Interpretable Strategy Synthesis for Competitive Games

Thesis Defense Presentation

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July 16, 2024

Publications

- **Krishnan, Abhijeet**, Colin M. Potts, Arnav Jhala, Harshad Khadilkar, Shirish Karande and Chris Martens. "Learning Explainable Representations of Complex Game-playing Strategies." *Proceedings of the Eleventh Annual Conference on Advances in Cognitive Systems*. 2024.
- Villalobos-Arias, Leonardo, Derek Martin, **Abhijeet Krishnan**, Madeleine Gagné, Colin M. Potts and Arnav Jhala. "Modeling Risk in Reinforcement Learning: A Literature Mapping." *arXiv preprint arXiv:2312.05231*. 2023.
- **Krishnan, Abhijeet** and Chris Martens. "Synthesizing Chess Tactics from Player Games." In *Workshop on Artificial Intelligence for Strategy Games (SG) and Esports Analytics (EA), 18th AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*. 2022.
- **Krishnan, Abhijeet** and Chris Martens. "Towards the Automatic Synthesis of Interpretable Chess Tactics." In *Explainable Agency in Artificial Intelligence Workshop, 36th AAAI Conference on Artificial Intelligence*. 2022.
- **Krishnan, Abhijeet**, Aaron Williams, and Chris Martens. "Towards Action Model Learning for Player Modeling." *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*. Vol. 16. No. 1. 2020.
- **Krishnan, Abhijeet** and Chris Martens. "Rule-based Cognitive Modeling via Human-Computer Interaction." Poster presented at: *5th LAS Research Symposium*; 2019 Dec 10; Raleigh, NC.

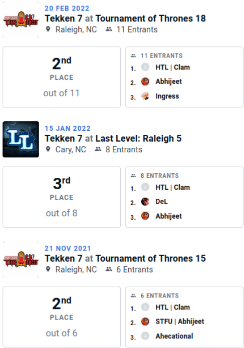
Getting Into Competitive Gaming

Kevin Brown

Participating in a competitive *Tekken 7* tournament

Wanting to Improve

Contender Esports



start.gg

Results of recent tournaments

Placing 3rd

How to Improve?

Improving at a skill —

How to Improve?

Improving at a skill —

- Play more

How to Improve?

Improving at a skill —

- Play more $\rightarrow$ *time-consuming*

How to Improve?

Improving at a skill —

- Play more $\rightarrow$ *time-consuming*
- Use a learning resource

How to Improve?

Improving at a skill —

- Play more $\rightarrow$ *time-consuming*
- Use a learning resource $\rightarrow$ *not standardized*

How to Improve?

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- Play more $\rightarrow$ *time-consuming*
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- Find a coach

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How to Improve?

Improving at a skill —

- Play more $\rightarrow$ *time-consuming*
- Use a learning resource $\rightarrow$ *not standardized*
- Find a coach $\rightarrow$ *not accessible*
- Study better players

How to Improve?

Improving at a skill —

- Play more $\rightarrow$ *time-consuming*
- Use a learning resource $\rightarrow$ *not standardized*
- Find a coach $\rightarrow$ *not accessible*
- Study better players $\rightarrow$ *difficult*

Possible Solution

Could we *automatically* generate *explainable* strategies for players to learn from?

Strategies are Mental Models of Games

Claim

Strategies can be treated as mental models of games

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- Players develop *mental models* of games to explain them (Boyan & Sherry, 2011)

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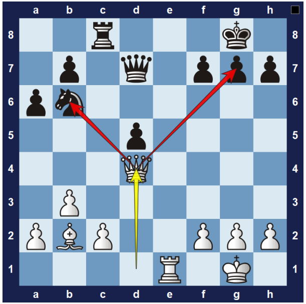
- Players acquire and *refine* their mental models through practice, instruction and discussion (of strategies) (Boyan et al., 2018)
- Strategies can be learned from *other players* (Weintrop & Wilensky, 2013)
- Learned strategies can be *transferred* to one's own gameplay (Paredes-Olay et al., 2002)

Real-world Strategies

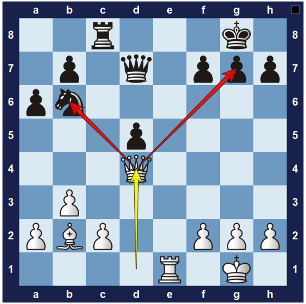
Real-world Strategies



Chessfox

An example of the *fork* tactic in chess

Real-world Strategies



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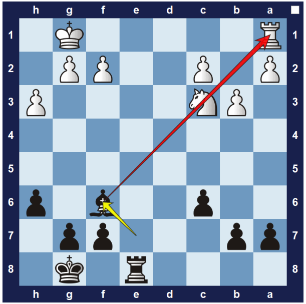


Chessfox

An example of the *pin* tactic in chess

Real-world Strategies

That Blasted Salami

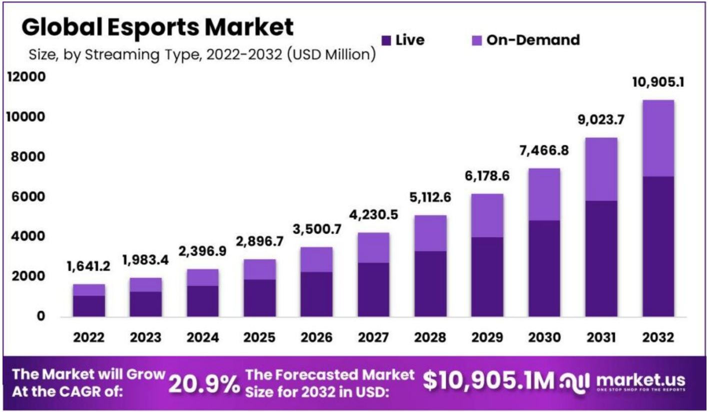
A mixed strategy in *Tekken*

Benefits

Benefits

- Competitive gaming $\rightarrow$ democratized access to strategies

Esports Viewership



market.us

Benefits

- Competitive gaming $\rightarrow$ democratized access to strategies
- Explainable AI $\rightarrow$ techniques for explainability

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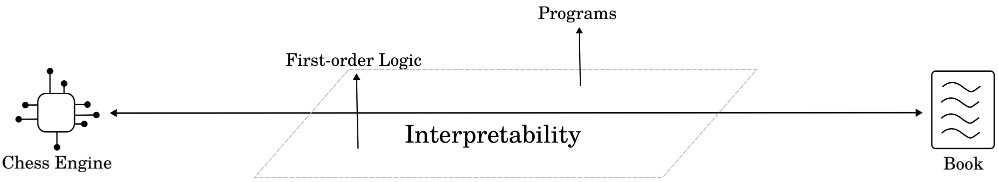

Thesis Statement

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A computational model of a game strategy, along with a synthesis method, could meet the goals of discovering high-quality, interpretable strategies and impact the fields of competitive gaming and explainable AI.

RQ1

Thesis Statement

A *computational model* of a game strategy, along with a *synthesis method*, could meet the goals of discovering *high-quality*, *interpretable* strategies and impact the fields of competitive gaming and explainable AI.

RQ1

How do we formally define the problem of *Interpretable Strategy Synthesis* (ISS)?

RQ2

Thesis Statement

A *computational model* of a game strategy, along with a synthesis method, could meet the goals of discovering high-quality, interpretable strategies and impact the fields of *competitive gaming* and explainable AI.

RQ2

How do we approach the problem of Interpretable Strategy Synthesis for the game of *chess*?

RQ3

Thesis Statement

A *computational model* of a game strategy, along with a synthesis method, could meet the goals of discovering high-quality, interpretable strategies and impact the fields of competitive gaming and *explainable AI*.

RQ3

How do we approach the problem of ISS using a *program-based* strategy model that is competitive with a neural network policy?

Research Question 1

RQ1

How do we formally define the problem of *Interpretable Strategy Synthesis* (ISS)?

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How do we formally define the problem of *Interpretable Strategy Synthesis* (ISS)?

- Why do we need a framework?

Research Question 1

RQ1

How do we *formally define* the problem of Interpretable Strategy Synthesis (ISS)?

- Why do we need a framework?
- Definitions of key elements —
  - ISS
  - Strategy Model
  - Strategy
  - Performance Measure
  - Interpretability Measure

The Need for a Framework

Paper	Number Used			Interpretability
	Games	Representations	Algorithms	
Spronck, Sprinkhuizen-Kuyper, and Postma (2004)	2	1	1	✗
de Mesentier Silva, Isaksen, Togelius, and Nealen (2016)	1	1	4	✓
Butler, Torlak, and Popović (2017)	1	1	1	✗
Canaan et al. (2018)	1	1	1	✗
de Freitas, de Souza, and Bernardino (2018)	1	1	1	✗
Mariño, Moraes, Oliveira, Toledo, and Lelis (2021)	1	1	1	✗
Mariño and Toledo (2022)	1	1	1	✗
Medeiros, Aleixo, and Lelis (2022)	2	1	2	✗

Table: List of works in ISS

Interpretable Strategy Synthesis (ISS)

Definition (ISS) Formal

Given a —

Interpretable Strategy Synthesis (ISS)

Definition (ISS) Formal

Given a —

- Game $\mathcal{G}$

Interpretable Strategy Synthesis (ISS)

Definition (ISS) Formal

Given a —

- Game $\mathcal{G}$
- Strategy model $\mathcal{M}$

Interpretable Strategy Synthesis (ISS)

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- Interpretability measure $\mathcal{I}$

Interpretable Strategy Synthesis (ISS)

Definition (ISS) Formal

Given a —

- Game $\mathcal{G}$
- Strategy model $\mathcal{M}$
- Performance measure J
- Interpretability measure $\mathcal{I}$

The problem of ISS is to find a strategy $\sigma^* \in \mathcal{M}$ that *maximizes both J and $\mathcal{I}$*.

Strategy (σ)

- A strategy is a *policy* that maps (some) states to actions
- A strategy is an *instance* of a strategy model

Strategy Model ($\mathcal{M}$)

- Defines the *space* (or architecture) of strategies

Strategy Model ($\mathcal{M}$)

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- Examples —
  - if-then rules
  - decision trees
  - programmatic scripts
  - neural networks

Performance Measure (J)

- $J_{\mathcal{G}}(\sigma)$: how *good* a strategy σ is

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Performance Measure (J)

- $J_{\mathcal{G}}(\sigma)$: how *good* a strategy σ is
- Understanding the pros/cons of strategies is important
- Examples —
  - strategy win rate
  - material advantage (chess)
  - resources harvested (StarCraft II)

Interpretability Measure ($\mathcal{I}$)

- $\mathcal{I}_{\mathcal{G}}(\sigma)$: how *easily understood* a strategy σ is

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  - number of statements (programmatic script)
  - number of nodes (decision tree)

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- *computational proxies* based on representation, $\mathcal{I}_{\mathcal{M}}$
- Examples —
  - number of statements (programmatic script)
  - number of nodes (decision tree)
- Use *readable* representations

Addressing RQ1

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How do we formally define the problem of Interpretable Strategy Synthesis (ISS)?

Addressing RQ1

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How do we *formally define* the problem of Interpretable Strategy Synthesis (ISS)?

- Motivated the need for a framework

Addressing RQ1

RQ1

How do we *formally define* the problem of Interpretable Strategy Synthesis (ISS)?

- Motivated the need for a framework
- Definition of ISS $\langle \mathcal{G}, \mathcal{M}, J, \mathcal{I} \rangle$ (Krishnan & Martens, 2022b)

Research Question 2

RQ2

How do we approach the problem of Interpretable Strategy Synthesis for the game of *chess*?

RQ2(a)

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How do we approach the problem of Interpretable Strategy Synthesis for the game of *chess*?

RQ2(a)

Could we represent known chess tactics as a strategy model for chess and develop metrics to show that they suggest better moves than a random baseline?

RQ2(b)

RQ2

How do we approach the problem of Interpretable Strategy Synthesis for the game of *chess*?

RQ2(b)

Do the chess strategies learned using inductive logic programming outperform a random baseline in how closely their divergence scores approximate a beginner player?

RQ2(c)

RQ2

How do we approach the problem of Interpretable Strategy Synthesis for the game of *chess*?

RQ2(c)

Do the chess strategies learned by an ILP system incorporating the changes of the new predicate vocabulary and precision/recall-based constraints produce moves better than those learned by an ILP system without these modifications?

ISS for Chess

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Could we represent known chess tactics as a strategy model for chess and develop metrics to show that they suggest better moves than a random baseline?

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- *Strategy model* for chess

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- Strategy model for chess
- *Performance measure* for chess

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First-Order Logic (FOL)

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- can represent *relationships* between objects
- E.g., in chess, a king is *in check* if an opponent's piece can capture it

$$\forall k{,}b\ \text{InCheck}(k{,}b) \iff \exists p\ \text{CanMove}(p,\ \text{Square}(p){,}\text{Square}(k){,}b)\ \wedge\ p{\neq}King \tag{1}$$

Prolog

- *Declarative* programming language

Prolog

- *Declarative* programming language
- *in check* in Prolog —

```
in_check(King, Board) :-
      can_move(Piece,Square(Piece),Square(King),Board),
      Piece \= king.
```

Why use FOL-based Strategies?

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- Prior work in *relational reinforcement learning* and *pattern learning* in chess
  - Handle domains with *large state spaces*
  - *Generalize* to similar domains
  - *Interpretability* of learned rules

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  - *Interpretability* of learned rules
- Rule-based models in *explainable AI* (Kliegr et al., 2021; Zhang et al., 2021)

Strategy Model for Chess

First-Order (FO) Logic Rule

$$\texttt{tactic}(\text{Position}, \text{Move}) \leftarrow$$
$$\texttt{feature\_1}(\cdots),$$
$$\texttt{feature\_2}(\cdots),$$
$$\vdots$$
$$\texttt{feature\_n}(\cdots)$$

Our chess strategy model expressed in Prolog pseudocode

Predicate Vocabulary

Strategy Model for Chess

First-Order (FO) Logic Rule

$$
\begin{aligned}
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\end{aligned}
$$

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Predicate Vocabulary

- Position =

```
[contents(c2,pawn,white),
 contents(g8,knight,black),
 contents(e8,king,black),

 turn(white),kingside_castle(white),...]
```

Strategy Model for Chess

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$\texttt{tactic}(\text{Position}, \textcolor{red}{\mathit{Move}}) \leftarrow$
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- Move = `[a7,a8,queen]`

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   turn(white),kingside_castle(white),...]
  ```
- Move = `[a7,a8,queen]`
- Features =
  - `attacks(Pos,Sq1,Sq2)`
  - `in_check(Pos,Side)`
  - `is_empty(Pos,Squares)`

Example

```
fork(Position,Move) ←
    legal_move(Position,Move),
    move(Move,_,To,_),
    make_move(Position,Move,NewPosition),
    can_capture(NewPosition,To,ForkSquare1),
    can_capture(NewPosition,To,ForkSquare2),
    different(ForkSquare1,ForkSquare2).
```

An interpretation of the *fork* tactic from the chess literature using our predicate vocabulary.

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- Who is “perceiving”?
    - Chess-playing agents with an *evaluation function* (chess “engines”)
    - e.g., Stockfish 14 (strong), Maia Chess (McIlroy-Young et al., 2020) (weak, human-like)

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Evaluation of Known Chess Tactics[1]

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Evaluation of Known Chess Tactics[1]

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- tactics $\xrightarrow{\text{translate}}$ chess strategy model
- Divergence(chess strategies, human beginner)
- Divergence(random baseline, human beginner)
- Using a human-like engine (McIlroy-Young et al., 2020)

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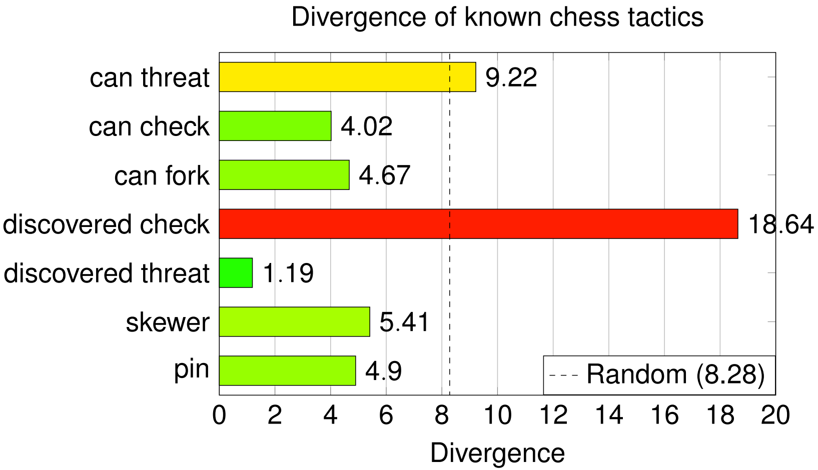
Results


Divergence of known chess tactics
can threat
9.22
can check
4.02
can fork
4.67
discovered check
18.64
discovered threat
1.19
skewer
5.41
pin
4.9
Random (8.28)
0
2
4
6
8
10
12
14
16
18
20
Divergence

RQ2(a)

RQ2

How do we approach the problem of Interpretable Strategy Synthesis for the game of *chess*?

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RQ2(b)

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Do the chess strategies *learned* using inductive logic programming outperform a random baseline in how closely their divergence scores approximate a beginner player?

- Strategy model for chess ✓
- Performance measure for chess ✓

RQ2(b)

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Do the chess strategies learned using *inductive logic programming* outperform a random baseline in how closely their divergence scores approximate a beginner player?

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- *Learning algorithm* for chess strategies

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Do the chess strategies learned using inductive logic programming *outperform a random baseline in how closely their divergence scores approximate a beginner player*?

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Inductive Logic Programming (ILP)

- *symbolic* machine learning technique

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Inductive Logic Programming (ILP)

- *symbolic* machine learning technique
- Learn *classifier* in the form of a FOL rule
- FOL rule expressed using *background knowledge*

Target Concept

- Want to learn `last` relating a list of characters to the last character in it

$$E^+ = \left\{ \begin{array}{l} \texttt{last([m,a,c,h,i,n,e], e).} \\ \texttt{last([l,e,a,r,n,i,n,g], g).} \\ \texttt{last([a,l,g,o,r,i,t,h,m], m).} \end{array} \right\}$$

$$E^- = \left\{ \begin{array}{l} \texttt{last([m,a,c,h,i,n,e], m).} \\ \texttt{last([m,a,c,h,i,n,e], c).} \\ \texttt{last([l,e,a,r,n,i,n,g], x).} \\ \texttt{last([l,e,a,r,n,i,n,g], i).} \end{array} \right\}$$

$$B = \left\{ \begin{array}{l} \texttt{empty(A) :- ...} \\ \texttt{head(A,B) :- ...} \\ \texttt{tail(A,B) :- ...} \end{array} \right\}$$

Possible Hypothesis

$$H = \left\{ \begin{array}{l} \texttt{last(A,B) :- head(A,B),tail(A,C),empty(C).} \\ \texttt{last(A,B) :- tail(A,C),last(C,B).} \end{array} \right\}$$

Learning Chess Strategies

- ISS problem $\langle \mathcal{G}, \mathcal{M}, J, \mathcal{I} \rangle \xrightarrow{\text{translate}}$ ILP problem $\langle E^+, E^-, B \rangle$

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- E^+: $\langle s, \pi(s) \rangle$ for some target policy π

Learning Chess Strategies

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- E^-: $\langle s, a' \rangle$ where $a' \in \mathcal{A}(s) - \pi(s)$

Learning Chess Strategies

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- E^+: $\langle s, \pi(s) \rangle$ for some target policy π
- E^-: $\langle s, a' \rangle$ where $a' \in \mathcal{A}(s) - \pi(s)$
- B: manual translation of $\mathcal{G}$ to FOL

Learning Chess Strategies

- ISS problem $\langle \mathcal{G}, \mathcal{M}, J, \mathcal{I} \rangle \xrightarrow{\text{translate}}$ ILP problem $\langle E^+, E^-, B \rangle$
- E^+: $\langle s, \pi(s) \rangle$ for some target policy π
- E^-: $\langle s, a' \rangle$ where $a' \in \mathcal{A}(s) - \pi(s)$
- B: manual translation of $\mathcal{G}$ to FOL
- ILP system$(\langle E^+, E^-, B \rangle) \xrightarrow{\textit{learn}}$ rule-based strategies

Learning Chess Strategies using ILP[2]

- Use *Popper* (Cropper & Morel, 2021) as ILP system

[2] Krishnan and Martens, 2022a.

Learning Chess Strategies using ILP[2]

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- Modifications —
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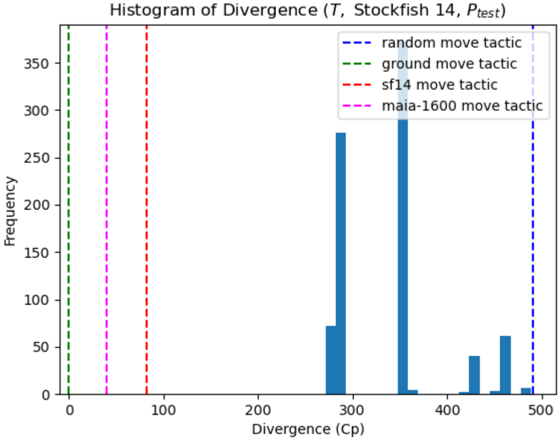
  - prevent generation of strategies that are too specific
- Evaluate using *divergence* with Stockfish 14 (strong)
- Compare to random, strong/human-like engine baselines

[2] Krishnan and Martens, 2022a.

Results


Histogram of Divergence (T, Stockfish 14, P_{test})
random move tactic
ground move tactic
sf14 move tactic
maia-1600 move tactic
Frequency
0
50
100
150
200
250
300
350
0
100
200
300
400
500
Divergence (Cp)

RQ2(b)

RQ2

How do we approach the problem of Interpretable Strategy Synthesis for the game of *chess*?

RQ2(b)

Do the chess strategies learned using inductive logic programming outperform a random baseline in how closely their divergence scores approximate a beginner player?

RQ2(c)

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Do the chess strategies learned by an ILP system incorporating the changes of the new predicate vocabulary and precision/recall-based constraints produce moves better than those learned by an ILP system without these modifications?

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RQ2(c)

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Do the chess strategies learned by an ILP system incorporating the changes of the new *predicate vocabulary* and precision/recall-based constraints produce moves better than those learned by an ILP system without these modifications?

- Constraints to limit search space of chess strategies
- *New* predicate vocabulary

Improvements to ILP for Chess Strategies[3]

- Domain-specific constraints — Constraints

[3] Krishnan et al., 2024.

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  - Allows *more efficient* search due to introduction of more types
  - More domain-specific state features like `can_threat` and `xrays`

[3] Krishnan et al., 2024.

Evaluation

- Conduct *ablation study* to measure impact of modifications

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  - Learn strategies using systems with/without constraints, predicate vocabulary

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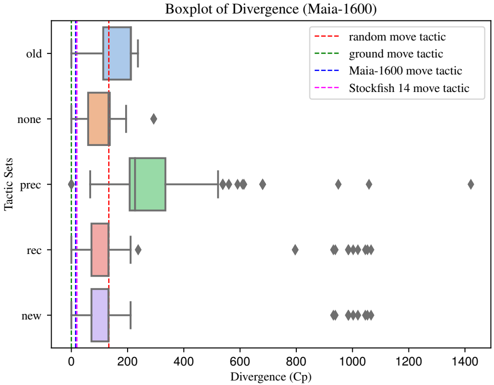
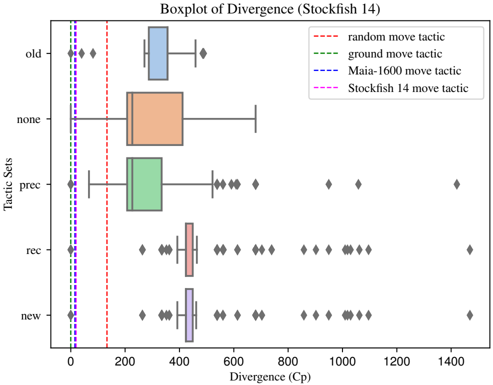
    - Measure average strategy divergence (using both strong and human-like engines)
    - Test decrease vs. old system using a *one-sided Welch's t-test*

Results



Boxplot of strategy divergence (evaluated using *human-like* engine) for each system



Boxplot of strategy divergence (evaluated using *strong* engine) for each system

RQ2(c)

RQ2

How do we approach the problem of Interpretable Strategy Synthesis for the game of *chess*?

RQ2(c)

Do the chess strategies learned by an ILP system incorporating the changes of the new predicate vocabulary and precision/recall-based constraints produce moves better than those learned by an ILP system without these modifications?

Addressing RQ2

RQ2

How do we approach the problem of Interpretable Strategy Synthesis for the game of *chess*?

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- Knowledge engineering
  - Improved predicate vocabulary represented *800+ LoC in Prolog*
- Performance
  - Playing strength not close to state-of-the-art

Solution: Strategies as Programs

Challenges with FOL-based strategies —

- Knowledge engineering
  - Programmatic strategies require *only a DSL* to be defined
- Performance
  - Success of RL methods (DeepMind, 2019; OpenAI et al., 2019; Silver et al., 2018)

RQ3

RQ3

How do we approach the problem of ISS using a *program-based* strategy model that is competitive with a neural network policy?

RQ3(a)

RQ3

How do we approach the problem of ISS using a *program-based* strategy model that is competitive with a neural network policy?

RQ3(a)

How do I formally map the problem of ISS to that of RL-based program synthesis?

RQ3(b)

RQ3

How do we approach the problem of ISS using a *program-based* strategy model that is competitive with a neural network policy?

RQ3b

Could a *decision transformer* model synthesize better strategies for a toy programming environment when compared to existing approaches?

Programmatic Strategy Model

Programmatic Strategy Model

- Programmatic strategy modeled as *domain-specific language (DSL) script*

Programmatic Strategy Model

- Programmatic strategy modeled as *domain-specific language (DSL) script*
- DSL defined as a context-free grammar (CFG) $\langle V, \Sigma, R, S\rangle$

$$
\begin{aligned}
P &::= (\epsilon - \mathbf{hd}(h_i)) \\
I &::= \mathbf{fold}(+, h_i) \\
D &::= \mathbf{hd}(\mathbf{tl}(h_i)) - \mathbf{hd}(h_i) \\
C &::= c_1 + c_2 * P + c_3 * I + c_4 * D \\
B &::= c_0 + c_1 * \mathbf{hd}(h_1) + \cdots + c_k * \mathbf{hd}(h_k) > 0 \mid \\
&\qquad B_1 \ \mathbf{or}\ B_2 \mid B_1 \ \mathbf{and}\ B_2 \\
E &::= C \mid \mathbf{if}\ B\ \mathbf{then}\ E_1\ \mathbf{else}\ E_2.
\end{aligned}
$$

The DSL for expressing PID controllers due to Verma et al. (2018).

Programmatic Strategy Model

- Strategy = string in the *language* of the DSL

$$
\begin{aligned}
&\textbf{if } (0.001 - \textbf{hd}(h_{\texttt{TrackPos}}) > 0) \textbf{ and } (0.001 + \textbf{hd}(h_{\texttt{TrackPos}}) > 0) \\
&\quad \textbf{then } 1.96 + 4.92 * (0.44 - \textbf{hd}(h_{\texttt{RPM}})) + 0.89 * \textbf{fold}(+, h_{\texttt{RPM}}) + 49.79 * (\textbf{hd}(\textbf{tl}(h_{\texttt{RPM}})) - \textbf{hd}(h_{\texttt{RPM}})) \\
&\quad \textbf{else } \ 1.78 + 4.92 * (0.40 - \textbf{hd}(h_{\texttt{RPM}})) + 0.89 * \textbf{fold}(+, h_{\texttt{RPM}}) + 49.79 * (\textbf{hd}(\textbf{tl}(h_{\texttt{RPM}})) - \textbf{hd}(h_{\texttt{RPM}}))
\end{aligned}
$$

A programmatic policy (strategy) for a PID controller.

Learning Programmatic Strategies

- Learning programmatic strategies = program synthesis —

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  - based on $\langle \text{input}, \text{output} \rangle$ pairs (X. Chen et al., 2019; Lázaro-Gredilla et al., 2019; Yang et al., 2021)

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  - demonstrations (Burke et al., 2019; Sun et al., 2018; Xu et al., 2018)

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ISS as RL-based Program Synthesis

- Idea: learn a policy to *derive* programs from a CFG

ISS as RL-based Program Synthesis

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$$S \rightarrow ASB|c$$
$$A \rightarrow aA|\epsilon$$
$$B \rightarrow bB|\epsilon$$

ISS as RL-based Program Synthesis

- Idea: learn a policy to *derive* programs from a CFG

$$
\begin{aligned}
S &\rightarrow ASB|c \\
A &\rightarrow aA|\epsilon \\
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\end{aligned}
$$

$$
\begin{aligned}
S &\Rightarrow ASB \Rightarrow SB \\
&\Rightarrow S \Rightarrow c
\end{aligned}
$$

Program Synthesis MDP[4]

Define a program synthesis MDP $\mathcal{M}_{\mathrm{syn}}$, where —

- States: *partially expanded* programs
- Actions: *rule applications* to valid non-terminals
- Transitions: effects of applying a rule
- Rewards: return from *executing program* in the target MDP

[4] Krishnan et al., 2024.

RQ3(a)

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RQ3(b)

RQ3b

Could a *decision transformer* model synthesize better strategies for a toy programming environment when compared to existing approaches?

Learning Programmatic Strategies using Decision Transformers[5]

ISS for programmatic strategies —

[5] Krishnan et al., 2024.

Learning Programmatic Strategies using Decision Transformers[5]

ISS for programmatic strategies —

- Strategy model = DSL

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- Strategy model = DSL
- Performance measure = reward from executing strategy in target environment

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Learning Programmatic Strategies using Decision Transformers[5]

ISS for programmatic strategies —

- Strategy model = DSL
- Performance measure = reward from executing strategy in target environment
- Learning method: Program synthesis MDP

[5]Krishnan et al., 2024.

Decision Transformer (DT)[6]

- Application of a *transformer* model (Vaswani et al., 2017) to RL
- Models the RL problem as a *sequence learning* problem
- Given an *trajectory* τ, predict the next action

$$\tau = \left(\widehat{R}_1, s_1, a_1, \widehat{R}_2, s_2, a_2, \cdots, \widehat{R}_T, s_T, a_T\right) \tag{2}$$

[6] Y. Chen, Wang, Bastani, Dillig, and Feng, 2020.

Methodology

Modifications to original architecture —

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- *Action Masking* to deal with invalid actions (Huang & Ontañón, 2022)

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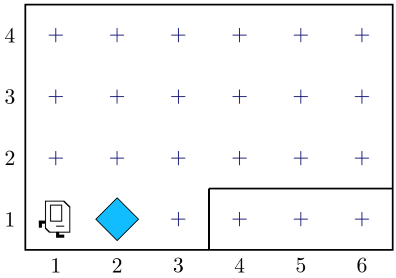
Methodology

Modifications to original architecture —

- *Action Masking* to deal with invalid actions (Huang & Ontañón, 2022)
- *Cross-entropy loss* to deal with discrete action spaces
- *GRU-based state embedding* to better encode state information

Karel Domain

- Simple programming language and environment for teaching
- Discrete action space
- Use task definitions from Trivedi, Zhang, Sun, and Lim (2021)



A sample Karel world

Training & Evaluation

- Randomly generated program dataset

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- Programs $\xrightarrow{\textit{parse}}$ trajectories in $\mathcal{M}_{\text{syn}}$

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- Train modified DT on generated trajectories
- Compare performance by sampling programs and measuring reward
- Baseline: LEAPS (Trivedi et al., 2021)
    - LEAPS *outperformed* prior neural network-based systems

Sample Program

```
DEF run m(
    WHILE c( noMarkersPresent c) w(
        turnRight
        move
    w)
    IF c( rightIsClear c) i(
        WHILE c( frontIsClear c) w(
            move
        w)
    i)
m)
```

A program learned by the DT

Program Description

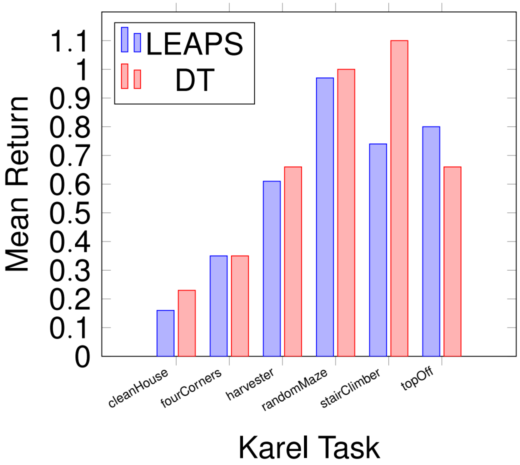
Strategy description as generated by Claude 3.5 Sonnet (Anthropic, 2024)

Claude 3.5 Sonnet Description

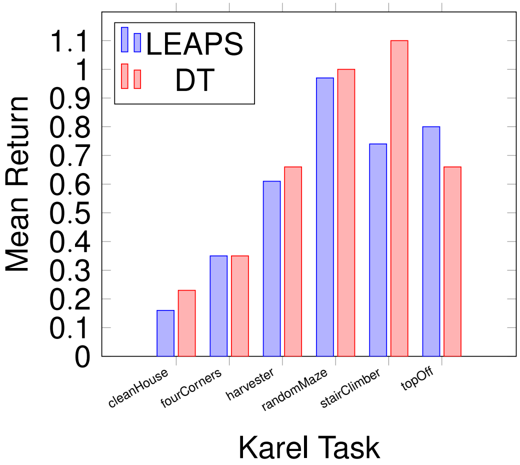
In summary, the strategy is:

1. Climb the stairs by repeatedly turning right and moving forward until a marker is found.
2. Once at the top (indicated by the marker), if there's clear space to the right, move forward along the top of the stairs until reaching an obstacle.

Results


LEAPS
DT
Mean Return
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
1.1
cleanHouse
fourCorners
harvester
randomMaze
stairClimber
topOff
Karel Task

Results



Task	Unique Programs	
	LEAPS	DT
cleanHouse	3627	59
fourCorners	9872	55
harvester	11708	28
randomMaze	295	63
stairClimber	298	49
topOff	30278	63

Table: Number of unique programs explored by LEAPS and the DT during their search (sampling) phases.

RQ3(b)

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Addressing RQ3

RQ3

How do we approach the problem of ISS using a *program-based* strategy model that is competitive with a neural network policy?

- Program synthesis MDP (Krishnan et al., 2024)
- Decision transformer matches SOTA performance with fewer programs sampled (Krishnan et al., 2024)

Conclusion

Thesis Statement

A computational model of a game strategy, along with a synthesis method, could meet the goals of discovering high-quality, interpretable strategies and impact the fields of competitive gaming and explainable AI.

Contributions —

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Thesis Statement

A *computational model* of a game strategy, along with a synthesis method, could meet the goals of discovering *high-quality*, *interpretable* strategies and impact the fields of competitive gaming and explainable AI.

Contributions —

- Defined a *framework* for ISS (Krishnan & Martens, 2022b)

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A computational model of a game strategy, along with a synthesis method, could meet the goals of discovering high-quality, interpretable strategies and impact the fields of *competitive gaming* and explainable AI.

Contributions —

- Applied *FOL-based* strategy model to solve ISS for chess

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Publications

- **Krishnan, Abhijeet**, Colin M. Potts, Arnav Jhala, Harshad Khadilkar, Shirish Karande and Chris Martens. "Learning Explainable Representations of Complex Game-playing Strategies." *Proceedings of the Eleventh Annual Conference on Advances in Cognitive Systems*. 2024.
- Villalobos-Arias, Leonardo, Derek Martin, **Abhijeet Krishnan**, Madeleine Gagné, Colin M. Potts and Arnav Jhala. "Modeling Risk in Reinforcement Learning: A Literature Mapping." *arXiv preprint arXiv:2312.05231*. 2023.
- **Krishnan, Abhijeet** and Chris Martens. "Synthesizing Chess Tactics from Player Games." In *Workshop on Artificial Intelligence for Strategy Games (SG) and Esports Analytics (EA), 18th AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*. 2022.
- **Krishnan, Abhijeet** and Chris Martens. "Towards the Automatic Synthesis of Interpretable Chess Tactics." In *Explainable Agency in Artificial Intelligence Workshop, 36th AAAI Conference on Artificial Intelligence*. 2022.
- **Krishnan, Abhijeet**, Aaron Williams, and Chris Martens. "Towards Action Model Learning for Player Modeling." *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*. Vol. 16. No. 1. 2020.
- **Krishnan, Abhijeet** and Chris Martens. "Rule-based Cognitive Modeling via Human-Computer Interaction." Poster presented at: *5th LAS Research Symposium*; 2019 Dec 10; Raleigh, NC.

Professional Service

- **Reviewer**, *AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, 2021-22,2024
- **Reviewer**, *International Conference on Foundations of Digital Games*, 2022
- **Reviewer**, *IEEE Conference on Games*, 2019-22
- **Reviewer**, *AAAI Experimental AI in Games, AIIDE Workshop*, 2020
- **Reviewer**, *IEEE Symposium Series on Computational Intelligence*, 2020

Thank You!

Questions?

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Interpretable Strategy Synthesis (ISS)

Definition (ISS)

Given a —

- Game environment $\mathcal{G}$ (i.e., an MDP $\langle \mathcal{S}, \mathcal{A}(s), \mathcal{P}, \mathcal{R}, \gamma \rangle$)
- Strategy model $\mathcal{M}$
- Performance measure $J \colon \mathcal{M} \times \mathcal{G} \to \mathbb{R}$
- Interpretability measure $\mathcal{I} \colon \mathcal{M} \times \mathcal{G} \to \mathbb{R}$

The problem of ISS is to find a strategy σ^* s.t. —

$$\sigma^* \doteq \arg\max_{\sigma} J(\sigma, \mathcal{G}) \mathcal{I}(\sigma, \mathcal{G}), \sigma \in \mathcal{M}$$

Strategy Model ($\mathcal{M}$)

Definition (strategy model)

A strategy model ($\mathcal{M}$) is a function $\mathcal{M} \colon \mathcal{S} \times \Theta \to \mathcal{A}$, where —

- $\mathcal{S}$ is the state space of $\mathcal{G}$,
- Θ is the associated parameter space of $\mathcal{M}$, and
- $\mathcal{A}$ is the action space of $\mathcal{G}$

Return

Strategy (σ)

Definition (strategy)

A strategy (σ) for $\mathcal{G}$ is a probability distribution over the available actions in a state, for a *subset* of states in the state space ($\mathcal{S}$), and parameterized by $\theta \in \Theta$. The states for which σ is defined are termed as the applicable states set, and are given by $\mathrm{A}_\sigma \subseteq \mathcal{S}$.

$$\sigma : \mathcal{S} \times \mathcal{A} \times \Theta \to [0, 1] \tag{3}$$

Return

Performance Measure (J)

Definition (performance measure)

The performance measure (J) is a function $J\colon \mathcal{M} \times \mathcal{G} \to \mathbb{R}$ that evaluates the performance of a strategy $\sigma \in \mathcal{M}$, in a game environment $\mathcal{G}$, by assigning it a numerical score.

Return

Interpretability Measure ($\mathcal{I}$)

Definition (interpretability measure) Formal

The interpretability measure ($\mathcal{I}$) is a function $\mathcal{I} \colon \mathcal{M} \times \mathcal{G} \to \mathbb{R}$ that evaluates the interpretability of a strategy (σ) in a game environment ($\mathcal{G}$) by assigning it a numerical score.

Return

Divergence

Move Evaluation Function

Given chess engine E with position evaluation function $v_E(s)$, we can obtain a move evaluation function $q_E(s, a)$ as —

$$q_E(s, a) = \sum_{s', r} \mathcal{P}(s', r|s, a)[r + v_E(s')] \tag{4}$$

$$= v_E(s'), s' \text{ is non-terminal} \tag{5}$$

Equation 5 follows from 4 since rewards in chess are 0 for non-terminal states, $\gamma = 1$, and chess rules are deterministic.

Divergence

Difference Function

Given two moves a_1, a_2 made in a position s, we can calculate their difference $d_E(s, a_1, a_2)$ as —

$$d_E(s, a_1, a_2) \doteq \mid q_E(s, a_1) - q_E(s, a_2) \mid \tag{6}$$

Return

Metrics

Definition

Coverage is the fraction of positions in a given set P to which the chess strategy model is *applicable*.

$$P_{\mathrm{A}} \doteq P \cap \mathrm{A}_{\sigma} \tag{7}$$

$$\mathrm{Coverage}(\sigma, P) \doteq \frac{|P_{\mathrm{A}}|}{|P|} \tag{8}$$

Divergence

Definition (Divergence)

Divergence of a tactic from a set of examples P is the average difference in *evaluation* between the moves suggested by the tactic and the ground truth move.

$$\text{Divergence}_E(\sigma, P) \doteq \frac{1}{|P_{\mathrm{A}}|} \sum_{(s,a_1) \in P_{\mathrm{A}}} \sum_{a_2 \in \mathcal{A}(s)} \sigma(a_2|s) d_E(s, a_1, a_2) \tag{9}$$

Return

PAL

- **P**atterns **a**nd **L**earning (Morales, 1992)
- ILP system to learn chess *patterns*
- Predicate vocabulary
- *rlgg* algorithm + heuristics to learn patterns
- Automatic *example generator* to learn target concepts

Return

Precision/Recall-based Constraints

Definition (Precision constraint)

A precision constraint prunes the specializations of a hypothesis if its precision on a set of examples is less than some pre-defined lower limit.

Definition (Recall constraint)

A recall constraint prunes specializations of a hypothesis if its recall on a set of examples is less than some pre-defined lower limit.

Return

Precision/Recall-based Constraints

Theorem

Given hypotheses $H_1, H_2 \in \mathbb{H}$ *with* $H_1 \preceq H_2$ *and having recall values of* r_1 *and* r_2 *on a training set respectively, then* $r_1 \leq r_2$.

Return

Precision/Recall-based Constraints

Proof.

$$\text{Recall} = \frac{tp}{tp + fn} \tag{10}$$

$$H_1 \preceq H_2 \tag{11}$$

$$r_1 = \frac{tp_1}{tp_1 + fn_1} \tag{12}$$

$$r_2 = \frac{tp_2}{tp_2 + fn_2} \tag{13}$$

By the definition of theory subsumption, we have

$$tp_1 \leq tp_2, \text{ and} \tag{14}$$

$$fp_1 \leq fp_2 \tag{15}$$

Since the number of positive examples is constant for the same population,

$$\therefore r_1 \leq r_2 \tag{16}$$

Return

Predicate Vocabulary

- Allows more *situational rule* expression – en passant, promotion
- Allows *more efficient* unification due to introduction of more types
- Adds higher-order state features like *can_threat* and *xrays*

Return

Interpretability Measure

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- *No explicit interpretability measure!* Only qualitative arguments

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- Logic rules are *acknowledged to be interpretable* (Zhang et al., 2021)

Answer Set Programming

- *Declarative programming* paradigm based on *stable models* (Gelfond & Lifschitz, 1988)
- ASP language (Gebser, Harrison, Kaminski, Lifschitz, & Schaub, 2015) allows using rules to —
  - *model* a design space
  - *restrict* it using integrity constraints
  - *generate* instances in the newly restricted space

Return

Example

```
#const width=10.

param("width",width).

dim(1..width).

tile((X,Y)) :- dim(X), dim(Y).

adj((X1,Y1),(X2,Y2)) :- tile((X1,Y1)), tile((X2,Y2)), \\
    #abs(X1-X2)+#abs(Y1-Y2) == 1.

start((1,1)). finish((width,width)).

% tiles have at most one named sprite
0 { sprite(T,wall;gem;altar) } 1 :- tile(T).

% there is exactly one altar and one gem in the whole level
:- not 1 { sprite(T,altar) } 1. :- not 1 { sprite(T,gem) } 1.
```

An ASP program which can generate maze-like levels with integrity constraints that specify the number of game objects.

Transformer

- Neural-network based model
- Great success at learning sequences
- Uses an *attention* mechanism to focus on relevant parts of a sequence

$$z_i = \sum_{j=1}^{n} \mathtt{softmax}\left(\{\langle q_i, k_{j'}\rangle\}_{j'=1}^{n}\right)_j \cdot v_j \tag{17}$$

Rise of Esports

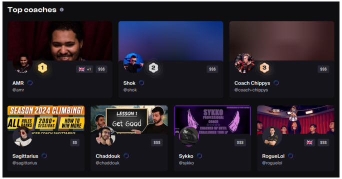
Colin Young-Wolff/Riot Games

T1 huddles with the trophy onstage after their victory at the League of Legends World Championship 2023 Finals at the Gocheok Sky Dome on November 19, 2023 in Seoul, South Korea.

Coaching in Esports


Robert Paul

Professional *Tekken 7* player Arslan Ash receives on-stage coaching during the Tekken World Tour 2023 Finals



Metafy

Top *League of Legends* coaches available for hire on the Metafy platform

RyderDie

A beginner guide for *Counter Strike 2* on YouTube

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Solution

A *principled* and *automated* approach to esports coaching could democratize access to it for all interested players.

Summary

Research Thrust	RQ	Sub-RQ	Publication
ISS Framework	RQ1	–	EAAI ’22 (Krishnan & Martens, 2022b)
ISS using Logic	RQ2	RQ2(a)	
		RQ2(b)	SG+EA Workshop @ AIIDE ’22 (Krishnan & Martens, 2022a)
		RQ2(c)	ACS ’24 (Krishnan et al., 2024)
ISS using Programs	RQ3	RQ3(a)	
		RQ3(b)	

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		RQ3(b)	ACS ’24 (Krishnan et al., 2024)

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Why Chess?

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- *Popular* game with a *long* competitive history

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Why Chess?

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- Extensive use as a *testbed for AI*
  - Convenient software implementations
  - Work in learning chess patterns
  - *Engines* for evaluation

Dataset

- Randomly generated program dataset (Trivedi et al., 2021)
- Convert programs into a trajectory in the program synthesis MDP

Transitions	870,782
Programs	50,000
Program Length	19.30 ± 5.96 ($\text{min} = 7, \text{max} = 50$)
Episode Length	17.42 ± 4.33 ($\text{min} = 5, \text{max} = 30$)

Table: Statistics for the LEAPS program dataset.

Sample Programs

```
DEF run m( WHILE c( markersPresent c) w( turnRight w) move IF c( not c( markersPresent c) c) i( turnRight
move i) m) DEF run m( WHILE c( noMarkersPresent c) w( turnRight move w) IF c ( rightIsClear c) i( WHILE c(
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The last 5 programs sampled from the decision transformer model for the stairClimber task.

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- Both achieve comparable performance on almost all tasks

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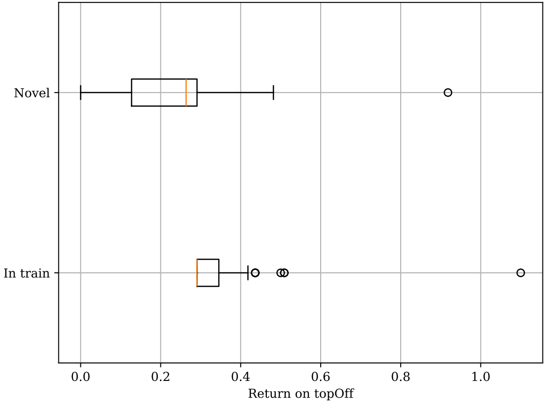
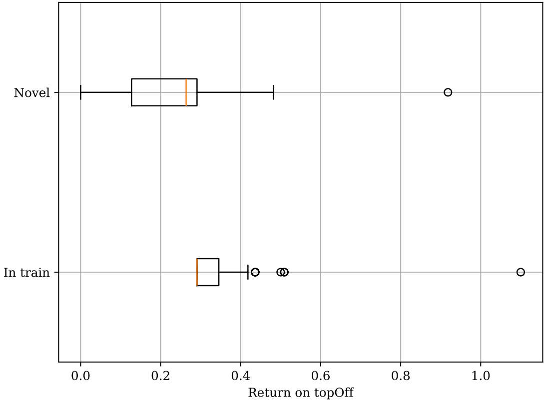


Box plot of returns for programs sampled from the decision transformer model.

Novelty of Generated Programs

- Plotted distribution of rewards for novel and non-novel programs
- Mean reward for novel programs is *lower* than non-novel programs ($p < 0.01$)



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Expected Outcomes

- Benefit esports industry $\rightarrow$ *better coaching* for players
- Benefit explainable AI research $\rightarrow$ generate *policy explanations*

Background and Related Work

Automated Coaching for Esports

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Automated Coaching for *Esports*

- Esports Analytics
- Automated Game Analysis

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- eye-tracking (Nagel, 2017; Stepanov et al., 2019)
- data collection (Frommel et al., 2019; Xenopoulos et al., 2022)

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- automated *game balancing* to ensure fairness (Beau & Bakkes, 2016; DeLaurentis et al., 2021)

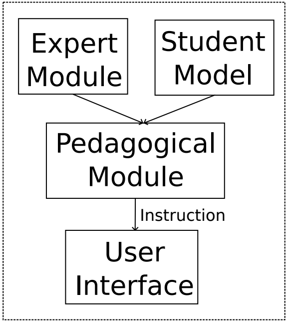
Background and Related Work

Automated *Coaching* for Esports

- Intelligent Tutoring System
- Player Modeling

Intelligent Tutoring System (ITS)

- *Automated*, *personalized* education system
- No ITS for esports (Mousavinasab et al., 2021)



ITS architecture

Player Modeling

- To provide *personalized* experiences in games
  - dynamic difficulty adjustment (Xue, Wu, Kolen, Aghdaie, & Zaman, 2017)
  - generated levels (Jennings-Teats, Smith, & Wardrip-Fruin, 2010)
- Strategy = player model (Smith, Lewis, Hullet, Smith, & Sullivan, 2011)

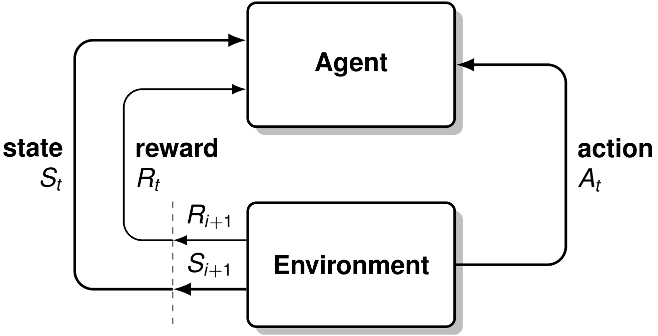
Background and Related Work

Automated Coaching for Esports

- Reinforcement Learning (RL)
- Explainable RL
- Strategy Synthesis

Reinforcement Learning (RL)

- ML paradigm where an agent *learns to act* in an environment
- Game strategies = RL *policies*



The agent-environment interaction interface in a MDP. Reproduced from Figure 3.1 of Sutton and Barto (2018).

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- XRL: field of study to devise techniques to interpret RL agents
- ISS = XRL for game environments

Strategy Synthesis

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- Subsequent work uses programmatic representations (Mariño et al., 2021; Mariño & Toledo, 2022; Medeiros et al., 2022)
- No unifying framework to synthesize goals and approaches