Interpretable Strategy Synthesis for Competitive Games

Thesis Defense Presentation

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Rise of Esports

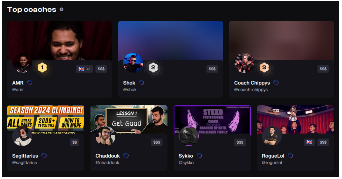
Colin Young-Wolff/Riot Games

Figure 1: 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

Figure 2: Professional *Tekken 7* player Arslan Ash receives on-stage coaching during the Tekken World Tour 2023 Finals



Metafy

Figure 3: Top *League of Legends* coaches available for hire on the Metafy platform

RyderDie

Figure 4: A beginner guide for *Counter Strike 2* on YouTube

Difficulties with Esports Coaching

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Solution

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

Strategies are Mental Models of Games

Claim

Strategies can be treated as mental models of games

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- Learned strategies can be *transferred* to one's own gameplay (Paredes-Olay et al., 2002)

Real-world Strategies

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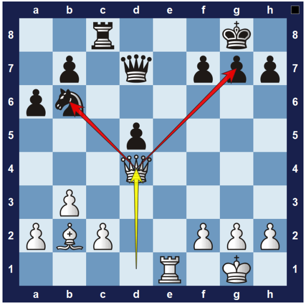

Chessfox

Figure 5: An example of the *fork* tactic in chess

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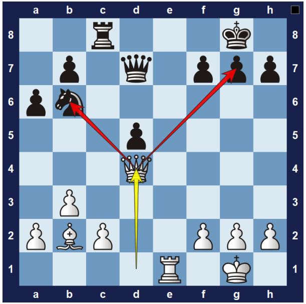

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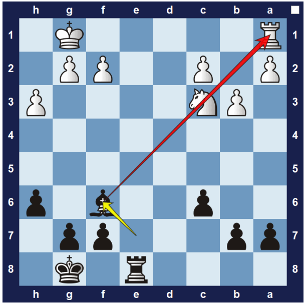

Chessfox

Figure 6: An example of the *pin* tactic in chess

Real-world Strategies

Go Full Build

Figure 7: A *cannon rush* in progress against an opponent in the game *StarCraft II*

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- Players communicate strategies and concepts using game-specific *jargon*

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- Players communicate strategies and concepts using game-specific *jargon*
- E.g., *okizeme* in fighting games, *tempo* in chess

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- Useful for *explainable AI*

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 esports and explainable AI.

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)
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- Why do we need a framework?

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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
	Domains	Models	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	✗
Krishnan and Martens (2022a)	1	1	1	✗
Mariño and Toledo (2022)	1	1	1	✗
Medeiros, Aleixo, and Lelis (2022)	2	1	2	✗

Table 1: List of works in ISS

Elements of a Good Framework

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- Facilitates *comparison*
  - multiple *games*
  - multiple *strategy representations*
  - multiple *learning algorithms*

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- Facilitates *comparison*
  - multiple *games*
  - multiple *strategy representations*
  - multiple *learning algorithms*
- Provides a clear definition of interpretability

Interpretable Strategy Synthesis (ISS)

Definition (ISS) Formal

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Definition (ISS) Formal

Given a —

- Game environment $\mathcal{G}$ (i.e., an MDP)
- 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 Model ($\mathcal{M}$)

Definition (strategy model) Formal

A strategy model ($\mathcal{M}$) is the set of all strategies based on a particular parameterization.

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

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

Strategy (σ)

Definition (strategy) Formal

A strategy (σ) for $\mathcal{G}$ is a mapping from a *subset* of states to actions.

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

Performance Measure (J)

Definition (performance measure) Formal

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

- How *good* a strategy is

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- Examples —
  - win rate
  - material advantage (chess)
  - resources harvested (StarCraft II)

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- Examples —
  - number of statements (programmatic script)
  - number of nodes (decision tree)
  - improvement in player win rate upon being explained strategy

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    - RQ2(c): Improving ILP learning using precision/recall constraints (Krishnan et al., 2024)

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- Prolog is a *declarative* programming language that allows specifying facts and rules in FOL

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

Inductive Logic Programming

- *symbolic* machine learning technique
- ILP problem $\langle E^+, E^-, B\rangle$
  - E^+: positive examples (of concept)
  - E^-: negative examples (of concept)
  - B: background knowledge
- **Goal**: *induce* hypothesis that entails (fits) E^+ but not E^-

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

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

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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  - Continuous learning
  - Predicate invention (Cropper & Dumančić, 2022)

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- *Interpretability* of rule-based models (Zhang et al., 2021)

Rule-based Strategy Model

FOL Rule

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Predicate Vocabulary

Rule-based Strategy Model

FOL Rule

$$\texttt{strategy}(\text{State}, \text{Action}) \leftarrow \\ \texttt{feature\_1}(\cdots), \\ \texttt{feature\_2}(\cdots), \\ \vdots \\ \texttt{feature\_n}(\cdots)$$

Figure 8: A FOL *policy rule* expressed in a *predicate vocabulary* $\mathcal{V}$

Predicate Vocabulary

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- Action = Prolog list of atoms
- Features = Prolog rules encoding higher-order state features

Learning Rule-based Policies

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- B: manual translation of $\mathcal{G}$ to FOL
- ILP system($\langle E^+, E^-, B \rangle$) $\xrightarrow{\textit{learn}}$ rule-based strategies

Application to Chess

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- *Popular* game with a *long* competitive history
- Has a large number of *player-discovered strategies*
- Extensive use as a *testbed for AI*
    - Convenient software implementations
    - Work in learning chess patterns
    - *Engines* for evaluation

ISS for Chess

- Strategy model for chess
- Performance measure for chess
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RQ2(a)

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Figure 9: Our chess strategy model expressed in Prolog pseudocode

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- Position =

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

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

Strategy Model for Chess

First-Order (FO) Logic Rule

$$\texttt{tactic}(\text{Position}, \textcolor{red}{\textit{Move}}) \leftarrow$$
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   turn(white),kingside_castle(white),...]
  ```
- Move = `[a7,a8,queen]`

Strategy Model for Chess

First-Order (FO) Logic Rule

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

Figure 9: Our chess strategy model expressed in Prolog pseudocode

Predicate Vocabulary

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

   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).
```

Figure 10: An interpretation of the *fork* tactic from the chess literature using our predicate vocabulary.

Example

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  legal_move(Position,Move),
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ISS for Chess

- ~~Strategy model for chess~~
- Performance measure for chess
- Interpretability measure for 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?

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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?

Performance Measure

Divergence Equation

- How *different* is one strategy from another?
- High divergence $\rightarrow$ strategies are very different
- Low divergence $\rightarrow$ strategies are quite similar
- Difference in terms of *perceived evaluation* of moves
- Who is “perceiving”?
  - Chess-playing agents with an *evaluation function* (chess “engines”)
  - e.g., Stockfish 14, Leela Chess Zero

Interpretability Measure

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- *No explicit interpretability measure!* Only qualitative arguments

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- FO-logic used extensively to model chess patterns (Berliner, 1975; Bramer, 1977; Bratko, 1982; Huberman, 1968; Morales, 1992; Pitrat, 1977; Wilkins, 1979)
- Logic rules are *acknowledged to be interpretable* (Zhang et al., 2021)

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Evaluation of Known Chess Tactics[1]

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- Both using strong/weak engine

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Results

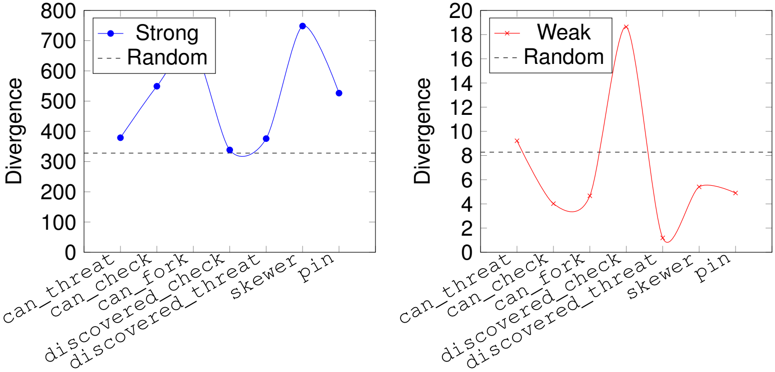

Figure 11: Divergence for each tactic

Analysis

- *Higher than random* divergence from human beginners (strong engine)
- *Lower than random* divergence from human beginners (weak engine)
- Known chess strategies approximate human beginners better than random according to a weak engine

Learning Chess Strategy Models

- ~~Strategy model for chess~~
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- ~~Strategy model for chess~~
- ~~Performance measure for chess~~
- ~~Interpretability measure for chess~~
- *Learning algorithm* for chess strategies

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?

Learning Chess Strategies using ILP[2]

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

[2] Krishnan and Martens, 2022a.

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- Compare to random, strong/weak engine baselines

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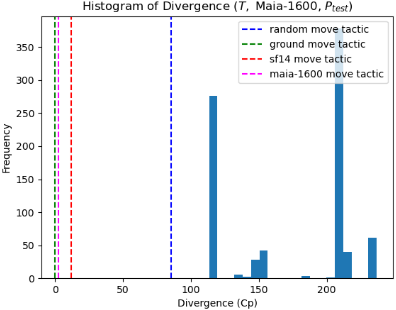

Figure 12: Divergence histogram for T evaluated using *weak* engine

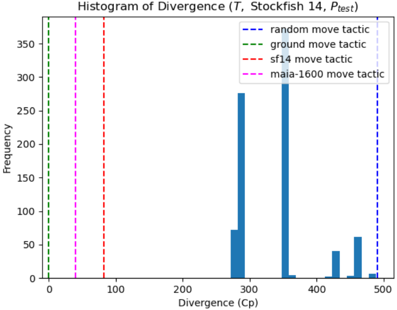

Figure 13: Divergence histogram for T evaluated using *strong* engine

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Improving the ILP Learning Method

- How do we *improve* upon “better than random”?

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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?

Improvements using Precision/Recall-based Constraints[3]

- Modifications —

[3] Krishnan et al., 2024.

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  - *Limit* chess strategy search space using precision/recall constraints

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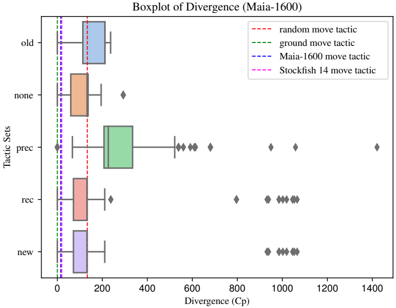

Figure 14: Boxplot of tactic divergence (evaluated using *weak* engine) for each system

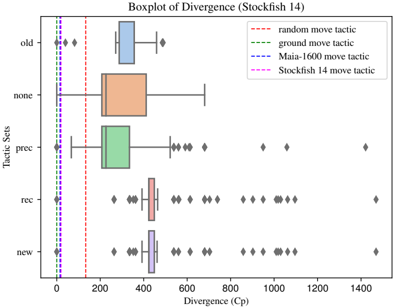

Figure 15: Boxplot of tactic divergence (evaluated using *strong* engine) for each system

Analysis

- New predicate vocabulary $\rightarrow$ improves divergence! ($p < 0.01$)
- precision constraint $\rightarrow$ improves divergence *only* when measured using strong engine
- recall constraint $\rightarrow$ improves divergence *only* when measured using weak engine

Limitations and Future Work

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- High cost of *knowledge engineering* – improved BK required $\sim$ 800 LoC of Prolog!

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- Interpretability for FOL-based strategies is poorly understood
  - study factors affecting interpretability (Kliegr et al., 2021)

Strategies as Programs

RQ3

How do we approach the problem of ISS using a *programmatic* strategy model?

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Strategies as Programs

RQ3

How do we approach the problem of ISS using a *programmatic* strategy model?

- Description of the programmatic strategy model
- RQ3(a) Reducing ISS using programs to RL-based program synthesis (Krishnan et al., 2024)
- RQ3(b) Learning programmatic strategies using decision transformers (Krishnan et al., 2024)

Motivation

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)

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) $\langle V, \Sigma, R, S \rangle$

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

Figure 16: The DSL for expressing PID controllers due to Verma et al. (2018).

Programmatic Strategy Model

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

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

Figure 17: A programmatic policy (strategy) for a PID controller.

Learning Programmatic Strategies

Approaches from —

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

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- Reinforcement learning —

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  - based on MDP rewards (Li et al., 2020; Qiu & Zhu, 2022)
- Reinforcement learning —
  - by casting program synthesis as a RL problem

Learning Programmatic Policies using Decision Transformers[4]

[4] Krishnan et al., 2024.

Learning Programmatic Policies using Decision Transformers[4]

- Cast ISS as a RL-based program synthesis problem

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Learning Programmatic Policies using Decision Transformers[4]

- Cast ISS as a RL-based program synthesis problem
- Use a decision transformer (DT) model to learn programmatic policies

[4]Krishnan et al., 2024.

ISS as RL-based Program Synthesis

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- Idea: to synthesize programs, learn a policy that generates programs by deriving them from a CFG

ISS as RL-based Program Synthesis

- Idea: to synthesize programs, learn a policy that generates programs by deriving them from a CFG
- Define a program synthesis MDP $\mathcal{M}_{\text{syn}}$, where —
  - States are partially expanded programs
  - Actions are rule applications to valid non-terminals
  - Transitions are the effect of applying a rule
  - Rewards are the return of the program from executing it in the target MDP

Decision Transformer (DT)[5]

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

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

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

Methodology

Modifications to original decision transformer architecture —

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- *Action Masking* to deal with invalid actions (Huang & Ontañón, 2022)
- *Cross-entropy loss* and *sampling from action distribution* 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)

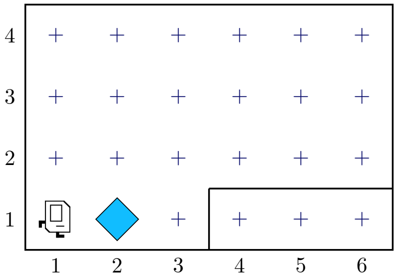

Figure 18: A sample Karel world of size 4×6. The blue diamond represents a marker. The agent cannot travel through walls.

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 2: Statistics for the LEAPS program dataset.

Training & Evaluation

- Train modified DT on generated trajectories

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- Compare performance with LEAPS (Trivedi et al., 2021)

Results

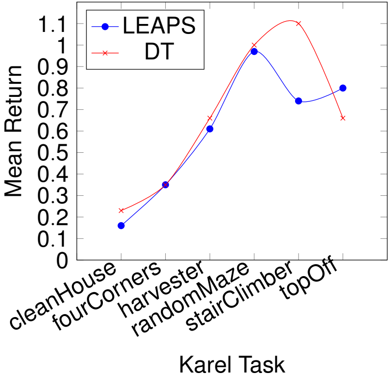

Figure 19: Mean return for LEAPS and DT on Karel tasks.

Results

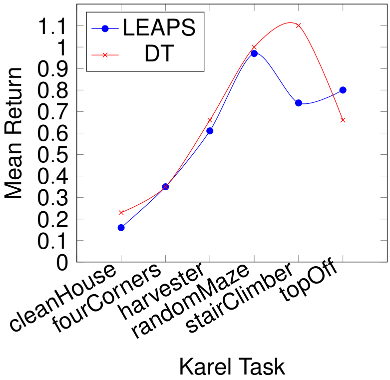

Figure 19: Mean return for LEAPS and DT on Karel tasks.

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

Table 3: Number of unique programs explored by LEAPS and the DT during their search (sampling) phases.

Sample Efficiency

- Search
  - LEAPS uses CEM search
  - DT uses random sampling
  - DT explores orders of magnitude fewer programs

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- Training
  - Optimal top-$k\%$ = 0.1%, implies DT trained on 500 programs
  - LEAPS trained on 35,000 programs
- Both achieve comparable performance on almost all tasks

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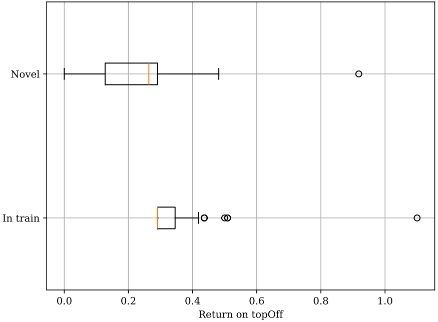

Figure 20: Box plot of returns for programs sampled from the decision transformer model.

Novelty of Generated Programs

- Plotted distribution of rewards for novel and non-novel programs (on the `topOff` task)
- Mean reward for novel programs is higher than non-novel programs ($p < 0.01$)

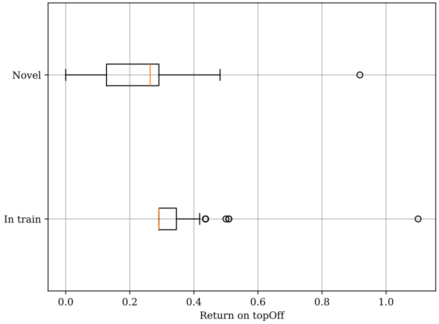

Figure 20: Box plot of returns for programs sampled from the decision transformer model.

Conclusion

- Applied DT model to learn programmatic strategies
- Achieved comparable performance to LEAPS on Karel tasks while being more sample efficient
- Novel programs generated by DT tend to have lower reward

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    - decision transformer-based learning method
- **Expected outcomes** —
  - Benefit esports industry → *better coaching* for players
  - Benefit explainable AI research → generate *policy explanations*

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.

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 —

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

Return

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.

$$\text{Divergence}_E(\sigma, P) \doteq \frac{1}{|P_\mathrm{A}|} \sum_{(s,a_1)\in P_\mathrm{A}} \sum_{a_2 \in \mathcal{A}(s)} \sigma(a_2|s) d_E(s, a_1, a_2) \quad (7)$$

◂ 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

Predicate Vocabulary

- Allows more *situational rule* expression – en passant, promotion
- Allows *more efficient* unification

Return

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.
```

Figure 21: 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

$$z_i = \sum_{j=1}^{n} \texttt{softmax}\left(\{\langle q_i, k_{j'} \rangle\}_{j'=1}^{n}\right)_j \cdot v_j \tag{8}$$

Background and Related Work

Automated Coaching for Esports

Background and Related Work

Automated Coaching for *Esports*

- Esports Analytics
- Automated Game Analysis

Esports Analytics

Esports Analytics

- *Data-driven* analysis of esports games to provide *support* to players

Esports Analytics

- *Data-driven* analysis of esports games to provide *support* to players
- win prediction (Clark et al., 2020; Hodge et al., 2021; Maymin, 2021; Novak et al., 2020; Schubert et al., 2016)

Esports Analytics

- *Data-driven* analysis of esports games to provide *support* to players
- win prediction (Clark et al., 2020; Hodge et al., 2021; Maymin, 2021; Novak et al., 2020; Schubert et al., 2016)
- patch-agnostic methods (Chitayat et al., 2023)

Esports Analytics

- *Data-driven* analysis of esports games to provide *support* to players
- win prediction (Clark et al., 2020; Hodge et al., 2021; Maymin, 2021; Novak et al., 2020; Schubert et al., 2016)
- patch-agnostic methods (Chitayat et al., 2023)
- eye-tracking (Nagel, 2017; Stepanov et al., 2019)

Esports Analytics

- *Data-driven* analysis of esports games to provide *support* to players
- win prediction (Clark et al., 2020; Hodge et al., 2021; Maymin, 2021; Novak et al., 2020; Schubert et al., 2016)
- patch-agnostic methods (Chitayat et al., 2023)
- eye-tracking (Nagel, 2017; Stepanov et al., 2019)
- data collection (Frommel et al., 2019; Xenopoulos et al., 2022)

Automated Game Analysis

Automated Game Analysis

- automated *testing* to discover bugs (Bergdahl et al., 2020; Pfau et al., 2017; Zheng et al., 2019)

Automated Game Analysis

- automated *testing* to discover bugs (Bergdahl et al., 2020; Pfau et al., 2017; Zheng et al., 2019)
- 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)

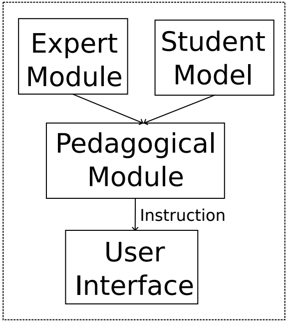

Figure 22: ITS architecture

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*

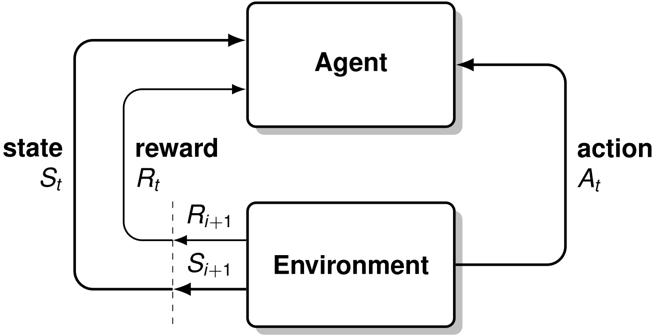

Figure 23: The agent-environment interaction interface in a MDP. Reproduced from Figure 3.1 of Sutton and Barto (2018).

Explainable Reinforcement Learning (XRL)

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- Modern RL agents are *difficult* to understand compared to earlier approaches

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

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- No unifying framework to synthesize goals and approaches