



02450 Introduction to Machine Learning and Data Mining

# **Week 12: Association mining**

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29 April 2025

DTU Compute, Technical University of Denmark

# Today

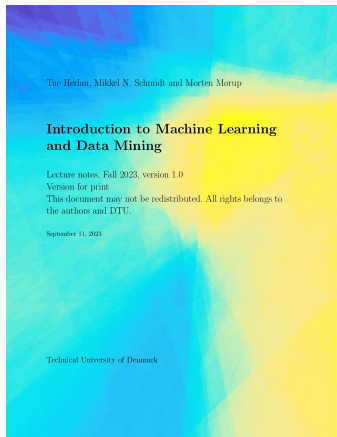
## Feedback Groups of the day:

Christian Torp, João Pires de Azevedo Teixeira dos Prazeres, Qiao Chih Lei, Frederik Springer Krehan, Andreas Abildgaard Ryberg, Noah Samuelson Schütze, Valdemar Sejersen, Ning Sun, Agathe Michot, Cecilia Haslund Oreskov, Dimitrios Papantzikos Moutafis, Konstantinos Tzimoulis, Zhetao Qu, Ignacio Ripoll González, Sebastian Timm, Sumaya Mahamed Mahamed, Rebekka Theilgaard Rosenkilde, Clara Ella Lassen, Aleksander Holm Lauridsen, Frede Søndergaard Møllegaard, Oscar Christen Thorning Engelstoft, Anastasia Maftei, Bogdan-Petru Pascut, Tomasz Gabriel Stepień, Mirka Katuscáková, Konstantin Takors, Nicolai Jess Møllnitz, Andrea Raithel, Zofia Agata Lenarczyk, Eric Torres García, Sarah Abigail Tauro, Marcus Prehn-Chang, Lars Henrik Dæhli Skjolding, Matias Haage Them Nielsen, Amanda Schriver Mårtensson, Anne Reimer, Madeline Shah, Stamatia Papageorgiou, Vasiliki Tsanaktsidou, Edvin Smajlovic, Zahra Soleimani, Leon Maximilian Spohn, Oscar Stilling, Victor Stubgaard, Peter Tang, Christian Holst Thomsen, Magnus Thorsteinsson

## Reading/homework material:

### Chapter 21

### P21.1, P18.2, P18.3



# Lecture Schedule

## 1 Introduction

4 February: C1,C2

Data: Feature extraction, and visualization

## 2 Summary statistics, similarity and visualization

11 February: C4,C7

## 3 Computational linear algebra and PCA

18 February: C3

## 4 Probability and probability densities

25 February: C5, C6

Supervised learning: Classification and regression

## 5 Decision trees and linear regression

4 March: C8, C9 (Project 1 due 6 March at 17:00)

## 6 Overfitting, cross-validation and Nearest

Neighbor

11 March: C10, C12

## 7 Performance evaluation, Bayes, and Naive

Bayes

18 March: C11, C13

## 8 Artificial Neural Networks and

Bias/Variance

25 March: C14, C15

## 9 AUC and ensemble methods

1 April: C16, C17

Unsupervised learning: Clustering and density estimation

## 10 K-means and hierarchical clustering

8 April: C18 (Project 2 due 10 April at 17:00)

## 11 Mixture models and density estimation

22 April: C19, C20

## 12 Association mining

29 April: C21

Recap

## 13 Recap and discussion of the exam

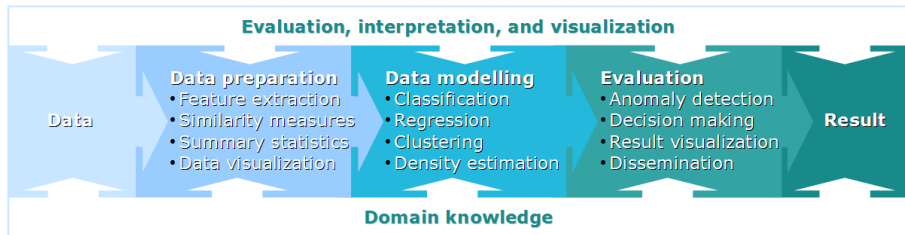
6 May: C1-C21

Online help: Piazza

Videos of lectures: <https://panopto.dtu.dk>

Streaming of lectures: Zoom (link on DTU Learn)

# Learning Objectives



## Learning Objectives

- Calculate support and confidence of association rules
- Describe the Apriori algorithm for association mining and how it is used for efficient estimation of association rules

# Association rule discovery: Definition

- Given a set of **records**
  - Each containing a number of **items from a set**
- **Goal:** Produce dependency rules
  - Predict the occurrence of an item based on occurrences of other items

# Association Mining

mining association rules



About 1.850.000 results (0,05 sec)

## [PDF] Fast algorithms for mining association rules

[R Agrawal](#), [R Srikant](#) - Proc. 20th int. conf. very large data bases, VLDB, 1994 - [it.uu.se](#)

We consider the problem of discovering **association rules** between items in a large database of sales transactions. We present two new algorithms for solving this problem that are fundamentally different from the known algorithms. Experiments with synthetic as well as real ...



Cited by 26110

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## Mining association rules between sets of items in large databases

[R Agrawal](#), [T Imieliński](#), [A Swami](#) - Proceedings of the 1993 ACM ..., 1993 - [dl.acm.org](#)

We are given a large database of customer transactions. Each transaction consists of items purchased by a customer in a visit. We present an efficient algorithm that generates all significant **association rules** between items in the database. The algorithm incorporates ...



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## An effective hash-based algorithm for mining association rules

[JS Park](#), [MS Chen](#), [PS Yu](#) - Acm sigmod record, 1995 - [dl.acm.org](#)

In this paper, we examine the issue of **mining association rules** among items in a large database of sales transactions. The **mining** of **association rules** can be mapped into the problem of discovering large itemsets where a large itemset is a group of items which ...



Cited by 2465

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# Association rule discovery: Example

## Market basket analysis

### Training set

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1. {Bread, Soda, Milk}
2. {Beer, Bread}
3. {Beer, Soda, Diaper, Milk}
4. {Beer, Bread, Diaper, Milk}
5. {Soda, Diaper, Milk}

### Rules discovered

---

{Milk}  $\blacktriangleright$  {Soda}  
{Diaper, Milk}  $\blacktriangleright$  {Beer}

# Market basket data

- Representation as:

**Transaction table**

ID	Items
1	Bread, Soda, Milk
2	Beer, Bread
3	Beer, Soda, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Soda, Diaper, Milk

**Data matrix**

ID	Bread	Soda	Milk	Beer	Diaper
1	1	1	1	0	0
2	1	0	0	1	0
3	0	1	1	1	1
4	1	0	1	1	1
5	0	1	1	0	1



# Association analysis, rules and support

- **Itemset**

- For example: {Bread, Soda, Milk}, {Milk, Diaper}, {}

- **Support** for an itemset  $X$

- Percentage of transactions that contain  $X$

- **Association rule**

- Expression of the form:  $X \rightarrow Y$   
where  $X$  and  $Y$  are disjoint sets

- **Support** for an association rule  $X \rightarrow Y$

- Percentage of transactions that contain  $X \cup Y$

$$\text{sup}(X \rightarrow Y) = \frac{\sigma(X \cup Y)}{N} = P(X, Y)$$

# Quiz 1: Support (Spring 2018)

	$x_1^L$	$x_1^H$	$x_2^L$	$x_2^H$	$x_3^L$	$x_3^H$	$x_4^L$	$x_4^H$	$x_5^L$	$x_5^H$	$x_6^L$	$x_6^H$
O1	1	0	1	0	1	0	1	0	1	0	1	0
O2	0	1	0	1	0	1	0	1	0	1	0	1
O3	1	0	0	1	1	0	1	0	1	0	1	0
O4	1	0	1	0	1	0	0	1	0	1	1	0
O5	0	1	1	0	1	0	1	0	1	0	1	0
O6	0	1	0	1	0	1	0	1	0	1	0	1
O7	0	1	1	0	1	0	0	1	0	1	0	1
O8	1	0	1	0	1	0	1	0	0	1	0	1
O9	0	1	0	1	1	0	1	0	0	1	0	1
O10	1	0	0	1	0	1	0	1	0	1	1	0

Table 1: The ten first observations of the airline safety dataset binarized considering the attribute  $x_1-x_6$ .

We consider a dataset of airline safety binarized according to the median value. Values below median is referred to with the superscript  $L$  and above the median value using the superscript  $H$ . In Table 1 is

given the first 10 observations O1–O10. Consider the association rule:

$$\{x_2^H, x_3^H, x_4^H, x_5^H\} \rightarrow \{x_6^H\}.$$

What is the support of the rule?

- A. 0.0 %
- B. 20.0 %
- C. 66.7 %
- D. 100.0 %
- E. Don't know.

# Association analysis, confidence

- **Itemset**

- For example: {Bread, Soda, Milk}, {Milk, Diaper}, {}

- **Support** for an itemset  $X$

- Percentage of transactions that contain  $X$

- **Association rule**

- Expression of the form:  $X \rightarrow Y$   
where  $X$  and  $Y$  are disjoint sets

- **Support** for an association rule  $X \rightarrow Y$

- Percentage of transactions that contain  $X \cup Y$

$$\text{sup}(X \rightarrow Y) = \frac{\sigma(X \cup Y)}{N} = P(X, Y)$$

- **Confidence** for an association rule  $X \rightarrow Y$

- Percentage of transactions containing  $X$  that also contain  $Y$

$$\text{conf}(X \rightarrow Y) = \frac{\sigma(X \cup Y)}{\sigma(X)} = \frac{P(X, Y)}{P(X)} = P(Y | X)$$

## Quiz 2: Confidence (Spring 2018)

	$x_1^L$	$x_1^H$	$x_2^L$	$x_2^H$	$x_3^L$	$x_3^H$	$x_4^L$	$x_4^H$	$x_5^L$	$x_5^H$	$x_6^L$	$x_6^H$
O1	1	0	1	0	1	0	1	0	1	0	1	0
O2	0	1	0	1	0	1	0	1	0	1	0	1
O3	1	0	0	1	1	0	1	0	1	0	1	0
O4	1	0	1	0	1	0	0	1	0	1	1	0
O5	0	1	1	0	1	0	1	0	1	0	1	0
O6	0	1	0	1	0	1	0	1	0	1	0	1
O7	0	1	1	0	1	0	0	1	0	1	0	1
O8	1	0	1	0	1	0	1	0	0	1	0	1
O9	0	1	0	1	1	0	1	0	0	1	0	1
O10	1	0	0	1	0	1	0	1	0	1	1	0

Table 1: The ten first observations of the airline safety dataset binarized considering the attribute  $x_1$ – $x_6$ .

We again consider the airline safety data and the rule

$$\{x_2^H, x_3^H, x_4^H, x_5^H\} \rightarrow \{x_6^H\}.$$

What is the confidence of the rule?

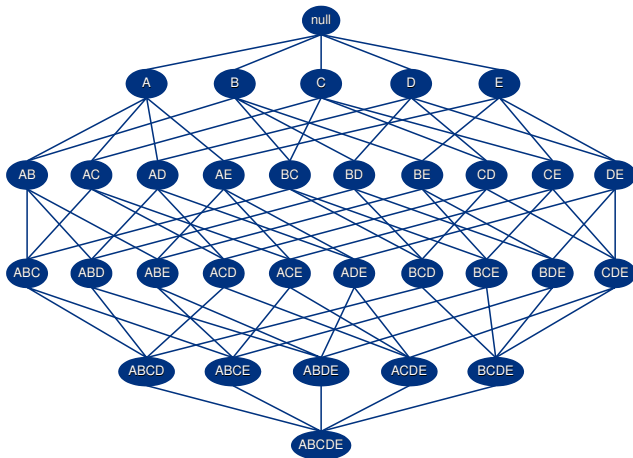
- A. 0.0 %
- B. 20.0 %
- C. 66.7 %
- D. 100.0 %
- E. Don't know.

# Association rule mining

- Find all association rules that have
  - **Support**  $\geq$  minsupport
  - **Confidence**  $\geq$  minconf
- Approach:
  - **Frequent itemset generation**
    - Generate a list of all **itemsets** with
  - **Association rule generation**
    - Generate all **association rules** with **Confidence**  $\geq$  minconf

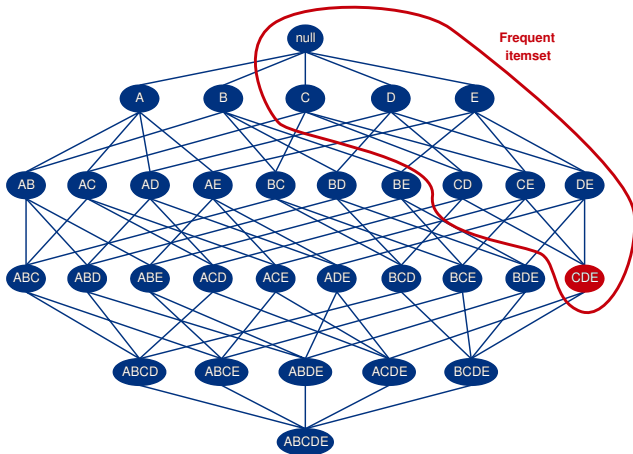
# Frequent itemset generation

How many different itemsets can be created for a problem with a total of D items?



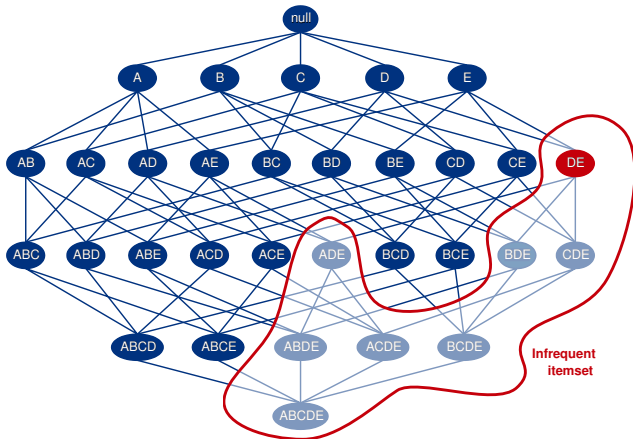
# Frequent itemset generation

If an itemset is frequent, then all of its subsets must also be frequent



# Frequent itemset generation

If an itemset is infrequent, then all of its supersets must also be infrequent





## The Apriori Algorithm

Find all 1-itemsets

Generate k-itemsets by merging single items to the k-1-itemsets

Remove all the generated itemsets for which subsets are not part of the k-1-itemsets

Keep remaining k-itemsets with enough support.

Output all frequent itemsets

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### Algorithm 8: Apriori algorithm

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```
1: Given  $N$  transactions and let  $\epsilon > 0$  be the minimum support count
2:  $L_1 = \{\{j\} | \text{supp}(\{j\}) \geq \epsilon\}$ 
3: for  $k = 2, \dots, M$  and  $L_k \neq \emptyset$  do
4:    $C'_k = \{s \cup \{j\} | s \in L_{k-1}, j \notin s\}$ 
5:   Set  $C_k = C'_k$ 
6:   for each  $c \in C'_k$  do
7:     for each  $s \subset c$  such that  $|s| = k - 1$  do
8:       if  $s$  is not frequent, i.e.  $s \notin L_{k-1}$  then
9:          $C_k = C_k \setminus \{c\}$  (Remove  $c$  from  $C_k$ )
10:      end if
11:    end for
12:  end for
13:   $L_k = \{c | c \in C_k, \text{supp}(c) \geq \epsilon\}$  (compute support)
14: end for
15:  $L_1 \cup L_2 \cup \dots \cup L_k$  are then all frequent itemsets
```

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## Quiz 3: A-priori (Fall 2018)

We will consider a binary dataset consisting of the  $M = 6$  features  $f_1, f_2, f_3, f_4, f_5, f_6$ . We wish to apply the Apriori algorithm to find all itemsets with support greater than  $\varepsilon = 0.15$ . Suppose at iteration  $k = 3$  we know that:

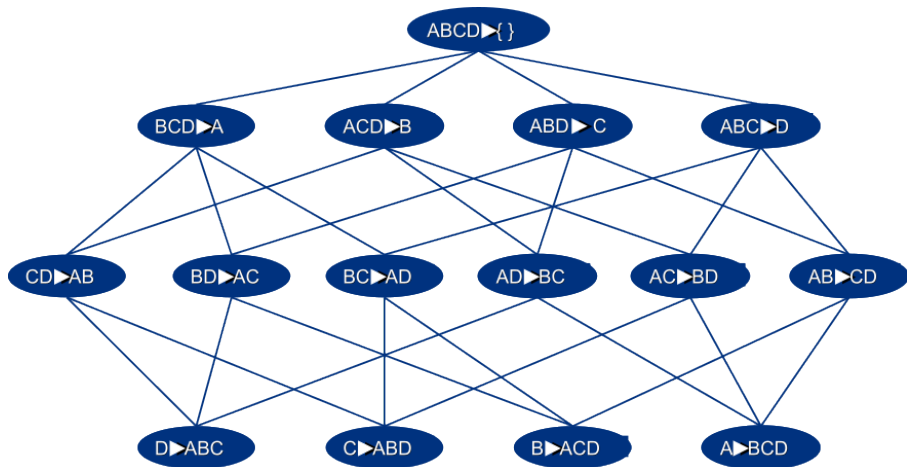
$$L_2 = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \end{bmatrix}$$

Recall the key step in the Apriori algorithm is to construct  $L_3$  by first considering a large number of can-

didate itemsets  $C'_3$ , and then rule out some of them using the downwards-closure principle thereby saving many (potentially costly) evaluations of support. Suppose  $L_2$  is given as above, which of the following itemsets does the Apriori algorithm *not* have to evaluate the support of?

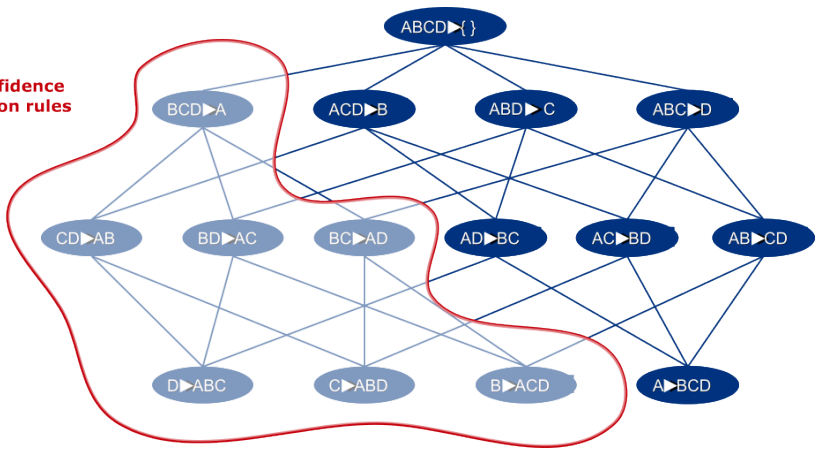
- A.  $\{f_2, f_3, f_4\}$
- B.  $\{f_1, f_2, f_6\}$
- C.  $\{f_2, f_3, f_6\}$
- D.  $\{f_1, f_3, f_4\}$
- E. Don't know.

# Association rule generation



# Association rule generation

Low confidence  
Association rules



# Results for market basket example

## Itemset Support

Milk	80%
Bread	60%
Soda	60%
Beer	60%
Diaper	60%
Diaper Milk	60%
Soda Milk	60%
Bread Beer	40%
Bread Milk	40%
Soda Diaper	40%
Beer Diaper	40%
Beer Milk	40%
Soda Diaper Milk	40%
Beer Diaper Milk	40%

## Association rule

{ } ► Milk
Soda ► Milk
Diaper ► Milk
Soda, Diaper ► Milk
Beer, Diaper ► Milk
Beer, Milk ► Diaper

## Support Confidence

80%	80%
60%	100%
60%	100%
40%	100%
40%	100%
40%	100%

ID	Bread	Soda	Milk	Beer	Diaper
1	1	1	1	0	0
2	1	0	0	1	0
3	0	1	1	1	1
4	1	0	1	1	1
5	0	1	1	0	1

- How can we do association mining for continuous data?

	Attribute 1	Attribute 2	Attribute 3
	0.3689	0.9827	0.6999
	0.4607	0.7302	0.6385
	0.9816	0.3439	0.0336
	0.1564	0.5841	0.0688
	0.8555	0.1078	0.3196
	0.6448	0.9063	0.5309
	0.3763	0.8797	0.6544
	0.1909	0.8178	0.4076
	0.4283	0.2607	0.8200
<b>X=</b>	0.4820	0.5944	0.7184
	0.1206	0.0225	0.9686
	0.5895	0.4253	0.5313
	0.2262	0.3127	0.3251
	0.3846	0.1615	0.1056
	0.5830	0.1788	0.6110
	0.2518	0.4229	0.7788
	0.2904	0.0942	0.4235
	0.6171	0.5985	0.0908
	0.2653	0.4709	0.2665
	0.8244	0.6959	0.1537

# Binarize data according to percentiles

AttributeNames=				AttributeNamesBin=							
				Attribute 1 0-50 %	Attribute 1 50-100 %	Attribute 2 0-33.3 %	Attribute 2 33.3-66.7 %	Attribute 2 66.7-100 %	Attribute 3 0-50%	Attribute 3 50-100%	
<b>X=</b>	0.3689	0.9827	0.6999	<b>Xbinary=</b>	1	0	0	0	1	0	1
	0.4607	0.7302	0.6385	0	1	0	0	1	0	1	
	0.9816	0.3439	0.0336	0	1	0	1	0	1	0	
	0.1564	0.5841	0.0688	1	0	0	1	0	1	0	
	0.8555	0.1078	0.3196	0	1	1	0	0	1	0	
	0.6448	0.9063	0.5309	0	1	0	0	1	0	1	
	0.3763	0.8797	0.6544	1	0	0	0	1	0	1	
	0.1909	0.8178	0.4076	1	0	0	0	1	1	0	
	0.4283	0.2607	0.8200	0	1	1	0	0	0	1	
	0.4820	0.5944	0.7184	0	1	0	1	0	0	1	
	0.1206	0.0225	0.9686	1	0	1	0	0	0	1	
	0.5895	0.4253	0.5313	0	1	0	1	0	0	1	
	0.2262	0.3127	0.3251	1	0	1	0	0	1	0	
	0.3846	0.1615	0.1056	1	0	1	0	0	1	0	
	0.5830	0.1788	0.6110	0	1	1	0	0	0	1	
	0.2518	0.4229	0.7788	1	0	0	1	0	0	1	
	0.2904	0.0942	0.4235	1	0	1	0	0	1	0	
	0.6171	0.5985	0.0908	0	1	0	1	0	1	0	
	0.2653	0.4709	0.2665	1	0	0	1	0	1	0	
	0.8244	0.6959	0.1537	0	1	0	0	1	1	0	

**Xbinary=**

# Recap of association rule discovery on Iris data

**X=**

	A	B	C	D	E	F	G
	Sepal Length	Sepal Width	Petal Length	Petal Width	Iris Setosa	Iris Versicolour	Iris Virginica
1	5.1	3.5	1.4	0.2	0.0	1.0	0.0
2	4.9	3.0	1.4	0.2	0.0	1.0	0.0
3	4.7	3.2	1.3	0.2	0.0	1.0	0.0
4	4.6	3.1	1.5	0.2	0.0	1.0	0.0
5	5.0	3.6	1.4	0.2	0.0	1.0	0.0
6	5.4	4.0	1.7	0.4	0.0	1.0	0.0
7	4.6	3.4	1.4	0.3	0.0	1.0	0.0
8	5.0	3.5	1.6	0.4	0.0	1.0	0.0
9	4.4	2.9	1.4	0.3	0.0	1.0	0.0
10	4.3	3.0	1.3	0.3	0.0	1.0	0.0
11	5.1	3.7	1.5	0.4	0.0	1.0	0.0
12	4.8	2.8	1.3	0.3	0.0	1.0	0.0
13	5.1	3.8	1.6	0.4	0.0	1.0	0.0
14	4.9	3.1	1.5	0.3	0.0	1.0	0.0
15	5.0	3.6	1.4	0.2	0.0	1.0	0.0
16	5.2	3.7	1.5	0.4	0.0	1.0	0.0
17	4.7	3.2	1.3	0.2	0.0	1.0	0.0
18	5.0	3.5	1.6	0.4	0.0	1.0	0.0
19	5.1	3.6	1.4	0.2	0.0	1.0	0.0
20	4.9	3.1	1.5	0.3	0.0	1.0	0.0
21	5.4	4.0	1.7	0.4	0.0	1.0	0.0
22	4.6	3.4	1.4	0.3	0.0	1.0	0.0
23	5.0	3.5	1.6	0.4	0.0	1.0	0.0
24	4.4	2.9	1.4	0.3	0.0	1.0	0.0
25	4.3	3.0	1.3	0.3	0.0	1.0	0.0
26	5.1	3.7	1.5	0.4	0.0	1.0	0.0
27	4.8	2.8	1.3	0.3	0.0	1.0	0.0
28	5.1	3.8	1.6	0.4	0.0	1.0	0.0
29	4.9	3.1	1.5	0.3	0.0	1.0	0.0
30	5.0	3.6	1.4	0.2	0.0	1.0	0.0
31	5.2	3.7	1.5	0.4	0.0	1.0	0.0
32	4.7	3.2	1.3	0.2	0.0	1.0	0.0
33	5.0	3.5	1.6	0.4	0.0	1.0	0.0
34	5.1	3.6	1.4	0.2	0.0	1.0	0.0
35	4.9	3.1	1.5	0.3	0.0	1.0	0.0
36	5.4	4.0	1.7	0.4	0.0	1.0	0.0
37	4.6	3.4	1.4	0.3	0.0	1.0	0.0
38	5.0	3.5	1.6	0.4	0.0	1.0	0.0
39	4.4	2.9	1.4	0.3	0.0	1.0	0.0
40	4.3	3.0	1.3	0.3	0.0	1.0	0.0
41	5.1	3.7	1.5	0.4	0.0	1.0	0.0
42	4.8	2.8	1.3	0.3	0.0	1.0	0.0
43	5.1	3.8	1.6	0.4	0.0	1.0	0.0
44	4.9	3.1	1.5	0.3	0.0	1.0	0.0
45	5.0	3.6	1.4	0.2	0.0	1.0	0.0
46	5.2	3.7	1.5	0.4	0.0	1.0	0.0
47	4.7	3.2	1.3	0.2	0.0	1.0	0.0
48	5.0	3.5	1.6	0.4	0.0	1.0	0.0
49	5.1	3.6	1.4	0.2	0.0	1.0	0.0
50	4.9	3.1	1.5	0.3	0.0	1.0	0.0

**Xbinary=**

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
	Sepal Length Low	Sepal Length High	Sepal Width Low	Sepal Width High	Petal Length Low	Petal Length High	Petal Width Low	Petal Width High	Iris Setosa	Iris Versicolour
1	1	0	0	1	1	0	1	0	1	0
2	1	0	0	1	1	0	1	0	1	0
3	1	0	0	1	1	0	1	0	1	0
4	1	0	0	1	1	0	1	0	1	0
5	1	0	0	1	1	0	1	0	1	0
6	1	0	0	1	1	0	1	0	1	0
7	1	0	0	1	1	0	1	0	1	0
8	1	0	0	1	1	0	1	0	1	0
9	1	0	0	1	1	0	1	0	1	0
10	1	0	0	1	1	0	1	0	1	0
11	1	0	0	1	1	0	1	0	1	0
12	1	0	0	1	1	0	1	0	1	0
13	1	0	0	1	1	0	1	0	1	0
14	1	0	0	1	1	0	1	0	1	0
15	1	0	0	1	1	0	1	0	1	0
16	1	0	0	1	1	0	1	0	1	0
17	1	0	0	1	1	0	1	0	1	0
18	1	0	0	1	1	0	1	0	1	0
19	1	0	0	1	1	0	1	0	1	0
20	1	0	0	1	1	0	1	0	1	0
21	1	0	0	1	1	0	1	0	1	0
22	1	0	0	1	1	0	1	0	1	0
23	1	0	0	1	1	0	1	0	1	0
24	1	0	0	1	1	0	1	0	1	0
25	1	0	0	1	1	0	1	0	1	0
26	1	0	0	1	1	0	1	0	1	0
27	1	0	0	1	1	0	1	0	1	0
28	1	0	0	1	1	0	1	0	1	0
29	1	0	0	1	1	0	1	0	1	0
30	1	0	0	1	1	0	1	0	1	0
31	1	0	0	1	1	0	1	0	1	0
32	1	0	0	1	1	0	1	0	1	0
33	1	0	0	1	1	0	1	0	1	0
34	1	0	0	1	1	0	1	0	1	0
35	1	0	0	1	1	0	1	0	1	0
36	1	0	0	1	1	0	1	0	1	0
37	1	0	0	1	1	0	1	0	1	0
38	1	0	0	1	1	0	1	0	1	0
39	1	0	0	1	1	0	1	0	1	0
40	1	0	0	1	1	0	1	0	1	0
41	1	0	0	1	1	0	1	0	1	0
42	1	0	0	1	1	0	1	0	1	0
43	1	0	0	1	1	0	1	0	1	0
44	1	0	0	1	1	0	1	0	1	0
45	1	0	0	1	1	0	1	0	1	0
46	1	0	0	1	1	0	1	0	1	0
47	1	0	0	1	1	0	1	0	1	0
48	1	0	0	1	1	0	1	0	1	0
49	1	0	0	1	1	0	1	0	1	0
50	1	0	0	1	1	0	1	0	1	0

**Example of association rules where y is also appended to Xbinary, i.e. [Xbinary Y], i.e. Y has three columns indicating which of the three flowers the observation belongs to.**

{Petal length Low, Petal Width low, Iris Setosa} -> {Sepal Length Low}  
(Conf 100, sup 33)

{Sepal Length Low, Petal Width low, Iris Setosa} -> {Petal length Low}  
(Conf 100, sup 33)

{Sepal length Low, Petal length Low, Iris Setosa} -> {Petal Width Low}  
(Conf 100, sup 33)

{Sepal length Low, Sepal Width High, Petal length Low, Petal Width Low} -> {Iris Setosa}  
(Conf 100, sup 28)



## Quiz 4: A-priori (Bonus)

Consider the dataset below consisting of 10 transactions Find all itemsets with support greater than 35 How many are there?

A: 7, B: 9, C: 11, D:13, E: Don't know

	Juice	Milk	Beer	Cheese	Chocolate	Yoghurt	Sugar	Flour	Egg	Wine
Customer 1	0	0	1	0	0	0	1	0	1	0
Customer 2	1	1	0	0	0	1	0	1	1	1
Customer 3	0	1	0	1	1	0	0	0	0	1
Customer 4	1	1	0	0	0	1	0	0	0	1
Customer 5	1	0	1	0	0	0	0	0	1	0
Customer 6	1	0	0	0	0	0	0	0	1	0
Customer 7	1	1	0	0	1	1	0	0	0	1
Customer 8	0	1	0	1	0	0	1	1	0	1
Customer 9	1	1	0	0	1	1	0	0	0	0
Customer 10	0	0	1	0	0	1	0	0	1	1

# Practicals

- Post-test on DTU Learn: Quizzes > Post test
  - Already open, closes Sunday at midnight
  - Similar to pre-test
  - We will present the results next week
- Mock exam from Fall 2024 is available from the 29th April 2025 after the lecture (also no aids)
  - **Optional:** pick up physical answer sheet and hand in next week (for us to test the setup)
- Next week (and beyond)
  - Recap of the course
  - Assistance via Piazza (limited TA availability, so help each other out)

# Resources

Fast Algorithms for Mining Association Rules Proc. 20th Int. Conf. Very Large Data Bases, 1994, Rakesh Agrawal and Ramakrishnan Srikan.