

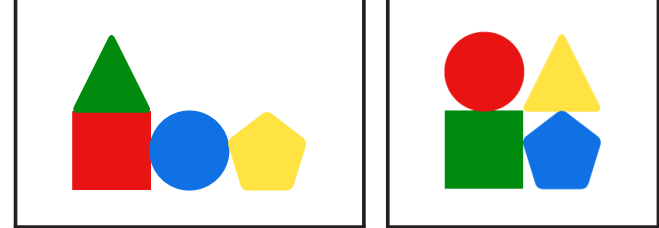
1 - Introduction

The goal of inductive logic programming (ILP) is to induce a program (a set of logical rules) that generalises training examples.

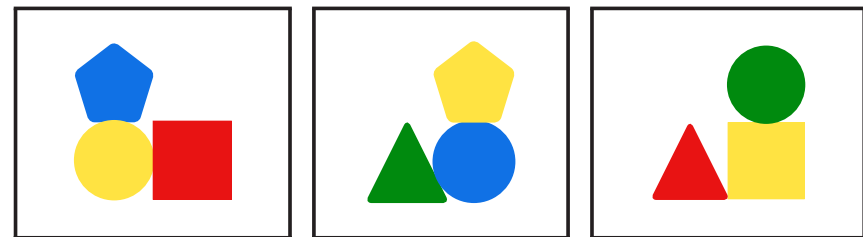
Problem: learning programs with big rules is difficult.

Example 1 (Zendo)

Positive examples:



Negative examples:



$zendo(S) \leftarrow \text{piece}(S,B), \text{blue}(B),$
 $\text{piece}(S,R), \text{red}(R),$
 $\text{piece}(S,G), \text{green}(G)$

We introduce an approach where we join small rules to learn big rules.

We first search for rules that entail at least one positive example, such as:

$zendo_1(S) \leftarrow \text{piece}(S,B), \text{blue}(B)$
 $zendo_2(S) \leftarrow \text{piece}(S,R), \text{red}(R)$
 $zendo_3(S) \leftarrow \text{piece}(S,G), \text{green}(G)$
 $zendo_4(S) \leftarrow \text{piece}(S,Y), \text{yellow}(Y)$

We then search for subsets of these rules which entail at least one positive example and no negative examples:

$zendo(S) \leftarrow zendo_1(S), zendo_2(S)$
 $zendo_3(S)$

Example 2 (List classification)

Positive	Negative
$f([a,b,c,d])$	$f([a,c,d,e])$
$f([c,b,d,e])$	$f([c,b])$
	$f([d,b])$

We first learn programs that entail at least one positive example:

$\{ f_1(\text{List}) \leftarrow \text{head}(\text{List},a) \}$
 $\{ f_2(\text{List}) \leftarrow \text{head}(\text{List},c) \}$
 $\{ f_3(\text{List}) \leftarrow \text{tail}(\text{List},\text{Tail}), \text{head}(\text{Tail},b) \}$
 $\{ f_4(\text{List}) \leftarrow \text{head}(\text{List},c) \}$
 $\{ f_4(\text{List}) \leftarrow \text{tail}(\text{List},\text{Tail}), f_4(\text{Tail}) \}$
 $\{ f_5(\text{List}) \leftarrow \text{head}(\text{List},d) \}$
 $\{ f_5(\text{List}) \leftarrow \text{tail}(\text{List},\text{Tail}), f_5(\text{Tail}) \}$

We then search for subsets of these rules which entail at least one positive example and no negative examples:

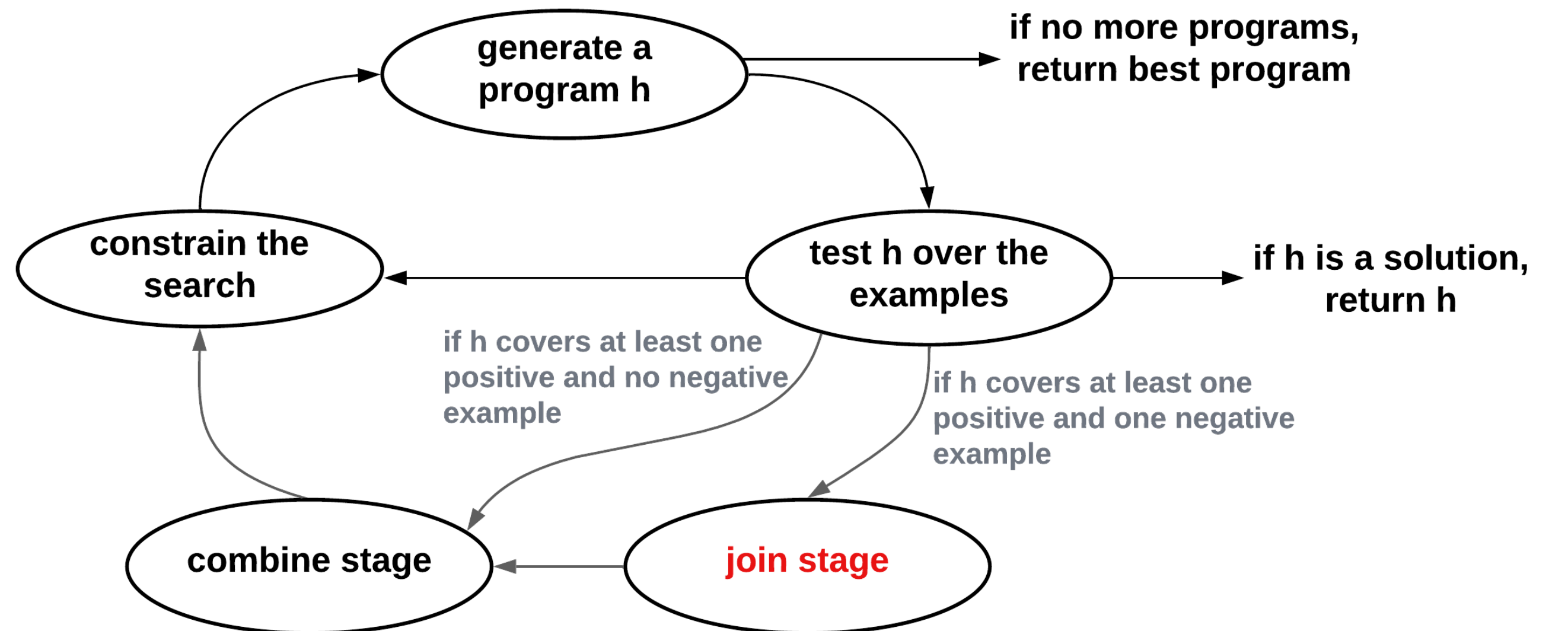
$f(\text{List}) \leftarrow f_3(\text{List}), f_4(\text{List}), f_5(\text{List})$

3 - Theoretical Analysis

Theorem JOINER learns an optimal solution (a program with minimal size).

2 - Our approach (JOINER)

Key idea: learn small programs independently and then try to find conjunctions of these programs which cover no negative examples.



We develop a Boolean satisfiability approach to find conjunctions in the join stage.

4 - Experiment

- Q1 Can the join stage improve learning performance?
- Q2 How well does JOINER scale with the size of rules?
- Q3 How well does JOINER compare against other approaches?

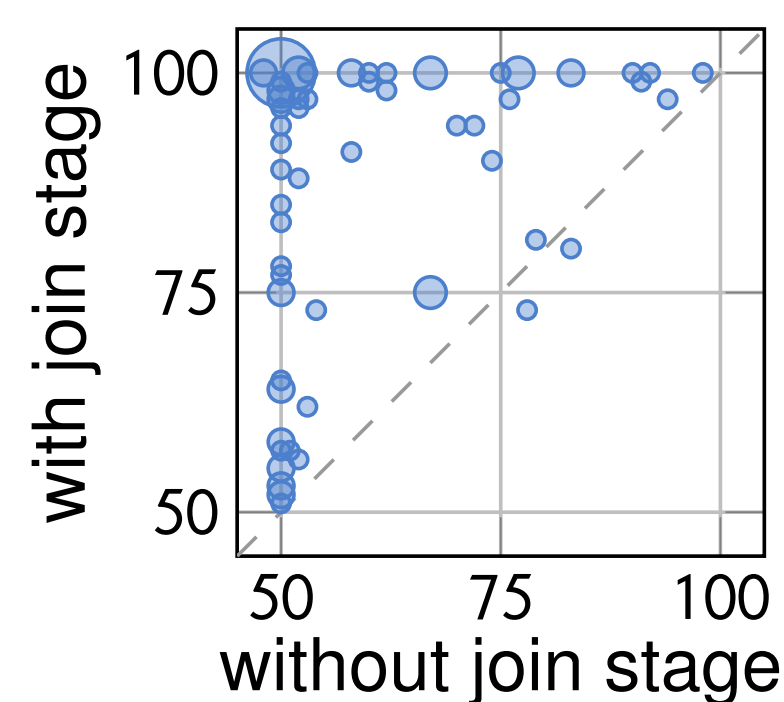


Fig. 1: Predictive accuracy (%) with and without join stage.

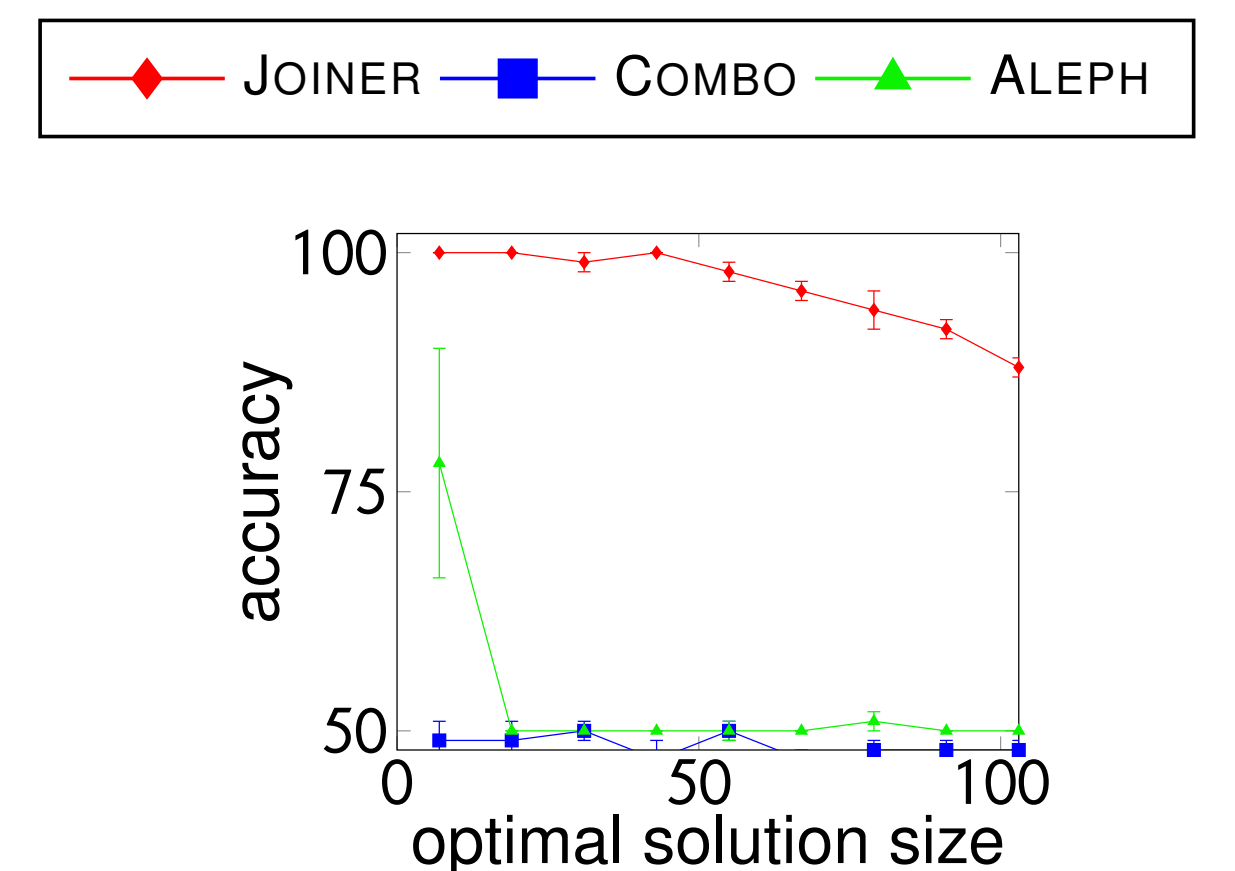


Fig. 2: Predictive accuracy versus the size of programs for *zendo*.

Task	ALEPH	COMBO	JOINER
<i>igpp</i>	78 ± 3	86 ± 2	96 ± 1
<i>zendo</i>	100 ± 0	86 ± 3	94 ± 2
<i>pharma</i>	50 ± 0	53 ± 2	98 ± 1
<i>imdb</i>	67 ± 6	100 ± 0	100 ± 0
<i>string</i>	50 ± 0	50 ± 0	100 ± 0
<i>onedarc</i>	51 ± 1	57 ± 2	89 ± 1

Table 1: Predictive accuracies (%).

- Q1 The join stage can substantially improve predictive accuracies.
- Q2 JOINER can learn rules with more than 100 literals.
- Q3 JOINER can outperform existing approaches in terms of predictive accuracies.

5 - Conclusion and Limitation

► An approach which learns big rules by joining small rules.

Future work: noisy examples.

Article



Code

