Prediction-based Search for Autonomous Game-Playing

PhD Defense Presentation

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Motivation

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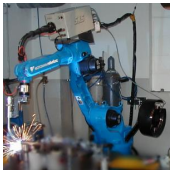

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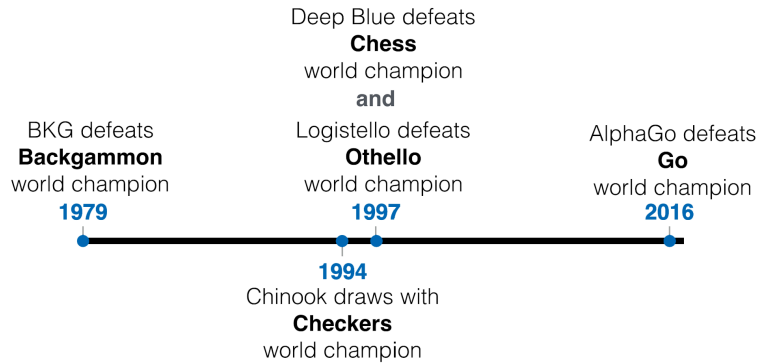
Games can be simulations of real world tasks

- quantifiable goal, varying difficulty, and large data sets
- digital games are fully accessible to computers

A Short History of Computational Intelligence in Games



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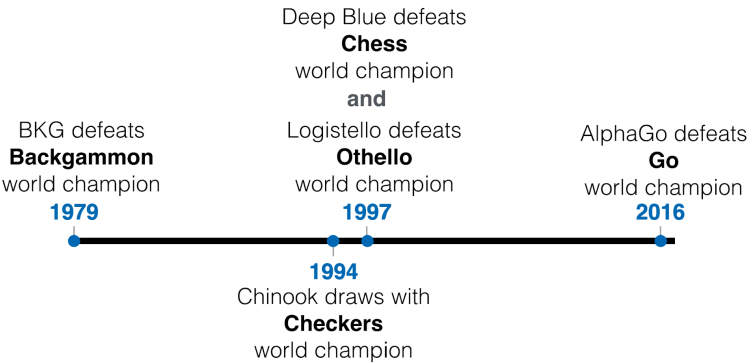


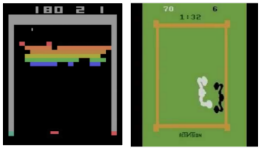
heuristic solutions, planning agents and **reinforcement learning agents**

A Short History of Computational Intelligence in Games

ATARI

StarCraft II

DOTA 2



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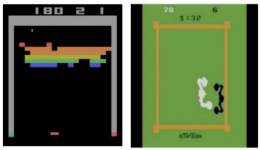
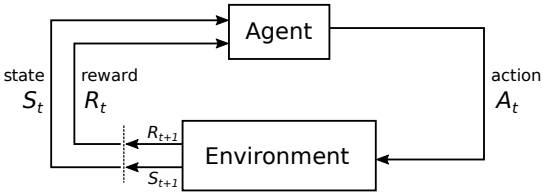


STARCRAFT II

DOTA 2

these were achieved using **reinforcement learning** algorithms and **months of training**

Agent-Environment Interface



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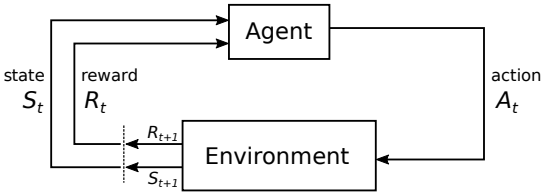

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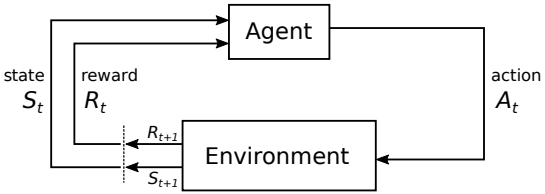

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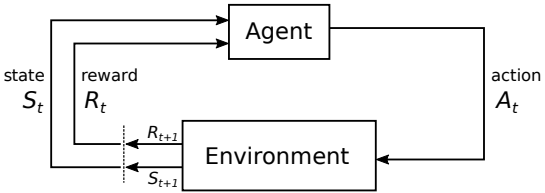

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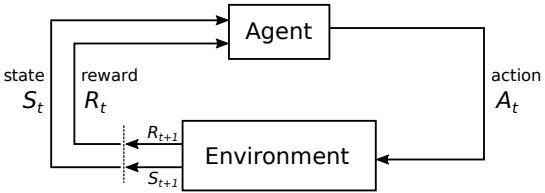

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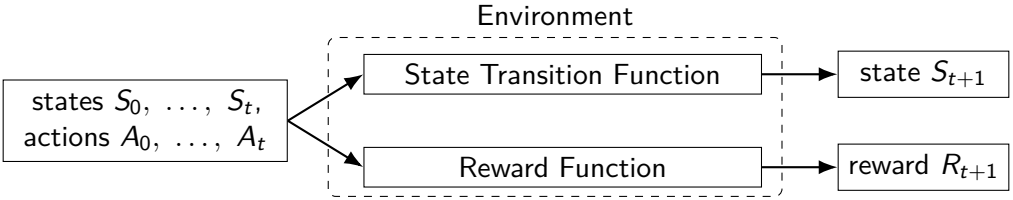
- **Reward:** numerical values provided that the agent tries to maximize over time.

Components of a Game



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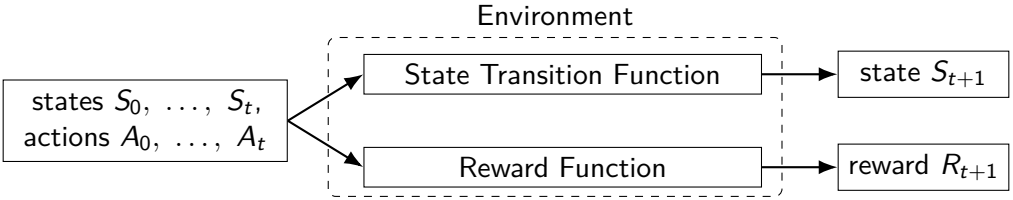

State $S_t \in \mathcal{S}$ can be perceived through multiple sensors $(S_t^{(1)}, S_t^{(2)}, \ldots, S_t^{(n)})$.

- a state may not be fully observable (partial information game)

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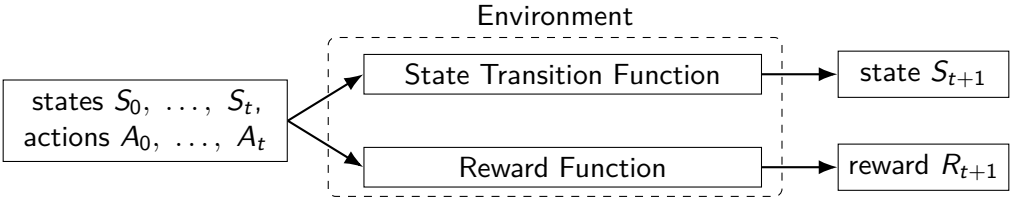

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The whole environment can be modelled as a probability distribution of possible outcomes:

$$P(R_{t+1}, S_{t+1} \mid S_0,\ A_0,\ S_1,\ A_1,\ \ldots,\ S_t,\ A_t)$$

- but we can also model both components separately

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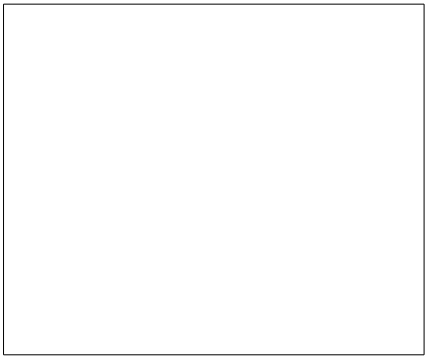

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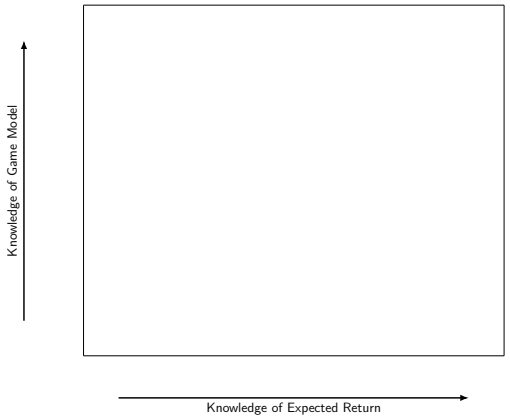

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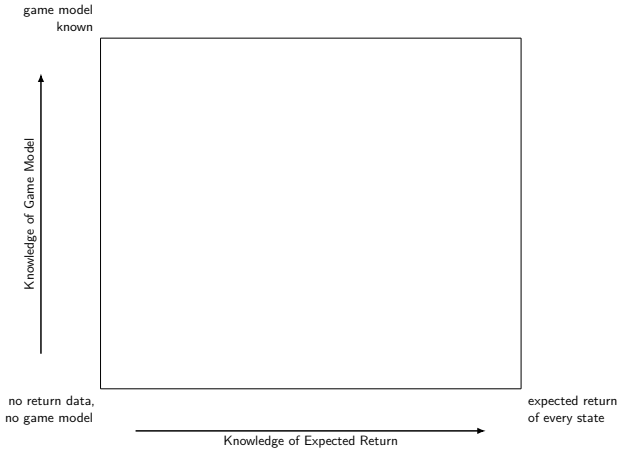

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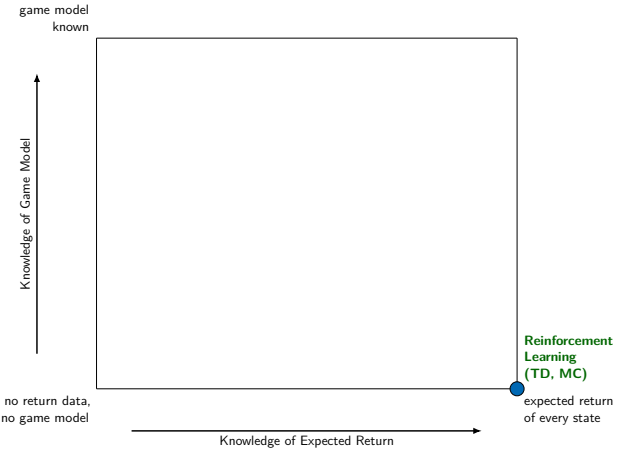

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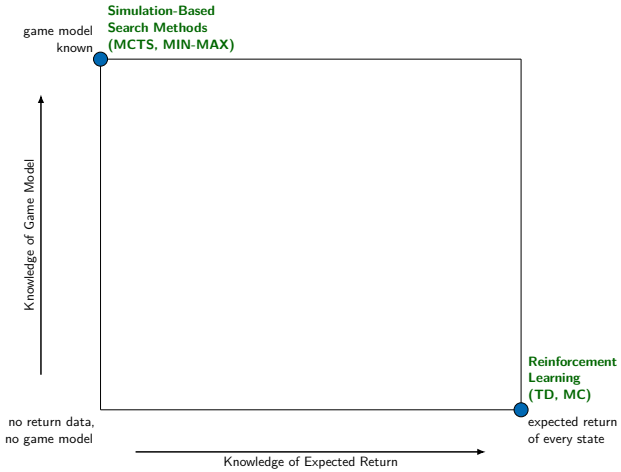

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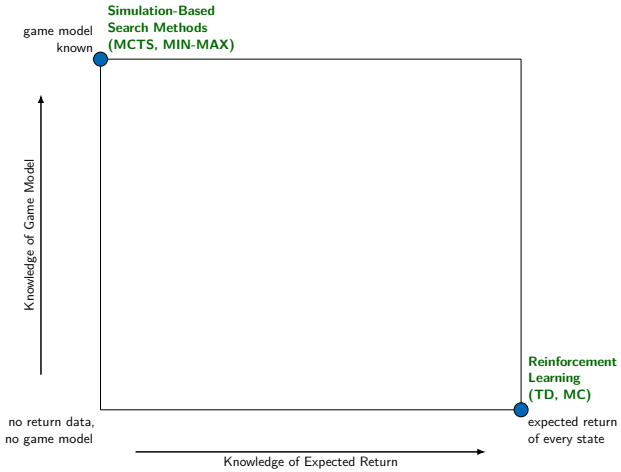

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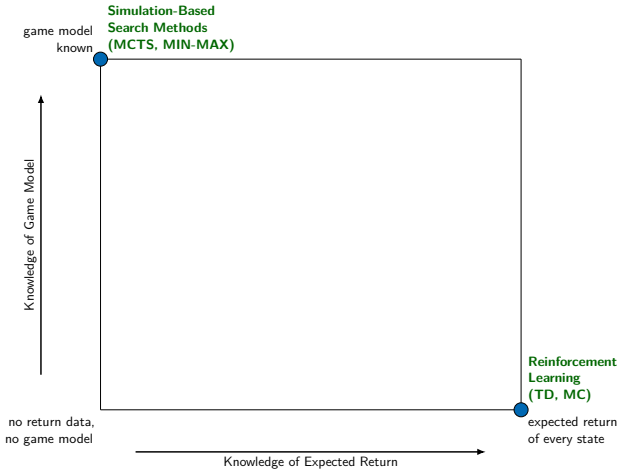

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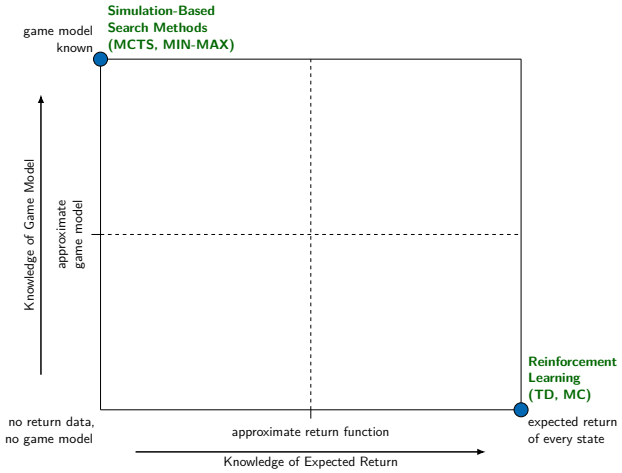

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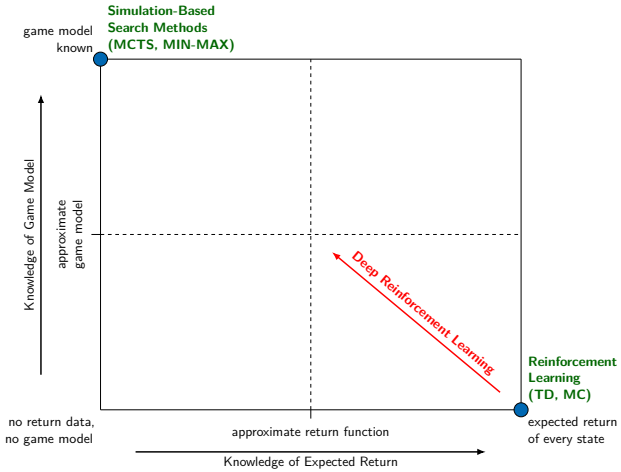

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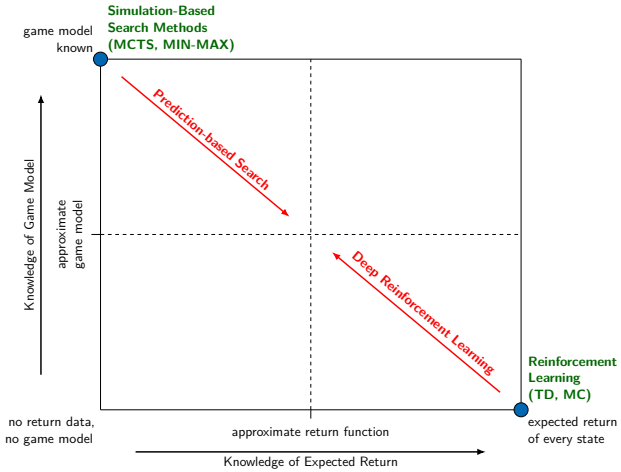

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- current state
- game-model

Output:

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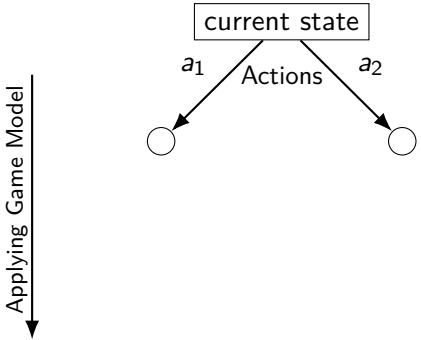

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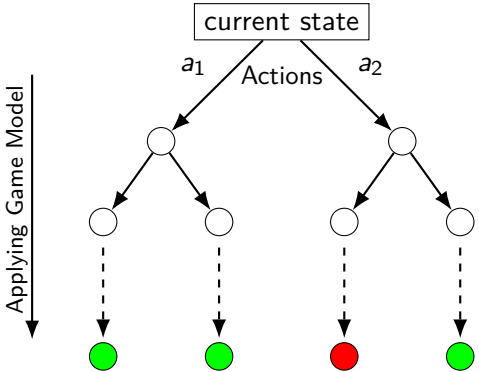

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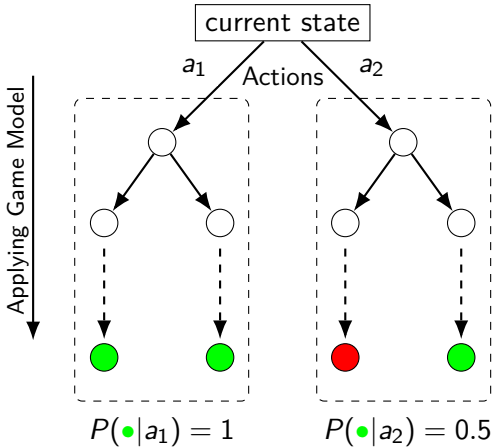

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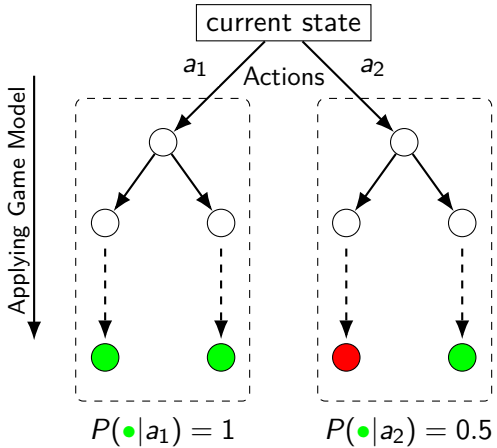

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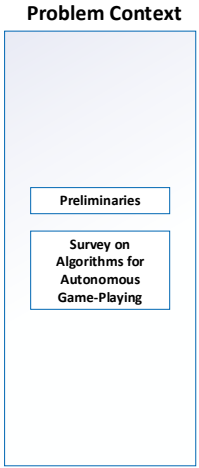
How to handle games for which:

- the game model is unknown?
- the state cannot be fully observed?

Graphical Overview of Contents



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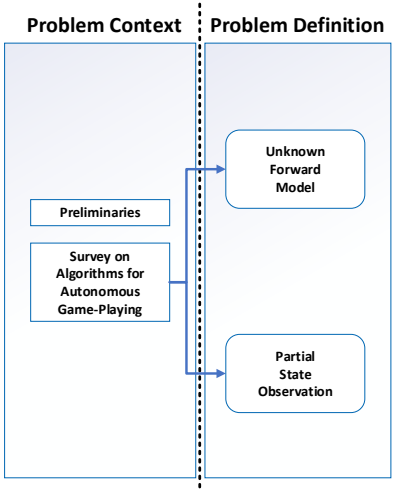

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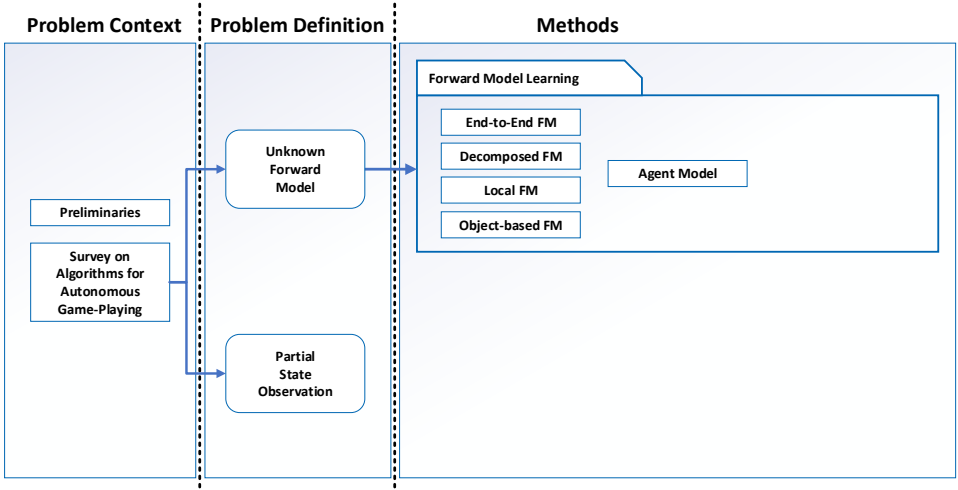

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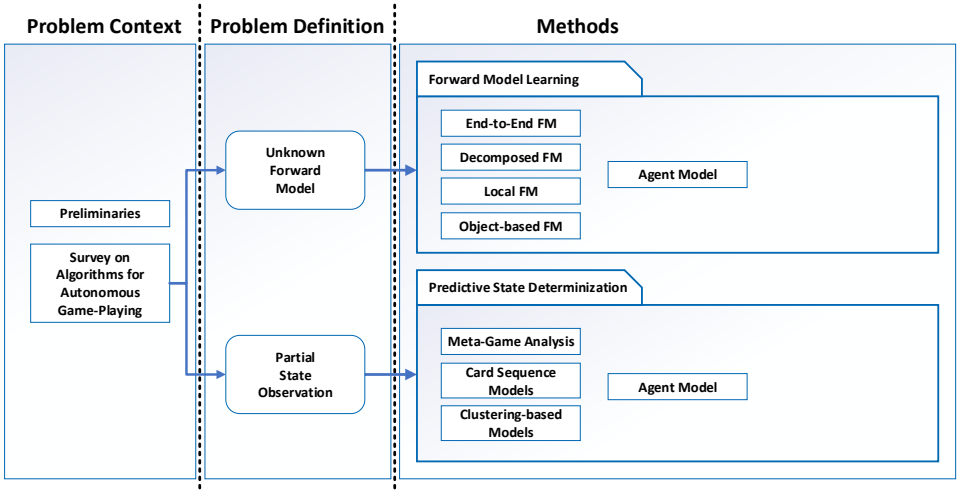

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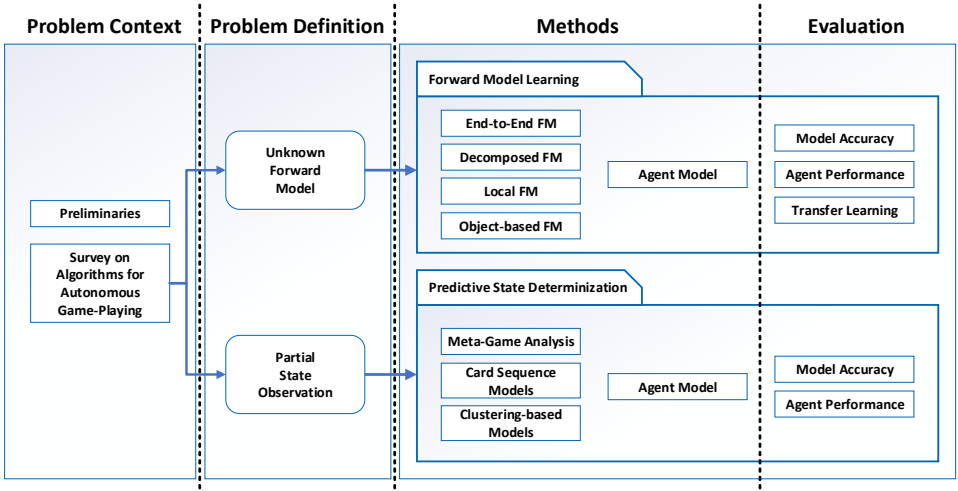

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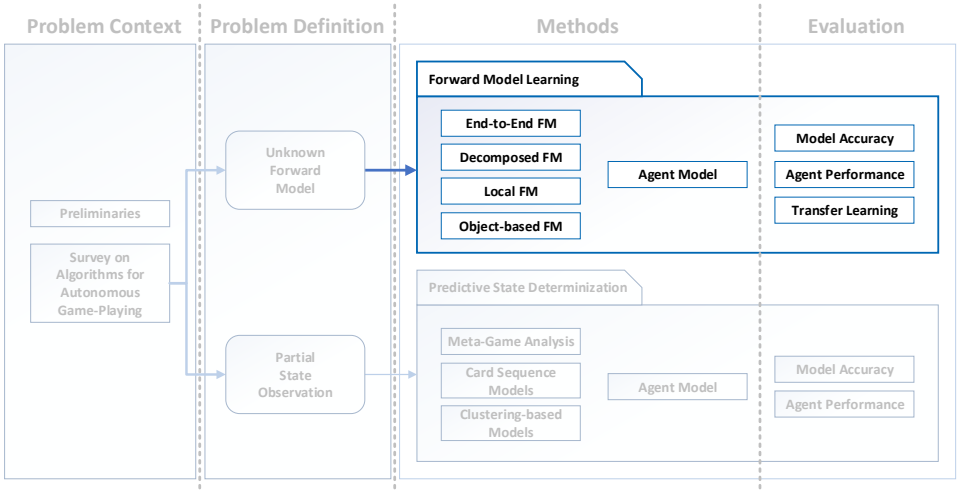

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Definition: Forward Model

- A forward model *fm* maps the environment's state S_t and the agent's action A_t at time t to the upcoming state S_{t+1} of the environment:

$$fm : (\mathcal{S} \times \mathcal{A}) \to \mathcal{S} \qquad (S_t, A_t) \longmapsto S_{t+1}$$

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Markov Property:

- The environment fulfills the Markov property in case the upcoming state is independent of all states but the present state.

$$P(S_{t+1} \mid S_0,\ A_0,\ S_1,\ A_1,\ \ldots,\ S_t,\ A_t) \quad \Rightarrow \quad P(S_{t+1} \mid S_t,\ A_t)$$

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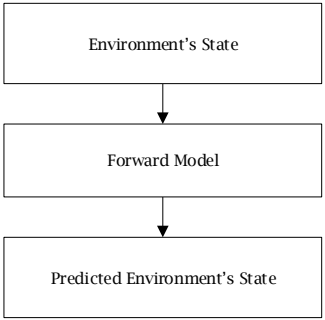

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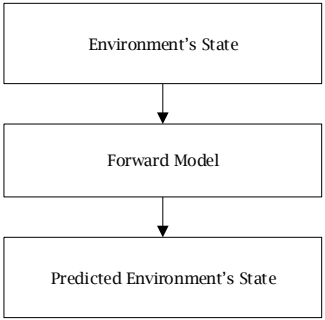

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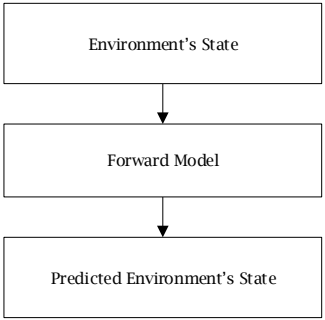

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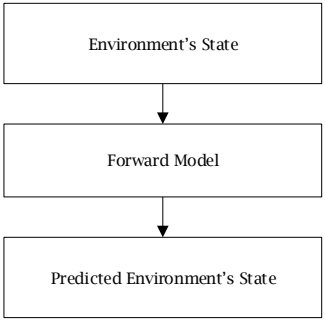
The following methods represent attempts to reduce the complexity of the learning problem.



Decomposed Forward Models[1]

Assumptions:

- sensor values can be modelled independently

$$\forall i, j \in 1..n : i \neq j \Rightarrow S_{t+1}^{(i)} \perp\!\!\!\perp S_{t+1}^{(j)} \mid S_t, A_t$$

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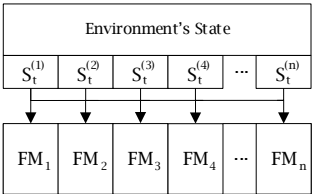
$$\underset{i}{fm} : (S_t,\ A_t) \longmapsto S_{t+1}^{(i)}$$



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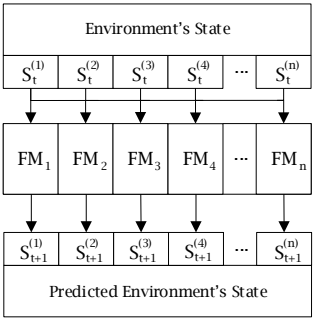
Aggregate the result of each sensor value prediction

$$fm(S_t, A_t) = (fm_1(S_t, A_t),\ fm_2(S_t, A_t),\ \ldots,\ fm_n(S_t, A_t))$$
$$= (S_{t+1}^{(1)},\ S_{t+1}^{(2)},\ \ldots,\ S_{t+1}^{(n)}) = S_{t+1}$$



[1] Dockhorn, A., Tippelt, T., & Kruse, R. (2018). Model Decomposition for Forward Model Approximation

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Assumptions:

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- requires a similarity or distance function for sensor values
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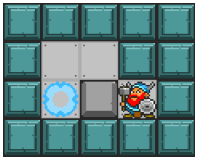

Game-State of Sokoban

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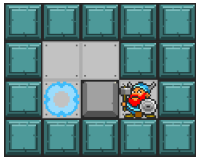

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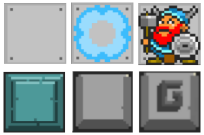

Tilemap Components

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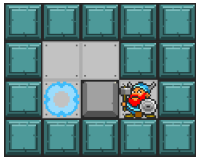


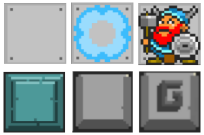
Game-State of Sokoban

Tile-based Representation (of Video Games):

- a state can be represented as a matrix T of size $n \times m$

$$T = \begin{bmatrix} T(1,1) & \dots & T(1,m) \\ \vdots & \ddots & \vdots \\ T(n,1) & \dots & T(n,m) \end{bmatrix}$$

- $T(x,y)$ specifies the observed tile at position (x,y)



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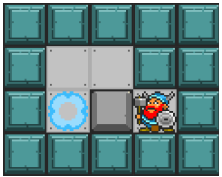

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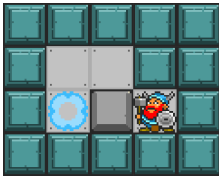

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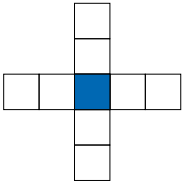

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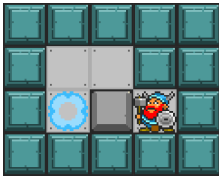

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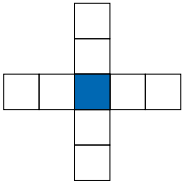

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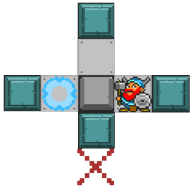

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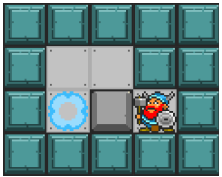

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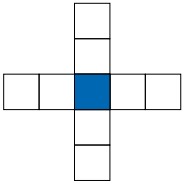

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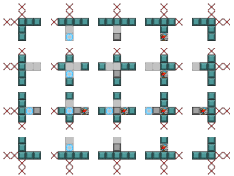

Extracted Patterns

Local Forward Model

Predict the next state by predicting each tile

$$T_{t+1} = \begin{bmatrix} fm_{1,1}(N(1,1), A_t) & \dots & fm_{1,m}(N(1,m), A_t) \\ \vdots & \ddots & \vdots \\ fm_{n,1}(N(n,1), A_t) & \dots & fm_{n,m}(N(n,m), A_t) \end{bmatrix}$$

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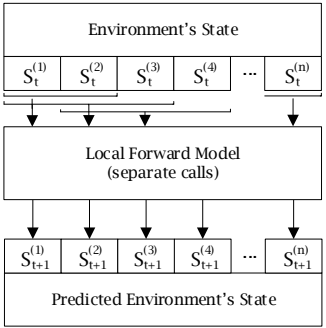

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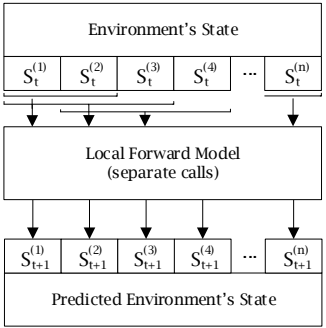

Advantage: higher sampling efficiency

- each observed state transition consists of one observed pattern per tile (in total: $n \times m$ patterns)

Modelling Entities of a Game I/II

Measuring the importance of each tile in the local neighborhood indicates a high importance of the center tile.

$\Rightarrow$ instead of modelling the change of each position, model the change of represented objects

Feature Importance of Neighborhood Tiles

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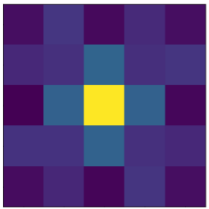

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- the state consists of multiple entities of which several attributes can be observed

$$\begin{aligned} \mathcal{S} &= (S^{(1)}, S^{(2)}, \ldots, S^{(n)}) \\ &= (\underbrace{S^{(1,1)}, \ldots, S^{(1,i)}}_{\text{Object 1}}, \underbrace{S^{(2,1)}, \ldots, S^{(2,j)}}_{\text{Object 2}}, \ldots, \underbrace{S^{(m,1)}, \ldots, S^{(m,k)}}_{\text{Object m}}) \end{aligned}$$

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Complex entities can be modelled using a decomposed forward model

- create one model for each observable sensor value

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Object-based Forward Model

Aggregate the prediction of each object and its associated sensor values:

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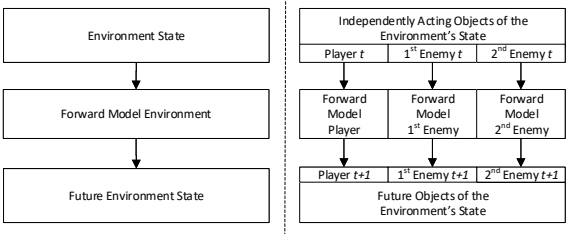

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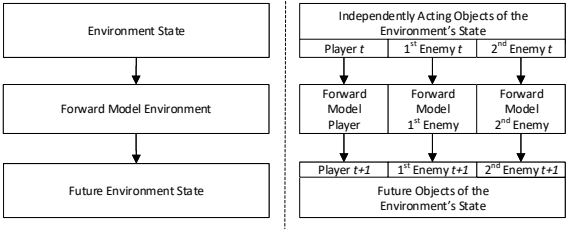

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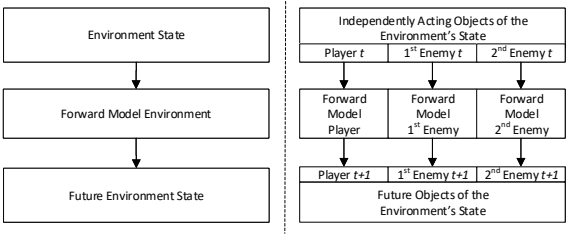

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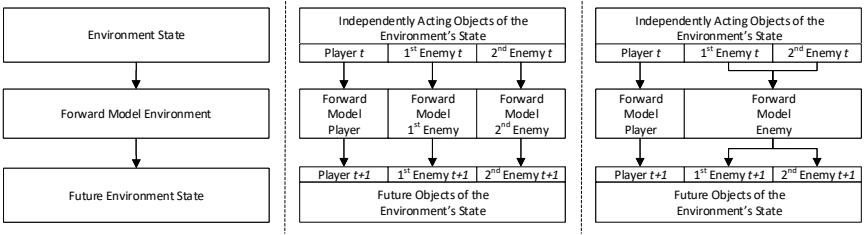
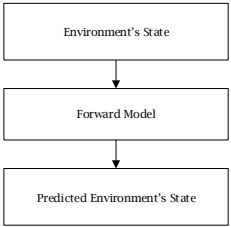
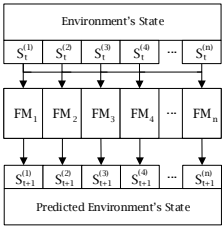


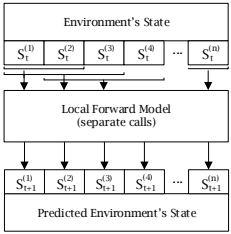
Comparison of Proposed Models



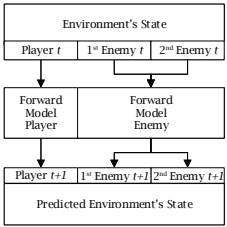
End-to-End FM



Decomposed FM



Local FM



Object-based FM

Comparison of Proposed Models

Qualitative comparison of proposed forward models architectures;

(+) well suited, (~) neutral, (—) poorly suited

Forward Model	#Models	Model Complexity	Interpret-ability	Transfer across levels
End-To-End				
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Prediction-based Search

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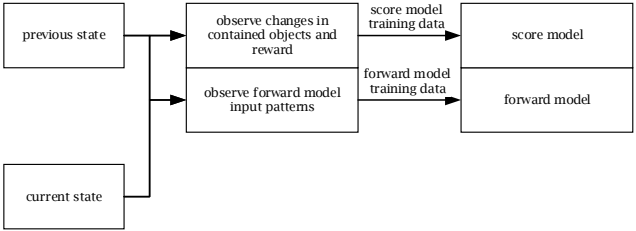

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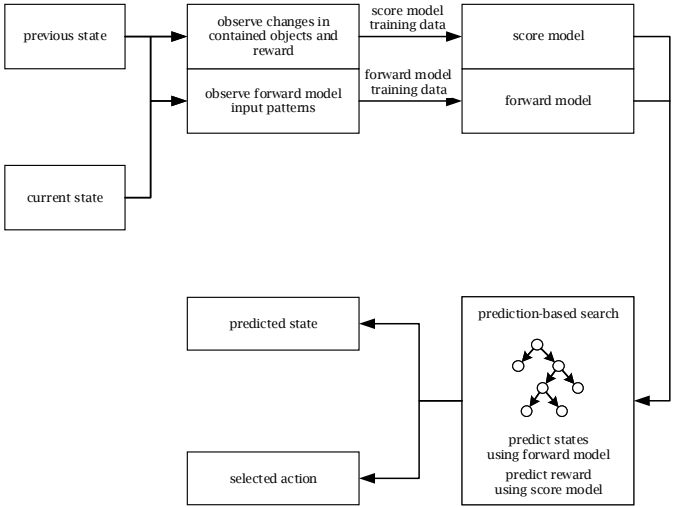

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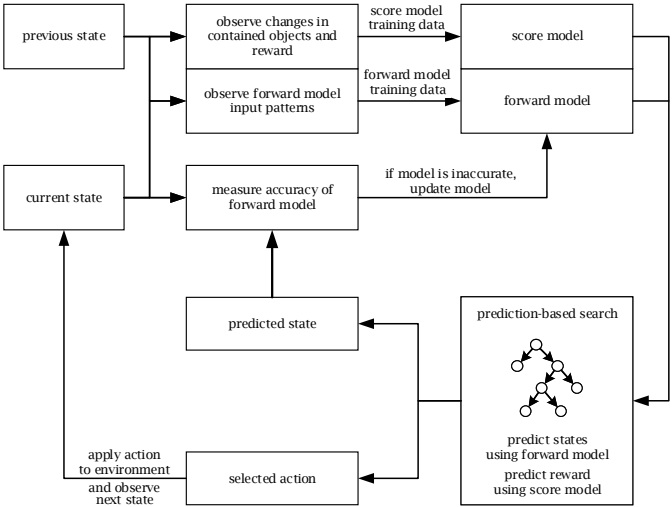

Evaluation Setup I/II

The evaluation is based on 30 games of the General Video Game AI (GVGAI) framework

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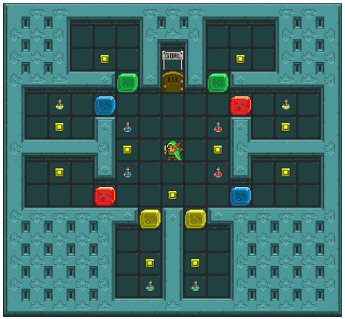
Varying Game Characteristics:

- types and number of NPCs
- use of a ressource system
- reward style (dense/sparse)
- the number and types of termination conditions
- determinism vs. non-determinism
- the number of actions available



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Learning a Constant Forward Model for each Game

Data Set Generation

- collection of observed state transitions of a random agent
- all 5 levels were played 10 times for a maximum of 200 ticks each
- 9 different local neighborhood patterns were extracted (one data set each)

Learning a Constant Forward Model for each Game

Data Set Generation

- collection of observed state transitions of a random agent
- all 5 levels were played 10 times for a maximum of 200 ticks each
- 9 different local neighborhood patterns were extracted (one data set each)

Accuracy Evaluation and Model Selection

- evaluation of 5 classifiers, multiple parameters

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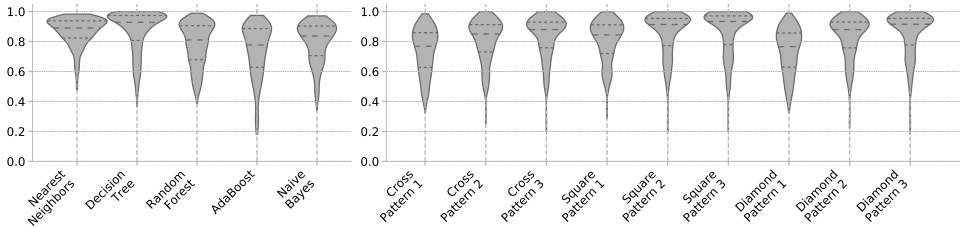

Evaluating Game-Playing Performance

agents are ranked according to their:

- average win-rate, average score, average ticks of won and lost games
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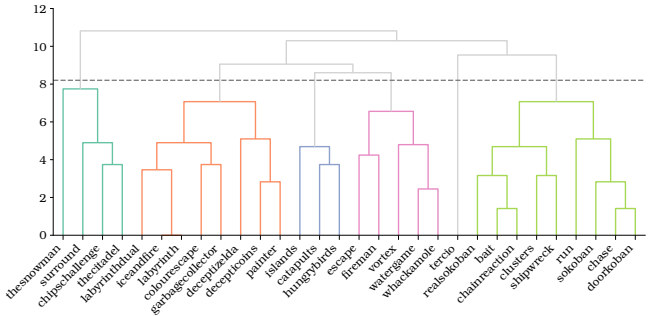
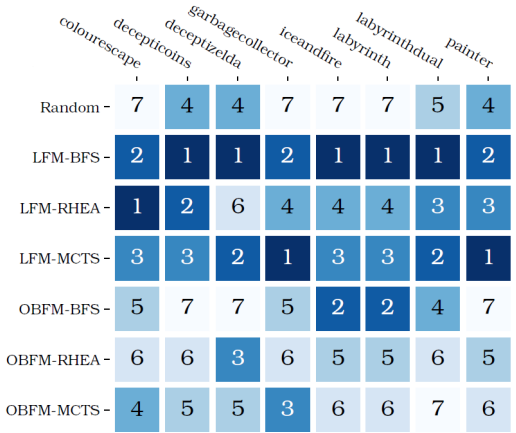


sparse reward, maze-like, long-term planning, randomness and ressources, puzzles

Detailed Game Results

Results on Maze-Like Games



Rank Comparison:

$$\text{BFS} = \text{MCTS} > \text{RHEA} > \text{Random}$$

$$\text{LFM} > \text{OBFM} > \text{Random}$$

all effects are local

decepticoins, deceptizelda and painter involve spawning elements, which OBFM cannot model

Detailed Game Results

Results on Puzzle Games

	bait	chainreaction	chase	clusters	doorkoban	realsokoban	run	shipwreck	sokoban
Random	7	7	6	7	6	7	6	7	6
LFM-BFS	3	4	7	2	7	4	5	4	7
LFM-RHEA	6	6	4	6	4	6	4	6	5
LFM-MCTS	4	3	3	3	3	5	7	1	4
OBFM-BFS	1	1	2	4	1	2	1	3	2
OBFM-RHEA	5	5	5	5	5	3	3	5	3
OBFM-MCTS	2	2	1	1	2	1	2	2	1

Rank Comparison:

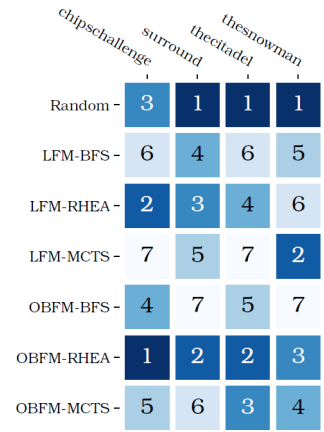
BFS $>$ MCTS $>$ RHEA $>$ Random

OBFM $>$ LFM $>$ Random

most but not all effects are local
(e.g. Doorkoban)

Detailed Game Results

Results on Games with Sparse Reward



Rank Comparison:

$$\text{Random} > \text{RHEA} > \text{BFS} = \text{MCTS}$$

$$\text{Random} > \text{OBFM} = \text{LFM}$$

rare rewards hinder in agent in distinguishing good and bad actions

more training data is required to create a reliable model

Aggregated Results: Game-Playing Performance

Aggregated ranks over all tested games and final score per agent

Agents		Rank 1st	2nd	3rd	4th	5th	6th	7th	Formula-1 Score
Random		4	0	1	3	3	4	15	303
LFM	BFS	10	5	4	4	2	2	3	502
	RHEA	3	3	3	8	3	10	0	380
	MCTS	5	3	8	4	2	4	4	423
OBFM	BFS	6	8	2	4	4	1	5	450
	RHEA	3	5	6	2	10	4	0	411
	MCTS	5	7	4	3	5	4	2	441

Formula-1 Scoring System: $1^{st} = 25$, $2^{nd} = 18$, $3^{rd} = 15$, $4th = 12$, $5th = 10$, $6th = 8$, $7th = 6$

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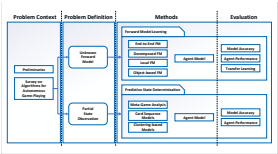
Conclusion

Simulation-based search requires extensions to be used in case:

- the environment's forward model is inaccessible
- the environment's state is partial observable



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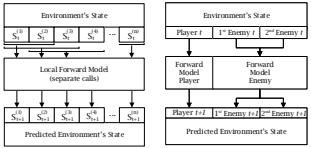

Four types of forward models were introduced.

- The underlying independency assumptions reduced the size of the model space and the required training time.
- A prediction-based search agent has been proposed.

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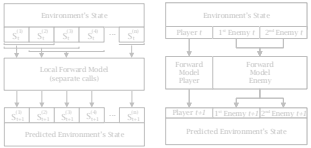

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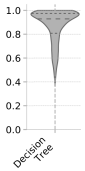
Agents were succesfully trained to play GVGAI games.

- trained agents achieved a high state prediction accuracy and game-playing performance
- learned models can be transferred to unobserved levels



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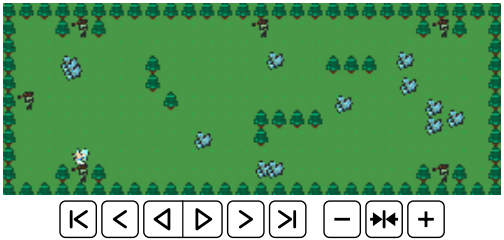
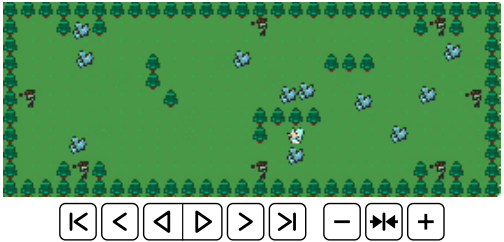
State-of-the-Art



Proposed Solution



Thank you for your attention!

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