

Rock'n'Roll

A Engine for the Board Game “EinStein Würfelt Nicht”™

Andreas Schäfer

Institut für Informatik
Friedrich-Schiller-Universität Jena

June 13, 2006

Outline

- 1 Introduction to EinStein
 - The Rules
- 2 Engine Algorithms
 - Heuristics
 - Minimax
 - Monte Carlo Method
- 3 Benchmarks
 - Best Parameter Sets
 - Optimal Starting Position
- 4 Summary

Outline

- 1 Introduction to EinStein
 - The Rules
- 2 Engine Algorithms
 - Heuristics
 - Minimax
 - Monte Carlo Method
- 3 Benchmarks
 - Best Parameter Sets
 - Optimal Starting Position
- 4 Summary

Outline

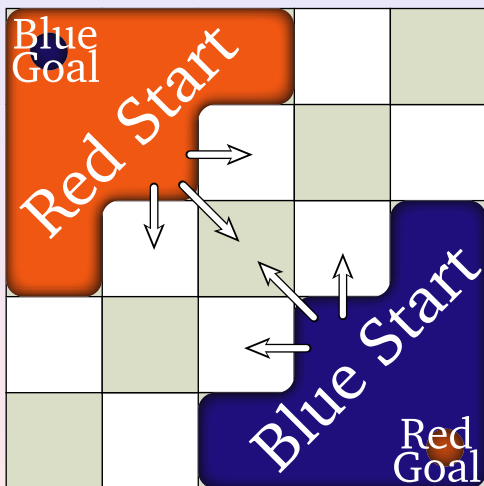
- 1 Introduction to EinStein
 - The Rules
- 2 Engine Algorithms
 - Heuristics
 - Minimax
 - Monte Carlo Method
- 3 Benchmarks
 - Best Parameter Sets
 - Optimal Starting Position
- 4 Summary

Outline

- 1 Introduction to EinStein
 - The Rules
- 2 Engine Algorithms
 - Heuristics
 - Minimax
 - Monte Carlo Method
- 3 Benchmarks
 - Best Parameter Sets
 - Optimal Starting Position
- 4 Summary

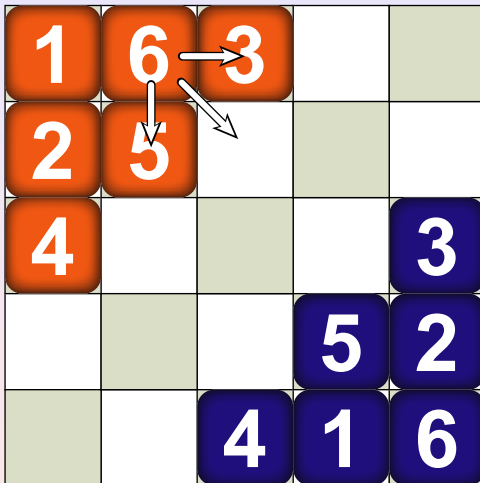
Outlook

- 1 Introduction to EinStein
 - The Rules
- 2 Engine Algorithms
 - Heuristics
 - Minimax
 - Monte Carlo Method
- 3 Benchmarks
 - Best Parameter Sets
 - Optimal Starting Position
- 4 Summary

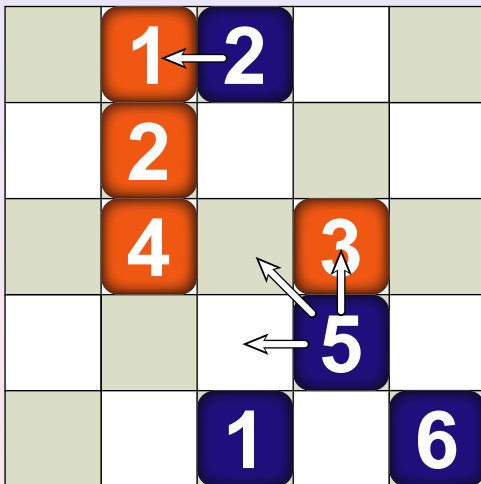


Objective:

- reach goal or
- capture every of the opponent's stones

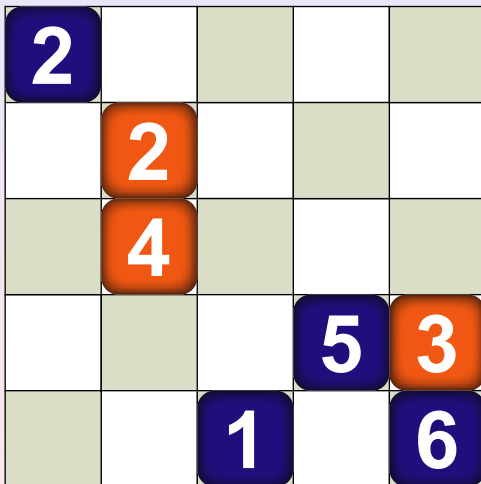


- 1 players take turns
- 2 dice determines which stone to move
- 3 self capturing is legal



If the rolled number is missing then an adjacent stone has to be moved





Blue won by reaching
his goal



Outlook

- 1 Introduction to EinStein
 - The Rules
- 2 **Engine Algorithms**
 - **Heuristics**
 - Minimax
 - Monte Carlo Method
- 3 Benchmarks
 - Best Parameter Sets
 - Optimal Starting Position
- 4 Summary

Heuristics

- heuristic = rule of thumb,
- computer needs to choose *good* moves,
- heuristic maps boards to the reals,
- good boards *hopefully* get higher ratings

Schwarz Tables

- estimate for each player, how many moves expected to reach goal
- difference of the two estimates is the board rating
- capturing is ignored

Example:
(one player only)

		4		

remaining moves = 4

Schwarz Tables (cont.)

Example 2:
(again just one player)

				6
			1	

$$\text{remaining moves} = \frac{5}{6} \cdot 1 + \frac{1}{6} \cdot 2 = \frac{7}{6}$$

Outlook

- 1 Introduction to EinStein
 - The Rules
- 2 **Engine Algorithms**
 - Heuristics
 - **Minimax**
 - Monte Carlo Method
- 3 Benchmarks
 - Best Parameter Sets
 - Optimal Starting Position
- 4 Summary

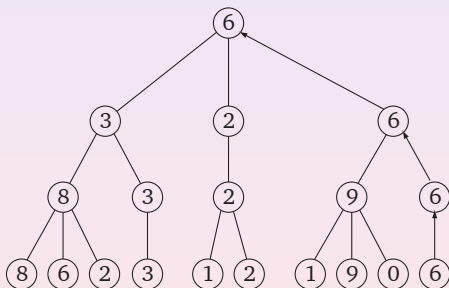
Basic Minimax

Depth 0:
(Max)

Depth 1:
(Min)

Depth 2:
(Max)

Depth 3:
(Heuristic)



- look some moves ahead
- cut at a given depth and assign ratings
- two players:
 - Max tries to *maximize*,
 - Min tries to *minimize*
- propagate values upwards

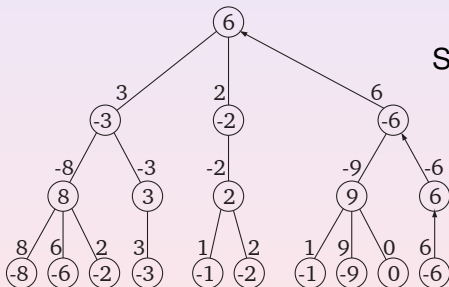
Basic Minimax (cont.)

Depth 0:
(Max)

Depth 1:
(Max)

Depth 2:
(Max)

Depth 3:
(Heuristic)



Simplification:

- invert values before propagation
- only maximizing nodes necessary

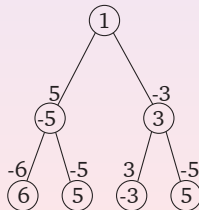
Expect Minimax

- problem: EinStein is randomized
- standard solution: introduction of dicing layers
- problem: much redundant evaluations

Depth 0:
(Random)

Depth 1:
(Max)

Depth 2:
(Heuristic)



Dicing Layer Reduction

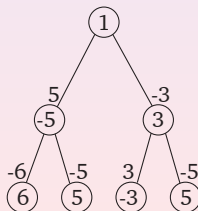
Unified Operator avoids unnecessary evaluations:

- calculate for each stone i the best move r_i
- determine for each stone i probability p_i to be moved
- rating $R = \sum_{i=1}^6 r_i p_i$

Depth 0:
(Random)

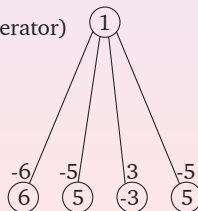
Depth 1:
(Max)

Depth 2:
(Heuristic)



Depth 0:
(Unified Operator)

Depth 1:
(Heuristic)



Outlook

- 1 Introduction to EinStein
 - The Rules
- 2 Engine Algorithms**
 - Heuristics
 - Minimax
 - Monte Carlo Method**
- 3 Benchmarks
 - Best Parameter Sets
 - Optimal Starting Position
- 4 Summary

The Monte Carlo Method

board evaluation:

- 2 simple players finish game (e.g. simple heuristic)
- many repeats (e.g. 200 times)
- hopefully: win/lose ratio is correlated to move quality
- improved long-term foresight
- worse short-term foresight

Outlook

- 1 Introduction to EinStein
 - The Rules
- 2 Engine Algorithms
 - Heuristics
 - Minimax
 - Monte Carlo Method
- 3 Benchmarks**
 - Best Parameter Sets**
 - Optimal Starting Position
- 4 Summary

Monte Carlo vs. Minimax

	Player	1	2	3	4	5	6	7
1	Random(1)	—	11	9	10	7	7	7
2	Monte(1, 50, Schwarz(1))	88	—	45	55	44	41	40
3	Monte(1, 200, Schwarz(1))	91	55	—	62	49	46	45
4	Schwarz(1)	90	44	38	—	41	40	39
5	Schwarz(5)	93	55	51	59	—	47	46
6	Monte(3, 20, Farmer(1))	93	59	54	60	53	—	50
7	Monte(3, 40, Farmer(1))	93	60	55	61	54	50	—

- Schwarz(n) = Minimax with depth n and Schwarz Tables
- Monte(n, r, p) = Minimax with depth n and subsequent Monte Carlo (r repeats and p as simulation players)

Outlook

- 1 Introduction to EinStein
 - The Rules
- 2 Engine Algorithms
 - Heuristics
 - Minimax
 - Monte Carlo Method
- 3 Benchmarks**
 - Best Parameter Sets
 - Optimal Starting Position**
- 4 Summary

Optimal Starting Positions

6	2	4		
1	5			
3				

56.056 %

6	5	2		
1	4			
3				

56.021 %

1	5	4		
6	2			
3				

55.913 %

Worst Starting Positions

3	5	1		
4	6			
2				

42.175%

3	4	2		
5	6			
1				

42.446%

4	2	6		
3	1			
5				

42.776%

Summary

- Unified Operator mitigates additional complexity introduced by dice
- a combination of Minimax and Monte Carlo yields strongest players
- strength limited by random component
- board setup important (1 and 6 behind other stones)

Thanks!



