BDA 2017

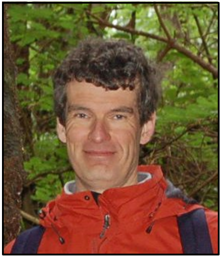
Preference-based Pattern Mining

Bruno Crémilleux, Marc Plantevit, Arnaud Soulet

Nancy, France - November 16, 2017

Introduction

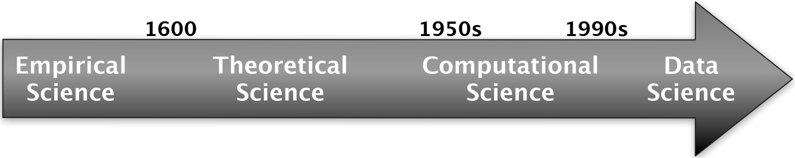
Who are we?

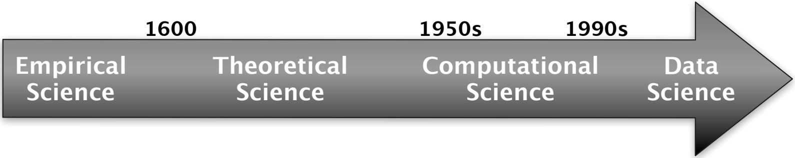
- Bruno Crémilleux, Professor, Univ. Caen, France.
- Marc Plantevit, Associate Professor, Univ. Lyon, France.
- Arnaud Soulet, Associate Professor, Univ. Tours, France.

Material available on `https://goo.gl/85HpNt`

Evolution of Sciences

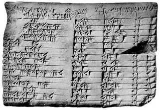


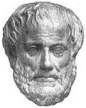
Evolution of Sciences



Before 1600: Empirical Science

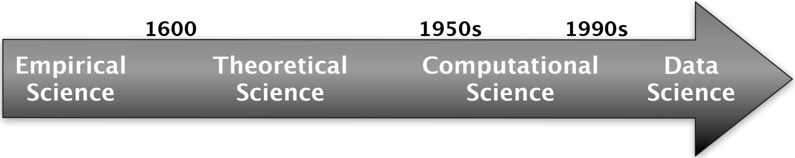
- Babylonian mathematics: 4 basis operations done with tablets and the resolution of practical problems based on words describing all the steps. $\Rightarrow$ able to solve 3-degree equations.
- Ancient Egypt: No theorization of algorithms. Only examples made empirically, certainly repeated by students and scribes. Empirical knowledge transmitted as such and not a rational mathematical science.
- Aristotle also produced many biological writings that were empirical in nature, focusing on biological causation and the diversity of life. He made countless observations of nature, especially the habits and attributes of plants and animals in the world around him, classified more than 540 animal species, and dissected at least 50.
- . . .





Wikipedia

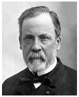
Evolution of Sciences



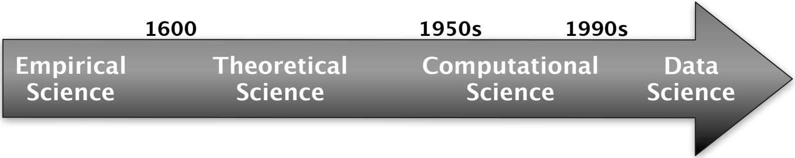
1600-1950s: Theoretical Science

Each discipline has grown a theoretical component. Theoretical models often motivate experiments and generalize our understanding.

- Physics: Newton, Max Planck, Albert Einstein, Niels Bohr, Schrödinger
- Mathematics: Blaise Pascal, Newton, Leibniz, Laplace, Cauchy, Galois, Gauss, Riemann
- Chemistry: R. Boyle, Lavoisier, Dalton, Mendeleev,
- Biology, Medecine, Genetics: Darwin, Mendel, Pasteur

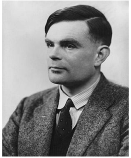
  

Evolution of Sciences

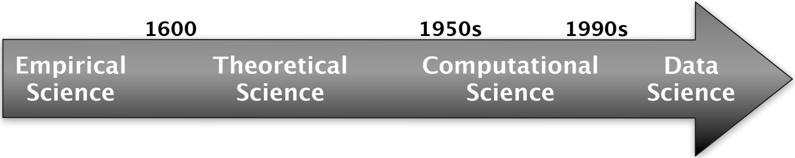


1950s–1990s, Computational Science

- Over the last 50 years, most disciplines have grown a third, computational branch (e.g. empirical, theoretical, and computational ecology, or physics, or linguistics.)
- Computational Science traditionally meant simulation. It grew out of our inability to find closed form solutions for complex mathematical models.



Evolution of Sciences



1990's-now, the Data Science Era

- The flood of data from new scientific instruments and simulations
- The ability to economically store and manage petabytes of data online
- The Internet and computing Grid that makes all these archives universally accessible
- Scientific info. management, acquisition, organization, query, and visualization tasks scale almost linearly with data volumes.

The Fourth Paradigm: Data-Intensive Scientific Discovery

Data mining is a major new challenge!

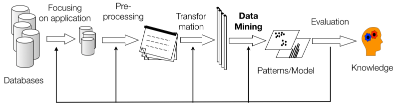
The Fourth Paradigm. Tony Hey, Stewart Tansley, and Kristin Tolle. Microsoft Research, 2009.

(Hey et al. WA09)

Evolution of Database Technology

- 1960s: Data collection, database creation, IMS and network DBMS
- 1970s : Relational data model, relational DBMS implementation
- 1980s: RDBMS, advanced data models (extended-relational, OO, deductive, etc.), application-oriented DBMS (spatial, scientific, engineering, etc.)
- 1990s: Data mining, data warehousing, multimedia databases, and Web databases
- 2000s: Stream data management and mining, Data mining and its applications, Web technology (XML, data integration) and global information systems, NoSQL, NewSQL.

KDD Process



Iterative and Interactive Process

Fayad et al., 1996

Data Mining

- Core of KDD
- Search for knowledge in data

Functionalities

- **Descriptive data mining** vs Predictive data mining
- **Pattern mining**, classification, clustering, regression
- Characterization, discrimination, association, classification, clustering, outlier and trend analysis, etc.

ML versus DM

Predictive (global) modeling

- Turn the data into an as accurate as possible prediction machine.
- Ultimate purpose is **automatization**.
- E.g., autonomously driving a car based on sensor inputs

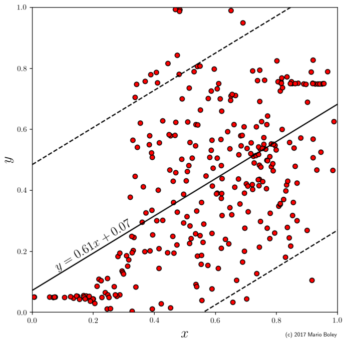
M. Boley www.realkd.org

Exploratory data analysis.

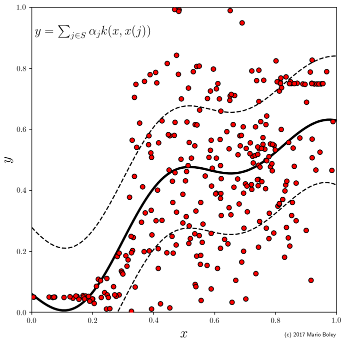
- Automatically discover novel insights about the domain in which the data was measured.
- Use machine discoveries to synergistically **boost** human expertise.
- E.g., understanding commonalities and differences among PET scans of Alzheimers patients.

ML versus DM

"A good prediction machine does not necessarily provide explicit insights into the data domains"

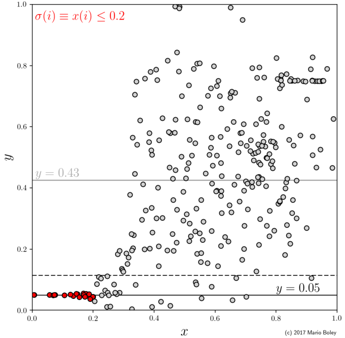


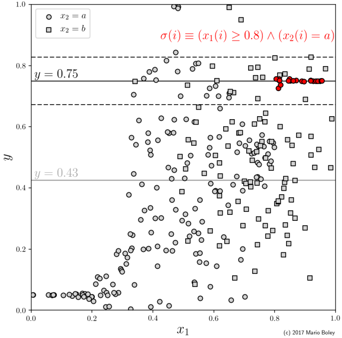
Global linear regression model



Gaussian process model.

"A complex theory of everything might be of less value than a simple observation about a specific part of the data space"

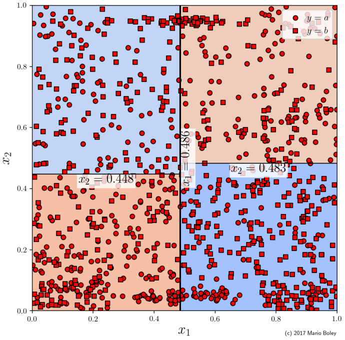


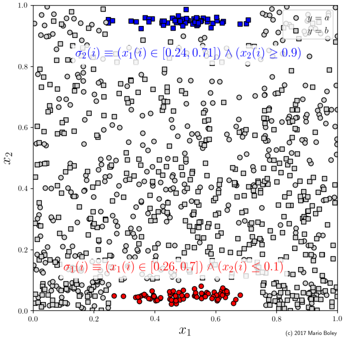


Identifying interesting subspace and the power of saying "I don't know for other points"

ML versus DM

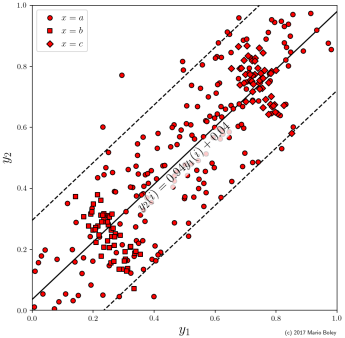
"Subgroups look similar to decision trees but good tree learners are forced to brush over some local structure in favor of the global picture"

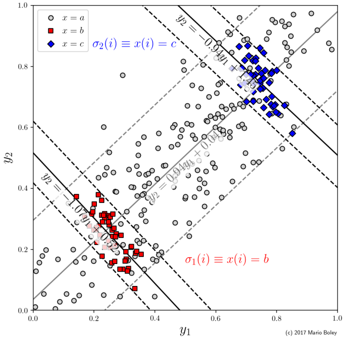




ML versus DM

“Going one step further, we can find local trends that are opposed to the global trend"





Roadmap

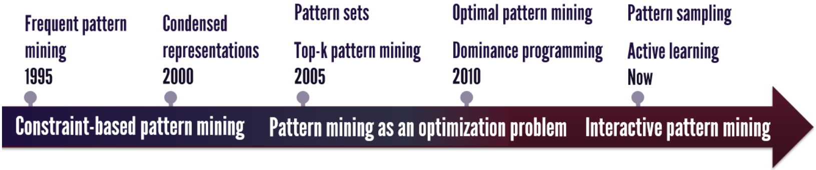
We will focus on **descriptive data mining** especially on Constraint-based Pattern Mining with an **inductive database vision**.

$$Th(\mathcal{L}, \mathcal{D}, \mathcal{C}) = \{\psi \in \mathcal{L} \mid \mathcal{C}(\psi, \mathcal{D}) \text{ is true}\}$$

- Pattern domain: itemset, sequences, graphs, dynamic graphs, etc.
- Constraints (frequency, area, statistical relevancy, cliqueness, etc.): How to efficiently push them?

Imielinski and Mannila: Communications of the ACM (1996).

Roadmap



How have we moved from (only) frequent pattern discovery to interactive pattern mining?
How have we moved from the retrieval era to the exploratory analysis era?

Roadmap

- A very short view on the constraint-based pattern mining toolbox and its limitation 
  - Claim #1: this is not a tutorial on constraint-based pattern mining!

Roadmap

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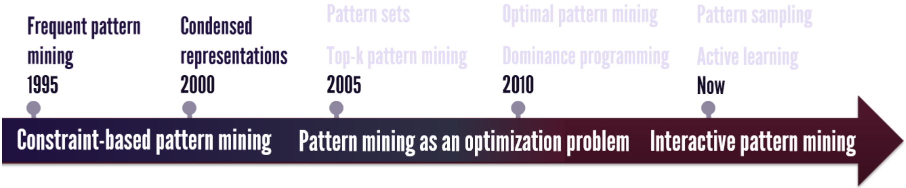
  - Claim #1: this is not a tutorial on constraint-based pattern mining!
- Pattern mining as an optimization problem based on user's preferences: 
  - From all solutions to the optimal ones (top k, skyline, pattern set, etc.).
  - Claim #2: this is not a tutorial on preference learning!

Roadmap

- A very short view on the constraint-based pattern mining toolbox and its limitation 
  - Claim #1: this is not a tutorial on constraint-based pattern mining!
- Pattern mining as an optimization problem based on user's preferences: 
  - From all solutions to the optimal ones (top k, skyline, pattern set, etc.).
  - Claim #2: this is not a tutorial on preference learning!
- Interactive pattern mining: 
  - Dealing with implicit user's preferences.
  - How to ensure interactivity (instant mining, pattern space sampling)
  - Forgetting the completeness of the extraction.
  - Claim #3: this is not a tutorial on preference learning either!

- We have done some enlightenment choices.
  - Linearisation of the pattern mining research history.
- We are not exhaustive !
  - Feel free to mention us some important papers that are missing.
- Most of the examples will consider the itemsets as pattern language.
  - It is the simplest to convey the main ideas and intuitions.
- Feel free to interrupt us at any time if you have some questions.



Constraint-based pattern mining:

the toolbox and its limits

➥ the need of preferences in pattern mining

Itemset: definition

Definition

Given a set of attributes $\mathcal{A}$, an itemset X is a subset of attributes, i. e., $X \subseteq \mathcal{A}$.

Input:

$$\begin{array}{c|cccc} & a_1 & a_2 & \dots & a_n \\ \hline o_1 & d_{1,1} & d_{1,2} & \dots & d_{1,n} \\ o_2 & d_{2,1} & d_{2,2} & \dots & d_{2,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ o_m & d_{m,1} & d_{m,2} & \dots & d_{m,n} \end{array}$$

where $d_{i,j} \in \{\text{true,false}\}$

Question

How many itemsets are there?
$2^{|\mathcal{A}|}$.

Transactional representation of the data

Relational representation: $\mathcal{D} \subseteq \mathcal{O} \times \mathcal{A}$

$$\begin{array}{c|cccc}
 & a_1 & a_2 & \dots & a_n \\
\hline
o_1 & d_{1,1} & d_{1,2} & \dots & d_{1,n} \\
o_2 & d_{2,1} & d_{2,2} & \dots & d_{2,n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
o_m & d_{m,1} & d_{m,2} & \dots & d_{m,n}
\end{array}$$

where $d_{i,j} \in \{\text{true,false}\}$

Transactional representation: $\mathcal{D}$ is an array of subsets of $\mathcal{A}$

$$\begin{array}{c}
t_1 \\
t_2 \\
\vdots \\
t_m
\end{array}$$

where $t_i \subseteq \mathcal{A}$

Example

	a_1	a_2	a_3
o_1	×	×	×
o_2	×	×	
o_3		×	
o_4			×

t_1	a_1, a_2, a_3
t_2	a_1, a_2
t_3	a_2
t_4	a_3

Frequency: definition

Definition (absolute frequency)

Given the objects in $\mathcal{O}$ described with the Boolean attributes in $\mathcal{A}$, the absolute frequency of an itemset $X \subseteq \mathcal{A}$ in the dataset $\mathcal{D} \subseteq \mathcal{O} \times \mathcal{A}$ is $|\{o \in \mathcal{O} \mid \{o\} \times X \subseteq \mathcal{D}\}|$.

Definition (relative frequency)

Given the objects in $\mathcal{O}$ described with the Boolean attributes in $\mathcal{A}$, the relative frequency of an itemset $X \subseteq \mathcal{A}$ in the dataset $\mathcal{D} \subseteq \mathcal{O} \times \mathcal{A}$ is $\frac{|\{o \in \mathcal{O} \mid \{o\} \times X \subseteq \mathcal{D}\}|}{|\mathcal{O}|}$.

The relative frequency is a joint probability.

Frequent itemset mining

Problem Definition

Given the objects in $\mathcal{O}$ described with the Boolean attributes in $\mathcal{A}$, listing every itemset having a frequency above a given threshold $\mu \in \mathbb{N}$.

Input:

$$
\begin{array}{c|cccc}
 & a_1 & a_2 & \dots & a_n \\
\hline
o_1 & d_{1,1} & d_{1,2} & \dots & d_{1,n} \\
o_2 & d_{2,1} & d_{2,2} & \dots & d_{2,n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
o_m & d_{m,1} & d_{m,2} & \dots & d_{m,n}
\end{array}
$$

and a minimal frequency $\mu \in \mathbb{N}$.

where $d_{i,j} \in \{\text{true,false}\}$

R. Agrawal; T. Imielinski; A. Swami: Mining Association Rules Between Sets of Items in Large Databases, SIGMOD, 1993.

Frequent itemset mining

Problem Definition

Given the objects in $\mathcal{O}$ described with the Boolean attributes in $\mathcal{A}$, listing every itemset having a frequency above a given threshold $\mu \in \mathbb{N}$.

Output: every $X \subseteq \mathcal{A}$ such that there are at least μ objects having all attributes in X.

R. Agrawal; T. Imielinski; A. Swami: Mining Association Rules Between Sets of Items in Large Databases, SIGMOD, 1993.

Frequent itemset mining: illustration

Specifying a minimal absolute frequency $\mu = 2$ objects (or, equivalently, a minimal relative frequency of 50%).

	a_1	a_2	a_3
o_1	$\times$	$\times$	$\times$
o_2	$\times$	$\times$	
o_3		$\times$	
o_4			$\times$

Frequent itemset mining: illustration

Specifying a minimal absolute frequency $\mu = 2$ objects (or, equivalently, a minimal relative frequency of 50%).

	a_1	a_2	a_3
o_1	×	×	×
o_2	×	×	
o_3		×	
o_4			×

The frequent itemsets are: $\emptyset$ (4), $\{a_1\}$ (2), $\{a_2\}$ (3), $\{a_3\}$ (2) and $\{a_1, a_2\}$ (2).

Inductive database vision

Querying data:

$$\{d \in \mathcal{D} \mid q(d, \mathcal{D})\}$$

where:

- $\mathcal{D}$ is a dataset (tuples),
- q is a query.

Inductive database vision

Querying patterns:

$$\{X \in P \mid \mathcal{Q}(X, \mathcal{D})\}$$

where:

- $\mathcal{D}$ is the dataset,
- P is the pattern space,
- $\mathcal{Q}$ is an inductive query.

Inductive database vision

Querying the frequent itemsets:

$$\{X \in P \mid \mathcal{Q}(X, \mathcal{D})\}$$

where:

- $\mathcal{D}$ is the dataset,
- P is the pattern space,
- $\mathcal{Q}$ is an inductive query.

Inductive database vision

Querying the frequent itemsets:

$$\{X \in P \mid \mathcal{Q}(X, \mathcal{D})\}$$

where:

- $\mathcal{D}$ is a subset of $\mathcal{O} \times \mathcal{A}$, i. e., objects described with Boolean attributes,
- P is the pattern space,
- $\mathcal{Q}$ is an inductive query.

Inductive database vision

Querying the frequent itemsets:

$$\{X \in P \mid \mathcal{Q}(X, \mathcal{D})\}$$

where:

- $\mathcal{D}$ is a subset of $\mathcal{O} \times \mathcal{A}$, i. e., objects described with Boolean attributes,
- P is $2^{\mathcal{A}}$,
- $\mathcal{Q}$ is an inductive query.

Inductive database vision

Querying the frequent itemsets:

$$\{X \in P \mid \mathcal{Q}(X, \mathcal{D})\}$$

where:

- $\mathcal{D}$ is a subset of $\mathcal{O} \times \mathcal{A}$, i. e., objects described with Boolean attributes,
- P is $2^{\mathcal{A}}$,
- $\mathcal{Q}$ is $(X, \mathcal{D}) \mapsto |\{o \in \mathcal{O} \mid \{o\} \times X \subseteq \mathcal{D}\}| \geq \mu$.

Inductive database vision

Querying the frequent itemsets:

$$\{X \in P \mid \mathcal{Q}(X, \mathcal{D})\}$$

where:

- $\mathcal{D}$ is a subset of $\mathcal{O} \times \mathcal{A}$, i. e., objects described with Boolean attributes,
- P is $2^{\mathcal{A}}$,
- $\mathcal{Q}$ is $(X, \mathcal{D}) \mapsto f(X, \mathcal{D}) \geq \mu$.

Inductive database vision

Querying the frequent itemsets:

$$\{X \in P \mid \mathcal{Q}(X, \mathcal{D})\}$$

where:

- $\mathcal{D}$ is a subset of $\mathcal{O} \times \mathcal{A}$, i. e., objects described with Boolean attributes,
- P is $2^{\mathcal{A}}$,
- $\mathcal{Q}$ is $(X, \mathcal{D}) \mapsto f(X, \mathcal{D}) \geq \mu$.

Listing the frequent itemsets is NP-hard.

Pattern flooding

$\mu = 2$

$\mathcal{O}$	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}
o_1	×	×	×	×	×										
o_2	×	×	×	×	×										
o_3	×	×	×	×	×										
o_4						×	×	×	×	×					
o_5						×	×	×	×	×					
o_6						×	×	×	×	×					
o_7											×	×	×	×	×
o_8											×	×	×	×	×

- How many frequent patterns?

Pattern flooding

$\mu = 2$

$\mathcal{O}$	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}
o_1	×	×	×	×	×										
o_2	×	×	×	×	×										
o_3	×	×	×	×	×										
o_4						×	×	×	×	×					
o_5						×	×	×	×	×					
o_6						×	×	×	×	×					
o_7											×	×	×	×	×
o_8											×	×	×	×	×

- How many frequent patterns? $1 + (2^5 - 1) \times 3 = 94$ patterns

Pattern flooding

$\mu = 2$

$\mathcal{O}$	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}
o_1	×	×	×	×	×										
o_2	×	×	×	×	×										
o_3	×	×	×	×	×										
o_4						×	×	×	×	×					
o_5						×	×	×	×	×					
o_6						×	×	×	×	×					
o_7											×	×	×	×	×
o_8											×	×	×	×	×

- How many frequent patterns? $1 + (2^5 - 1) \times 3 = 94$ patterns but actually 4 (potentially) interesting ones: $\{\}, \{a_1, a_2, a_3, a_4, a_5\}, \{a_6, a_7, a_8, a_9, a_{10}\}, \{a_{11}, a_{12}, a_{13}, a_{14}, a_{15}\}$.

Pattern flooding

$\mu = 2$

$\mathcal{O}$	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}
o_1	×	×	×	×	×										
o_2	×	×	×	×	×										
o_3	×	×	×	×	×										
o_4						×	×	×	×	×					
o_5						×	×	×	×	×					
o_6						×	×	×	×	×					
o_7											×	×	×	×	×
o_8											×	×	×	×	×

- How many frequent patterns? $1 + (2^5 - 1) \times 3 = 94$ patterns but actually 4 (potentially) interesting ones: $\{\}, \{a_1, a_2, a_3, a_4, a_5\}, \{a_6, a_7, a_8, a_9, a_{10}\}, \{a_{11}, a_{12}, a_{13}, a_{14}, a_{15}\}$.

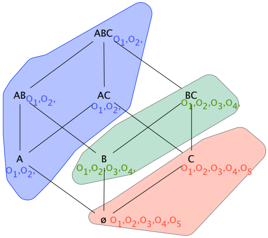
☞ the need to focus on a **condensed representation** of frequent patterns.

Toon Calders, Christophe Rigotti, Jean-François Boulicaut: A Survey on Condensed Representations for Frequent Sets. Constraint-Based Mining and Inductive Databases 2004: 64-80.

Closed and Free Patterns

Equivalence classes based on support.

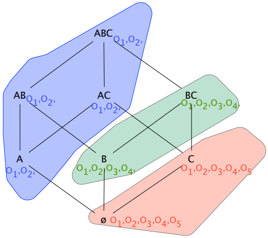
$\mathcal{O}$	A	B	C
o_1	×	×	×
o_2	×	×	×
o_3		×	×
o_4		×	×
o_5			×



Closed and Free Patterns

Equivalence classes based on support.

$\mathcal{O}$	A	B	C
o_1	×	×	×
o_2	×	×	×
o_3		×	×
o_4		×	×
o_5			×

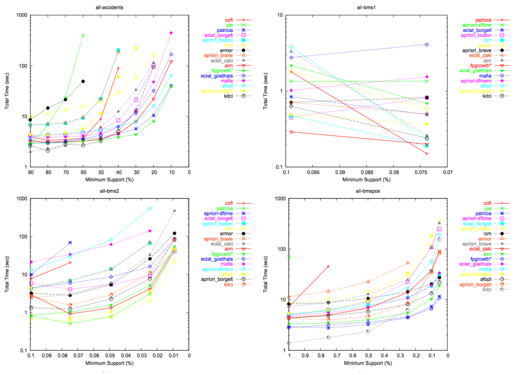


- **Closed** patterns are maximal element of each equivalence class (Bastide et al., SIGKDD Exp. 2000): ABC, BC, and C.
- **Generators** or **Free** patterns are minimal elements (not necessary unique) of each equivalent class (Boulicaut et al, DAMI 2003): $\{\}$, A and B

A strong intersection with Formal Concept Analysis (Ganter and Wille, 1999).

Few researchers (in DM) are aware about this strong intersection.

- transactional DB $\equiv$ **formal context** is a triple $K = (G, M, I)$, where G is a set of objects, M is a set of attributes, and $I \subseteq G \times M$ is a binary relation called incidence that expresses which objects have which attributes.
- closed itemset $\equiv$ **concept intent**
- FCA gives the mathematical background about closed patterns.
- Algorithms: **LCM** is an efficient implementation of **Close By One.** (Sergei O. Kuznetsov, 1993).



(FIMI Workshop@ICDM, 2003 and 2004)

The FIM Era: during more than a decade, only ms were worth it!
Even if the complete collection of frequent itemsets is known useless, the main objective of many algorithms is to earn ms according to their competitors!!
What about the end-user (and the pattern interestingness)?
➜ partially answered with constraints.

Pattern constraints

Constraints are needed for:

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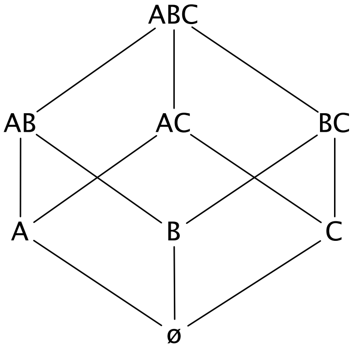
Constraint properties are used to infer constraint values on (many) patterns without having to evaluate them individually.

➜ They are defined up to the partial order $\preceq$ used for listing the patterns

Search space traversal

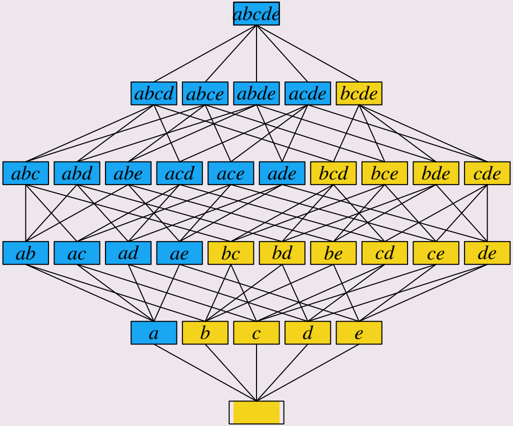


Levelwise enumeration vs depth-first enumeration.

Whatever the enumeration principles, we have to derive some pruning properties from the constraints.

Enumeration strategy

Binary partition: the element 'a' is enumerated



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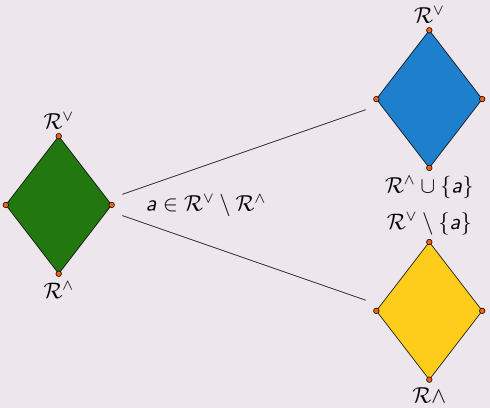


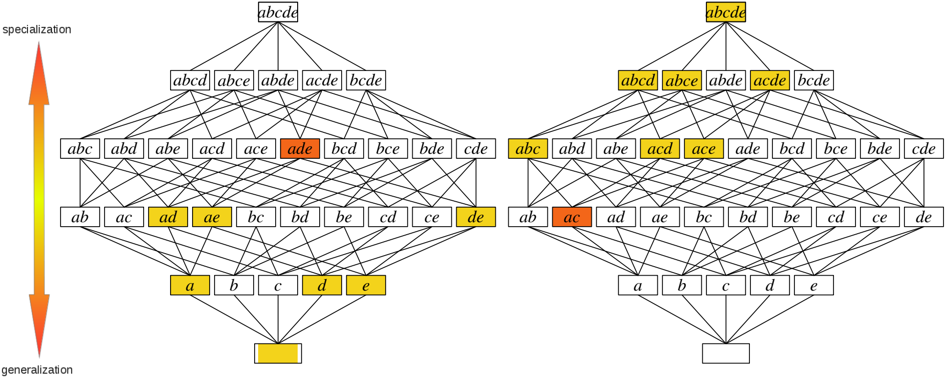
(Anti-)Monotone Constraints

Monotone constraint

$\forall \varphi_1 \preceq \varphi_2, \mathcal{C}(\varphi_1, \mathcal{D}) \Rightarrow \mathcal{C}(\varphi_2, \mathcal{D})$

Anti-monotone constraint

$\forall \varphi_1 \preceq \varphi_2, \mathcal{C}(\varphi_2, \mathcal{D}) \Rightarrow \mathcal{C}(\varphi_1, \mathcal{D})$

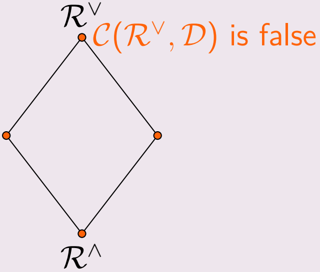


$\mathcal{C}(\varphi, \mathcal{D}) \equiv b \in \varphi \vee c \in \varphi$

$\mathcal{C}(\varphi, \mathcal{D}) \equiv a \notin \varphi \wedge c \notin \varphi$

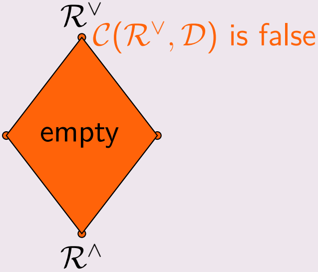
Constraint evaluation

Monotone constraint



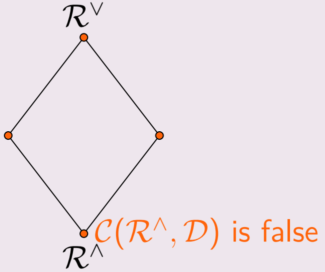
Constraint evaluation

Monotone constraint



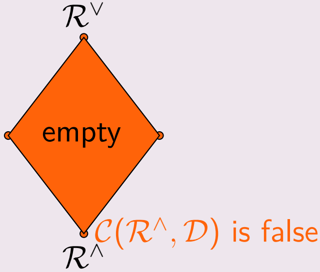
Constraint evaluation

Anti-monotone constraint



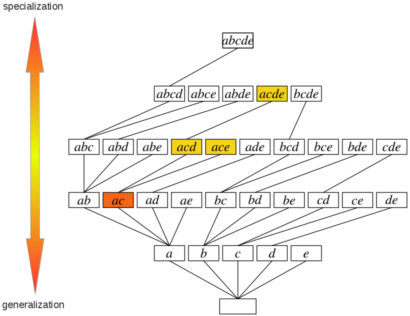
Constraint evaluation

Anti-monotone constraint



Convertible constraints (Pei et al., DAMI 2004)

$\preceq$ is extended to the prefix order $\leq$ so that $\forall \varphi_1 \leq \varphi_2$, $\mathcal{C}(\varphi_2, \mathcal{D}) \Rightarrow \mathcal{C}(\varphi_1, \mathcal{D})$

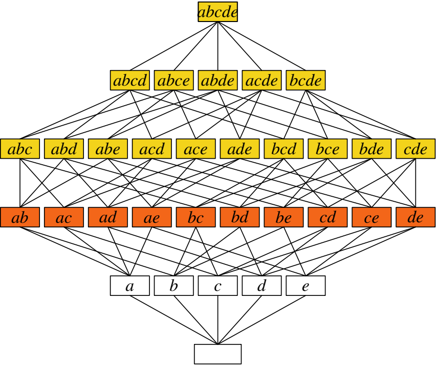


$$\mathcal{C}(\varphi, w) \equiv \text{avg}(w(\varphi)) > \sigma$$
$$w(a) \geq w(b) \geq w(c) \geq w(d) \geq w(e)$$

Loose AM Constraints

Loose AM constraints

$\mathcal{C}(\varphi, \mathcal{D}) \Rightarrow \exists e \in \varphi \ : \ \mathcal{C}(\varphi \setminus \{e\}, \mathcal{D})$



$$\mathcal{C}(\varphi, w) \equiv \mathrm{var}(w(\varphi)) \leq \sigma$$

Bonchi and Lucchese – DKE 2007

Uno, ISAAC07

Examples

$v \in P$	M
$P \supseteq S$	M
$P \subseteq S$	AM
$min(P) \leq \sigma$	AM
$min(P) \geq \sigma$	M
$max(P) \leq \sigma$	M
$max(P) \leq \sigma$	AM
$range(P) \leq \sigma$	AM
$range(P) \geq \sigma$	M
$avg(P)\theta\sigma, \theta \in \{\leq, =, \geq\}$	Convertible
$\text{var}(w(\varphi)) \leq \sigma$	LAM

A larger class of constraints

Some constraints can be decomposed into several pieces that are either monotone or anti-monotone.

- Piecewise monotone and anti-monotone constraints
  L. Cerf, J. Besson, C. Robardet, J-F. Boulicaut: Closed patterns meet n-ary relations. TKDD 3(1) (2009)
- Primitive-based constraints
  A.Soulet, B. Crémilleux: Mining constraint-based patterns using automatic relaxation. Intell. Data Anal. 13(1): 109-133 (2009)
- Projection-antimonotonicity
  A. Buzmakov, S. O. Kuznetsov, A.Napoli: Fast Generation of Best Interval Patterns for Nonmonotonic Constraints. ECML/PKDD (2) 2015: 157-172

An example

- $\forall e,\ w(e) \geq 0$
- $\mathcal{C}(\varphi, w) \equiv \text{avg}(w(\varphi)) > \sigma \equiv \frac{\sum_{e \in \varphi} w(e)}{|\varphi|} > \sigma$.

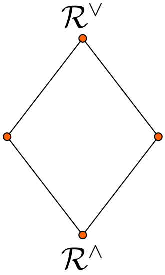
$\mathcal{C}(\varphi, \mathcal{D})$ is piecewise monotone and anti-monotone with

$$f(\varphi_1, \varphi_2, \mathcal{D}) = \frac{\sum_{e \in \varphi_1} w(e)}{|\varphi_2|}$$

$\forall x \preceq y$,

- $f_{1,\varphi}$ is monotone: $f(x, \varphi_2, \mathcal{D}) = \frac{\sum_{e \in x} w(e)}{|\varphi_2|} > \sigma \Rightarrow \frac{\sum_{e \in y} w(e)}{|\varphi_2|} > \sigma$
- $f_{2,\varphi}$ is anti-monotone:
  $f(\varphi_1, y, \mathcal{D}) = \frac{\sum_{e \in \varphi_1} w(e)}{|y|} > \sigma \Rightarrow \frac{\sum_{e \in \varphi_1} w(e)}{|x|} > \sigma$

Piecewise constraint exploitation



Evaluation

If $f(\mathcal{R}^\vee, \mathcal{R}^\wedge, \mathcal{D}) = \frac{\sum_{e \in \mathcal{R}^\vee} w(e)}{|\mathcal{R}^\wedge|}$

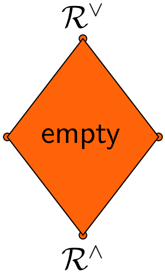
Propagation

- $\exists e \in \mathcal{R}^\vee \setminus \mathcal{R}^\wedge$ such that $f(\mathcal{R}^\vee \setminus \{e\}, \mathcal{R}^\wedge, \mathcal{D}) \leq \sigma$, then e is moved in $\mathcal{R}^\wedge$
- $\exists e \in \mathcal{R}^\vee \setminus \mathcal{R}^\wedge$ such that $f(\mathcal{R}^\vee, \mathcal{R}^\wedge \cup \{e\}, \mathcal{D}) \leq \sigma$, then e is removed from $\mathcal{R}^\vee$

Piecewise constraint exploitation

Evaluation

If $f(\mathcal{R}^\vee, \mathcal{R}^\wedge, \mathcal{D}) = \frac{\sum_{e \in \mathcal{R}^\vee} w(e)}{|\mathcal{R}^\wedge|} \leq \sigma$ then $\mathcal{R}$ is empty.



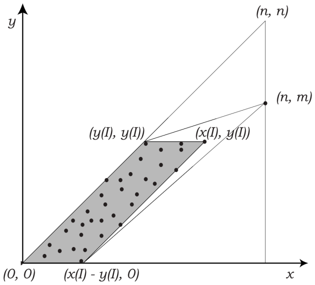
Propagation

- $\exists e \in \mathcal{R}^\vee \setminus \mathcal{R}^\wedge$ such that $f(\mathcal{R}^\vee \setminus \{e\}, \mathcal{R}^\wedge, \mathcal{D}) \leq \sigma$, then e is moved in $\mathcal{R}^\wedge$
- $\exists e \in \mathcal{R}^\vee \setminus \mathcal{R}^\wedge$ such that $f(\mathcal{R}^\vee, \mathcal{R}^\wedge \cup \{e\}, \mathcal{D}) \leq \sigma$, then e is removed from $\mathcal{R}^\vee$

Tight Upper-bound computation

- Convex measures can be taken into account by computing some upper bounds with $\mathcal{R}^{\wedge}$ and $\mathcal{R}^{\vee}$.
- Branch and bound enumeration

Shinichi Morishita, Jun Sese: Traversing Itemset Lattice with Statistical Metric Pruning. PODS 2000: 226-236



Studying constraints $\equiv$ looking for efficient and effective upper bound in a branch and bound algorithm !

Toward declarativity

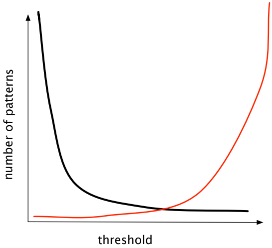
Why declarative approaches?

- for each problem, do not write a solution from scratch

Declarative approaches:

- CP approaches (Khiari et al., CP10, Guns et al., TKDE 2013)
- SAT approaches (Boudane et al., IJCAI16, Jabbour et al., CIKM13)
- ILP approaches (Mueller et al, DS10, Babaki et al., CPAIOR14, Ouali et al. IJCAI16)
- ASP approaches (Gebser et al., IJCAI16)

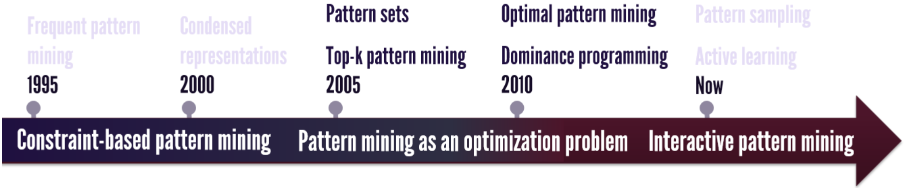
Thresholding problem



- A too stringent threshold: trivial patterns
- A too weak threshold: too many patterns, unmanageable and diversity not necessary assured.
- Some attempts to tackle this issue:
  - Interestingness is not a dichotomy! [BB05]
  - Taking benefit from hierarchical relationships [HF99, DPRB14]
- But setting thresholds remains an issue in pattern mining.

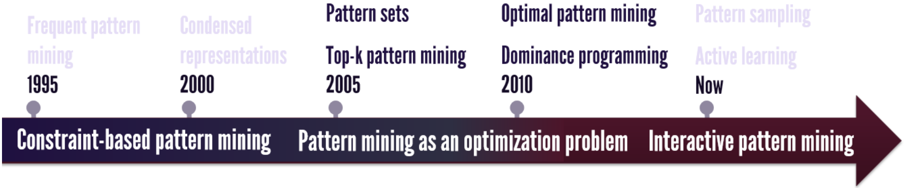
Constraint-based pattern mining: concluding remarks

- how to fix thresholds?
- how to handle numerous patterns including non-informative patterns? how to get a global picture of the set of patterns?
- how to design the proper constraints/preferences?



Pattern mining as an optimization problem

Pattern mining as an optimization problem



- performance issue
- the more, the better
- data-driven

- quality issue
- the less, the better
- user-driven

In this part:

- preferences to express user's interests
- focusing on the best patterns:
  dominance relation, optimal pattern sets, subjective interest

Addressing pattern mining tasks with user preferences

Idea: a preference expresses a user's interest (no required threshold)

Examples based on measures/dominance relation:

- *"the higher the frequency, growth rate and aromaticity are, the better the patterns"*
- *"I prefer pattern X_1 to pattern X_2 if X_1 is not dominated by X_2 according to a set of measures"*

➥ measures/preferences: a natural criterion for ranking patterns and presenting the "best" patterns

Preference-based approaches in this tutorial

- **in this part**: preferences are explicit (typically given by the user depending on his/her interest/subjectivity)

  in the last part: preferences are implicit

- *quantitative/qualitative preferences:*
  - **quantitative:**

$$measures \begin{cases} \textit{constraint-based data mining}: \textit{frequency}, \textit{size}, \ldots \\ \textit{background knowledge}: \textit{price}, \textit{weight}, \textit{aromaticity}, \ldots \\ \textit{statistics}: \textit{entropy}, \textit{pvalue}, \ldots \end{cases}$$

  - **qualitative:** "I prefer pattern X_1 to pattern X_2" (pairwise comparison between patterns).

    With qualitative preferences: two patterns can be incomparable.

Measures

Many works on:

- interestingness measures (Geng et al. ACM Computing Surveys06)
- utility functions (Yao and Hamilton DKE06)
- statistically significant rules (Hämäläinen and Nykänen ICDM08)

Examples:

- $area(X) = frequency(X) \times size(X)$ (tiling: surface)
- $lift(X_1 \rightarrow X_2) = \frac{\mathcal{D} \times frequency(X_1 X_2)}{frequency(X_2) \times frequency(X_1)}$
- *utility functions:* utility of the mined patterns (e.g. weighted items, weighted transactions).
  An example: No of Product $\times$ Product profit

Putting the pattern mining task to an optimization problem

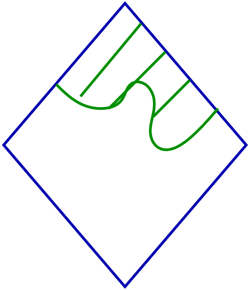
The most interesting patterns according to measures/preferences:

- **free/closed patterns** (Boulicaut et al. DAMI03, Bastide et al. SIGKDD Explorations00)
  ➥ given an equivalent class, I prefer the shortest/longest patterns
- **one measure**: top-k patterns (Fu et al. Ismis00, Jabbour et al. ECML/PKDD13)
- **several measures**: how to find a trade-off between several criteria?
  ➥ skyline patterns (Cho et al. IJDWM05, Soulet et al. ICDM'11, van Leeuwen and Ukkonen ECML/PKDD13)
- **dominance programming** (Negrevergne et al. ICDM13), **optimal patterns** (Ugarte et al. ICTAI15)
- **subjective interest/interest according to a background knowledge** (De Bie DAMI2011)

top-k pattern mining: an example

Goal: finding the k patterns maximizing an interestingness measure.

Tid	Items					
t_1		B			E	F
t_2		B	C	D		
t_3	A				E	F
t_4	A	B	C	D	E	
t_5		B	C	D	E	
t_6		B	C	D	E	F
t_7	A	B	C	D	E	F



- the 3 most frequent patterns: B, E, BE[a]

  ➥ easy due to the anti-monotone property of frequency

[a] Other patterns have a frequency of 5: C, D, BC, BD, CD, BCD

top-k pattern mining: an example

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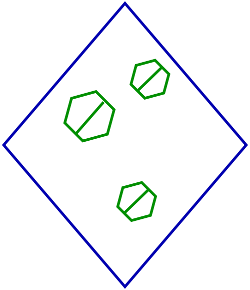


- the 3 most frequent patterns: *B*, *E*, *BE*[a]
  ➥ easy due to the anti-monotone property of frequency
- the 3 patterns maximizing area: *BCDE*, *BCD*, *CDE*
  ➥ branch & bound
  (Zimmermann and De Raedt MLJ09)

[a] Other patterns have a frequency of 5: *C*, *D*, *BC*, *BD*, *CD*, *BCD*

top-k pattern mining
an example of pruning condition

top-k patterns according to *area*, $k = 3$

Tid	Items					
t_1		B			E	F
t_2		B	C	D		
t_3	A				E	F
t_4	A	B	C	D	E	
t_5		B	C	D	E	
t_6		B	C	D	E	F
t_7	A	B	C	D	E	F

Principle:

- $\mathcal{C}and$: the current set of the k best candidate patterns
- when a candidate pattern is inserted in $\mathcal{C}and$, a more efficient pruning condition is deduced

A: lowest value of *area* for the patterns in $\mathcal{C}and$

L: size of the longest transaction in $\mathcal{D}$ (here: $L = 6$)

a pattern X must satisfy $frequency(X) \geq \frac{A}{L}$ to be inserted in $\mathcal{C}and$

➥ pruning condition according to the frequency (thus anti-monotone)

Example with a depth first search approach:

- initialization: $\mathcal{C}and = \{B, BE, BEC\}$
  ($area(BEC) = 12$, $area(BE) = 10$, $area(B) = 6$)
  ➥ $frequency(X) \geq \frac{6}{6}$
- new candidate *BECD*: $\mathcal{C}and = \{BE, BEC, BECD\}$
  ($area(BECD) = 16$, $area(BEC) = 12$, $area(BE) = 10$)
  ➥ $frequency(X) \geq \frac{10}{6}$ which is more efficient than $frequency(X) \geq \frac{6}{6}$
- new candidate *BECDF*...

top-k pattern mining in a nutshell

Advantages:

- compact
- threshold free
- best patterns

Drawbacks:

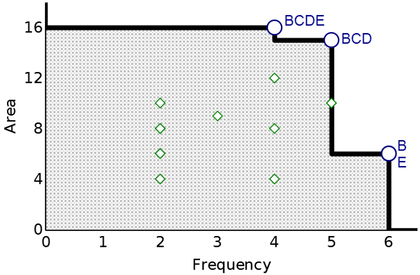
- complete resolution is costly, sometimes heuristic search (beam search)
  (van Leeuwen and Knobbe DAMI12)
- diversity issue: top-k patterns are often very similar
- several criteria must be aggregated
  ➥ skylines patterns: a trade-off between several criteria

Skypatterns (Pareto dominance)

Notion of skylines (database) in pattern mining (Cho at al. IJDWM05, Papadopoulos et al. DAMI08, Soulet et al. ICDM11, van Leeuwen and Ukkonen ECML/PKDD13)

Tid	Items					
t_1		B			E	F
t_2		B	C	D		
t_3	A				E	F
t_4	A	B	C	D	E	
t_5		B	C	D	E	
t_6		B	C	D	E	F
t_7	A	B	C	D	E	F

Patterns	freq	area
~~*AB*~~	2	4
~~*AEF*~~	2	6
B	6	6
BCDE	4	16
~~*CDEF*~~	2	8
E	6	6
⋮	⋮	⋮



$|\mathcal{L}_{\mathcal{I}}| = 2^6$, but only 4 skypatterns

$Sky(\mathcal{L}_{\mathcal{I}}, \{freq, area\}) = \{BCDE, BCD, B, E\}$

Skylines vs skypatterns

Problem	Skylines	Skypatterns
Mining task	a set of non dominated transactions	a set of non dominated patterns
Size of the space search	$\mid \mathcal{D} \mid$	$\mid \mathcal{L} \mid$
domain	a lot of works	very few works

usually: $\mid \mathcal{D} \mid << \mid \mathcal{L} \mid$

$\mathcal{D}$	set of transactions
$\mathcal{L}$	set of patterns

Skypatterns: how to process?

A naive enumeration of all candidate patterns ($\mathcal{L}_\mathcal{I}$) and then comparing them is not feasible...

Two approaches:

1. take benefit from the pattern condensed representation according to the condensable measures of the given set of measures M
   - skylineability to obtain M' ($M' \subseteq M$) giving a more concise pattern condensed representation
   - the pattern condensed representation w.r.t. M' is a superset of the representative skypatterns w.r.t. M which is (much smaller) than $\mathcal{L}_\mathcal{I}$.

2. use of the dominance programming framework (together with skylineability)

Dominance programming

Dominance: a pattern is optimal if it is not dominated by another.
Skypatterns: dominance relation = Pareto dominance

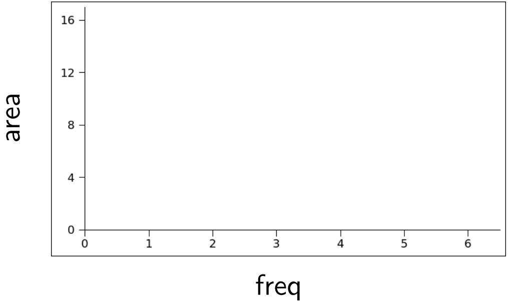
1. **Principle:**
   - starting from an initial pattern s_1
   - searching for a pattern s_2 such that s_1 is not preferred to s_2
   - searching for a pattern s_3 such that s_1 and s_2 are not preferred to s_3

     ⋮
   - until there is no pattern satisfying the whole set of constraints
2. **Solving:**
   - constraints are dynamically posted during the mining step

Principle: increasingly reduce the dominance area by processing pairwise comparisons between patterns. Methods using Dynamic CSP (Negrevergne et al. ICDM13, Ugarte et al. CPAIOR14, AIJ 2017).

Dominance programming: example of the skypatterns

Trans.	Items					
t_1		B			E	F
t_2		B	C	D		
t_3	A				E	F
t_4	A	B	C	D	E	
t_5		B	C	D	E	
t_6		B	C	D	E	F
t_7	A	B	C	D	E	F



$$M = \{freq, area\}$$

$$q(X) \equiv closed_{M'}(X)$$

$$Candidates =$$

Dominance programming: example of the skypatterns

Trans.	Items					
t_1		B			E	F
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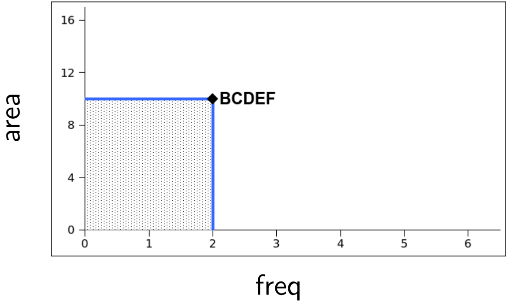

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Dominance programming: example of the skypatterns

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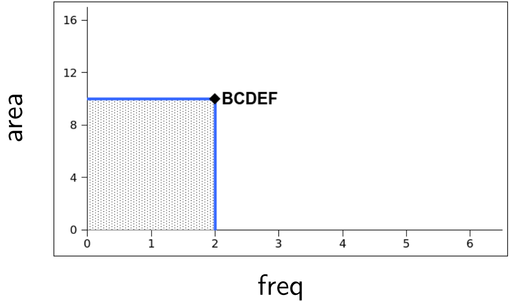

$$M = \{freq, area\}$$

$$q(X) \equiv closed_{M'}(X) \wedge \neg(s_1 \succ_M X)$$

$$Candidates = \{\underbrace{\text{BCDEF}}_{s_1},$$

Dominance programming: example of the skypatterns

Trans.	Items					
t_1		B			E	F
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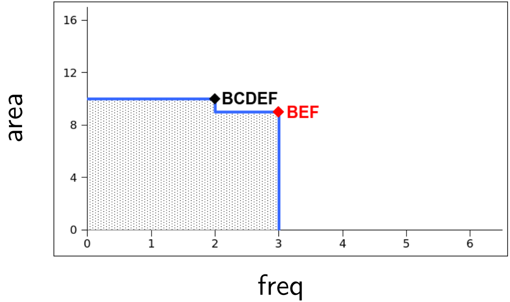

$$M = \{freq, area\}$$

$$q(X) \equiv closed_{M'}(X) \wedge \neg(s_1 \succ_M X)$$

$$Candidates = \{\underbrace{\text{BCDEF}}_{s_1}, \underbrace{\text{BEF}}_{s_2},$$

Dominance programming: example of the skypatterns

Trans.	Items					
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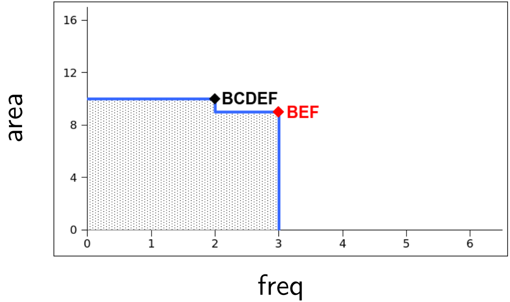


$$M = \{freq, area\}$$

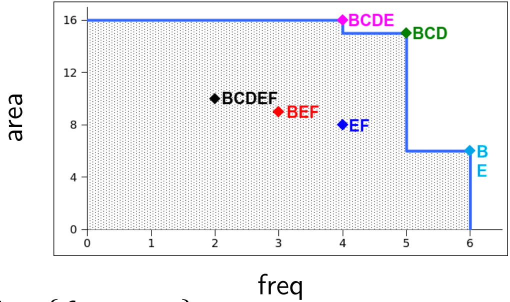
$$q(X) \equiv closed_{M'}(X) \wedge \neg(s_1 \succ_M X) \wedge \neg(s_2 \succ_M X)$$

$$Candidates = \{\underbrace{BCDEF}_{s_1}, \underbrace{BEF}_{s_2},$$

Dominance programming: example of the skypatterns

Trans.	Items					
t_1		B			E	F
t_2		B	C	D		
t_3	A				E	F
t_4	A	B	C	D	E	
t_5		B	C	D	E	
t_6		B	C	D	E	F
t_7	A	B	C	D	E	F

$\mid \mathcal{L}_{\mathcal{I}} \mid = 2^6 = 64$ patterns
4 skypatterns



$$M = \{freq, area\}$$

$$q(X) \equiv closed_{M'}(X) \wedge \neg(s_1 \succ_M X) \wedge \neg(s_2 \succ_M X) \wedge \neg(s_3 \succ_M X) \wedge \neg(s_4 \succ_M X) \wedge \neg(s_5 \succ_M X) \wedge \neg(s_6 \succ_M X) \wedge \neg(s_7 \succ_M X)$$

$$Candidates = \{\underbrace{\cancel{BCDEF}}_{s_1}, \underbrace{\cancel{BEF}}_{s_2}, \underbrace{\cancel{EF}}_{s_3}, \underbrace{\underbrace{BCDE}_{s_4}, \underbrace{BCD}_{s_5}, \underbrace{B}_{s_6}, \underbrace{E}_{s_7}}_{\text{Sky}(\mathcal{L}_{\mathcal{I}}, M)}\}$$

Dominance programming: to sum up

The dominance programming framework encompasses many kinds of patterns:

	dominance relation
maximal patterns	inclusion
closed patterns	inclusion at same frequency
top-k patterns	order induced by the interestingness measure
skypatterns	Pareto dominance

maximal patterns $\subseteq$ closed patterns

top-k patterns $\subseteq$ skypatterns

A step further

a preference is defined by any property between two patterns (i.e., pairwise comparison) and not only the Pareto dominance relation: measures on a set of patterns, overlapping between patterns, coverage,. . .

➥ preference-based optimal patterns

In the following:
(1) define preference-based optimal patterns,
(2) show how many tasks of local patterns fall into this framework,
(3) deal with optimal pattern sets.

Preference-based optimal patterns

A preference $\triangleright$ is a strict partial order relation on a set of patterns $\mathbb{S}$.
$x \triangleright y$ indicates that x is preferred to y

(Ugarte et al. ICTAI15): a pattern x is optimal (OP) according to $\triangleright$ iff $\nexists y_1, \ldots y_p \in \mathbb{S}, \forall 1 \leq j \leq p,\ y_j \triangleright x$
(a single y is enough for many data mining tasks)

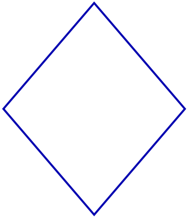
Characterisation of a set of OPs: a set of patterns:

$$\left\{ x \in \mathbb{S} \mid \ \texttt{fundamental}(x) \ \wedge \nexists y_1, \ldots y_p \in \mathbb{S}, \forall 1 \leq j \leq p,\ y_j \triangleright x \ \right\}$$

$\texttt{fundamental}(x)$: x must satisfy a property defined by the user
for example: having a minimal frequency, being closed, ...

Local patterns: examples

Trans.	Items					
t_1		B			E	F
t_2		B	C	D		
t_3	A				E	F
t_4	A	B	C	D	E	
t_5		B	C	D	E	
t_6		B	C	D	E	F
t_7	A	B	C	D	E	F



$\mathbb{S} = \mathcal{L}_{\mathcal{I}}$

(Mannila et al. DAMI97)

Large tiles

$c(x) \equiv \mathit{freq}(x) \times \mathtt{size}(x) \geq \psi_{area}$

Example: $\mathit{freq}(BCD) \times \mathtt{size}(BCD) = 5 \times 3 = 15$

Frequent sub-groups

$$c(x) \equiv \mathit{freq}(x) \geq \psi_{freq} \wedge \nexists\, y \in \mathbb{S} : T_1(y) \supseteq T_1(x) \wedge T_2(y) \subseteq T_2(x) \wedge (T(y) = T(x) \Rightarrow y \subset x)$$

Skypatterns

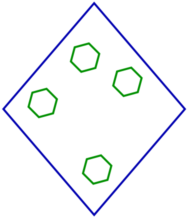
$$c(x) \equiv \mathtt{closed}_M(x) \wedge \nexists\, y \in \mathbb{S} : y \succ_M x$$

Frequent top-k patterns according to m

$$c(x) \equiv \mathit{freq}(x) \geq \psi_{freq} \wedge \nexists\, y_1, \ldots, y_k \in \mathbb{S} : \bigwedge_{1 \leq j \leq k} \mathtt{m}(y_j) > \mathtt{m}(x)$$

Local (optimal) patterns: examples

Trans.	Items					
t_1		B			E	F
t_2		B	C	D		
t_3	A				E	F
t_4	A	B	C	D	E	
t_5		B	C	D	E	
t_6		B	C	D	E	F
t_7	A	B	C	D	E	F



$\mathbb{S} = \mathcal{L}_{\mathcal{I}}$

(Mannila et al. DAMI97)

Large tiles

$\mathrm{c}(x) \equiv \mathit{freq}(x) \times \mathtt{size}(x) \geq \psi_{\mathit{area}}$

Frequent sub-groups

$$\mathrm{c}(x) \equiv \quad \mathit{freq}(x) \geq \psi_{\mathit{freq}} \ \wedge \nexists\, y \in \mathbb{S} : T_1(y) \supseteq T_1(x) \wedge T_2(y) \subseteq T_2(x) \wedge (T(y) = T(x) \Rightarrow y \subset x)$$

Skypatterns

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Pattern sets: sets of patterns

Patterns sets (De Raedt and Zimmermann SDM07): sets of patterns satisfying a global viewpoint (instead of evaluating and selecting patterns based on their individual merits)

Search space ($\mathbb{S}$): local patterns versus pattern sets

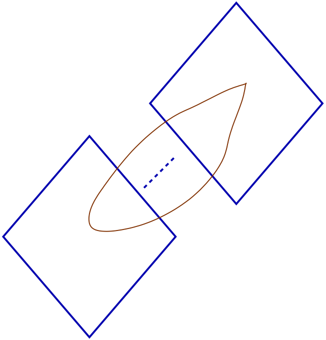
example: $\mathcal{I} = \{A, B\}$

- all local patterns: $\mathbb{S} = \mathcal{L}_{\mathcal{I}} = \{\emptyset, A, B, AB\}$
- all pattern sets:
  $\mathbb{S} = 2^{\mathcal{L}_{\mathcal{I}}} = \{\emptyset, \{A\}, \{B\}, \{AB\}, \{A, B\}, \{A, AB\}, \{B, AB\}, \{A, B, AB\}\}$

Many data mining tasks: classification (Liu et al. KDD98), clustering (Ester et al. KDD96), database tiling (Geerts et al. DS04), pattern summarization (Xin et al. KDD06), pattern teams (Knobbe and Ho PKDD06),...

Many input ("preferences") can be given by the user:
coverage, overlapping between patterns, syntactical properties, measures, number of local patterns,...

Pattern sets of length k: examples



$\mathbb{S} \subset 2^{\mathcal{L}_{\mathcal{I}}}$

(sets of length k)

Conceptual clustering (without overlapping)

$$\texttt{clus}(x) \equiv \bigwedge_{i \in [1..k]} \texttt{closed}(x_i) \wedge \bigcup_{i \in [1..k]} \texttt{T}(x_i) = \mathcal{T} \wedge \bigwedge_{i,j \in [1..k]} \texttt{T}(x_i) \cap \texttt{T}(x_j) = \emptyset$$

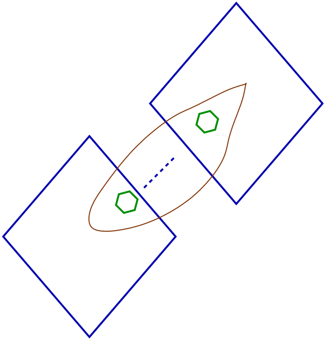
Conceptual clustering with optimisation

$$\texttt{c}(x) \equiv \texttt{clus}(x) \wedge \nexists\, y \in 2^{\mathcal{L}_{\mathcal{I}}}, \min_{j \in [1..k]} \{freq(y_j)\} > \min_{i \in [1..k]} \{freq(x_i)\}$$

Pattern teams

$$\texttt{c}(x) \equiv \texttt{size}(x) = k \wedge \nexists\, y \in 2^{\mathcal{L}_{\mathcal{I}}}, \Phi(y) > \Phi(x)$$

(Optimal) pattern sets of length k: examples



$\mathbb{S} \subset 2^{\mathcal{L}_\mathcal{I}}$

(sets of length k)

Conceptual clustering (without overlapping)

$$\mathtt{clus}(x) \equiv \bigwedge_{i \in [1..k]} \mathtt{closed}(x_i) \wedge \bigcup_{i \in [1..k]} \mathtt{T}(x_i) = \mathcal{T} \wedge \bigwedge_{i,j \in [1..k]} \mathtt{T}(x_i) \cap \mathtt{T}(x_j) = \emptyset$$

Conceptual clustering with optimisation

$$\mathtt{c}(x) \equiv \mathtt{clus}(x) \wedge \nexists\, y \in 2^{\mathcal{L}_\mathcal{I}}, \min_{j \in [1..k]} \{freq(y_j)\} > \min_{i \in [1..k]} \{freq(x_i)\}$$

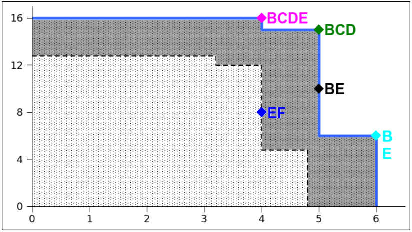
Pattern teams

$$\mathtt{c}(x) \equiv \mathtt{size}(x) = k \wedge \nexists\, y \in 2^{\mathcal{L}_\mathcal{I}}, \Phi(y) > \Phi(x)$$

Relax the dogma "must be optimal": soft patterns

Stringent aspect of the classical constraint-based pattern mining framework: *what about a pattern which slightly violates a query?*

example: introducing softness in the skypattern mining:
➥ soft-skypatterns



put the user in the loop to determine the best patterns w.r.t. his/her preferences

Introducing softness is easy with Constraint Programming:
➥ same process: it is enough to update the posted constraints

Many other works in this broad field

Example: heuristic approaches

pattern sets based on the Minimum Description Length principle: a small set of patterns that compress - KRIMP (Siebes et al. SDM06)

$L(D, CT)$: the total compressed size of the encoded database and the code table:

$$L(D, CT) = L(D|CT) + L(CT|D)$$

Many usages:

- characterizing the differences and the norm between given components in the data - DIFFNORM (Budhathoki and Vreeken ECML/PKDD15)
- causal discovery (Budhathoki and Vreeken ICDM16)
- missing values (Vreeken and Siebes ICDM08)
- handling sequences (Bertens et al. KDD16)
- ...

and many other works on data compression/summarization (e.g. Kiernan and Terzi KDD08),...

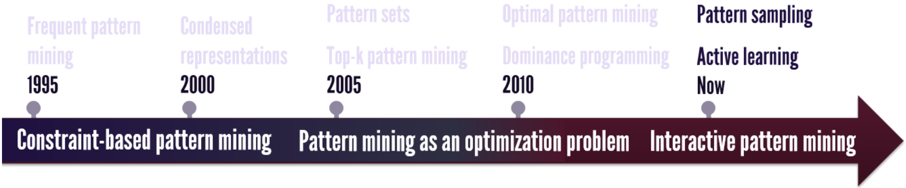
Nice results based on the frequency. How handling other measures?

Pattern mining as an optimization problem: concluding remarks

In the approaches indicated in this part:

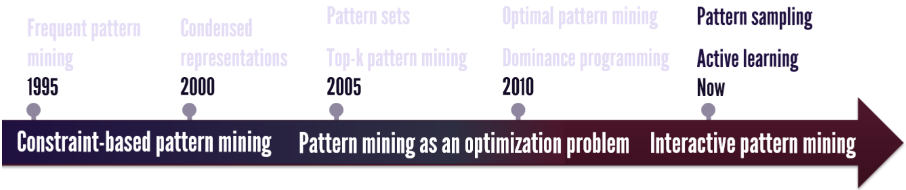
- measures/preferences are explicit and must be given by the user... (but there is no threshold :-)
- diversity issue: top-k patterns are often very similar
- complete approaches (optimal w.r.t the preferences):
  ➥ stop completeness "Please, please stop making new algorithms for mining *all* patterns"
  Toon Calders (ECML/PKDD 2012, most influential paper award)

A further step: interactive pattern mining (including the instant data mining challenge), implicit preferences and learning preferences



Interactive pattern mining

Interactive pattern mining



Idea: *"I don't know what I am looking for, but I would definitely know if I see it."*

➠ preference acquisition

In this part:

- Easier: no user-specified parameters (constraint, threshold or measure)!
- Better: learn user preferences from user feedback
- Faster: instant pattern discovery

Addressing pattern mining with user interactivity

Advanced Information Retrieval-inspired techniques

- Query by Example in information retrieval (QEIR) (Chia et al. SIGIR08)
- Active feedback with Information Retrieval (Shen et al. SIGIR05)
- SVM Rank (Joachims KDD02)
- ...

Challenge: pattern space $\mathcal{L}$ is often much larger than the dataset $\mathcal{D}$

Interactive pattern mining: overview

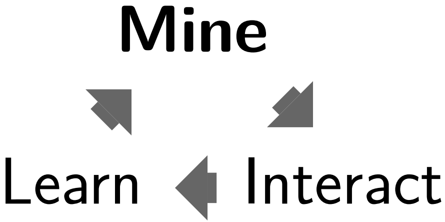
Interactive data exploration using pattern mining. (van Leeuwen 2014)

Mine

Learn Interact

Interactive pattern mining: overview

Interactive data exploration using pattern mining. (van Leeuwen 2014)

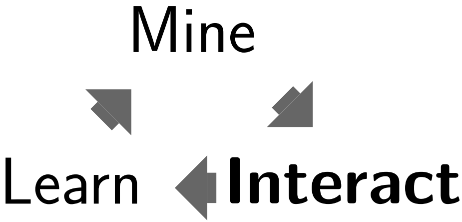


Mine

- Provide a sample of k patterns to the user (called the query $\mathcal{Q}$)

Interactive pattern mining: overview

Interactive data exploration using pattern mining. (van Leeuwen 2014)



Interact

- Like/dislike or rank or rate the patterns

Interactive pattern mining: overview

Interactive data exploration using pattern mining. (van Leeuwen 2014)

Mine

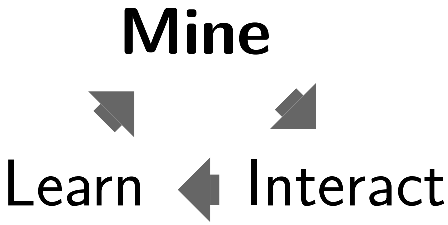
Learn Interact

Learn

- Generalize user feedback for building a preference model

Interactive pattern mining: overview

Interactive data exploration using pattern mining. (van Leeuwen 2014)

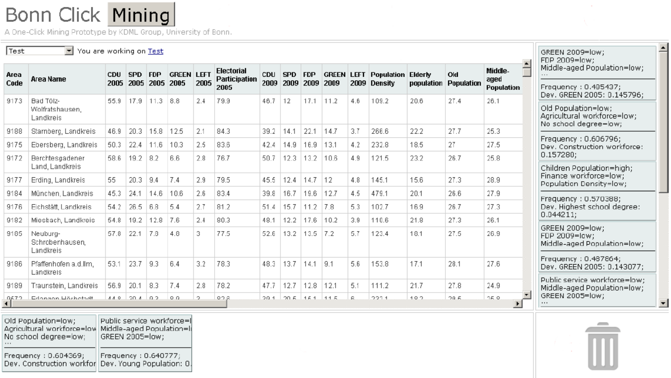


Mine (again!)

- Provide a sample of k patterns **benefiting from the preference model**

Interactive pattern mining

Multiple mining algorithms

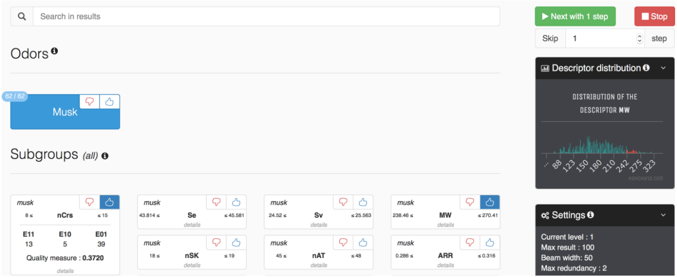


Area Code	Area Name	CDU 2005	SPD 2005	FDP 2005	GREEN 2005	LEFT 2005	Electorial Participation 2005	CDU 2009	SPD 2009	FDP 2009	GREEN 2009	LEFT 2009	Population Density	Elderly population	Old Population	Middle-aged Population
9173	Bad Tölz-Wolfratshausen, Landkreis	55.9	17.9	11.3	8.8	2.4	79.9	46.7	12	17.1	11.2	4.6	109.2	20.6	27.4	26.1
9188	Starnberg, Landkreis	46.9	20.3	15.8	12.5	2.1	84.3	39.2	14.1	22.1	14.7	3.7	266.6	22.2	27.7	25.3
9175	Ebersberg, Landkreis	50.3	22.4	11.6	10.3	2.5	83.6	42.4	14.9	16.9	13.1	4.2	232.8	18.5	27	27.5
9172	Berchtesgadener Land, Landkreis	58.6	19.2	8.2	6.6	2.8	76.7	50.7	12.3	13.2	10.6	4.9	121.5	23.2	26.7	25.8
9177	Erding, Landkreis	55	20.3	9.4	7.4	2.9	79.5	45.5	12.4	14.7	12	4.8	145.1	15.6	27.3	28.9
9184	München, Landkreis	45.3	24.1	14.6	10.6	2.6	83.4	39.8	16.7	19.6	12.7	4.5	479.1	20.1	26.6	27.9
9176	Eichstätt, Landkreis	54.2	26.5	6.8	5.4	2.7	81.2	51.4	15.7	11.2	7.8	5.3	102.7	16.9	26.7	27.3
9182	Miesbach, Landkreis	54.8	19.2	12.8	7.6	2.4	80.3	48.1	12.2	17.6	10.2	3.9	110.6	21.8	27.3	26.1
9185	Neuburg-Schrobenhausen, Landkreis	57.8	22.1	7.8	4.8	3	77.5	52.6	13.2	13.5	7.2	5.7	123.4	18.1	27.5	26.9
9186	Pfaffenhofen a.d.Ilm, Landkreis	53.1	23.7	9.3	6.4	3.2	78.3	48.3	13.7	14.1	9.1	5.6	153.8	17.1	28.1	27.6
9189	Traunstein, Landkreis	56.9	20.1	8.3	7.4	2.8	78.2	47.7	12.7	12.8	12.1	5.1	111.2	21.7	27.8	24.9

One Click Mining - Interactive Local Pattern Discovery through Implicit Preference and Performance Learning. (Boley et al. IDEA13)

Interactive pattern mining

Platform that implements descriptive rule discovery algorithms suited for neuroscientists



h(odor): Interactive Discovery of Hypotheses on the Structure-Odor Relationship in Neuroscience. (Bosc et al. ECML/PKDD16 (demo))

Interactive pattern mining: challenges

- MINE
  - Instant discovery for facilitating the iterative process
  - Preference model integration for improving the pattern quality
  - Pattern diversity for completing the preference model
- INTERACT
  - Simplicity of user feedback (binary feedback $>$ graded feedback)
  - Accuracy of user feedback (binary feedback $<$ graded feedback)
- LEARN
  - Expressivity of the preference model
  - Ease of learning of the preference model

Interactive pattern mining: challenges

- MINE
  - *Instant discovery for facilitating the iterative process*
  - *Preference model integration for improving the pattern quality*
  - Pattern diversity for completing the preference model
- INTERACT
  - Simplicity of user feedback (binary feedback $>$ graded feedback)
  - Accuracy of user feedback (binary feedback $<$ graded feedback)
- LEARN
  - *Expressivity of the preference model*
  - Ease of learning of the preference model

➠ Optimal mining problem (according to preference model)

Interactive pattern mining: challenges

- Mine
  - Instant discovery for facilitating the iterative process
  - Preference model integration for improving the pattern quality
  - *Pattern diversity for completing the preference model*
- Interact
  - *Simplicity of user feedback (binary feedback $>$ graded feedback)*
  - *Accuracy of user feedback (binary feedback $<$ graded feedback)*
- Learn
  - Expressivity of the preference model
  - *Ease of learning of the preference model*

➠ Active learning problem

LEARN: Preference model

How user preferences are represented?

Problem

- Expressivity of the preference model
- Ease of learning of the preference model

Learn: Preference model

How user preferences are represented?

Problem

- Expressivity of the preference model
- Ease of learning of the preference model

Weighted product model

- A weight on items $\mathcal{I}$
- Score for a pattern X = product of weights of items in X
- (Bhuiyan et al. CIKM12, Dzyuba et al. PAKDD17)

$$\begin{array}{ccccccccc} & \omega_A & & \omega_B & & \omega_C & & \\ AB & 4 & \times & 1 & & & = & 4 \\ BC & & & 1 & \times & 0.5 & = & 0.5 \end{array}$$

Learn: Preference model

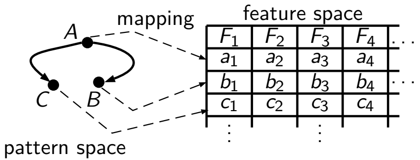
How user preferences are represented?

Problem

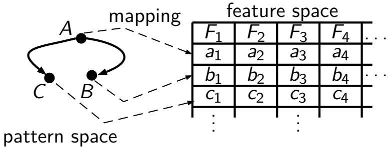
- Expressivity of the preference model
- Ease of learning of the preference model

Feature space model

- Partial order over the pattern language $\mathcal{L}$
- Mapping between a pattern X and a set of features:



LEARN: Feature space model



Feature space

- = assumption about the user preferences
- the more, the better

Different feature spaces:

- Attributes of the mined dataset (Rueping ICML09)
- Expected and measured frequency (Xin et al. KDD06)
- Attributes, coverage, chi-squared, length and so on (Dzyuba et al. ICTAI13)

INTERACT: User feedback

How user feedback are represented?

Problem

- Simplicity of user feedback (binary feedback $>$ graded feedback)
- Accuracy of user feedback (binary feedback $<$ graded feedback)

INTERACT: User feedback

How user feedback are represented?

Problem

- Simplicity of user feedback (binary feedback > graded feedback)
- Accuracy of user feedback (binary feedback < graded feedback)

Weighted product model

- Binary feedback (like/dislike) (Bhuiyan et al. CIKM12, Dzyuba et al. PAKDD17)

pattern	feedback
A	like
AB	like
BC	dislike

Interact: User feedback

How user feedback are represented?

Problem

- Simplicity of user feedback (binary feedback $>$ graded feedback)
- Accuracy of user feedback (binary feedback $<$ graded feedback)

Feature space model

- Ordered feedback (ranking) (Xin et al. KDD06, Dzyuba et al. ICTAI13)

$$A \succ AB \succ BC$$

- Graded feedback (rate) (Rueping ICML09)

pattern	feedback
A	0.9
AB	0.6
BC	0.2

LEARN: Preference learning method

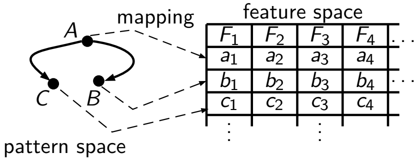
How user feedback are generalized to a model?

- **Weighted product model**
  - Counting likes and dislikes for each item: $\omega = \beta^{(\#\text{like - }\#\text{dislike})}$ (Bhuiyan et al. ICML12, Dzyuba et al. PAKDD17)

pattern	feedback	A	B	C
A	like	1		
AB	like	1	1	
BC	dislike		-1	-1
		$2^{2-0} = 4$	$2^{1-1} = 1$	$2^{0-1} = 0.5$

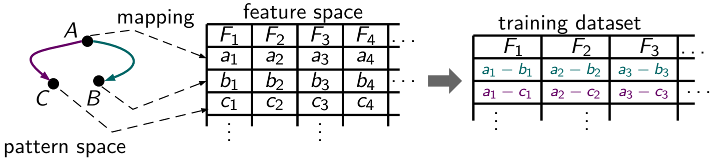
- **Feature space model**
  - $=$ learning to rank (Rueping ICML09, Xin et al. KDD06, Dzyuba et al. ICTAI13)

How to learn a model from a ranking?



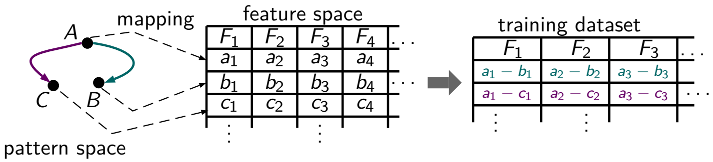
LEARN: Learning to rank

How to learn a model from a ranking?



1. Calculate the distances between feature vectors for each pair (training dataset)

How to learn a model from a ranking?



1. Calculate the distances between feature vectors for each pair (training dataset)
2. Minimize the loss function stemming from this training dataset

Algorithms: SVM Rank (Joachims KDD02), AdaRank (Xu et al. SIGIR07),...

LEARN: Active learning problem

How are selected the set of patterns (query $\mathcal{Q}$)?

Problem

- Mining the most relevant patterns according to *Quality*
- Querying patterns that provide more information about preferences
  (NP-hard problem for pair-wise preferences (Ailon JMLR12))

- Heuristic criteria:
  - **Local diversity:** diverse patterns among the current query $\mathcal{Q}$
  - **Global diversity:** diverse patterns among the different queries $\mathcal{Q}_i$
  - **Density:** dense regions are more important

Learn: Active learning heuristics

(Dzyuba et al. ICTAI13)

What is the interest of the pattern X for the current pattern query $\mathcal{Q}$?

- **Maximal Marginal Relevance:** querying diverse patterns in $\mathcal{Q}$

$$\alpha Quality(X) + (1-\alpha)\min_{Y \in \mathcal{Q}} dist(X,Y)$$

- **Global MMR:** taking into account previous queries

$$\alpha Quality(X) + (1-\alpha)\min_{Y \in \bigcup_i \mathcal{Q}_i} dist(X,Y)$$

- **Relevance, Diversity, and Density:** querying patterns from dense regions provides more information about preferences

$$\alpha Quality(X) + \beta Density(X) + (1-\alpha-\beta)\min_{Y \in \mathcal{Q}} dist(X,Y)$$

MINE: Mining strategies

What method is used to mine the pattern query Q?

Problem

- Instant discovery for facilitating the iterative process
- Preference model integration for improving the pattern quality
- Pattern diversity for completing the preference model

MINE: Mining strategies

What method is used to mine the pattern query $\mathcal{Q}$?

Problem

- Instant discovery for facilitating the iterative process
- Preference model integration for improving the pattern quality
- Pattern diversity for completing the preference model

Post-processing

- Re-rank the patterns with the updated quality (Rueping ICML09, Xin et al. KDD06)
- Clustering as heuristic for improving the local diversity (Xin et al. KDD06)

MINE: Mining strategies

What method is used to mine the pattern query $\mathcal{Q}$?

Problem

- Instant discovery for facilitating the iterative process
- Preference model integration for improving the pattern quality
- Pattern diversity for completing the preference model

Optimal pattern mining (Dzyuba et al. ICTAI13)

- Beam search based on reweighing subgroup quality measures for finding the best patterns
- Previous active learning heuristics (and more)

MINE: Mining strategies

What method is used to mine the pattern query $\mathcal{Q}$?

Problem

- Instant discovery for facilitating the iterative process
- Preference model integration for improving the pattern quality
- Pattern diversity for completing the preference model

Pattern sampling (Bhuiyan et al. CIKM12, Dzyuba et al. PAKDD17)

- Randomly draw pattern with a distribution proportional to their updated quality
- Sampling as heuristic for diversity and density

Objective evaluation protocol

Methodology = simulate a user

1. Select a subset of data or pattern as **user interest**
2. Use a metric for simulating user feedback

User interest:

- A set of items (Bhuiyan et al. CIKM12, Dzyuba et al. PAKDD17)
- A sample for modeling the user's prior knowledge (Xin et al. KDD06)
- A class (Rueping ICML09, Dzyuba et al. ICTAI13)

Results

Objective evaluation results

- Dozens of iterations for few dozens of examined patterns
- Important pattern features depends on the user interest
- Randomized selectors ensure high diversity

Results

Objective evaluation results

- Dozens of iterations for few dozens of examined patterns
- Important pattern features depends on the user interest
- Randomized selectors ensure high diversity

Questions?

- How to select the right set of (hidden) features for modeling user preferences?
- How to subjectively evaluate interactive pattern mining?
  ➠ qualitative benchmarks for pattern mining

Creedo – Scalable and Repeatable Extrinsic Evaluation for Pattern Discovery Systems by Online User Studies. (Boley et al. IDEA15)

Instant pattern discovery

The need

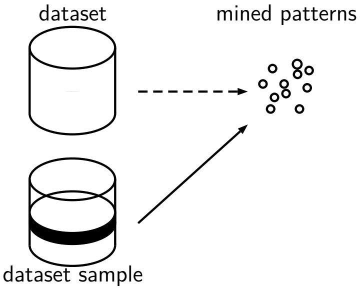
"the user should be allowed to pose and refine queries at any moment in time and the system should respond to these queries instantly"
Providing Concise Database Covers Instantly by Recursive Tile Sampling. (Moens et al. DS14)
➠ few seconds between the query and the answer

Methods

- ~~Sound and complete pattern mining~~
- Beam search Subgroup Discovery methods
- Monte Carlo tree search (Bosc et al. 2016)
- **Pattern sampling**

Dataset sampling vs Pattern sampling

Dataset sampling



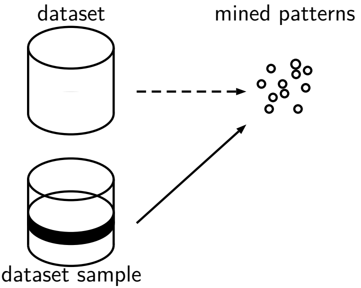
Finding all patterns from a transaction sample

➠ input space sampling

Sampling large databases for association rules. (Toivonen et al. VLDB96)

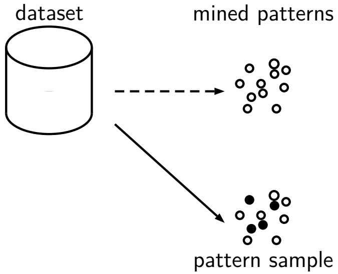
Dataset sampling vs Pattern sampling

Dataset sampling



Finding all patterns from a transaction sample
➠ input space sampling

Pattern sampling



Finding a pattern sample from all transactions
➠ output space sampling

Random sampling from databases. (Olken, PhD93)

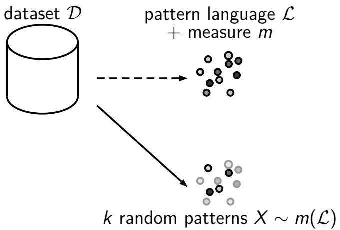
Pattern sampling: References

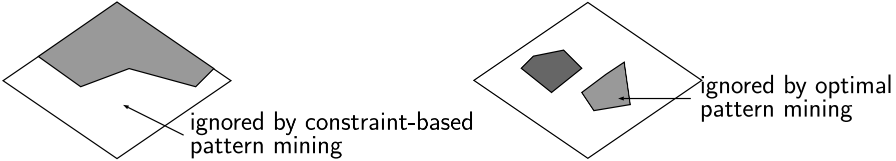
- Output Space Sampling for Graph Patterns. (Al Hasan et al. VLDB09)
- Direct local pattern sampling by efficient two-step random procedures. (Boley et al. KDD11)
- Interactive Pattern Mining on Hidden Data: A Sampling-based Solution. (Bhuiyan et al. CIKM12)
- Linear space direct pattern sampling using coupling from the past. (Boley et al. KDD12)
- Randomly sampling maximal itemsets. (Moens et Goethals IDEA13)
- Instant Exceptional Model Mining Using Weighted Controlled Pattern Sampling. (Moens et al. IDA14)
- Unsupervised Exceptional Attributed Sub-graph Mining in Urban Data (Bendimerad et al. ICDM16)

Pattern sampling: Problem

Problem

- **Inputs:** a pattern language $\mathcal{L}$ + a measure $m : \mathcal{L} \to \Re$
- **Output:** a family of k realizations of the random set $R \sim m(\mathcal{L})$



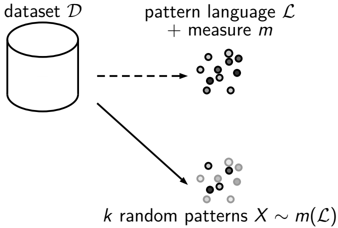


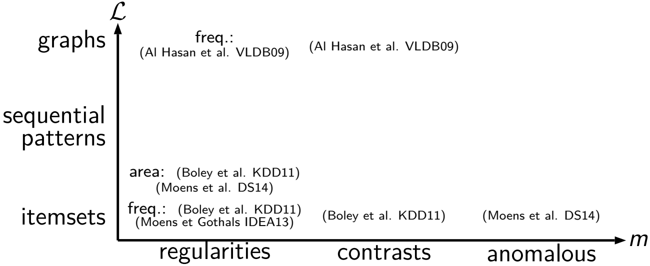
Pattern sampling addresses the full pattern language $\mathcal{L}$ ➠ **diversity!**

Pattern sampling: Problem

Problem

- **Inputs:** a pattern language $\mathcal{L}$ + a measure $m : \mathcal{L} \rightarrow \Re$
- **Output:** a family of k realizations of the random set $R \sim m(\mathcal{L})$



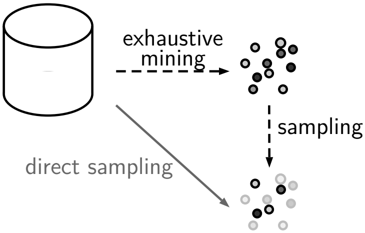


Pattern sampling: Challenges

Naive method

1. Mine all the patterns with their interestingness m
2. Sample this set of patterns according to m

➠ Time consuming / infeasible



Pattern sampling: Challenges

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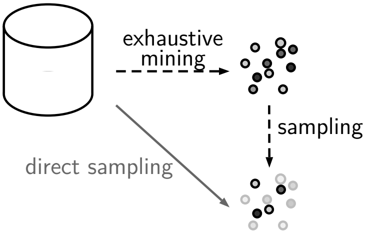


➠ Time consuming / infeasible

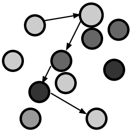
Challenges

- Trade-off between pre-processing computation and processing time per pattern
- Quality of sampling

Two main families

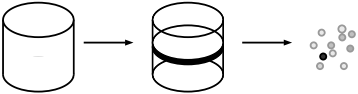
1. Stochastic techniques

- Metropolis-Hastings algorithm
- Coupling From The Past



2. Direct techniques

- Item/transaction sampling with rejection
- **Two-step random procedure**



Two-step procedure: Toy example

Direct local pattern sampling by efficient two-step random procedures. (Boley et al. KDD11)

TId	Items		
t_1	A	B	C
t_2	A	B	
t_3		B	C
t_4			C

Mine all frequent patterns

Itemset	freq.
A	2
B	3
C	3
AB	2
AC	1
BC	2
ABC	1

Pick 14 itemsets

Itemsets
A, A
B, B, B
C, C, C
AB, AB
AC
BC, BC
ABC

Two-step procedure: Toy example

Direct local pattern sampling by efficient two-step random procedures. (Boley et al. KDD11)

TId	Items		
t_1	A	B	C
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infeasible

~~Mine all frequent patterns~~

Itemset	freq.
A	2
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Pick 14 itemsets

Direct sampling

Itemsets
A, A
B, B, B
C, C, C
AB, AB
AC
BC, BC
ABC

Two-step procedure: Toy example

Direct local pattern sampling by efficient two-step random procedures. (Boley et al. KDD11)

TId	Items		
t_1	A	B	C
t_2	A	B	
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infeasible

~~Mine all frequent patterns~~

Itemset	freq.
A	2
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BC	2
ABC	1

Pick 14 itemsets

Itemsets
A, A
B, B, B
C, C, C
AB, AB
AC
BC, BC
ABC

Rearrange itemsets

TId	Itemsets
t_1	A, B, C, AB, AC, BC, ABC
t_2	A, B, AB
t_3	B, C, BC
t_4	C

Two-step procedure: Toy example

Direct local pattern sampling by efficient two-step random procedures. (Boley et al. KDD11)

infeasible

~~Mine all frequent patterns~~

Itemset	freq.
A	2
B	3
C	3
AB	2
AC	1
BC	2
ABC	1

Pick 14 itemsets

TId	Items			weight ω
t_1	A	B	C	$2^3 - 1 = 7$
t_2	A	B		$2^2 - 1 = 3$
t_3		B	C	$2^2 - 1 = 3$
t_4			C	$2^1 - 1 = 1$

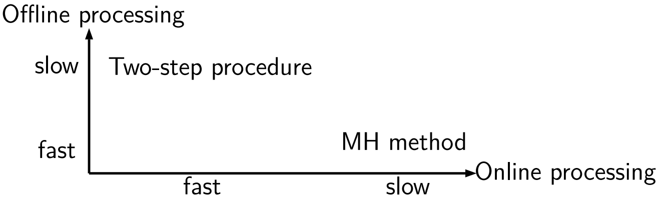
Itemsets
A, A
B, B, B
C, C, C
AB, AB
AC
BC, BC
ABC

1. Pick a transaction proportionally to ω

TId	Itemsets
t_1	A, B, C, AB, AC, BC, ABC
t_2	A, B, AB
t_3	B, C, BC
t_4	C

2. Pick an itemset uniformly

Two-step procedure: Comparison

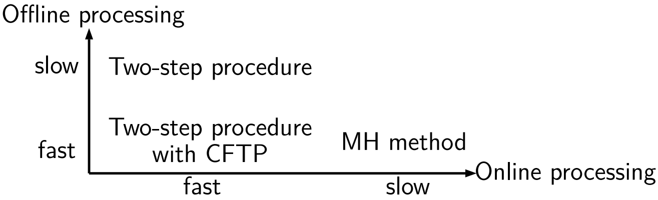


Complexity depends on the measure m:

Measure $m(X)$	Preprocessing	k realizations
$supp(X, \mathcal{D})$	$O(\lvert\mathcal{I}\rvert \times \lvert\mathcal{D}\rvert)$	$O(k(\lvert\mathcal{I}\rvert + \ln\lvert\mathcal{D}\rvert))$
$supp(X, \mathcal{D}) \times \lvert X\rvert$	$O(\lvert\mathcal{I}\rvert \times \lvert\mathcal{D}\rvert)$	$O(k(\lvert\mathcal{I}\rvert + \ln\lvert\mathcal{D}\rvert))$
$supp_{+}(X, \mathcal{D}) \times (\lvert\mathcal{D}_{-}\rvert - supp_{-}(X, \mathcal{D}))$	$O(\lvert\mathcal{I}\rvert^2 \times \lvert\mathcal{D}\rvert^2)$	$O(k(\lvert\mathcal{I}\rvert + \ln^2\lvert\mathcal{D}\rvert))$
$supp(X, \mathcal{D})^2$	$O(\lvert\mathcal{I}\rvert^2 \times \lvert\mathcal{D}\rvert^2)$	$O(k(\lvert\mathcal{I}\rvert + \ln^2\lvert\mathcal{D}\rvert))$

Preprocessing time may be prohibitive

Two-step procedure: Comparison



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$supp(X, \mathcal{D}) \times \lvert X\rvert$	$O(\lvert\mathcal{I}\rvert \times \lvert\mathcal{D}\rvert)$	$O(k(\lvert\mathcal{I}\rvert + \ln \lvert\mathcal{D}\rvert))$
$supp_+(X, \mathcal{D}) \times (\lvert\mathcal{D}_-\rvert - supp_-(X, \mathcal{D}))$	$O(\lvert\mathcal{I}\rvert^2 \times \lvert\mathcal{D}\rvert^2)$	$O(k(\lvert\mathcal{I}\rvert + \ln^2 \lvert\mathcal{D}\rvert))$
$supp(X, \mathcal{D})^2$	$O(\lvert\mathcal{I}\rvert^2 \times \lvert\mathcal{D}\rvert^2)$	$O(k(\lvert\mathcal{I}\rvert + \ln^2 \lvert\mathcal{D}\rvert))$

Preprocessing time may be prohibitive ➠ hybrid strategy with stochastic process for the first step:

Linear space direct pattern sampling using coupling from the past. (Boley et al. KDD12)

Pattern sampling

Summary

Pros

- Compact collection of patterns
- Threshold free
- Diversity
- Very fast

Cons

- Patterns far from optimality
- Not suitable for all interestingness measures

Pattern sampling

Summary

Pros

- Compact collection of patterns
- Threshold free
- Diversity
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Cons

- Patterns far from optimality
- Not suitable for all interestingness measures

Interactive pattern sampling

Interactive Pattern Mining on Hidden Data: A Sampling-based Solution. (Bhuiyan et al. CIKM12)

➠ how to integrate more sophisticated user preference models?

Pattern set and sampling

Pattern-based models with iterative pattern sampling

- ORIGAMI: Mining Representative Orthogonal Graph Patterns. (Al Hasan et al. ICDM07)
- Randomly sampling maximal itemsets. (Moens et Goethals IDEA13)
- Providing Concise Database Covers Instantly by Recursive Tile Sampling. (Moens et al. DS14)

➠ how to sample a set of patterns instead of indivual patterns?

- Flexible constrained sampling with guarantees for pattern mining. (Dzyuba et al. 2016)

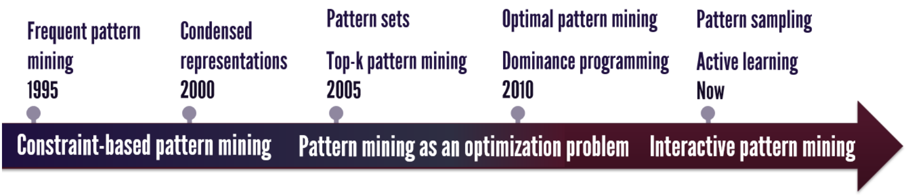
Interactive pattern mining: concluding remarks

- Preferences are not explicitly given by the user…
  …but, representation of user preferences should be anticipated in upstream.

- Instant discovery enables a tight coupling between user and system…
  …but, most advanced models are not suitable.

Concluding remarks

Preference-based pattern mining

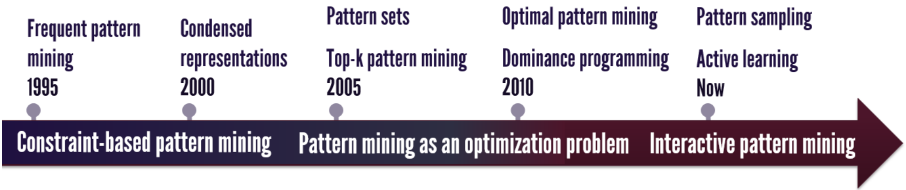


User preferences are more and more prominent...

from simple preference models to complex ones

- from frequency to anti-monotone constraints and more complex ones
- from 1 criterion (top-k) to multi-criteria (skyline)
- from weighted product model to feature space model

Preference-based pattern mining

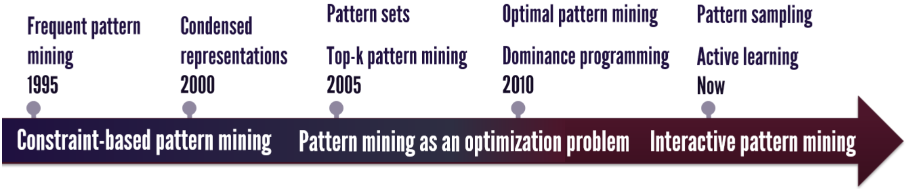


User preferences are more and more prominent...

from preference elicitation to preference acquisition

- user-defined constraint
- no threshold with optimal pattern mining
- no user-specified interestingness

Preference-based pattern mining



User preferences are more and more prominent in the community...

from data-centric methods:

- 2003-2004: Frequent Itemset Mining Implementations
- 2002-2007: Knowledge Discovery in Inductive Databases

to user-centric methods:

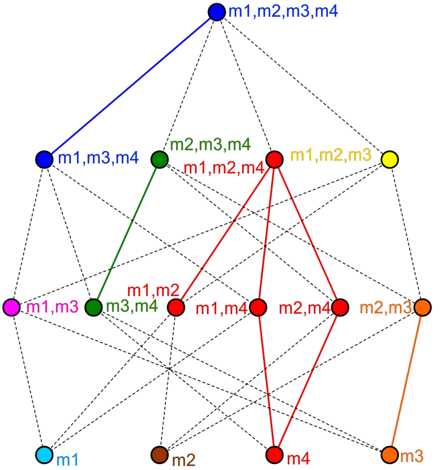
- 2010-2014: Useful Patterns
- 2015-2017: Interactive Data Exploration and Analytics

Multi-pattern domain exploration

- The user has to choose its pattern domain of interest.
- What about (interactive) multi-pattern domain exploration?
  - Some knowledge nuggets can be depicted with simple pattern domain (e.g., itemset) while others require more sophisticated pattern domain (e.g., sequence, graph, dynamic graphs, etc.).
  - Examples in Olfaction:
    - Odorant molecules.
    - unpleasant odors in presence of Sulfur atom in chemicals $\Rightarrow$ itemset is enough.
    - Some chemicals have the same 2-d graph representation and totally different odor qualities (e.g., isomers) $\Rightarrow$ need to consider 3-d graph pattern domain.
  - How to fix the good level of description?
- Toward pattern sets involving several pattern domains.

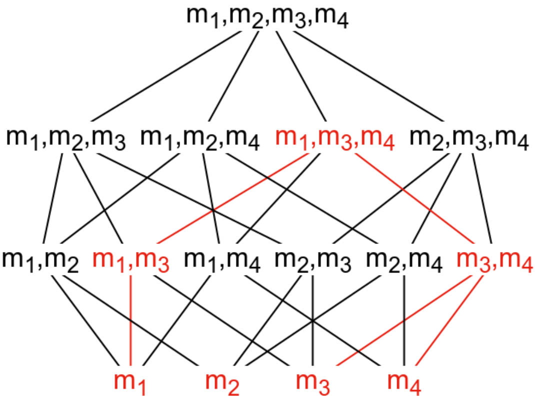
Role/acquisition of preferences through the skypattern cube

- equivalence classes on measures
  ➠ highlight the role of measures



Role/acquisition of preferences through the skypattern cube

- equivalence classes on measures
  ➠ highlight the role of measures
- skypattern cube compression: user navigation and recommendation
- preference acquisition



Pattern mining in the AI field

- **cross-fertilization between data mining and constraint programming/SAT/ILP** (De Raedt et al. KDD08):
  designing generic and declarative approaches

  ➥ make easier the exploratory data mining process

  - avoiding writing solutions from scratch
  - easier to model new problems

- **open issues:**

  - how go further to integrate preferences?
  - how to define/learn constraints/preference?
  - how to visualize results and interact with the end user?
  - ...

Many other directions associated to the AI field:
integrating background knowledge, knowledge representation,...

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