Simply Mining Data

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17 August 2015

UNIVERSITÄT DES SAARLANDES

M2CI CLUSTER OF EXCELLENCE

mpi max planck institut informatik

So, how do you pronounce…

Jilles

Yill-*less*

Vreeken

Fray-*can*

Okay, now we can talk.

Exploratory Data Analysis

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The goal

Theory and methods for getting **insight** from data

summarising its main characteristics in **easily understandable terms**

So, what kind of data?

real-valued

GRIM	REAPER	INDY
0.7	0.9	1.0
0.5	0.8	0.2
0.3	0.0	0.8

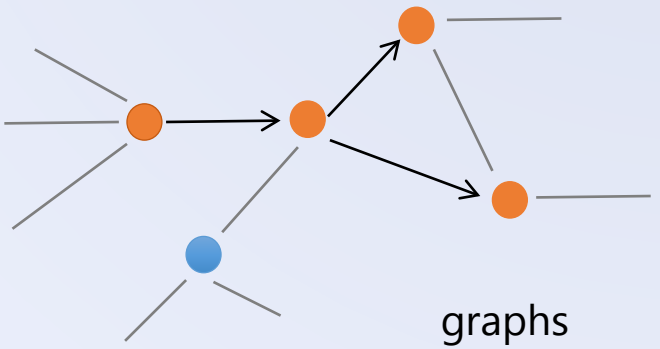
binary

A	B	C
0	0	1
1	1	1
0	1	1

* 1

* *

multi-relational

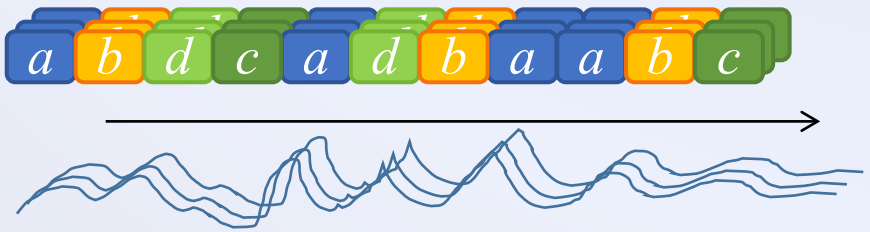


graphs
(un)directed,
(un)weighted,
(un)attributed

Eyes	Hair	Course
Blue	Red	TADA
Brown	Brown	TADA
Brown	Blue	WTF

categorical

time series



So, what kinds of analysis?

pattern mining, summarisation, clustering,
outlier detection, correlations measures,
distance measures, missing value estimation,
graph clustering, influence propagation, classification…

all at an *explorative* angle

as assumption-free as possible
identify interesting **local** structure
describing structures in **simple** terms
such that ***you*** learn about ***your*** data

So, what is your signature then?

defining well-founded
objective functions
for **exploratory** tasks

using **information theory**
for measuring how many bits
of information a result gives

MDL, Kolmogorov Complexity, Kullback-Leibler,
Maximum Entropy, (cumulative) entropy

What is your signature?

data analysis ↔ communication

transfer the data
to the analyst
in as **few** as possible bits

'induction by compression'

The Menu

In three lectures, I will give an introduction to modern **exploratory data analysis**.

Lecture 1: **How can we summarise complex data?**

Lecture 2: **How to solve data mining tasks by compression?**

Lecture 3: **How to discover causal relations from data?**

Simply Summarising Data

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Question of the day

How can we mine
a small, non-redundant set of
interesting patterns that together
describe the data well?

Traditional pattern mining

For a database *db*

- a pattern language $\mathcal{P}$ and a set of constraints $\mathcal{C}$

the goal is to find the set of patterns $\mathcal{S} \subseteq \mathcal{P}$ such that

- each $p \in \mathcal{P}$ satisfies each c $\in \mathcal{C}$ on *db,* and $\mathcal{S}$ is maximal

That is, find **all** patterns that satisfy the constraints

Problems in pattern paradise

The pattern explosion

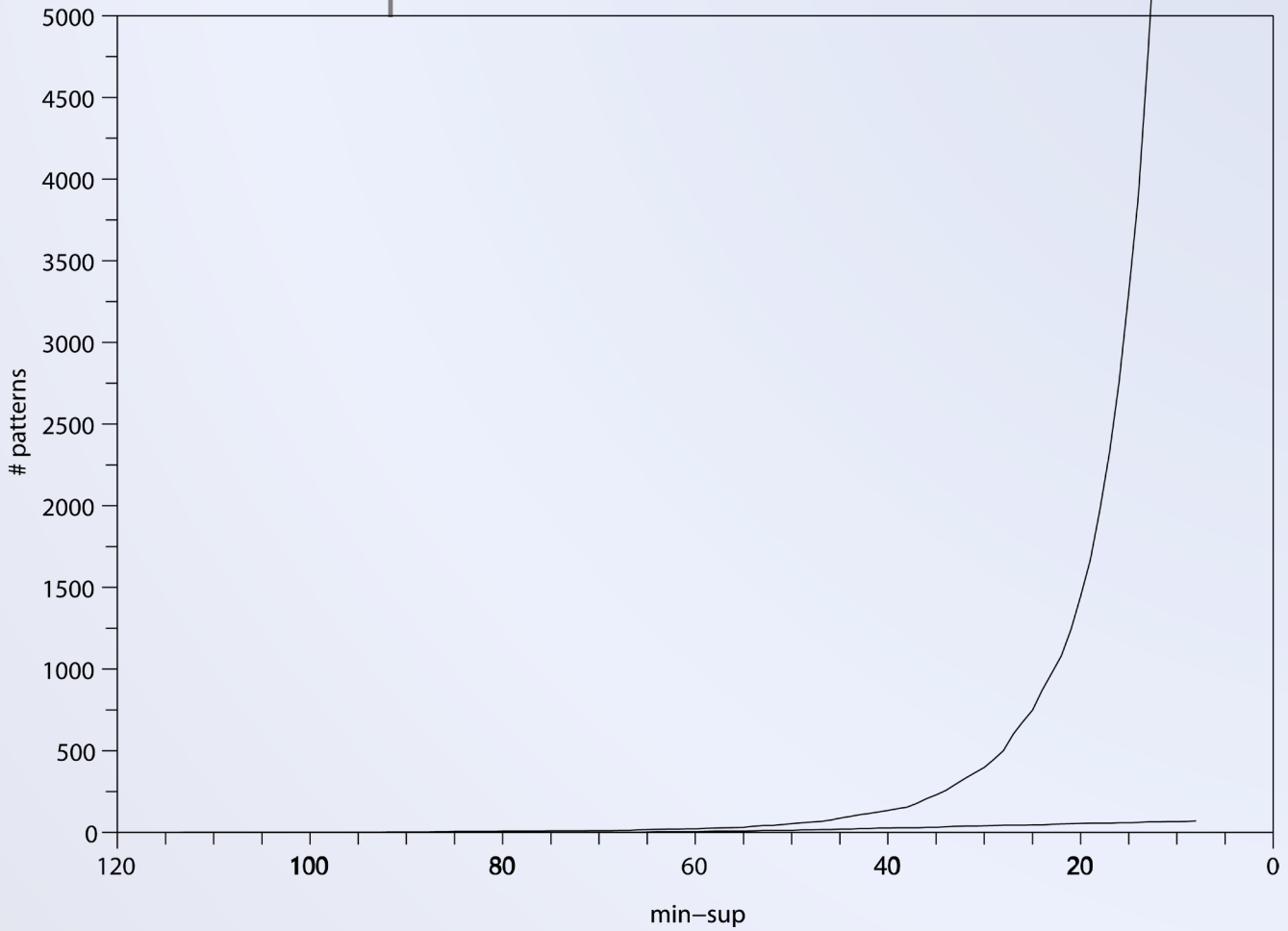
- high thresholds
  few, but well-known patterns
- low thresholds
  a gazillion patterns

Many patterns are redundant

Unstable

- small data change,
  yet different results
- even when distribution
  did not really change

The Wine Explosion



the *Wine* dataset has 178 rows, 14 columns

Be careful what you wish for

The root of all evil is,

- we **ask** for **all** patterns that satisfy some constraints,
- while we want a small set that shows the structure of the data

In other words, we should ask for a *set of patterns* such that

- all members of the set **satisfy** the constraints
- the set is **optimal** with regard to some criterion

Intuitively

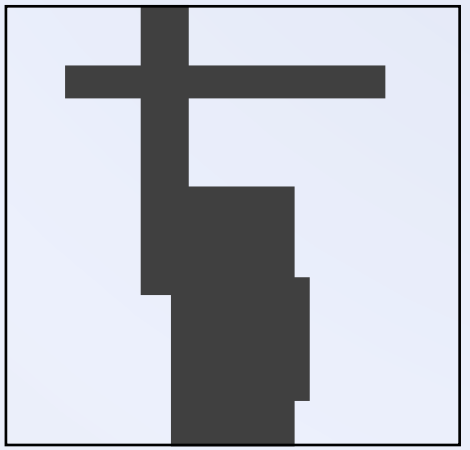
M

patterns

a pattern identifies
local properties
of the data

e.g. itemsets

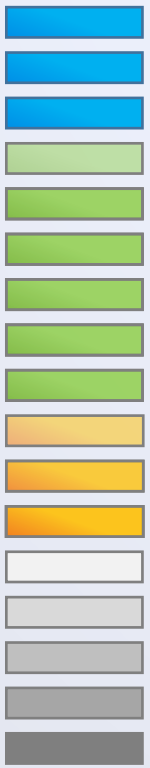
D



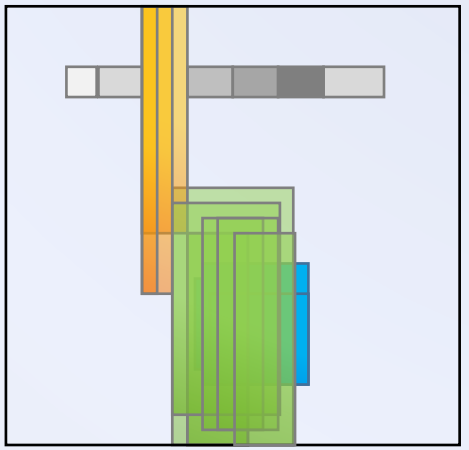
a toy 0-1 dataset

Intuition Bad

M



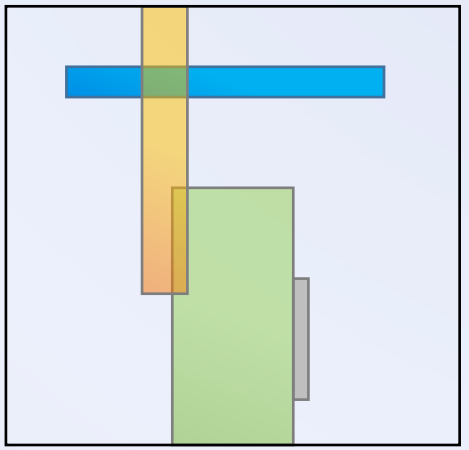
$D|M$



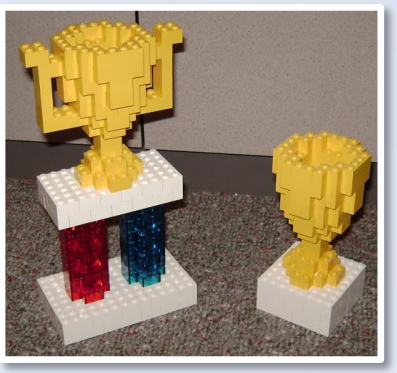
Intuition Good

M

$D|M$



Optimality and Induction



What is the **optimal** set?

- the set that generalises the data best
- generalisation = induction
  we should employ an inductive principle

So, which principle should we choose?

- observe: patterns are descriptive for local parts of the data
- MDL is *the* induction principle for descriptions

Hence, MDL is a **natural** choice

MD-what?

The Minimum Description Length (MDL) principle

given a set of models $\mathcal{M}$, the best model $M \in \mathcal{M}$
is that M that minimises

$$L(M) + L(D|M)$$

in which

$L(M)$ is the length, in bits, of the description of M

$L(D \mid M)$ is the length, in bits, of the description of the data when encoded using M

(see, e.g., Rissanen 1978, 1983, Grünwald, 2007)

Does this make sense?

Models describe the data

- that is, they capture regularities
- hence, in an abstract way, they compress it

MDL makes this observation concrete

the best model gives the best lossless compression

and is related to Kolmogorov complexity

Kolmogorov Complexity

$$K(s)$$

The Kolmogorov complexity of a binary string s
is the length of the shortest program $k(s)$
for a universal Turing Machine U
that generates s and halts.

(Kolmogorov, 1963)

Kolmogorov Complexity

$$K(s)$$

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is the length of the shortest program $k(s)$
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that generates s and **halts**.

(Kolmogorov, 1963)

Conditional Complexity

$$K(s \mid t)$$

The **conditional** Kolmogorov complexity of a string s
is the length of the shortest program $k(s)$
for a universal Turing Machine U
that given string t as input
generates s and halts.

Two-part Complexity

$$K(s) \triangleq K(s') + K(s \mid s')$$

The *two-part* Kolmogorov complexity of a string s decomposes the shortest program $k(s)$ into **two** parts

length of the `**algorithm**'
length of its `**parameters**'

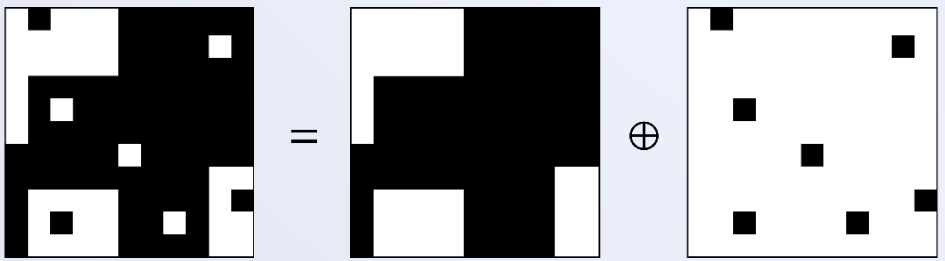
(equality up to a constant)

Two-part Complexity

$$K(s) \triangleq K(S) + \log |S|$$

The *two-part* Kolmogorov complexity of a string s decomposes the shortest program $k(s)$ into **two** parts

length of the `model' $S \ni s$
length of `data given model' $\log |S|$



MDL

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How to use MDL

If we could use Kolmogorov complexity, we'd be done.

To use MDL, however, we need to define

- how many bits it takes to encode a **model**
- how many bits it takes to encode the **data given this model**

And, of course, an algorithm to discover the optimal model for this score

How to use MDL

To use MDL, we need to define

- how many bits it takes to encode a **model**
- how many bits it takes to encode the **data given this model**

Essentially…

- defining an encoding ↔ defining a prior
- codes and probabilities are tightly linked:
  higher probability ↔ shorter code

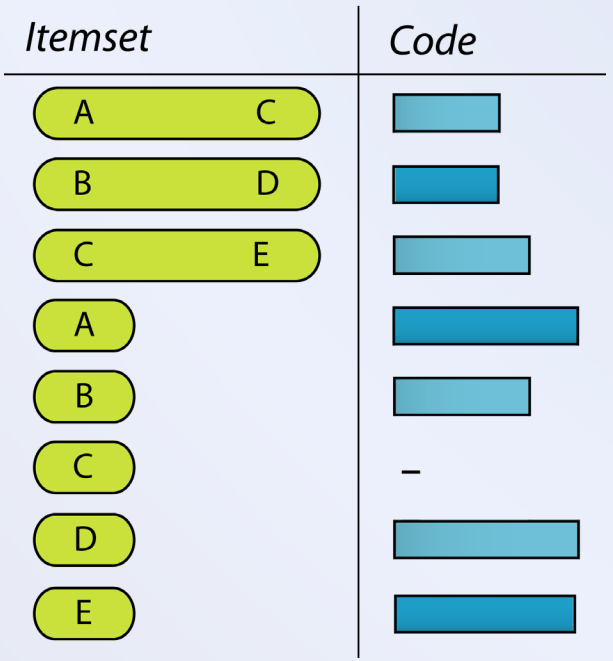
So, although we don't know overall probabilities

- we can exploit knowledge on local probabilities

Model

$\mathcal{I} = \{ A, B, C, D, E \}$

Code Table



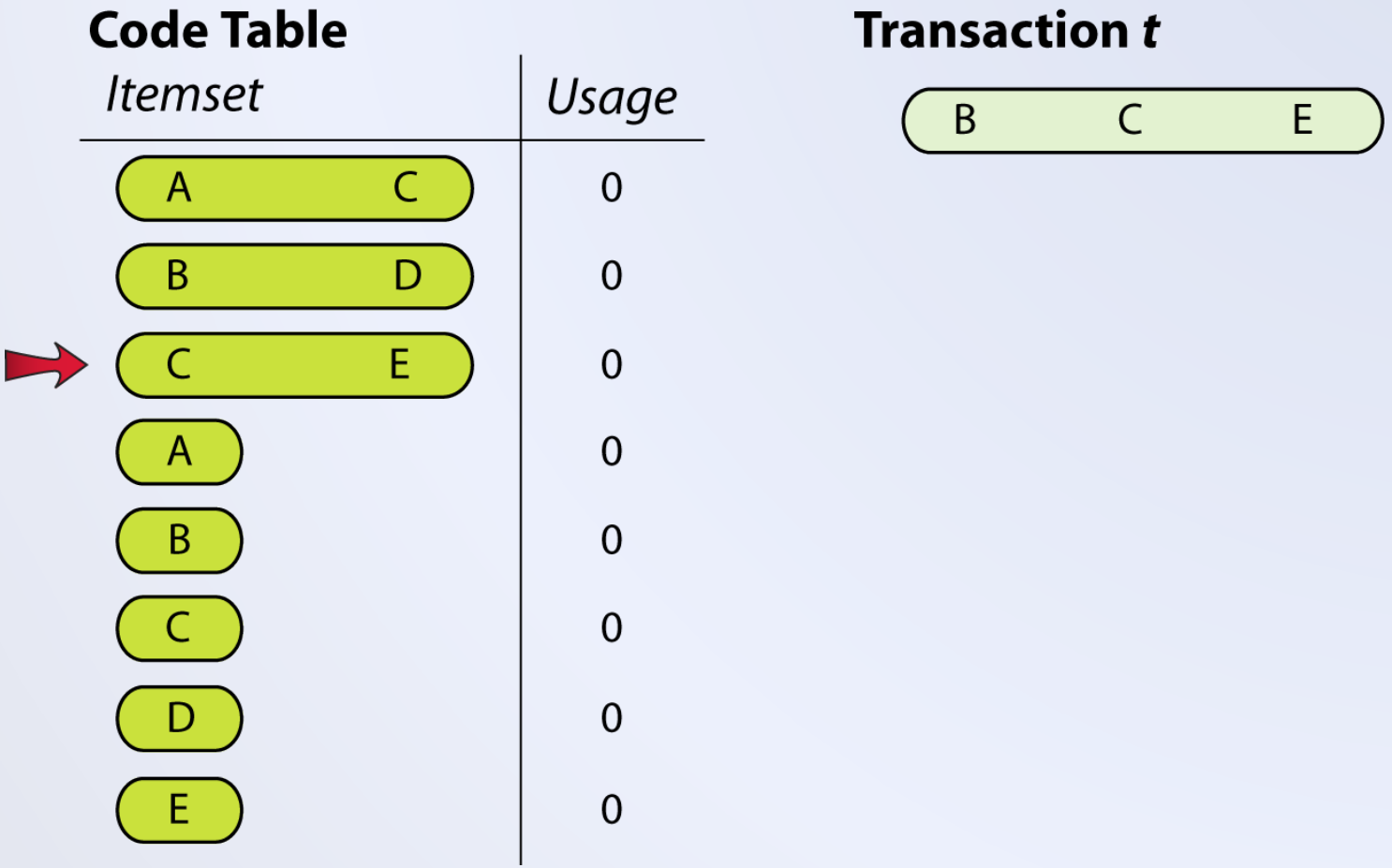
(Vreeken et al 2011 / Siebes et al 2006)

Code Table

Itemset	*Usage*
A C	0
B D	0
C E	0
A	0
B	0
C	0
D	0
E	0

Transaction *t*

B C E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A C
0
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0
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0
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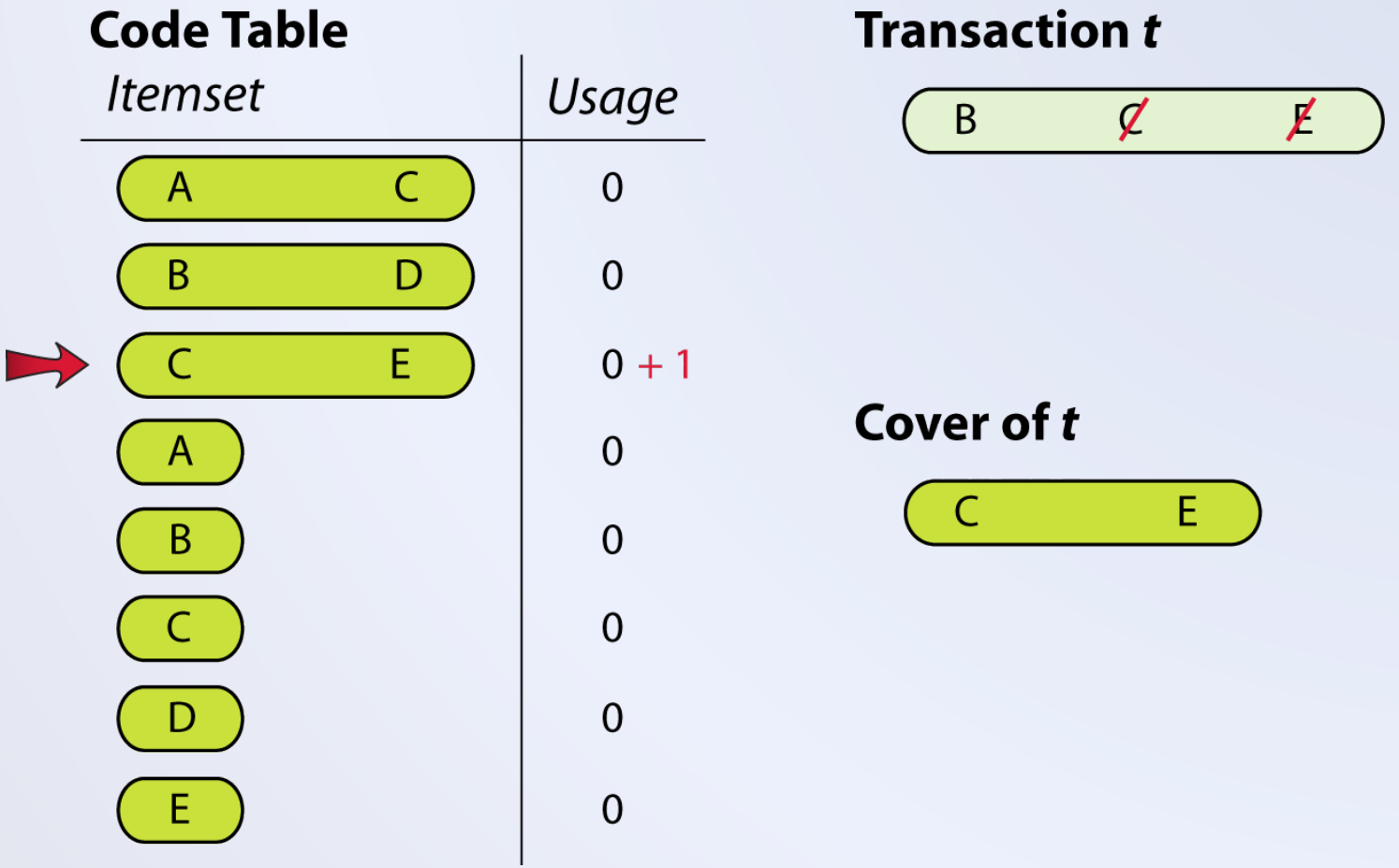
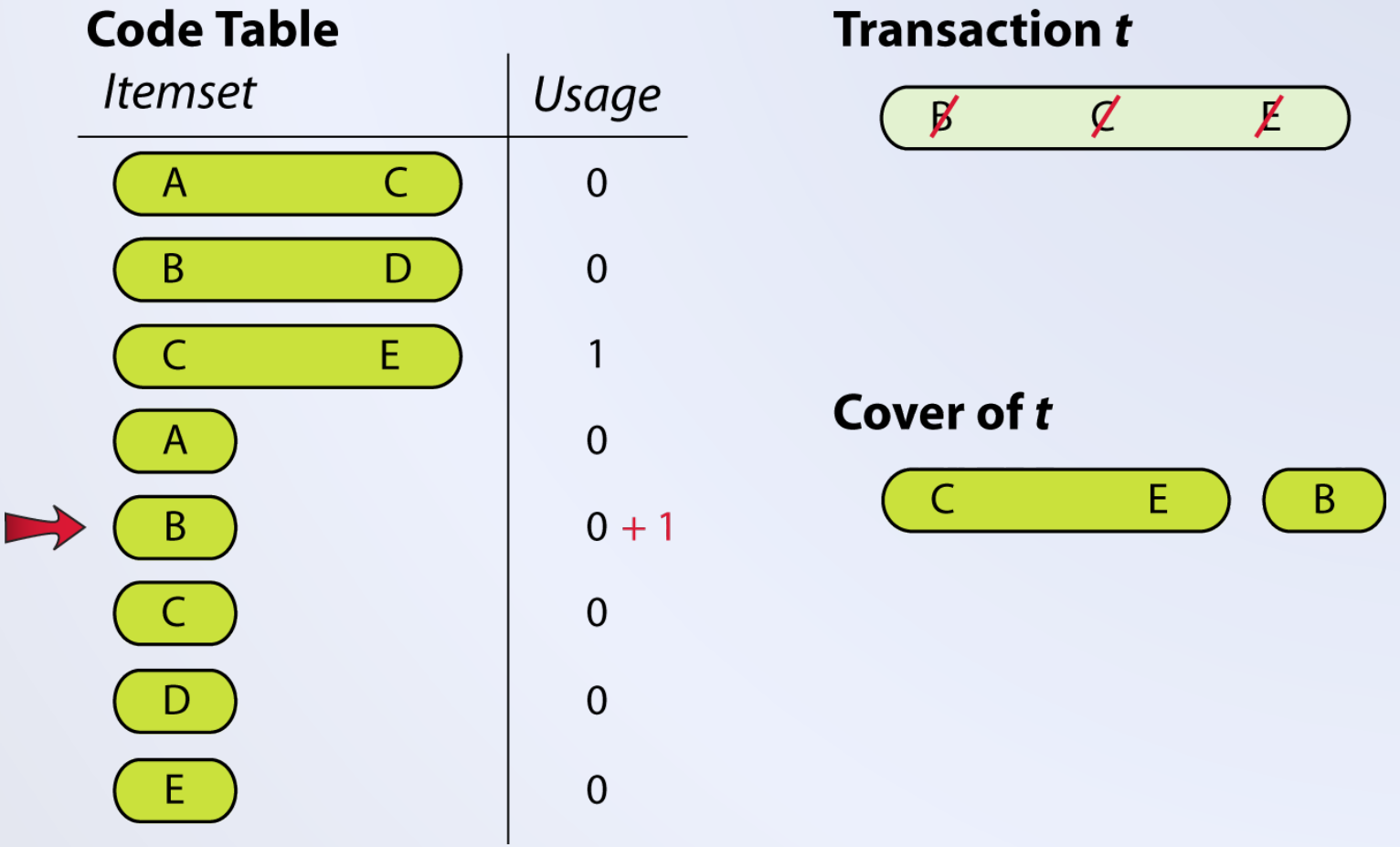
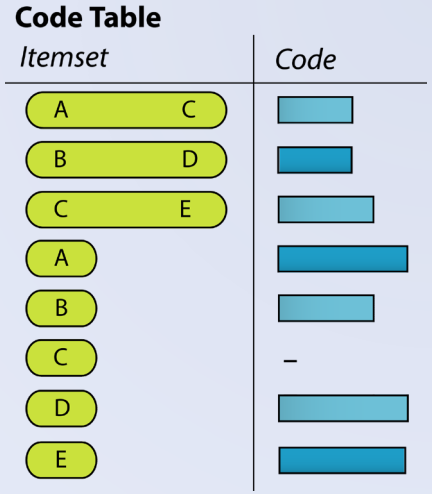
0
B
0
C
0
D
0
E
0
Transaction t
B C E


Code Table
Itemset
Usage
A C
0
B D
0
C E
0 + 1
A
0
B
0
C
0
D
0
E
0
Transaction t
B C E
Cover of t
C E


Code Table
Itemset
Usage
A C
0
B D
0
C E
1
A
0
B
0 + 1
C
0
D
0
E
0
Transaction t
B C E
Cover of t
C E
B

Encoding a database



Database

A	C	E	
B			
A	C		
A	B	C	D
B	C	E	
D			
B	C	D	E
A	B	D	

Database Cover

A	C	E	
B			
A	C		
A	C	B	D
C	E	B	
D			
B	D	C	E
B	D	A	

Optimal codes

For $c \in CT$ define

$$usage(c) = |\{\, t \in D \mid c \in cover(t, CT) \,\}|$$

$$P(\, X \mid CT, D \,) = \frac{usage(X)}{\sum_{Y \in CT} usage(Y)}$$

The optimal code for the coding distribution P assigns a code to $X \in CT$ with length

$$L(\, X \mid CT \,) = -\log(P(\, X \mid CT, D \,))$$

(Shannon, 1948; Thomas & Cover, 1991)

Encoding a code table

The size of a code table CT depends on

the left column

- length of itemsets as encoded with independence model

the right column

- the optimal code length

Thus, the size of a code table, is

$$L(CT \mid D) = \sum_{X \in CT : usage(X) \neq 0} L(X \mid ST) + L(X \mid CT)$$

Encoding a database

For $t \in D$ we have

$$L(t \mid CT) = \sum_{X \in cover(t, CT)} L(X \mid CT, D)$$

$$L(D \mid CT) = \sum_{t \in D} L(t \mid CT)$$

Hence we have

The Total Size

The total size of data D and code table CT is

$$L(CT, D) = L(\, CT \mid D \,) + L(D \mid CT)$$

Note, we disregard Cover as it is identical for all CT and D, and hence is only a constant

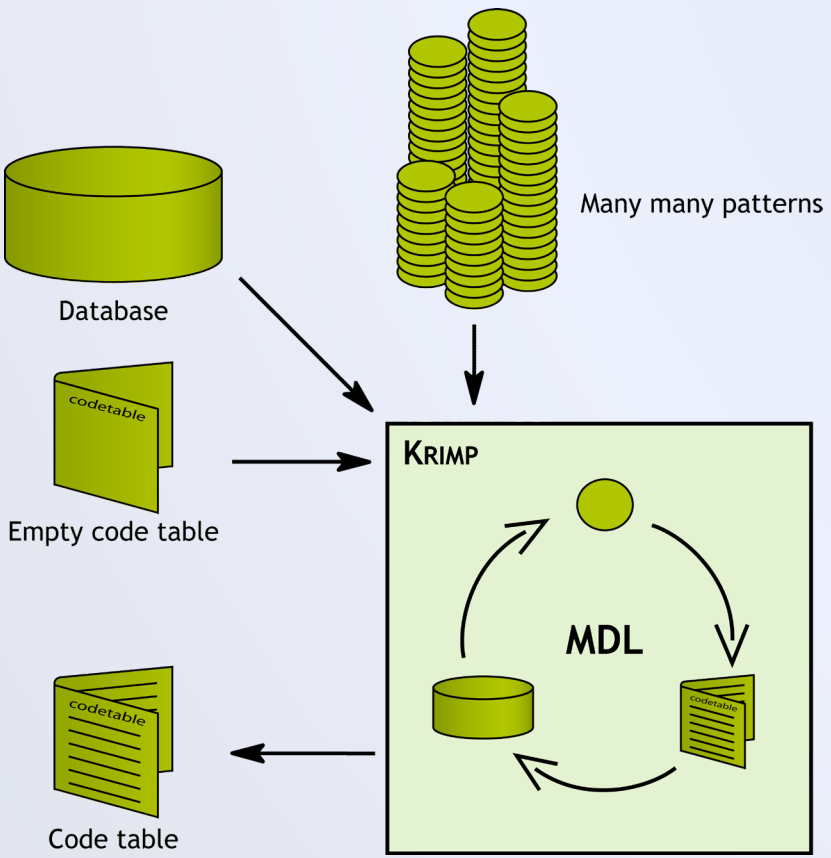
And now, the optimal code table…

Easier said than done

- the number of possible code tables is huge
- no useful structure to exploit

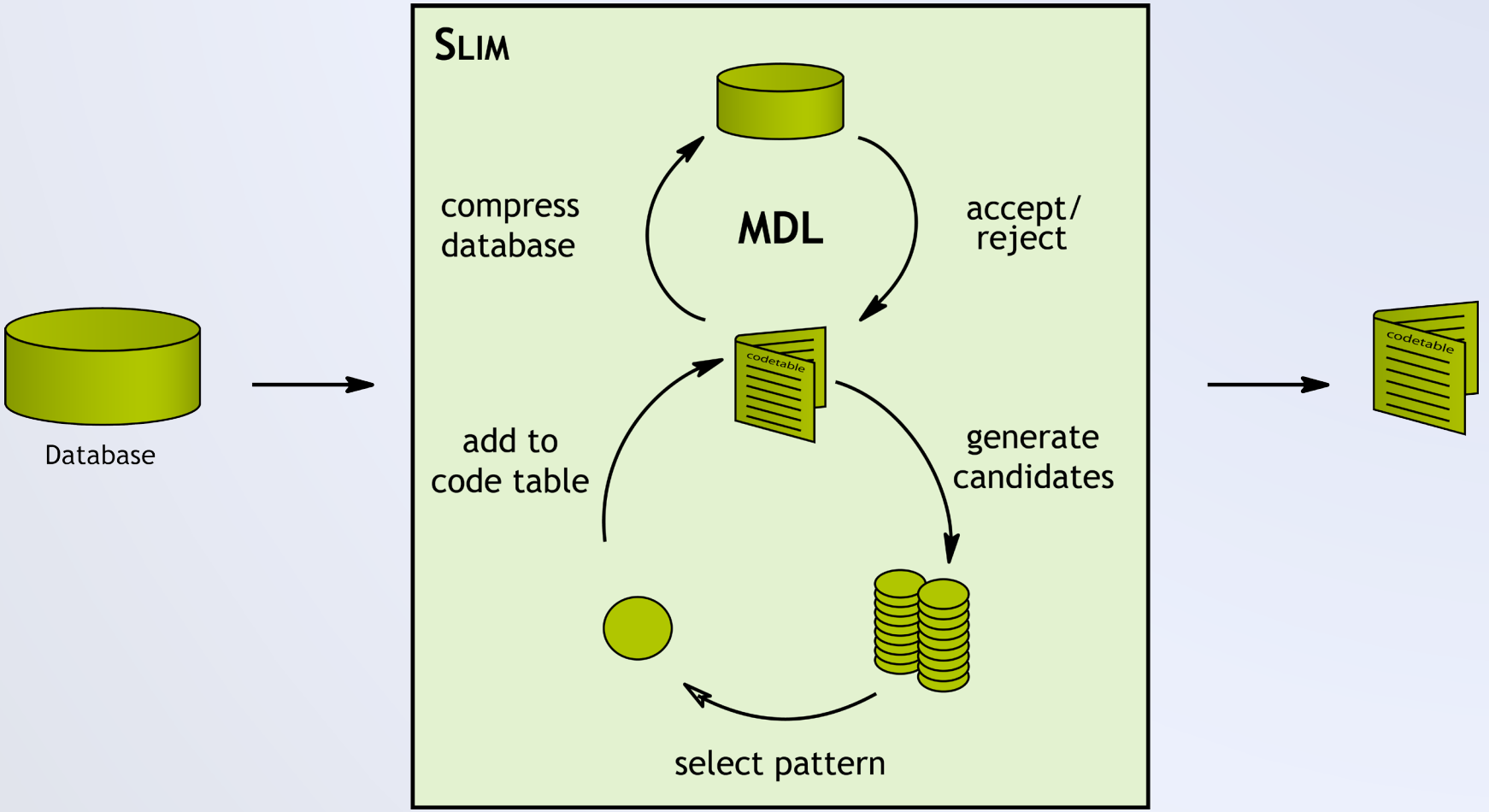
Hence, we resort to heuristics

KRIMP



- mine candidates from D
- iterate over candidates
  - Standard Candidate Order
- covers data greedily
  - no overlap
  - Standard Code Table Order
- select by MDL
  - better compression? candidates may stay, reconsider old elements

SLIM – smarter KRIMP

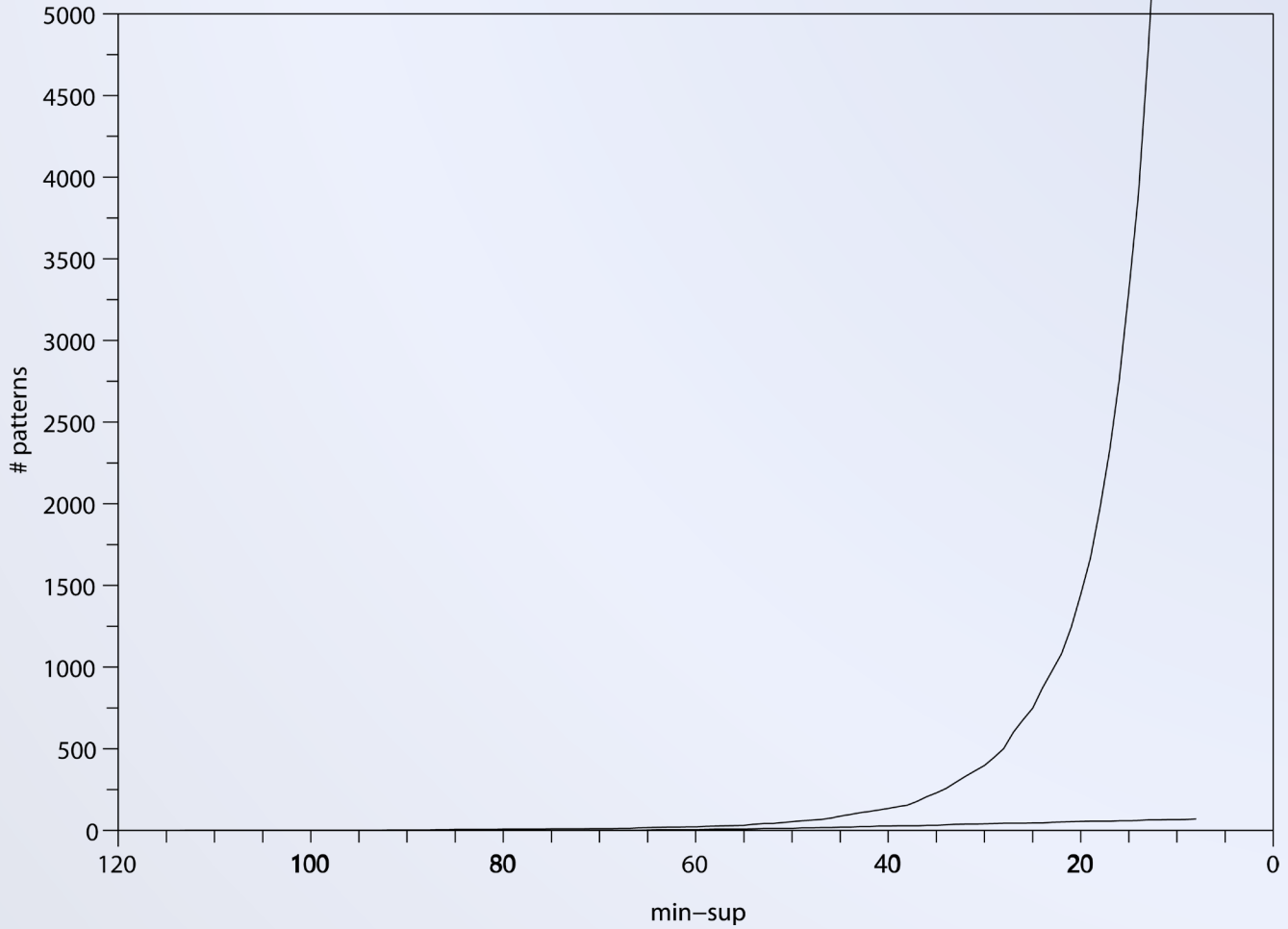


(Smets & Vreeken, SDM'12)

SLIM in Action

Dataset	$\lvert\mathcal{D}\rvert$	$\lvert\mathcal{F}\rvert$	$\lvert CT \setminus \mathcal{I}\rvert$	$L\%$
Accidents	340183	2881487	467	55.1
Adult	48842	58461763	1303	24.4
Letter Recog.	20000	580968767	1780	35.7
Mushroom	8124	5574930437	442	24.4
Wine	178	2276446	63	77.4

SLIM in Action



SLIM in Action

SLIM in Action

Reductions of up to 1 in 10^7, only one in 10.000.000 is chosen!

Are you impressed?

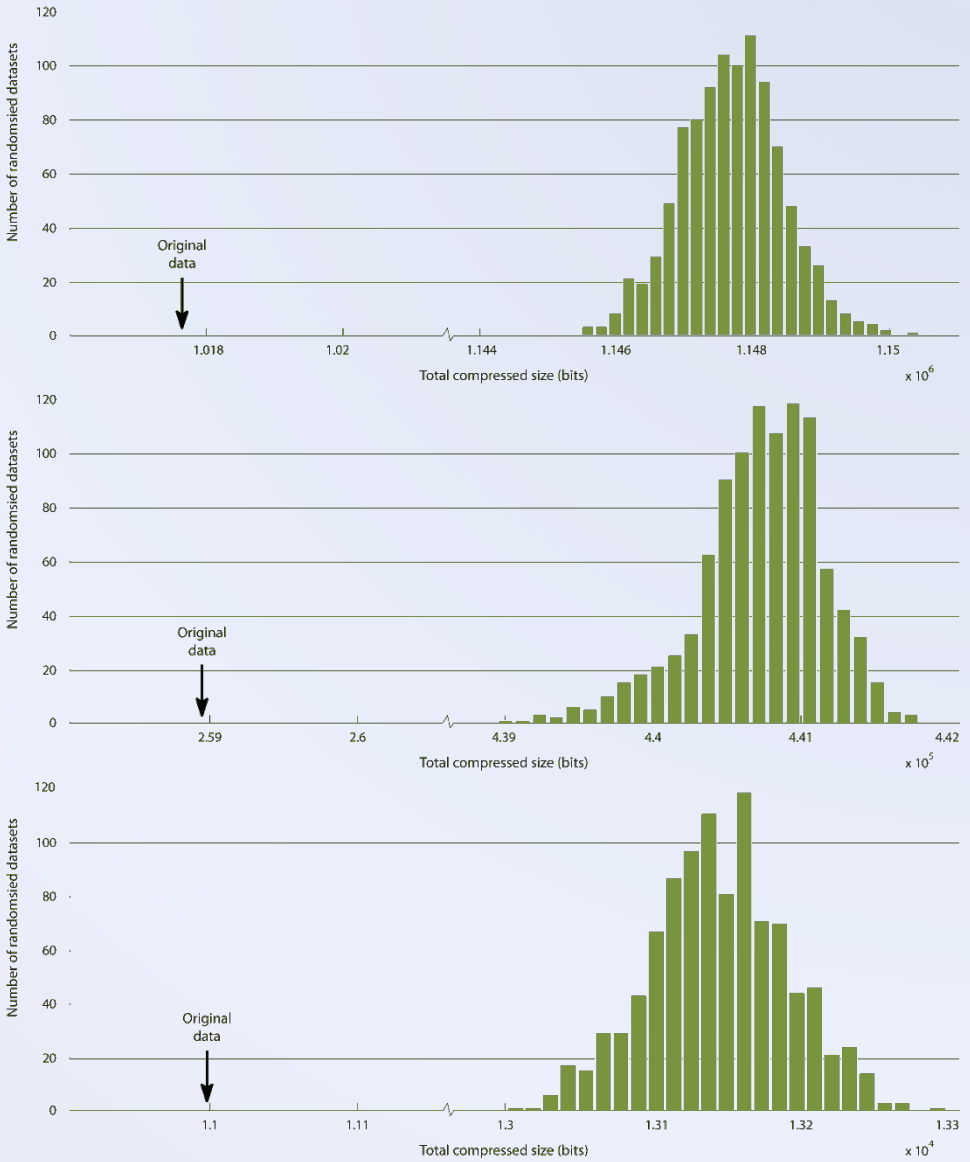
Permutations

How characteristic are our models for our data?

This we can test through permutation testing.

We generate 1000 random datasets of the same row and column margins as D.

We can now determine empirical p-values.



Results on text data

JMLR

support vector machine
machine learning
state [of the] art
data set
Bayesian network

(top-5 from 563)

Pres. Addresses

unit[ed] state[s]
take oath
army navy
under circumst.
econ. public expenditur

(selection from top-25)

(Tatti & Vreeken, KDD'12)

So, are KRIMP code tables good?

At first glance, yes

- the code tables are characteristic in the MDL-sense
  - they compress well
- the code tables are small
  - consist of few patterns
- the code tables are specific
  - contain relatively long itemsets

But, are these patterns useful?

The proof of the pudding

We tested the quality of the KRIMP code tables by

- classification (ECML PKDD'06)
- measuring dissimilarity (KDD'07)
- generating data (ICDM'07)
- concept-drift detection (ECML PKDD'08)
- estimating missing values (ICDM'08)
- clustering (ECML PKDD'09)
- sub-space clustering (CIKM'09)
- one-class classification/anomaly detection (SDM'11, CIKM'12)
- characterising uncertain 0-1 data (SDM'11)
- tag-recommendation (IDA'12)

Conclusions

MDL is great for picking *important* and *useful* patterns

KRIMP approximates the MDL ideal **very well**

- **vast** reduction of the number of itemsets
- works for other pattern types equally well:
  itemsets, sequences, trees, streams, low-entropy sets

Local patterns and information theory

- naturally induce good classifiers, clusterers, distance measures
- with **instant** *characterisation* and *explanation*,
- and, **without** (explicit) parameters

Thank you!

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