Evolutionary Learning of Policies for MCTS Simulations

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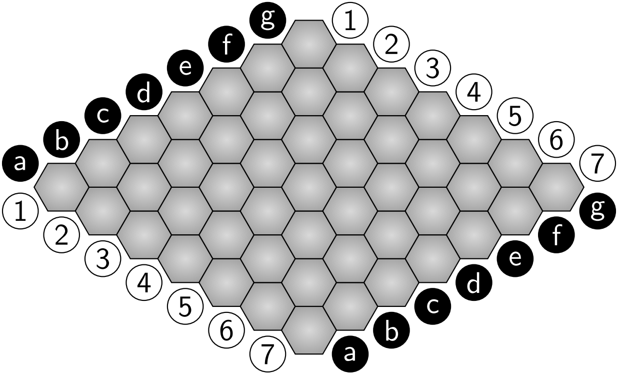
Motivation

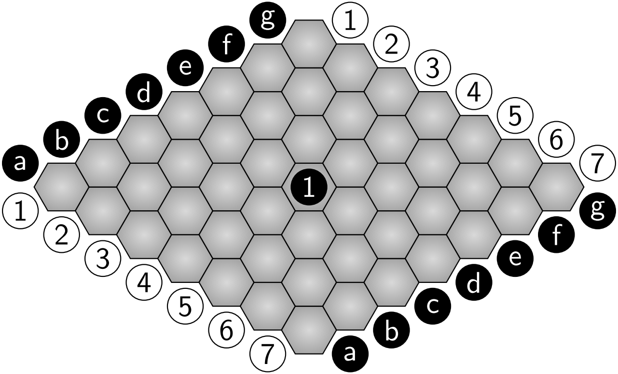
1. Cutting and connecting games are hard
2. Computer Go - Next AI Grand Challenge
3. Monte Carlo techniques promising
4. Tuning policies difficult
5. Solution: use evolution and self-play to learn better policies

The Game of Hex - Good for AI



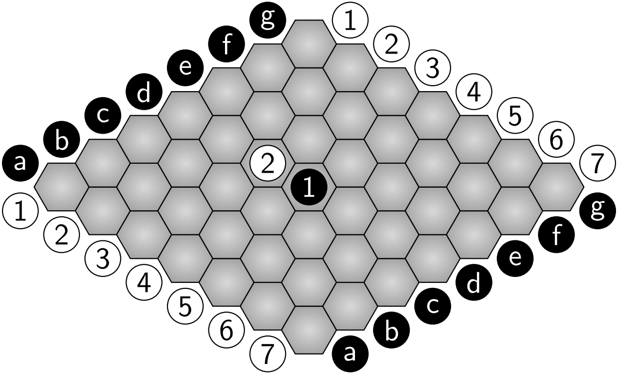
- 2 player, perfect information
- Easy to program
- Clear-cut winning condition
- Large problem space
- Solved for boards up to 7x7
- Common sizes: 11x11, 13x13

The Game of Hex - Example Game



- Connect opposing sides
- Cut opponents connections

The Game of Hex - Example Game



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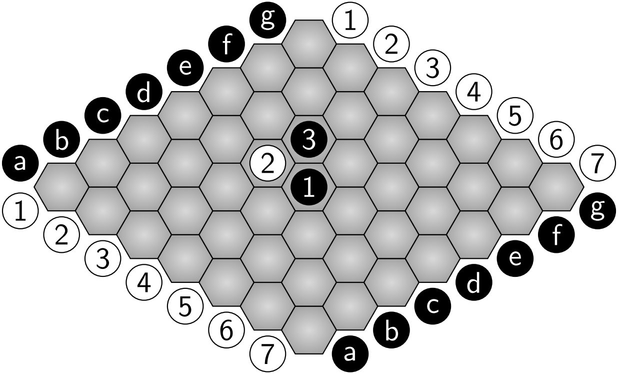

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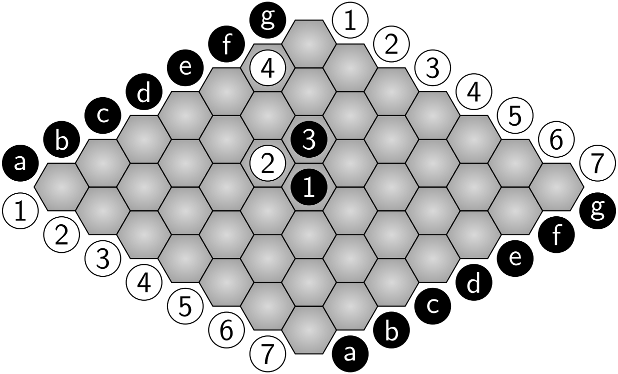

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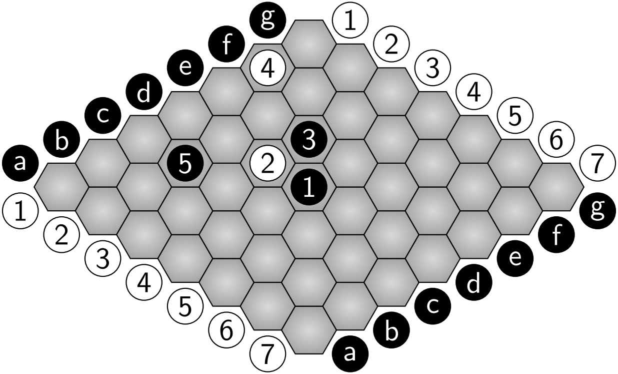

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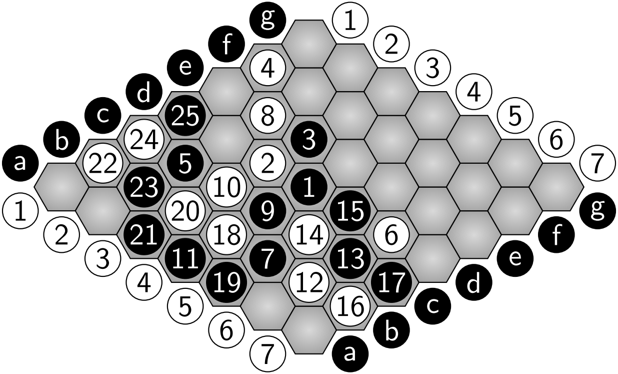


- Connect opposing sides
- Cut opponents connections

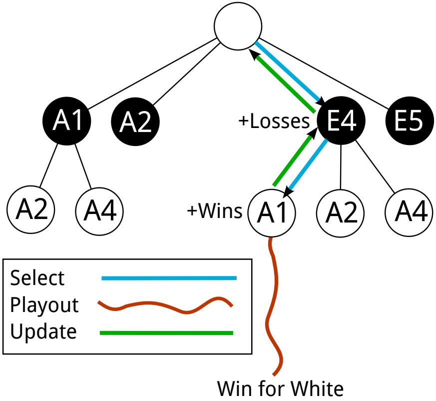
Tree Search

- Game tree grows exponentially
  - Hex on a general board is PSPACE-complete
- No effective position evaluation heuristic
  - *Six*, previous champion until 2006, used circuit simulation
- Limited opportunities for provable pruning
  - *MoHex*, current champion, does lots of this

Monte Carlo Tree Search

- Grow tree dynamically
- Use random playouts to estimate minimax value
- In the limit, converges to true minimax value
- Simple idea, remarkably successful
- Computationally expensive

Monte Carlo Tree Search - Overview

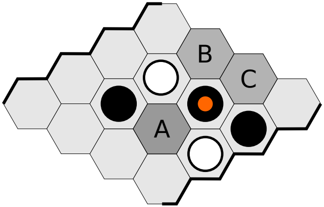


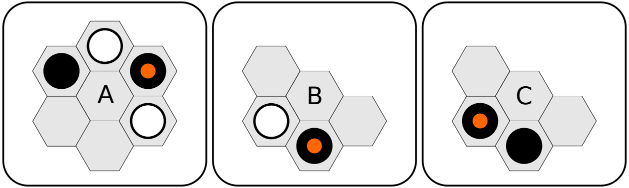
- *Select* - using win/loss statistics, traverse tree to a leaf
- **Playout** - from selected position, *randomly* play out game until final position
- *Update* - using results of playout, update win/loss statistics

Monte Carlo Tree Search - Playout Policies

- Playout policy a critical part of overall performance
- We examine 4 different policies:
  - Default - uniform random
  - Uniform Local - play in local neighborhood first
  - Uniform Local with Tenuki (Play-Away) - possibly play in local neighborhood first
  - Local Pattern Weighted - stochastic, weighted local neighborhood

Weighting the Playout Policy

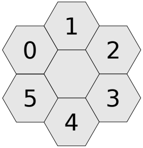


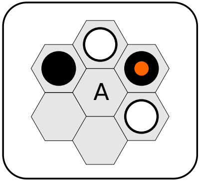


weight=6 weight=2 weight=0.1

- Use patterns to weight moves
- Weight moves local to last-played move
- If local area is filled, use default policy

Example Encoding





Encoding

Empty: 00
Black: 01
White: 10
Off: 11

vertex:	color	n/a	5	4	3	2	1	0
	1	...	00	00	10	01	10	01
bit:	31	12-30	10-11	8-9	6-7	4-5	2-3	0-1

0b00000000000000000000000010011001 = 102

- Fast lookup table mapping pattern to weight
- Plenty of unused space in upper bits for storing extra info

Monte Carlo Tree Search - Playout Policy

- Execution time is critical
- Requires deep insight to develop weights, then careful and expensive testing to verify improvement
- Naively "improving" the strength of the playout policy can hurt overall performance
  - Subtle interaction between selection, update, and playout
  - Example: fully deterministic policy equivalent to an evaluation function
- We want a technique to learn weights automatically

Evolutionary Learning

- Idea: Evolve playout policy
- Policy = set of all possible local patterns + weights for those patterns
- Individual policies compete via self-play to propagate
- Best individuals are selected for reproduction
- Mutation/recombination operates on individual's pattern weights
- Individuals play *complete* games against each other using *complete* MCTS system

Evolution

- Init
  1. Generate n individuals (population)
- Each Generation
  1. Evaluate fitness
  2. Rank by fitness
  3. Select top c individuals, $c < n$
  4. Recombine individuals into n new children
  5. Mutate children

Results of learning after training on 7x7

Figure: Trained on 7x7 board

	opponent		
player	default	uniform local	uniform local (tenuki)
uniform local	70.50%		
uniform local (tenuki)	61.00%	50.00%	
learned	90.00%	84.00%	86.00%

- All-play-all tournament of the 4 policy variants.
- Each element is the percent win-rate of the row variant versus the column variant.
- 200 games per pair.

Generalization to Different Board Sizes

	default		uniform local	
	11x11	13x13	11x11	13x13
learned	92.5 %	94 %	88.5%	85%

Figure: Trained on 7x7 board

	default	uniform local
learned	90.00%	84.00%

Results versus MoHex

	MoHex on 7x7
default	11.75%
uniform local	26%
learned	42%

	MoHex on 11x11	Relative CPU
default	0.5%	100%
uniform local	0.0%	107%
learned	11%	122%

- MoHex, the current world-champion, uses lots of expert and domain-specific knowledge
- Good results on small board
- Dramatic improvement for modest overhead

Conclusion

- Computer Hex/Go present a huge problem space
- MCTS is an effective technique to navigate that space
- Shown we can automatically learn to guide MCTS to play computer Hex better
- Future work - apply results to different games
- Source code available at `https://github.com/etherealmachine/hivemind`

Conclusion

Thank you for the time
Questions?