Investigating the Utility of Answer Set Programming and Inductive Logic Techniques in Learning Two-Player Game Strategies

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Cognitive Systems: Language, Learning, and Reasoning (M.Sc.)

PM - Computational Intelligence
Knowledge Processing and Information Systems

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Overview

Introduction

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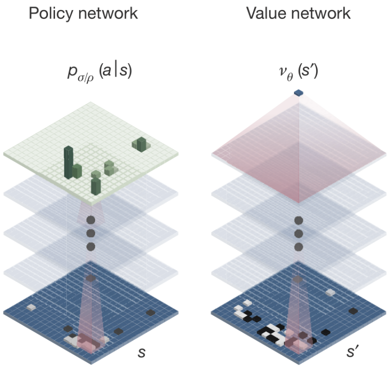

Figure 1: Schematic of policy and value neural networks in AlphaGo

- New advancements in computer agents using AI for two-players games *AlphaGo*
  - Deep reinforcement learning
  - GPU hardware-acceleration
  - Monte-Carlo tree search

✓ Make decisions for games with exponentially complex search spaces

× Lack of interpretability of black-box models

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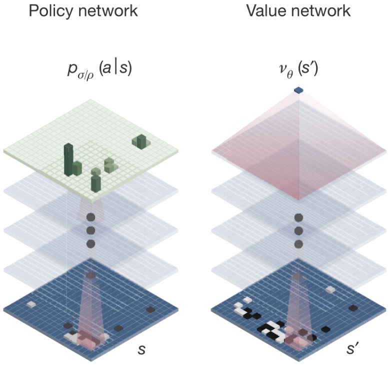

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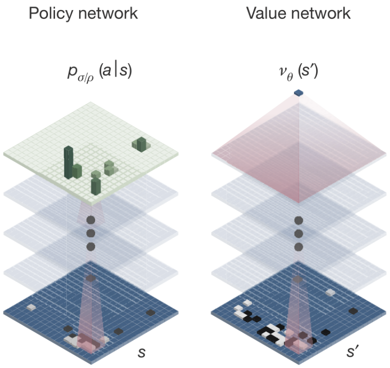

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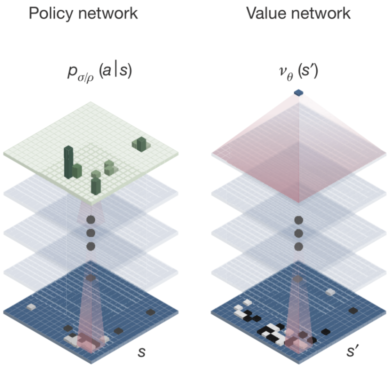

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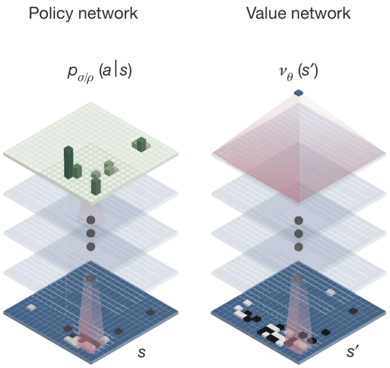

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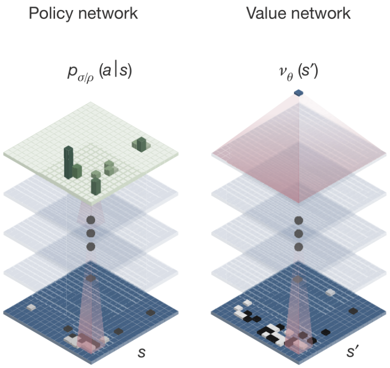

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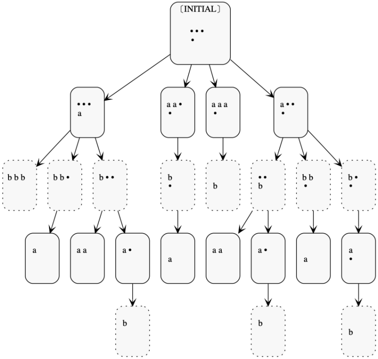

Figure 2: Schematic of game tree

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  - ✓ Interpretability of strategies
  - × Search large game spaces to learn strategies
- Small two-player games: *Nim* and *Tic-Tac-Toe*
- Use formalisms from Game Description Language
- Use Answer Set Programming and Inductive Logic Techniques to learn interpretable game-winning strategies

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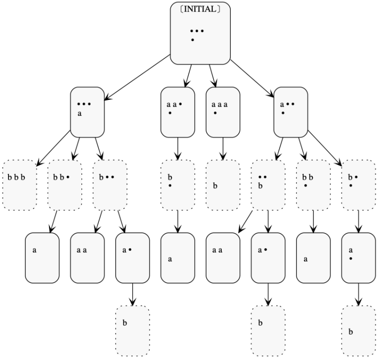

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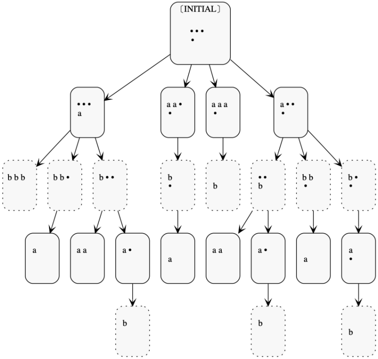

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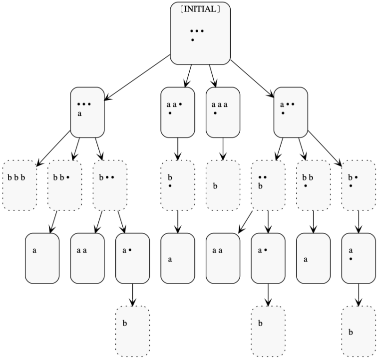

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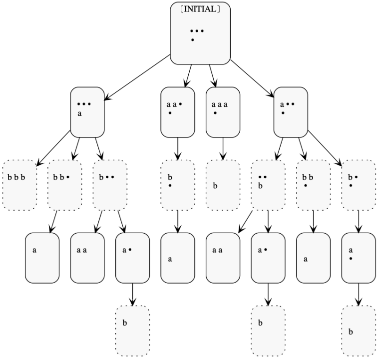

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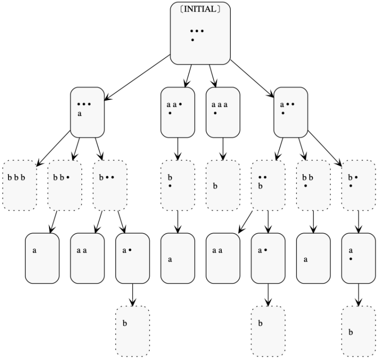

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Background Concepts

Two-Player Game: Nim

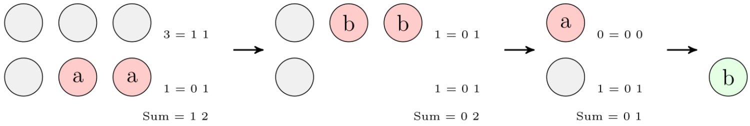
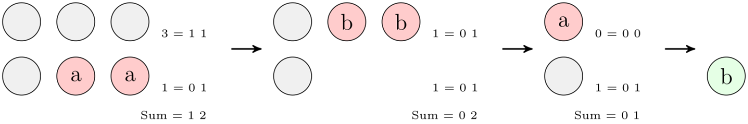


Figure 3: Schematic of Nim gameplay; red implies counters taken while green implies win

- *Nim* is an old game from Ancient China
- Players play alternately and must take at least one counter from each pile
- The player which takes the last counter wins the game
  $\implies$ there is always a winning strategy
- Mathematical strategy is to leave the next player with even *Nim Sums*, where a *Nim Sum* is the binary digital sum of counters in each pile

Two-Player Game: Nim



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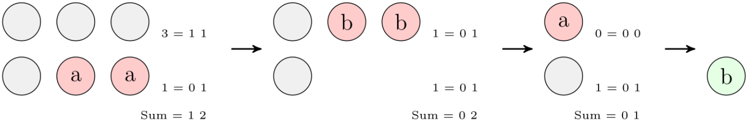

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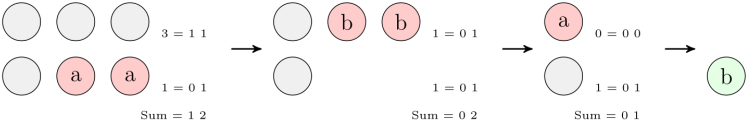

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Two-Player Game: Tic-Tac-Toe

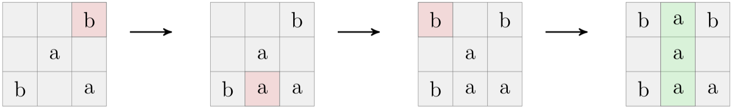

Figure 4: Schematic of Tic-Tac-Toe gameplay; red implies square taken while green implies winning streak

- *Tic-Tac-Toe* is a (m, n, k) type game which is played on a $m \times n$ size grid where each player alternately places a unique object on the grid
- The first player to place k of its items in a row, column or diagonal wins
- *Tic-Tac-Toe* will be treated here as a $(m, n, k) \equiv (3, 3, 3)$ game
- Unlike *Nim*, a winning strategy cannot be guaranteed (might end in draw)

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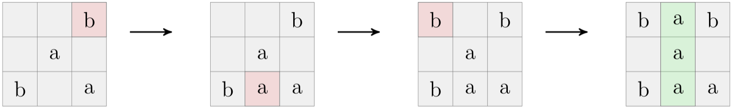

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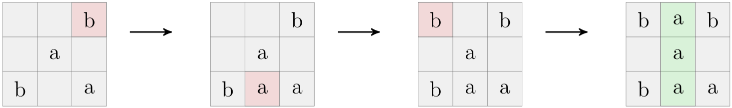

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Game Description Language (GDL)

- GDL is declarative programming language
- Representation formalism for axiomatising the rules of any game

Relevant GDL relations

$\boldsymbol{role(r)}$: r is a valid role in the game

$\boldsymbol{true(p)}$: proposition p is true in the current state

$\boldsymbol{next(p)}$: proposition p is true in the next state

$\boldsymbol{legal(r,a)}$: player with role r can legally perform action a in current state

$\boldsymbol{does(r,a)}$: player with role r performs action a in the current state

$\boldsymbol{goal(r,n)}$: player with role r achieves a utility of n in the current state

$\boldsymbol{terminal}$: the current state is the final or terminal state

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Inductive Learning of Answer Set Programs (ILASP)

- Inductive Logic Programming is to find a hypothesis that explains a set of examples with some background knowledge
- ILASP is an inductive logic framework developed largely by Mark Law from the Imperial College London

Overview of ILASP framework

Given an ASP program B called the **background knowledge**, a set of ASP rules S called the **search space** and two sets of partial interpretations E^+ and E^- called the **positive and negative examples** respectively, the goal is to find another program H called a **hypothesis** such that:

1. H is composed of the rules in S ($H \subseteq S$)
2. Each positive example is extended by at least one answer set of $B \cup H$ (can be a different answer set for each positive example)
3. No negative example is extended by any answer set of $B \cup H$

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Inductive Learning of Answer Set Programs (ILASP)

- Provides a method to extend the above workflow to learn weak constraints from ordered examples
- Particularly powerful for situations in two-player games with multiple optimum decisions with varying degrees of preference

Key Definitions from ILASP extension

Ordering example: An ordering example is a tuple $o = \langle e_1, e_2 \rangle$, where e_1 and e_2 are partial (positive-example) interpretations.

Brave ordering: An ASP program P bravely respects o iff $\exists A_1, A_2 \in AS(P)$, such that $AS(P)$ is the answer set of P, A_1 extends e_1, A_2 extends e_2 and $A_1 \succ_p A_2$.

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Methodologies

Overview of Methodologies

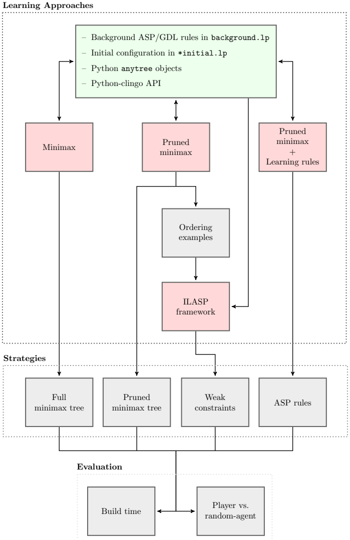

Figure 5: Overview and segmentation of methodologies

- Exploit ASP and python-clingo API to create a dynamic game system governed with GDL relations
- Python *anytree* module to represent the game trees which are annotated with scores and produce pretty visualizations
- Flavours of the *Minimax* algorithm in ASP to learn optimum game strategies
- Pipe optimum decisions as bravely ordered positive examples for ILASP
- Evaluate different methodologies by comparing build times and performance against a control (random) player

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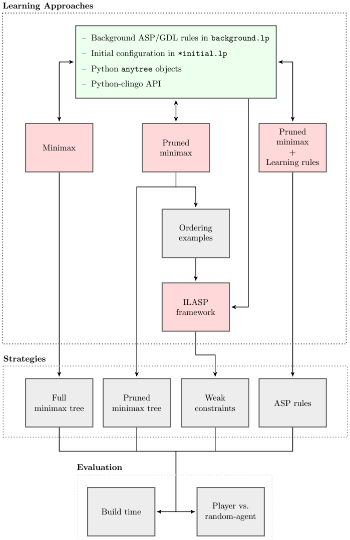

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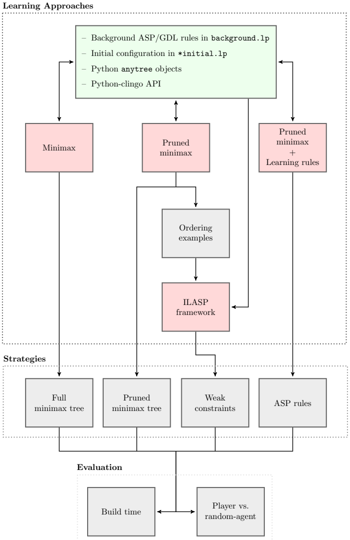

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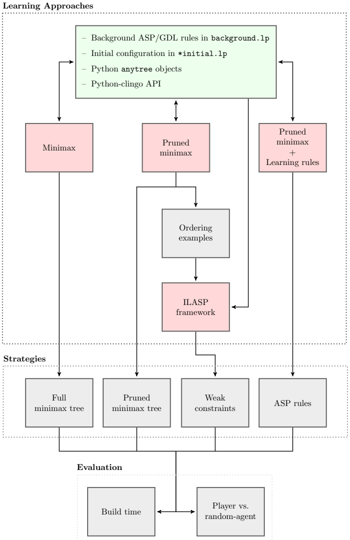

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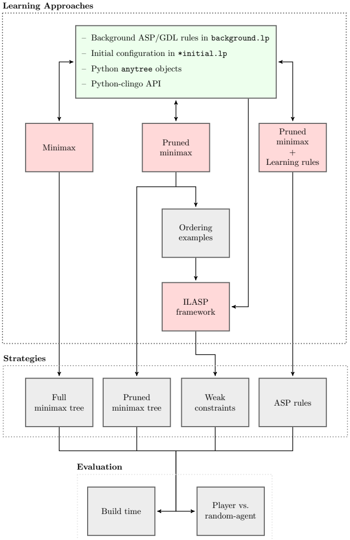

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Game simulation

ASP program encoding the rules of the game for one step

Example (Rules TicTacToe)

```
1 {does(X,A):legal(X,A)} 1 :-
  true(control(X)),
  not terminal.

next(control(a)) :-
  true(control(b)),
  not terminal.

goal(P,1) :-
  true(has(P,C1)),
  true(has(P,C2)),
  true(has(P,C3)),
  in_line(C1,C2,C3).
...
```

Facts defining the state

Example (State TicTacToe)

```
true(control(a)).
true(free(1,3)).
true(free(3,1)).
true(free(2,3)).
...
```

↓ (Clingo's API)

One stable model per legal action

Example (Next state TicTacToe)

```
does(a,take(2,2))
next(control(b))
next(free(1,3))
next(free(2,3))
...
```

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```

Facts defining the state

Example (State TicTacToe)

```
true(control(a)).
true(free(1,3)).
true(free(3,1)).
true(free(2,3)).
...
```

↓ (Clingo's API)

One stable model per legal action

Example (Next state TicTacToe)

```
does(a,take(2,2))
next(control(b))
next(free(1,3))
next(free(2,3))
...
```

Game simulation

ASP program encoding the rules of the game for one step

Example (Rules TicTacToe)

```
1 {does(X,A):legal(X,A)} 1 :-
  true(control(X)),
  not terminal.

next(control(a)) :-
  true(control(b)),
  not terminal.

goal(P,1) :-
  true(has(P,C1)),
  true(has(P,C2)),
  true(has(P,C3)),
  in_line(C1,C2,C3).
...
```

Facts defining the state

Example (State TicTacToe)

```
true(control(a)).
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true(free(3,1)).
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```
does(a,take(2,2))
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next(free(1,3))
next(free(2,3))
...
```

Minimax Algorithm

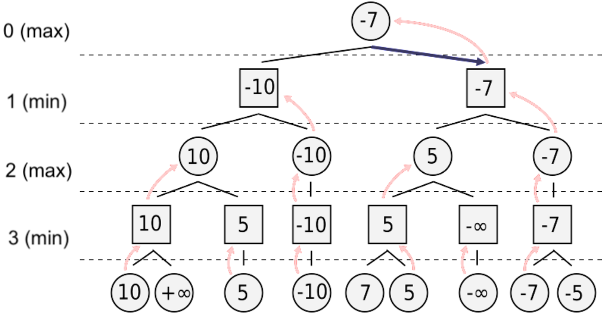
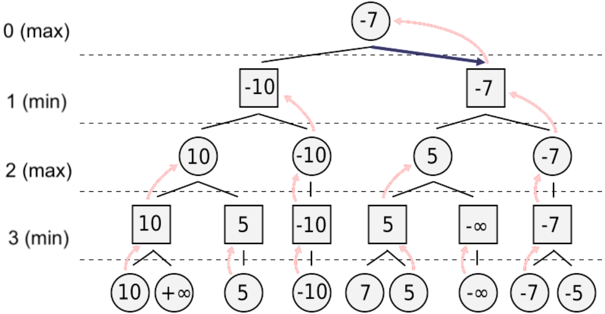


Figure 6: Minimax sample schematic for a two-player game

- One player maximizes utility while another minimizes utility
- Bottom-Up procedure assuming there is a complete game tree with utility-annotated leaf nodes
- Time complexity: $O(b^D)$; Space complexity: $O(bD)$; where b is the average branching factor and D is the maximum depth of the tree

Minimax Algorithm



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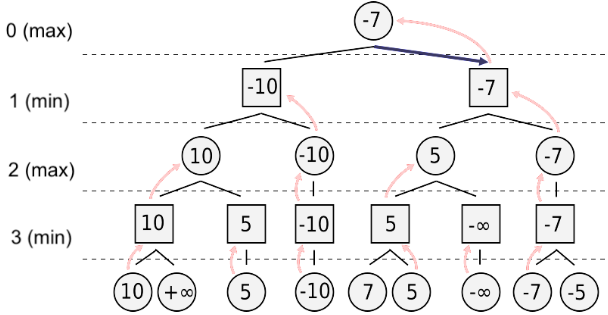

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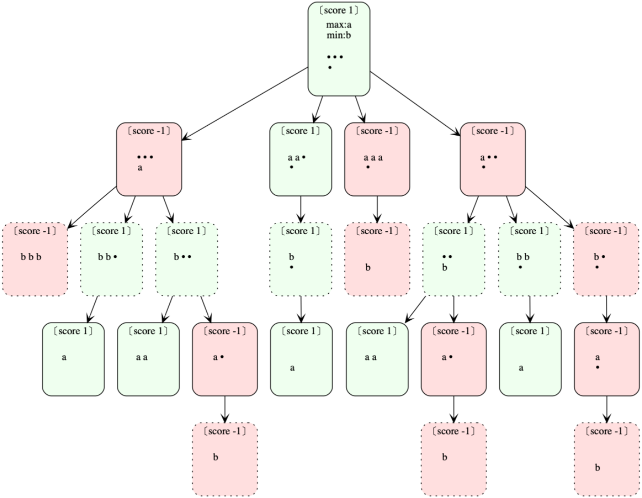

Figure 7: Minimax schematic for a small Nim game where player a maximizes utility while player b minimizes utility; using the Minimax algorithm we can deduce that player a starts off with a winning strategy

Pruned Minimax Algorithm

Motivation

- Construct only the necessary parts of the tree (Alphabeta pruning)
- Treat it as a planning problem
- Use optimization statements from *clingo*

Explicit time encoding

1. Replace `true(F)` by `holds(F,T)`
2. Replace `next(F)` by `holds(F,T+1)`
3. Replace `p(F1..Fn)` by `p(F1..Fn,T)` for $\{legal, does, goal, terminal\}$
4. Add the time in in the body with predicate `time(T)`
5. Add a new fact `time(0..N).` for horizon N

Optimization statements

- `#maximize{N,T:goal(a,N,T)}`

× Assumes player b will chose actions under the same optimization.

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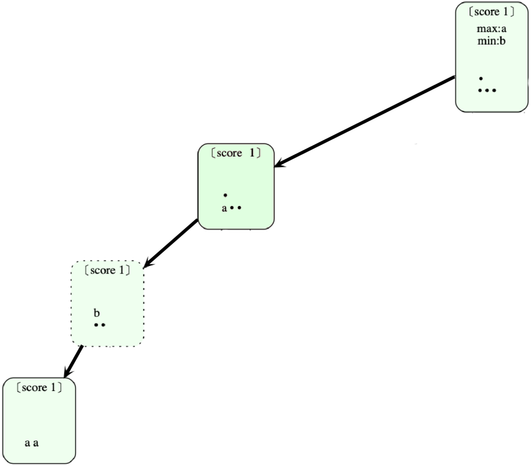
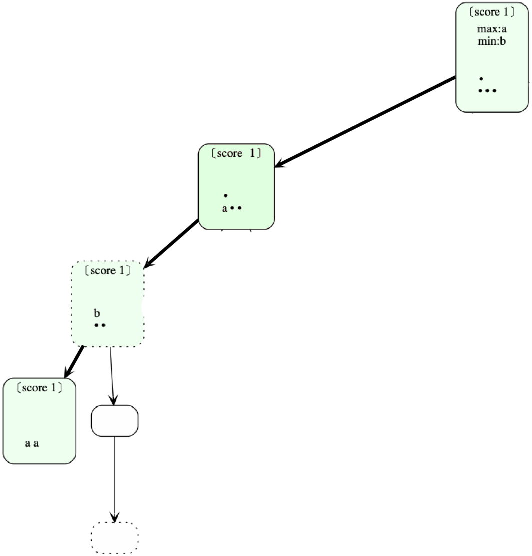


Pruned Minimax Algorithm



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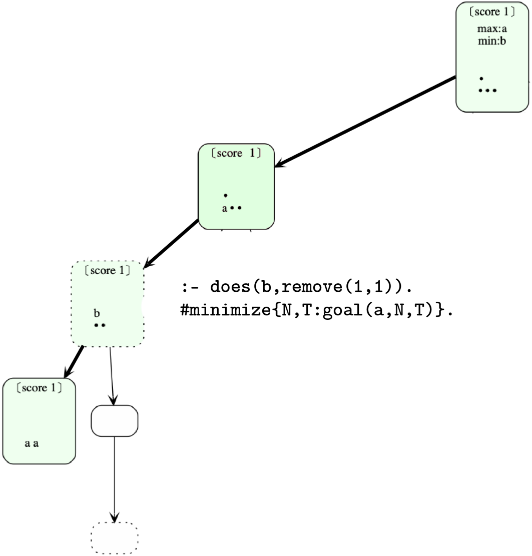
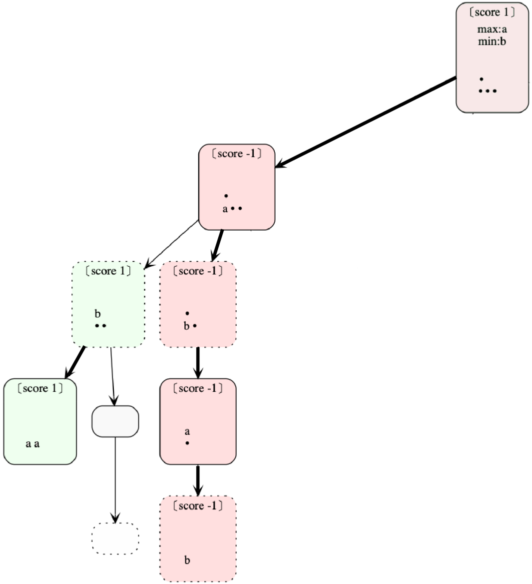



```
:- does(b,remove(1,1)).
#minimize{N,T:goal(a,N,T)}.
```

Pruned Minimax Algorithm



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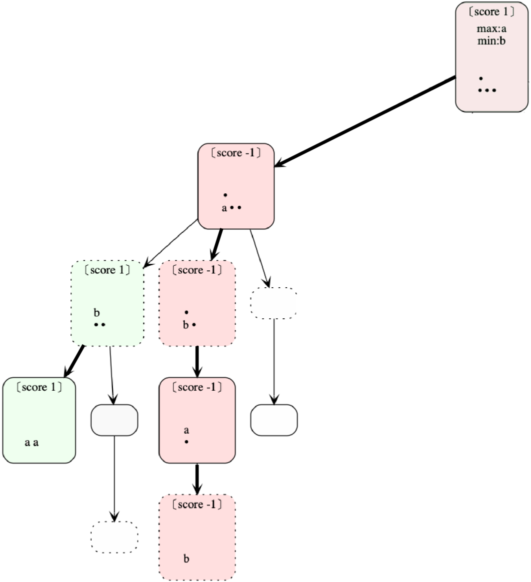
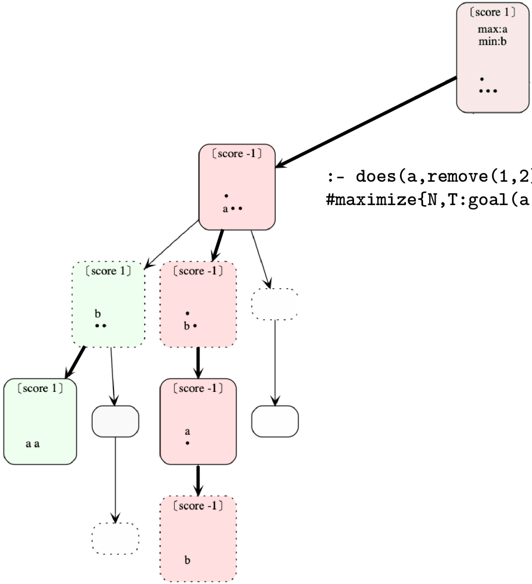
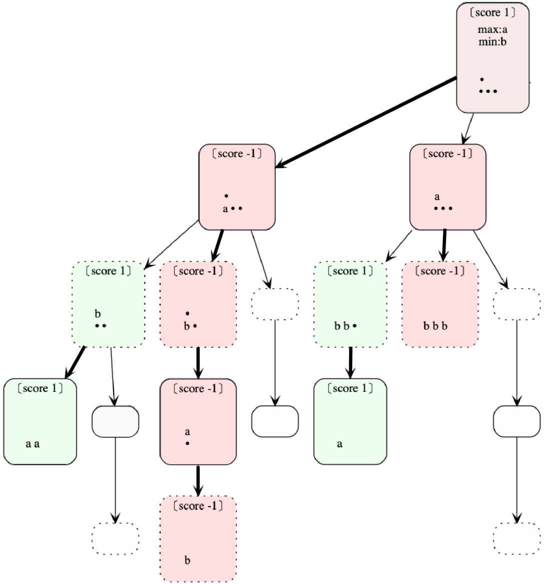


Pruned Minimax Algorithm




```
:- does(a,remove(1,2)).
#maximize{N,T:goal(a,N,T)}.
```

Pruned Minimax Algorithm



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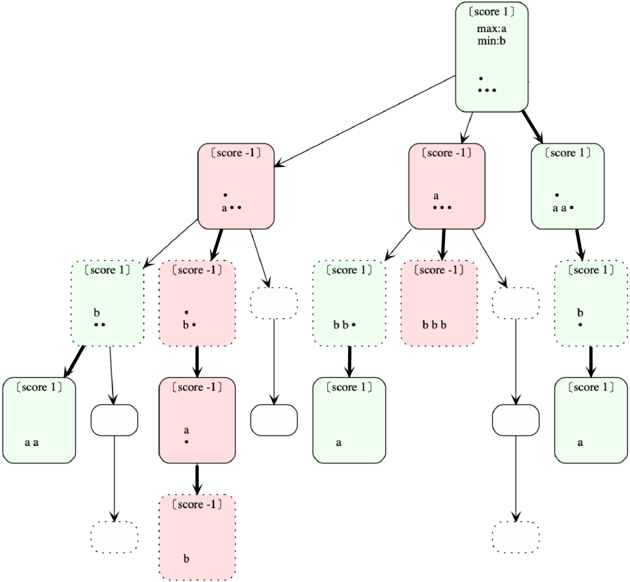

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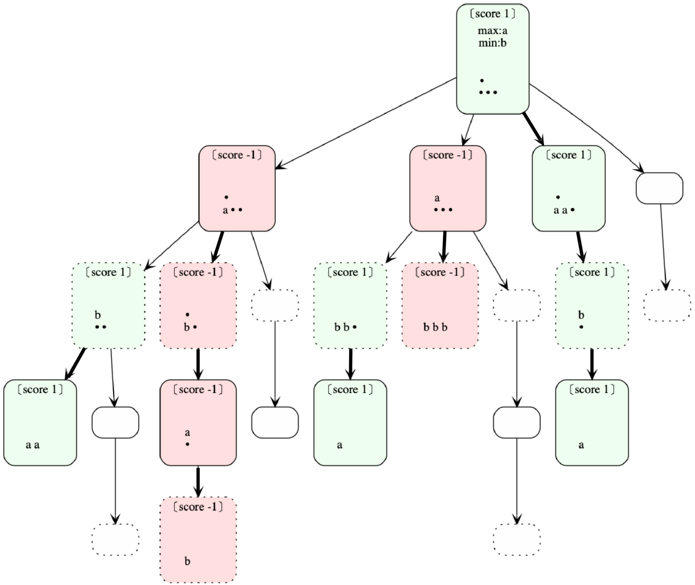

Pruned Minimax Algorithm + Learning Rules

Learn Rules: Create a representation of the best moves using ASP

Example

```
best_do(a,remove(2,2),T):- holds(control(a),T), holds(has(1,0),T),
                           holds(has(2,2),T), holds(has(3,0),T),
                           holds(has(4,0),T).
```

Enforce the use of these best actions

```
1{does(P,A,T):best_do(P,A,T)}1:- time(T), not goal(_,_,T),
                                 best_do(P,A,T)>0, true(control(P)).
```

Generalize using predefined options for substitution

Example

```
best_do(Va,remove(V2,1),T):- holds(control(Va),T),
                            holds(has(V1,0),T), holds(has(V2,2),T),
                            holds(has(V3,0),T), holds(has(V4,0),T),
                            V1!=V3,V1!=V2,V1!=Va,
                            V3!=V2,V3!=Va,V2!=Va.
```

Pruned Minimax Algorithm + Learning Rules

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```

Weak constraints with ILASP

- Background Knowledge: Encoding with rules
- Ordered positive examples: Generated in the decision points of Pruned Minimax

Example

```
#pos(e0,{}, {},{
  true(control(a)). true(has(1,0)). true(has(2,2)).
  true(has(3,0)). true(has(3,0)). does(a,remove(2,2)).}).
#pos(e1,{}, {}, {
  true(control(a)). true(has(1,0)). true(has(2,2)).
  true(has(3,0)). true(has(4,0)). does(a,remove(2,1)). }).
#brave_ordering(e0,e1).
```

- Language bias: Must be handcrafted to define the search space of the ILASP framework

$\implies$ Hypotheses: Weak constraints representing the strategy

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  true(has(3,0)). true(has(4,0)). does(a,remove(2,1)). }).
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Results

Setup

- Time to learn strategy and its size
- Abstraction of strategy from a smaller instance

Setup

- Time to learn strategy and its size
- Abstraction of strategy from a smaller instance

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- Abstraction of strategy from a smaller instance

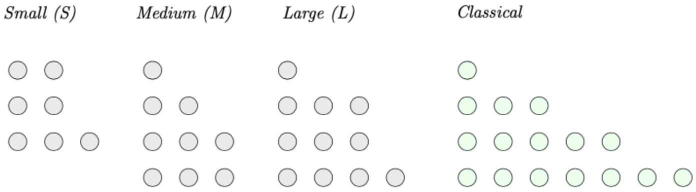

Fig. 14. Initial configurations for *Nim*.

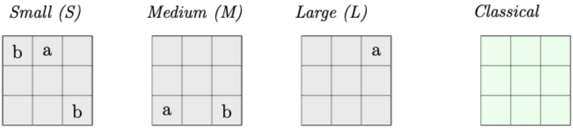

Fig. 15. Initial configurations for *TicTacToe*

Learning phase

Approach	*Nim*			*TicTacToe*		
	S	M	L	S	M	L
Minimax	390	4630	61023	896	7583	59704
Pruned minimax tree	83	347	2675	105	73	2835
Pruned minimax rules	35	85	283	109	61	2399

Table 1: Number of nodes in the computed trees

Learning phase ILASP strategies

Example (TicTacToe instance M)

```
:~ next(has(V0,V1)), next(has(V0,V2)), next(has(V0,V3)),
   in_line(V1,V2,V3).[-1@2, 2, V0, V1, V2, V3]
:~ in_line(V0,V1,V2), next(free(V2)).[-1@1, 1, V0, V1, V2]
```

Example (Language bias TicTacToe)

```
#modeo(3,next(has(var(player),var(cell))),(positive)).
#modeo(1,in_line(var(cell),var(cell),var(cell)),(positive)).
#modeo(1,next(free(var(cell))),(positive)).
#modeo(1,next(control(var(player))),(positive)).
#weight(-1). #weight(1).
#maxp(2). #maxv(4).
```

Learning phase ILASP strategies

Example (TicTacToe instance M)

```
:~ next(has(V0,V1)), next(has(V0,V2)), next(has(V0,V3)),
   in_line(V1,V2,V3).[-1@2, 2, V0, V1, V2, V3]
:~ in_line(V0,V1,V2), next(free(V2)).[-1@1, 1, V0, V1, V2]
```

Example (Language bias TicTacToe)

```
#modeo(3,next(has(var(player),var(cell))),(positive)).
#modeo(1,in_line(var(cell),var(cell),var(cell)),(positive)).
#modeo(1,next(free(var(cell))),(positive)).
#modeo(1,next(control(var(player))),(positive)).
#weight(-1). #weight(1).
#maxp(2). #maxv(4).
```

Learning phase ILASP strategies

Example (Nim instances M and L)

```
b_pile(V3,V1,V2) :- binary(V0,V1,V2), next(has(V3,V0)).
nim_sum(V1,0,0) :- b_pile(_,V1,_).
nim_sum(V1,V3+V2,V0) :- b_pile(V0,V1,V2), nim_sum(V1,V3,V0-1).
:~ nim_sum(V0,V1,4), V1\2 != 0.[1@1, 4, V0, V1]
```

Example (Language bias Nim)

```
#constant(pile,1..4).
#modeh(b(var(pile),var(d),var(bool)),(positive)).
#modeh(nim_sum(var(d),var(total)+var(bool),var(pile)),(positive)).
#modeh(nim_sum(var(d),0,0),(positive)).
#modeb(1,b(var(pile),var(d),var(bool)),(positive)).
#modeb(1,nim_sum(var(d),var(total),var(pile)-1),(positive)).
#modeb(1,binary(var(num),var(d),var(bool)),(positive)).
#modeb(1,next(has(var(pile),var(num))),(positive)).
#modeo(1,nim_sum(var(d),var(t),const(pile))).
#modeo(1,var(t)\2 != 0).
#weight(1). #weight(-1). #maxp(1). #maxv(4).
```

Learning phase ILASP strategies

Example (Nim instances *M* and *L*)

```
b_pile(V3,V1,V2) :- binary(V0,V1,V2), next(has(V3,V0)).
nim_sum(V1,0,0) :- b_pile(_,V1,_).
nim_sum(V1,V3+V2,V0) :- b_pile(V0,V1,V2), nim_sum(V1,V3,V0-1).
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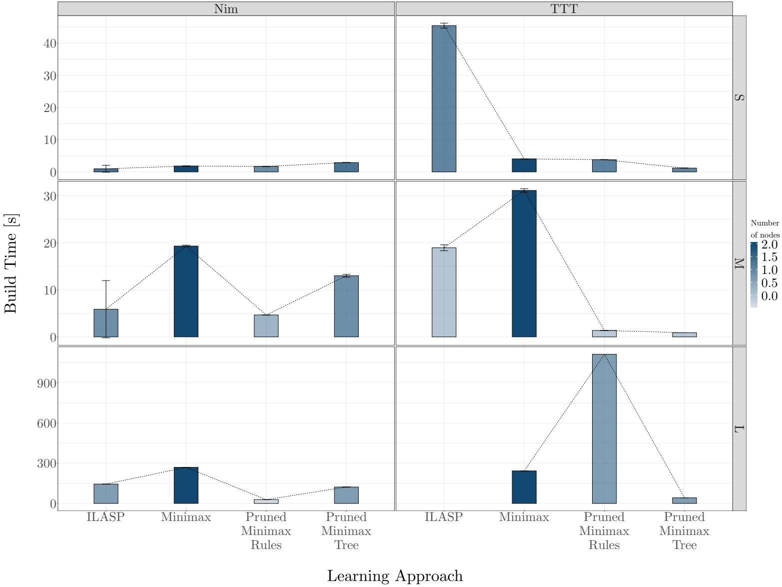
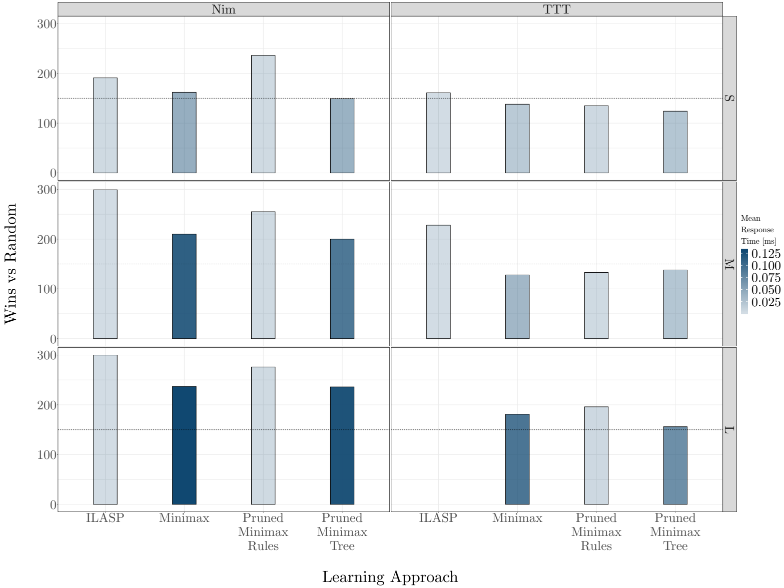
Example (Language bias Nim)

```
#constant(pile,1..4).
#modeh(b(var(pile),var(d),var(bool)),(positive)).
#modeh(nim_sum(var(d),var(total)+var(bool),var(pile)),(positive)).
#modeh(nim_sum(var(d),0,0),(positive)).
#modeb(1,b(var(pile),var(d),var(bool)),(positive)).
#modeb(1,nim_sum(var(d),var(total),var(pile)-1),(positive)).
#modeb(1,binary(var(num),var(d),var(bool)),(positive)).
#modeb(1,next(has(var(pile),var(num))),(positive)).
#modeo(1,nim_sum(var(d),var(t),const(pile))).
#modeo(1,var(t)\2 != 0).
#weight(1). #weight(-1). #maxp(1). #maxv(4).
```

Learning phase



Play against Random-Agent



Conclusion

Conclusion

- Minimax
  - ✓ Good for small instances
  - × Slow learning and not scalable
- Pruned Minimax
  - ✓ Reduces tree search space
- Pruned Minimax Learning Rules
  - ✓ Reduces tree search space
  - ✓ Faster making decision
  - ✓ Allow generalization
  - × Requires symmetry specification
  - ✓ Novel approach
- ILASP
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Our framework

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