Interpretable Strategy Synthesis for Competitive Games

Thesis Defense Presentation

Abhijeet Krishnan

Department of Computer Science
North Carolina State University

July 16, 2024

Rise of Esports

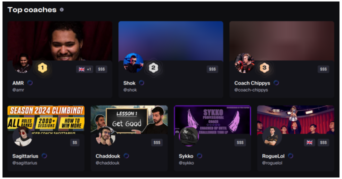
Colin Young-Wolff/Riot Games

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

Esports coaching is –

Difficulties with Esports Coaching

Esports coaching is –

- not *standardized*: no “textbook” to follow

Difficulties with Esports Coaching

Esports coaching is –

- not *standardized*: no “textbook” to follow
- *confined* to popular games

Difficulties with Esports Coaching

Esports coaching is –

- not *standardized*: no “textbook” to follow
- *confined* to popular games
- *difficult* due to a shifting *“meta”*

Difficulties with Esports Coaching

Esports coaching is –

- not *standardized*: no “textbook” to follow
- *confined* to popular games
- *difficult* due to a shifting *“meta”*
- not *scalable*

Difficulties with Esports Coaching

Esports coaching is –

- not *standardized*: no “textbook” to follow
- *confined* to popular games
- *difficult* due to a shifting *“meta”*
- not *scalable*

Solution

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

What is a Principled Approach?

- principled approach = evidence-based, standardized, agreed-upon

What is a Principled Approach?

- principled approach = evidence-based, standardized, agreed-upon
- None so far – players simply play more to get better

What is a Principled Approach?

- principled approach = evidence-based, standardized, agreed-upon
- None so far – players simply play more to get better
- Inspiration from ITS design —

What is a Principled Approach?

- principled approach = evidence-based, standardized, agreed-upon
- None so far – players simply play more to get better
- Inspiration from ITS design —
    - Intelligent Tutoring System (ITS): *automated*, *personalized* education systems

What is a Principled Approach?

- principled approach = evidence-based, standardized, agreed-upon
- None so far – players simply play more to get better
- Inspiration from ITS design —
  - Intelligent Tutoring System (ITS): *automated*, *personalized* education systems
  - Model a student to provide personalized instruction

What is a Principled Approach?

- principled approach = evidence-based, standardized, agreed-upon
- None so far – players simply play more to get better
- Inspiration from ITS design —
  - Intelligent Tutoring System (ITS): *automated*, *personalized* education systems
  - Model a student to provide personalized instruction
  - Use of **cognitive theories** as a *student modelling* approach (Chrysafiadi & Virvou, 2013)

What is a Principled Approach?

- principled approach = evidence-based, standardized, agreed-upon
- None so far – players simply play more to get better
- Inspiration from ITS design —
  - Intelligent Tutoring System (ITS): *automated*, *personalized* education systems
  - Model a student to provide personalized instruction
  - Use of **cognitive theories** as a *student modelling* approach (Chrysafiadi & Virvou, 2013)
  - use insights from psychology and education

What is a Principled Approach?

- principled approach = evidence-based, standardized, agreed-upon
- None so far – players simply play more to get better
- Inspiration from ITS design —
    - Intelligent Tutoring System (ITS): *automated*, *personalized* education systems
    - Model a student to provide personalized instruction
    - Use of **cognitive theories** as a *student modelling* approach (Chrysafiadi & Virvou, 2013)
    - use insights from psychology and education
    - e.g., F-SMILE system (Virvou & Kabassi, 2002)

Strategies are Mental Models of Games

Claim

Strategies can be treated as mental models of games

Strategies are Mental Models of Games

Claim

Strategies can be treated as mental models of games

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

Strategies are Mental Models of Games

Claim

Strategies can be treated as mental models of games

- Players develop *mental models* of games to explain them (Boyan & Sherry, 2011)
- Players acquire and *refine* their mental models through practice, instruction and discussion (of strategies) (Boyan et al., 2018)

Strategies are Mental Models of Games

Claim

Strategies can be treated as mental models of games

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

Strategies are Mental Models of Games

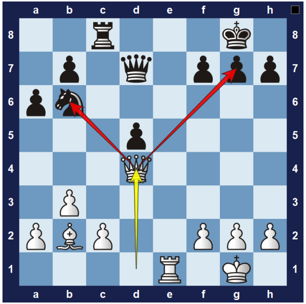
Claim

Strategies can be treated as mental models of games

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

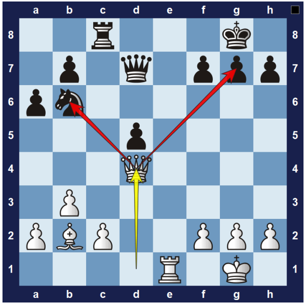
Real-world Strategies



Chessfox

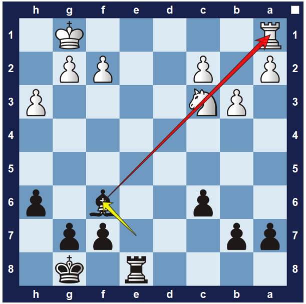
Figure 5: An example of the *fork* tactic in chess

Real-world Strategies



Chessfox

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



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*

Strategies should be “explainable”

Strategies should be “explainable”

- Generated strategies need to be *communicated* to players

Strategies should be “explainable”

- Generated strategies need to be *communicated* to players
- Players communicate strategies and concepts using game-specific *jargon*

Strategies should be "explainable"

- Generated strategies need to be *communicated* to players
- Players communicate strategies and concepts using game-specific *jargon*
- E.g., *okizeme* in fighting games, *tempo* in chess

Strategies should be "explainable"

- Generated strategies need to be *communicated* to players
- Players communicate strategies and concepts using game-specific *jargon*
- E.g., *okizeme* in fighting games, *tempo* in chess

Explainability

A strategy's explainability is the ease with which a player can use it to refine their mental model

Benefits of Explainability

- Generating explainable strategies increases their value to players

Benefits of Explainability

- Generating explainable strategies increases their value to players
- Could contribute to the shared vocabulary of concepts for a game

Benefits of Explainability

- Generating explainable strategies increases their value to players
- Could contribute to the shared vocabulary of concepts for a game
- Useful for *explainable AI*

Thesis Statement

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 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)
ISS using Programs	RQ3	RQ3(a)	
		RQ3(b)	

RQs

RQs

RQ1

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

RQs

RQ1

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

RQ2

How do we approach the problem of ISS using a *logic-based* strategy model?

RQs

RQ1

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

RQ2

How do we approach the problem of ISS using a *logic-based* strategy model?

RQ3

How do we approach the problem of ISS using a *program-based* strategy model?

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)

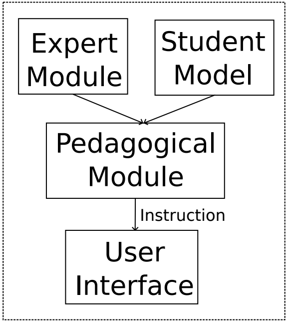


Figure 8: ITS architecture

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*

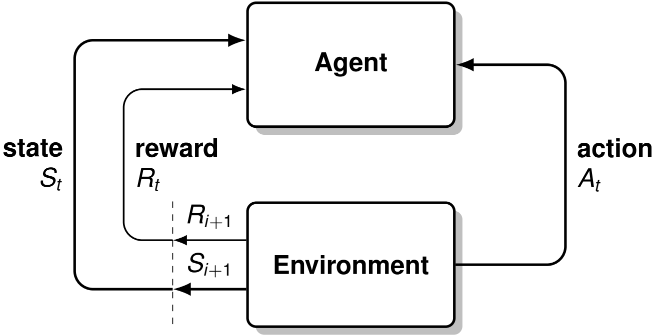


Figure 9: The agent-environment interaction interface in a MDP. Reproduced from Figure 3.1 of Sutton and Barto (2018).

Explainable Reinforcement Learning (XRL)

Explainable Reinforcement Learning (XRL)

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

Explainable Reinforcement Learning (XRL)

- Modern RL agents are *difficult* to understand compared to earlier approaches
- Agents are being used in *high-stakes* applications

Explainable Reinforcement Learning (XRL)

- Modern RL agents are *difficult* to understand compared to earlier approaches
- Agents are being used in *high-stakes* applications
- Necessary to *interpret* an agent and *explain* their decisions

Explainable Reinforcement Learning (XRL)

- Modern RL agents are *difficult* to understand compared to earlier approaches
- Agents are being used in *high-stakes* applications
- Necessary to *interpret* an agent and *explain* their decisions
- XRL: field of study to devise techniques to interpret RL agents

Explainable Reinforcement Learning (XRL)

- Modern RL agents are *difficult* to understand compared to earlier approaches
- Agents are being used in *high-stakes* applications
- Necessary to *interpret* an agent and *explain* their decisions
- XRL: field of study to devise techniques to interpret RL agents
- ISS = XRL for game environments

Strategy Synthesis

Strategy Synthesis

- Early work uses rule-based models (Butler et al., 2017; Canaan et al., 2018; de Freitas et al., 2018; de Mesentier Silva et al., 2016; Spronck et al., 2004)

Strategy Synthesis

- Early work uses rule-based models (Butler et al., 2017; Canaan et al., 2018; de Freitas et al., 2018; de Mesentier Silva et al., 2016; Spronck et al., 2004)
- Subsequent work uses programmatic representations (Mariño et al., 2021; Mariño & Toledo, 2022; Medeiros et al., 2022)

Strategy Synthesis

- Early work uses rule-based models (Butler et al., 2017; Canaan et al., 2018; de Freitas et al., 2018; de Mesentier Silva et al., 2016; Spronck et al., 2004)
- Subsequent work uses programmatic representations (Mariño et al., 2021; Mariño & Toledo, 2022; Medeiros et al., 2022)
- No unifying framework to synthesize goals and approaches

Introduction

RQ1

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

Introduction

RQ1

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

- Why do we need a framework?

Introduction

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 et al. (2004)	2	1	1	✗
de Mesentier Silva et al. (2016)	1	1	4	✓
Butler et al. (2017)	1	1	1	✗
Canaan et al. (2018)	1	1	1	✗
de Freitas et al. (2018)	1	1	1	✗
Mariño et al. (2021)	1	1	1	✗
Krishnan and Martens (2022a)	1	1	1	✗
Mariño and Toledo (2022)	1	1	1	✗
Medeiros et al. (2022)	2	1	2	✗

Table 1: List of works in ISS

Elements of a Good Framework

Elements of a Good Framework

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

Elements of a Good Framework

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

Interpretable Strategy Synthesis (ISS)

Definition (ISS) Formal

Given a —

Interpretable Strategy Synthesis (ISS)

Definition (ISS) Formal

Given a —

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

Interpretable Strategy Synthesis (ISS)

Definition (ISS) Formal

Given a —

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

Interpretable Strategy Synthesis (ISS)

Definition (ISS) Formal

Given a —

- Game environment $\mathcal{G}$ (i.e., an MDP)
- Strategy model $\mathcal{M}$
- Performance measure J

Interpretable Strategy Synthesis (ISS)

Definition (ISS) Formal

Given a —

- Game environment $\mathcal{G}$ (i.e., an MDP)
- Strategy model $\mathcal{M}$
- Performance measure J
- Interpretability measure $\mathcal{I}$

Interpretable Strategy Synthesis (ISS)

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.

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

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
- 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.

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

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
- Players generally only study good strategies

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
- Players generally only study good strategies
- Examples —
  - win rate
  - material advantage (chess)
  - resources harvested (StarCraft II)

Interpretability Measure ($\mathcal{I}$)

Definition (interpretability measure) Formal

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

Interpretability Measure ($\mathcal{I}$)

Definition (interpretability measure) Formal

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

- How *easily understood* a strategy is

Interpretability Measure ($\mathcal{I}$)

Definition (interpretability measure) Formal

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

- How *easily understood* a strategy is
- Players only benefit from a strategy they understand

Interpretability Measure ($\mathcal{I}$)

Definition (interpretability measure) Formal

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

- How *easily understood* a strategy is
- Players only benefit from a strategy they understand
- Examples —
  - number of statements (programmatic script)
  - number of nodes (decision tree)
  - improvement in player win rate upon being explained strategy

Introduction

RQ2

How do we approach the problem of ISS using a *logic-based* strategy model?

Introduction

RQ2

How do we approach the problem of ISS using a *logic-based* strategy model?

- Description of logic-based strategy model

Introduction

RQ2

How do we approach the problem of ISS using a *logic-based* strategy model?

- Description of logic-based strategy model
- Application to *chess* —

Introduction

RQ2

How do we approach the problem of ISS using a *logic-based* strategy model?

- Description of logic-based strategy model
- Application to *chess* —
  - RQ2(a): Representing chess tactics as FOL rules and evaluating them (Krishnan & Martens, 2022b)

Introduction

RQ2

How do we approach the problem of ISS using a *logic-based* strategy model?

- Description of logic-based strategy model
- Application to *chess* —
  - RQ2(a): Representing chess tactics as FOL rules and evaluating them (Krishnan & Martens, 2022b)
  - RQ2(b): Learning chess strategies using ILP (Krishnan & Martens, 2022a)

Introduction

RQ2

How do we approach the problem of ISS using a *logic-based* strategy model?

- Description of logic-based strategy model
- Application to *chess* —
  - RQ2(a): Representing chess tactics as FOL rules and evaluating them (Krishnan & Martens, 2022b)
  - RQ2(b): Learning chess strategies using ILP (Krishnan & Martens, 2022a)
  - RQ2(c): Improving ILP learning using precision/recall constraints (Krishnan et al., 2024)

First-Order Logic and Prolog

First-Order Logic and Prolog

- FOL is a *formal* language that can compactly represent *relationships* between objects in an environment

First-Order Logic and Prolog

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

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

First-Order Logic and Prolog

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

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

- 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?

Why use FOL-based Strategies?

- 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

Why use FOL-based Strategies?

- 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
- Unique capabilities of rule-based strategy representations
  - Continuous learning
  - Predicate invention (Cropper & Dumančić, 2022)

Why use FOL-based Strategies?

- 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
- Unique capabilities of rule-based strategy representations
  - Continuous learning
  - Predicate invention (Cropper & Dumančić, 2022)
- *Interpretability* of rule-based models (Zhang et al., 2021)

Rule-based Strategy Model

FOL Rule

Rule-based Strategy Model

FOL Rule

Predicate Vocabulary

Rule-based Strategy Model

FOL Rule

$$
\begin{aligned}
&\texttt{strategy}(\text{State}, \text{Action}) \leftarrow \\
&\qquad \texttt{feature\_1}(\cdots), \\
&\qquad \texttt{feature\_2}(\cdots), \\
&\qquad \vdots \\
&\qquad \texttt{feature\_n}(\cdots)
\end{aligned}
$$

Figure 10: A FOL *policy rule* expressed in a *predicate vocabulary* $\mathcal{V}$

Predicate Vocabulary

Rule-based Strategy Model

FOL Rule

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

Figure 10: A FOL *policy rule* expressed in a *predicate vocabulary* $\mathcal{V}$

Predicate Vocabulary

- State $=$ Prolog list of atoms

Rule-based Strategy Model

FOL Rule

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

Figure 10: A FOL *policy rule* expressed in a *predicate vocabulary* $\mathcal{V}$

Predicate Vocabulary

- State = Prolog list of atoms
- Action = Prolog list of atoms

Rule-based Strategy Model

FOL Rule

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

Figure 10: A FOL *policy rule* expressed in a *predicate vocabulary* $\mathcal{V}$

Predicate Vocabulary

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

Learning Rule-based Policies

Learning Rule-based Policies

- Can be learned using ILP

Learning Rule-based Policies

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

Learning Rule-based Policies

- Can be learned using ILP
- 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

Learning Rule-based Policies

- Can be learned using ILP
- 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 $a' \in \mathcal{A}(s) - \pi(s)$

Learning Rule-based Policies

- Can be learned using ILP
- 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 $a' \in \mathcal{A}(s) - \pi(s)$
- ILP system($\langle E^+, E^-, B \rangle$) $\xrightarrow{\textit{learn}}$ rule-based strategies

Logic-based Strategy Model for Chess

Logic-based Strategy Model for Chess

- ISS for chess $\langle \text{chess}, \mathcal{M}_{\text{FOL}}, J_{\text{chess}}, \mathcal{I}_{\text{chess}} \rangle$

Logic-based Strategy Model for Chess

- ISS for chess $\langle \text{chess}, \mathcal{M}_{\text{FOL}}, J_{\text{chess}}, \mathcal{I}_{\text{chess}} \rangle$
- Learning method

Why Chess?

- *Popular* game with a *long* competitive history
- Has a large number of *player-discovered strategies*
- Extensive use as a *testbed for AI*

Application to Chess

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

Application to 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?

Application to 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?

Strategy Model for Chess

First-Order (FO) Logic Rule

Strategy Model for Chess

First-Order (FO) Logic Rule

Predicate Vocabulary

Strategy Model for Chess

First-Order (FO) Logic Rule

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

Figure 11: Our chess strategy model expressed in Prolog pseudocode

Predicate Vocabulary

Strategy Model for Chess

First-Order (FO) Logic Rule

$$
\begin{aligned}
&\texttt{tactic}(\textit{Position}, \text{Move}) \leftarrow \\
&\qquad \texttt{feature\_1}(\cdots), \\
&\qquad \texttt{feature\_2}(\cdots), \\
&\qquad \vdots \\
&\qquad \texttt{feature\_n}(\cdots)
\end{aligned}
$$

Figure 11: 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),...]
```

Strategy Model for Chess

First-Order (FO) Logic Rule

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

Figure 11: 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]`

Strategy Model for Chess

First-Order (FO) Logic Rule

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

Figure 11: 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

$$
\begin{aligned}
&\texttt{fork}(\mathrm{Position},\mathrm{Move}) \leftarrow \\
&\qquad \texttt{legal\_move}(\mathrm{Position},\mathrm{Move}), \\
&\qquad \texttt{move}(\mathrm{Move},\_,\mathrm{To},\_), \\
&\qquad \texttt{make\_move}(\mathrm{Position},\mathrm{Move},\mathrm{NewPosition}), \\
&\qquad \texttt{can\_capture}(\mathrm{NewPosition},\mathrm{To},\mathrm{ForkSquare1}), \\
&\qquad \texttt{can\_capture}(\mathrm{NewPosition},\mathrm{To},\mathrm{ForkSquare2}), \\
&\qquad \texttt{different}(\mathrm{ForkSquare1},\mathrm{ForkSquare2}).
\end{aligned}
$$

Figure 12: An interpretation of the *fork* tactic from the chess literature using our predicate vocabulary.

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

Application to 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?

Application to 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?

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

Interpretability Measure

- *No explicit interpretability measure!* Only qualitative arguments

Interpretability Measure

- *No explicit interpretability measure!* Only qualitative arguments
- Human players *think* and *train* using chess tactics (Gobet & Jansen, 2006; Szabo, 1984)
- 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)

Application to 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*?

Evaluation of Known Chess Tactics[1]

[1] Krishnan and Martens, 2022b.

Evaluation of Known Chess Tactics[1]

- PAL (Morales, 1992) $\xrightarrow{\text{learn}}$ *known* chess patterns (tactics) PAL

[1] Krishnan and Martens, 2022b.

Evaluation of Known Chess Tactics[1]

- PAL (Morales, 1992) $\xrightarrow{\text{learn}}$ known chess patterns (tactics) PAL
- tactics $\xrightarrow{\text{translate}}$ chess strategy model

[1]Krishnan and Martens, 2022b.

Evaluation of Known Chess Tactics[1]

- PAL (Morales, 1992) $\xrightarrow{\text{learn}}$ known chess patterns (tactics) PAL
- tactics $\xrightarrow{\text{translate}}$ chess strategy model
- Divergence(chess strategies, *human beginner*)

[1] Krishnan and Martens, 2022b.

Evaluation of Known Chess Tactics[1]

- PAL (Morales, 1992) $\xrightarrow{\text{learn}}$ known chess patterns (tactics) PAL
- tactics $\xrightarrow{\text{translate}}$ chess strategy model
- Divergence(chess strategies, human beginner)
- Divergence(*random baseline*, human beginner)

[1] Krishnan and Martens, 2022b.

Evaluation of Known Chess Tactics[1]

- PAL (Morales, 1992) $\xrightarrow{\text{learn}}$ known chess patterns (tactics) PAL
- tactics $\xrightarrow{\text{translate}}$ chess strategy model
- Divergence(chess strategies, human beginner)
- Divergence(random baseline, human beginner)
- Both using strong/weak engine

[1] Krishnan and Martens, 2022b.

Results

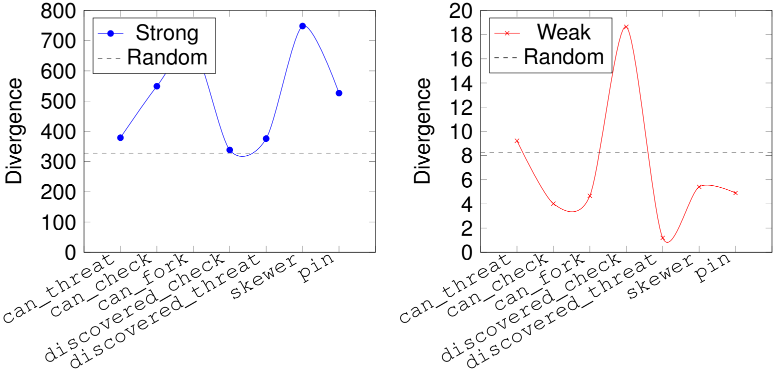


Figure 13: Divergence for each tactic

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~~
- ~~Performance measure for chess~~
- ~~Interpretability measure for chess~~

Learning Chess Strategy Models

- ~~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]

- Inductive Logic Programming (ILP): *symbolic ML* technique ILP

[2]Krishnan and Martens, 2022a.

Learning Chess Strategies using ILP[2]

- Inductive Logic Programming (ILP): *symbolic ML* technique ILP
- ISS for chess $\langle \mathcal{G}, \mathcal{M}, J, \mathcal{I} \rangle \xrightarrow{\text{translate}}$ ILP problem $\langle E^+, E^-, B \rangle$

[2] Krishnan and Martens, 2022a.

Learning Chess Strategies using ILP[2]

- Inductive Logic Programming (ILP): *symbolic ML* technique ILP
- ISS for chess $\langle \mathcal{G}, \mathcal{M}, J, \mathcal{I} \rangle \xrightarrow{\text{translate}}$ ILP problem $\langle E^+, E^-, B \rangle$
- ILP system($\langle E^+, E^-, B \rangle$) $\xrightarrow{\textit{learn}}$ chess strategies

[2]Krishnan and Martens, 2022a.

Learning Chess Strategies using ILP[2]

- Inductive Logic Programming (ILP): *symbolic ML* technique ILP
- ISS for chess $\langle \mathcal{G}, \mathcal{M}, J, \mathcal{I} \rangle \xrightarrow{\text{translate}}$ ILP problem $\langle E^+, E^-, B \rangle$
- ILP system($\langle E^+, E^-, B \rangle$) $\xrightarrow{\textit{learn}}$ chess strategies
- Use *divergence* to evaluate learned chess strategies

[2] Krishnan and Martens, 2022a.

Learning Chess Strategies using ILP[2]

- Inductive Logic Programming (ILP): *symbolic ML* technique ILP
- ISS for chess $\langle \mathcal{G}, \mathcal{M}, J, \mathcal{I} \rangle \xrightarrow{\text{translate}}$ ILP problem $\langle E^+, E^-, B \rangle$
- ILP system($\langle E^+, E^-, B \rangle$) $\xrightarrow{\textit{learn}}$ chess strategies
- Use *divergence* to evaluate learned chess strategies
- Compare to random, strong/weak engine baselines

[2] Krishnan and Martens, 2022a.

Results

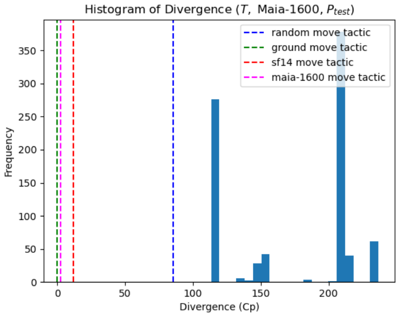


Figure 14: Divergence histogram for T evaluated using *weak* engine

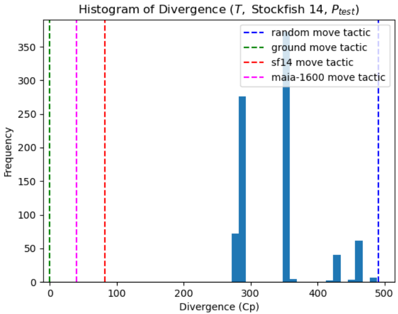


Figure 15: Divergence histogram for T evaluated using *strong* engine

Analysis

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

Improving the ILP Learning Method

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

Improving the ILP Learning Method

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

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.

Improvements using Precision/Recall-based Constraints[3]

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

[3]Krishnan et al., 2024.

Improvements using Precision/Recall-based Constraints[3]

- Modifications —
  - *Limit* chess strategy search space using precision/recall constraints
  - Introduce a *new* predicate vocabulary

[3] Krishnan et al., 2024.

Improvements using Precision/Recall-based Constraints[3]

- Modifications —
  - *Limit* chess strategy search space using precision/recall constraints
  - Introduce a *new* predicate vocabulary
- Conduct *ablation study* to measure impact of modifications

[3] Krishnan et al., 2024.

Improvements using Precision/Recall-based Constraints[3]

- Modifications —
  - *Limit* chess strategy search space using precision/recall constraints
  - Introduce a *new* predicate vocabulary
- Conduct *ablation study* to measure impact of modifications
  - Learn strategies using systems with/without constraints, predicate vocabulary

[3]Krishnan et al., 2024.

Improvements using Precision/Recall-based Constraints[3]

- Modifications —
  - *Limit* chess strategy search space using precision/recall constraints
  - Introduce a *new* predicate vocabulary
- Conduct *ablation study* to measure impact of modifications
  - Learn strategies using systems with/without constraints, predicate vocabulary
  - Measure average strategy divergence

[3]Krishnan et al., 2024.

Improvements using Precision/Recall-based Constraints[3]

- Modifications —
  - *Limit* chess strategy search space using precision/recall constraints
  - Introduce a *new* predicate vocabulary
- Conduct *ablation study* to measure impact of modifications
  - Learn strategies using systems with/without constraints, predicate vocabulary
  - Measure average strategy divergence
  - Test decrease vs. old system using *one-sided Welch's t-test*

[3] Krishnan et al., 2024.

Results

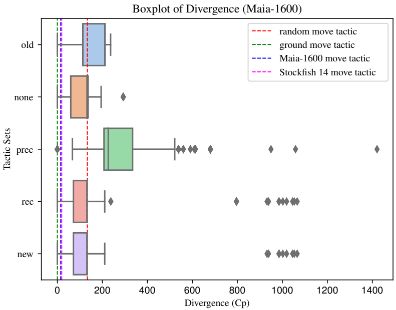


Figure 16: Boxplot of tactic divergence (evaluated using *weak* engine) for each system

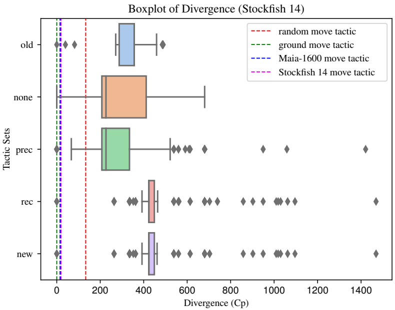


Figure 17: Boxplot of tactic divergence (evaluated using *strong* engine) for each system

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

Limitations and Future Work

- High cost of *knowledge engineering* – improved BK in Krishnan et al. (2023) required $\sim$ 800 LoC of Prolog!

Limitations and Future Work

- High cost of *knowledge engineering* – improved BK in Krishnan et al. (2023) required $\sim$ 800 LoC of Prolog!
  - *general* policy BK

Limitations and Future Work

- High cost of *knowledge engineering* – improved BK in Krishnan et al. (2023) required $\sim$ 800 LoC of Prolog!
  - *general* policy BK
- Performance not competitive with state-of-the-art

Limitations and Future Work

- High cost of *knowledge engineering* – improved BK in Krishnan et al. (2023) required $\sim$ 800 LoC of Prolog!
  - *general* policy BK
- Performance not competitive with state-of-the-art
  - experiment with *task-specific* BK

Limitations and Future Work

- High cost of *knowledge engineering* – improved BK in Krishnan et al. (2023) required $\sim$ 800 LoC of Prolog!
  - *general* policy BK
- Performance not competitive with state-of-the-art
  - experiment with *task-specific* BK
  - use *neural* ILP systems (Evans & Grefenstette, 2018)

Limitations and Future Work

- High cost of *knowledge engineering* – improved BK in Krishnan et al. (2023) required $\sim$ 800 LoC of Prolog!
  - *general* policy BK
- Performance not competitive with state-of-the-art
  - experiment with *task-specific* BK
  - use *neural* ILP systems (Evans & Grefenstette, 2018)
- Interpretability for FOL-based strategies is poorly understood

Limitations and Future Work

- High cost of *knowledge engineering* – improved BK in Krishnan et al. (2023) required $\sim$ 800 LoC of Prolog!
  - *general* policy BK
- Performance not competitive with state-of-the-art
  - experiment with *task-specific* BK
  - use *neural* ILP systems (Evans & Grefenstette, 2018)
- Interpretability for FOL-based strategies is poorly understood
  - study factors affecting interpretability of FOL-based policies (Kliegr et al., 2021)

Strategies as Programs

RQ3

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

Strategies as Programs

RQ3

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

- Description of the programmatic strategy model

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)

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

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 18: 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 19: A programmatic policy (strategy) for a PID controller.

Learning Programmatic Strategies

Approaches from —

Learning Programmatic Strategies

Approaches from —

- Program synthesis —

Learning Programmatic Strategies

Approaches from —

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

Learning Programmatic Strategies

Approaches from —

- Program synthesis —
  - based on $\langle$input, output$\rangle$ pairs (X. Chen et al., 2019; Lázaro-Gredilla et al., 2019; Yang et al., 2021)
  - based on MDP rewards (Li et al., 2020; Qiu & Zhu, 2022)

Learning Programmatic Strategies

Approaches from —

- Program synthesis —
  - based on $\langle \text{input}, \text{output} \rangle$ pairs (X. Chen et al., 2019; Lázaro-Gredilla et al., 2019; Yang et al., 2021)
  - based on MDP rewards (Li et al., 2020; Qiu & Zhu, 2022)
- Reinforcement learning —

Learning Programmatic Strategies

Approaches from —

- Program synthesis —
  - based on $\langle \text{input}, \text{output} \rangle$ pairs (X. Chen et al., 2019; Lázaro-Gredilla et al., 2019; Yang et al., 2021)
  - based on MDP rewards (Li et al., 2020; Qiu & Zhu, 2022)
- Reinforcement learning —
  - by casting program synthesis as a RL problem (Krishnan et al., 2024)

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

[4]Krishnan et al., 2024.

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

- Idea: to synthesize programs, learn a policy that generates programs by deriving them from a CFG
- Define a program synthesis MDP $\mathcal{M}_{\mathsf{syn}}$, 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

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

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

Methodology

Modifications to original decision transformer architecture —

Methodology

Modifications to original decision transformer architecture —

- *Action Masking* to deal with invalid actions

Methodology

Modifications to original decision transformer architecture —

- *Action Masking* to deal with invalid actions
- *Cross-entropy loss* and *sampling from action distribution* to deal with discrete action spaces

Methodology

Modifications to original decision transformer architecture —

- *Action Masking* to deal with invalid actions
- *Cross-entropy loss* and *sampling from action distribution* to deal with discrete action spaces
- *GRU-based state embedding* following similar approaches for sentence embedding

Karel Domain

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

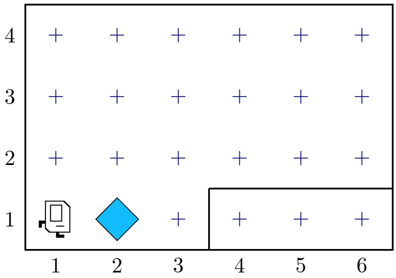


Figure 20: A sample Karel world of size 4×6. The blue diamond represents a marker. The agent cannot travel through walls.

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

Training & Evaluation

- Train modified DT on generated trajectories
- Tune hyperparameters using *Optuna* framework (Akiba et al., 2019)

Training & Evaluation

- Train modified DT on generated trajectories
- Tune hyperparameters using *Optuna* framework (Akiba et al., 2019)
- Parameterize top-k% of the programs based on reward to train on

Training & Evaluation

- Train modified DT on generated trajectories
- Tune hyperparameters using *Optuna* framework (Akiba et al., 2019)
- Parameterize top-k% of the programs based on reward to train on
- Compare performance with LEAPS (Trivedi et al., 2021)

Results

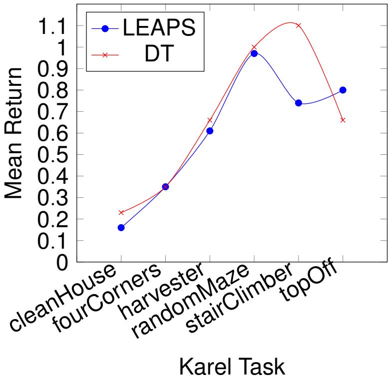


Figure 21: Mean return for LEAPS and DT on Karel tasks.

Results

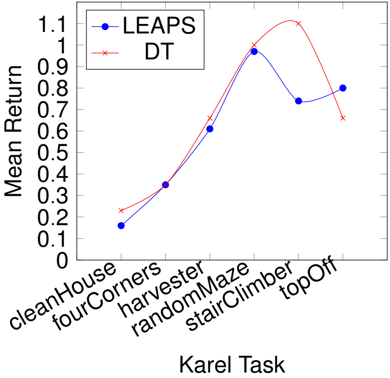


Figure 21: Mean return for LEAPS and DT on Karel tasks.

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

Sample Efficiency

- Search
  - LEAPS uses CEM search
  - DT uses random sampling
  - DT explores orders of magnitude fewer programs
- Training
  - Optimal top-$k\%$ = 0.1%, implies DT trained on 500 programs
  - LEAPS trained on 35,000 programs

Sample Efficiency

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

Novelty of Generated Programs

Novelty of Generated Programs

- Plotted distribution of rewards for novel and non-novel programs (on the `topOff` task)

Novelty of Generated Programs

- Plotted distribution of rewards for novel and non-novel programs (on the `topOff` task)

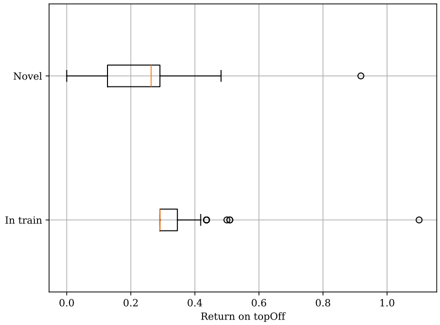


Figure 22: Box plot of returns for programs sampled from the decision transformer model.

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 ($p < 0.01$)

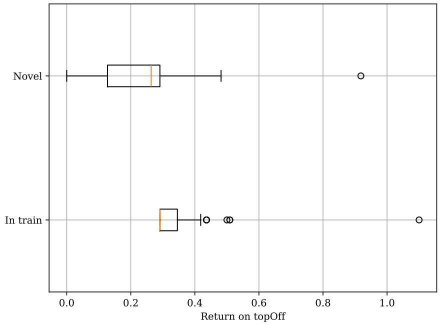


Figure 22: Box plot of returns for programs sampled from the decision transformer model.

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

Limitations and Future Work

Limitations and Future Work

- Different DSLs required for different domains

Limitations and Future Work

- Different DSLs required for different domains
  - *general* policy DSL (Qiu & Zhu, 2022; Verma et al., 2018)

Limitations and Future Work

- Different DSLs required for different domains
  - *general* policy DSL (Qiu & Zhu, 2022; Verma et al., 2018)
- Interpretability for programmatic strategies is poorly understood

Limitations and Future Work

- Different DSLs required for different domains
  - *general* policy DSL (Qiu & Zhu, 2022; Verma et al., 2018)
- Interpretability for programmatic strategies is poorly understood
  - study factors affecting interpretability of programmatic strategies

Conclusion

- **Goal**: investigate approaches to the problem of *ISS*

Conclusion

- **Goal**: investigate approaches to the problem of *ISS*
- **Contributions** —

Conclusion

- **Goal**: investigate approaches to the problem of *ISS*
- **Contributions** —
  - Defined a *framework* for ISS

Conclusion

- **Goal**: investigate approaches to the problem of *ISS*
- **Contributions** —
  - Defined a *framework* for ISS
  - Approached ISS using *FOL-based* strategy model for chess
    - FOL-based chess strategy model
    - ILP-based learning method
    - Improvement to ILP-based learning method

Conclusion

- **Goal**: investigate approaches to the problem of *ISS*
- **Contributions** —
  - Defined a *framework* for ISS
  - Approached ISS using *FOL-based* strategy model for chess
    - FOL-based chess strategy model
    - ILP-based learning method
    - Improvement to ILP-based learning method
  - Approached ISS using *programmatic* strategy model
    - Reduction of ISS to RL-based program synthesis
    - decision transformer-based learning method

Conclusion

- **Goal**: investigate approaches to the problem of *ISS*
- **Contributions** —
  - Defined a *framework* for ISS
  - Approached ISS using *FOL-based* strategy model for chess
    - FOL-based chess strategy model
    - ILP-based learning method
    - Improvement to ILP-based learning method
  - Approached ISS using *programmatic* strategy model
    - Reduction of ISS to RL-based program synthesis
    - decision transformer-based learning method
- **Expected outcomes** —
  - Benefit esports industry $\rightarrow$ *better coaching* for players
  - Benefit explainable AI research $\rightarrow$ 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.

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?

References I

Akiba, T., Sano, S., Yanase, T., Ohta, T., & Koyama, M. (2019). Optuna: A next-generation hyperparameter optimization framework. In *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery and data mining*.

Beau, P., & Bakkes, S. (2016, September). Automated game balancing of asymmetric video games. In *2016 ieee conference on computational intelligence and games (cig)* (pp. 1–8). doi:10.1109/CIG.2016.7860432

References II

Bergdahl, J., Gordillo, C., Tollmar, K., & Gisslén, L. (2020, August). Augmenting automated game testing with deep reinforcement learning. In *2020 ieee conference on games (cog)* (pp. 600–603). doi:10.1109/CoG47356.2020.9231552

Berliner, H. J. (1975). *A representation and some mechanisms for a problem solving chess program*. Carnegie-Mellon Univ Pittsburgh PA Dept of Computer Science.

References III

Boyan, A., McGloin, R., & Wasserman, J. A. (2018). Model matching theory: A framework for examining the alignment between game mechanics and mental models. *Media and Communication*, *6*(2), 126–136. doi:https://doi.org/10.17645/mac.v6i2.1326

Boyan, A., & Sherry, J. L. (2011). The challenge in creating games for education: Aligning mental models with game models. *Child Development Perspectives*, *5*(2), 82–87. doi:10.1111/j.1750-8606.2011.00160.x

References IV

Bramer, M. A. (1977). *Representation of knowledge for chess endgames towards a self-improving system*. (Doctoral dissertation, Open University (United Kingdom)).

Bratko, I. (1982). Knowledge-based problem-solving in al3. *Machine intelligence*, *10*, 73–100.

Butler, E., Torlak, E., & Popović, Z. (2017). Synthesizing interpretable strategies for solving puzzle games. In *Proceedings of the 12th international conference on the foundations of digital games*. doi:10.1145/3102071.3102084

References V

Canaan, R., Shen, H., Torrado, R., Togelius, J., Nealen, A., & Menzel, S. (2018). Evolving agents for the hanabi 2018 cig competition. In *2018 ieee conference on computational intelligence and games (cig)* (pp. 1–8). doi:10.1109/CIG.2018.8490449

Chen, X., Liu, C., & Song, D. (2019). Execution-guided neural program synthesis. In *International conference on learning representations*. Retrieved from https://openreview.net/forum?id=H1gfOiAqYm

References VI

Chen, Y., Wang, C., Bastani, O., Dillig, I., & Feng, Y. (2020). Program Synthesis Using Deduction-Guided Reinforcement Learning. In S. K. Lahiri & C. Wang (Eds.), *Computer Aided Verification* (pp. 587–610). doi:10.1007/978-3-030-53291-8_30

Chitayat, A. P., Block, F., Walker, J., & Drachen, A. (2023). Beyond the meta: Leveraging game design parameters for patch-agnostic esport analitics. *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, *19*(11), 116–125. doi:10.1609/aiide.v19i1.27507

References VII

Chrysafiadi, K., & Virvou, M. (2013). Student modeling approaches: A literature review for the last decade. *Expert Systems with Applications*, *40*(11), 4715–4729. doi:https://doi.org/10.1016/j.eswa.2013.02.007

Clark, N., Macdonald, B., & Kloo, I. (2020). A bayesian adjusted plus-minus analysis for the esport dota 2. *Journal of Quantitative Analysis in Sports*, *16*(4), 325–341. doi:10.1515/jqas-2019-0103

References VIII

Cropper, A., & Dumančić, S. (2022). Inductive logic programming at 30: A new introduction. *Journal of Artificial Intelligence Research*, *74*, 765–850. doi:10.1613/jair.1.13507

DeepMind. (2019, January). Alphastar: Mastering the real-time strategy game starcraft ii. Retrieved September 21, 2022, from https://www.deepmind.com/blog/alphastar-mastering-the-real-time-strategy-game-starcraft-ii

References IX

de Freitas, J. M., de Souza, F. R., & Bernardino, H. S. (2018). Evolving controllers for mario ai using grammar-based genetic programming. In *2018 ieee congress on evolutionary computation (cec)* (pp. 1–8). doi:10.1109/CEC.2018.8477698

DeLaurentis, D. A., Panchal, J. H., Raz, A. K., Balasubramani, P., Maheshwari, A., Dachowicz, A., & Mall, K. (2021, August). Toward automated game balance: A systematic engineering design approach. In *2021 ieee conference on games (cog)* (pp. 1–8). doi:10.1109/CoG52621.2021.9619032

References X

de Mesentier Silva, F., Isaksen, A., Togelius, J., & Nealen, A. (2016). Generating heuristics for novice players. In *2016 ieee conference on computational intelligence and games (cig)* (pp. 1–8). IEEE.

Evans, R., & Grefenstette, E. (2018). Learning explanatory rules from noisy data. *Journal of Artificial Intelligence Research*, *61*, 1–64.

References XI

Frommel, J., Gugenheimer, J., & Rogers, K. (2019). Opportunities and challenges of using game video stream data for games research. In *All the (world wide) webs a stage: A workshop on live streaming, workshop at chi 2019*.

Gebser, M., Harrison, A., Kaminski, R., Lifschitz, V., & Schaub, T. (2015). Abstract gringo. *Theory and Practice of Logic Programming*, *15*(4-5), 449–463.

References XII

Gelfond, M., & Lifschitz, V. (1988). The stable model semantics for logic programming.. In *Iclp/slp* (Vol. 88, pp. 1070–1080). Cambridge, MA.

Gobet, F., & Jansen, P. J. (2006). Training in chess: A scientific approach. *Education and chess*.

Hodge, V. J., Devlin, S., Sephton, N., Block, F., Cowling, P. I., & Drachen, A. (2021). Win prediction in multiplayer esports: Live professional match prediction. *IEEE Transactions on Games*, *13*(4), 368–379. doi:10.1109/TG.2019.2948469

References XIII

Huberman, B. J. (1968, July). *A program to play chess end games*. (Doctoral dissertation, Department of Computer Science, Stanford University.).

Jennings-Teats, M., Smith, G., & Wardrip-Fruin, N. (2010). Polymorph: Dynamic difficulty adjustment through level generation. In *Proceedings of the 2010 workshop on procedural content generation in games* (pp. 1–4).

References XIV

Kliegr, T., Bahník, Š., & Fürnkranz, J. (2021). A review of possible effects of cognitive biases on interpretation of rule-based machine learning models. *Artificial Intelligence*, *295*, 103458. doi:https://doi.org/10.1016/j.artint.2021.103458

References XV

Krishnan, A., & Martens, C. (2022a, October). Synthesizing interpretable chess tactics from player games. In *Proceedings of the workshop on artificial intelligence for strategy games (sg) and esports analytics (ea), 18th aaai conference on artificial intelligence and interactive digital entertainment*, American Association for Artificial Intelligence.

References XVI

Krishnan, A., & Martens, C. (2022b, March). Towards the automatic synthesis of interpretable chess tactics. In *Proceedings of the explainable agency in artificial intelligence workshop, 36th aaai conference on artificial intelligence* (pp. 91–97). American Association of Artificial Intelligence.

Krishnan, A., Martens, C., & Jhala, A. (2023, March). Improving strategy synthesis for chess using precision and recall. [Manuscript submitted for publication].

References XVII

Krishnan, A., Potts, C. M., Jhala, A., Khadilkar, H., Karande, S., & Martens, C. (2024, June). Learning explainable representations of complex game-playing strategies. In *Proceedings of the eleventh annual conference on advances in cognitive systems*. (to appear).

Lázaro-Gredilla, M., Lin, D., Guntupalli, J. S., & George, D. (2019). Beyond imitation: Zero-shot task transfer on robots by learning concepts as cognitive programs. *Science Robotics*, *4*(26), eaav3150. doi:10.1126/scirobotics.aav3150

References XVIII

Li, Y., Gimeno, F., Kohli, P., & Vinyals, O. (2020). Strong generalization and efficiency in neural programs. arXiv: 2007.03629 [cs.LG]

Mariño, J. R. H., Moraes, R. O., Oliveira, T. C., Toledo, C., & Lelis, L. H. S. (2021). Programmatic strategies for real-time strategy games. *Proceedings of the AAAI Conference on Artificial Intelligence*, *35*(1), 381–389. doi:10.1609/aaai.v35i1.16114

References XIX

Mariño, J. R., & Toledo, C. F. (2022). Evolving interpretable strategies for zero-sum games. *Applied Soft Computing*, *122*, 108860.

Maymin, P. Z. (2021). Smart kills and worthless deaths: Esports analytics for league of legends. *Journal of Quantitative Analysis in Sports*, *17*(1), 11–27. doi:10.1515/jqas-2019-0096

References XX

Medeiros, L. C., Aleixo, D. S., & Lelis, L. H. S. (2022). What can we learn even from the weakest? learning sketches for programmatic strategies. (arXiv:2203.11912). arXiv:2203.11912 [cs]. Retrieved from http://arxiv.org/abs/2203.11912

Morales, E. (1992). *First order induction of patterns in chess*. (Doctoral dissertation, PhD thesis, The Turing Institute-University of Strathclyde).

References XXI

Mousavinasab, E., Zarifsanaiey, N., R. Niakan Kalhori, S., Rakhshan, M., Keikha, L., & Ghazi Saeedi, M. (2021). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments*, *29*(1), 142–163. doi:10.1080/10494820.2018.1558257

References XXII

Nagel, G. L. (2017, January). *Use of eye tracking for esports analytics in a moba game*. (Master thesis, The University of Bergen). Accepted: 2017-05-18T12:37:39Z. Retrieved from https://bora.uib.no/bora-xmlui/handle/1956/15875

Novak, A. R., Bennett, K. J., Pluss, M. A., & Fransen, J. (2020). Performance analysis in esports: Modelling performance at the 2018 league of legends world championship. *International Journal of Sports Science & Coaching*, *15*(56), 809–817. doi:10.1177/1747954120932853

References XXIII

OpenAI, : Berner, C., Brockman, G., Chan, B., Cheung, V., . . . Zhang, S. (2019). Dota 2 with large scale deep reinforcement learning. arXiv: 1912.06680 [cs.LG]

Paredes-Olay, C., Abad, M. J. F., Gámez, M., & Rosas, J. M. (2002). Transfer of control between causal predictive judgments and instrumental responding. *Animal Learning & Behavior*, *30*(3), 239–248. doi:10.3758/BF03192833

References XXIV

Pfau, J., Smeddinck, J. D., & Malaka, R. (2017). Automated game testing with icarus: Intelligent completion of adventure riddles via unsupervised solving. In *Extended abstracts publication of the annual symposium on computer-human interaction in play* (pp. 153–164). doi:10.1145/3130859.3131439

Pitrat, J. (1977). A chess combination program which uses plans. *Artificial Intelligence*, *8*(3), 275–321.

References XXV

Qiu, W., & Zhu, H. (2022). Programmatic reinforcement learning without oracles. In *International conference on learning representations*. Retrieved from https://openreview.net/forum?id=6Tk2noBdvxt

Schubert, M., Drachen, A., & Mahlmann, T. (2016). Esports analytics through encounter detection. In *Proceedings of the mit sloan sports analytics conference* (Vol. 1, p. 2016). MIT Sloan Boston, MA.

References XXVI

Silver, D., Hubert, T., Schrittwieser, J., Antonoglou, I., Lai, M., Guez, A., . . . Hassabis, D. (2018). A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. *Science*, *362*(6419), 1140–1144. Publisher: American Association for the Advancement of Science. doi:10.1126/science.aar6404

References XXVII

Smith, A. M., Lewis, C., Hullet, K., Smith, G., & Sullivan, A. (2011). An inclusive view of player modeling. In *Proceedings of the 6th international conference on foundations of digital games* (pp. 301–303).

Spronck, P., Sprinkhuizen-Kuyper, I., & Postma, E. (2004). Online adaptation of game opponent ai with dynamic scripting. *International Journal of Intelligent Games and Simulation*, *3*(1), 45–53.

References XXVIII

Stepanov, A., Lange, A., Khromov, N., Korotin, A., Burnaev, E., & Somov, A. (2019, July). Sensors and game synchronization for data analysis in esports. In *2019 ieee 17th international conference on industrial informatics (indin)* (Vol. 1, pp. 933–938). doi:10.1109/INDIN41052.2019.8972249

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT press.

References XXIX

Szabo, A. (1984). *Computer chess tactics and strategy*. (Doctoral dissertation, University of British Columbia). doi:http://dx.doi.org/10.14288/1.0051870

References XXX

Trivedi, D., Zhang, J., Sun, S.-H., & Lim, J. J. (2021). Learning to Synthesize Programs as Interpretable and Generalizable Policies. In *Advances in Neural Information Processing Systems* (Vol. 34, pp. 25146–25163). Curran Associates, Inc. Retrieved June 7, 2023, from https://proceedings.neurips.cc/paper/2021/hash/d37124c4c79f357cb02c655671a432fa-Abstract.html

References XXXI

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., . . . Polosukhin, I. (2017). Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, & R. Garnett (Eds.), *Advances in neural information processing systems* (Vol. 30), Curran Associates, Inc. Retrieved from https://proceedings.neurips.cc/paper_files/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf

References XXXII

Verma, A., Murali, V., Singh, R., Kohli, P., & Chaudhuri, S. (2018, July). Programmatically interpretable reinforcement learning. In J. Dy & A. Krause (Eds.), *Proceedings of the 35th international conference on machine learning* (Vol. 80, pp. 5045–5054). PMLR. Retrieved from https://proceedings.mlr.press/v80/verma18a.html

References XXXIII

Virvou, M., & Kabassi, K. (2002). F-smile: An intelligent multi-agent learning environment. In *Proceedings of 2002 ieee international conference on advanced learning technologies-icalt* (pp. 144–149). Citeseer.

Weintrop, D., & Wilensky, U. (2013). Know your enemy: Learning from in-game opponents. In *Proceedings of the 12th international conference on interaction design and children* (pp. 408–411). doi:10.1145/2485760.2485789

References XXXIV

Wilkins, D. E. (1979). *Using patterns and plans to solve problems and control search*. Stanford University.

Xenopoulos, P., Rulff, J., & Silva, C. (2022). Ggviz: Accelerating large-scale esports game analysis. *Proc. ACM Hum.-Comput. Interact.*, *6*(CHI PLAY), 238:1–238:22. doi:10.1145/3549501

References XXXV

Xue, S., Wu, M., Kolen, J., Aghdaie, N., & Zaman, K. A. (2017). Dynamic difficulty adjustment for maximized engagement in digital games. In *Proceedings of the 26th international conference on world wide web companion* (pp. 465–471). doi:10.1145/3041021.3054170

References XXXVI

Yang, Y. D., Inala, J. P., Bastani, O., Pu, Y., Solar-Lezama, A., & Rinard, M. (2021, November). Program Synthesis Guided Reinforcement Learning for Partially Observed Environments. arXiv:2102.11137 [cs]. arXiv. Retrieved June 28, 2023, from http://arxiv.org/abs/2102.11137

Zhang, Y., Tio, P., Leonardis, A., & Tang, K. (2021). A survey on neural network interpretability. *IEEE Transactions on Emerging Topics in Computational Intelligence*, *5*(5), 726–742. doi:10.1109/TETCI.2021.3100641

References XXXVII

Zheng, Y., Xie, X., Su, T., Ma, L., Hao, J., Meng, Z., . . . Fan, C. (2019, November). Wuji: Automatic online combat game testing using evolutionary deep reinforcement learning. In *2019 34th ieee/acm international conference on automated software engineering (ase)* (pp. 772–784). doi:10.1109/ASE.2019.00077

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 $\mathrm{A}_\sigma \subseteq \mathcal{S}$.

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

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 —

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

◂ 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.

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

◂ 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 23: 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

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