

# Predicate Invention in Rule Learning with Popper use case - When What is Known is not Enough

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# Inductive Logic Programming (ILP)

- ▶ ILP is a form of symbolic machine learning.
- ▶ Introduced in the early 90s (Muggleton, 1991).
- ▶ **Goal:** Form an **explanatory hypothesis** using:
  - 1) Positive and negative **evidence**
  - 2) Provided **background knowledge**

## Background Knowledge (BK)

mother( $a, b$ ).   father( $g, b$ ).  
mother( $a, c$ ).   father( $g, c$ ).  
mother( $b, d$ ).   father( $f, d$ ).  
mother( $e, f$ ).   father( $c, h$ ).

## Evidence

grandparent( $a, d$ )<sup>+</sup>.  
grandparent( $g, d$ )<sup>+</sup>.  
grandparent( $a, h$ )<sup>+</sup>.  
grandparent( $g, h$ )<sup>+</sup>.  
grandparent( $a, e$ )<sup>-</sup>.

- ▶ mother( $a, b$ ) denotes **a** is a mother of **b**.

# Grandparent Example

- ▶ From *mother/2* and *father/2* we learn a **logic program** for  
*X is a grandparent of Y*
- ▶ One solution is

```
grandparent(X, Y):-mother(X, Z), mother(Z, Y)
grandparent(X, Y):-mother(X, Z), father(Z, Y)
grandparent(X, Y):-father(X, Z), mother(Z, Y)
grandparent(X, Y):-father(X, Z), father(Z, Y)
```

- ▶ A popular learning paradigm is **Learning from Entailment**:

$$BK, \mathbf{H} \models E^+ \qquad BK, \mathbf{H} \not\models E^-$$

- ▶ Goal: Find **H**.

# A “Better” Grandparent

BK

mom(a, b). dad(e, b).  
 mom(a, c). dad(e, c).  
 mom(b, d). dad(c, f).

E<sup>+</sup>

gp(a, d). gp(e, d).  
 gp(a, f). ~~gp(e, f).~~

E<sup>-</sup>

gp(a, b). gp(b, c).  
 gp(c, f). gp(d, f).

Learning is less brittle with the parent predicate

gp(X, Y):-mom(X, C), mom(C, Y)  
 gp(X, Y):-mom(X, C), dad(C, Y)  
 gp(X, Y):-dad(X, C), mom(C, Y)  
~~gp(X, Y):-dad(X, C), dad(C, Y)~~

gp(X, Y):-**p**(X, C), **p**(C, Y)  
**p**(X, Y):-mom(X, Y)  
**p**(X, Y):-dad(X, Y)

# What is Predicate Invention (PI)?

- ▶ When learning a model (logic program) for a task, introduction of a concept which is neither:
  - ▶ given as part of the background knowledge, nor
  - ▶ the solution to the task itself.

$qsort([], []).$   
 $qsort([H|T], S) :- \text{part}(H, T, L1, L2), qsort(L1, S1),$   
 $qsort(L2, S2), \text{append}(S1, [H|L2], S).$

- ▶ In “*The Appropriateness of PI as Bias Shift...*”, I. Stahl suggest that **recursive** PI is **Essential** to learning.

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$part(-, [], [], []).$

$part(P, [H|T1], [H|T2], L) :- X \leq P, part(P, T1, T2, L).$

$part(P, [H|T1], L, [H|T2]) :- X > P, part(P, T1, L, T2).$

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# Other Types of Predicate Invention

- ▶ **Compressive PI**

Reduces program size

**grandparent using parent**

- ▶ **Bias Expansion PI**

New operations beyond the bias specified in the task

**defining repeated and useful predicate sequences**

- ▶ **Negative PI**

Provides the complement of bias expansion PI

**universal search over a finite domain**

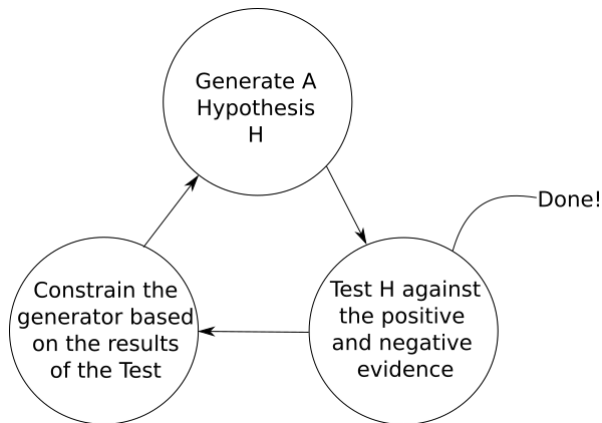
- ▶ **Higher-Order PI**

Provides input for higher-order definitions

**Mix of all the above**

# Popper

- ▶ You heard a lot about Popper last seminar from Celine:
- ▶ **Recap:**

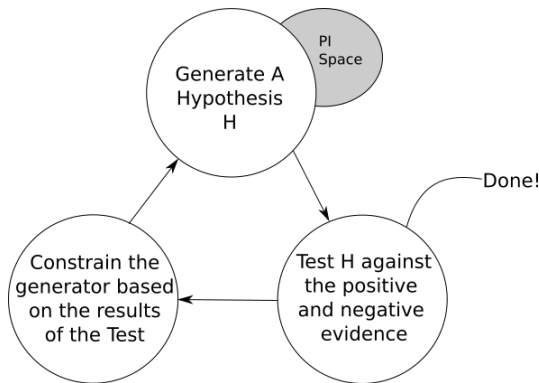


- ▶ What changes when PI is involved?



# Popper with PI

- ▶ The main difference is a larger search space.



- ▶ Within this larger search space **multiple representations** of the same program exists,
- ▶ Some **much smaller** than others.

# Popper With Higher-order Definitions?

- ▶ Similar to PI, but invented predicates used for HO definitions.

$\text{map}(P, [], []).$

$\text{map}([H1|T1], [H2|T2], P):-P(H1, H2), \text{map}(T1, T2).$

$\text{fold}(_, X, [], X).$

$\text{fold}(P, Acc, [H|T], Y):-P(Acc, H, W), \text{fold}(P, W, T, Y).$

$\text{any}(P, [H|_], B):-P(H, B).$

$\text{any}(P, [_|T], B):-\text{any}(P, T, B).$

- ▶ Additional bias used to learn solutions for tasks.

# Introducing Higher-order Definitions

- ▶ Higher-order definitions, larger space  $\Rightarrow$  smaller programs:

```
map(P, [], []).
```

```
map([H1 | T1], [H2 | T2], P):-P(H1, H2), map(T1, T2).
```

- ▶ First-order dropLast:

```
dropLast(A, B):- empty(A), empty(B).
```

```
dropLast(A, B):- con(A, B, C), reverse(C, E),  
                 tail(E, F), reverse(F, G),  
                 con(B, G, H), dropLast(D, H).
```

- ▶ Higher-order dropLast:

```
dropLast(A, B):- map(inv, A, B).
```

```
inv(A, B):- reverse(A, C), tail(C, D),  
           reverse(D, B).
```

## Interesting Examples

- ▶ Is B a subtree of A:

`isSubTree(A, B):- eq(A, B).`

`isSubTree(A, B):- children(A, C), any(p, C, B).`

`p(A, B):- isSubTree(A, B).`

- ▶ Is list B the second half of list A:

`lastHalf(A, B):- reverse(A, C), caseList(p, q, C, B).`

`p(A):- empty(A).`

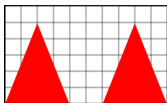
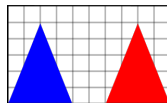
`q(A, B, C):- front(B, E), caseList(p, q, E, D),  
app(D, A, C).`

- ▶ **Problem:** many programs are semantically equivalent.
- ▶ **Open:** how to efficiently learn such programs?

# Motivating Negative PI

## Consider the following game

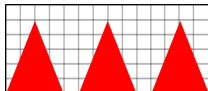
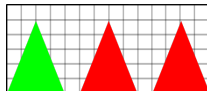
- ▶ A **teacher** chooses examples which follow a **hidden rule**.

 $E^+$  $E^-$  $E^-$ 

- ▶ The **students**, based on the examples, **guess** possible rules.
- ▶ For example, *"there are two red cones"*

# Motivating Negative PI

- ▶ What if the **teacher** provided additional examples?

 $E^+$  $E^-$ 

- ▶ “[there are two red cones] or [there are three red cones]”?
- ▶ What if the **teacher** provided examples **with up to n cones**?

# Motivating Negative PI

- ▶ Obviously, we want to generalize beyond case enumeration.

**“All cones are red”**

- ▶ Most **ILP** approaches struggle to learn such rules.
- ▶ Often the *hypothesis space* is restricted to
  - ▶ Datalog,
  - ▶ Datalog<sup>+</sup>, or
  - ▶ Definite programs

# Motivating Negative PI

- ▶ None are capable of encoding the required **universal** search.

$$\begin{aligned} f(S) &:- \text{scene}(S), \mathbf{not} \text{ inv}_1(S). \\ \text{inv}_1(S) &:- \text{cone}(S, P), \mathbf{not} \text{ red}(P). \end{aligned}$$

- ▶ that is “**there does not exists a cone which is not red.**”
- ▶ How does one learn such *Stratified Logic Programs*?



# Beyond Definite Clause Subsumption

## Definition

A clause  $C_1$  **subsumes** a clause  $C_2$  if and only if there exists a substitution  $\theta$  such that  $C_1\theta \subseteq C_2$ .

## Definition

A *definite program*  $P$  subsumes a definite program  $Q$  ( $P \preceq_\theta Q$ ) if and only if  $\forall r_2 \in Q, \exists r_1 \in P$  such that  $r_1$  **subsumes**  $r_2$ .

## Theorem (**Entailment property**)

Let  $P$  and  $Q$  be definite programs s.t.  $P \preceq_\theta Q$ . Then  $P \models Q$ .

- Does not hold for **Stratified Programs**.

# Beyond Definite Clause Subsumption

$$P = \left\{ \begin{array}{l} a. \\ f :- \textbf{not } inv_1. \\ inv_1 :- b. \\ inv_1 :- a. \end{array} \right\} \quad Q = \left\{ \begin{array}{l} a. \\ f :- \textbf{not } inv_1. \\ inv_1 :- b. \end{array} \right\}$$

$P \preceq_{\theta} Q$  and  $Q \models f$  but  $P \not\models f$ . (**P more specialised**)

$$P' = \left\{ \begin{array}{l} a. \\ f :- \textbf{not } inv_1. \\ inv_1 :- a, b. \end{array} \right\} \quad Q' = \left\{ \begin{array}{l} a. \\ f :- \textbf{not } inv_1. \\ inv_1 :- a. \end{array} \right\}$$

$Q' \preceq_{\theta} P'$  and  $P' \models f$  but  $Q' \not\models f$ . (**P' more general**)

**Generality and speciality swap.**

# Polar Fragment

## ► **Stratified Program:**

Strict order on negated occurrences of head predicate symbols.

⇒ **No Recursion** through negation.

⇒ A head predicate symbol may occur both **negated and non-negated**. (*Breaks subsumption*)

► We label head symbols as **Positive**, **Negative**, or **Neither**.

► Depends on use of negation relative to symbol occurrence.

## Definition (**Polar program**)

A stratified program  $P$  is polar if and only if every head predicate symbol in  $P$  is **exclusively positive or negative**.

# Polar Subsumption

- Rules of  $P$  with **positive** (**negative**) head symbols are **positive**, that is in  $P^+$  (**negative**, that is in  $P^-$ ).

$r_1 : \text{unconnected}(A, B) \text{ :- not } \text{inv}_1(A, B)$

$r_2 : \text{inv}_1(A, B) \text{ :- edge}(A, B)$

$r_3 : \text{inv}_1(A, B) \text{ :- edge}(A, C), \text{inv}_1(C, B)$

- For  $\text{unconnected}/2$ ,  $P^+ = \{r_1\}$  and  $P^- = \{r_2, r_3\}$ .

## Definition (Polar subsumption)

Let  $P$  and  $Q$  be polar programs. Then  $P$  *polar subsumes*  $Q$  ( $P \preceq_{\diamond} Q$ ) iff  $P^+ \preceq_{\theta} Q^+$  and  $Q^- \preceq_{\theta} P^-$ .

## Theorem (Entailment property)

Let  $P$  and  $Q$  be polar programs:  $P \preceq_{\diamond} Q \implies P \models Q$ .

# Learning from Failures with Negation (LFFN)

- ▶ An extension of **Learning from Failures** (A. Cropper & R. Morel, 2020) to polar programs
- ▶ Takes as input *positive* ( $E^+$ ) and *negative* ( $E^-$ ) examples, *background* ( $B$ ), polar programs ( $\mathcal{H}$ ), and constraints ( $C$ ).

## Definition (LFFN solution)

Given  $(E^+, E^-, B, \mathcal{H}, C)$ , an  $H \in \mathcal{H}_C$  is a **solution** if  $H$  is *complete* ( $\forall e \in E^+, B \cup H \models e$ ) and *consistent* ( $\forall e \in E^-, B \cup H \not\models e$ ).

**Constraint Soundness:** Let  $(E^+, E^-, B, \mathcal{H}, C)$  and  $H_1, H_2 \in \mathcal{H}_C$ :

### Generalisation

If  $H_1$  is inconsistent and  $H_2 \preceq_{\diamond} H_1$ , then  $H_2$  is not a solution.

### Specialisation

If  $H_1$  is incomplete and  $H_1 \preceq_{\diamond} H_2$ , then  $H_2$  is not a solution.

# NOPI

- ▶ *NOPI* Learns **Polar Programs** and
- ▶ prunes the search space using **non-monotonic constraints**.

**H<sub>1</sub>:**

$r_1 : \quad f(S) \text{ :- } scene(S), \textbf{not } inv_1(S)$

$r_2 : \quad inv_1(A, B) \text{ :- } cone(S, A)$

**H<sub>2</sub>:**

$r_1 : \quad f(S) \text{ :- } scene(S), \textbf{not } inv_1(S)$

$r_2 : \quad inv_1(A, B) \text{ :- } cone(S, A)$

$r_3 : \quad inv_1(A, B) \text{ :- } contact(S, A, _), red(A), \textbf{not } blue(A)$

- ▶ Observe,  $H_1 \preceq_{\diamond} H_2$ . If  $H_1$  is **incomplete**, then  $H_2$  is pruned by a **polar specialisation constraint**.

# Example Programs

- Is  $B$  an independent set of  $A$ :

$ind(A, B) :- \text{not } inv1(B, A).$

$inv1(A, B) :- member(C, A), edge(B, D, C), member(D, A).$

- Is  $B$  a dominating set of  $A$ :

$dominating(A, B) :- \text{not } inv1(A, B).$

$inv1(A, B) :- node(A, C), \text{not } member(C, B),$   
 $\text{not } inv2(A, B, C).$

$inv2(A, B, C) :- edge(A, C, D), member(D, B).$

- **English:** For all nodes  $C$  in the graph  $A$  that are not members  $B$  there exists a node  $D$  in  $B$  such that there is an edge from  $C$  to  $D$ .

# Future Work

- ▶ There are many open problems concerning PI:
  - ▶ **Obstructive**: When PI is unnecessary it makes learning harder
  - ▶ **Twins**: There are many ways to write the same program
  - ▶ **Efficiency**: are some uses of PI completely useless
  - ▶ **modularity**: separating PI from the main program
  - ▶ **Domain Specificity**: What problems need which type of PI