Learning Rules With Numerical and Categorical Attributes from Linked Data Sources

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March 18, 2013

Overview

Semantic Web

Semantic Web

"provides a common framework that allows data to be shared and reused across application, enterprise, and community boundaries"

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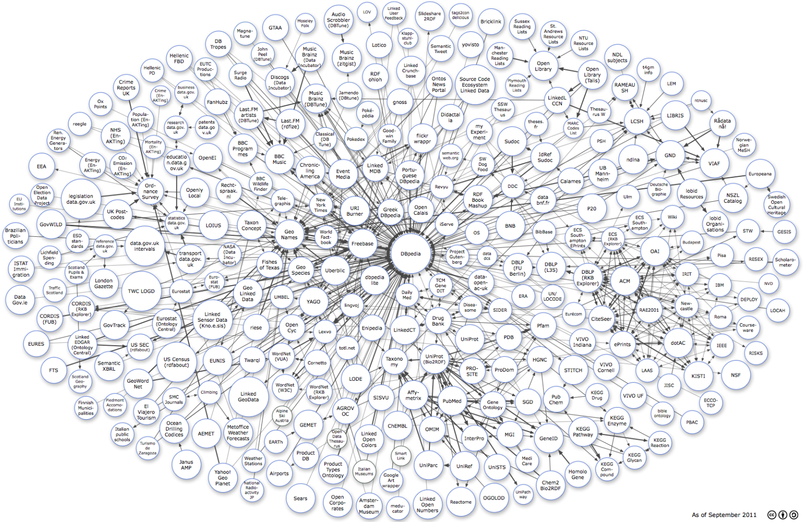
"provides a common framework that allows data to be shared and reused across application, enterprise, and community boundaries"

Linked Data

"collection of interrelated datasets on the Web"

"recommended best practises for exposing, sharing, and connecting pieces of data, information and knowledge on the Semantic Web"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St. Andrews Resource Lists
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DB Tropes
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Music Brainz (Data Incubator)
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KEGG Drug
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ECCO-TCP
Finnish Munici-palities
Piedmont Accomo-dations
El Viajero Tourism
SMC Journals
Alpine Ski Austria
AGROV OC
bible ontology
PBAC
Italian public schools
Turismo de Zaragoza
Ocean Drilling Codices
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Metoffice Weather Forecasts
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GeneID
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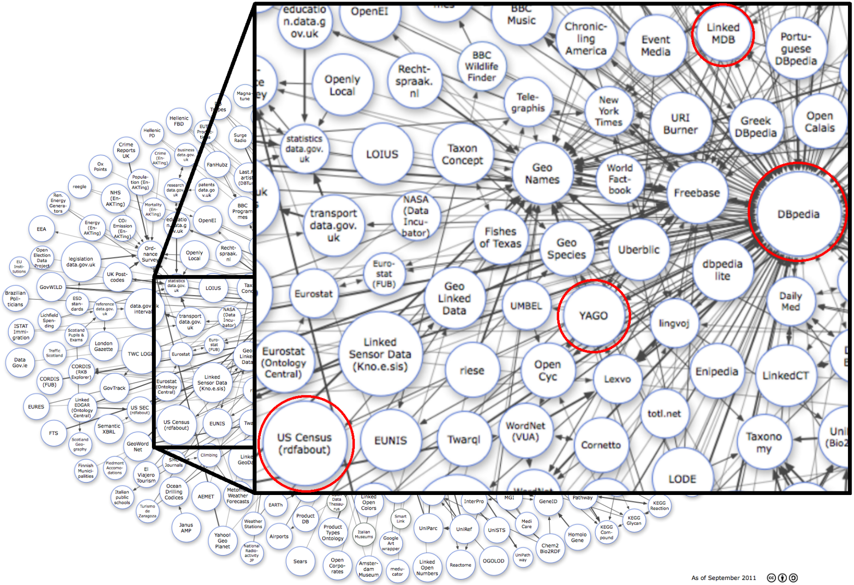
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Motivation

Learn Datalog rules from data:

$$\underbrace{livesIn(X, Y)}_{head} \text{ :- } \underbrace{isMarriedTo(X, Z), livesIn(Z, Y)}_{body}$$

Support and confidence thresholds

- Support: $supp(head \text{ :- } body) = supp(head \wedge body)$
- Confidence: $conf(head \text{ :- } body) = \dfrac{supp(head \wedge body)}{supp(body)}$

Rules with constants

Refining rules with constants is relevant

$$speaks(X, Z) \text{ :- } livesIn(X, W)$$

Searching constants for Z and W we can learn:

$$speaks(X, englsih) \text{ :- } livesIn(X, australia)$$
$$speaks(X, spanish) \text{ :- } livesIn(X, argentina)$$
$$speaks(X, portuguese) \text{ :- } livesIn(X, brasil)$$

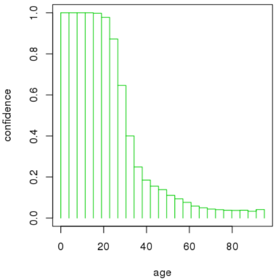
What about numerical constants?

$$speaks(X, english) \text{ :- } hasIncome(X, \$3.71Billion)$$
$$speaks(X, portuguese) \text{ :- } livesIn(X, W), hasPopulation(W, 193946886)$$

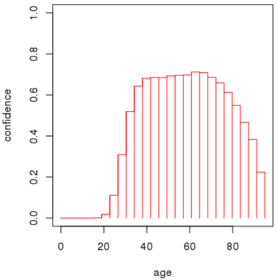
Refining rules with numerical intervals

maritalStatus(X, single) :- age(X,Y) [conf=0.40]
maritalStatus(X,married) :- age(X,Y) [conf=0.46]
maritalStatus(X,widowed) :- age(X,Y) [conf=0.06]

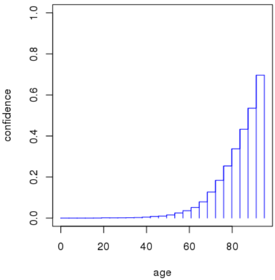
Single



Married



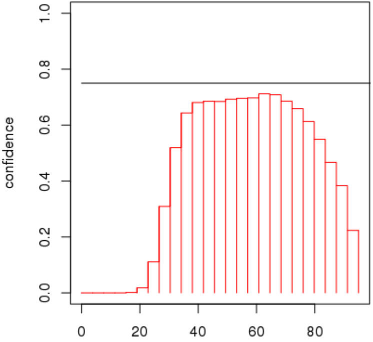
Widowed



Combine with categorical constants

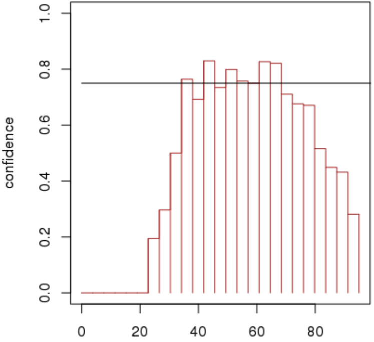
For $maritalStatus(X, married)$, $minConf = 0.75$ is not satisfied.
Refine by State?

USA



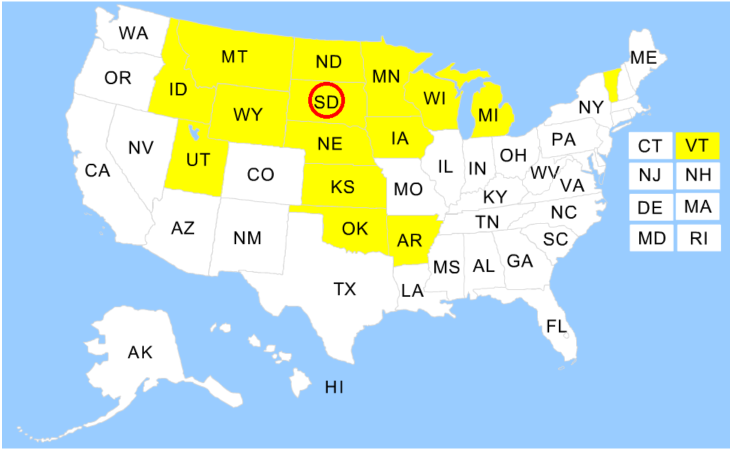
$\Rightarrow$

South Dakota



Combine with categorical constants

We can find intervals for Y that satisfy $minConf = 0.75$ for *maritalStatus(X,widowed) :- livesIn(X,sd),age(X,Y)* and...



Base-rule and Refined-rule

- **Base-rule**: Numerical argument with no constant
  r_1 : $marritalStatus(X, single)$:- $livesIn(X, sd), age(X, Y)$
  [conf=0.49,supp=2368]
- **Refined-rule**: Base-rule with restricted numerical variable
  r_2 : $marritalStatus(X, single)$:- $livesIn(X, sd), age(X, Y), Y \in [33, 67]$
  [conf=0.77,supp=1092]

We are interested in refinements that bring a significant confidence gain:

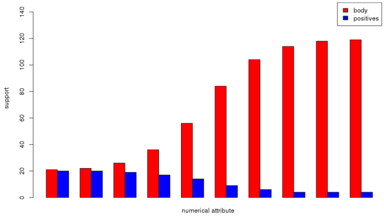
$$gain_{r_{ref}, r_{base}} = \frac{conf(r_{ref})}{conf(r_{base})} \tag{1}$$

For our example: $gain_{r_2, r_1} = \frac{0.77}{0.49} = 1.57$

What base-rules have refined-rules with significant confidence gain?

- Satisfy support threshold
- Do not necessarily satisfy confidence threshold
- Divergent body and positives (body$\wedge$head) probability distributions

Frequency histograms



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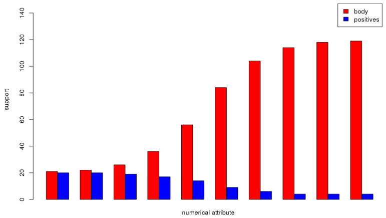
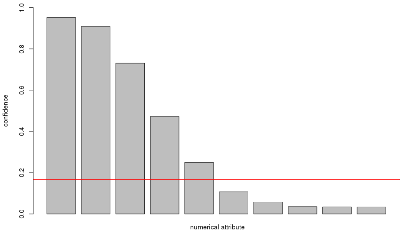
Frequency histograms



$\Rightarrow$

Confidence distribution



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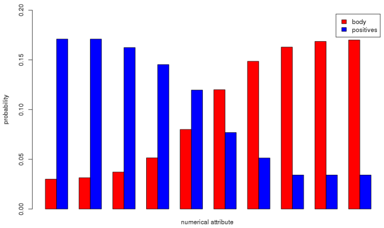
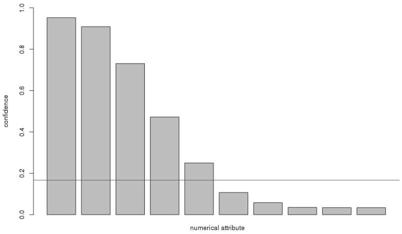
Body and Positives distributions



$\Rightarrow$

Confidence distribution



Motivation

Problem?

- Search space grows exponentially with the number of predicates and constants
- Querying support and confidence distributions is very expensive

Idea:

- Analyze combinations of numerical and categorical properties
- Measure their level of interestingness
- Extend top-down ILP to detect and suggest interesting combinations

Logic Programming Concepts

- Literal: predicate symbol with bracketed n-tuple, e.g:
  $L = livesIn(X, Y)$
- Clause: a disjunction of literals (negated or not), e.g:
  $c = (L_1 \vee L_2 \vee \ldots \vee \neg L_{m-1} \vee \neg L_m)$
- Safe Datalog Rule: every variable in the head appear in a non-negated literal in the body, negated literal variables in the body should appear in some positive literal in the body, e.g.:
  $speaks(X, Y)$:- $wasBornIn(X, Z), hasOfficialLanguage(Z, Y)$
- Hypothesis: a set of clauses $\mathcal{H}$
  - Completeness: $\mathcal{H}$ covers all positive examples
  - Consistency: $\mathcal{H}$ covers no negative examples

Inductive Logic Programming (ILP)

Inductive Logic Programming: Finds a hypothesis $\mathcal{H}$ that covers all positive, and no negative examples

$$positiveExamples + negativeExamples + backgroundKnowledge \rightarrow hypothesis$$

Training Examples	**Background Knowledge**
daughter(mary,ann) +	parent(ann,mary)
daughter(eve,tom) +	parent(ann, tom)
daughter(tom,ann) -	parent(tom,eve)
daughter(eve,ann) -	parent(tom,ian)
	female(ann)
	female(mary)
	female(eve)

$$\mathcal{H} = daughter(X, Y) \text{ :- } female(X), parent(Y, X)$$

Inductive Logic Programming (ILP)

Approaches

- Bottom-up: Start with least general $\mathcal{H}$ then perform generalizations
- **Top-down**: Start with most general $\mathcal{H}$ then perform specializations
  - Specialization loop: adds literals to a clause and ensures consistency
  - Covering loop: adds clauses to the hypothesis and ensures completeness
  - Apriori-style pruning

What about large, noisy, and incomplete LOD datasets such as YAGO and DBpedia?:

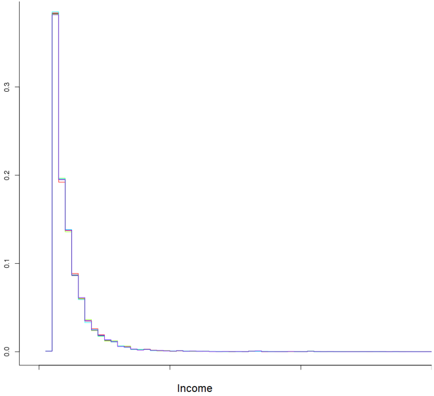
- Sample data to reduce size
- Restrict the number of literals in a clause
- Tolerate a certain level of inconsistency and incompleteness

$$\text{Expected Accuracy: } A(c) = P(e \in \mathcal{E}^+ | c) = \frac{n^+(c)}{n^+(c) + n^-(c)}$$

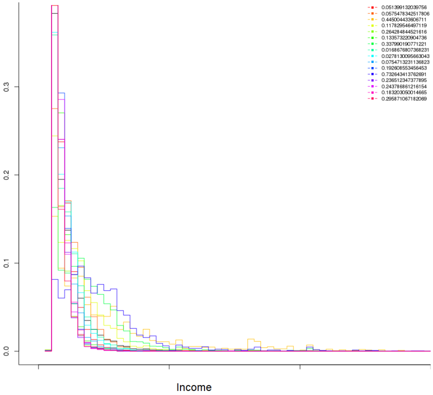
Correlation between Literals

Let's say we want to refine a clause with $hasIncome(X, Y)$ with an interval for Y. Refine by $quarterOfBirth$ or $hasEducation$?

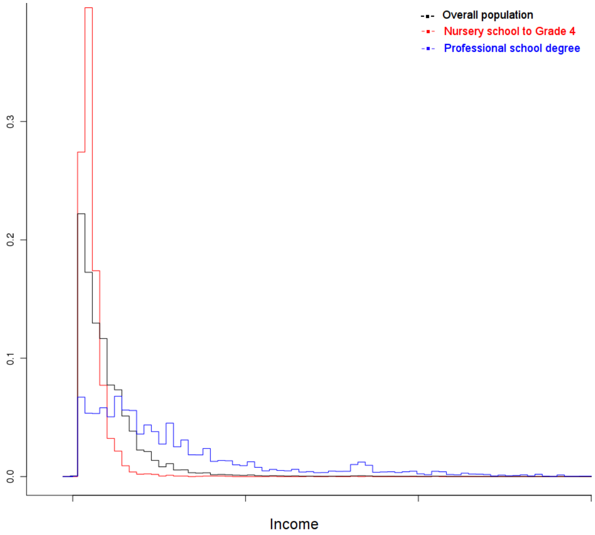
$hasIncome(X, Y), quarterOfBirth(X, Z)$



$hasIncome(X, Y), hasEducation(X, Z)$



Correlation between Literals



Educational Levels
Nursery school to grade 4
Grade 5 or grade 6
Grade 7 or grade 8
Grade 9
Grade 10
Grade 11
Grade 12 no diploma
High school graduate
Some college ($<$ 1 year)
Some college ($\geq$ 1 year)
Associate's degree
Bachelor's degree
Master's degree
Professional school degree
Doctorate degree

Interestingness Measure

How to measure the interestingness of adding a literal l to a clause c?

- Extract the frequency histograms of $\{c\}$ and $\{c \wedge l\}$ over a numerical attribute Y
- Normalize the histograms to obtain their probability distributions, and measure their divergence (e.g., with Kullback-Leibler)

But, divergence alone isn't a good idea because:

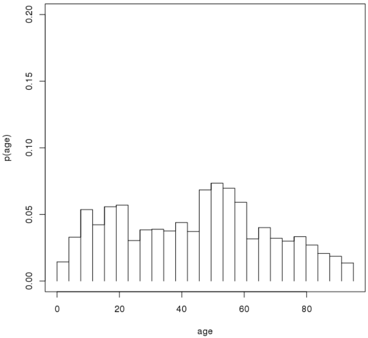
- Lower support histograms are more likely to have a divergent distribution (*sampling error*)
- Rules with high support are still interesting

Then combine both measures: divergence*support

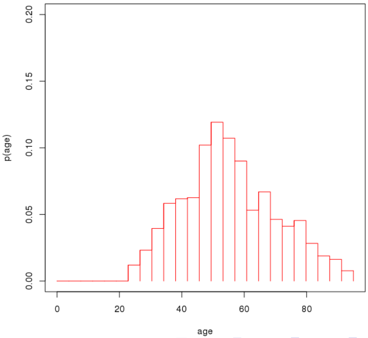
Interestingness Measure

$$\underbrace{maritalStatus(X, married)}_{l=head} \text{ :- } \underbrace{livesIn(X, sd), age(X, Y)}_{c=body}$$

age(X,Y),livesIn(X,sd)



age(X,Y),livesIn(X,sd),marriedStatus(X,married)



Correlation Lattice

- Build a lattice similar to an *itemset lattice*
- Numerical property $r(X, Y)$ as root
- The "items" are literals that can be joined with the root's non-numerical variable X
- Root's numerical attribute Y is discretized in k buckets $\{b_1, \ldots, b_k\}$
- Each node x has a frequency histogram $h(x) =< h_1(x), \ldots, h_k(x) >$ from its clause support distribution

  where $h_i(x) = supp(x|Y \in b_i)$ and $|h(x)|_1 = supp(x)$

Correlation Lattice

$$hasIncome(X, Y)$$

Correlation Lattice

$hasIncome(X, Y)$

$\ldots$

$hasIncome(X, Y),$
$quarterOfBirth(X, q1)$

$hasIncome(X, Y),$
$quarterOfBirth(X, q4)$

Correlation Lattice

$hasIncome(X, Y)$

$\ldots$ $\ldots$

$hasIncome(X, Y)$, $quarterOfBirth(X, q1)$

$hasIncome(X, Y)$, $quarterOfBirth(X, q4)$

$hasIncome(X, Y)$, $hasEducation(X, nursery)$

$hasIncome(X, Y)$, $hasEducation(X, phd)$

Correlation Lattice

$hasIncome(X, Y)$

. . .   .

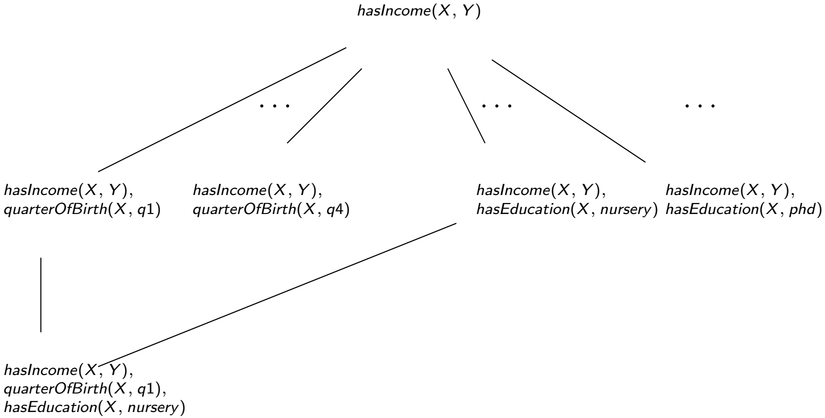
$hasIncome(X, Y)$, $quarterOfBirth(X, q1)$

$hasIncome(X, Y)$, $quarterOfBirth(X, q4)$

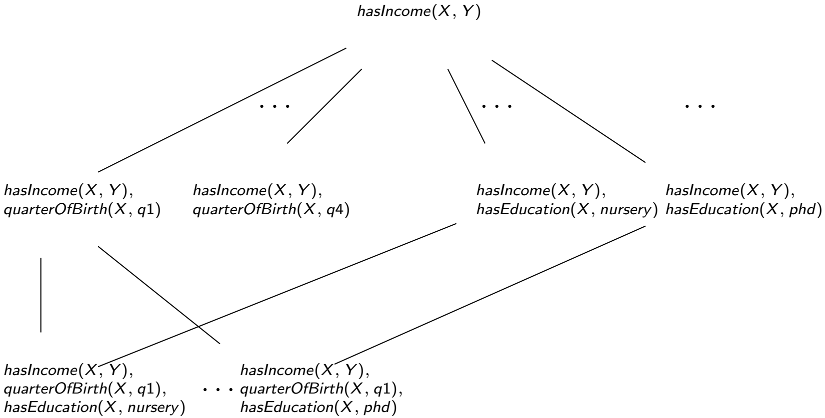
$hasIncome(X, Y)$, $hasEducation(X, nursery)$

$hasIncome(X, Y)$, $hasEducation(X, phd)$

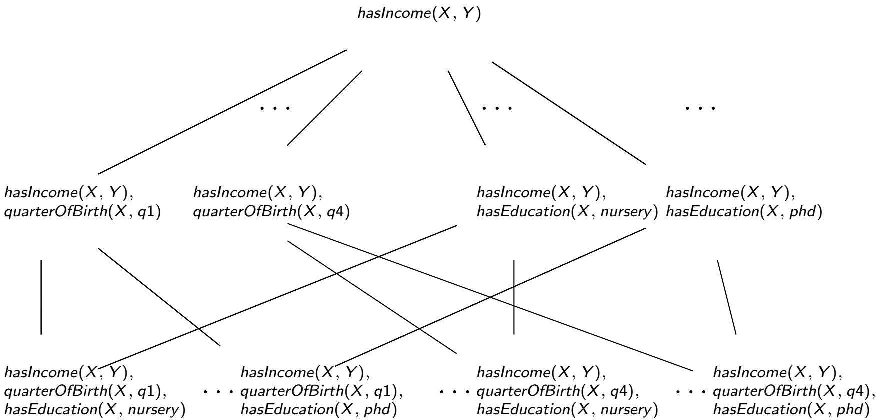
Correlation Lattice



Correlation Lattice



Correlation Lattice



Correlation Lattice

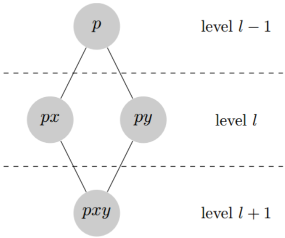
- Number of nodes in a lattice with ℓ levels n properties and m constants per property:

$$\sum_{i=1}^{\ell} \binom{nm}{i} \tag{2}$$

- Too expensive, we need to reduce size
  - Prune by support (safe)
  - Restrict ℓ to the maximum clause size allowed in the core-ILP
  - Restrict the literals added to the lattice in order to reduce n and m
  - Prune by interestingness or independence (heuristics)

Independence checks

- Checks if a pair of nodes joining nodes are independent given their common parent



(where p is a clause, x and y are literals, s.t. $x \neq y$ and $x, y \notin p$)

- Estimate $\hat{h}(pxy)$ assuming independence of x and y given p
- Query actual $h(pxy)$ and perform a Pearson's chi-squared test

  $H_0 = x$ and y are independent given p

  $H_1 = x$ and y are dependent given p

Independence checks

$hasIncome(X, Y)$
$h =< 6, 10, 8, 4, 2, 1 >$

$hasIncome(X, Y), marritalStatus(X, single)$
$h =< 4, 5, 4, 3, 1, 0 >$

$hasIncome(X, Y), employmentStatus(X, employed)$
$h =< 3, 6, 6, 4, 2, 1 >$

$hasIncome(X, Y), marritalStatus(X, single), employmentStatus(X, employed)$
$h =< 2, 4, 2, 4, 1, 0 >$
$\hat{h} =< 2, 3, 3, 3, 1, 0 >$

$$\chi^2 = \sum_{i=1}^{k} \frac{(h_i - \hat{h}_i)^2}{\hat{h}_i} = 1 \quad \Rightarrow \quad p\text{-}value = 0.96$$

Independence checks

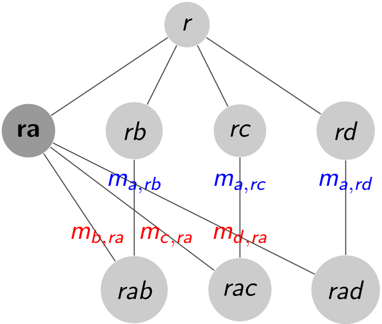
- If there's not enough evidence of dependence, we assume independence, then:

  x :- $p, y \equiv x$:- p

  y :- $p, x \equiv y$:- p
- The lower the p-value (greater χ^2), the greater the evidence that x and y are dependent given p, therefore the more interesting it is to join the nodes py and px
- As heuristics, we can set a maximum *p-value* threshold to prune independent nodes

Refinement Suggestions

In the ILP refinement loop, the clauses have a fixed head while the body is refined. Assuming we have *a* as head literal, *r* as root and *b*, *c*, *d* as possible new literals:

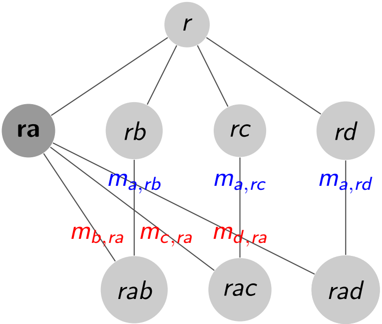


$$a \;\Big|\; \begin{array}{l} b\ [m_{a,rb}] \\ c\ [m_{a,rc}] \\ d\ [m_{a,rd}] \end{array}$$

What literal is more interesting to add to the clause a:-r?

Refinement Suggestions

In the ILP refinement loop, the clauses have a fixed head while the body is refined. Assuming we have a as head literal, r as root and b, c, d as possible new literals:



a	b $[m_{a,rb}]$
	c $[m_{a,rc}]$
	d $[m_{a,rd}]$

What literal is more interesting to add to the clause a:-r?

$argmax_{i \in \{b,c,d\}} m_{a,ri}$

Search in the Lattice

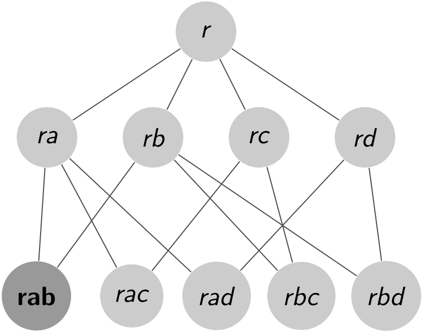
What has to be done?

- Search the node with body literals
- For each child of such node check head literal can be further added, if so collect the new literal and the interestingness value of adding the head
- Sort the possible new literals by interestingness

Alternative?

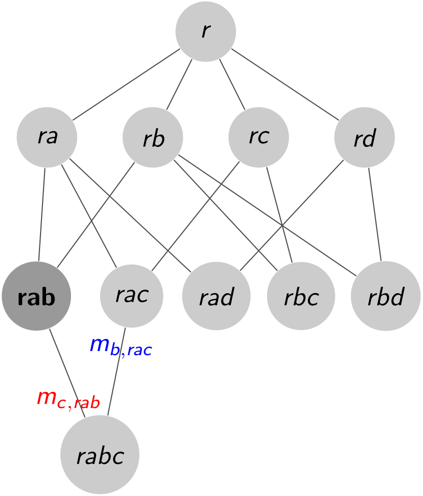
- Create mapping in every node with the possible head literals as key and sorted literals to be added to body as value
- Only add entry if head and new literal not independent given body

Refinement Suggestions



Suggestions Map

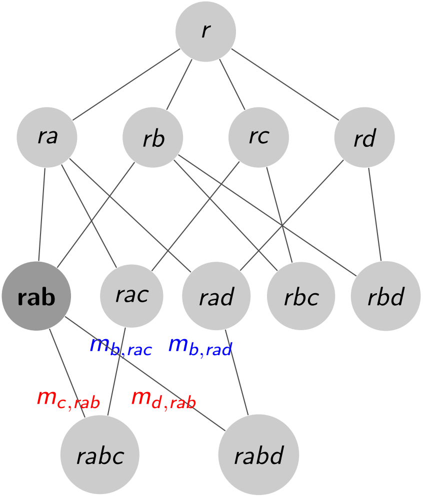
Refinement Suggestions



Suggestions Map

b	$c\ [m_{b,rac}]$

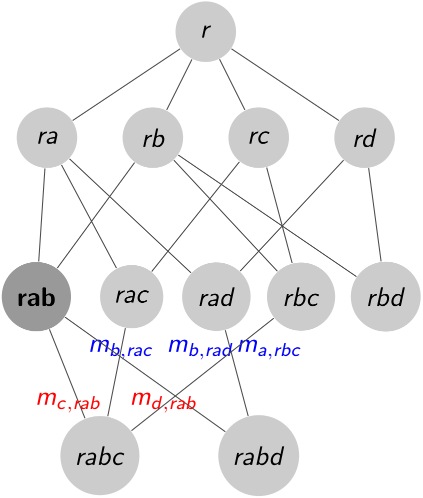
Refinement Suggestions



Suggestions Map

b	$c\ [m_{b,rac}]$ $d\ [m_{b,rad}]$

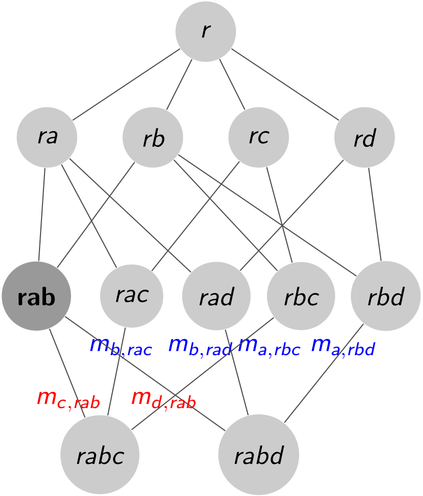
Refinement Suggestions



Suggestions Map

b	$c\ [m_{b,rac}]$ $d\ [m_{b,rad}]$
a	$c\ [m_{a,rbc}]$

Refinement Suggestions



Suggestions Map

b	$c\ [m_{b,rac}]$ $d\ [m_{b,rad}]$
a	$c\ [m_{a,rbc}]$ $d\ [m_{a,rbd}]$

Incorporating the Lattice in the Core-ILP

In the refinement step, we detect clauses with body containing a lattice root

- If clause satisfies support threshold and does not satisfy confidence threshold
- Then search in lattice for body literals and head
- Check the interestingness of adding the head to the body and analyze whether to search for numerical intervals
- Query the lattice for suggestions of interesting literals to be added to the clause

Experiments

Overall Settings:

- We compare 4 interestingness measures:
  1. ● *supp*: Support Only
  2. ■ *klsupp*: KL-divergence*Support
  3. ● *kldiv*: KL-divergence Only
  4. $\star$ *jssupp*: JS-divergence*Support
- Thresholds:
  - $minConf = 0.75$
  - $minSupp = 25$
  - $minGain = 1.25$

1^{st} Experiment: evaluation of the Correlation Lattice

- All data joined by person only (anonymized)
- All properties categorical (categories as literals)
- Create a lattice for *hasIncome* property

2^{nd} Experiment: evaluation of the ILP extension

- All data joined by person only (anonymized)
- All properties categorical (categories as literals)

1^{st} Experiment

Figure: Build time per lattice size

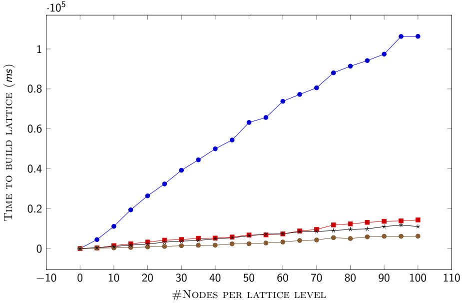
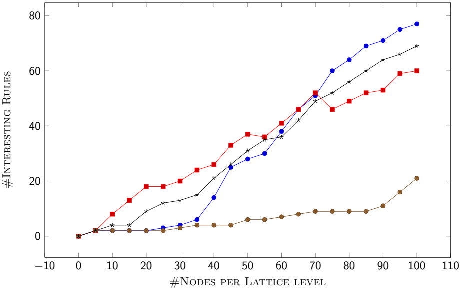


Figure: Interesting rules per lattice size



Legend: [● *supp* ■ *klsupp* ● *kldiv* ⋆ *jssupp*]

2^{nd} Experiment

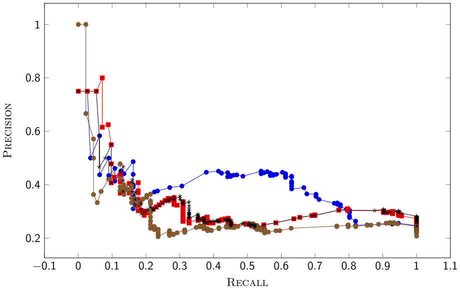


Figure: Precision-Recall graph from interestingness predictions (rules with *runtime* attribute)

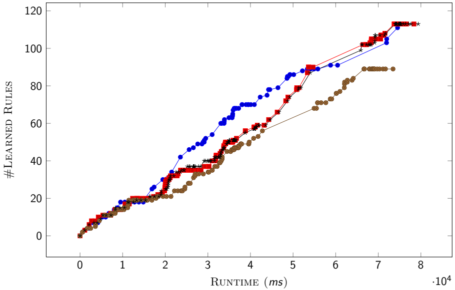


Figure: Interesting rules per runtime (rules with attribute *runtime*)

Legend: [● *supp* ■ *klsupp* ● *kldiv* ⋆ *jssupp*]

1^{st} Experiment

Figure: Precision-Recall graph from interestingness predictions (rules with *budget* attribute)

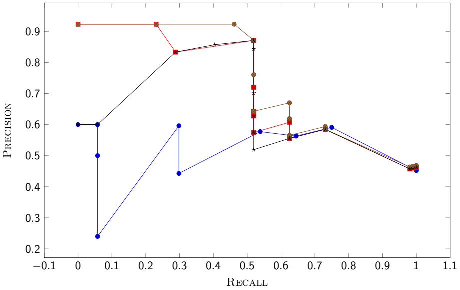
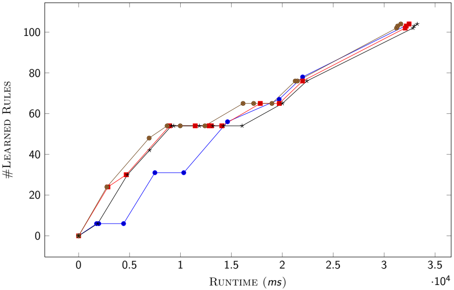


Figure: Interesting rules per runtime (rules with *budget* attribute)



Legend: [● *supp* ■ *klsupp* ● *kldiv* ⋆ *jssupp*]

Thank you