Knowledge Refinement via Rule Selection (AAAI-19)

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Motivation

Rules (Horn formulas) are ubiquitous in AI $\forall x,y,z \; (PARENT(x,z) \land PARENT(y,z) \rightarrow SIBLING(x,y))$ SIBLING(x,y):- PARENT(x,z), PARENT(y,z)



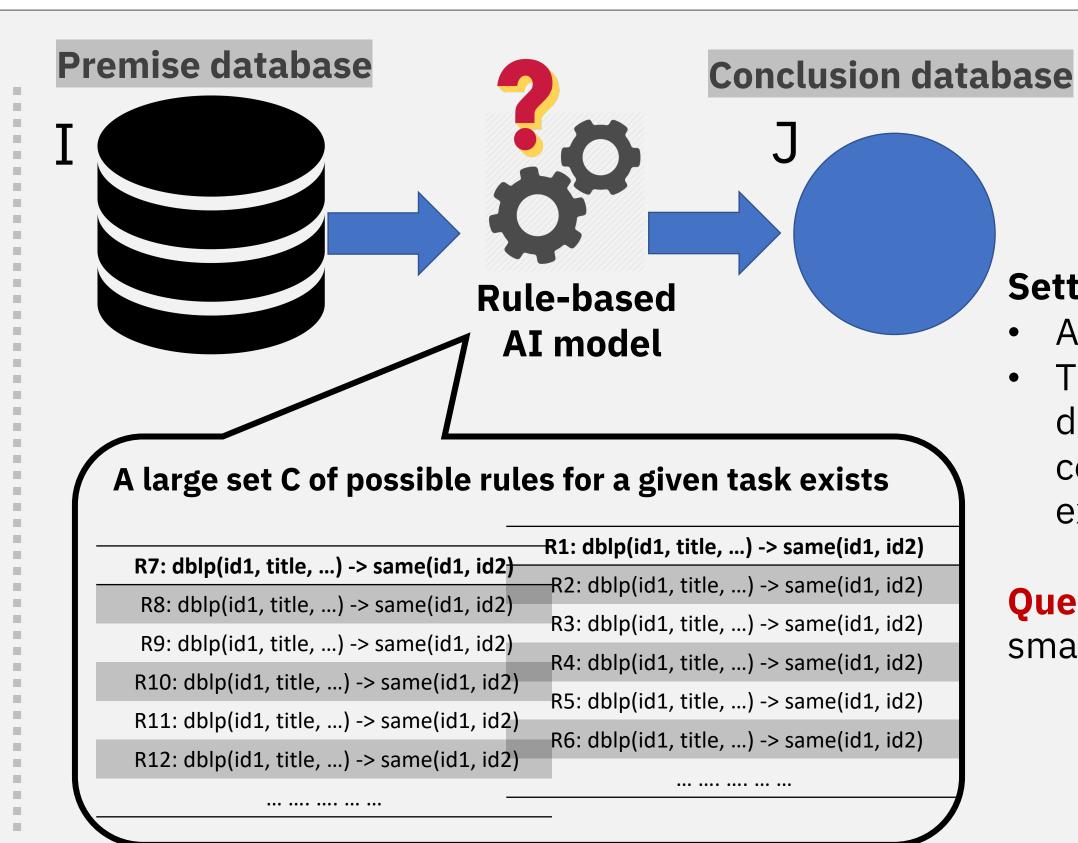
TID	Items	
1	Cake, Milk	{Cake} -> {Milk}
2	Cake, Diaper, Beer	{Cake, Diaper} -> {Beer} {Diaper} -> {Beer} {Beef, Diaper} -> {Beer}
3	Diaper, Beer, Coke	{Diaper} -> {Beer}
4	Beef, Diaper, Beer	{Beet, Diaper} -> {Beet}
5	Diaper, Bread, Milk, Coke	•••••

Entity resolution rules

Matching publications

DBLP(id, title, authors, venue, year)

∧ ACM(id', title, authors, venue, year') → Same(id,id')

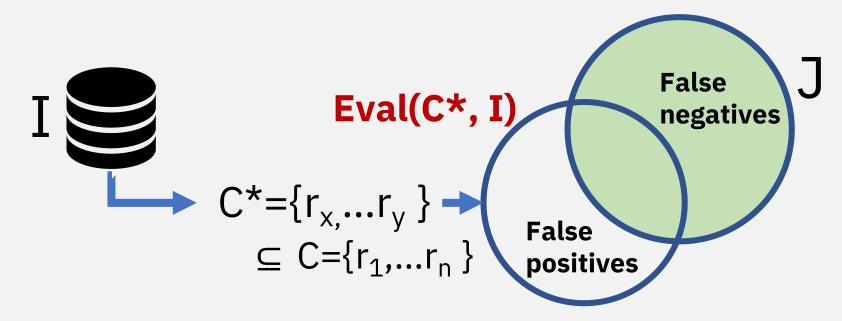


Setting:

- A large set C of possible rules is available.
- The actual semantics of the task is given via data: a premise database I together with a conclusion database J that represents the expected output of the task on input I.

Question: Can we capture the semantics via a small subset of C?

Min Rule Selection Problem



• **Total error** = false positives + false negatives

Definition. Min Rule-Select Problem

Given a pair (I, J) of a premise and a conclusion database, and a set C of rules, find a subset C* of C such that the total error of Eval(C*, I) w.r.t. J is minimized.

Theorem 1

Min Rule-Select is an NP-hard optimization problem.

Hence, unless NP=P, there is no polynomial time algorithm that solves the problem exactly.



Pare there PTIME approximation algorithms with formal guarantees?

Theorem 2

Min Rule-Select is approximable within a factor of $2\sqrt{|C|} + |J| \cdot \log |J|$, where |C| is the number of input rules and |J| is the size of the conclusion instance.

We show that Min Rule-Select is "equivalent" to the Positive-Negative Partial Set-Cover Problem [Miettinen, 2008]

Bi-objective and Bi-level Optimization



What if we want to optimize both the error and the size of the set of rules? (Note that error and size are incomparable quantities.)

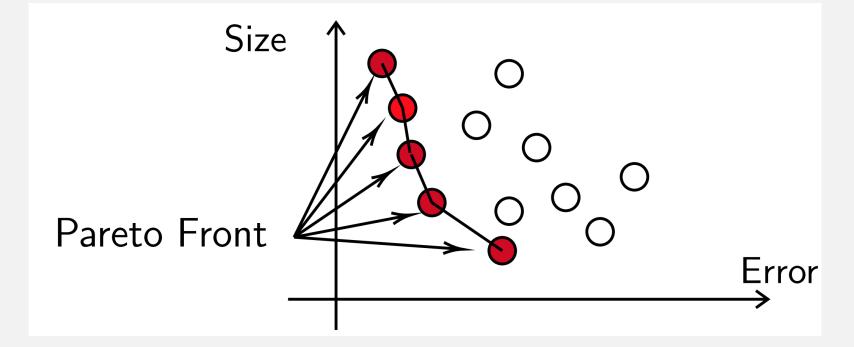
Definition. Pareto Optimal Solution

Given a set C of rules and a pair (I,J) of a premise and a conclusion database, a subset C* of C is a *Pareto optimal* solution if there is no subset C' of C such that $size(C') < size(C^*)$ and $error(C') < error(C^*)$.

The *Pareto front* is the set of all pairs (s*, e*) of integers such that there is a Pareto optimal solution C^* with size(C^*)=s* and error(C^*)=e*.

Definition. Bi-level Optimal Solution

Given a set C of rules and a pair (I,J) of a premise and a conclusion database, a subset C* of C is a *Bi-level optimal* solution if it has both minimum error and minimum size among all minimum-error solutions.



Theorem 3

The following problems are coNP-complete:

Given a pair (I,J) of a premise and a conclusion database, a set C of rules, and a subset C* of C:

- is C* a Pareto optimal solution?
- is C* a bi-level optimal solution?

Summary of Results

		FP	FP+FN
Rule-Select		NP-complete	NP-complete
Exact Rule-Select		DP-complete	DP-complete
Min Dula Calaat	approx. upper	$2\sqrt{ \mathcal{C} \log J }$	$2\sqrt{(\mathcal{C} + J)\log J }$
Min Rule-Select	approx. lower	$2^{\log^{1-\epsilon}(\mathcal{C})}$, $\forall \epsilon > 0$	$2^{\log^{1-\epsilon}(J)}$, $\forall \epsilon > 0$
Pareto Optimal Solution		coNP-complete	coNP-complete
Pareto Front	Membership	DP-complete	DP-complete
Bi-level Optin	nal Solution	coNP-complete	coNP-complete
Bi-level Optimal Value		DP-complete	DP-complete

Directions for future work

- Experimental evaluation of the approximation algorithms for Min Rule-Select.
- Heuristics or approximation algorithms for constructing the Pareto front of rule selection.