Mining the strongest emerging patterns characterizing patients affected by diseases due to atherosclerosis

Bruno Crémilleux and Arnaud Soulet and François Rioult

GREYC - CNRS UMR 6072

Université de Caen - France

Context

STULONG data (atherosclerosis).

twenty-year long longitudinal study of the risk factors of the atherosclerosis (1417 men, former Czechoslovakia)

Main goal of the STULONG study:

identify atherosclerosis risk factors and follow the development of these risk factors and their impacts

Our contribution in this discovery challenge:

search of strong emerging patterns characterizing patients affected by diseases due to atherosclerosis

Motivations

- evaluate the potential impact of the search of emerging patterns in domains like medicine
- discover useful emerging patterns in atherosclerosis data

what is it difficult?

- a huge number of potential emerging patterns

  ➥ requires powerful Knowledge Discovery in Databases (KDD) methods.

- selection of “interesting” emerging patterns

  ➥ **strong emerging patterns.**

Emerging patterns: running example

emerging pattern (EP): pattern whose frequency increases significantly from one data set to another

Patient	Items					
P_1	A	B	C	D		$\mathcal{D}_1$
P_2	A	B	C	D		
P_3	A	B	C			
P_4	A			D	E	
P_5	A	B	C			$\mathcal{D}_2$
P_6		B	C	D	E	
P_7		B	C		E	
P_8		B			E	

2 data sets: $\mathcal{D}_1$ and $\mathcal{D}_2$

5 **items**: A, B, C, D, E (e.g., level of reached education, level of total cholesterol)

pattern: set of items

$\mathcal{F}$: **frequency**

$\mathcal{F}(ABC, \mathcal{D}_1) = 3$

$\mathcal{F}(ABC, \mathcal{D}_2) = 1$

Emerging patterns: definition

X: pattern *growth rate* of X from $\mathcal{D}_2$ to $\mathcal{D}_1$:

$$GR_1(X) = \frac{|\mathcal{D}_2| \times \mathcal{F}(X, \mathcal{D}_1)}{|\mathcal{D}_1| \times \mathcal{F}(X, \mathcal{D}_2)}$$

$\rho > 1$: X is a ρ-**EP** (or EP) from $\mathcal{D}_2$ to $\mathcal{D}_1$ if $GR_1(X) \geq \rho$

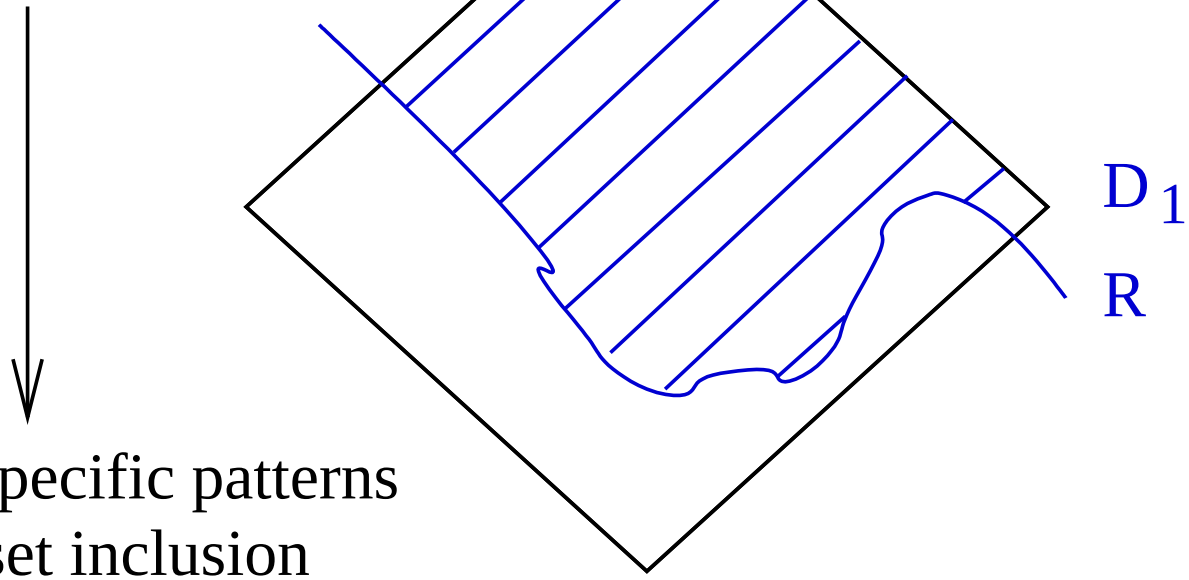
Running example: $\rho = 3$ from $\mathcal{D}_2$ to $\mathcal{D}_1$

- ABC is an EP ($GR_1(ABC) = 3$)
- BCD is not an EP ($GR_1(BCD) = 2$)
- $ABCD$ is a jumping emerging pattern ($GR_1(ABCD) = \infty$)

It is easy to generalize the definition to k data sets

Common approaches: use of borders

most general patterns
w.r.t. set inclusion



most specific patterns
w.r.t. set inclusion

γ: frequency threshold

$\mathcal{R}$: right-hand bound: maximal frequent patterns in $\mathcal{D}_1$ ($\mathcal{F}(X) \geq \gamma$)

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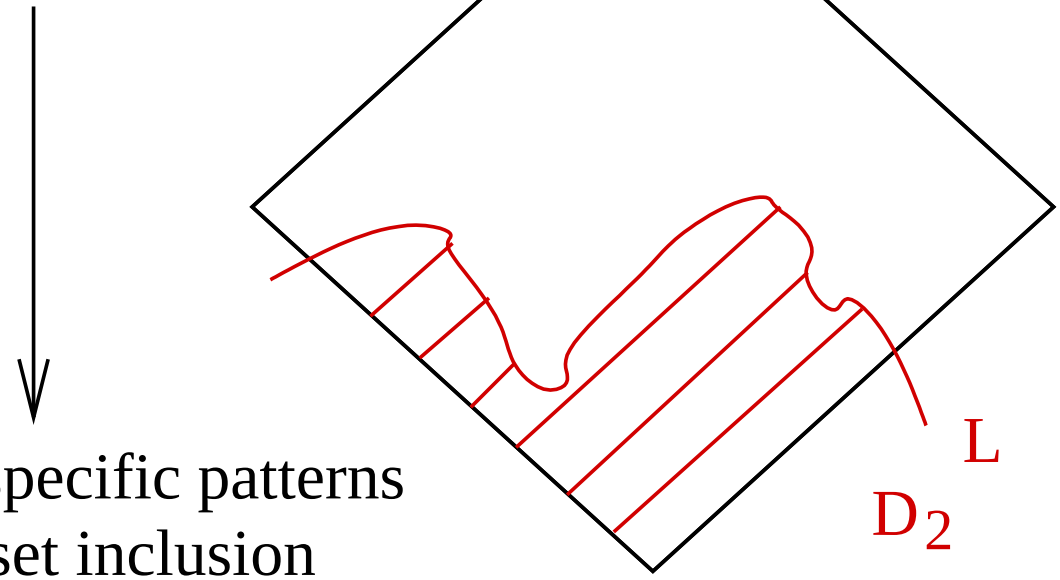

most specific patterns
w.r.t. set inclusion

γ: frequency threshold

$\mathcal{R}$: right-hand bound: maximal frequent patterns in $\mathcal{D}_1$ ($\mathcal{F}(X) \geq \gamma$)

$\mathcal{L}$: left-hand bound: minimal infrequent patterns in $\mathcal{D}_2$ ($\mathcal{F}(X) \leq \gamma/\rho$)

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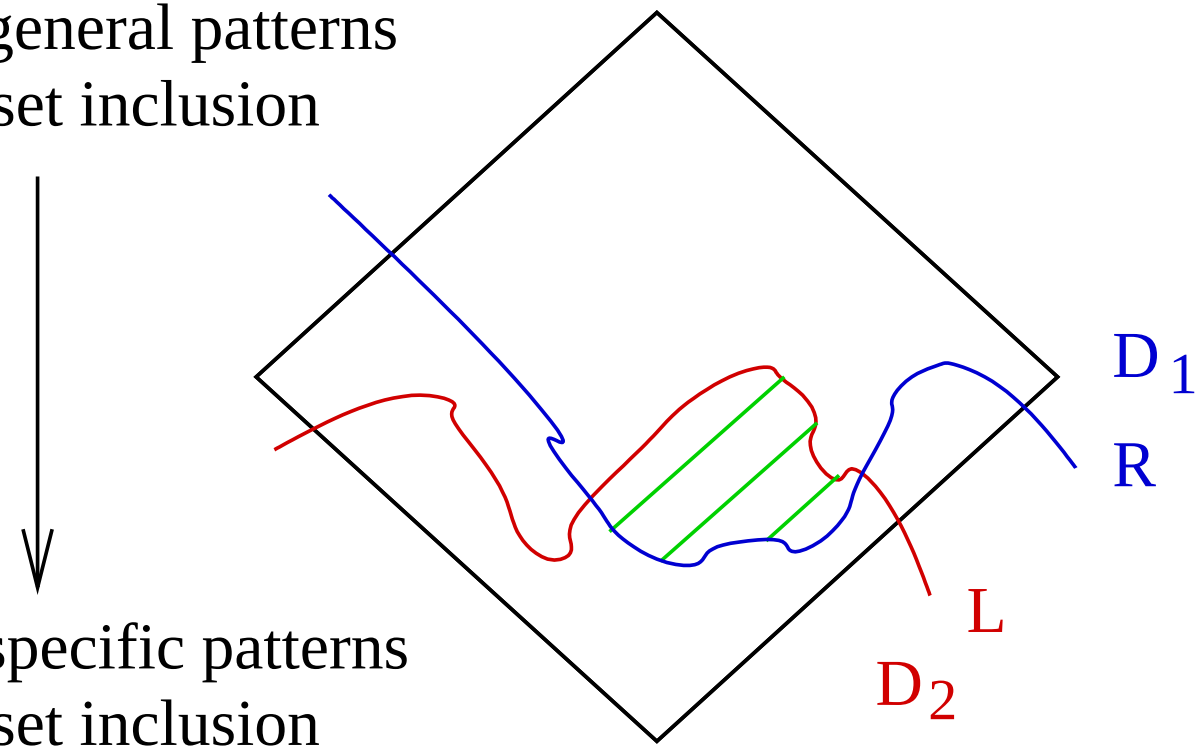

most specific patterns
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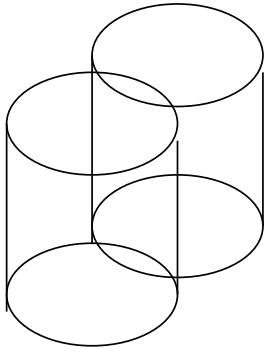
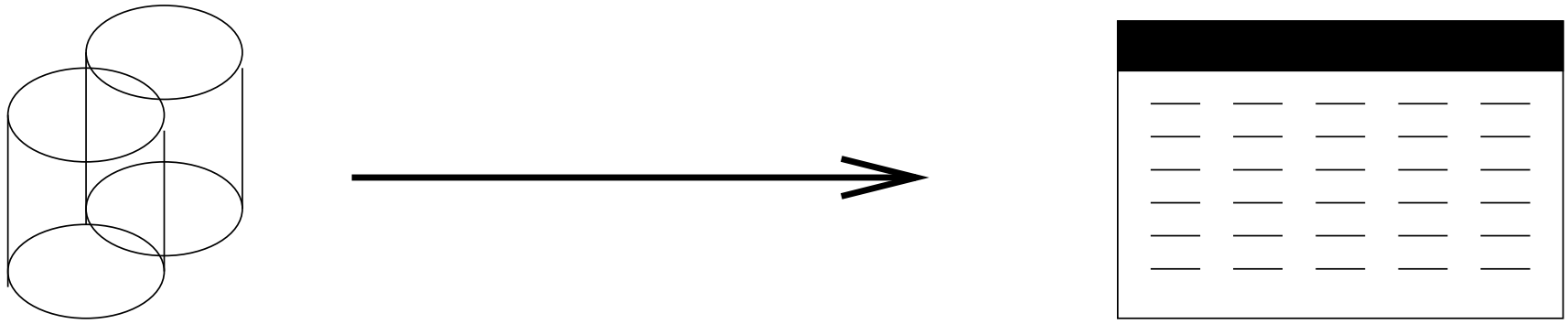
EPs are in $[\mathcal{L}, \mathcal{R}]$

Our proposition: use of condensed representations



data base

Our proposition: use of condensed representations



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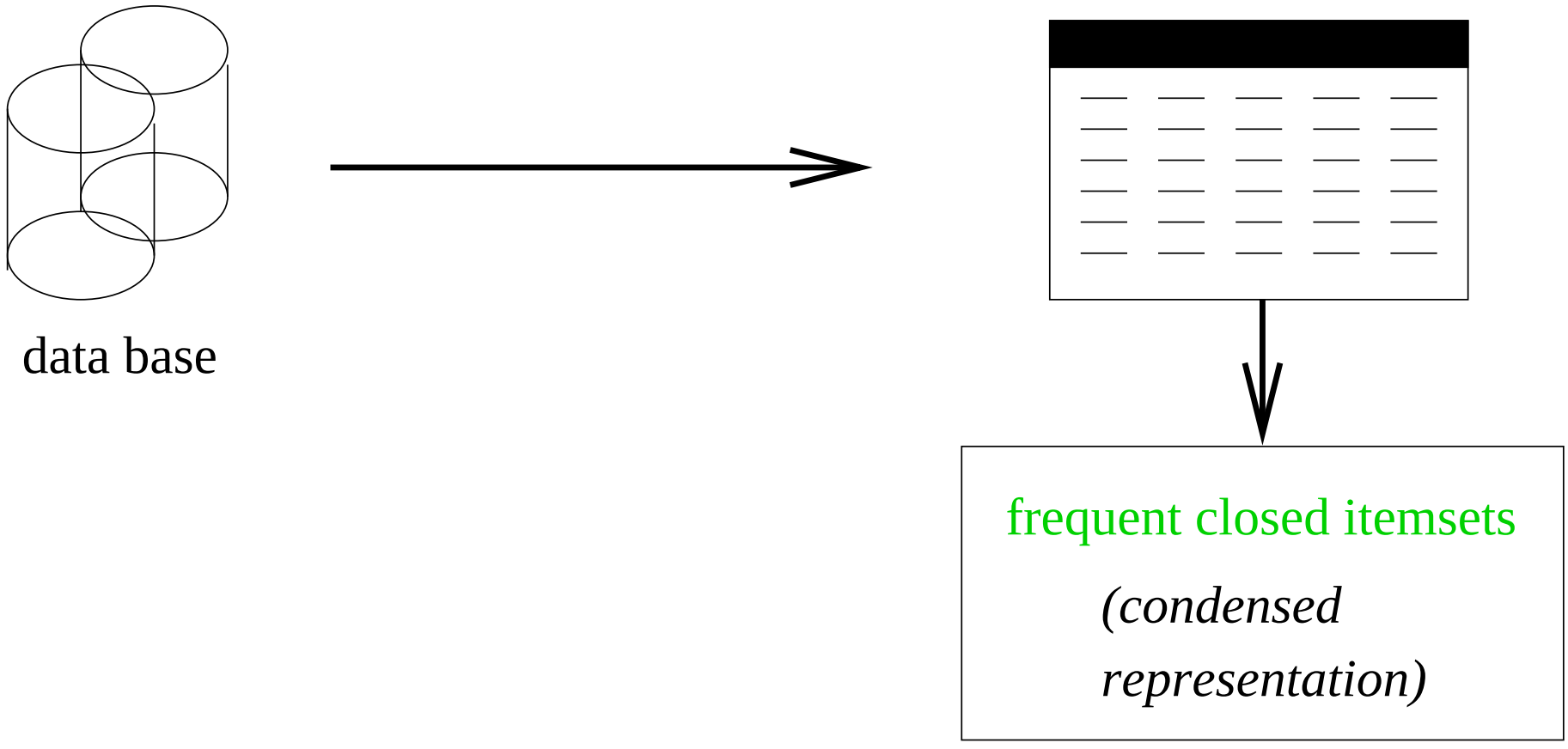

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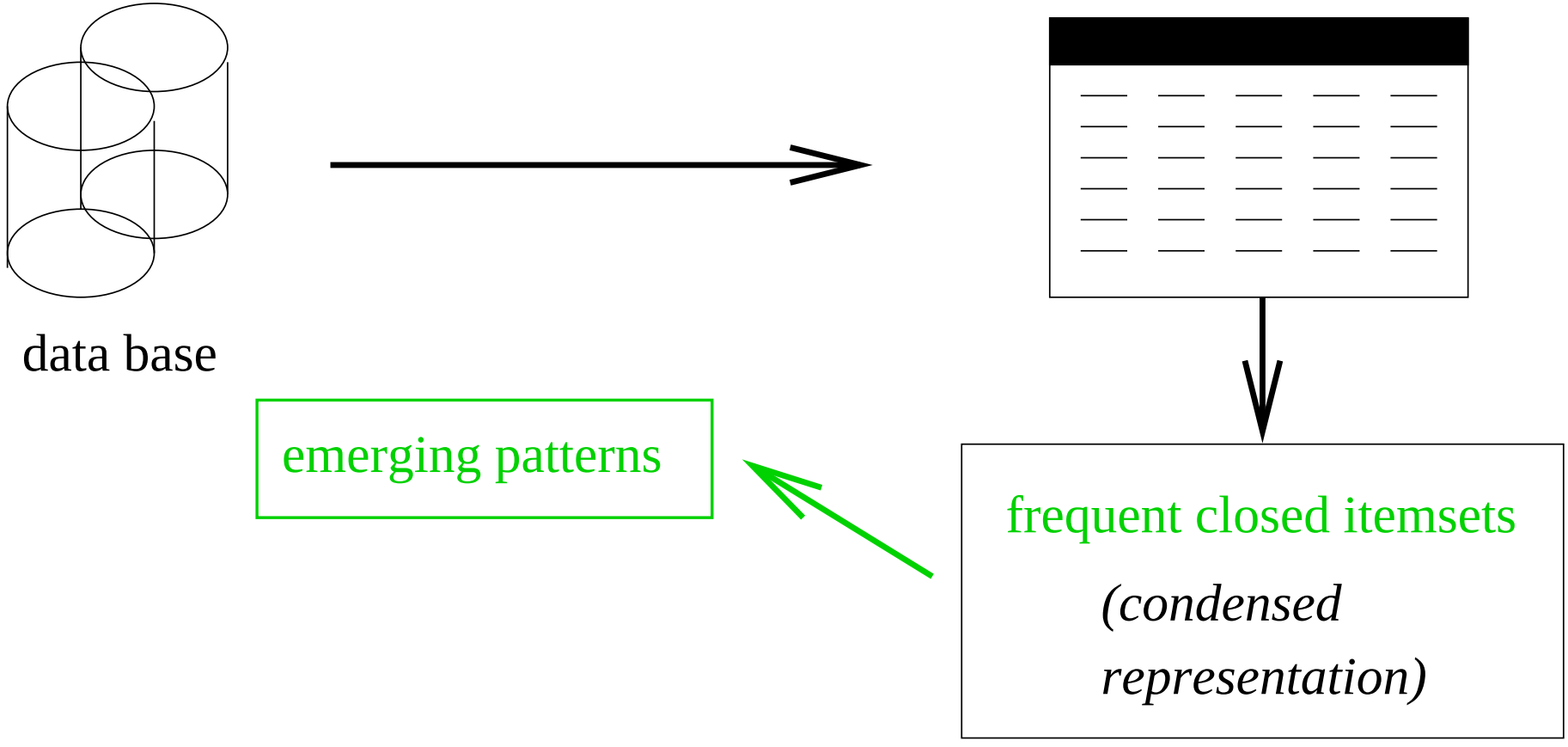

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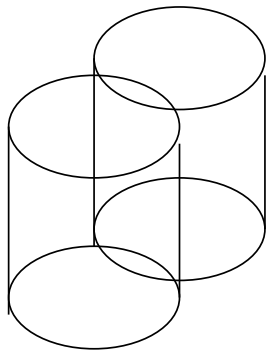

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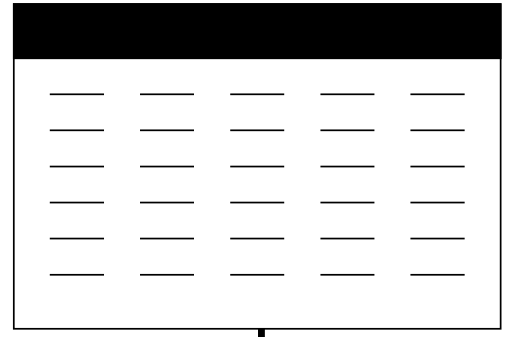

frequent closed itemsets

(condensed representation)

emerging patterns

characterization of classes

clustering

classification

missing values

rules

...

Condensed representations based on closed patterns

closed patterns in a database $\mathcal{D}$:

➠ the maximal set of items shared by a set of examples.

Running example:

- ABC is a closed pattern on $\mathcal{D}_1$
- BC is not a closed pattern on $\mathcal{D}_1$ (A is always present when BC is present)

$h(X, \mathcal{D})$: **closure** of X in $\mathcal{D}$. It is a *closed pattern* with the same frequency of X: $\mathcal{F}(X, \mathcal{D}) = \mathcal{F}(h(X, \mathcal{D}), \mathcal{D})$

Running example: $h(BC, \mathcal{D}) = ABC$

There are efficient algorithms to extract all frequent closed patterns

Strong emerging patterns

$\mathcal{D} = \bigcup_i \mathcal{D}_i$ (k classes)

strong emerging pattern (SEP) from $\mathcal{D} \backslash \mathcal{D}_i$ to $\mathcal{D}_i$

➠ EP based on a closed frequent pattern in $\mathcal{D}_i$

SEPs have two main advantages:

- their growth rate is directly obtained from the condensed representation of closed patterns in $\mathcal{D}$
- SEPs have the highest growth rates:

$$GR_i(X) \leq GR_i(h(X, \mathcal{D}_i))$$

Running example:

- BC is not a closed pattern in $\mathcal{D}_1$: $GR_1(BC) = 1$
- $h(BC, \mathcal{D}_1) = ABC$: $GR_1(ABC) = 3$

Aim of experiments

from the features available when patients are entered in the study (i.e. features of the table `Entry`)

- `Experiment 1`: distinguish the patients *who died* from atherosclerosis from the others
- `Experiment 2`: distinguish patients *who came down* with the observed cardiovascular diseases from those who stayed healthy

long-term information needed:

➥ focus on patients from `normal studied group`, `intervened risk group` and `control risk group` (899 patients).

Experiment 1: data preparation

assumption: all patients dying from atherosclerosis are recorded in the table `Death`

Table `Death`: 165 patients died due to atherosclerosis:

➠ values `myocardial infarction`, `coronary heart disease`, `stroke` and `general atherosclerosis` of the attribute `PRICUMAR`

join these patients with patients followed during all the study:

➥ 124 patients remain

Experiment 2: data preparation

assumption: all patients suffering from atherosclerosis are recorded in the table `Control`

remark: these patients may suffer from another disease

From the web pages:

patient affected by a cardiovascular disease:

➠ illness based on attributes `HODN1`, `HODN2`, `HODN3`, `HODN11`, `HODN12`, `HODN13`, `HODN14`, `HODN21`, `HODN23`

join these patients with patients followed during all the study:

➥ 281 patients remain

Data preparation (cont'd)

keep all attributes of the table `Entry` except the deletion of:

- the attribute KONSUP: may introduce a bias
- the attributes relating to risk factors: already taken into account by other attributes
- attributes relating to the personal anamnesis: very low frequencies of values
- the attributes ROKNAR (year of birth) and ROKVSTUP (year of entry into the study)

  ➥ replaced by the age of the patient when he was entered in the study.

Data preparation (cont'd)

- binary segmentation of the attributes `CHLST` (cholesterol) and `TRIGL` (triglycerides) according to the thresholds given in the web pages
- segmentation in three values of each other continuous attribute

➥ finally: 119 items.

Characteristics of the files and results

- `athero`: patients who died (`Experiment 1`) or ill (`Experiment 2`)
- `healthy`: other patients.

15: absolute frequency SEPs with at most 8 items

	Experiment 1		Experiment 2	
	athero	healthy	athero	healthy
No. of patients	124	624	281	618
γ (%)	12.1%	2.4%	5.3%	2.4%
$GR \in [1..2[$	32606	2,278,346	510,901	2,845,756
$GR \in [2..5[$	6254	1,229,359	69609	605,312
$GR \in [5..\infty[$	47	94,921	1038	61168
JEP	132	387,203	2690	16916

Results:
Experiment 1 (atherosclerosis)

items of SEPs	GR	$\mathcal{F}$ (%)
the way to work takes around 1 hour ; smoker of 21 and more cigarettes per day ; smoking during 21 and more years ; do not drink liquors	6.71	11.3
weight $\leq$ 74 kg ; blood pressure II diastolic > 92 mm Hg ; normal urine	6.29	11.3
height $\leq$ 1.72 m ; blood pressure II diastolic > 92 mm Hg	3.91	16.9
blood pressure II diastolic > 92 mm Hg	1.72	32.3
age of entry in the study $\in$ [43,47] ; moderate activity after his job ; level of total cholesterol $\geq$ 200 mg/dL	∞	18.5

Results: Experiment 1 (healthy)

items of SEPs	GR	$\mathcal{F}$ (%)
partly independent worker ; blood pressure II systolic $\leq$ 118 mm Hg	11.7	9.46
reached education: university ; level of total cholesterol < 200 mg/dL	8.35	6.7
age of entry in the study $\in$ [44,47] ; level of total cholesterol < 200 mg/dL	8.15	6.6
age of entry in the study $\leq$ 43 years	2.21	30.3
reached education: university ; blood pressure II diastolic $\leq$ 78 mm Hg	∞	8.7
age of entry in the study $\leq$ 43 years ; mainly standing at work	∞	5.0
non-smoker ; blood pressure I systolic $\leq$ 120 mm Hg	∞	4.5

Results:
Experiment 2 (atherosclerosis)

items of SEPs	GR	$\mathcal{F}$ (%)
1 or 2 cups of coffee per day ; height < 1.72 m ; blood pressure I diastolic $\in$ [75,92] ; skinfold above musculus triceps > 11	7.48	6.0
more than 6 sugar lumps per day ; skinfold above musculus triceps > 11	2.30	8.2
height $\leq$ 1.72 m ; blood pressure I systolic > 135	2.00	14.6
drinking of alcohol: occasionally ; drinking of vine ; up to half a litre of vine per day ; level of triglycerides > 150 mg/dL	∞	14.2
reached education: secondary school ; drinking of vine ; up to half a litre of vine per day ; blood pressure II diastolic $\in$ [78,92]	∞	12.5

Results: Experiment 2 (healthy)

items of SEPs	GR	$\mathcal{F}$ (%)
single ; do not drink coffee	8.64	3.1
lower limbs pain is non-ischaemic ; blood pressure I diastolic $\leq$ 75 mm Hg	8.64	3.1
mainly walks at work ; drink daily more than 1 litre of beer	5.12	7.3
partly independent worker ; blood pressure I systolic $\leq$ 120 mm Hg ; blood pressure I diastolic $\leq$ 75 mm Hg	5	7.1
drinking of 10° beer ; daily consumption of 2 at 6 sugar lumps ; blood pressure I diastolic $\leq$ 75 mm Hg ; normal urine	∞	7.3
blood pressure II systolic $\in$ [118,138] ; blood pressure II diastolic > 92 mm Hg	∞	3.8

Results (cont'd)

- `Experiment 1`: a lot of SEPs to `atherosclerosis` have the item "smoking during 21 and more years", the blood pressure seems to have an important role.
- `Experiment 2`: all JEPs to `atherosclerosis` have at least 4 items.

It is likely that most associations highlighting by SEPs are expected (and already known) by physicians:

➥ but SEPs quantify such associations (e.g., how much increases the risk of atherosclerosis with respect to precise features?)

Conclusion

- *strong emerging patterns* (best growth rate, efficient method to extract them from condensed representation)
- search of SEPs characterizing patients with respect to atherosclerosis: it allows to quantify associations highlighted by SEPs
- *further work:*
  - how to select the most interesting SEPs (or EPs) from a data set?
  - build condensed representations of EPs including the patterns and their growth rates.