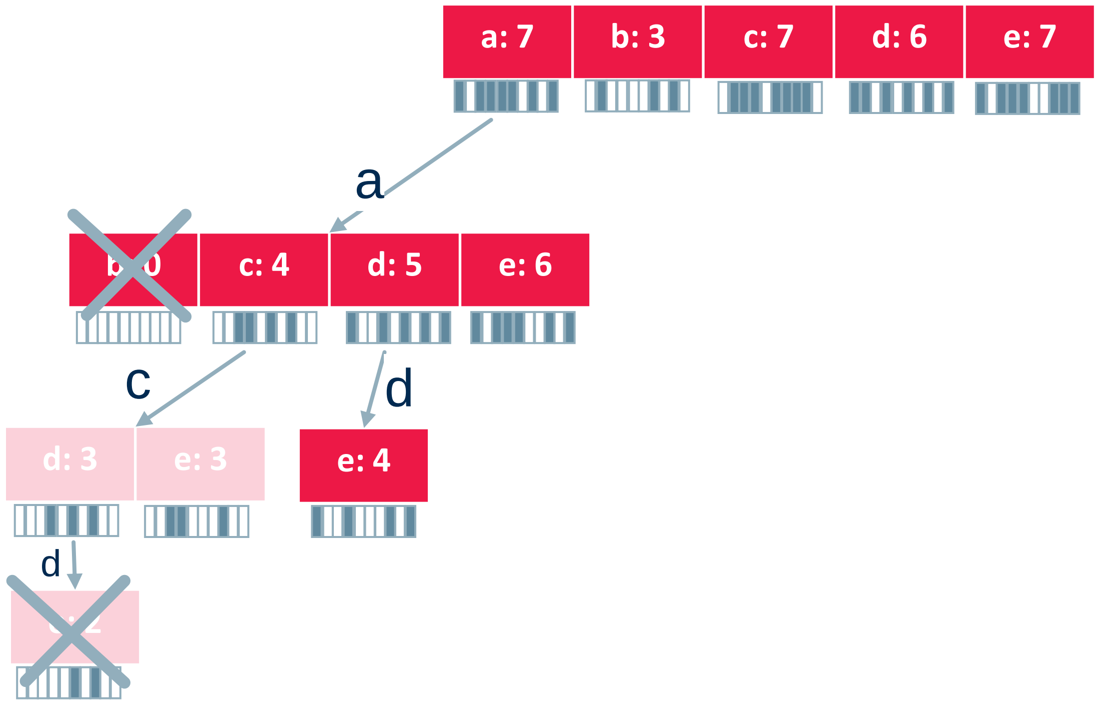
1. {*a*, *d*, *e*}
2. {*b*, *c*, *d*}
3. {*a*, *c*, *e*}
4. {*a*, *c*, *d*, *e*}
5. {*a*, *e*}
6. {*a*, *c*, *d*}
7. {*b*, *c*}
8. {*a*, *c*, *d*, *e*}
9. {*c*, *b*, *e*}
10. {*a*, *d*, *e*}



- 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.

Eclat Depth first Search

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*}

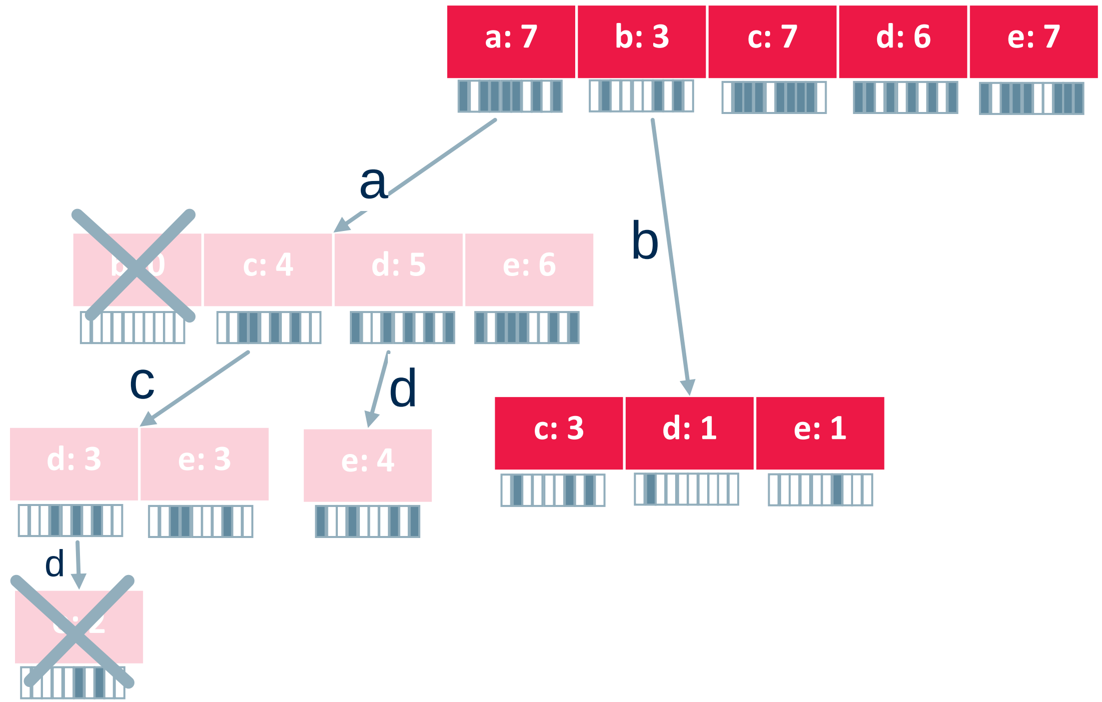


– Backtrack to the second level of the search tree and intersect the transaction list for {*a*, *d*} and {*a*, *e*}.

– Result: Transaction list for {*a*, *d*, *e*}.

Eclat Depth first Search

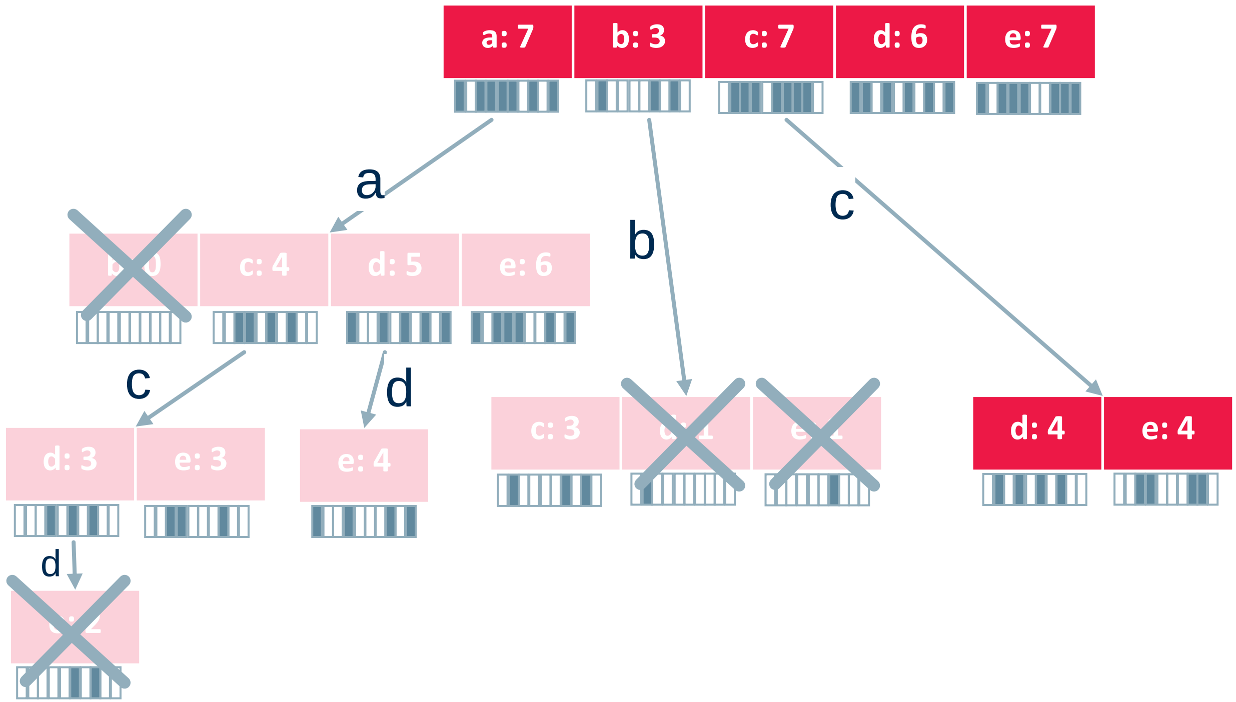
1. {*a*, *d*, *e*}
2. {*b*, *c*, *d*}
3. {*a*, *c*, *e*}
4. {*a*, *c*, *d*, *e*}
5. {*a*, *e*}
6. {*a*, *c*, *d*}
7. {*b*, *c*}
8. {*a*, *c*, *d*, *e*}
9. {*c*, *b*, *e*}
10. {*a*, *d*, *e*}



- 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*}.
- Only one item set with sufficient support -> prune all subtrees.

Eclat Depth first Search

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*}

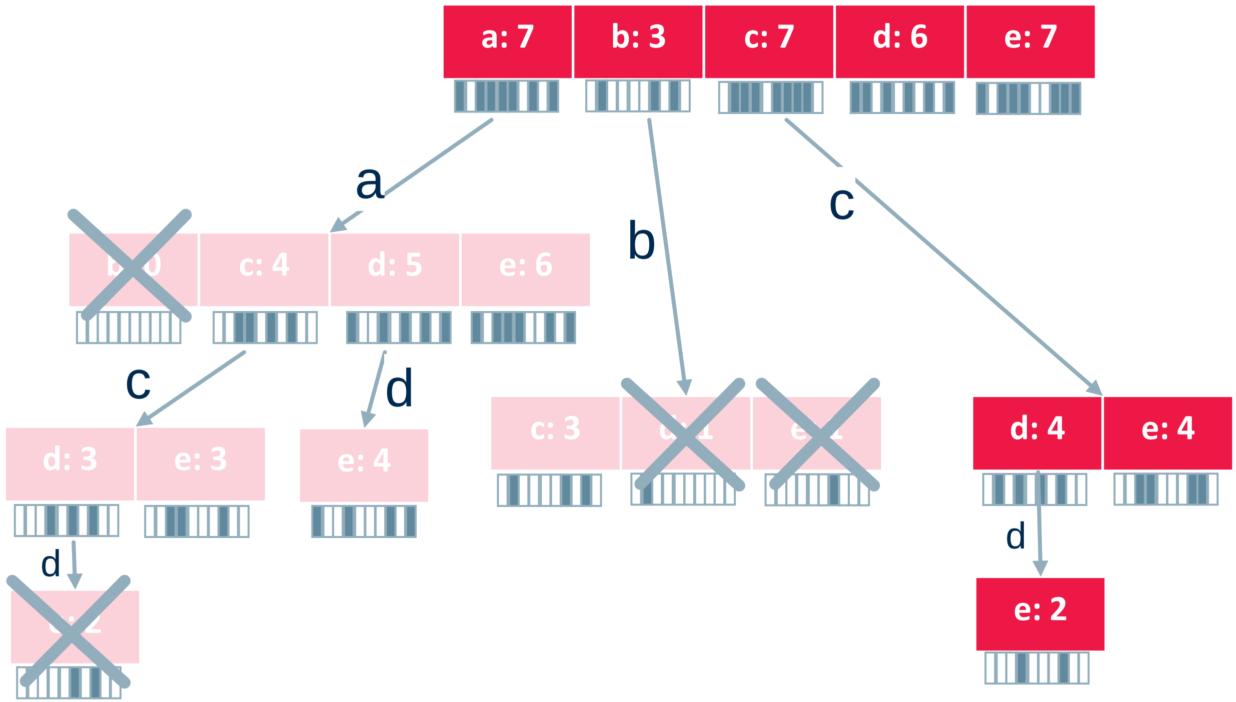


– Backtrack to the first level of the search tree and intersect the transaction list for *c* with the transaction lists for *d* and *e*.

– Result: Transaction lists for the item sets {*c*, *d*} and {*c*, *e*}.

Eclat Depth first Search

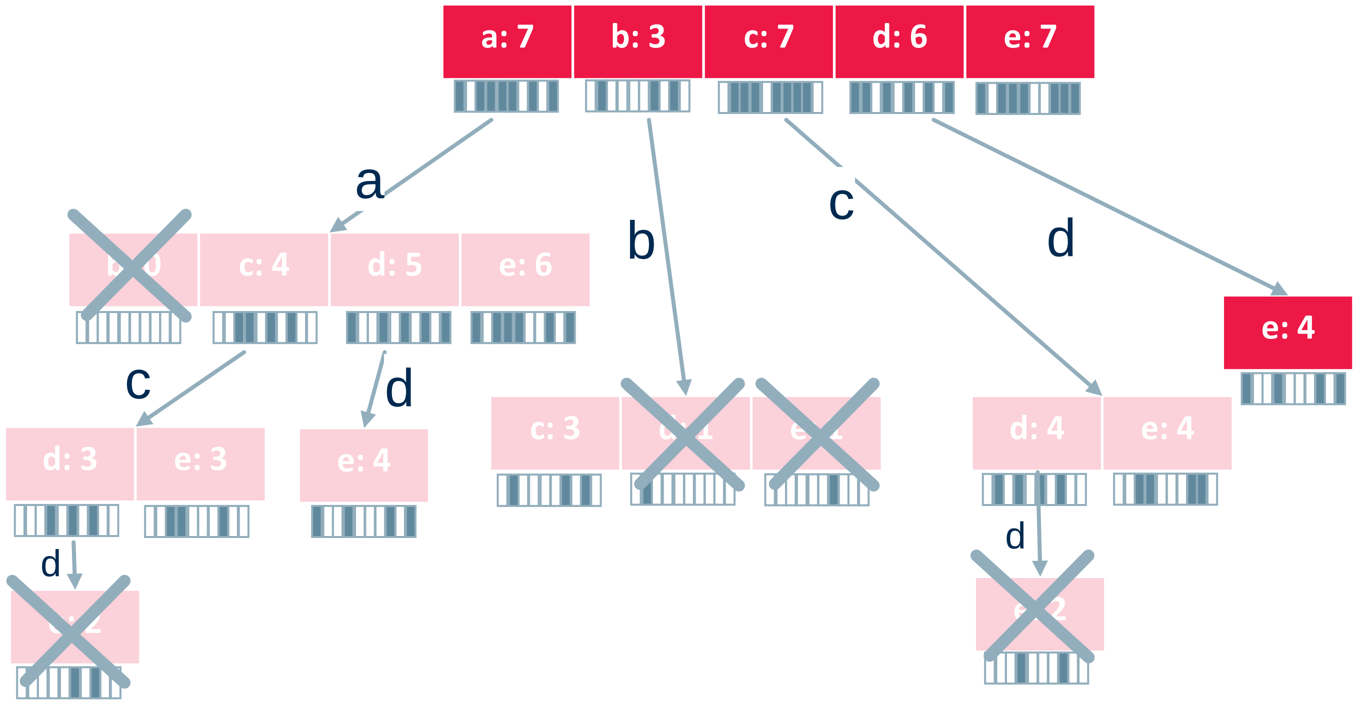
1. {*a*, *d*, *e*}
2. {*b*, *c*, *d*}
3. {*a*, *c*, *e*}
4. {*a*, *c*, *d*, *e*}
5. {*a*, *e*}
6. {*a*, *c*, *d*}
7. {*b*, *c*}
8. {*a*, *c*, *d*, *e*}
9. {*c*, *b*, *e*}
10. {*a*, *d*, *e*}



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

Eclat Depth first Search

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*}



– 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
$\{a\}^{+}: 70\%$	$\{a,c\}^{+}: 40\%$	$\{c,e\}^{+}: 40\%$	$\{a,c,d\}^{+*}: 30\%$
$\{b\} \quad : 30\%$	$\{a,d\}^{+}: 50\%$	$\{d,e\}^{+}: 40\%$	$\{a,c,e\}^{+*}: 30\%$
$\{c\}^{+}: 70\%$	$\{a,e\}^{+}: 60\%$		$\{a,d,e\}^{+*}: 40\%$
$\{d\}^{+}: 60\%$	$\{b,c\}^{+*}: 30\%$		
$\{e\}^{+}: 70\%$	$\{c,d\}^{+}: 40\%$		

- **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 **closed** 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
- X = antecedent, Y = consequent
- Form the association rule $X \rightarrow Y$ and compute its confidence.

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

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

From “Frequent Itemsets“ to “Rules“

{A, B, F, H} →

{A, B, F} → H

{A, B, H} → F

{A, F, H} → B

{B, F, H} → A

Which rules shall I choose?

{A, B, F} → H

- Item set support $\boldsymbol{s} = \frac{freq(A,B,F,H)}{N}$ ← How often these items are found together

- Rule confidence $\boldsymbol{c} = \frac{freq(A,B,F,H)}{freq(A,B,F)}$ ← How often the antecedent is together with the consequent

- Rule lift $= \frac{support\ (\{A,B,F\} \Rightarrow H)}{support\ (A,B,F) \times support(H)}$ ← How often antecedent and consequent happen together compared with random chance

The rules with support, confidence and lift above a threshold → most reliable ones

Association Rule Mining (ARM): Two Phases

Discover all frequent and strong association rules

$X \Rightarrow Y$ → "if X then Y"

with sufficient support and confidence

Two phases:

1. find all frequent itemsets (FI) ← Most of the complexity
   - Select itemsets with a minimum support

$$FI = \{\{X, Y\}, X, Y \subset I \,|\, s(X, Y) \geq S_{min}\}$$

2. build strong association rules
   - Select rules with a minimum confidence:

$$Rules: \{X \Rightarrow Y, X, Y \subset FI, |c(X \Rightarrow Y) \geq C_{min}\}$$

User parameters

Generating Association Rules: Example

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

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

- **Minimum confidence: 80%**

Association 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%

A-Priori Algorithm: Example

- Let's consider milk, diaper, and beer: $\{milk, diaper\} \Rightarrow beer$

- How often are they found together across all shopping baskets?
- How often are they found together across all shopping baskets containing the antecedents?

TID	Transactions
1	Bread, Milk
2	Bread, Diaper, Beer, Eggs
3	Milk, Diaper, Beer, Coke
4	Bread, Milk, Diaper, Beer
5	Bread, Milk, Diaper, Coke

support

$$s(milk, diaper, beer) = \frac{P(milk, diaper, beer)}{|T|} = \frac{2}{5} = 0.4$$

$$c = \frac{P(milk, diaper, beer)}{P(milk, diaper)} = \frac{2}{3} = 0.67$$

confidence

A-priori algorithm: an example

- Let‘s consider milk, diaper, and beer: $\{milk, diaper\} \Rightarrow beer$
- How often are they found together across all shooping baskets?
- How often are they found together across all shopping baskets containing the antecedents?

TID	Transactions
1	Bread, Milk
2	Bread, Diaper, Beer, Eggs
3	Milk, Diaper, Beer, Coke
4	Bread, Milk, Diaper, Beer
5	Bread, Milk, Diaper, Coke

$$s(milk, diaper) = \frac{P(milk, diaper)}{|T|} = \frac{3}{5} = 0.6$$

$$s(beer) = \frac{P(beer)}{|T|} = \frac{3}{5} = 0.6$$

$$Rule\ lift = \frac{s(milk, diaper, beer)}{s(milk, diaper) \times s(beer)}$$

$$= \frac{0.4}{0.6 \times 0.6} = 1.11$$

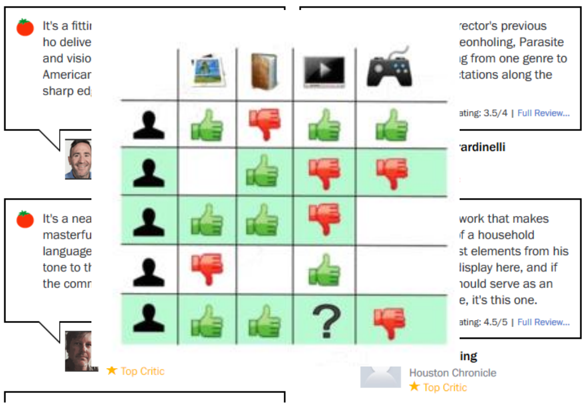
Summary Association Rules

- **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.*
- **Generating the Association Rules**
  - Form all possible association rules from the frequent item sets.
  - Filter “interesting” association rules.

Collaborative Filtering

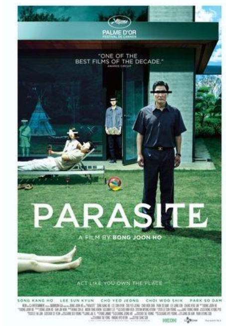
Recommendation Engines or Market Basket Analysis

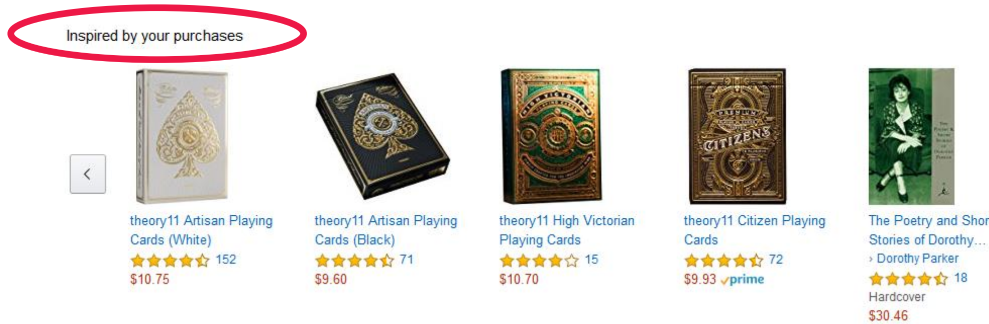
From the analysis of the reactions of many people to the same item ...



Collaborative Filtering

Recommendation

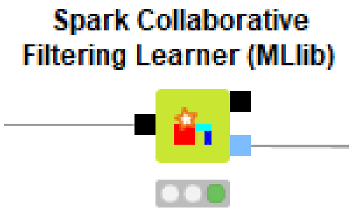




IF *A* has the same opinion as *B* on an item,
THEN A is more likely to have B's opinion on another item than that of a randomly chosen person

Collaborative filtering systems have many forms, but many common systems can be reduced to two steps:

1. Look for users who share the same rating patterns with the active user (the user whom the recommendation is for)
2. Use the ratings from those like-minded users found in step 1 to calculate a prediction for the active user
3. Implemented in Spark



https://www.knime.com/blog/movie-recommendations-with-spark-collaborative-filtering

- User u to give recommendations to
- U = set of top N users most similar to user u
- Rating of user u on item i calculated as average of ratings of all similar users in U:

$$r_{u,i} = \frac{1}{N}\sum_{u' \in U} r_{u',i}$$ or weighted $$r_{u,i} = \frac{1}{N}\sum_{u' \in U} simil(u,u')\, r_{u',i}$$

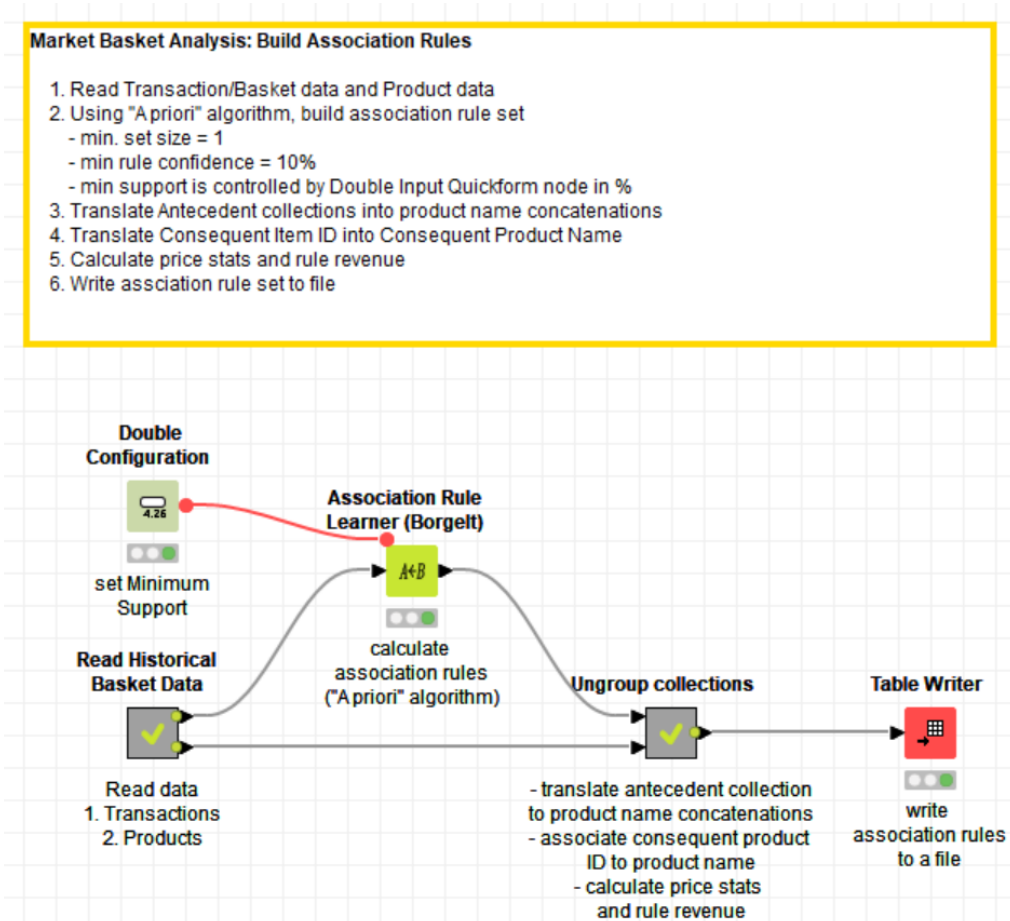
Pearson correlation

$$simil(u,u') = \frac{\sum_{i \in I_{xy}} (r_{u,i} - \overline{r_u})(r_{u',i} - \overline{r_{u'}})}{\sqrt{\sum_{i \in I_{xy}} (r_{u,i} - \overline{r_u})^2} \sqrt{\sum_{i \in I_{xy}} (r_{u',i} - \overline{r_{u'}})^2}}$$

Set of items rated by both user x and y

Association Rules in Practice

... In practice


Market Basket Analysis: Build Association Rules
1. Read Transaction/Basket data and Product data
2. Using "Apriori" algorithm, build association rule set
- min. set size = 1
- min rule confidence = 10%
- min support is controlled by Double Input Quickform node in %
3. Translate Antecedent collections into product name concatenations
4. Translate Consequent Item ID into Consequent Product Name
5. Calculate price stats and rule revenue
6. Write assciation rule set to file
Double Configuration
4.26
set Minimum Support
Association Rule Learner (Borgelt)
A←B
calculate association rules ("Apriori" algorithm)
Read Historical Basket Data
Read data
1. Transactions
2. Products
Ungroup collections
- translate antecedent collection to product name concatenations
- associate consequent product ID to product name
- calculate price stats and rule revenue
Table Writer
write association rules to a file

Thank you

For any questions please contact: education@knime.com