OTTO VON GUERICKE UNIVERSITÄT MAGDEBURG

INF FAKULTÄT FÜR INFORMATIK

SwarmLab

Generalisation of Simulation-Based Search for Autonomous Gameplaying

Doktorandentag Presentation

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Faculty of Computer Science

Institute for Intelligent Cooperating Systems

Motivation

Computational Intelligence is about task automation, e.g.:

- developing self-driving cars

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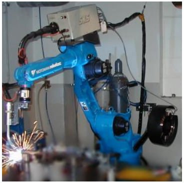

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Practical Solution:

- test algorithms in a simulation

Games and General Game Learning

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- quantifiable goal, varying difficulty, popular (large data sets)
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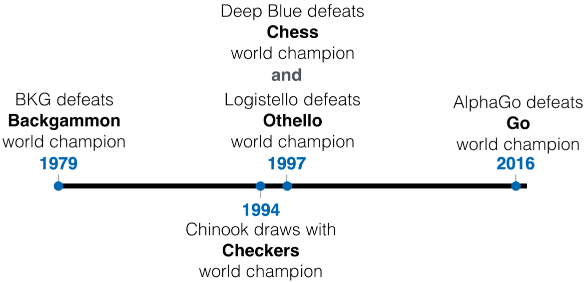

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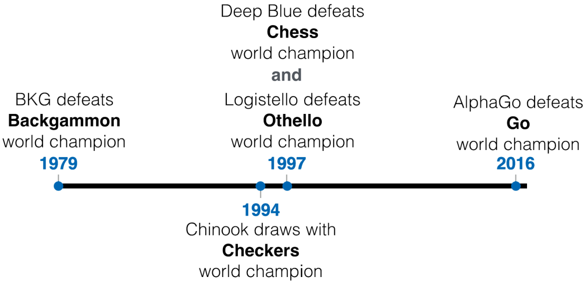

General Game Playing/Learning generalizes learning strategy across games but ignores learning the game's specific representation

Survey of Related Methods

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Knowledge of Expected Return

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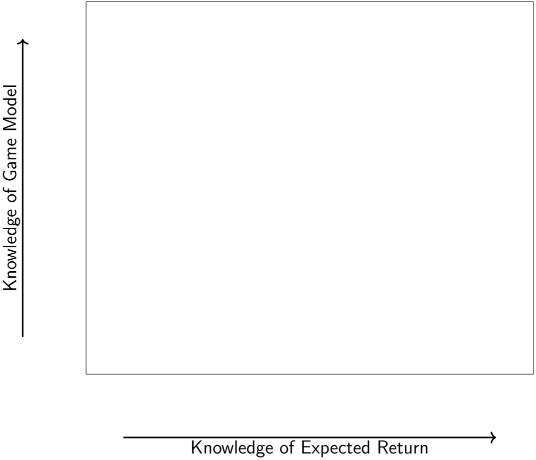

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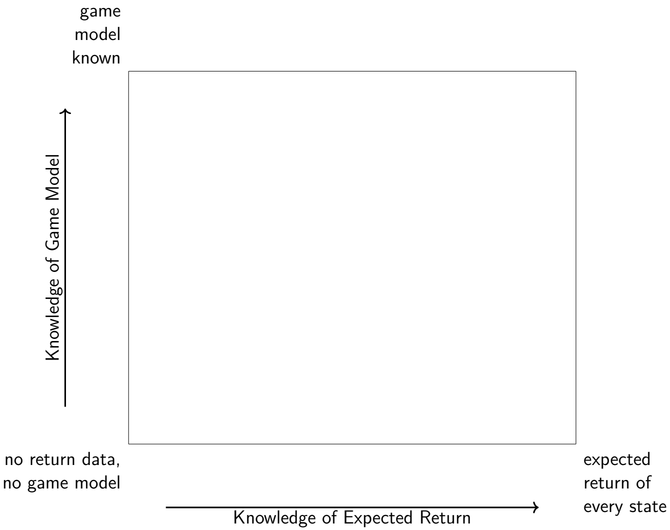

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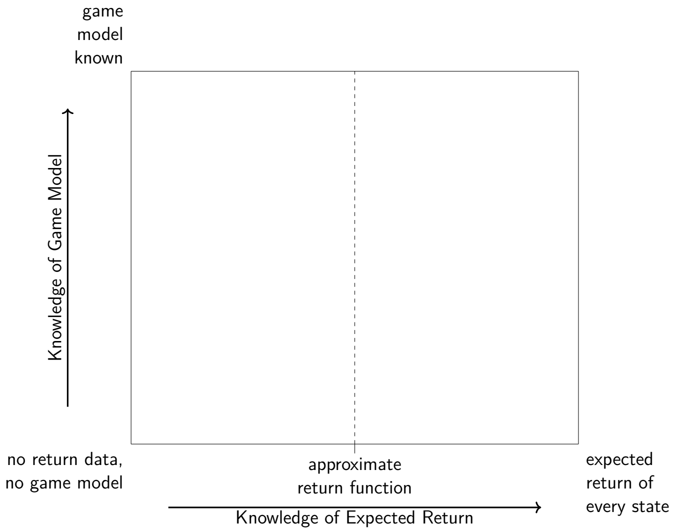

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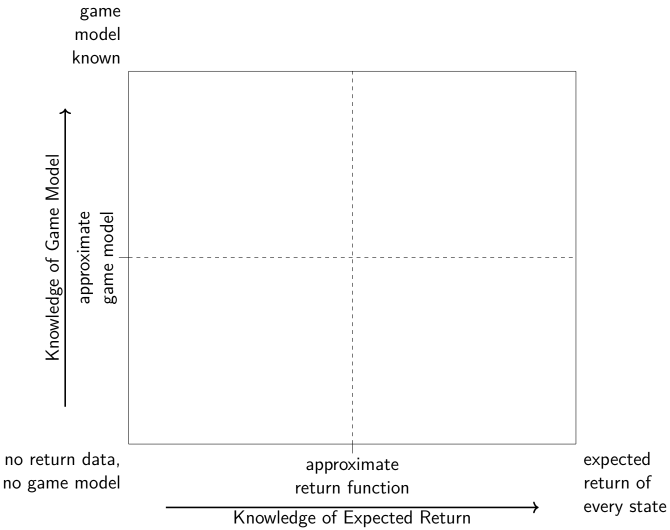

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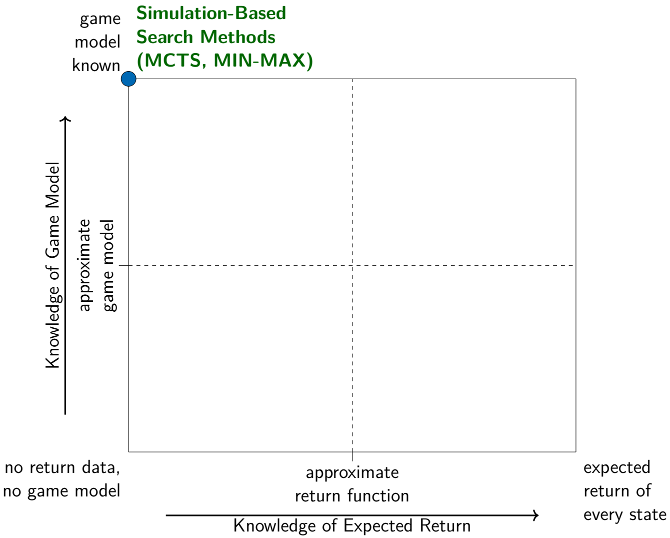

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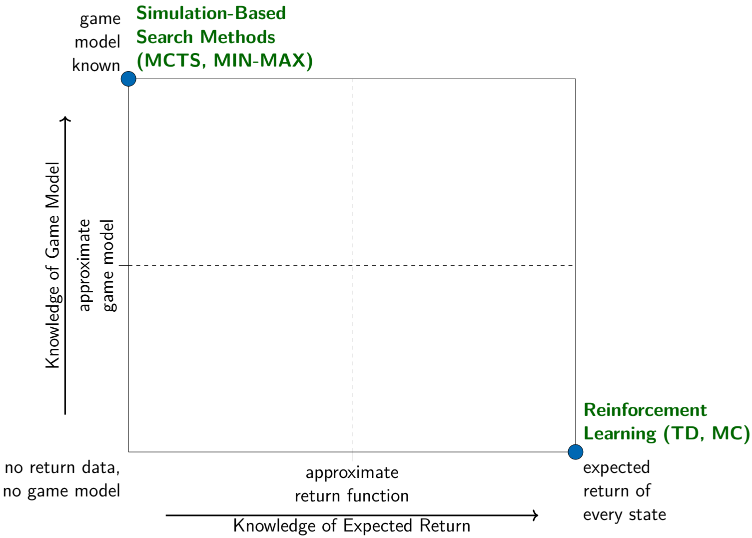

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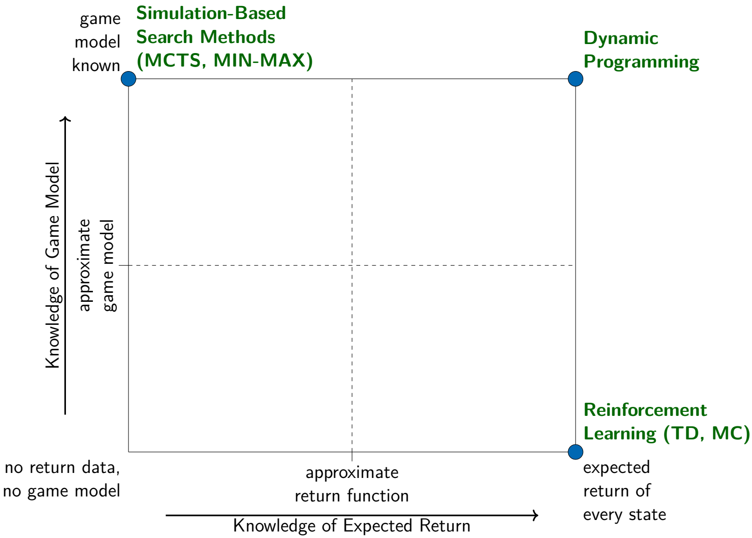

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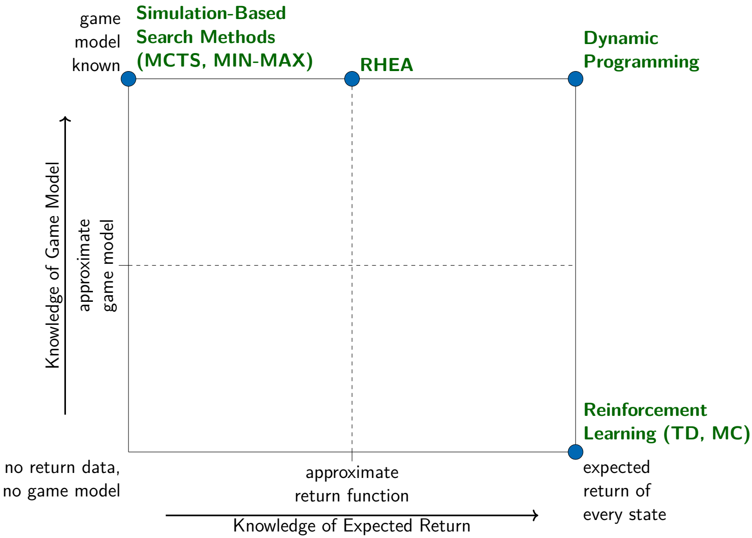

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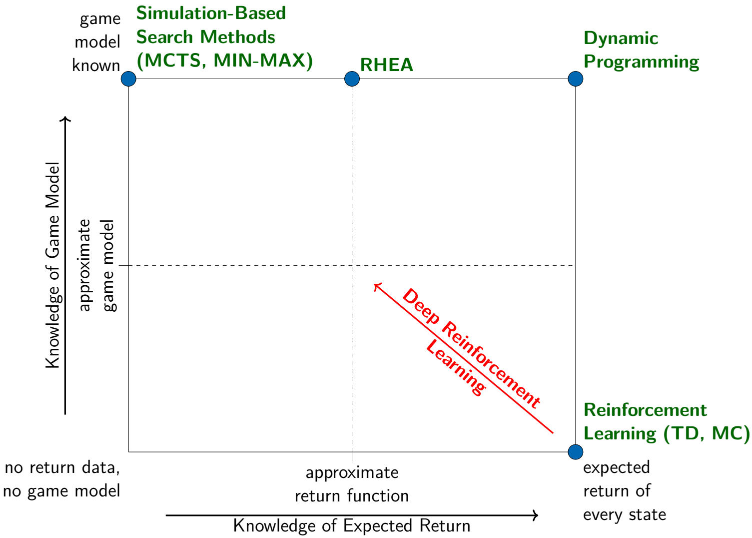

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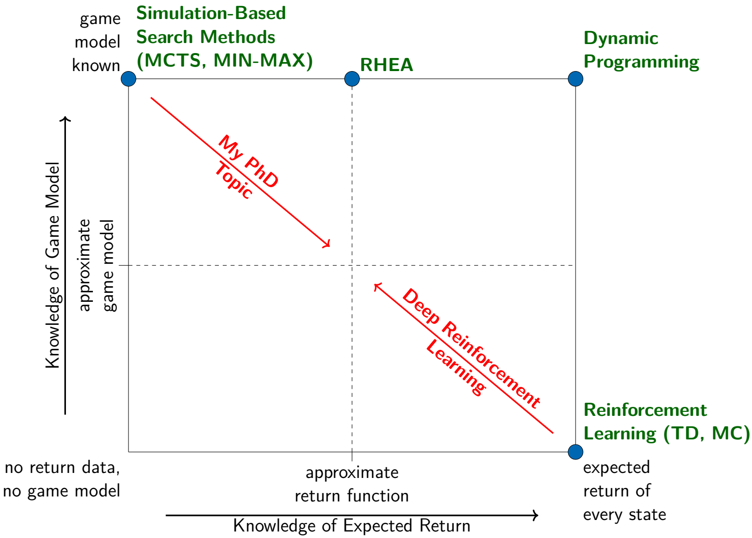

Simulation-Based Search Algorithms

Input:

- current state
- game-model

Output:

- action with highest win-rate

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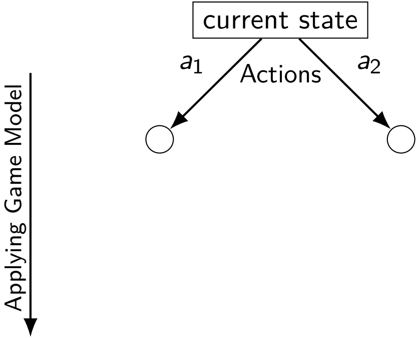

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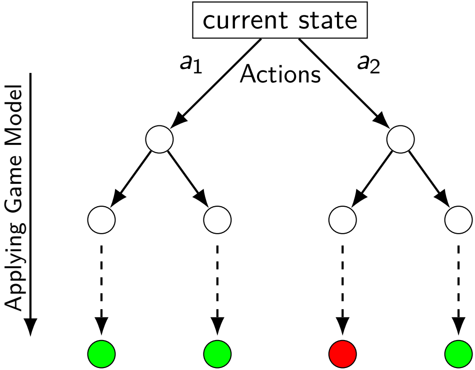

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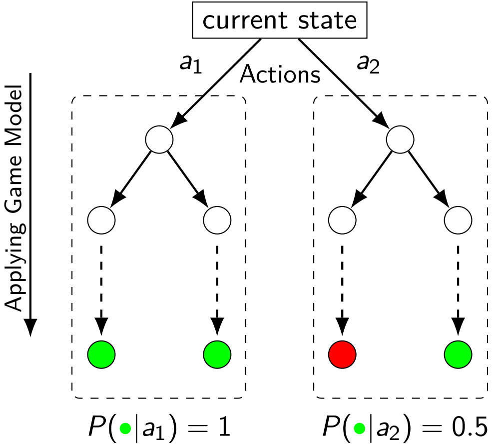

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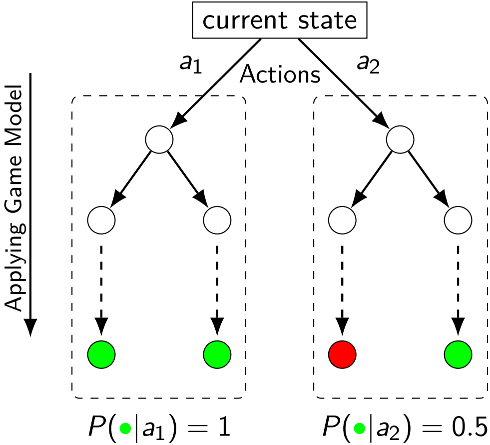

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Advantage:

- no evaluation function needed

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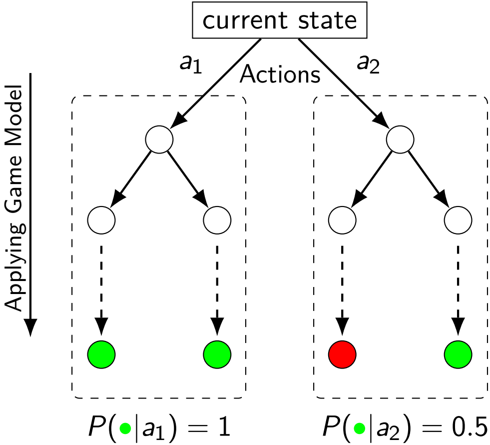

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Problem:

- game model unknown

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Identify, develop and evaluate different methods for general game learning that enable simulation-based search in scenarios without knowledge of the game's model.

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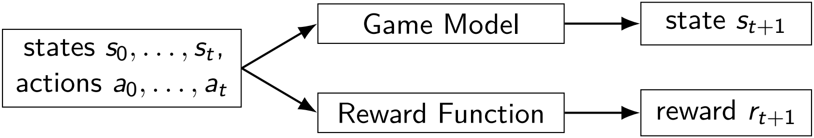
Evaluation:

- How do the developed models compare with state-of-the-art methods in terms of performance and learning speed?
- Which properties influence their applicability?

Forward Model Approximation

Developing techniques for approximating a game's model from previous interactions.

Components of a Game



state s_t perceived through multiple sensors $(s_t^{(1)}, s_t^{(2)}, \ldots, s_t^{(n)})$

- state may not be fully accessible (partial information game)

reward r_t is a performance signal

- how good do we perform in solving the task

game description as a probability distribution over possible outcomes

$$P(r_{t+1}, s_{t+1} \mid s_0, a_0, s_1, a_1, \ldots, s_t, a_t)$$

The Markov Property

Markov Property:

- the environments response at time $t+1$ only depends on the state s_t and the agent's action a_t

$$P(r_{t+1}, s_{t+1} \mid s_0, a_0, s_1, a_1, \ldots, s_t, a_t) = P(r_{t+1}, s_{t+1} \mid s_t, a_t)$$

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If the markov property holds, the environment dynamics can be defined by specifying:

$$P(s_{t+1} \mid s_t, a_t) \quad \text{and} \quad P(r_{t+1} \mid s_t, a_t)$$

Learning Target

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Reinforcement Learning

predict upcoming reward signals to maximize expected reward over time

$$\mathbb{E}[G \mid s_t, a_t] \qquad G = \sum_{k=0}^{T} R_{t+k+1}$$

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Simulation-based search

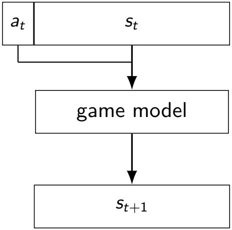
predict next game state for searching promising actions in the game tree

$$\mathbb{E}[s_{t+1} \mid s_t, a_t]$$

Analysis of the Model Space

$$P(s_{t+1} \mid s_t, a_t)$$

$$f : (s_t, a_t) \mapsto s_{t+1}$$



Analysis of the Model Space

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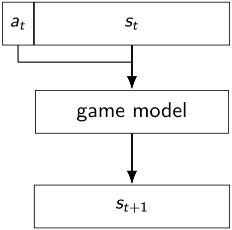

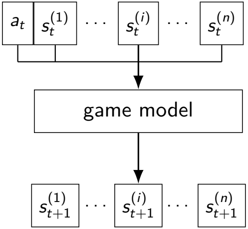

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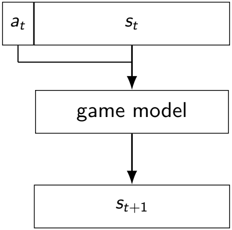

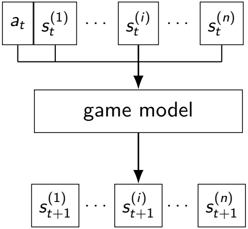

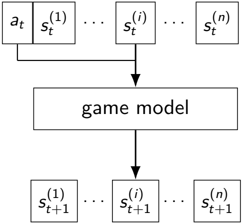

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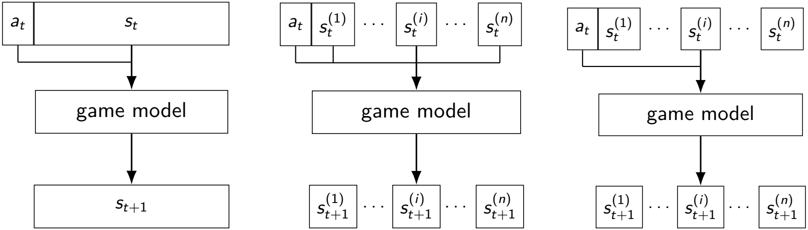

Prerequisites	Game Model Characteristics	✓
	Approximation of a Game Model	?

Forward Model Approximation Implementations

Association Rule Learning[1]

- learning an understandandable ruleset of an unknown game
- special handling of termination rules

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- rule learning through reinforcement learning
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Composite Model of Decision Trees[3]

- modelling sensor values individually
- speeds up model learning and increases model accuracy

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Evaluation of Prediction Accuracy[1]

General Video Game AI Framework:

- similar state representation for ∼100 games with 5 levels each
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- Evaluate the composite model on unseen levels
  - model accuracy ranging from 60%-95%

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Evaluation of Playing Performance[1]

General Video Game AI Competition:

- 6 agents entered in 2017/2018
- evaluation is based on a set of 10 games
- Formula-1 scoring system

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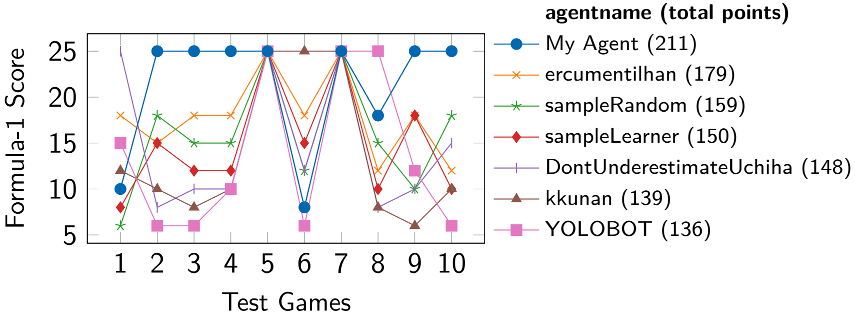

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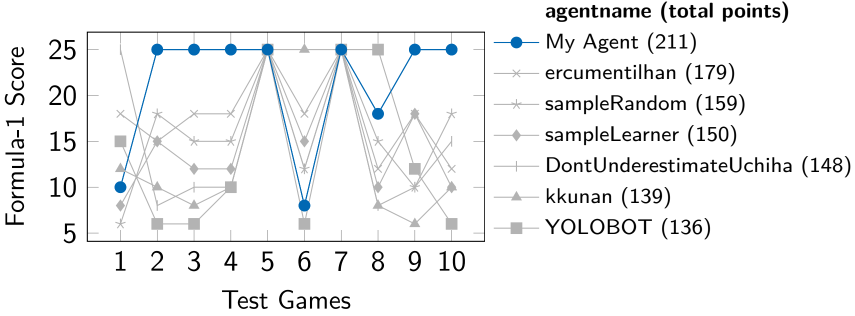

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Summary

Prerequisites	Game Model Characteristics Approximation of a Game Model
Algorithm	Applying Model to Search Risk Measures
Evaluation	Performance Comparison Applicability Analysis

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→ Categorization of state-of-the-art methods

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→ Categorization of state-of-the-art methods

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→ Game models can be learned using supervised learning

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Summary

→ Categorization of state-of-the-art methods

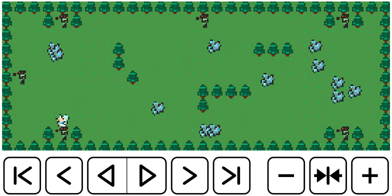
→ Analysis of game model characteristics

→ Game models can be learned using supervised learning

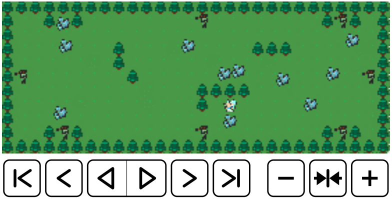
→ The proposed model is able to outperform state-of-the-art methods

Prerequisites	Game Model Characteristics	✓
	Approximation of a Game Model	✓
Algorithm	Applying Model to Search	✓
	Risk Measures	
Evaluation	Performance Comparison	(✓)
	Applicability Analysis	

State-of-the-Art



Proposed Solution



Thank you for your attention!

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Otto-von-Guericke University of Magdeburg
Faculty of Computer Science
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My Related Publications I/II

Book Chapters

Alexander Dockhorn, Chris Saxton, and Rudolf Kruse; *Association Rule Mining for Unknown Video Games*, A fuzzy dictionary of fuzzy modelling. Common concepts and perspectives (tentative title), accepted, 2019

Conference Papers

Alexander Dockhorn, Tim Tippelt, and Rudolf Kruse; *Model Decomposition for Forward Model Approximation*, IEEE Symposium Series on Computational Intelligence (SSCI), IEEE, November 2018, pp. 1751–1757

Alexander Dockhorn and Daan Apeldoorn; *Forward Model Approximation for General Video Game Learning*, 2018 IEEE Conference on Computational Intelligence and Games (CIG), IEEE, August 2018, pp. 425-432

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My Related Publications II/II

Conference Papers

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Alexander Dockhorn and Rudolf Kruse; *Detecting Sensor Dependencies for Building Complementary Model Ensembles*, 28. Workshop Computational Intelligence, KIT Publishing, November 2018, pp. 217-233

Further References

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Appendix (Appendix)

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Otto-von-Guericke University of Magdeburg
Faculty of Computer Science
Institute for Intelligent Cooperating Systems

Planning

Planning

November - January 2019: planning missing experiments

January 2019: Doktorandentag

February - April 2019: theoretic generalisation of simulation-based search without partial information, finishing the remaining experiments

May - August 2019: finished first draft

September - November 2019: necessary changes and adjustments

December 2019: Submission of the thesis

State	Nov 18	Dez 18	Jan 19	Feb 19	Mar 19	Apr 19	May 19	Jun 19	Jul 19	Aug 19	Sep 19	Oct 19	Nov 19	Dec 19
Thesis Proposal														
Writing Contents														
Doktorandentag														
Remaining Experiments														
First Complete Draft														
Minor Changes														
Submission														

Risks

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- many agent configurations need to be tested
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The framework consists of multiple exchangable components

- the influence on the performance needs to be evaluated on each of them, no single best component (no free lunch theorem)

General Game Playing/Learning

Why is Game-AI Research so Popular?

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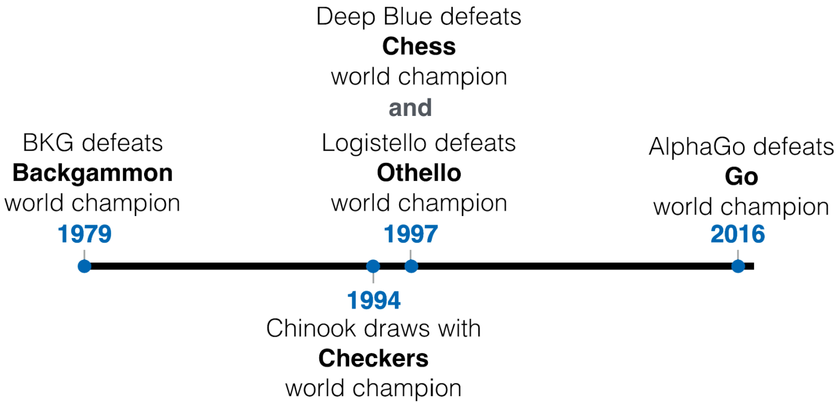
Games are popular!

- more players, more games, more data

What did AI in Games Achieve?



What did AI in Games Achieve?

BKG defeats **Backgammon** world champion **1979**

1994 Chinook draws with **Checkers** world champion

Deep Blue defeats **Chess** world champion **and** Logistello defeats **Othello** world champion **1997**

AlphaGo defeats **Go** world champion **2016**

All these solutions are based on search algorithms.

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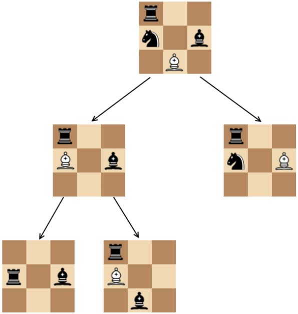
Action-Selection in Games

Action-Selection: search and select the best action among several alternative possibilities



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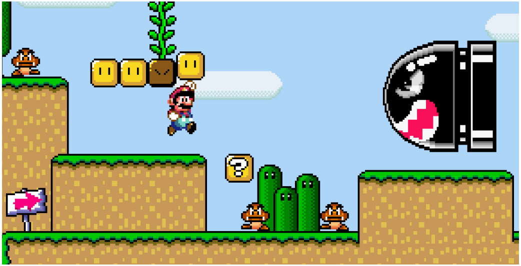

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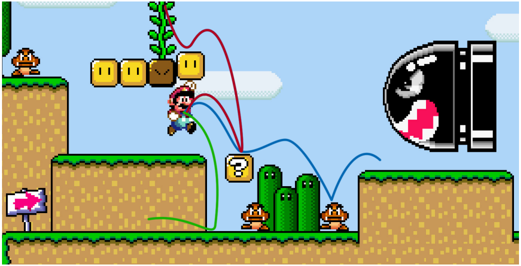

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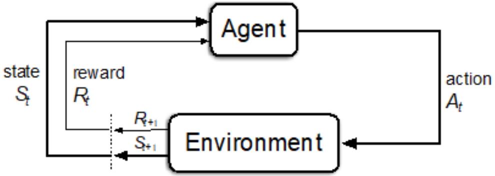


General Video Game AI

General Video Game AI (GVGAI) Competition

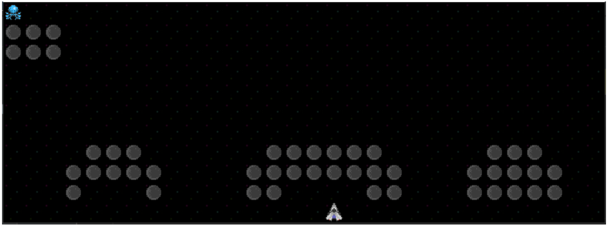
Competition framework including more than 100 games using Video Game Definition Language (VGDL) providing:

- general rules of a game and its forward model
- multiple levels per game
- visual representation

Example game: Butterflies

Game 1 - Aliens

- Destroy all aliens by shooting them
- Don't get shot or destroyed by touching an alien
- Aliens move from left to right and change direction at the end



Game 2 - Boulderdash

- Dig your way to the diamonds
- Don't get crushed by a boulder or touched by an enemy
- Leave through the door

Game 3 - Butterflies

- **Fairy:** the agent's representation in game, moved via actions
- **Butterfly:** moves randomly, removed when touched by the fairy
- **Cocoon:** static, becomes a butterfly when touched by a butterfly
- **Tree:** static, obstacle hindering movement other objects

Player actions: 4 way movement, moves the fairy in a direction
Win-Condition: no butterflies left, **Lose-Condition:** no cocoons left

Game 4 - Chase

- White birds fly away from you
- Catch all birds by cornering them

Game 5 - Frogs

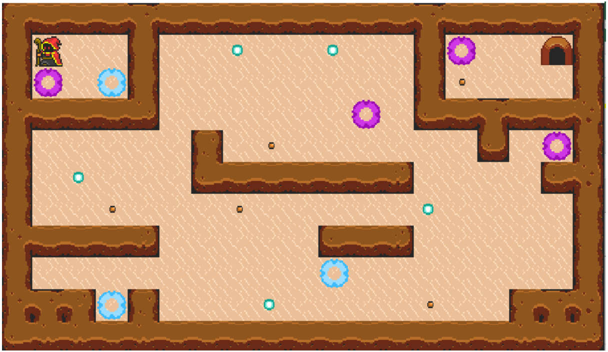
- Get to the goal post at the top
- . . . without getting hit by a car
- . . . and don't jump into the water

Game 6 - Missile Command

- Destroy all fireballs (comets) before they hit the city

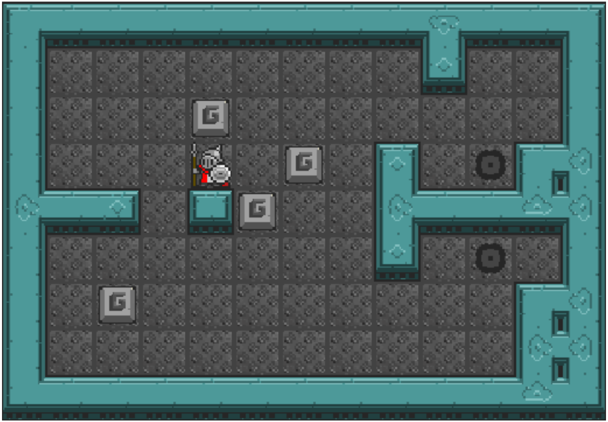
Game 7 - Portals

- Find the door to win the level



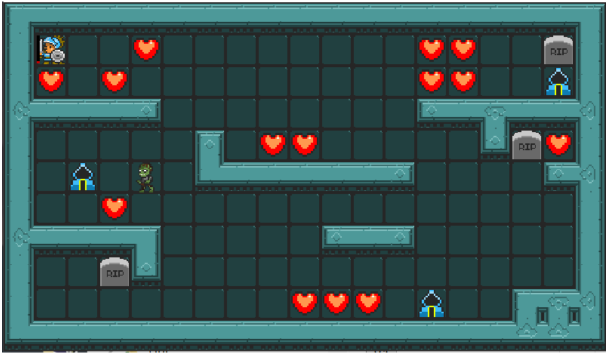
Game 8 - Sokoban

- Move the boulders to a hole in the ground



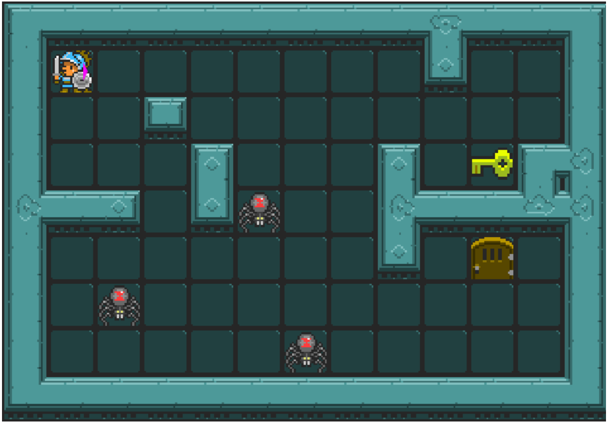
Game 9 - Survive Zombies

- Kill zombies and survive as long as possible
- Get healed by collecting hearts
- Stop magicians from getting killed



Game 10 - Zelda

- Kill the enemies
- Collect the key
- Flee through the door



Forward Model Learning

Forward Models

Using a forward model we can predict the outcome of an action.

- defined by the rules of the game being played

Search algorithms use the forward model to traverse the state-space

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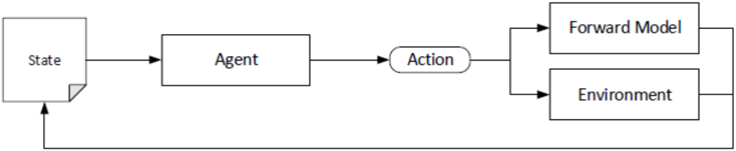

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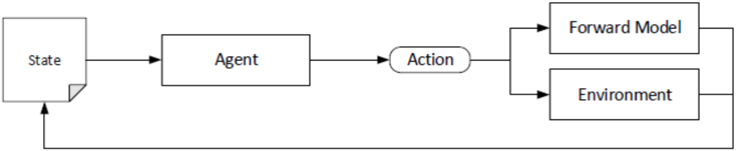

Examples

- **Robotics:** activating a motor to adjust the leg
- **Gameplaying Chess:** taking the king wins the game

FMA vs RL: Concept

Reinforcement Learning

- estimates the value of an action based on previous data
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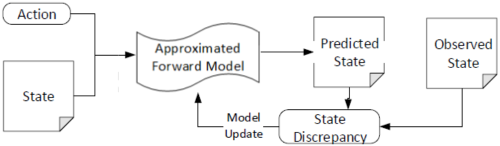

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Simulation-Based Search cannot be applied when the game's model is unknown

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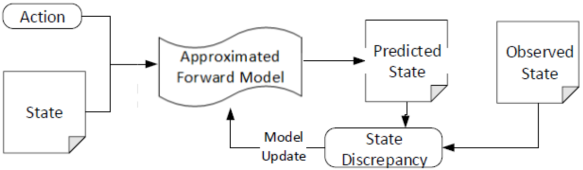

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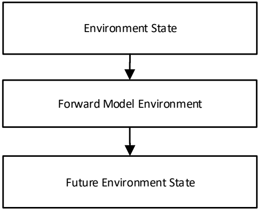

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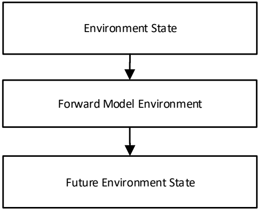

Markov property (order 1):

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Problem:

- the state can be arbitrarily complex

Can we further reduce the number of possible models?

Composite Model using Background Knowledge

Inherent constraint of the VGDL:

- model components individually and combine the result model
- simple component models are combined to a complex game model

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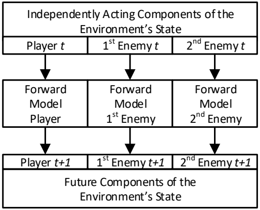

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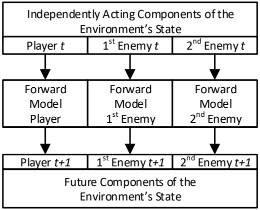

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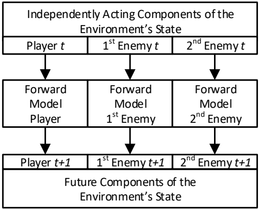

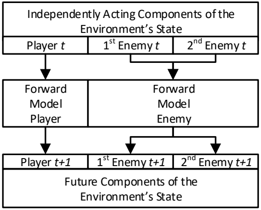

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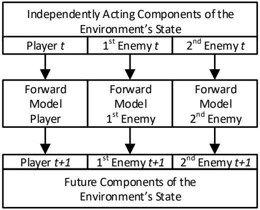
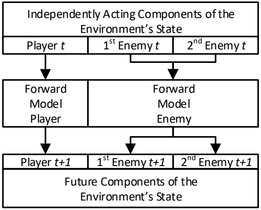


Idea:

- reduce the number of considered sensors to an interesting subset
- predict the change of all components/sensors individually



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Finding a Composite Model

Can we somehow build composite models?

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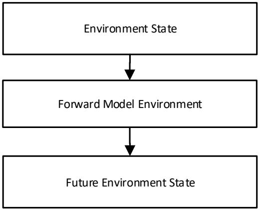
Modelling the complete state transition is very complex for a lot of applications



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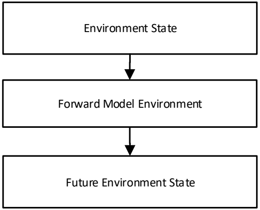

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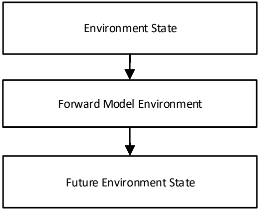
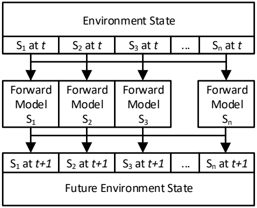




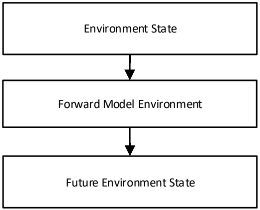
Finding a Composite Model

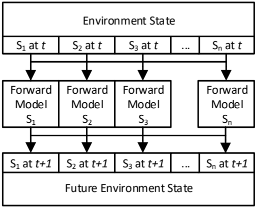
Can we somehow build composite models?

Modelling the complete state transition is very complex for a lot of applications

- ... because of a lot of variables
- ... that are dependent on each other

Use dependency analysis to find groups of dependent variables.





Finding a Composite Model

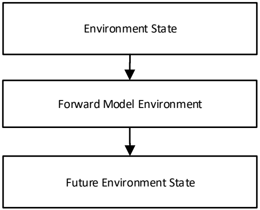
Can we somehow build composite models?

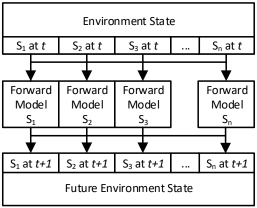
Modelling the complete state transition is very complex for a lot of applications

- … because of a lot of variables
- … that are dependent on each other

Use dependency analysis to find groups of dependent variables.

- filter unrelevant variables
- speeds up model building
- reduces noise in each submodel





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- predict the change of each sensor variable
- using a simple model

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To build a simple model for a single variable

- we want to find all non-independent variables
- to describe its change

We can do this for all variables at once by learning a belief net structure.

- it encodes the necessary independencies for all involved nodes
- only variable that is known in advance is the players action

Dependency Analysis Algorithms

Scoring-based Structure Learning Algorithms

- rates candidate structures based on a goodness of fit measure
- greedy algorithms iteratively modify an existing structure

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Hybrid Structure Learning Algorithms

- 2-phase algorithms combining restriction and maximation phase
- restriction phase: find undirected candidate structure
- maximation phase: find best configuration for all edge directions

Results - Model Decomposition I/II

Found substructures contain:

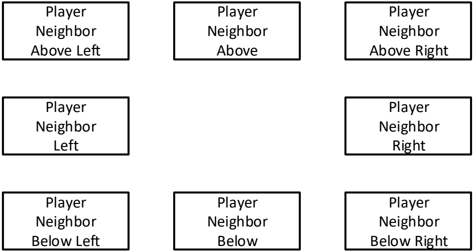
- position changes

- explanations for an component's death

Results - Model Decomposition II/II

Some patterns evolve over a lot of timesteps

- e.g. neighboring relations
- starting without any connection



Results - Model Decomposition II/II

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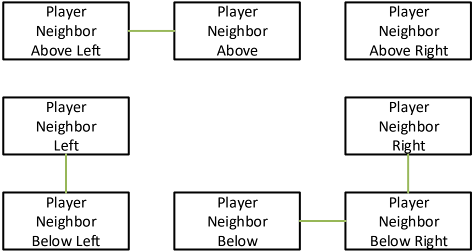

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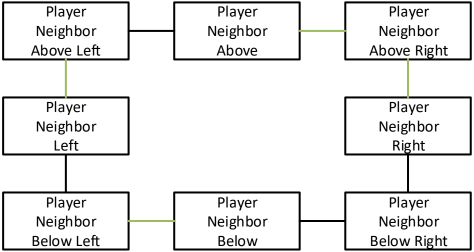
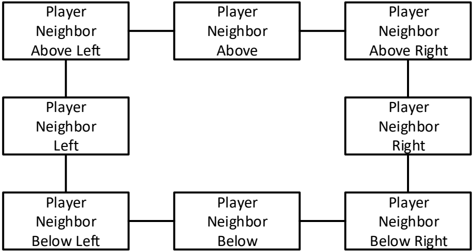


Results - Model Decomposition II/II

Some patterns evolve over a lot of timesteps

- e.g. neighboring relations
- starting without any connection
- adding edges dependencies over time
- and hopefully converge



Open Research Questions Decomposition

Can we merge similar sub-structures?

- multiple game components can have the same behavior
- e.g. instances of the same character type (butterflies)

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- The number of variables to consider grows exponentially with the number of time-steps to consider.
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How good is Forward Model Approximation if the approximation does not completly fit the distribution?

- it depends!
- some games can be played even without "understanding" all

Imperfect Information Games

Scenario 2) Partially Unknown Game State

Simulation-based search can be applied to full information games.

- What to do in partial information games?

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Each sensor value provides information on the current state of the game.

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- the actual gamestate is unknown

Popular example: simple card games like Uno, MauMau

- our own hand cards are known
- the opponent's cards are hidden
- the card draw is random

Proposal 2) State Induction

Use information from replays to guess a probable state during run-time.

- apply simulation-based search with the estimated state

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Can observable sensor variables be used to guess the gamestate?

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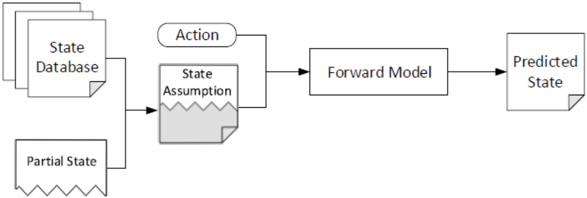

General Video Game AI (GVGAI) Competition

Competition framework including more than 100 games using Video Game Definition Language providing :

- general rules of a game and its forward model
- multiple levels per game
- visual representation

Example game: Butterflies

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Comparison of GVGAI Tracks

Planning Track

- forward model available,
  10 trials for training

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Comparison of GVGAI Tracks

Planning Track

- forward model available, 10 trials for training
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- algorithm performance close to or better than human

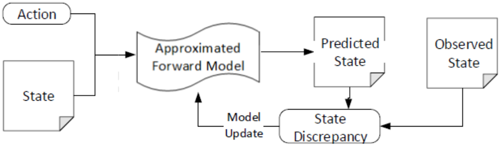
Learning Track

- no forward model, 5 minutes of training
- reinforcement learning and heuristics are widely applied
- algorithm performance on par with random decision-making

Generating a Data Set

Forward Model Approximation is an iterative framework

- our data set of observations grows over time
- model building needs to be repeated in case of errors



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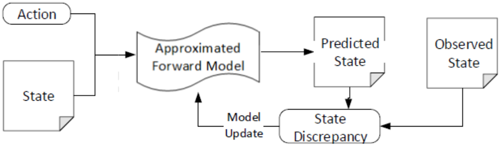


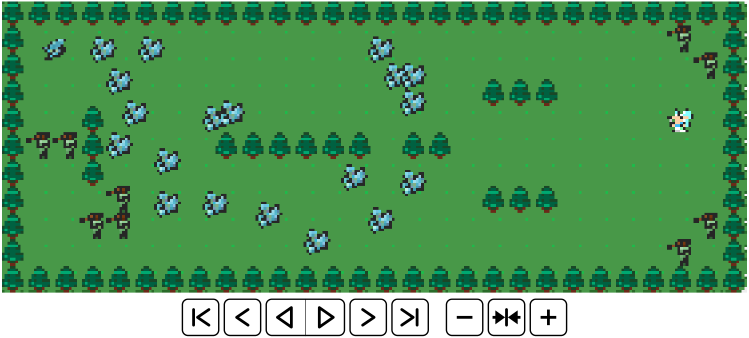
For testing purposes we collect a dataset using a random agent

- the player's actions will be independent from the game state

Each time frame we store all observable variables.

- contains an object's position, neighbors, movement and death

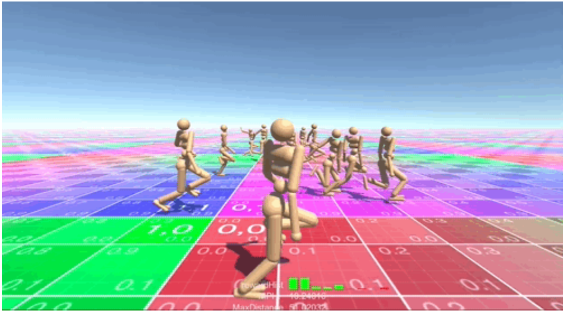
Demo Gameplaying FMA



Benchmarks

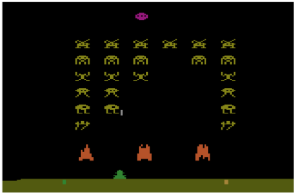
Marathon Environment

- high-dimensional continuous control environments
- $\longrightarrow$ complex game model



Arcade Learning Environment

- Atari 2600 games,
- screen capture: 160 pixel wide and 210 pixels high, 128-colours
- 18 actions: joystick direction and buttons



[1] Bellemare, M. G., Naddaf, Y., Veness, J., and Bowling, M. (2013); *The Arcade Learning Environment: An Evaluation Platform for General Agents*, Journal of Artificial Intelligence Research, 47, pp. 253–279

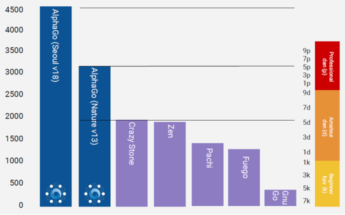
AlphaGO and AlphaZero

Playstrength of Computer Go Agents

Decreasing performance gain of computer agents in previous years

- Methods based on MCTS struggle with the extreme size of the search tree
- Playing Go on an expert level was thought to be unsolvable using known methods

Playstrength of agents in the last years:

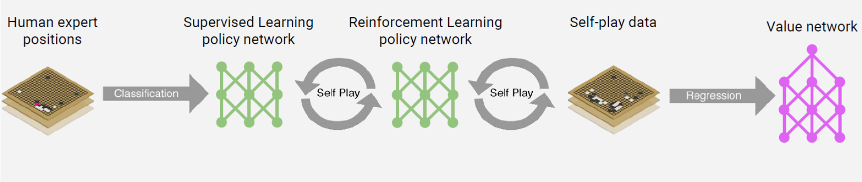


Alpha Go drastically changed the way in which we approach playing Go

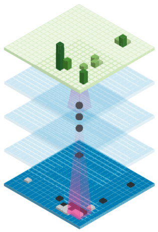
Alpha Go Learning Pipeline

Alpha Go combines the following ideas:

- Learning from Human expert data (gameplay recordings)
- Analysing board states on multiple levels of abstraction
- Predicting the probability of winning on any mid-gamestate
- Predicting valuable moves for better simulations



Policy Network



Try to predict the next best move depending on the current board state

- Classification problem: which move is likely to be played by an expert

Solution:

- Train two Convolutional Neural Networks

A small network was learned for fast rollouts, while a larger more accurate network was used during expansion.

The network receives an encoded input of 25 features per board position.

- Those features were first constructed by humans and automatically adapted in the learning phase.

Convolutional Neural Networks (CNN)

CNNs are a common network type in image processing:

- Feed-Forward Neural Networks
- Efficient processing using feature kernels
- Shift and rotation invariant (depending on the kernels)

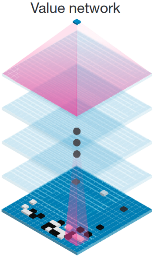
Each layer of a CNN has increasing complexity:

First Layer Representation Second Layer Representation Third Layer Representation

Value Network

Try to predict the probable outcome of the match

- Regression problem: what is the value of the current state

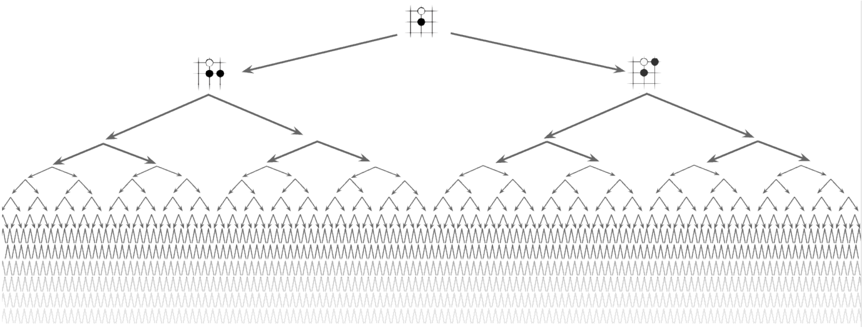


Solution:

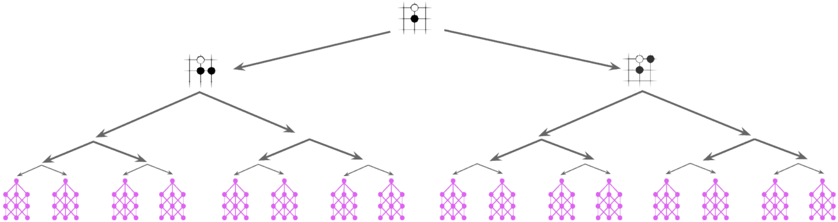
- Train another Convolutional Neural Network using Regression

The value network will be used to differ between good and bad states during the simulation.

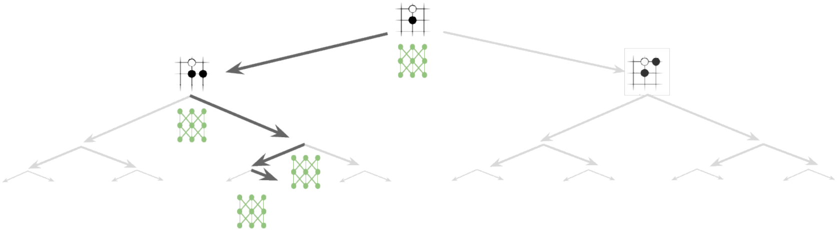
Exhaustive Search



Reducing Depth with the Value Network



Reducing Breadth with the Policy Network



Continuous Self-Improvement

With this approach machines can reach human expert performance

- How can we improve even further?

All networks were further trained by self-play:

- The networks in their current state were used to simulate 2 players in multiple games of Go.
- Those games produce a new database for further learning.

Based on the huge success of training based on Reinforcement Learning Alpha, Alpha Zero was developed

- no expert play training, just reinforcement learning
- faster adaptation, due to multiple improvements and various parallel processing adaptations
- top-performing agent in the games Go, Chess, and Shogi

Limiting Factors

Hardware (Training): the total Hardware costs to develop AlphaZero are about $25 million.

- it involves specialized Tensor Processing Units (TPU)
- the distributed version was using 1,202 CPUs and 176 GPUs

Hardware (End User): for each single position that AlphaGo analyzes, its neural network needs to do almost 20 billion operations

- many states need to be analyzed during the search
- either the user or the server needs to do these computations

Time: replicating the training done on a single machine would take about 1,700 years!

Paper Summaries

Model Decomposition for Forward Model Approximation

Model Building Requirements:

- **Learning Speed:** GVGAI-framework limits learning time to a total of 5 minutes
- **Processing Speed:** Monte Carlo Tree Search benefits from many simulations, applying the model needs to be fast
- **Generalization:** use the model for the prediction of unseen situations or levels
- **Accuracy:** high prediction accuracy for repeated application of the model
- **Interpretability:** beneficial to have an interpretable model

Model Decomposition Accuracy I/II

	Mean Accuracy (unpruned / pruned)				
	G1	G2	G3	G4	G5
1x training level 2	**0.970 / 0.970**	**0.998 / 0.998**	**0.980** / 0.962	0.996 / **0.997**	0.466 / **0.992**
1x training level 3	0.991 / **0.998**	**0.999** / 0.998	0.933 / **0.947**	**0.997** / 0.995	**0.975 / 0.975**
1x validation level 1	**0.806** / 0.753	**0.636** / 0.616	**0.664** / 0.663	0.667 / **0.704**	0.700 / **0.803**
3x validation level 1	**0.773** / 0.663	0.616 / **0.621**	0.666 / **0.718**	**0.850** / 0.776	0.736 / **0.804**
5x validation level 1	**0.717** / 0.677	**0.593** / 0.583	**0.665 / 0.665**	**0.811** / 0.801	0.670 / **0.804**
1x validation level 2	0.707 / **0.708**	0.595 / **0.561**	**0.666 / 0.666**	0.645 / **0.667**	**0.667 / 0.667**
3x validation level 2	0.730 / **0.742**	**0.591** / 0.508	**0.666** / 0.665	0.671 / **0.692**	**0.667 / 0.667**
5x validation level 2	0.647 / **0.780**	**0.614** / 0.581	**0.744** / 0.723	0.667 / **0.671**	**0.667 / 0.667**

Model Decomposition Accuracy II/II

	Mean Accuracy (unpruned / pruned)				
	G6	G7	G8	G9	G10
1x training level 2	0.990 / **0.991**	**0.998 / 0.998**	0.994 / **1.000**	**0.996** / 0.995	**0.987 / 0.987**
1x training level 3	**0.996 / 0.996**	**0.998** / 0.997	**1.000 / 1.000**	**0.995 / 0.995**	**0.998** / 0.997
1x validation level 1	0.635 / **0.643**	**0.980** / 0.936	**0.667 / 0.667**	**0.670** / 0.604	**0.688** / 0.674
3x validation level 1	**0.654** / 0.647	**0.960** / 0.786	0.667 / **0.727**	0.648 / **0.687**	**0.783** / 0.721
5x validation level 1	0.640 / **0.667**	0.667 / **0.950**	**0.941** / 0.733	**0.714** / 0.679	**0.752** / 0.726
1x validation level 2	0.420 / **0.539**	0.773 / **0.798**	**0.667** / 0.633	0.692 / **0.707**	0.683 / **0.724**
3x validation level 2	**0.903** / 0.658	**0.837** / 0.769	**0.667** / 0.542	**0.749** / 0.721	**0.773** / 0.733
5x validation level 2	0.664 / **0.659**	**0.667 / 0.667**	0.667 / **0.733**	**0.699** / 0.646	0.735 / **0.751**

Association Rule Mining for Unknown Video Games

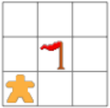
Procedure:

- Repeatedly play a level
  - store two separate interaction datasets: termination interaction and continuouing interactions
- Separately learn rules on both datasets
- Filter rules of the termination set
  - Remove all rules that conflict with rules from the continuouing interaction set

Example Game

(a) Level 1

(b) Level 2



(c) Level 3

Example Rules I/II

1. Moving right wins the game.
2. Moving left wins the game.
3. Reaching the flag wins the game.
4. Moving right and reaching the flag wins the game.
5. Moving left and reaching the flag wins the game.

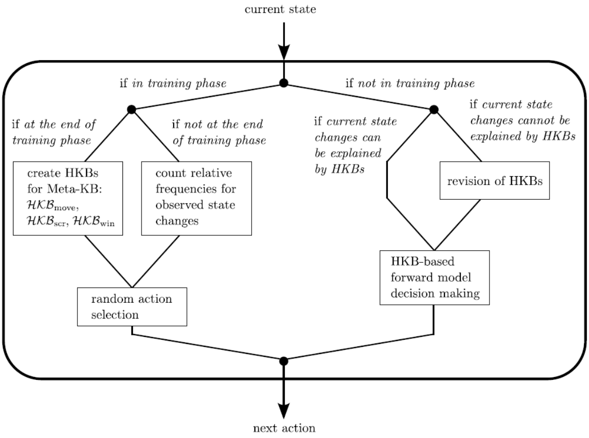
1. Reaching the flag wins the game.
2. Reaching the flag loses the game
3. Moving right and reaching the flag wins the game.
4. Moving left and reaching the flag wins the game.
5. Moving up and reaching the flag loses the game.
6. Moving down and reaching the flag loses the game.

Association Rules Results

Table 2: Association rules extracted from play-trace analysis.

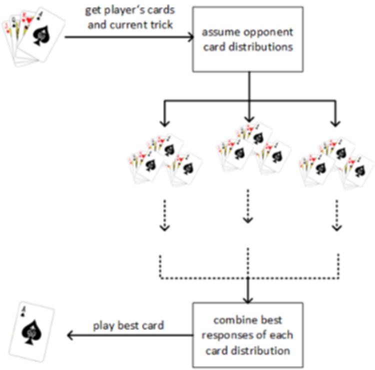
Rule			Support	Confidence
ActionLeft	→	MoveLeft	0.32	1.00
ActionRight	→	MoveRight	0.31	0.98
ActionUse	→	Stay	0.36	1.00
ObjectAbove, ActionUse	→	Stay	0.05	1.00
ObjectAbove, ActionLeft	→	MoveLeft	0.05	1.00
ObjectAbove, ActionRight	→	MoveRight	0.06	0.92
SpriteCollision	↔	HigherScore	0.06	1.00
PlayerCollision, ScoreDecrease	→	GameLost	1.00	1.00

Forward Model Approximation for General Video Game Learning



Predicting Opponent Moves for Improving Hearthstone AI

In case the current state is not known start multiple searches and combine their result.

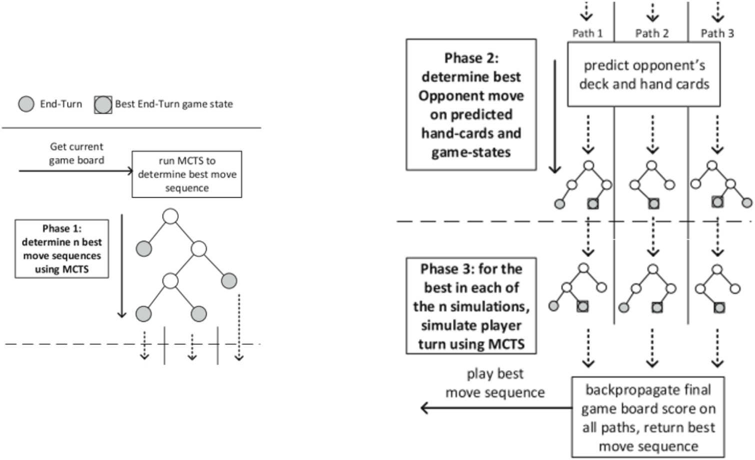


Monte Carlo Tree Search Ensemble I/II

Procdure

- A set of hand-cards is determined using the bi-gram database and all previously seen cards
  - determine the number of co-occurences of each card
  - filter possible cards by the rules of the deckbuilding process
  - sample the opponent's hand cards based on the normalized co-occurence values
- Generate multiple set of opponent's hand cards and run MCTS on each of them
- Use (weighted) majority vote to determine the best card to be played

Monte Carlo Tree Search Ensemble II/II



Monte Carlo Tree Search Ensemble Results

- We tested our agent against multiple other agents playing multiple decks
  - Random = randomly choose the next action
  - flatMC = flat Monte Carlo algorithm, simulate n times for each action
  - plainMCTS = MCTS using a randomly guessed game states
  - foMCTS = MCTS using the true game state (cheating)
  - Exh.s. = exhaustive search for best action, does not consider the opponent

Wins in %	Aggro	Mid	Control
Random	95	100	100
flatMC	81	73	94
plainMCTS	59	47	58
foMCTS	46	36	60
exh.s.	65	47	70

(a) predMCTS Aggro Deck

Wins in %	Aggro	Mid	Control
Random	99	98	100
flatMC	88	85	99
plainMCTS	71	55	76
foMCTS	59	50	76
exh.s.	62	70	85

(b) predMCTS Mid-Range Deck

Wins in %	Aggro	Mid	Control
Random	97	97	100
flatMC	73	54	89
plainMCTS	36	31	68
foMCTS	41	16	51
exh.s.	45	20	61

(c) predMCTS Control Deck