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A framework for mining interesting pattern sets

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INTELLIGENT SYSTEMS LAB

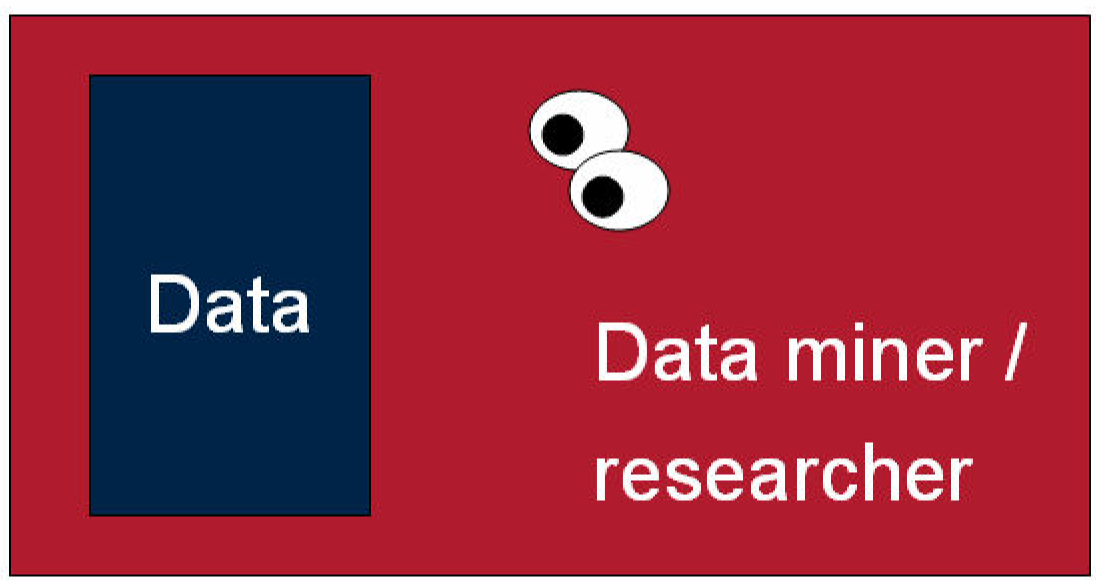
A zoo of interestingness measures

- Survey (Geng and Hamilton, 2006): 38 different probabilistically inspired interestingness measures for association rules / itemsets
- Often not relevant
- Often redundant

- Support
- Confidence
- Coverage
- Recall
- Specificity
- Accuracy
- Lift
- Leverage
- …
- Support x size (tiles)
- MDL-based (KRIMP)
- Comparison to subsets (Tatti)

A zoo of interestingness measures

- Exploratory data mining = intentionally ill-defined?
  - Each interestingness measure has benefits
  - Choice can be task dependent
- All the above: ‘objective’ measures



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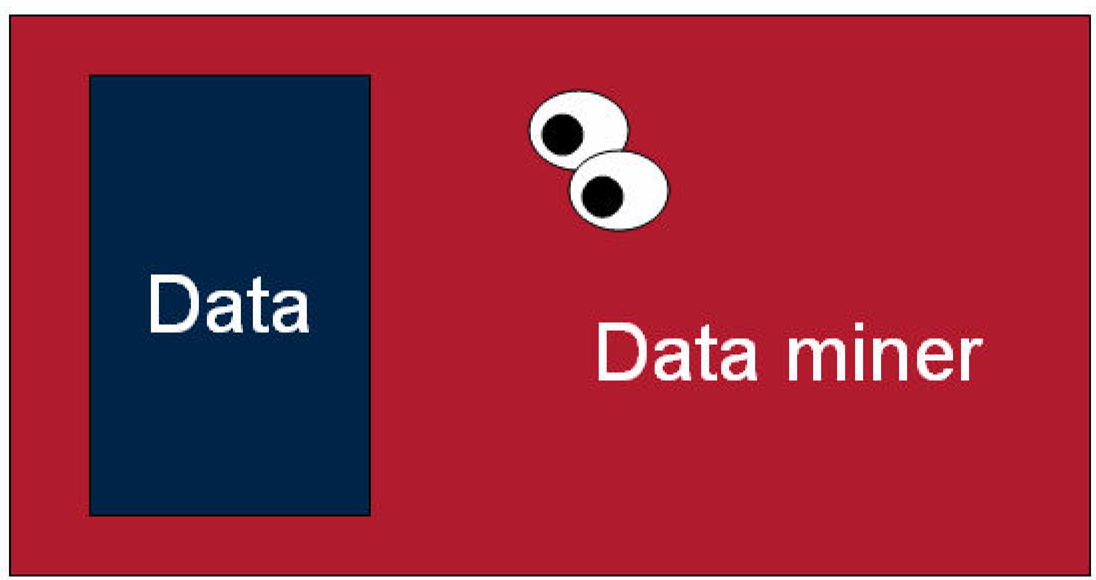
Interesting to whom?

'Objective interestingness measure' = a mirage



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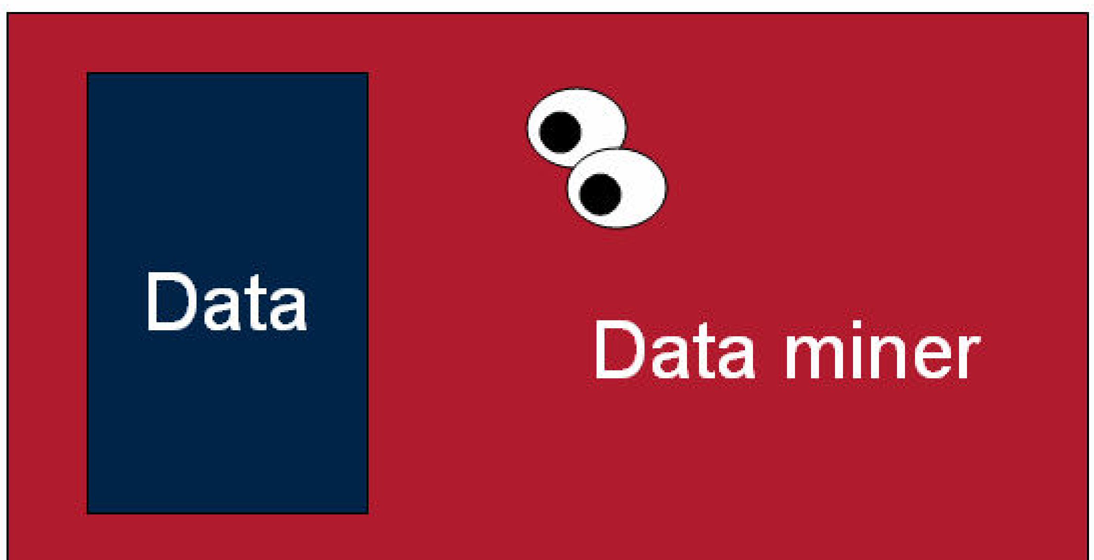
Subjective interestingness: interesting to a subject (the data miner)

(Tuzhilin and Silberschatz, 1996)



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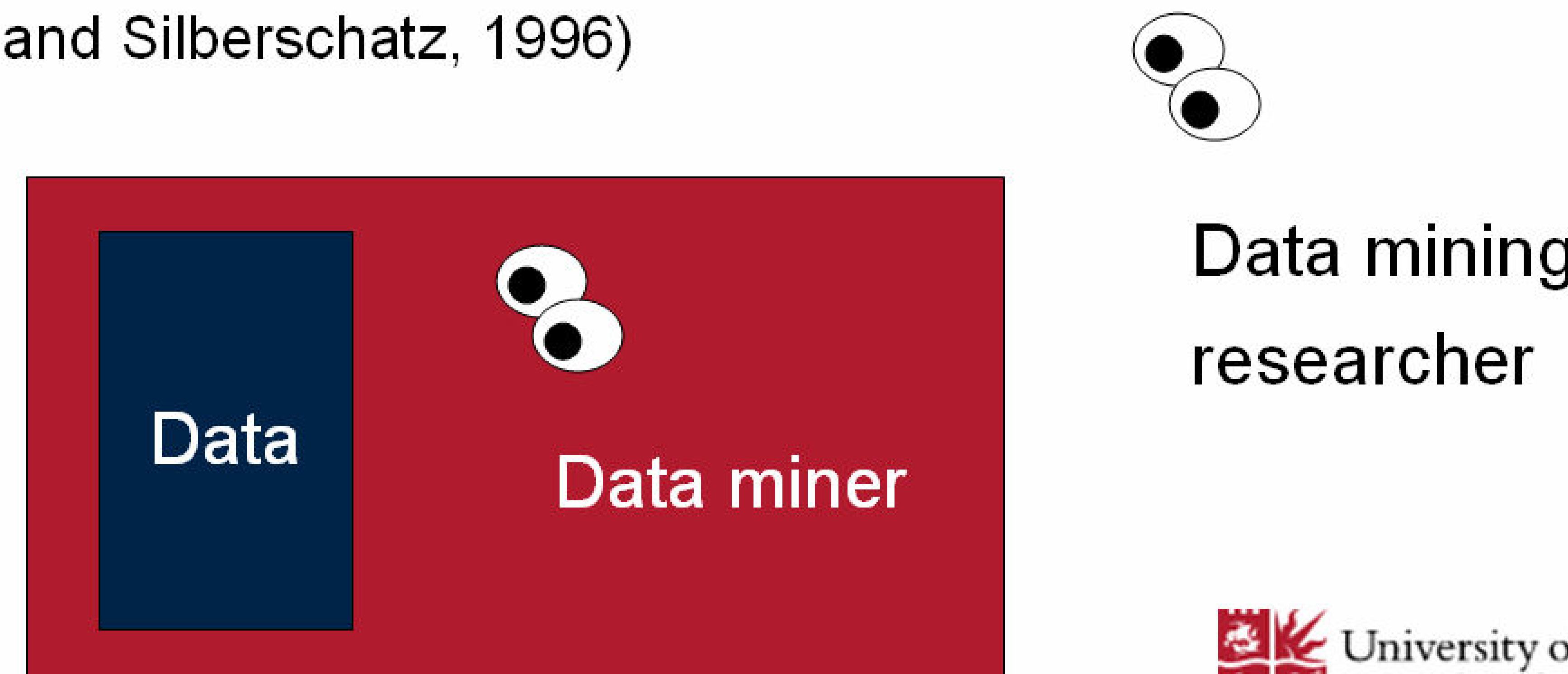

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Data mining as 2-way communication

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Data mining as 2-way communication

Data mining as 2-way communication

Tell me what you know about the data.

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Data mining as 2-way communication

Tell me what you know about the data.

I have expectations about certain aspects of the data.

Alice
(data)

Bob
(data miner)

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Data mining as 2-way communication

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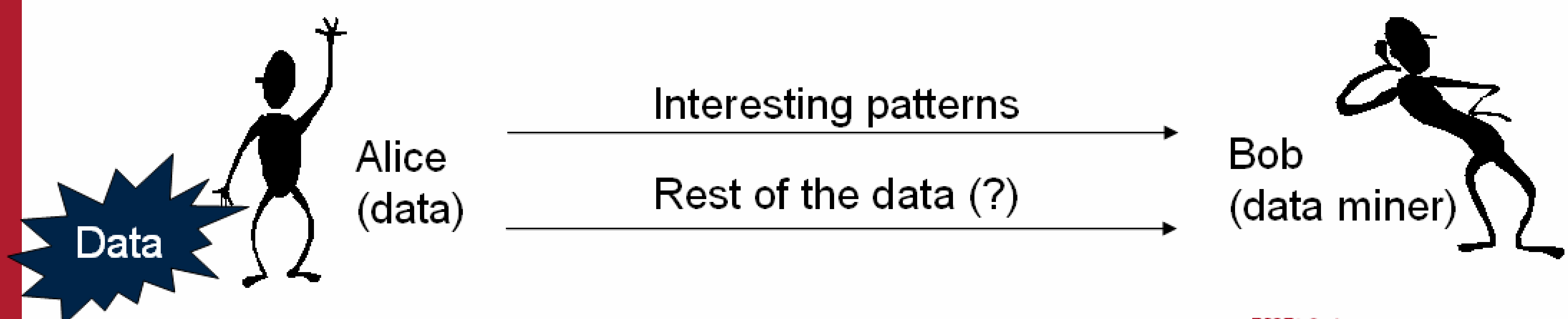

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Components of a framework

Formalize prior expectations

Probabilistic background model

Prior expectations as constraints

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Components of a framework

Formalize prior expectations	Choose pattern syntax
Probabilistic background model	Chosen by data miner
Prior expectations as constraints	Task dependent

Components of a framework

Formalize prior expectations

Probabilistic background model

Prior expectations as constraints

→ Self-information

Choose pattern syntax

Chosen by data miner

Task dependent

→ Description length (complexity)

Self-information ⟷ Description length (complexity)

Contrast patterns with prior expectations

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Case study

- Binary database
- Prior expectations on row and column sums
- Tiles as patterns

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Case study – Background model

Formalize prior expectations

Probabilistic background model

Prior expectations as constraints

Choose pattern syntax

Chosen by data miner

Task dependent

Self-information ⟷ Description length (complexity)

Contrast patterns with prior expectations

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Case study – Background model

- Binary database $\mathbf{D}$
- Expectations about row and column sums
  → constraints on the background model
- Pick Maximum Entropy (MaxEnt) distribution
- Product of independent Bernoulli distributions:

$$P(\mathbf{D}) = \prod_{i,j} P_{ij}(\mathbf{D}(i,j))$$

$$P_{ij}(\mathbf{D}(i,j)) = \begin{cases} p_{ij} & \text{if } \mathbf{D}(i,j) = 1 \\ 1 - p_{ij} & \text{if } \mathbf{D}(i,j) = 0 \end{cases}$$

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Case study – Tiles as patterns

Formalize

prior expectations

Probabilistic background model

Prior expectations as constraints

Choose

pattern syntax

Chosen by data miner

Task dependent

Self-information

Description length (complexity)

Contrast patterns

with prior expectations

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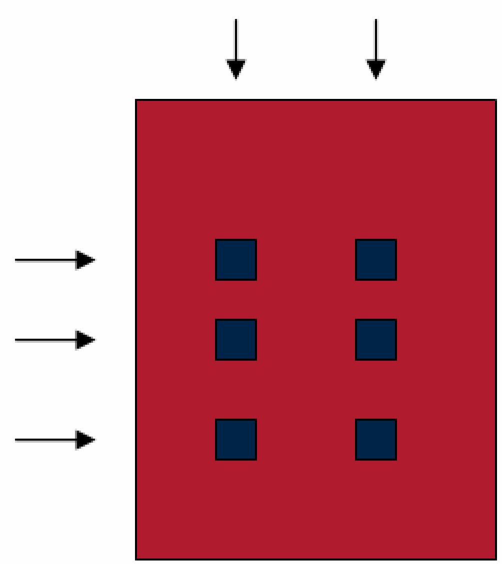
Case study – Tiles as patterns

- Pattern syntax
- E.g. tiles (Geerts, Goethals, Mielikäinen, 2004), i.e. pairs of:
  - row set
  - column set

  such that there are 1's in the intersection



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Case study – Which tiles are interesting?

Formalize prior expectations	Choose pattern syntax
Probabilistic background model	Chosen by data miner
Prior expectations as constraints	Task dependent
↓	↓
Self-information ⟷	Description length (complexity)

Contrast patterns with prior expectations

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Case study – Which tiles are interesting?

- Self-information (SI) of a tile pattern
  - The negative log-probability under the background model
  - Smaller probability
    = more informative w.r.t. prior expectations
- Description length (DL) of a tile pattern
  - Perceived complexity of a tile
  - E.g. an affine function of the tile's circumference
- SI / DL = 'information density'

Case study – Interesting sets of tiles

- Data miner has limited processing capacity
  - Bounds the total description length of tile patterns
- Find the pattern set that:
  - Has maximal total self-information
  - Subject to an upper bound on the total description length
- Maximally compresses the data
- Weighted budgeted set coverage problem
  - Hard to solve exactly, but greedy is a good approximation

Case study – Results

Rows = KDD abstracts

Columns = stemmed words

KDD

Mining interesting pattern sets (current paper)	$\|I\|$	Tiling databases as described in [7]	$\|I\|$
machin support svm vector	25	data paper	389
art state	39	algorithm propos	246
labeled learn supervised unlabeled	10	data mine	312
associ mine rule	36	base method	202
express gene	25	result show	196
frequent itemset	28	problem	373
graph larg network social	15	data set	279
column row	13	approach	330
algorithm faster magnitud order	12	model	301
algorithm data paper propos real synthetic	27	present	296
answer question	18	larg	286
nearest neighbor	13	applic	271
classifi featur machin support text vector	9	perform	266
precis recal	14	real	255
decis tree	33	inform	240

[7] Geerts, Goethals, Mielikäinen, 2004

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Final thoughts and conclusions

- Current focus
  - Other constraints of the form $\sum_{\mathbf{x}} f(\mathbf{x})P(\mathbf{x}) = d$
  - Other data types (networks, relational databases)
  - Other pattern types (syntax)
  - Other contrast measures
- Open problem: the empirical results trap…
  - Risk of missing the target, we should not test:
    - number of patterns,
    - speed,
    - classification accuracy…

    unless they are actually the goal
  - We tend to use text (but…)

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