# Applied machine learning in game theory

Dmitrijs Rutko Faculty of Computing University of Latvia

Joint Estonian-Latvian Theory Days at Rakari, 2010

# Topic outline

- Game theory
  - Game Tree Search
  - Fuzzy approach
- Machine learning
  - Heuristics
  - Neural networks
  - Adaptive / Reinforcement learning
- Card games



# Deterministic / stochastic games Perfect / imperfect information games



#### Finite zero-sum games

	deterministic	chance
perfect information	chess, checkers, go, othello	backgammon, monopoly, roulette
imperfect information	battleship, kriegspiel, rock- paper-scissors	bridge, poker, scrabble

# Topic outline

#### Game theory

- Game Tree Search
- Fuzzy approach
- Machine learning
  - Heuristics
  - Neural networks
  - Adaptive / Reinforcement learning
- Card games

#### Game trees



#### Classical algorithms



#### Advanced search techniques

- Transposition tables
- Time efficiency / high cost of space
  - PVS
  - Negascout
  - NegaC\*
  - SSS\* / DUAL\*
  - MTD(f)

#### Fuzzy approach





# BNS enhancement through selftraining

#### Traditional statistical approach





# Two dimensional game sub-tree distribution

															Tree
	23	24	25	26	27	28	29	30	31	32	33	34	35	36	count
23	0														0
24	0	0													0
25	0	1	0												1
26	0	0	2	3											5
27	0	0	5	3	3										11
28	0	1	0	12	12	13									38
29	0	0	2	10	35	43	34								124
30	1	2	6	9	26	58	71	33							206
31	0	0	6	10	27	41	78	57	33						252
32	0	1	3	13	17	30	32	41	38	14					189
33	0	0	1	2	8	12	26	28	21	11	2				111
34	0	0	0	1	3	5	13	8	6	2	2	2			42
35	0	0	0	0	0	2	4	3	2	3	0	0	0		14
36	0	0	0	0	0	0	1	2	2	1	1	0	0	0	7

#### Statistical sub-tree separation



#### Experimental results. 2-width trees



#### Experimental results. 3-width trees



Future research directions in game tree search

- Multi-dimensional self-training
- Wider trees
- Real domain games

# Topic outline

- Game theory
  - Game Tree Search
  - Fuzzy approach
- Machine learning
  - Heuristics
  - Neural networks
  - Adaptive / Reinforcement learning
- Card games

#### Games with element of chance



#### Expectiminimax algorithm

- Expectiminimax(n) =
  - Utility(n)
    - If n is a terminal state
  - Max s ∈ Successors(n) Expectiminimax(s)
    - if n is a max node
  - Min s ∈ Successors(n) Expectiminimax(s)
    - if n is a min node
  - $\Sigma s \in Successors(n) P(s) * Expectiminimax(s)$ 
    - if n is a chance node

 $\blacksquare O(w^d c^d)$ 

#### Perfomance in Backgammon



\*-Minimax Performance in Backgammon, Thomas Hauk, Michael Buro, and Jonathan Schaeer

### Backgammon

- Evaluation methods
  - Static pip count
  - Heuristic key points
  - Neural Networks





# Temporal difference (TD) learning

- Reinforcement learning
- Prediction method



#### Experimental setup

- Multi-layer perceptron
- Representation encoding
  - Raw data (27 inputs)
  - Unary (157 inputs)
  - Extended unary (201 inputs)
  - Binary (201 input)



Training game series – 400 000 games

# Learning results



#### Program "DM Backgammon"



# Topic outline

- Game theory
  - Game Tree Search
  - Fuzzy approach
- Machine learning
  - Heuristics
  - Neural networks
  - Adaptive / Reinforcement learning
- Card games

#### Artificial Intelligence and Poker\*

AI Problems	Poker problems
Imperfect information	Hidden cards
Multiple agents	Multiple human players
Risk management	Bet strategy and outcome
Agent modeling	Opponent(s) modeling
Misleading information	Bluffing
Unreliable information	Taking bluffing into account
*	Joint work with Annija Rupeneite

