

# Implicitly Learning to Reason in First-Order Logic

**Brendan Juba**

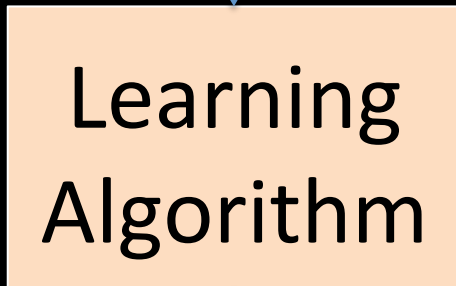
*Washington University in St. Louis*

*joint work with Vaishak Belle*

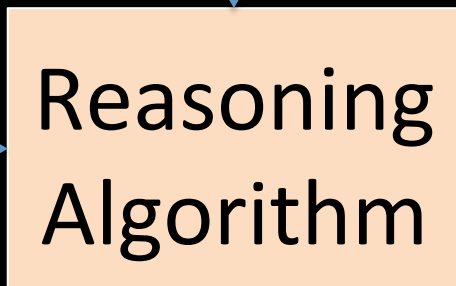
*University of Edinburgh & Alan Turing Institute*

# “*Implicit learning*”: simulating learning without explicit representations

Examples:  $x^1, x^2, \dots, x^m$

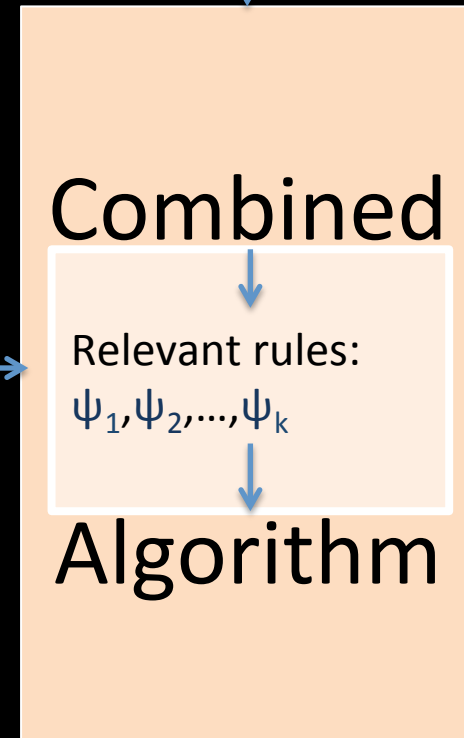


Rules:  $\psi_1, \psi_2, \dots, \psi_k$



Decision: *accept/reject*

Examples:  $x^1, x^2, \dots, x^m$



Decision: *accept/reject*

Query:  $\varphi$

Query:  $\varphi$

# *Why not use explicit representations?*

- Often, **intractable** to guarantee that we discover all relevant rules
- *This work:* explicit representations are **impossible to learn.**

# *Language and reasoning task:*

## universal clauses; ground clausal queries

- Language: First-Order Logic with equality, countably infinite domain of names (**N** wlog)
  - Variables  $x, y, z, \dots$
  - Relation symbols  $P(x), \dots, Q(x_1, \dots, x_k), \dots$
  - Usual connectives/quantifiers:  $\wedge, \vee, \neg, \supset, \forall, \exists$
- Fragment: proper<sup>+</sup> KBs: finite set of  $\forall$ -clauses
  - Equality formulas: built over equality expressions of form “ $x = a$ ” (*variable = name*) and  $\wedge, \vee, \neg$
  - $\forall$ -clause:  $\forall [e \supset c]$  where  $e$  is an equality formula,  $c$  is a quantifier-free clause,  $\forall []$  is universal closure
- Queries: ground clauses (OR of ground atoms)
  - Ground atoms: relations applied to names

## *Learning model:*

### “Probably Approximately Correct”

- Suppose there exists an *arbitrary* probability distribution  $D$  on valuations of ground atoms
- Masking function  $\theta$ : given valuation of ground atoms  $M$ , returns finite subset of the valuations  $N$
- Suppose there exists an arbitrary masking process  $\Theta$ : distribution on masking functions
- Given  $N^1, N^2, \dots, N^m$  drawn independently from  $\Theta(D)$ , ground clausal query  $\varphi$ , wish to certify  $\varphi$  is “ $1-\varepsilon$  valid” with high probability (over  $\Theta(D)$  draw)
  - $1-\varepsilon$  valid:  $\Pr_D[M \models \varphi] \geq 1-\varepsilon$  ( $M \models \varphi$  means true on  $M$ )

# Problem: nontrivial $\forall$ -clauses can't be learned

- We'd like to *learn* a proper<sup>+</sup> KB –  
i.e., identify  $\forall$ -clauses that are  $1-\epsilon$  valid  
using partial valuations  $N^1, N^2, \dots, N^m$  from  $\Theta(D)$ .
  - But, a  $\forall$ -clause  $\forall [e \supset c]$  either
    1. is equivalent to a ground clause (if  $c$  is trivial or  $e$  only permits a finite number of bindings)
    2. or else has an *infinite number of bindings* that must all be satisfied in the *full* valuation  $M$
- ☞ In case 2, using (finite) partial  $N^i$  we *can't distinguish true  $\forall$ -clauses from false  $\forall$ -clauses.*

# This work: *solution* using *implicit learning*

- We propose a new “testability” property that *proper*<sup>+</sup> KBs may satisfy w.r.t. partial valuations.
- We describe a reduction of *learning and reasoning to classical reasoning*: using partial valuations, distinguish *ground clausal queries*  $\varphi$ 
  - that are provable from a (implicit) testable *proper*<sup>+</sup> KB
  - from those that are not *1- $\epsilon$  valid* (thus: sound).
- Using, e.g., Liu et al. '04, obtain *polynomial-time learning and reasoning* for limited belief system

# *What's new?*

## Relationship to other work

- Sound learning and reasoning for **proper<sup>+</sup>** KBs in infinite domains, with arbitrary distributions
  - Prior work on *learning to reason/reasoning in PAC-semantics* was **essentially propositional**, resorted to *propositionalization* for first-order
  - Work in *statistical relational learning* generally relies on *independence structure* in distributions (but produces more *explicit representations*)
  - *Inductive Logic Programming* treats input as *defining* a correct solution, rather than analyzing *predictive power* against unknown “ground truth”



# OUR APPROACH

# Key observation: the “grounding trick”

(Levesque’98, Belle’07)

- Observation: Names not appearing in the KB or query behave identically

**Theorem (Belle’07):** For a proper<sup>+</sup> KB  $\Delta$  and a ground clause  $\varphi$ ,  $\Delta \models \varphi$  iff  $\text{GND}^-(\Delta \wedge \neg\varphi)$  is unsatisfiable.

- *Formally:* for a proper<sup>+</sup> KB  $\Delta$ ,  $\text{GND}^-(\Delta)$  is the set of all  $c\theta$  for  $\forall [e \supset c]$  in  $\Delta$  such that  $e\theta$  is valid and  $\theta$  ranges over all variables in a set  $Z$  containing the names appearing in  $\Delta$  plus  $\text{rank}(\Delta)$  (arbitrary) additional names
  - $\text{rank}(\Delta)$ : max # of quantified variables over clauses in  $\Delta$ .

# The *grounding trick* enables *evaluation* from partial valuations

- *Grounding trick*: As long as a partial valuation  $N^i$  gives values to a suitable set of names, we can check that a KB  $\Delta$  entails a query  $\varphi$ .
- *Witnessing*: recursive evaluation on partial valuation  $N^i$ .
  - Propositional formulas: substitute partial valuation for atoms,  $\varphi \vee \psi$  is *witnessed true* if either  $\varphi$  or  $\psi$  is; *witnessed false* if both are. (Other connectives similar.)
  - $\forall$ -clause :  $\forall x \varphi(x)$  is *witnessed true* for the set of names  $C$  if for all bindings of  $x$  to  $c$  from  $C$ , the propositional formula  $\varphi(c)$  is *witnessed true*.

# The *grounding trick* enables *evaluation* from partial valuations

- *Grounding trick*: As long as a partial valuation  $N^i$  gives values to a suitable set of names, we can check that a KB  $\Delta$  entails a query  $\varphi$ .
- *Witnessing*: recursive evaluation on partial valuation  $N^i$ .
- Implicit KB  $I$  is *witnessed true* in  $N^i$  for a query  $\varphi$  and explicit KB  $\Delta$  if for a set of names  $C$  containing all of the names appearing in  $I$ ,  $\Delta$ , and  $\varphi$  plus  $\text{rank}(\Delta \wedge I)$  additional ones, every  $\forall$ -clause in  $I$  is *witnessed true*.
- Implicit KB  $I$  is *1- $\epsilon$  testable* for a query  $\varphi$  and explicit KB  $\Delta$  if it is *witnessed true* with probability at least  $1-\epsilon$  on partial valuations from  $\Theta(D)$ .

# Main Theorem

**Theorem.** For confidence  $\delta$ , accuracy  $\gamma$ , and rank bound  $k$ , there is an algorithm that given a KB  $\Delta$ , query  $\varphi$ , and  $m \geq \frac{1}{2\gamma^2} \ln \frac{2}{\delta}$  partial valuations from  $\Theta(D)$ , returns an estimate of validity  $\tilde{v}$  such that with probability at least  $1-\delta$ ,

1. (*sound*) If  $\Delta \supset \varphi$  is  $v$ -valid (w.r.t.  $D$ ),  $\tilde{v} \leq v + \gamma$
2. (*complete*) If there is an (implicit) KB  $I$  such that
  - $\Delta \wedge I \models \varphi$
  - Both  $I$  and  $\Delta$  have rank at most  $k$ , and
  - $I$  is  $v$ -testable for  $\varphi$  and  $\Delta$then  $\tilde{v} \geq v - \gamma$ .

Can compare  $\tilde{v}$  to  $1-\epsilon$  to decide “accept”/“reject”

# **THE ALGORITHM & SKETCH OF ITS ANALYSIS**

# *The algorithm*

## *(reduction to classical reasoning)*

1. Initialize count = 0
2. Loop over partial valuations  $N^1, N^2, \dots, N^m$ 
  - Loop over k-tuples of names  $c_1, \dots, c_k$  from  $N^i$  not appearing in  $\varphi$  or  $\Delta$ 
    - a. Construct  $\Gamma$  from  $\text{GND}(\Delta \wedge \neg\varphi)$  using  $\{c_1, \dots, c_k\}$  as the additional names by recursively substituting truth values for subformulas witnessed in  $N^i$
    - b. If  $\Gamma$  is (detected) unsatisfiable, increment count and skip to next partial valuation  $N^{i+1}$ .
3. Return  $\tilde{v} = \text{count}/m$ .

# Sketch of analysis, condition 1 (“soundness”)

- When  $\Delta \supset \varphi$  is falsified on complete valuation  $M$  drawn from  $D$ ,  $\Delta \wedge \neg \varphi$  is satisfied by  $M$
- Therefore, it must also be satisfiable on any partial valuation  $N$  obtained from  $M$ , and in particular, satisfiable for any grounding.
- Therefore, the fraction of times  $\Gamma$  could be refuted is at most the fraction of times  $\Delta \supset \varphi$  was satisfied on the actual valuations  $M$ .
- *Chernoff bound*: the observed fraction is greater than the true probability by at most  $\gamma$ .



# Sketch of analysis, condition 2 (“completeness”)

- *Grounding trick*:  $\Delta \wedge I \models \varphi$  iff  $\text{GND}^-(\Delta \wedge I \wedge \neg\varphi)$  is unsatisfiable for any suitable choice of names.
- Substituting truth values for *witnessed* subformulas for any partial valuation  $N$  still yields an unsatisfiable formula.
- When  $I$  is *witnessed true* for the set of additional names  $\{c_1, \dots, c_k\}$ , we’d substitute  $T$  for every clause of  $I$  in  $\text{GND}^-(\Delta \wedge I \wedge \neg\varphi)$ ; the result is identical to the  $\Gamma$  we obtain.
- Therefore, when  $I$  is *witnessed true*,  $\Delta \wedge I \models \varphi$  iff  $\Gamma$  is unsatisfiable.
- *Chernoff bound, again*: the observed fraction is less than the true probability (*testability* of  $I$ ) by at most  $\gamma$ .

# Recap: *learning and reasoning* for **proper<sup>+</sup>** KBs using *implicit learning*

- Obtain sound learning and reasoning for **proper<sup>+</sup>** KBs in infinite domains, with arbitrary distributions
- We proposed a new “**testability**” property that **proper<sup>+</sup>** KBs may satisfy w.r.t. partial valuations.
- We described a reduction of *learning and reasoning* to *classical reasoning*: using partial valuations, we distinguish **ground clausal queries  $\varphi$** 
  - that are provable from a (implicit) **testable proper<sup>+</sup>** KB
  - from those that are not **1- $\epsilon$  valid** (thus: sound).
- Using, e.g., Liu et al. '04, obtain *polynomial-time learning and reasoning* for **limited belief system**

# *Future directions*

- Queries on atoms with names that are rarely/  
never observed
- Queries with quantifiers

Both require new assumptions for learning from partial valuations – perhaps “*bounded concealment*” (Michael ‘10).