

universite Paris-saclay



Constraint & Data Mining

Cours2

Master 2 - DS

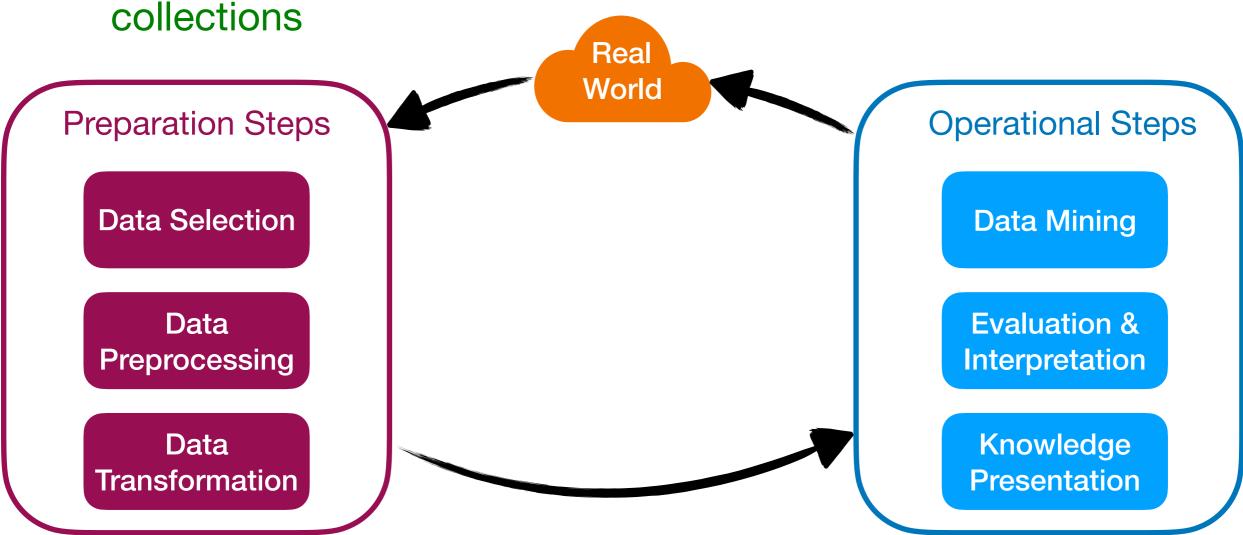
Nadjib Lazaar

Ing - Phd - HDR - Professor - Paris-Saclay University - LISN - LaHDAK https://perso.lisn.upsaclay.fr/lazaar/
20/01/2025

Knowledge Discovery in Databases (KDD)

Definition and steps

 Knowledge Discovery in Databases (KDD) revolves around the investigation and creation of knowledge, processes, algorithms, and the mechanisms for retrieving potential knowledge from data



Motivations

- Purpose: A key method in market basket analysis, aimed at identifying patterns in customer purchasing behavior
- Goal: To discover frequently co-occurring products, which are items that customers often buy together
- Applications of Frequent Itemsets:
 - Product Arrangement: Optimize product placement on store shelves or within catalogs
 - Cross-Selling: Suggest related products to customers (e.g., recommending additional products during online shopping)
 - Product Bundling: Offer product bundles based on co-purchase patterns
 - Other Applications: Fraud detection, dependency analysis, fault localization, and more

Basic Notions

• Items:
$$I = \{p_1, ..., p_n\}$$

• Itemset, transaction:
$$P, T \subseteq I$$

• Transactional dataset:
$$D = \{T_1, ..., T_m\}$$

• Language of itemsets:
$$\mathcal{L}_I = 2^I$$

• Cover of an itemset:
$$cover(P) = \{T_i \in D : P \subseteq T_i\}$$

• Absolute Frequency:
$$freq(P) = |cover(P)|$$

. Relative Frequency:
$$freq(P) = \frac{|\mathit{cover}(P)|}{|D|}$$

Problem Definition

Given:

- A set of items $I = \{p_1, ..., p_n\}$
- A transactional dataset $D = \{T_1, ..., T_m\}$
- A minimum support α

The need:

• The set of itemset P s.t.: $freq(P) \ge \alpha$

Example(1)

•
$$I = \{a, b, c, d, e\}$$

•
$$D = \{T_1, ..., T_{10}\}$$

H_D

1:	a			d	е
2:		b	С	d	
3:	a		С		е
4:	a		С	d	е
5:	a				е
6:	a		С	d	
7:		b	С		
8:	a		С	d	е
9:		b	С		е
10:	а			d	E

cover(bc) = ?

freq(bc) = ?

V_D

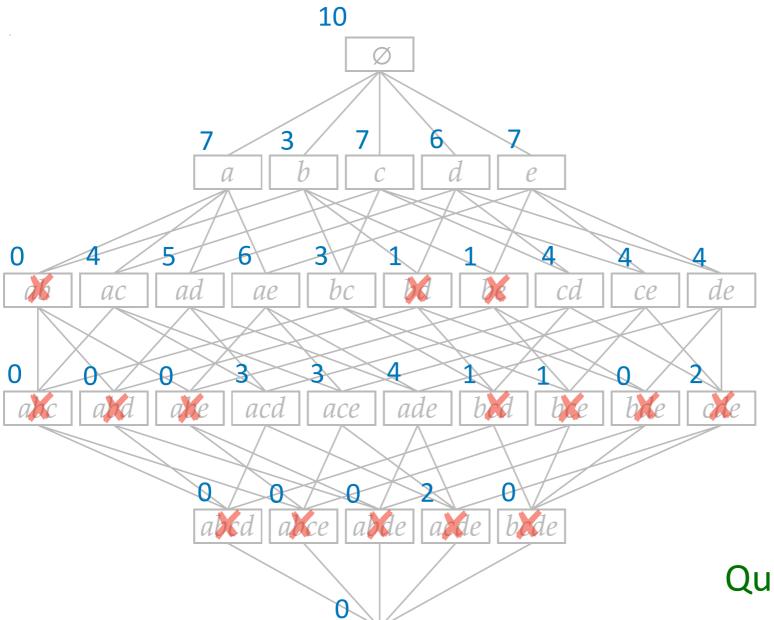
а	b	С	d	е
1	2	2	1	1
3	7	2 3	2	3
4	9	4 6	4	4 5
4 5 6 8			6	5
6		7	8	8
8		8	10	9
10		9		10

M_D

	а	b	С	d	е
1:	1	0	0	1	1
2:	0	1	1	1	0
3:	1	0	1	0	1
4:	1	0	1	1	1
5:	1	0	0	0	1
6:	1	0	1	1	0
7:	0	1	1	0	0
8:	1	0	1	1	1
9:	0	1	1	0	1
10:	1	0	0	1	1

Example(1)

Query-2: Frequent itemset with minimum support $\alpha = 3$?



	r Д

	а	b		•	
		D	С	d	е
1:	1	0	0	1	1
2:	0	1	1	1	0
3:	1	0	1	0	1
4:	1	0	1	1	1
5:	1	0	0	0	1
6:	1	0	1	1	0
7:	0	1	1	0	0
8:	1	0	1	1	1
9:	0	1	1	0	1
10:	1	0	0	1	1

Query-1: Frequent itemset?

Naïve Search

 A naïve search that consists of enumerating and testing the frequency of itemset candidates in a given dataset is usually infeasible

Number of items (n)	Search space (2 ⁿ)
10	≈ 10 ³
20	≈ 10 ⁶
30	≈ 10 ⁹
100	≈ 10 ³⁰
128	≈ 10^{68} (atoms in the universe)
1000	≈ 10 ³⁰¹

Anti-Monotonicity Property

Given a transaction database D over items I and two itemsets P and Q:

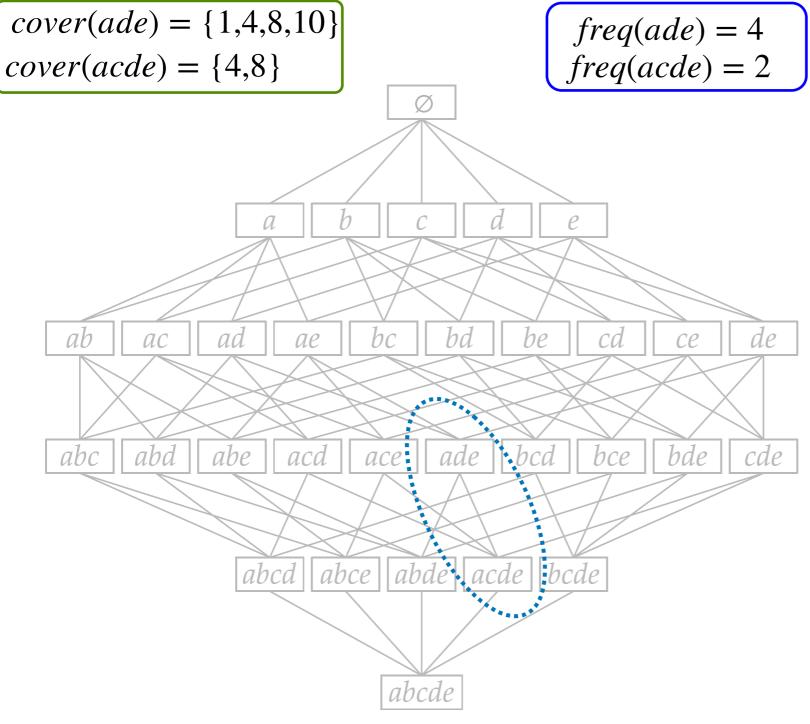
$$Q \subseteq P \Rightarrow cover(P) \subseteq cover(Q)$$

That is,

$$Q \subseteq P \Rightarrow freq(P) \leq freq(Q)$$

Anti-Monotonicity Property

Example(2)



M_D

	а	b	С	d	е
1:	1	0	0	1	1
2:	0	1	1	1	0
3:	1	0	1	0	1
4:	1	0	1	1	1
5:	1	0	0	0	1
6:	1	0	1	1	0
7:	0	1	1	0	0
8:	1	0	1	1	1
9:	0	1	1	0	1
10:	1	0	0	1	1

Apriori Property

• Given a transaction database D over items I, a minsup α and two itemsets P and Q:

$$Q \subseteq P \Rightarrow freq(P) \leq freq(Q)$$

• It follows: $Q \subseteq P \land freq(P) \ge \alpha \Rightarrow freq(Q) \ge \alpha$

All subsets of a frequent itemset are frequent!

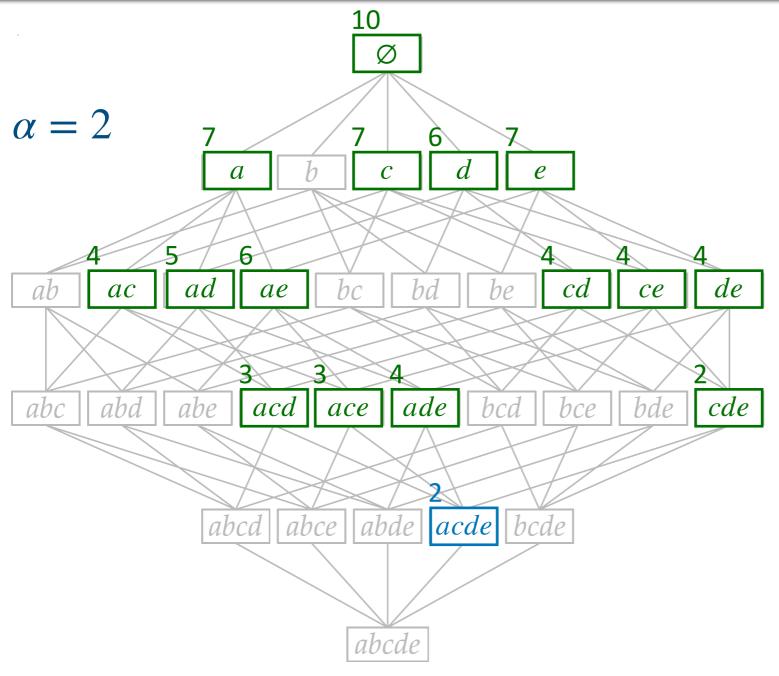
• Contraposition: $Q \subseteq P \land freq(Q) < \alpha \Rightarrow freq(P) < \alpha$

All supersets of an infrequent itemset are infrequent!

Apriori Property

Example(3)

All subsets of a frequent itemset are frequent!



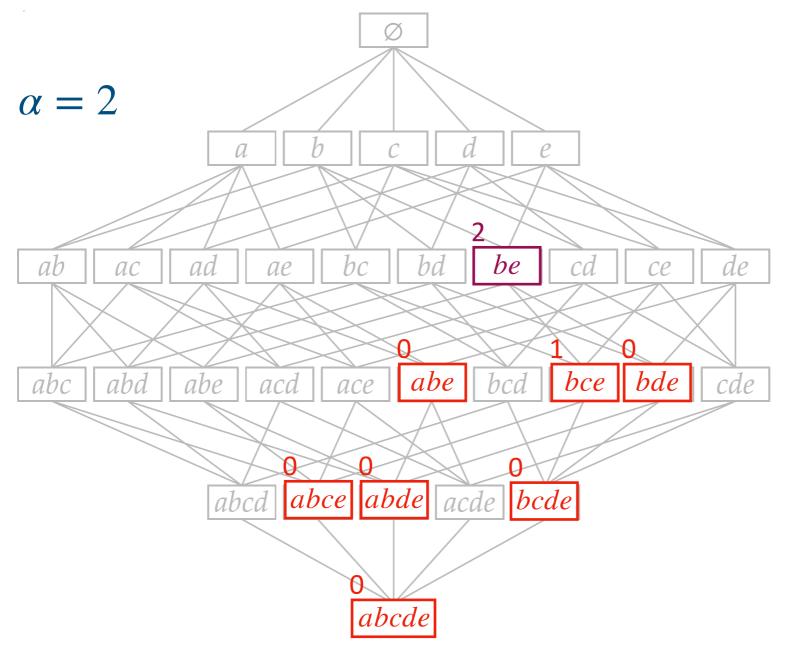
M_D

	а	b	С	d	е
1:	1	0	0	1	1
2:	0	1	1	1	0
3:	1	0	1	0	1
4:	1	0	1	1	1
5:	1	0	0	0	1
6:	1	0	1	1	0
7:	0	1	1	0	0
8:	1	0	1	1	1
9:	0	1	1	0	1
10:	1	0	0	1	1

Apriori Property

Example(3)

All supersets of an infrequent itemset are infrequent!



M_D

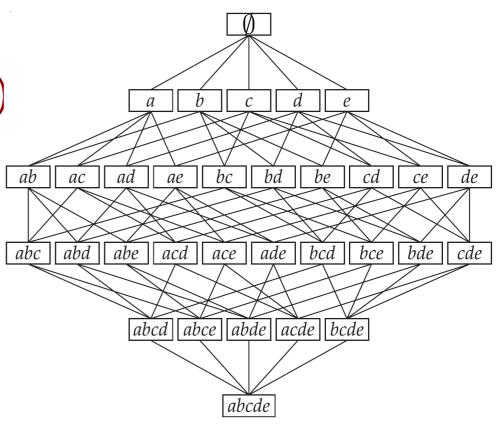
	а	b	C	d	е
1:	1	0	0	1	1
2:	0	1	1	1	0
3:	1	0	1	0	1
4:	1	0	1	1	1
5:	1	0	0	0	1
6:	1	0	1	1	0
7:	0	1	1	0	0
8:	1	0	1	1	1
9:	0	1	1	0	1
10:	1	0	0	1	1

Poset $(2^I, \subseteq)$

- Test A partial order is a binary relation R over a set S:
- $\forall x, y, z \in S$
- $\bullet x R x$

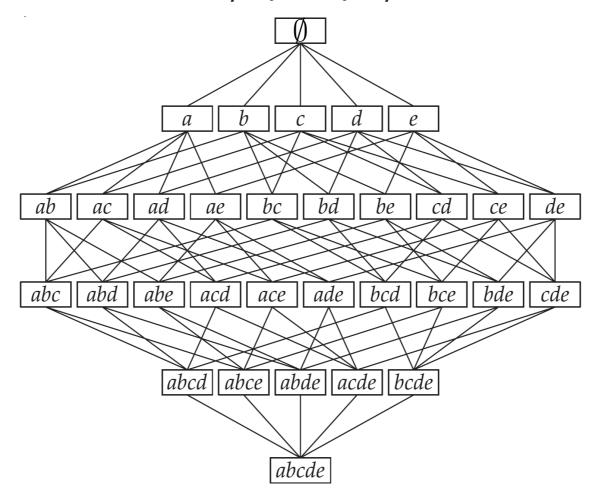
(reflexivity)

- $x R y \land y R x \Rightarrow x = y$ (anti-symmetry)
- $x R y \land y R z \Rightarrow x R z$ (transitivity)
- What are S and R in Itemset Mining?



Partially ordered sets (review)

- Comparable itemsets: $x \subseteq y \lor y \subseteq x$
- Incomparable itemsets: $x \not\subseteq y \land y \not\subseteq x$



Apriori Algorithm [Agrawal and Srikant 1994]

- Determine the support of the one-element item sets (i.e. singletons) and discard the infrequent items
- Form candidate itemsets with two items (both items must be frequent), determine their support, and discard the infrequent itemsets
- Form candidate item sets with three items (all contained pairs must be frequent), determine their support, and discard the infrequent itemsets
- And so on!

Based on candidate generation and pruning

Apriori Algorithm [Agrawal and Srikant 1994]

```
Algorithm 1: Apriori Algorithm
  Input: Transaction database \mathcal{D}, minimum support threshold \alpha
  Output: Frequent itemsets
  k \leftarrow 1;
  L_k \leftarrow \{p_i \mid p_i \in \mathcal{I} \land \mathtt{freq}(p_i) \geq \alpha\} ;
  while L_k \neq \emptyset do
       C \leftarrow \operatorname{aprioriGen}(L_k);
      k \leftarrow k+1;

L_k \leftarrow \{c \mid c \in C \land freq(c) \ge \alpha\};
  return \bigcup_i L_i;
```

Apriori Algorithm [Agrawal and Srikant 1994]

```
Function aprioriGen(L_k):
      E \leftarrow \emptyset;
      for each pair of itemsets P', P'' \in L_k such that
        P' = \{p_{i_1}, \dots, p_{i_{k-1}}, p_{i_k}\} and P'' = \{p_{i_1}, \dots, p_{i_{k-1}}, p_{i'_k}\} do
            if p_{i_k} \neq p_{i'_k} then

\begin{vmatrix}
P \leftarrow P' \cup P'' ; \\
\mathbf{if} \quad \forall p_i \in P, P \setminus \{p_i\} \in L_k \mathbf{then} \\
E \leftarrow E \cup \{P\};
\end{vmatrix}

      return E;
```

Apriori Algorithm [Agrawal and Srikant 1994] Improving candidates generation

• Using aprioriGen function, an item of k+1 size can be generated in a δ possible ways:

$$\delta = \frac{k(k+1)}{2}$$

6 possibilities to generate (abcd)

	abc	abd	acd	bcd
abc	_	abcd	abcd	abcd
abd	abcd	_	abcd	abcd
acd	abcd	abcd	_	abcd
bcd	abcd	abcd	abcd	_

Apriori Algorithm [Agrawal and Srikant 1994] Improving candidates generation

• Using aprioriGen function, an item of k+1 size can be generated in a δ possible ways:

$$\delta = \frac{k(k+1)}{2}$$

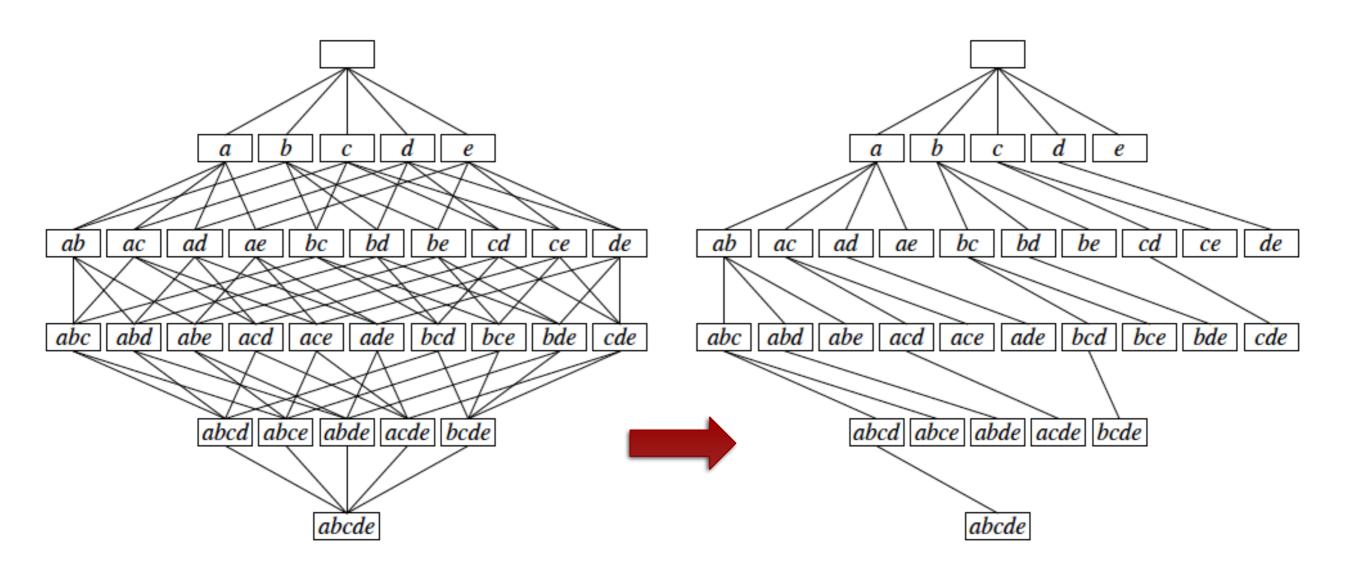
Need: Generate itemset candidate only once

How: Assign a unique parent itemset to each candidate, ensuring that it is generated only from its parent itemset

Apriori Algorithm [Agrawal and Srikant 1994]

Improving candidates generation

Assigning unique parents turns the poset lattice into a tree:



Apriori Algorithm [Agrawal and Srikant 1994]

Canonical form for itemsets

- ullet An itemset can be represented as a word over an alphabet I
 - Question: how many words of k items can we have?
 - Answer: k-permutations of k items: k!
- By imposing an arbitrary order (e.g., lexicography order) on the items, we can define a canonical form—a unique representation of itemsets that eliminates symmetries
 - Lex on items : abc < acb < bac < bca...
 - $\kappa(abc) = \kappa(acb) = \kappa(bac) = \kappa(bca) = abc$
 - $\kappa(abc,1) = a; \ \kappa(abc,2) = b; \ \kappa(abc,3) = c$

Apriori Algorithm [Agrawal and Srikant 1994] Recursive processing with Canonical forms

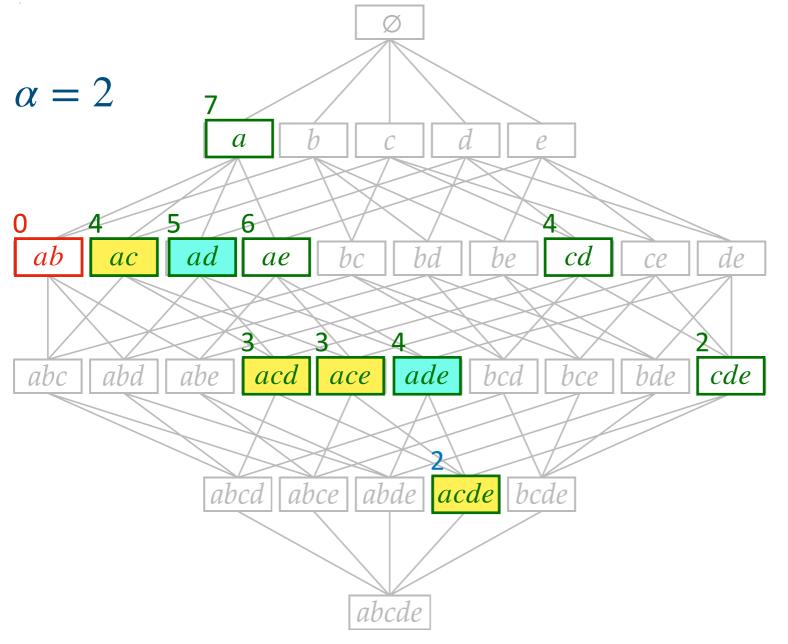
• For each itemset of a given size, generate all possible extensions of the itemset by adding one item, subject to the condition that:

$$child(P, \alpha) = \{P' : (P' = P \cup \{p_i\}) \land (\kappa(P, |P|) < p_i) \land (freq(P') \ge \alpha)\}$$

Recursive processing with Canonical forms

Example(4)

 $child(P,\alpha) = \{P': (P' = P \cup \{p_i\}) \land (\kappa(P, |P|) < p_i) \land (freq(P') \ge \alpha)\}$



M_D

	а	b	С	d	е
1:	1	0	0	1	1
2:	0	1	1	1	0
3:	1	0	1	0	1
4:	1	0	1	1	1
5:	1	0	0	0	1
6:	1	0	1	1	0
7:	0	1	1	0	0
8:	1	0	1	1	1
9:	0	1	1	0	1
10:	1	0	0	1	1

Items Ordering

- Any order can be used, but:
 - The structure of the search space depends heavely on the chosen order
 - Algorithm efficiency varies significantly based on the item order
- Advanced methods dynamically adjust the order during teh search:
 - Use different but « compatible » orders in different branches

Items Ordering (heuristics)

• Sort the items w.r.t. their frequency (decreasing/increasing) : Frequent itemsets are composed of frequent items

 Sort items based on the size of the area they cover : considering both their frequency and the sizes of the transactions that include them



universite Paris-saclay



Constraint & Data Mining

Cours2

Master 2 - DS

Nadjib Lazaar

Ing - Phd - HDR - Professor - Paris-Saclay University - LISN - LaHDAK https://perso.lisn.upsaclay.fr/lazaar/
20/01/2025