Interpretable Strategy Synthesis for Competitive Games

Thesis Defense Presentation

Abhijeet Krishnan

Department of Computer Science
North Carolina State University

July 16, 2024

Previous Work

- **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.

Story Time!

Yogender Pal

Figure 1: Priya, a normal girl

Story Time!

Netflix

Story Time!

Chess.com

Figure 2: Beth Harmon bots on Chess.com

Story Time!

Chess.com

Figure 3: Beth Harmon (bot) at 8 years old

Story Time!

ChessKid

ChessKid

Story Time!

Chess.com

Figure 4: Beth Harmon (bot) at 15 years old

Story Time!

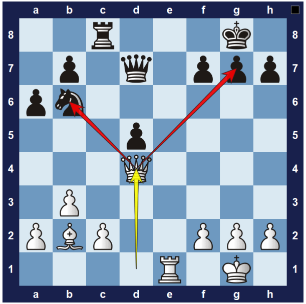
Arjun Somasekharan

Figure 5: What should Priya do now?

Story Time!

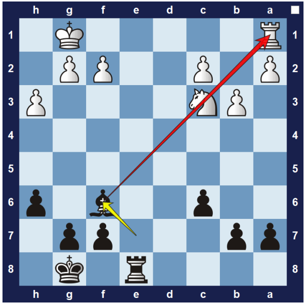
Could the Beth Harmon bots *explain* their *strategy* to Priya to help her get better?

Real-world Strategies



Chessfox

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



Chessfox

Figure 7: An example of the *pin* tactic in chess

Real-world Strategies

Go Full Build

Figure 8: A *cannon rush* in progress against a Terran opponent in the game *StarCraft II*

Value of Strategies

- Esports is a *massive* industry
- Could be used to *coach players* at all levels of skill
  - Over 200,000 active ChessKid users
- Better strategies → higher player skill → *more earning* potential

Tournament	Game	Prize Pool (USD)
World Blitz Chess Championship	Chess	350,000
IEM Katowice	StarCraft II	500,000

Thesis Statement

Thesis Statement

A *computational model* of a game strategy, along with a *learning method*, could meet the goals of discovering good, communicable strategies and impact the fields of competitive esports and explainable AI.

Summary

Research Thrust	RQ	Sub-RQ	Publication
ISS Framework	RQ1	–	EAAI ’22 (Krishnan and Martens 2022b)
ISS for Chess	RQ2	RQ2(a)	EAAI ’22 (Krishnan and Martens 2022b)
		RQ2(b)	SG+EA Workshop @ AIIDE ’22 (Krishnan and Martens 2022a)
		RQ2(c)	
ISS for Karel	RQ3	RQ3(a)	ACS ’24 (Krishnan, Potts, et al. 2024)
		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 for the game of chess?

RQs

RQ1

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

RQ2

How do we approach the problem of ISS for the game of chess?

RQ3

How do we approach the problem of ISS using programmatic strategies?

ISS Framework

RQ1

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

Elements of a Good Framework

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

The Need for a Framework

Paper	Number Used			Interpretability
	Domains	Models	Algorithms	
Spronck et al. (2004)	2	1	1	✗
Mesentier Silva et al. (2016)	1	1	4	✓
Butler et al. (2017)	1	1	1	✗
Canaan et al. (2018)	1	1	1	✗
Freitas et al. (2018)	1	1	1	✗
Mariño, Moraes, 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	✗

Interpretable Strategy Synthesis (ISS)

Definition (ISS)

Given a —

- Game environment $\mathcal{G}$
- Strategy model $\mathcal{M}$
- Performance measure $\mathcal{R} \colon \mathcal{M} \to \mathbb{R}$
- Interpretability measure $\mathcal{I} \colon \mathcal{M} \to \mathbb{R}$

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

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

Strategy (σ) Formal Definition

- Strategy $=$ RL policy $-$ universal applicability
- Strategy *not* applicable to all states
- Describes an *oft-seen pattern* in gameplay

Strategy Model ($\mathcal{M}$)

- Defines the *space* of strategies
- Examples —
  - if-then rules
  - decision trees
  - programmatic scripts

Performance Measure ($\mathcal{R}(\sigma)$)

- How *good* a strategy is
- Players generally study good strategies
- Examples —
  - win rate
  - material advantage (chess)
  - resources harvested (MicroRTS)

Interpretability Measure ($\mathcal{I}(\sigma)$)

- How *interpretable* a strategy is
- Players need to be able to *understand* a strategy to benefit from it
- Examples —
  - number of statements (programmatic script)
  - number of nodes (decision tree)
  - set of conditions and actions used (if-then rule)
  - improvement in player win rate upon being explained strategy

Interpretable Strategy Synthesis (ISS)

Definition (ISS)

Given a —

- Game environment $\mathcal{G}$
- Strategy model $\mathcal{M}$
- Performance measure $\mathcal{R}\colon \mathcal{M} \rightarrow \mathbb{R}$
- Interpretability measure $\mathcal{I}\colon \mathcal{M} \rightarrow \mathbb{R}$

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

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

ISS for Chess

RQ2

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

Why Chess?

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

Towards ISS for Chess

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

Towards 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?

Towards 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?

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 9: Our chess strategy model expressed in Prolog pseudocode

Predicate Vocabulary

Strategy Model for Chess

First-Order (FO) Logic Rule

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

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),...]
```

Strategy Model for Chess

First-Order (FO) Logic Rule

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

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]`

Strategy Model for Chess

First-Order (FO) Logic Rule

`tactic`(Position, Move) $\leftarrow$
feature_1$(\cdots)$,
feature_2$(\cdots)$,
$\vdots$
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

```
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.

Towards 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?

Towards 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?

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 (Szabo 1984; Gobet and Jansen 2006)
- FO-logic used extensively to model chess patterns (Berliner 1975; Pitrat 1977; Wilkins 1979; Huberman 1968; Bramer 1977; Bratko 1982; Morales 1992)
- Logic rules are *acknowledged to be interpretable* (Zhang et al. 2021)

Towards 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*?

Evaluating Chess Tactics[1]

[1] Krishnan and Martens 2022b.

Evaluating Chess Tactics[1]

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

[1] Krishnan and Martens 2022b.

Evaluating 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.

Evaluating 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.

Evaluating 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.

Evaluating 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

Tactic	Divergence	
	Strong	Weak
can_threat	378.94	9.22
can_check	549.19	4.02
can_fork	676.45	4.67
discovered_check	338.55	18.64
discovered_threat	375.97	1.19
skewer	748.40	5.41
pin	526.45	4.90
random	328.09	8.28

Table 2: 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 $\langle \mathcal{G}, \mathcal{M}, \mathcal{R} \rangle \xrightarrow{\text{translate}}$ 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 $\langle \mathcal{G}, \mathcal{M}, \mathcal{R} \rangle \xrightarrow{\text{translate}}$ 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 $\langle \mathcal{G}, \mathcal{M}, \mathcal{R} \rangle \xrightarrow{\text{translate}}$ 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 $\langle \mathcal{G}, \mathcal{M}, \mathcal{R} \rangle \xrightarrow{\text{translate}}$ 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

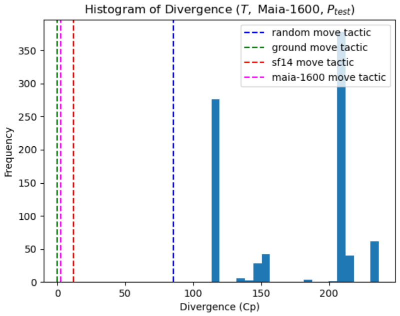


Figure 11: Divergence histogram for T evaluated using *weak* engine

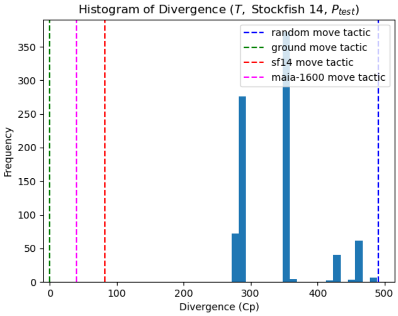


Figure 12: Divergence histogram for T evaluated using *strong* engine

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, Martens, and Jhala 2023.

Improvements using Precision/Recall-based Constraints[3]

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

[3] Krishnan, Martens, and Jhala 2023.

Improvements using Precision/Recall-based Constraints[3]

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

[3] Krishnan, Martens, and Jhala 2023.

Improvements using Precision/Recall-based Constraints[3]

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

[3]Krishnan, Martens, and Jhala 2023.

Improvements using Precision/Recall-based Constraints[3]

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

[3] Krishnan, Martens, and Jhala 2023.

Improvements using Precision/Recall-based Constraints[3]

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

[3] Krishnan, Martens, and Jhala 2023.

Improvements using Precision/Recall-based Constraints[3]

- Modifications —
  1. *Limit* chess strategy search space using precision/recall constraints
  2. Introduce a *new* predicate vocabulary
- Conduct *ablative 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, Martens, and Jhala 2023.

Results

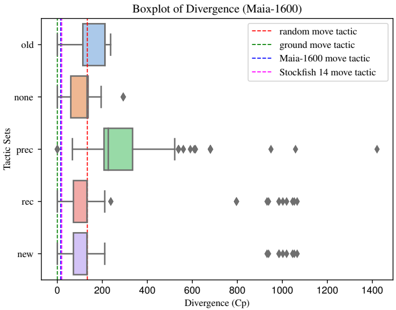


Figure 13: Boxplot of tactic divergence (evaluated using *weak* engine) for each system

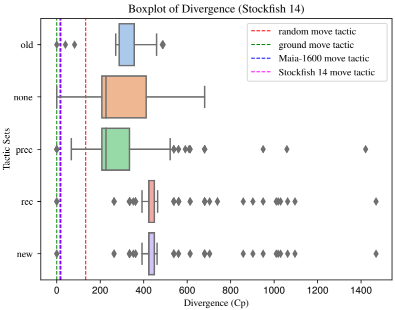


Figure 14: Boxplot of tactic divergence (evaluated using *strong* engine) for each system

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

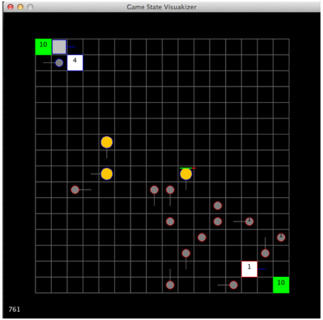
ISS for MicroRTS

RQ3

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

Why MicroRTS?

- Simplified **r**eal-**t**ime **s**trategy game *for AI research* (Ontanon 2021)
- Active *research community*
- *Qualitatively different* from chess – *real-time, partially observable*
- *Popular genre* for esport titles



Google Code Archive

Figure 15: A MicroRTS game in progress

Towards ISS for MicroRTS

- Strategy model for MicroRTS
- Performance measure for MicroRTS
- Interpretability measure for MicroRTS
- Learning method for MicroRTS strategies

Towards ISS for MicroRTS

- ~~Strategy model for MicroRTS~~
- ~~Performance measure for MicroRTS~~
- ~~Interpretability measure for MicroRTS~~
- Learning method for MicroRTS strategies

} SynProS

SynProS Competition

- SynProS: **Syn**thesis of **Pro**grammatic **S**trategies

SynProS Competition

- SynProS: Synthesis of Programmatic Strategies
- Research competition (Moraes 2021) to test ISS approaches for MicroRTS with a *fixed strategy model*

SynProS Competition

- SynProS: Synthesis of Programmatic Strategies
- Research competition (Moraes 2021) to test ISS approaches for MicroRTS with a *fixed strategy model*
- MicroRTS strategy model = *CFG*

SynProS Competition

- SynProS: Synthesis of Programmatic Strategies
- Research competition (Moraes 2021) to test ISS approaches for MicroRTS with a *fixed strategy model*
- MicroRTS strategy model $=$ *CFG*

$$
\begin{aligned}
S_1 &\to C\ S_1 \mid S_2\ S_1 \mid S_3\ S_1 \mid \epsilon \\
S_2 &\to \text{if } (S_5) \text{ then } \{C\} \mid \text{if } (S_5) \text{ then } \{C\} \text{ else } \{C\} \\
S_3 &\to \text{for (each unit } u) \ \{S_4\} \\
S_4 &\to C\ S_4 \mid S_2\ S_4 \mid \epsilon \\
S_5 &\to \text{not } B \mid B \\
B &\to b_1 \mid b_2 \mid \cdots \mid b_m \\
C &\to c_1\ C \mid c_2\ C \mid \cdots \mid c_n\ C \mid c_1 \mid c_2 \mid \cdots \mid c_n \mid \epsilon
\end{aligned}
$$

Figure 16: The production rules of a context-free grammar (CFG) describing the strategy model for MicroRTS.

Performance Measure

- *win rate* (against fixed set of test scripts)

Interpretability Measure

- Inversely proportional to *number of statements*

Interpretability Measure

- Inversely proportional to *number of statements*
- *No justification* for use! → proposed study in RQ3b

Learning MicroRTS Strategies using ASP

RQ3(a)

How does an ASP-based approach towards developing a synthesizer for the *SynProS competition* compare to other synthesizers in this competition?

Answer Set Programming (ASP)

- **A**nswer **S**et **P**rogramming ASP

Answer Set Programming (ASP)

- **A**nswer **S**et **P**rogramming ASP
- ASP $\rightarrow$ *declarative programming* paradigm (like Prolog)

Answer Set Programming (ASP)

- **A**nswer **S**et **P**rogramming ASP
- ASP → *declarative programming* paradigm (like Prolog)
- Can *model* and *generate* game levels (Smith and Mateas 2011; Smith, Andersen, et al. 2012)

Answer Set Programming (ASP)

- **A**nswer **S**et **P**rogramming ASP
- ASP → *declarative programming* paradigm (like Prolog)
- Can *model* and *generate* game levels (Smith and Mateas 2011; Smith, Andersen, et al. 2012)
- Can model and generate *optimized* data viz. layouts (Moritz et al. 2018)

Learning MicroRTS Strategies using ASP

- MicroRTS strategy model (CFG) $\xrightarrow{\text{convert}}$ ASP model

Learning MicroRTS Strategies using ASP

- MicroRTS strategy model (CFG) $\xrightarrow{\text{convert}}$ ASP model
- MicroRTS strategy $\xrightarrow{\text{encode}} \langle f_{\theta,1}, f_{\theta,2}, \cdots, f_{\theta,i} \rangle$ using predicate vocabulary θ

Learning MicroRTS Strategies using ASP

- MicroRTS strategy model (CFG) $\xrightarrow{\text{convert}}$ ASP model
- MicroRTS strategy $\xrightarrow{\text{encode}}$ $\langle f_{\theta,1}, f_{\theta,2}, \cdots, f_{\theta,i} \rangle$ using predicate vocabulary θ
- Train a *linear model* ($\mathcal{L}$) to *predict* win rate given feature encoding

Learning MicroRTS Strategies using ASP

- MicroRTS strategy model (CFG) $\xrightarrow{\text{convert}}$ ASP model
- MicroRTS strategy $\xrightarrow{\text{encode}}$ $\langle f_{\theta,1}, f_{\theta,2}, \cdots, f_{\theta,i} \rangle$ using predicate vocabulary θ
- Train a *linear model* ($\mathcal{L}$) to *predict* win rate given feature encoding
- $\mathcal{L} \xrightarrow{\text{convert}}$ ASP constraints as in Moritz et al. (2018)

Learning MicroRTS Strategies using ASP

- MicroRTS strategy model (CFG) $\xrightarrow{\text{convert}}$ ASP model
- MicroRTS strategy $\xrightarrow{\text{encode}}$ $\langle f_{\theta,1}, f_{\theta,2}, \cdots, f_{\theta,i} \rangle$ using predicate vocabulary θ
- Train a *linear model* ($\mathcal{L}$) to *predict* win rate given feature encoding
- $\mathcal{L} \xrightarrow{\text{convert}}$ ASP constraints as in Moritz et al. (2018)
- Evaluate resultant system using SynProS framework

Interpretability Factors for MicroRTS Strategies

- How to design an *evidence-based* interpretability measure for MicroRTS?

Interpretability Factors for MicroRTS Strategies

- How to design an *evidence-based* interpretability measure for MicroRTS?

RQ3(b)

Which features of a MicroRTS strategy model have a statistically significant correlation with the interpretability of said strategy?

Task Design

- Conduct a *human-grounded* (Doshi-Velez and Kim 2017) evaluation
- Use a *forward simulation/prediction* task
- Subjects presented with —
  - Strategy
  - Game state (current)
  - Options for future states (1 correct, 3 incorrect)
- **Task**: predict expected future state from current state if strategy is followed and select option
- Generate tasks using ASP model of MicroRTS strategy

Obtaining Significant Factors

Prior Experience			Strategy				Successful?
Programming	RTS Games	$\cdots$	$f_{\theta,1}$	$f_{\theta,2}$	$\cdots$	$f_{\theta,i}$	
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$

Table 3: Sample dataset envisioned from study

- Train *decision tree* model to predict whether strategy will be correctly simulated

Obtaining Significant Factors

Prior Experience			Strategy				Successful?
Programming	RTS Games	$\cdots$	$f_{\theta,1}$	$f_{\theta,2}$	$\cdots$	$f_{\theta,i}$	
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$

Table 3: Sample dataset envisioned from study

- Train *decision tree* model to predict whether strategy will be correctly simulated
- Obtain significant factors by measuring *Gini index* (Molnar 2018)

Conclusion

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

Conclusion

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

Conclusion

- **Goal**: investigate approaches to the problem of *ISS for games*
- Defined a *framework* for ISS
- Approached ISS for *chess*
  - FO-logic based chess strategy model
  - ILP-based learning method
  - Improvement to ILP-based learning method

Conclusion

- **Goal**: investigate approaches to the problem of *ISS for games*
- Defined a *framework* for ISS
- Approached ISS for *chess*
  - FO-logic based chess strategy model
  - ILP-based learning method
  - Improvement to ILP-based learning method
- Proposal to approach ISS for *MicroRTS*
  - ASP-based learning method
  - Evidence-based interpretability measure

Conclusion

- **Goal**: investigate approaches to the problem of *ISS for games*
- Defined a *framework* for ISS
- Approached ISS for *chess*
  - FO-logic based chess strategy model
  - ILP-based learning method
  - Improvement to ILP-based learning method
- Proposal to approach ISS for *MicroRTS*
  - ASP-based learning method
  - Evidence-based interpretability measure
- Expected outcomes –
  - Benefit *esports industry* $\rightarrow$ *better analytics* for player performance
  - Benefit *explainable AI research* $\rightarrow$ generate *policy explanations*

Thank You!

Questions?

References I

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

Bramer, Max Arthur (1977). "Representation of Knowledge for Chess Endgames Towards a Self-Improving System." PhD thesis. Open University (United Kingdom).

Bratko, Ivan (1982). "Knowledge-based problem-solving in AL3." In: *Machine intelligence* 10, pp. 73–100.

References II

Butler, Eric, Emina Torlak, and Zoran Popović (2017). "Synthesizing Interpretable Strategies for Solving Puzzle Games." In: *Proceedings of the 12th International Conference on the Foundations of Digital Games*. FDG '17. Hyannis, Massachusetts: Association for Computing Machinery. ISBN: 9781450353199. DOI: 10.1145/3102071.3102084. URL: https://doi.org/10.1145/3102071.3102084.

References III

Canaan, Rodrigo et al. (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.

Doshi-Velez, Finale and Been Kim (2017). *Towards A Rigorous Science of Interpretable Machine Learning*. arXiv: 1702.08608 [stat.ML].

References IV

Freitas, João Marcos de, Felipe Rafael de Souza, and Heder S. Bernardino (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.

Gebser, Martin et al. (2015). "Abstract gringo." In: *Theory and Practice of Logic Programming* 15.4-5, pp. 449–463.

References V

Gelfond, Michael and Vladimir Lifschitz (1988). "The stable model semantics for logic programming.." In: *ICLP/SLP*. Vol. 88. Cambridge, MA, pp. 1070–1080.

Gobet, Fernand and Peter J Jansen (2006). "Training in chess: A scientific approach." In: *Education and chess*.

Huberman, Barbara Jane (July 1968). "A program to play chess end games." PhD thesis. Department of Computer Science, Stanford University.

References VI

Krishnan, Abhijeet and Chris Martens (Oct. 2022a). "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 VII

Krishnan, Abhijeet and Chris Martens (Mar. 2022b). "Towards the automatic synthesis of interpretable chess tactics." In: *Proceedings of the Explainable Agency in Artificial Intelligence Workshop, 36th AAAI Conference on Artificial Intelligence*. American Association of Artificial Intelligence, pp. 91–97.

Krishnan, Abhijeet, Chris Martens, and Arnav Jhala (Mar. 2023). "Improving strategy synthesis for chess using precision and recall." In: [Manuscript submitted for publication].

References VIII

Krishnan, Abhijeet, Colin M. Potts, et al. (June 2024). “Learning explainable representations of complex game-playing strategies.” In: *Proceedings of the Eleventh Annual Conference on Advances in Cognitive Systems*. (to appear).

Mariño, Julian R. H., Rubens O. Moraes, et al. (May 2021). “Programmatic Strategies for Real-Time Strategy Games.” In: *Proceedings of the AAAI Conference on Artificial Intelligence* 35.1, pp. 381–389. DOI: 10.1609/aaai.v35i1.16114. URL: https://ojs.aaai.org/index.php/AAAI/article/view/16114.

References IX

Mariño, Julian RH and Claudio FM Toledo (2022). "Evolving interpretable strategies for zero-sum games." In: *Applied Soft Computing* 122, p. 108860.

Medeiros, Leandro C., David S. Aleixo, and Levi H. S. Lelis (Mar. 2022). "What can we Learn Even From the Weakest? Learning Sketches for Programmatic Strategies." en. In: arXiv:2203.11912. arXiv:2203.11912 [cs]. URL: http://arxiv.org/abs/2203.11912.

References X

Mesentier Silva, Fernando de et al. (2016). "Generating heuristics for novice players." In: *2016 IEEE Conference on Computational Intelligence and Games (CIG)*. IEEE, pp. 1–8.

Molnar, Christoph (2018). "A guide for making black box models explainable." In: *URL: https://christophm. github. io/interpretable-ml-book*, p. 3.

References XI

Moraes, Rubens (July 2021). *SynProS - Synthesis of Programmatic Strategies*. URL: https://rubensolv.github.io/synpros-microrts/ (visited on 03/26/2023).

Morales, Eduardo (1992). "First order induction of patterns in Chess." PhD thesis. PhD thesis, The Turing Institute-University of Strathclyde.

References XII

Moritz, Dominik et al. (2018). “Formalizing visualization design knowledge as constraints: Actionable and extensible models in draco.” In: *IEEE transactions on visualization and computer graphics* 25.1, pp. 438–448.

References XIII

Ontanon, Santiago (June 2021). “The Combinatorial Multi-Armed Bandit Problem and Its Application to Real-Time Strategy Games.” In: *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment* 9.1, pp. 58–64. DOI: 10.1609/aiide.v9i1.12681. URL: https://ojs.aaai.org/index.php/AIIDE/article/view/12681.

Pitrat, Jacques (1977). “A chess combination program which uses plans.” In: *Artificial Intelligence* 8.3, pp. 275–321.

References XIV

Smith, Adam M, Erik Andersen, et al. (2012). "A case study of expressively constrainable level design automation tools for a puzzle game." In: *Proceedings of the International Conference on the Foundations of Digital Games*, pp. 156–163.

Smith, Adam M and Michael Mateas (2011). "Answer set programming for procedural content generation: A design space approach." In: *IEEE Transactions on Computational Intelligence and AI in Games* 3.3, pp. 187–200.

References XV

Spronck, Pieter, Ida Sprinkhuizen-Kuyper, and Eric Postma (2004). "Online adaptation of game opponent AI with dynamic scripting." In: *International Journal of Intelligent Games and Simulation* 3.1, pp. 45–53.

Szabo, Alexander (1984). "Computer chess tactics and strategy." PhD thesis. University of British Columbia. DOI: http://dx.doi.org/10.14288/1.0051870. URL: https://open.library.ubc.ca/collections/ubctheses/831/items/1.0051870.

References XVI

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

Zhang, Yu et al. (Oct. 2021). "A Survey on Neural Network Interpretability." In: *IEEE Transactions on Emerging Topics in Computational Intelligence* 5.5, pp. 726–742. ISSN: 2471-285X. DOI: 10.1109/TETCI.2021.3100641.

Strategy (σ)

Definition (Strategy)

Given a game environment $\mathcal{G}$ modeled as a finite, episodic MDP $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle$, a *strategy* σ is —

$$\sigma(a|s) \doteq \mathbb{P}[A_t = a|S_t = s], \forall s \in \mathrm{A}_\sigma, a \in \mathcal{A}(s)$$

A_σ: set of *applicable* states

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 —

$$q_E(s,a) = \sum_{s',r} \mathcal{P}(s', r|s,a)[r + v_E(s')] \quad (1)$$

$$= v_E(s'), s' \text{ is non-terminal} \quad (2)$$

Equation 2 follows from 1 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 —

$$d_E(s, a_1, a_2) \doteq | \, q_E(s, a_1) - q_E(s, a_2) \, | \tag{3}$$

◂ 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.

$$\text{Divergence}_E(\sigma, P) \doteq \frac{1}{|P_\mathrm{A}|} \sum_{(s,a_1)\in P_\mathrm{A}} \sum_{a_2\in\mathcal{A}(s)} \sigma(a_2|s) d_E(s, a_1, a_2) \tag{4}$$

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

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^-

Return

Target Concept

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

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

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

Possible Hypothesis

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

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 and Lifschitz 1988)
- ASP language (Gebser et al. 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 17: An ASP program which can generate maze-like levels with integrity constraints that specify the number of game objects.