

# Game Algorithms

## Go and MCTS

Petr Baudiš, 2013

# ***Outline***

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- What is Go and why is it interesting
- Possible approaches to solving Go
- Monte Carlo and UCT
- Enhancing the MC simulations
- Enhancing the tree search
- Automatic pattern extraction
- Unsolved problems

# ***What is Go***

History

Concepts

Rules

Basic Tactics



# ***The Go Board Game***

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- Go / Igo / Goe / Baduk / Wei-Qi
- ~3000 years old - the oldest board game
- Very simple rules, very high complexity
- Wide-spread in China, Korea, Japan
- Rich culture surrounds the game
- <http://senseis.xmp.net/>

# ***Go: Basic Concepts***

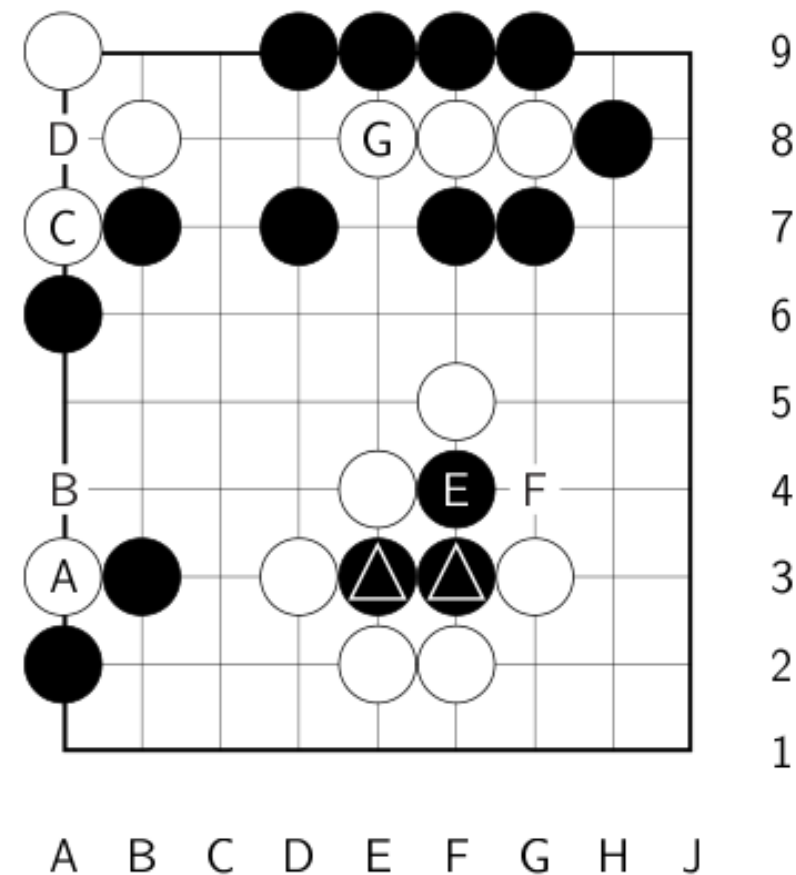
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- Square board with 19x19 intersections
  - Small board variation with 9x9
- Black and white players alternate in placing stones on the intersections
- Stones do not move; they can be removed if completely surrounded
- Players surround territory and capture enemy stones



# Go: Capturing Stones

- Directly connected stones == *group*
- #of unoccupied intersections around group == *liberties*
- When group has no liberties, it is removed from board
- Removed group: *capture*; single lib.: *atari*
- Ko rule - later



# ***Go: Tromp-Taylor Rules***

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- Players place stones alternately
- If the board is filled, players play “pass”
- The player controlling more intersections wins
- *Eye*: empty places completely surrounded by stones of one color
- Controlling intersection: Either occupied by a stone, or an eye of given color
- *Komi*: Point bonus for white

# ***Go: Other Rulesets***

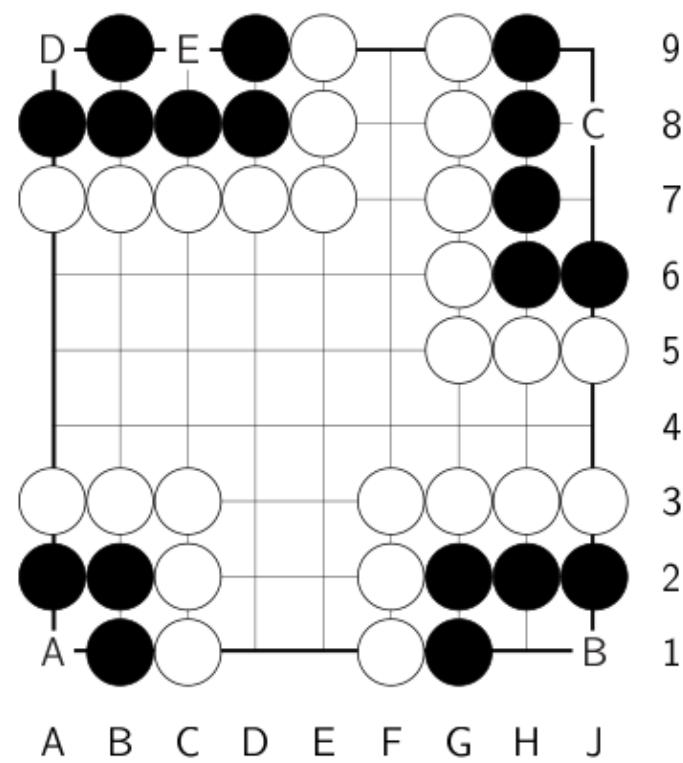
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- Many Go rulesets: Tromp-Taylor, Chinese, Japanese, ...
- *Tromp-Taylor*: Formal, terse, easy for computers
- *Japanese*: Easier for humans, most common, hard for computers; slightly different counting
- All rulesets are equivalent or 1pt-equivalent in common situations



# Go: Life and Death

- So much for the rules; now basic tactics!
- Group is *alive*: Can form *two eyes*
- Group is *dead*: Can be always captured locally
- Group is *in seki*: Cannot form two eyes, but opponent cannot capture it
- *Semeai*: Capturing race between two groups



# ***Go: Tactical Concepts***

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- *Semeai*: Capturing race between two groups, the one which captures first also kills the other
- *Ladder*: Player keeps escaping, but opponent always plays atari and eventually captures
  - Extremely long move sequence, but easy even for beginners to read
- *Net*: Player plays a distant move preventing enemy group from escaping

# ***Go: The Ko Rule***

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- *Ko*: The same board position cannot repeat in single game
- To re-take ko: Play a *ko threat* elsewhere on the board
  - Opponent replies and ko can be re-taken
  - Opponent connects ko and you can follow up on the threat
- Group is \* *in ko*: Goal can be achieved if player wins a ko fight

# ***Go: Strategic Concepts***

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- *Territory*: Empty area where opponent cannot make live group anymore
- *Moyo*: Territorial framework part of which can be still reduced by the opponent (at the cost of turning the rest to territory)
- *Influence*: Using hard-to-kill group to attack weak group of the opponent

# ***Ranking in Go***

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- Several rating systems
- We will use KGS server ranking system:
  - 30kyu ... absolute beginner
  - 15kyu ... average beginner after 4 weeks
  - 5kyu – 1kyu ... intermediate player
  - 1dan – 9dan ... advanced to expert ama.
  - 1pro – 9pro ... professional player
- Handicaps based on rank difference



# ***Solving Go***

	A	B	C	D	E	F	G	H	J	K	L	M	N	O	P	Q	R	S	T	
19	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	19
18	.	.	0	.	0	0	.	.	.	.	.	0	0	X	.	.	.	.	.	18
17	.	X	0	0	X	0	.	.	0	.	0	.	X	.	.	.	.	.	.	17
16	X	X	X	X	X	0	X	X	.	+	.	.	X	.	X	+	X	.	.	16
15	.	X	0	.	0	X	.	.	.	0	0	0	X	.	.	.	.	.	.	15
14	0	0	0	.	0	X	.	X	.	0	X	0	0	X	X	.	.	.	.	14
13	.	X	.	.	0	.	.	.	X	X	X	X	X	0	X	.	.	.	.	13
12	.	X	X	.	.	0	0	.	.	X	.	.	0	0	.	X	.	.	.	12
11	X	0	.	.	X	.	0	.	X	0	0	.	.	0	.	0	X	.	.	11
10	.	X	X	+	X	.	.	0	0	X(X)	.	.	0	.	0	X	.	.	.	10
9	.	X	0	0	.	X	X	.	.	X	.	0	.	0	X	0	X	.	.	9
8	.	0	.	0	.	X	.	.	0	0	0	.	0	.	X	X	.	X	.	8
7	.	0	0	0	.	.	.	X	0	X	0	.	.	.	.	.	.	.	X	7
6	.	.	.	.	X	.	X	.	.	X	0	.	X	.	X	X	X	X	0	6
5	.	.	.	.	.	.	X	0	0	0	X	X	.	X	0	.	0	0	0	5
4	.	.	0	+	0	.	X	X	.	0	0	0	0	X	0	+	0	X	.	4
3	.	.	.	.	.	0	0	X	X	.	.	.	X	.	X	X	0	.	0	3
2	.	.	.	.	.	0	.	0	X	X	.	X	.	.	.	X	0	.	0	2
1	.	.	.	.	.	0	.	0	.	.	.	.	.	.	.	X	X	0	.	1
	A	B	C	D	E	F	G	H	J	K	L	M	N	O	P	Q	R	S	T	

The Problem

Special Sub-Problems

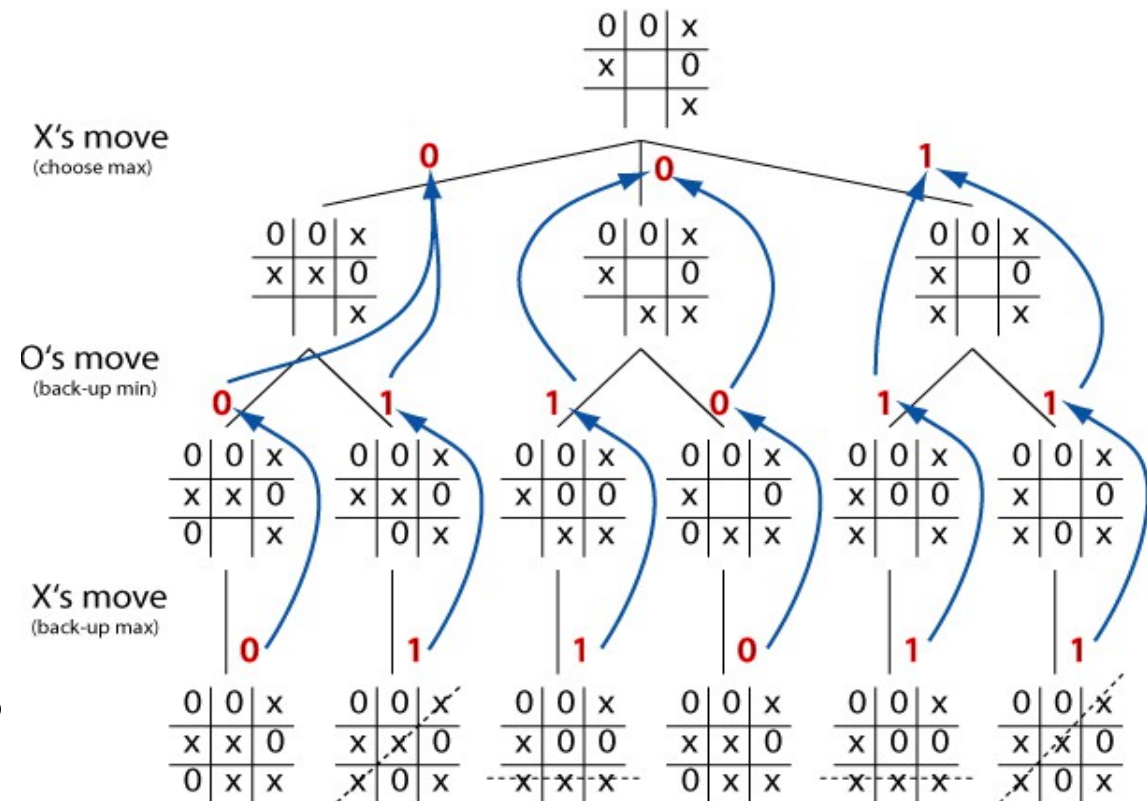
Possible Approaches

Classic Solutions

# Programming Game Solvers

- Move combinations in “game tree”
- Leaves assessed by “evaluation function”
- “Minimax” decision
- Heuristics:

- pruning branches
- evaluation order
- transpositions



# ***What's So Hard?***

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- Extreme branching factor
  - Chess:  $10^{126}$ ; Go:  $10^{360}$
  - Transposition tables are ineffective
- Evaluation function is difficult
  - Has to take into account changing status of stones
  - Influence, territory-moyo hard to assess
- Pruning branches is difficult
  - Universal pruning function hard to find

# ***Specialized Sub-Problems***

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- Playing perfect late endgame (Berlekamp,1994)
  - Combinatorial Game Theory, performs better than professional players
  - Does not scale before last few moves
- Solving tsumego problems
  - Small board sub-section, short sequence
  - Best solvers can find the move in few seconds (Wolf, 2007)



# ***How To Do It?***

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- alpha,beta search + hand-coded patterns
  - GNUGO, weaker MFoG, ~6kyu
- Neural networks, pure (auto-gen.) patterns
  - Unsuccessful in general (~15-20kyu?)  
(Ezenberger, 1996)
- Monte Carlo, Monte Carlo Tree Search
  - Most modern bots, on commodity HW  
up to ~6dan (on 9x9, up to 9dan)



# ***Classic Approach***

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- GNUGO – complex classic knowledge, many hand-coded patterns, alpha,beta search
  - Very useful test opponent for MC bots
- Frequently misses moves – overpruning
  - Causes major tactical mistakes
- Drastic misjudgements of group status
- Points-greedy move choice (cannot adjust style for disparate situation)
- Strength does not scale with time

# ***Monte Carlo and UCT***

Monte Carlo Approach  
Multi-armed Bandits  
Upper Confidence Trees



# ***Monte Carlo Go***

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- Basic idea: evaluate a position by playing many random games (simulations) and averaging the outcome
- Primitive: Run N simulations for each valid move, pick the one with best value (reward)  
(Bruegmann, 1993)

# ***Monte Carlo Go***

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- Basic idea: evaluate a position by playing many random games (simulations) and averaging the outcome
- Primitive: Run N simulations for each valid move, pick the one with best value (reward) (Bruegmann, 1993)
- Outcome coding:
  - points\_difference: too unstable
  - 0,1 (loss,win): usual approach
  - 0.01 for pts difference is slight bonus

# ***Monte Carlo Tree Search***

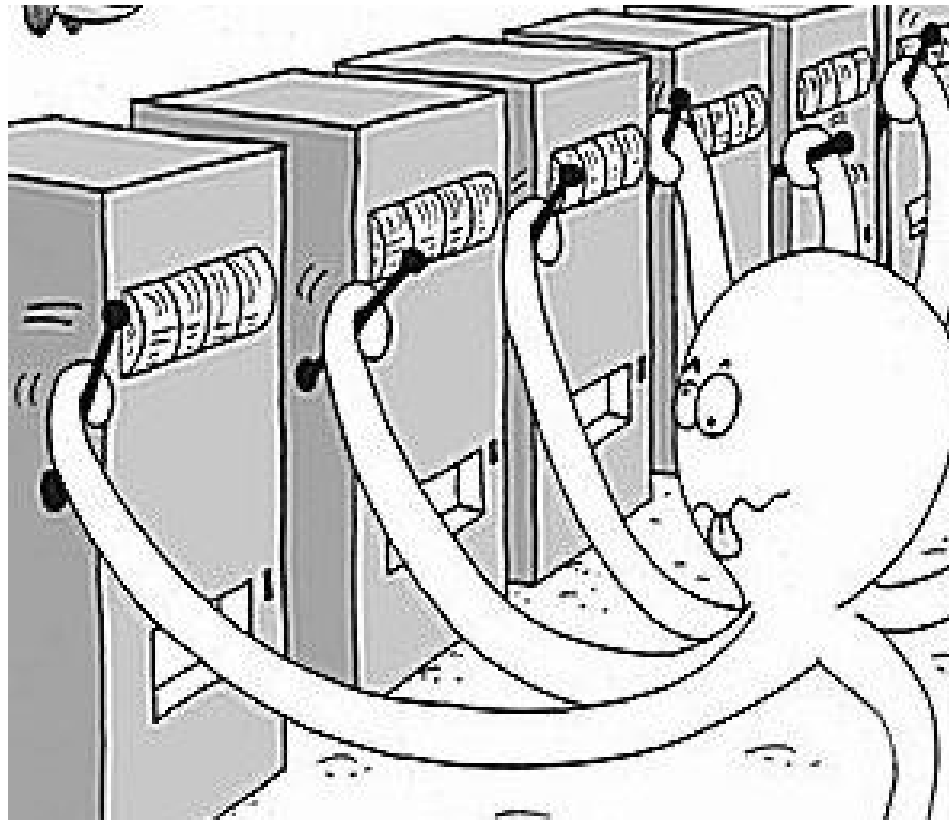
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- Primitive MC cannot converge to best result
  - Does not discover forced sequences
- Tree Search: Explore best replies of best replies of best replies of best moves... (minimax tree)
- Exploration vs exploitation:
  - Focus simulations on the best candidates
  - Make sure we know which are the best



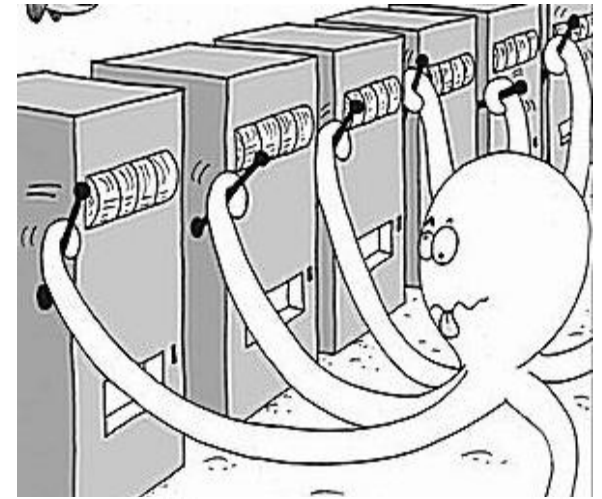
# ***Multi-armed Bandit***

- => **Multi-armed bandit**



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- => **Multi-armed bandit**
- Each node has *urgency* based on value and exploration desire
- **Urgency policy:** Minimize *regret* – expected total loss of selecting suboptimal nodes



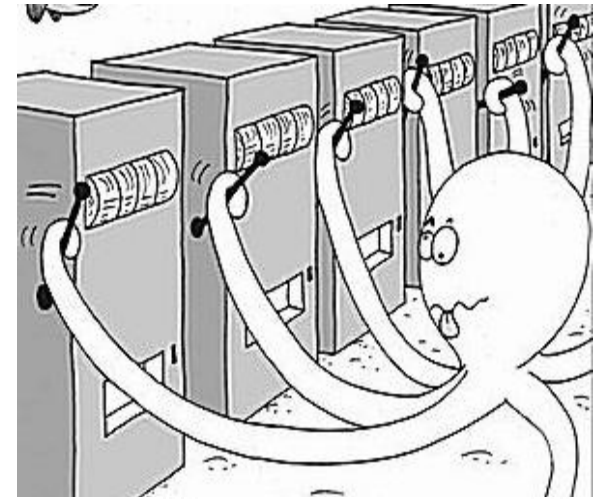
$$\mu_i = \mathbb{E} \left[ \frac{1}{T_i(n)} \sum_{t=1}^{T_i(n)} X_{it} \right]$$

$$\mu^* = \max_i \mu_i$$

$$R_n = n\mu^* - \sum_{i=1}^K \mathbb{E}[T_i(n)] \mu_i$$

# Multi-armed Bandit

- => **Multi-armed bandit**
- Each node has *urgency* based on value and exploration desire
- **Urgency policy:** Minimize *regret* – expected total loss of selecting suboptimal nodes
- Several approaches:  $\epsilon$ -greedy, upper confidence bounds



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$$\mu^* = \max_i \mu_i$$

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# Upper Confidence Bound

- $urgency = value + bias$
- $value = expectation = wins / simulations$
- $bias = UCB1$  (Auer, 2002)  
upper bound on possible value  $\sqrt{c \frac{\ln(n_0)}{n}}$

$$\pi_{UCB1}(n) = \operatorname{argmax}_i \left( \mu_i + c \sqrt{\frac{2 \ln n}{T_i(n)}} \right)$$

- $c$  is parameter; best for random Go  $\sim 0.2$
- **Optimistic** strategy – try most *promising* node



# UCB1 Hardcore

(supplementary slide)

- (Lai & Robbins, 1985) #tries bound:

$$E[T_j(n)] \geq \frac{\ln(n)}{D(p_j \| p^*)}$$

- $D(P|Q)$  – Kullback-Leibler divergence

$$D(p_i \| p^*) = \int p_i \ln \left( \frac{p_i}{p^*} \right)$$

- In good policies, the optimal node is selected exponentially more often than any other, i.e. asymptotically logarithmic regret
- UCB1: uniformly logarithmic regret!



# ***Upper Confidence Tree***

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- Minimax tree with UCB-based urgencies (Kocsis & Szepesvari, 2006)
- Leaf node: MC simulation, expand after  $k$  visits
- Converges – given unlimited time, will find optimal solution
- Online algorithm – can be stopped anytime and give meaningful result

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- Leaf node: MC simulation, expand after  $k$  visits
- Converges – given unlimited time, will find optimal solution
- Online algorithm – can be stopped anytime and give meaningful result
  - Final move selection: node with highest #simulations

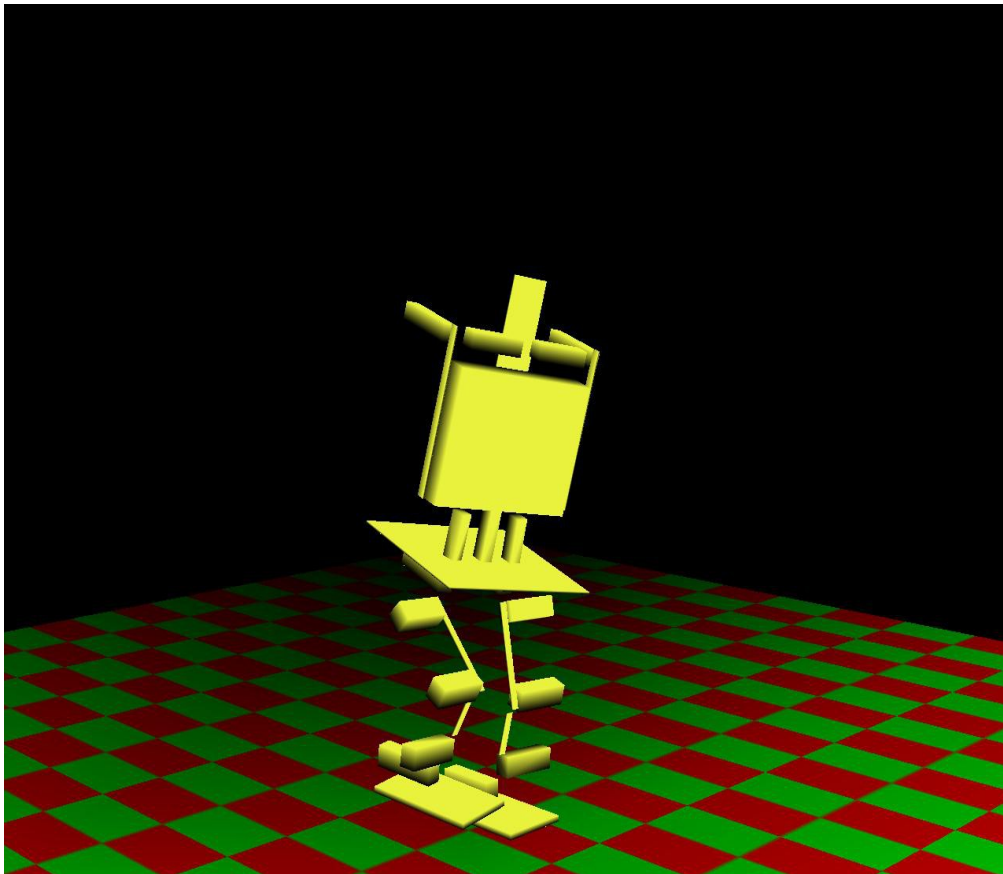
# ***MCTS: Other Applications***

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- General planning tasks with large search space and stochastic evaluation function
- Other games (Poker, Amazons, Arima, ...)
- Robot online task planning
- Sailing “auto-navigator”
- Etc. etc.

# ***Better Simulations***

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Basic Implementation

Trivial Heuristics

Local Patterns

Caveats!

# ***Uniformly Random...***

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- In each move, pick a random element from the set of legal moves \ pass
- Never fill single-point eyes
- **Common termination rule:**
  - Pass only if no valid move remains
  - => Easy + fast counting
  - Mercy rule



# ***Playout Requirements***

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- **Speed** – more simulations mean deeper tree and more accurate values
  - Small board, light playouts: Tens of thousands playouts per second
  - Large board, heavy playouts:  $\sim 2000$  pPs
- **Plausibility** – situations should be resolved like in a real game

**X**

- **Balance** – all reasonable results should have the chance to appear in playouts (**x** policy drift)

# ***Simple Heuristics***

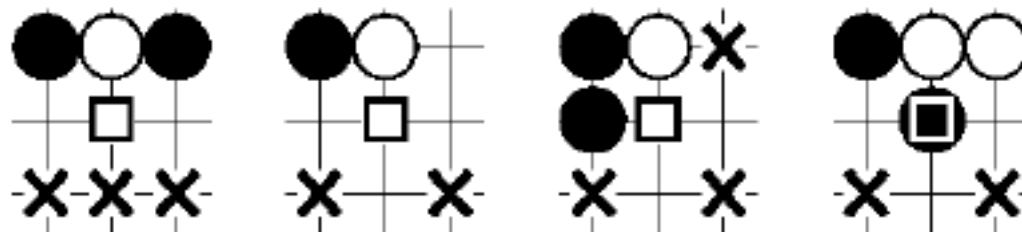
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- Hard to find heuristics that don't fail often
- Capture stones in atari vs. escape with stones in atari (possibly detect ladders)
  - Except when the stones cannot escape
- Do not self-atari – *but sometimes do!*
  - Putting large group in atari instead of connecting is bad
  - Self-atari of your stones in opponent's dead eyespace is necessary
- 2-liberty tactics similar to atari tactics

# 3x3 Patterns

- ~10 wildcard 3x3 patterns centered at the candidate move (Gelly, 2006)
- Check only around last move; play on match
- => Produces "nice" local sequences
- 3x3 patterns = 16bit numbers => Very fast
- Optional: atari info in four directions (+4 bits)

appendix 5



# ***Balanced Patterns***

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- Stronger playout is not better playout!
  - Imbalance => consistently biased assessment of position, UCT misbehaves
- Fresh approach – machine learning of patterns based on playout balance, not strength
  - (Silver, 2009) Don't minimize *error* but *expected error* – error over multiple moves in row (small mistakes cancel)
  - (Huang, 2010) Works on 19x19 too



# ***Better Tree Search***

Prior Node Values  
All Moves As First  
Rapid Action EValuation  
Criticality  
Dynamic komi  
Multithreaded Search  
Time Management





# ***Fresh Nodes***

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- UCT: Play each node once first – too ineffective
- **First Play Urgency:** Initialize *urgency* with fixed value ( $\sim 1.2$ ), start UCB-selecting nodes
- “Progressive widening”, initialize *value* heuristically
- “Progressive unpruning”, rank nodes heuristically, consider only  $f(n)$  best nodes

# ***Prior Values***

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- **Priors:**
  - Playout policy hinting – capture, atari, 3x3 patterns, eye filling
  - Distance from the board border
  - CFG distance from the last move
  - Smart static evaluation function

# ***Common Fate Graph***

(Graepel, 2001)

- Intersections: vertices, lines: edges
- Edges between same color:  $d=0$ , others:  $d=1$
- CFG distance: the shortest path in CFG
  - Useful for the concept of “tactical locality”
  - Takes into account all moves affecting local groups

# ***All Moves As First***

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- UCT converges very slowly, especially on large boards – no information sharing
- Idea: Find out and prefer moves that give good performance in all games (Bruegmann, 1993)
- *UCT value of  $M$* : Winrate of games starting by  $M$
- *AMAF value of  $M$* : Winrate of games where we played  $M$  anytime in the rest of the game(!)
- Moves in-tree and in most of the playout are considered (late moves cut, or weighting)

# ***Rapid Action Evaluation***

- How to incorporate AMAF in the node value?  
(Gelly & Silver, 2007)

- $value = \beta \times amafval + (1-\beta) \times uctval$

$$\beta = amafsims \times \left( amafsims + uctsims + \frac{amafsims \times uctsims}{r} \right)^{-1}$$

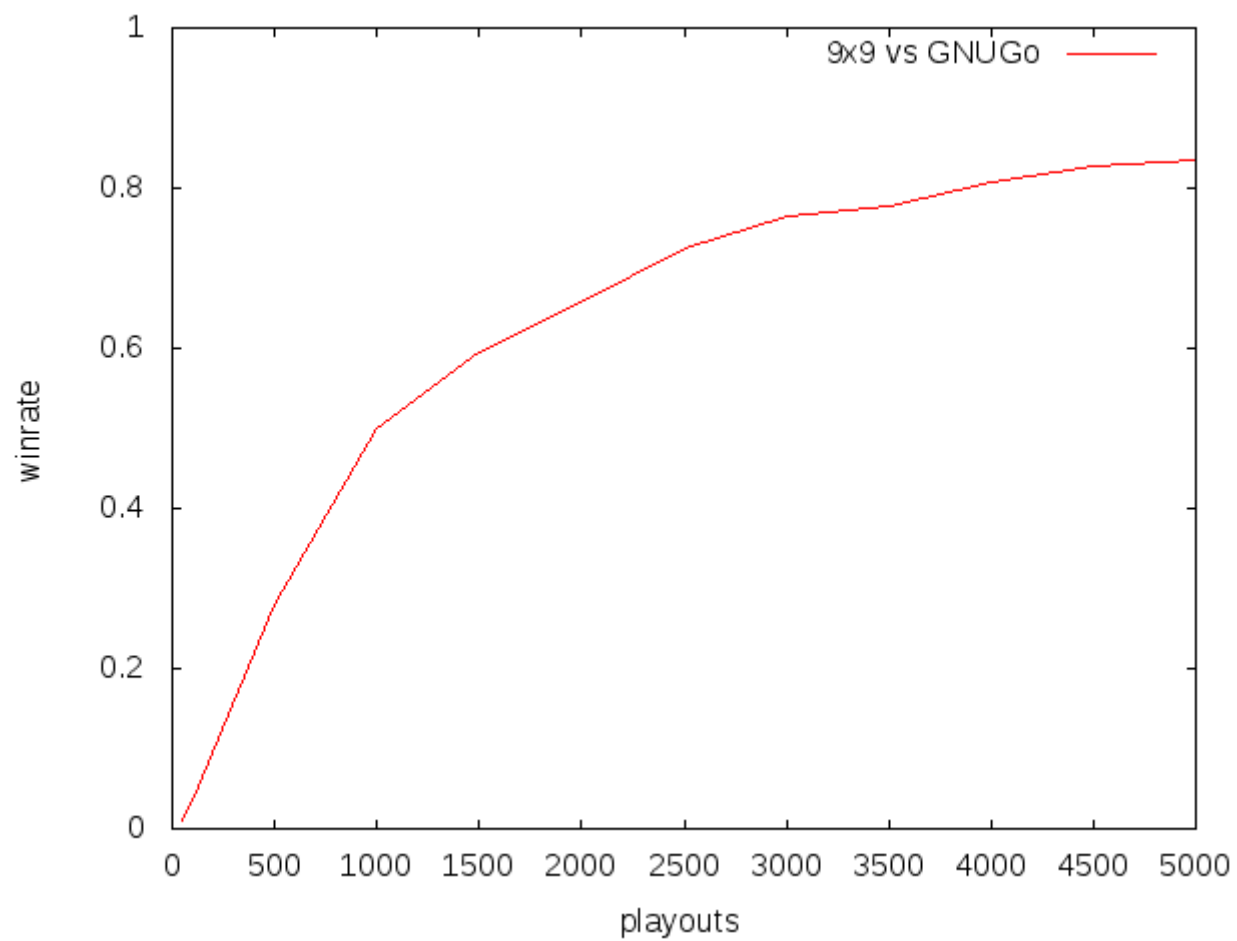
- With small  $uctsims$ ,  $\beta \sim 1$ , but goes  $\rightarrow 0$
- $r$ : RAVE weight (“equivalence”) parameter, e.g.  $\sim 3000$



# ***RAVE Aftermath***

- **Key result** in MCTS Go, making it stronger than the classical engines:
  - $\sim 30\%$  UCT  $\rightarrow 70\%$  UCT-RAVE
- Good playout policy is crucial for good AMAF!
- Priors: *amafval* vs *uctval* – small difference
  - Important new prior: “Even game”  $p=0.5$  protects against inaccurate first results
- No exploration: Best results with  $c=0$  on  $19 \times 19$  ( $c \sim 0.005$  on  $9 \times 9$ ) – AMAF is sufficiently noisy

# ***RAVE Performance***



# Criticality

- (Coulom, 2009) Focus on places that are “key” for both players – owning the point is important for winning the game
- Similar to AMAF, but statistical covariance of winrates for *both* players

$$\frac{v(x)}{N} - \left( \frac{w(x)}{N} \frac{W}{N} + \frac{b(x)}{N} \frac{B}{N} \right)$$

- Small improvement (49% → 54%)

# ***Playing in Extreme Situations***

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- **Extreme situation:** The computer has either a huge advantage or a huge disadvantage
- Common in handicap games
- Black: **big advantage** – suboptimal moves, no account for difference in strength
- White: **big disadvantage** – the problem is not so visible and harder to solve
- Interpretation: Too low signal-noise ratio when the outlook is extreme

# ***Black in Handicap***

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- Linear dynamic komi, situational dynamic komi, artificial passes
- **Dynamic komi:** Before counting the final position in the simulation, subtract a certain amount of points from black score
- **Situational komi:** Adjust the komi to keep probabilities between  $\sim[0.4, 0.5]$ ; universal (not only handicap games),  $\sim 57\%$  self-play
  - Fixed step or avgscore-based step



# ***Linear Dynamic Komi***

- **Linear DK:** Calculate komi value  $K$  based on the handicap amount
- $K \approx -cH$  where  $c$  is point value of handi stone
  - $c=8$  (based on default komi value) seems optimal; non-linear scaling experiments discouraging
- Apply for first  $M$  moves:  $k = K(1-m/M)$
- $M=200$  works well on 19x19
- **Adaptive:** Keep winrate between 0.85 and 0.8

# Handicap Performance

(19x19 vs GNUGo level 10)

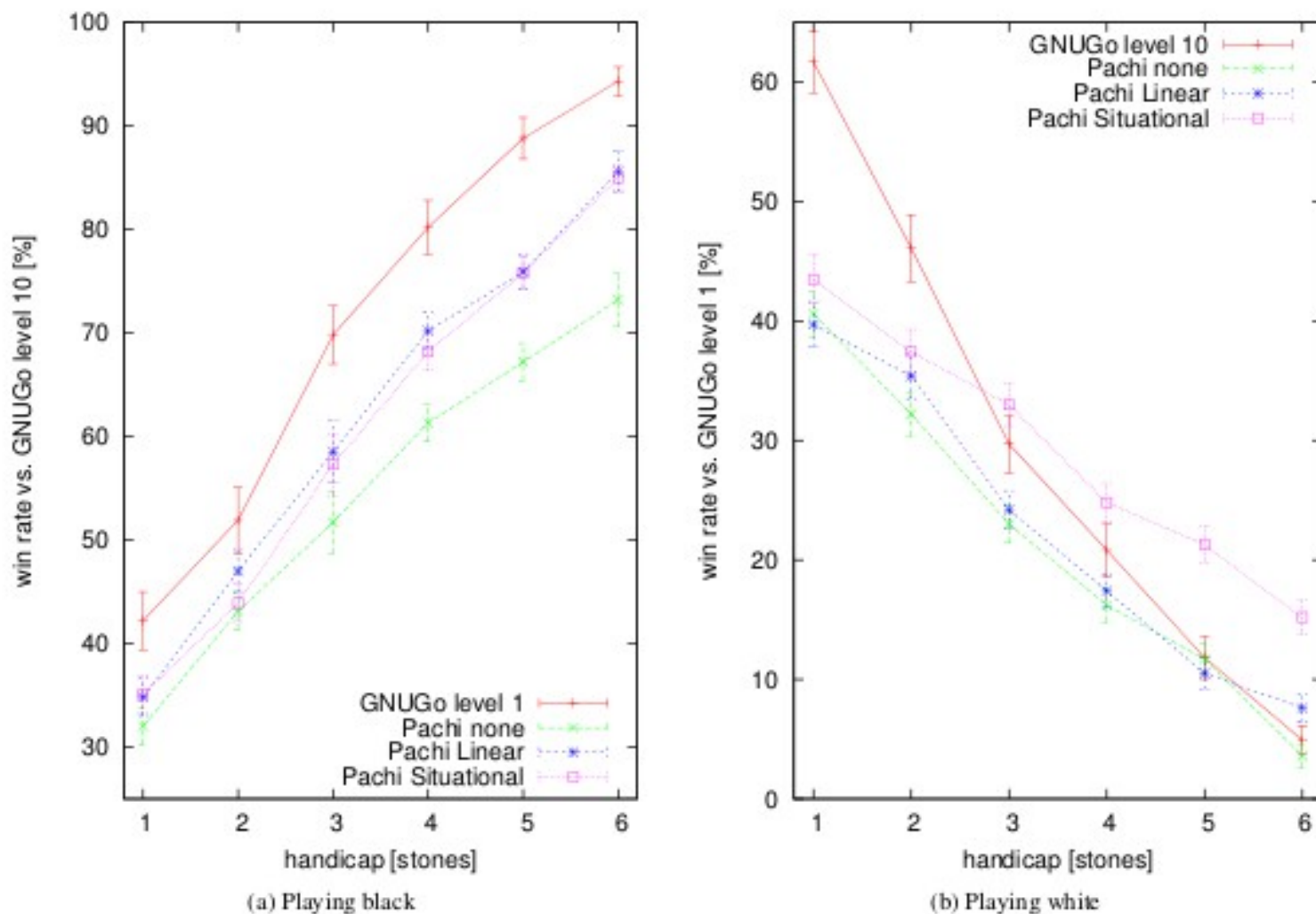


Figure 2: Dynamic komi in handicap games.

# ***Parallel MCTS***

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- **Root-level**
- **Leaf-level**
- **In-tree**

# ***Parallel MCTS***

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(Chaslot, 2008)

- **Root-level** – independent search in each thread, merge at the end
  - Threads “vote” on best move
  - Slight-to-medium improvement, does not seem to scale much
- **Leaf-level** – single thread searches, all threads play in parallel
  - More accurate node value
  - Small improvement, large overhead

# ***Parallel MCTS in-tree***

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- **In-tree** – all threads search in the same tree
  - No locking necessary if we are careful  
(Enzenberger, 2009)
  - Never delete nodes during search
  - Update values atomically
  - *Virtual loss* spreads exploration (add loss in descend, remove during update)



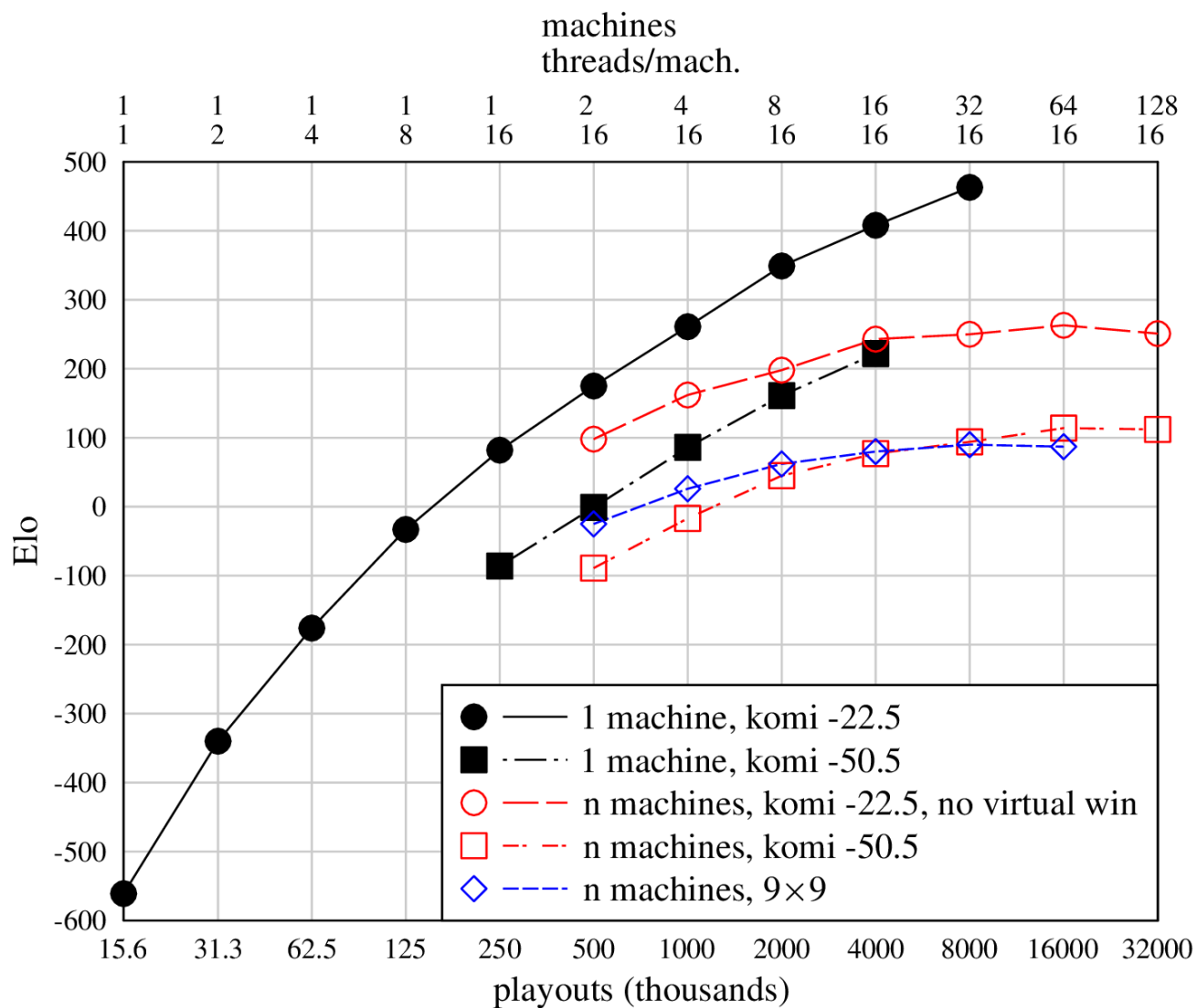
# ***Distributed MCTS***

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- **Distributed** – cluster of machines (nodes) with separate trees
- Independent searches + information exchange
- Information exchange = higher overhead
- Best: *Little* exchange, e.g. only single level
- Virtual wins (Baudiš and Gailly, 2011)

# Parallel Performance

## (19x19 vs Fuego)



# ***Time Management***

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- How to allocate time during the game?
- Main time, overtime  $n$  periods of  $m$  moves
- Pachi: *Default* and *maximal* time, unclear results imply overspending
- Allocate most time in the “middle game”



# ***Learning Patterns***

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Pattern Features  
ELO Pattern Ranking  
Storing Patterns  
Pattern Usage

# ***Pattern Usage***

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- Wildcard 3x3 centered patterns: see before
- Circular  $n$ -radius patterns – hash matching
- Arbitrarily shaped patterns: incremental decision trees
- Shape matching only
- Tactical goal matching
- Point owner matching
- Used both in playouts (simplified) and in priors (full features set)



# ***Zobrist Hashing***

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- Hashing board positions (Zobrist, 1990)

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- Hashing board positions (Zobrist, 1990)
- Initialization: Each point gets assigned random numbers  $b$ ,  $w$
- Position: XOR of  $b$  values for all black stones and  $w$  values for all white stones
- Good uniform distribution, reasonable hash size
- Incremental updates on move plays possible!

# ***Shape Patterns***

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- Represented as Zobrist hashes of the area
  - All rotations and color reversals
  - Matching can be incremental for multiple shape sizes
  - Lookup is very fast
- Extended board with special “edge color” - already common in fast board implementations

# ***Circular Shapes***

- ...on square grid?  
(Stern, 2006)
- Metric?

[illegible]

# ***Circular Shapes***

- ...on square grid?  
(Stern, 2006)
- Metric:
$$d(x,y) = |dx| + |dy| + \max(|dx|, |dy|)$$
- Incrementally matched nested circles
- Commonly used

[illegible]



# ***Arbitrary Shapes***

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- Hard to recognize and harvest automatically, useful mostly for expert patterns
- Use probably uncommon

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---

- Hard to recognize and harvest automatically, useful mostly for expert patterns
- Use probably uncommon
- Proposed method: Incremental Patricia trees (Boon, 2009)
  - Build a decision tree (node-per-intersection) from the patterns
  - For each intersection, store nodes from decision trees
  - When the point changes, re-walk branch

# ***Pattern Features***

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- For each candidate move, a pattern is matched:
- Shape – as just described
- Capture, atari, selfatari, liberty counts, ko...  
(van der Werf, 2002)
- Distance to the last, next-to-last move
  - CFG distance or circular distance
- Monte Carlo owner – portion of simulations where I am point owner at the game end
- Each feature can have its zobrist hash

# ***Elo Ratings***

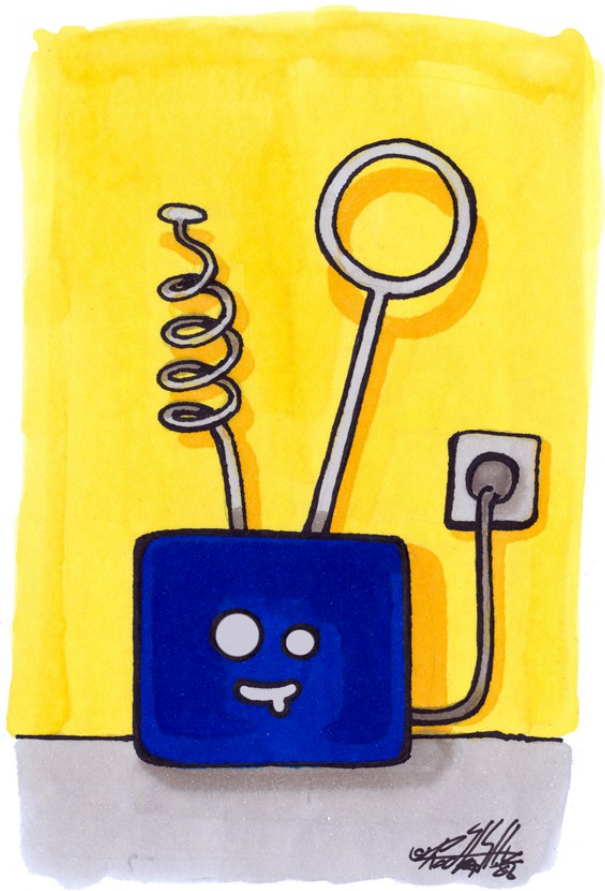
- Elo: Putting competitive strength of many individuals on a single scale (Elo, 1978)
- Used in Chess and Go to rate players strength
- Based on **Bradley-Terry model**:
  - Each individual has *strength*  $\gamma$
  - $P(i \text{ beats } j) = \gamma_i / (\gamma_i + \gamma_j)$
- Works for competition of  $>2$  players too
- Works for teams:  $\gamma_1\gamma_3 / (\gamma_1\gamma_2\gamma_3 + \gamma_1\gamma_2 + \gamma_1\gamma_3)$
- Makes rather strong assumptions

# ***Elo Patterns***

- **Key result:** 38.2% → 90% (Coulom, 2007)
- Consider *teams of pattern features*, assign each feature its “strength”
  - capture=30, atari=1.7 self-atari=0.06
- Total strength of each intersection is product of the features strength
- Produces probability distribution over moves
- Use to choose the next move in playout; only easy features (e.g. shapes up to 3x3) are used
- Use to progressively unprune nodes



# ***Current Programs***



- Mogo – UCT pioneer
- CrazyStones – Elo
- ManyFaces – UCT+classic
- Zen – Elo reimplemented?
- Erica – Elo + Balancing

Opensource UCT:

- Fuego – complex, general
- **Pachi** – simple, Go focus

# ***Current Strength***

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- WCCI 2010 Barcelona
- @9x9: MoGoTW -9p, **+9p**; MoGo -4p, -4p;  
Fuego -4p, **+4p**, -9p, -9p;  
Zen **+6d**, **+6d**, -6d, **+6d**
- @13x13H2: MoGo **+6d**, **+6d**; Fuego -6d, -6d;  
MFoG -6d, **+6d**
- @19x19: Zen -9p@H7, **+4p**@H6;  
MFoG -4p@H6, -9p@H7
- <http://wcci2010.nutn.edu.tw/result.htm>
- MoGo: 15x8c, BlueFuego: 112c w/ shared mem.

# ***Pachi***

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- Densely-commented C code, about 17k LOC
- Modular architecture for play engines (random, playout, MonteCarlo, UCT)
- Modular architecture for UCT policies (UCB1, UCB1AMAF/RAVE)
- Modular architecture for playout policies (random, “Moggy”, probability distribution)
- Modular dynamic komi policy, priors, etc.
- **Autotest** – generic UNIX framework for testing of stochastic engines performance



# ***Unsolved Problems***

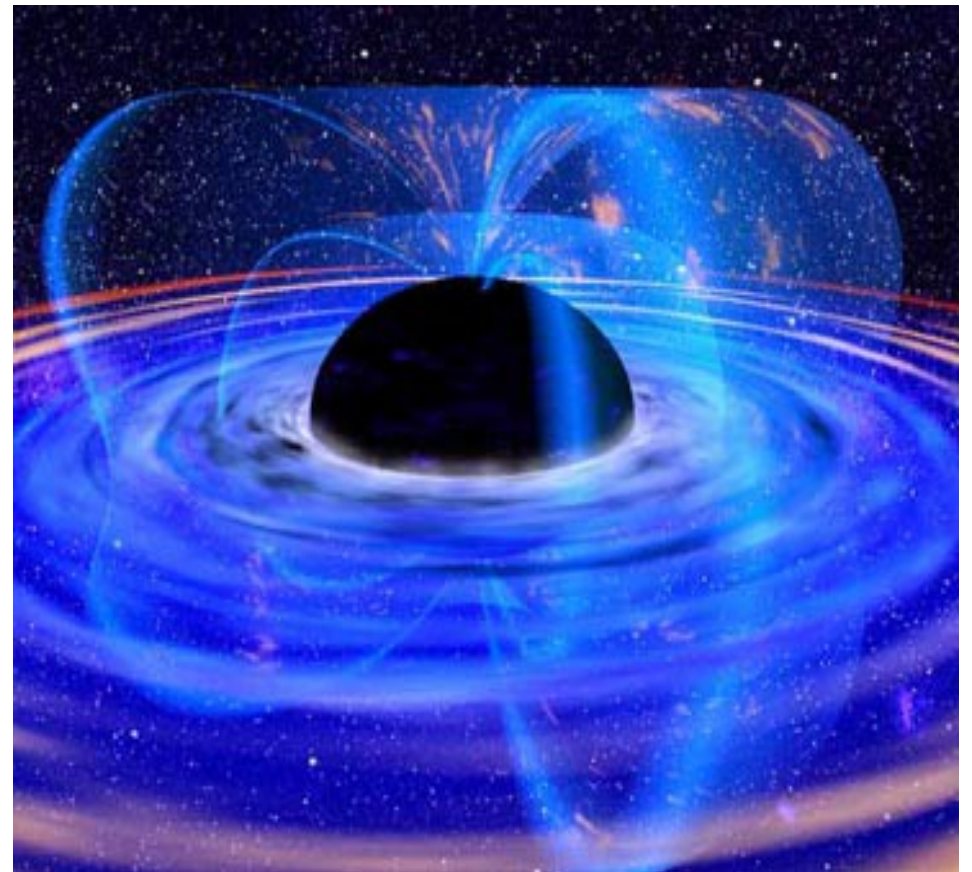
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Narrow sequences

HPC implementation

Aesthetically  
pleasing play

Abstract understanding  
of the board



# ***Narrow Sequences***

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- The most visible and probably most important current issue
- UCT/RAVE bots miserably fail in most semeai situations, some classes of unsettled tsumego and sometimes even misread simple ladders
- RAVE gives single-level information, same problem as Monte Carlo vs UCT



# ***Narrow Sequences: The Problem***

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- General situation description: After one player's move  $X$ , the other player has one right reply  $Y^*$  (winrate converges) and many wrong replies  $\{Y^-\}$  (winrate diverges)
- All replies have equal simulation probability, giving player's move  $X$  too high winrate
- Thus, RAVE gives the move massive bias everywhere in the tree; tree quickly discovers  $Y^*$ , but this only pushes  $X$  down in tree

# ***Narrow Sequences: Solutions?***

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- Common: Enhance simulations to natively choose  $Y^*$  after  $X$  with high probability
  - Simulations must be fast, only static evaluation reasonably possible, case-by-case, tedious
- Prefer best local moves found by tree search in simulations?
- Pre-bias node values based on local sequences found in other tree branches?
- Preliminary results promising, still researching

# ***High Performance Computing***

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- Big clusters tried – Mogo on 900 cores etc.
- Mix of root and tree parallelization
- Scaling limits: overhead, limited information sharing
- GPGPU needs a lot of research, preliminary experiments not too encouraging
  - Game parallelization – playout / thread
  - Point parallelization – intersection / thread

# ***Aesthetically Pleasing Play***

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- Computers like to play “strange-looking” moves
- Unclear if solving these problems would improve win rate
- Playing opening moves very far from the edge
- Playing suboptimal moves at the game end when win is secured

# ***Abstract Understanding***

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- Useful since simulations cannot be deep enough to assess true values of some aspects
- E.g. solidness of territory and groups, thickness value, ko fights status, latent aji
- Maybe ManyFaces does it to a degree, no published results; can be obsoleted by narrow sequences solution
- Describe point/chain dynamics as polynomial system (nice prediction results, in research – **Wolf, 2009** preprint)



A faded background image showing two Go players, a man and a woman, sitting at a table and playing Go. The man is on the left, wearing a dark jacket, and the woman is on the right, wearing a dark jacket. They are both looking at the board. The board is a Go board with stones on it. The background is a light-colored wall.

# ***Thank you!***

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<http://pasky.or.cz/go/>

<http://senseis.xmp.net/>

<http://gokgs.com/>

<http://computer-go.org/>

<http://www.citeulike.org/group/5884/library>

Go player. How much Go player's last official game, his opponent being the class player. (Kobayashi)