

Relational Redescription Mining

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joint work with Pauli Miettinen and Angelika Kimmig

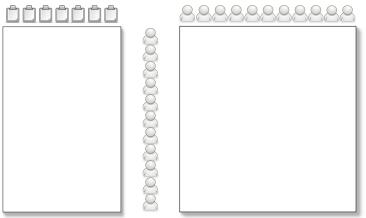
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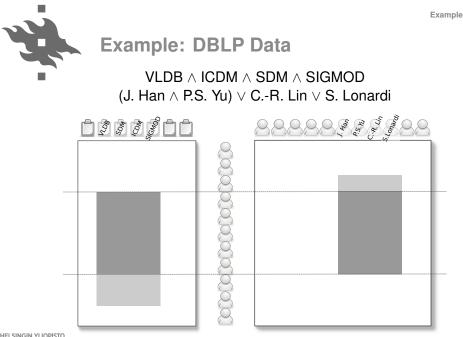
MPI-INF SB — Dec 3, 2012







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Redescription Mining



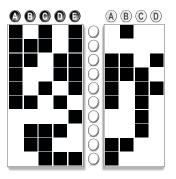
Redescription Given two datasets over the same entities, a **redescription** is a pair of queries (q_L, q_R) over the two dataset respectively, characterizing approximately the same sets of entities.



- Find coherent sets of objects
- Find sets of related attributes
- View the same objects under different perspectives

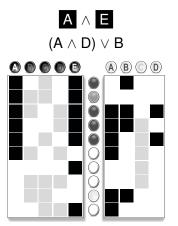


Dataset Boolean matrices





Boolean Redescriptions

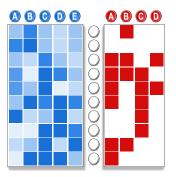


Dataset Boolean matrices Queries Boolean formulae Accuracy Jaccard coefficient $J(q_L, q_R) = \frac{|\operatorname{supp}(q_L) \cap \operatorname{supp}(q_R)|}{|\operatorname{supp}(q_L) \cup \operatorname{supp}(q_R)|}$ $= \frac{|E_{1,1}|}{|E_{1,0}| + |E_{1,1}| + |E_{0,1}|}$

Redescription Mining



Real-Valued Redescriptions

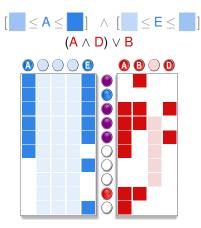


Dataset Real-valued matrices

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Real-Valued Redescriptions



Dataset Real-valued matrices Queries Intervals Accuracy Jaccard coefficient $J(q_L, q_R) = \frac{|\sup p(q_L) \cap \sup p(q_R)|}{|\sup p(q_L) \cup \sup p(q_R)|}$ $= \frac{|E_{1,1}|}{|E_{1,0}| + |E_{1,1}| + |E_{0,1}|}$



Geospatial Redescriptions

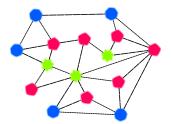
| le <u>R</u> ede | escrip | tions <u>W</u> indow | <u>H</u> elp | | | | | | | |
|-----------------|-----------|-----------------------------|-------------------|--------------------------|---|--------------------------------------|--------------------------------|-----------|----------|--------|
| IS Varial | bles | RHS Variables | Redescriptions | Expanding | | | | | | |
| | Query LHS | | | LHS | Que | ry RHS | Acc † | p-Value | Support | |
| 1 | | Polar bear | | | [1.0 ≤ to ⁺ ≤ 3.5] | | 0.973 | 0.0 | 36 | |
| 2 | | Polar bear | | | [-9.6 ≤ tu ⁺ ≤ -5.6] 0.973 0.0 36 | | | | | |
| 3 | V | Polar bear | | | [-7.0727 ≤ ts ⁺ ≤ -3.375] | - | SIREN :: map | s | - | |
| 4 | | Polar bear | | | [-4.5 ≤ t10 ⁺ ≤ -1.0] | | 7 | C'M'S | | |
| 5 | | Polar bear | | | [-16.694 ≤ ts ≤ -11.462] | ×. | 3 | E | | |
| 6 | | Polar bear | | | [-11.9 ≤ ts ⁺ ≤ -7.3] | 1.11 | | | | |
| 7 | V | Wood mouse | v Azores Noctule | | $(([3.0 \le t_{3}^+] \land [9.8 \le t_{10}^+]))$ | 1 | 5 | | | |
| 8 | V | Wood mouse | v Azores Noctule | v Harp Seal | (([2.9 ≤ ts ⁺] v [9.7 ≤ ts ⁺ ≤ 1 | 23 | | | 1/1/12 | |
| 9 | 1 | Bank Vole v M | Northern Red-back | ed Vole v Steppe Mouse v | [-9.2 ≤ t12 ⁺ ≤ 12.8] ∧ [7.15 | | | Jeff | ALC . | |
| 10 | | Wood mouse v Azores Noctule | | | $(([2.9 \le t_3^+] \land [8.3 \le t_4^+]))$ | 4 | m | - Allihil | 國則有 | |
| 11 | | Wood mouse | v Azores Noctule | v Harp Seal | (([-0.8 ≤ t₂ ⁺] ∧ [-0.14118 ≤ | 2 | | . ANNP | ANNE | |
| 12 | 1 | Wood mouse | v Harp Seal | | (([-0.8 ≤ ti ⁺ ≤ 17.2] ∧ [-4.9 | | | | | |
| 13 | | Wood mouse | v Harp Seal | | ([-9.4 ≤ ti ⁻ ≤ 8.2] ∧ [-8.3 ≤ | | 54 | Carrie | SIL . | |
| 14 | 1 | Wood mouse | | | $(([3.0 \le t_0^+] \land [4.2 \le t_0^+])))$ | | sta | | | |
| 15 | | Wood mouse | | | ([9.7 ≤ t) ⁺ ≤ 13.2] v [-5.16 | | 9 M | | | |
| 16 | | Bank Vole v N | Northern Red-back | ed Vole v Steppe Mouse v | (([11.2 ≤ t) ⁺ ≤ 13.4] v [13.1 | | E C | 5.52 | <u> </u> | |
| 17 | 1 | Arctic Fox v S | Stoat | | (([2.6 ≤ t ₆ ⁺ ≤ 8.5] v [7.2 ≤ | | 7 | 2 AA | (• ¥ | |
| 18 | 1 | Stoat v Walru | IS | | (([7.2 ≤ to ⁺ ≤ 22.2] v [21.1] | | 5-3 | SIS. | | |
| 19 | | Stoat v Walru | IS | | ([11.6 ≤ ts ⁺ ≤ 25.3] v [21.1 | | 41 5 | 0 768 | 22 | |
| 20 | | Arctic Fox v S | Stoat | | (([ts ⁺ ≤ 25.5] ∧ [0.68824 ≤ | | ~~~ | 73 4 | ~ ~ | |
| 21 | 1 | Arctic Fox v S | Stoat | | (([0.8 \leq tr $^ \leq$ 13.9] \wedge [ts $^+$ $<$ | Moose | | | | |
| | - 20 | Cana Hara y I | European Hara u | Algorian Mouro | / f 10 0 2 4 2 0 01 + 115 5 | [-10.0 ≤ t₂ ⁺ ≤ 0.0] ∧ [] | 12.0 < t/ ⁺ < 25.0] | | | |
| | | | | | | J= 0.74513 | | | LHS \ R | |
| | | | | | | pVal= 0.00000 | D LHS U RHS | = 718 | RHS \ LI | HS = 5 |

Redescription Mining



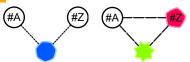
Relational Redescriptions

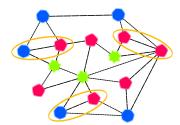
Dataset A network with node and egde attributes



Redescription Mining

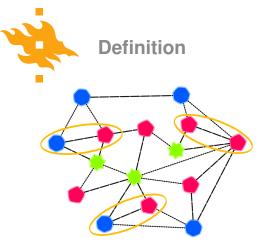
Relational Redescriptions





Dataset A network with node and egde attributes Queries Connection patterns Accuracy Jaccard coefficient $J(q_L, q_R) = \frac{|\operatorname{supp}(q_L) \cap \operatorname{supp}(q_R)|}{|\operatorname{supp}(q_L) \cup \operatorname{supp}(q_R)|}$

Relational Redescriptions

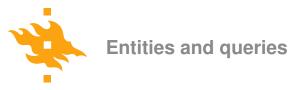


Dataset A network with node and egde attributes

Task Find structurally different patterns covering (almost) the same pairs of nodes.

#A #2

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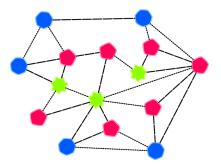
pairs of nodes and their connections. *individual nodes* and surrounding relations.

× a transactional graph and occuring subgraphs.

Relational Redescriptions

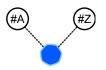


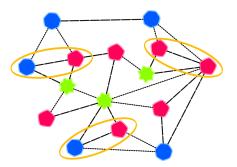
Alternating Scheme





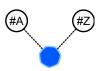
1. Fix a pattern to obtain examples

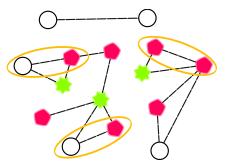






- 1. Fix a pattern to obtain examples
- 2. Consider remaining attributes

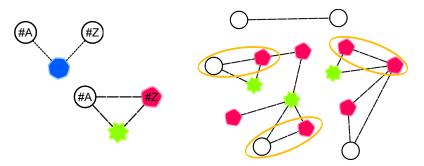




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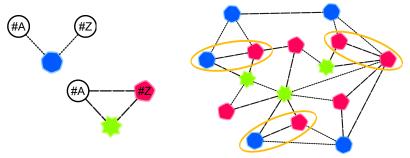


- 1. Fix a pattern to obtain examples
- 2. Consider remaining attributes
- 3. Find a matching pattern



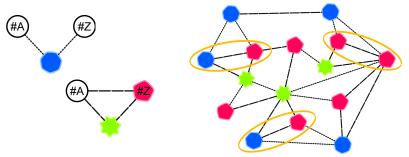


- 1. Fix a pattern to obtain examples
- 2. Consider remaining attributes
- 3. Find a matching pattern
- 4. Swap roles and iterate





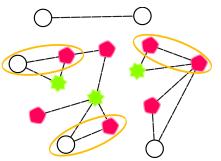
- 1. Fix a pattern to obtain examples
- 2. Consider remaining attributes
- 3. Find a matching pattern
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Subproblem: Query mining

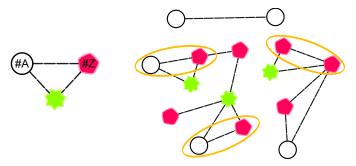
 Given a set of examples and a subset of attributes
 Find a matching pattern





Subproblem: Query mining

 Given a set of examples and a subset of attributes
 Find a matching pattern





FpQm: Stepwise Approach

1. Enumerate connecting paths and mine frequent path patterns

- 2. Build graph patterns from path patterns
- 3. Select a subset of graph patterns

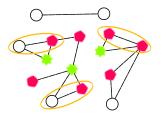


1. Find path patterns

Starting with paths of length k = 1

- 1. Enumerate connecting paths
- 2. Mine frequent path patterns
- 3. Increase k by one and iterate
- Until all examples are connected or *k* exceeds a chosen threshold

Outcome a set of frequent path patterns







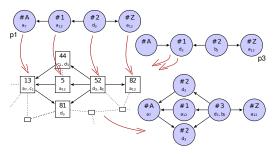
2. Build graph patterns

- Given a set of path patterns and of examples
- Combine paths to build graph patterns



2. Build graph patterns

Given a set of path patterns and of examples
 Combine paths to build graph patterns
 Combination based on the instances

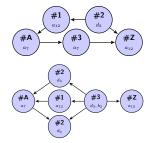




2. Build graph patterns

Given a set of path patterns and of examples
Combine paths to build graph patterns

Outcome a set of graph patterns



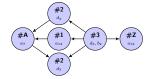


3. Select graph patterns

Given a set of graph patterns and of examples

Select a good cover

Outcome a small set of graph patterns best matching the examples





1. Enumerate connecting paths and mine frequent path patterns

- 2. Build graph patterns from path patterns
- 3. Select a subset of graph patterns

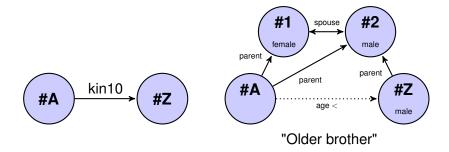


- 1: initialize candidates
- 2: for each candidate do
- 3: for each matching clause found with FpQm do
- 4: if turns limit not reached and no equivalent clause then
- 5: add to candidates
- 6: extract good pairs of adjacent clauses from the exploration tree

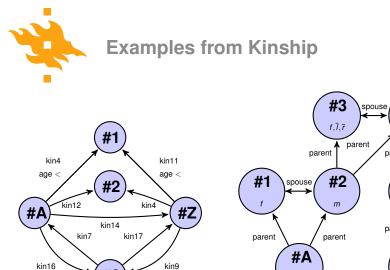
Examples

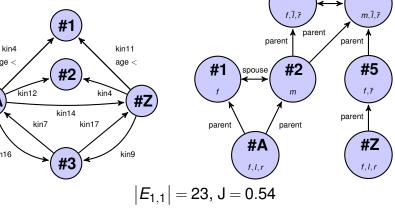


Examples from Kinship

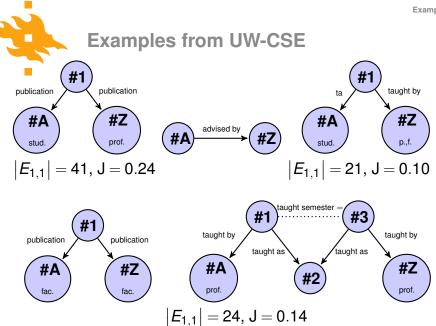


#4

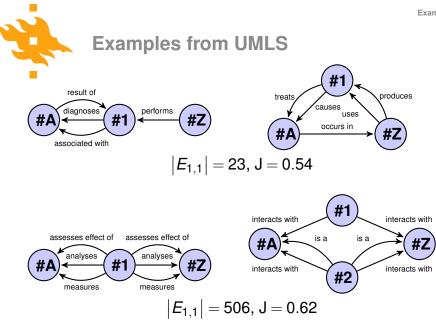




Examples



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But this is just ILP ?...

ILP tools (from my uninitiated point of view)

- general approach, encompassing various strategies
- progressive generalization / refinement of clauses
- heavy use of background knowledge, bias, types and co.
 FpQM
- adapted to finding linked patterns
- purely data based, no additional knowledge
- relies on frequent paths

Experimental comparison: our approach out-performed c-armr on this task

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Discussion



How does it scale?

| Dataset | N | E | #np. | #ep. | #cp. | R | M | Tot. T | T/cla | ause |
|---------|------|-------|------|------|------|----|-----|-----------|-------|------|
| | | | | | | | | | max | avg |
| Kinship | 381 | 24053 | 3 | 31 | 1 | 96 | 340 | 3h 36min | 254s | 38s |
| Umls | 135 | 4181 | _ | 46 | _ | 15 | 81 | 13min 29s | 79s | 10s |
| Uwcse | 1042 | 1674 | 6 | 7 | 5 | 8 | 25 | 39s | 4s | 2s |

Strong impact on the running times:

- Network density
- Presence of symmetries



Relational Redescription Mining

- Find structurally different patterns covering (almost) the same pairs of nodes.
- An expressive tool for finding corresponding connections patterns in a network.



Relational Redescription Mining

- Find structurally different patterns covering (almost) the same pairs of nodes.
- An expressive tool for finding corresponding connections patterns in a network.

Thank you ...