Game Algorithms
Go and MCTS

Petr Baudiš, 2011

Outline

- 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

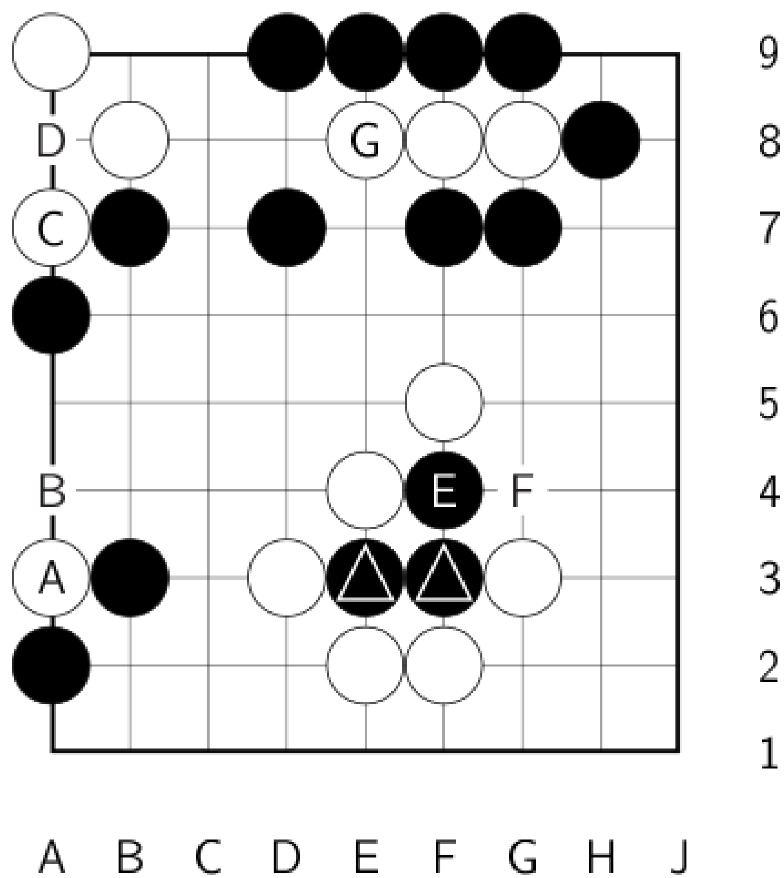
- Go / Igo / Goe / Baduk / Wei-Qi
- ~3000 years old - the oldest board game
- Very simple rules, very high complexity
- Wide-spread in China, Korea, Japan
- Rich culture surrounds the game
- http://senseis.xmp.net/

Go: Basic Concepts

- 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

- 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

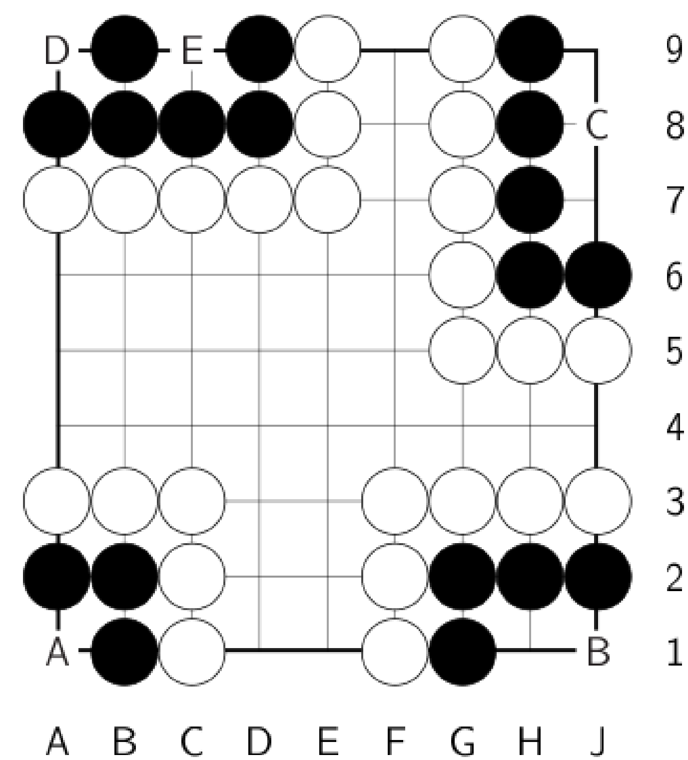
final position – appendix 4

Go: Other Rulesets

- 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

- *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

appendix 2

Go: The Ko Rule

- *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

- *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

appendix 3

Ranking in Go

- 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

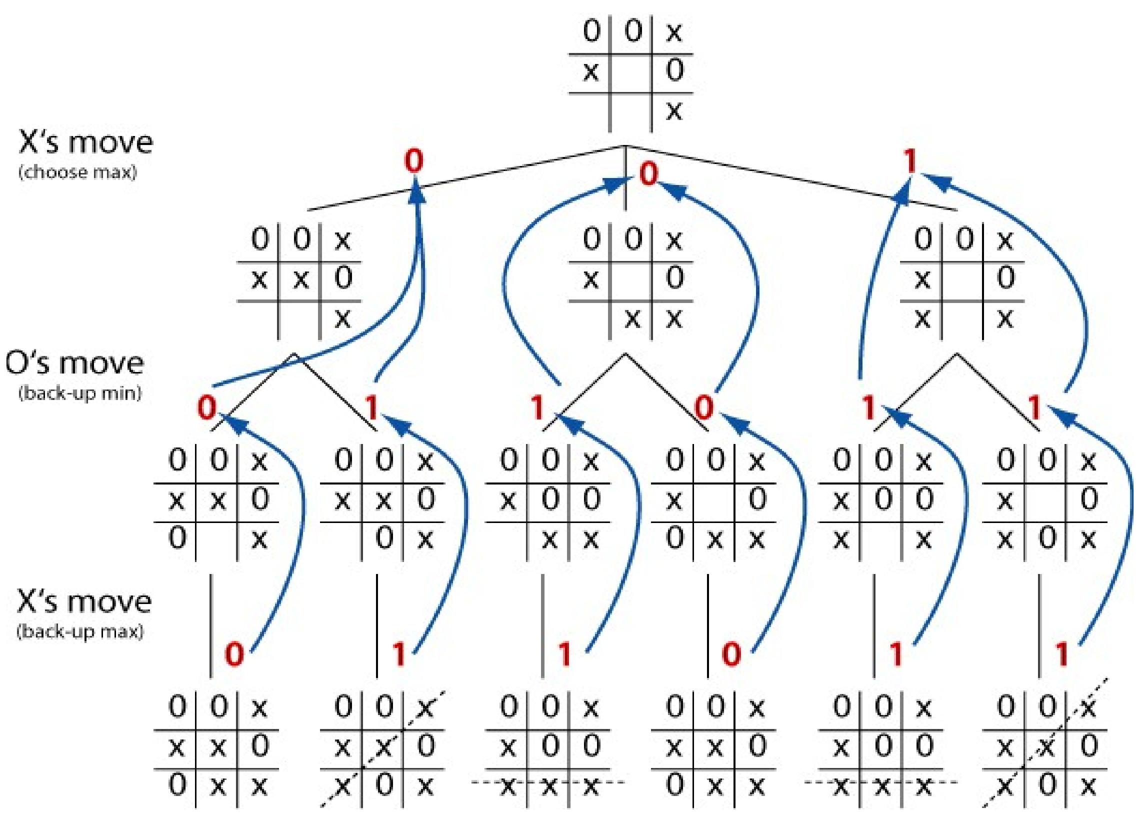
Special Sub-Problems

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?

- 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

- 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?

- 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 ~3-4dan (on 9x9, up to ~8dan?)

Classic Approach

- 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

- 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)

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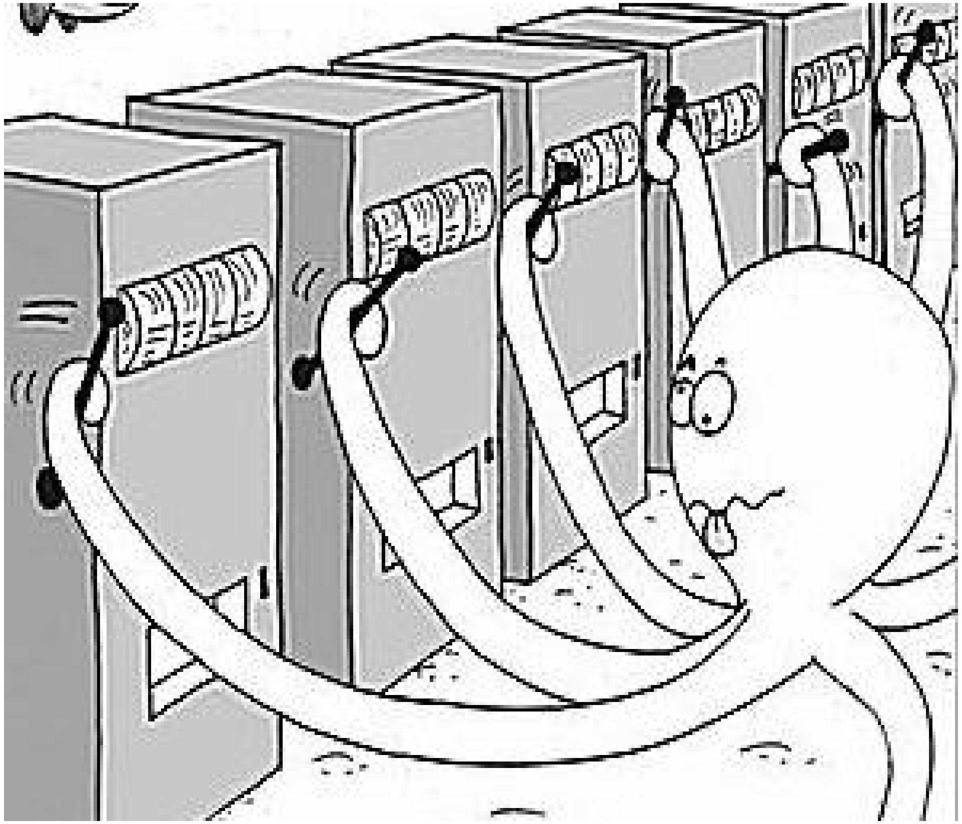
- Primitive: Run N simulations for each valid move, pick the one with best value (reward) (Bruegmann, 1993)
- Outcome coding:
  - points_difference: too unstable
  - 0,1 (loss,win): usual approach
  - 0.01 for pts difference is slight bonus

Monte Carlo Tree Search

- 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 replies of best moves... (minimax tree)
- Exploration vs exploitation:
  - Focus simulations on the best candidates
  - Make sure we know which are the best

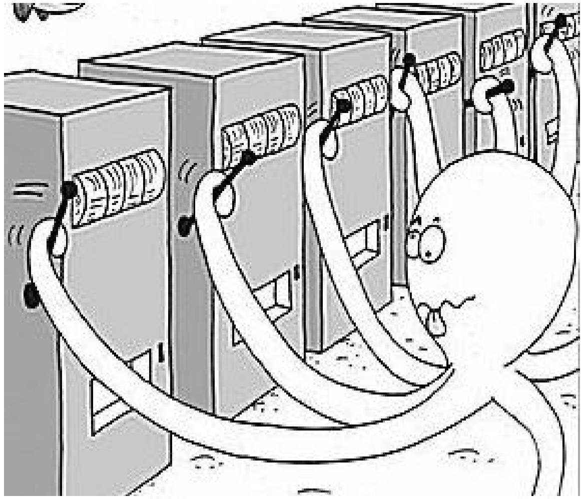
Multi-armed Bandit

- => Multi-armed bandit



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



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

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

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

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- Each node has *urgency* based on value and exploration desire
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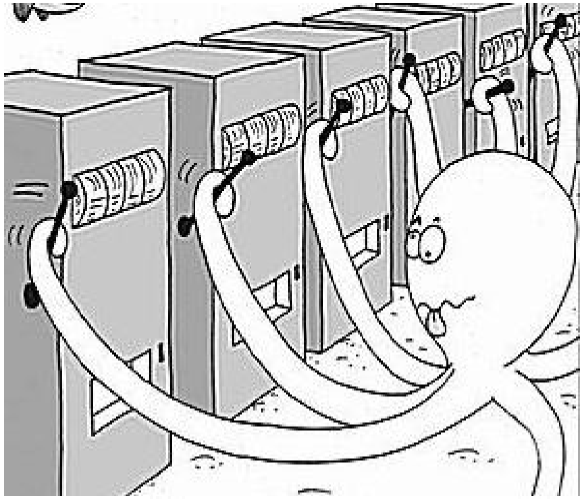
- Several approaches: ε-greedy, upper confidence bounds



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Upper Confidence Bound

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

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

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

UCB1 Hardcore

(supplementary slide)

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

$$E[T_j(n)] = \theta\left(\left(\frac{1}{D(p_j \| p)} + o(1)\right)\ln(n)\right)$$

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

$$D(P \| Q) = \int P \ln\left(\frac{P}{Q}\right)$$

- 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

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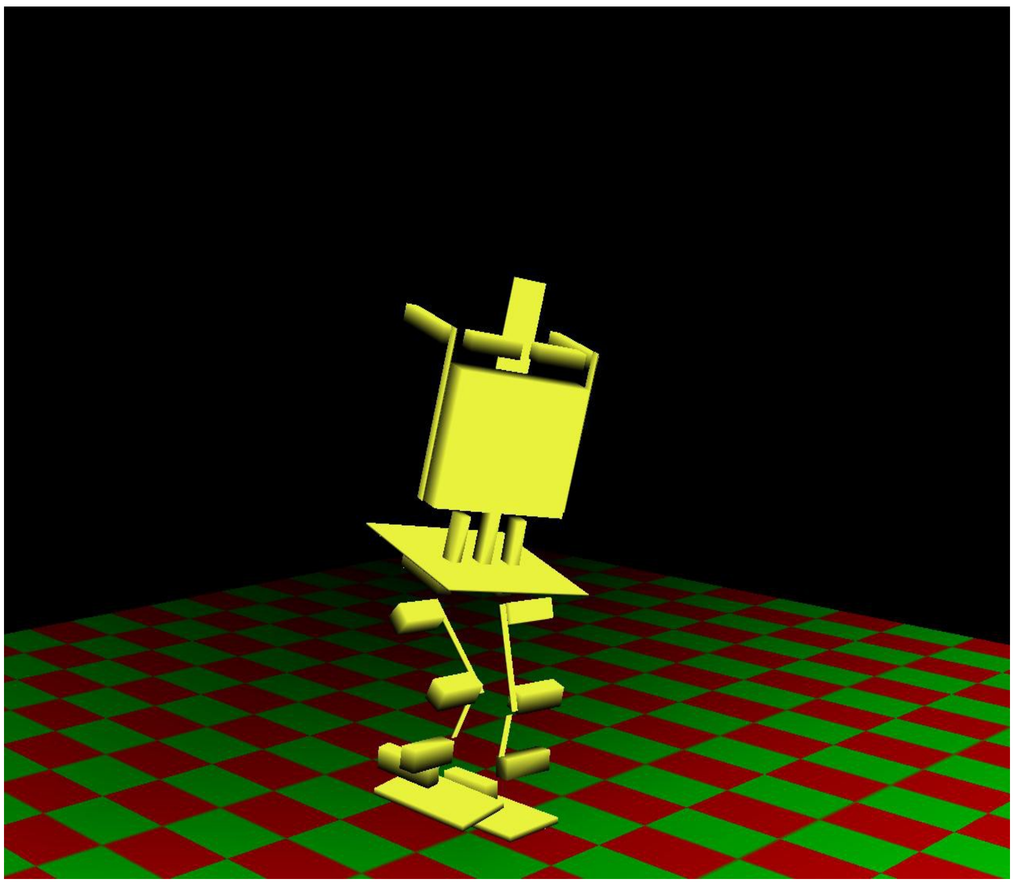
- Leaf node: MC simulation, expand after *k* visits
- Converges – given unlimited time, will find optimal solution
- Online algorithm – can be stopped anytime and give meaningful result
  - Final move selection: node with highest #simulations

MCTS: Other Applications

- 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



Basic Implementation

Trivial Heuristics

Local Patterns

Caveats!

Uniformly Random...

- 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

appendix 4

Playout Requirements

- **Speed** – more simulations mean deeper tree and more accurate values
  - Small board, light playouts: Tens of thousands playouts per second
  - Large board, heavy playouts: ~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

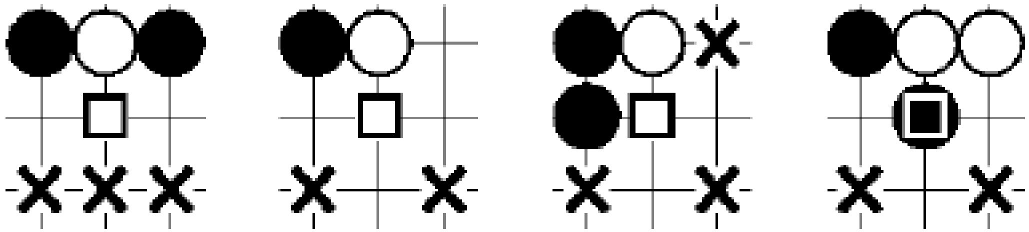
Simple Heuristics

- 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)
- Considered only around last move
- => Produces “nice” local sequences
- 3x3 patterns = 16bit numbers => Very fast

appendix 5



Balanced Patterns

- 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

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

Prior Values

- **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

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

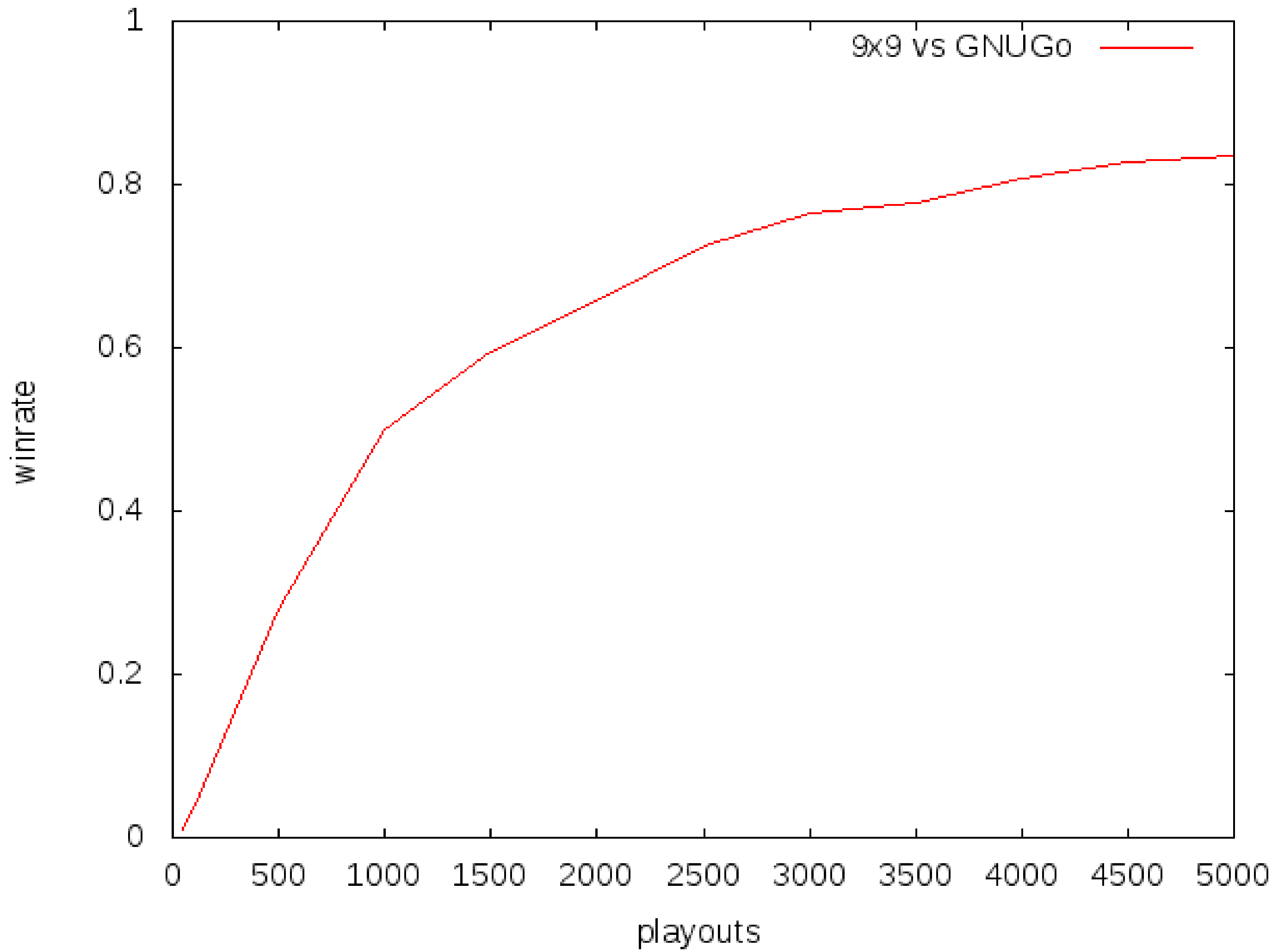
$$\beta = amafsims \times \left(amafsims + uctsims + \frac{amafsims \times uctsims}{r} \right)^{-1}$$

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

RAVE Aftermath

- **Key result** in MCTS Go, making it stronger than the classical engines:
  - ~ 30% UCT → 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 19x19 ($c=\sim 0.005$ on 9x9) – 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

- **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

- 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 ~[0.4,0.5]; universal (not only handicap games), ~57% self-play
  - Fixed step or avgscore-based step

Linear Dynamic Komi

- **Linear DK:** Calculate komi value K based on the handicap amount
- K ~= $-cH$ 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)

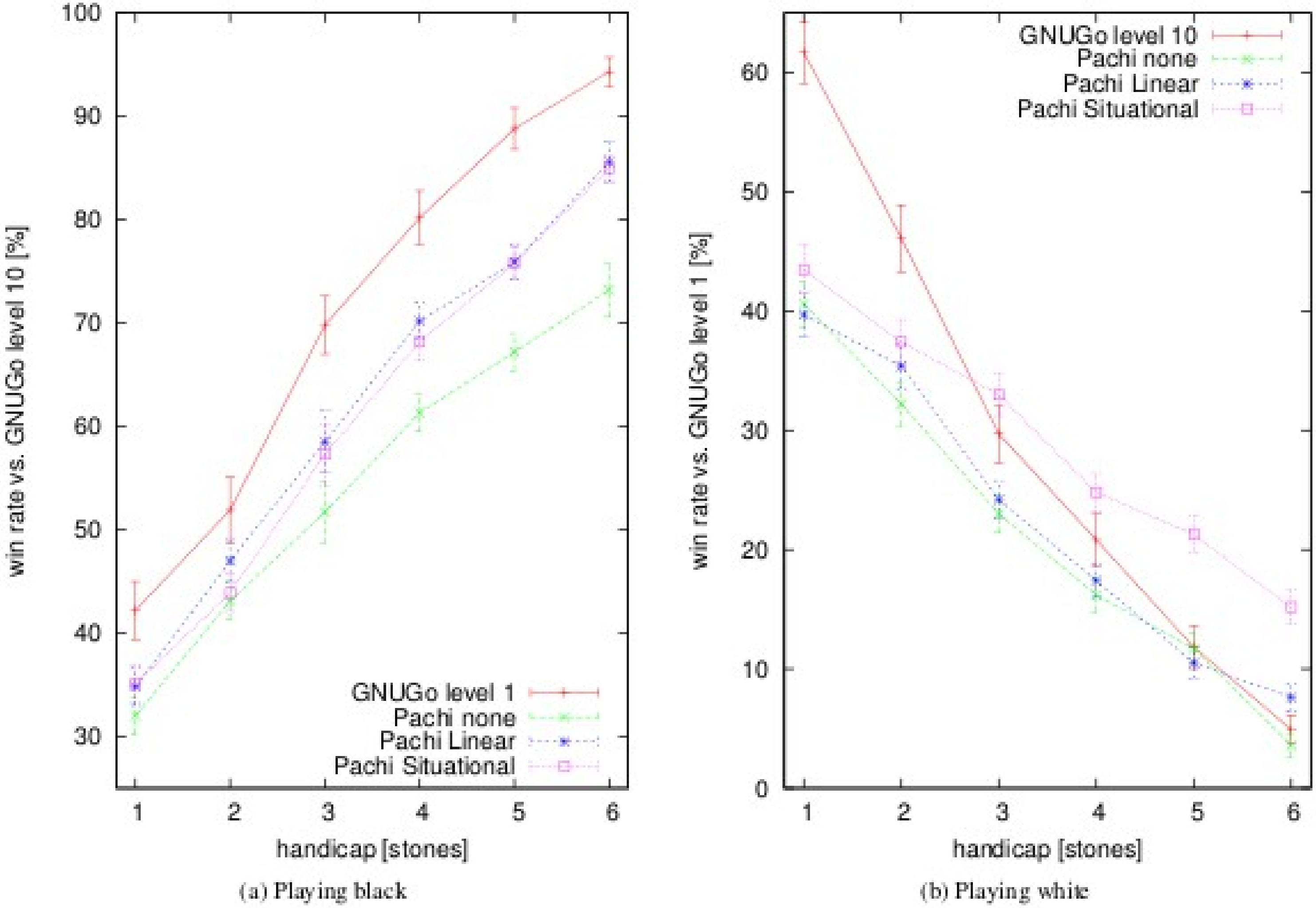


Figure 2: Dynamic komi in handicap games.

Parallel MCTS

(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

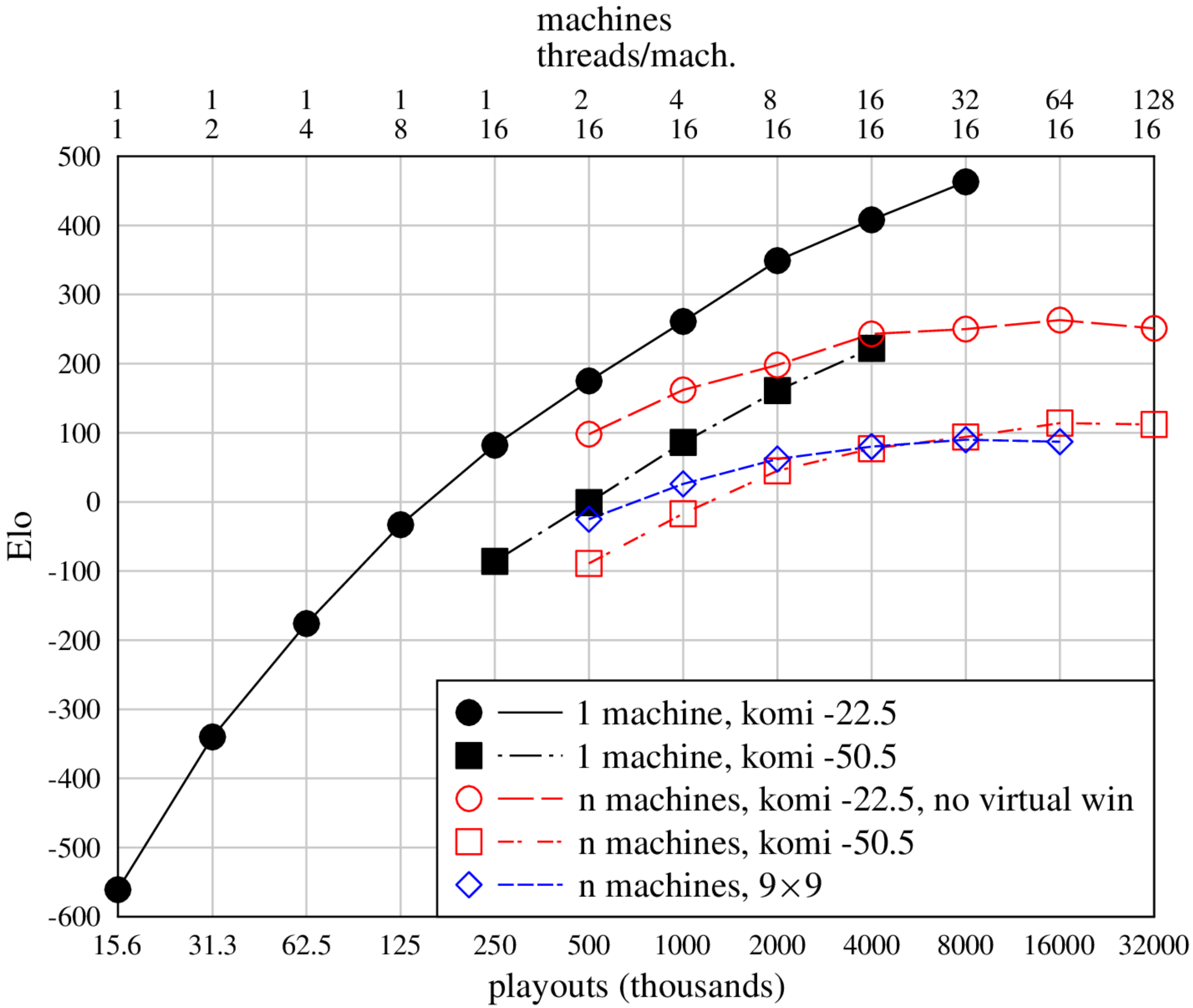
- **In-tree** – all threads search in the same tree
  - No locking necessary if we are careful (Enzenberger, 2009)
  - Never delete nodes during search
  - Update values atomically
  - *Virtual loss* spreads exploration (add loss in descend, remove during update)

Distributed MCTS

- **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

- 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

Pattern Features

ELO Pattern Ranking

Storing Patterns

Pattern Usage

Pattern Usage

- 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

- Hashing board positions (Zobrist, 1990)

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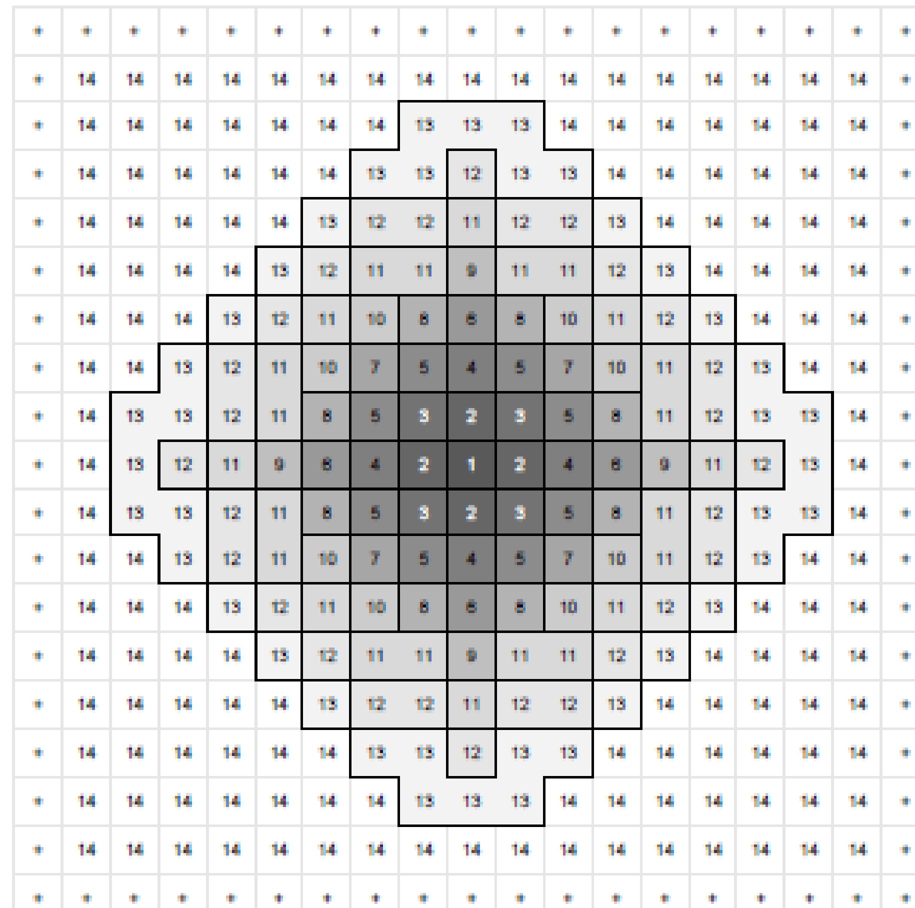
- Initialization: Each point gets assigned random numbers *b*, *w*
- Position: XOR of *b* values for all black stones and *w* values for all white stones
- Good uniform distribution, reasonable hash size
- Incremental updates on move plays possible!

Shape Patterns

- 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

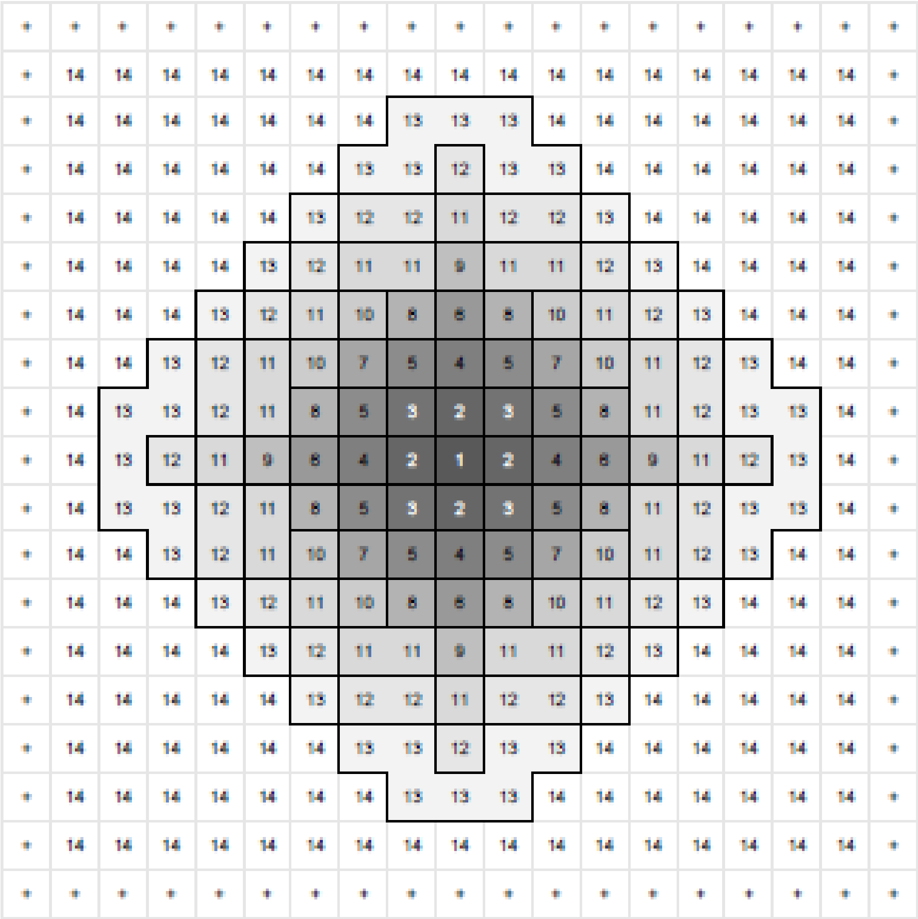
- ...on square grid? (Stern, 2006)
- Metric?



Circular Shapes

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

  $d(x,y) = |dx| + |dy| + \max(|dx|,|dy|)$
- Incrementally matched nested circles
- Commonly used



Arbitrary Shapes

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

Arbitrary Shapes

- 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

- 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

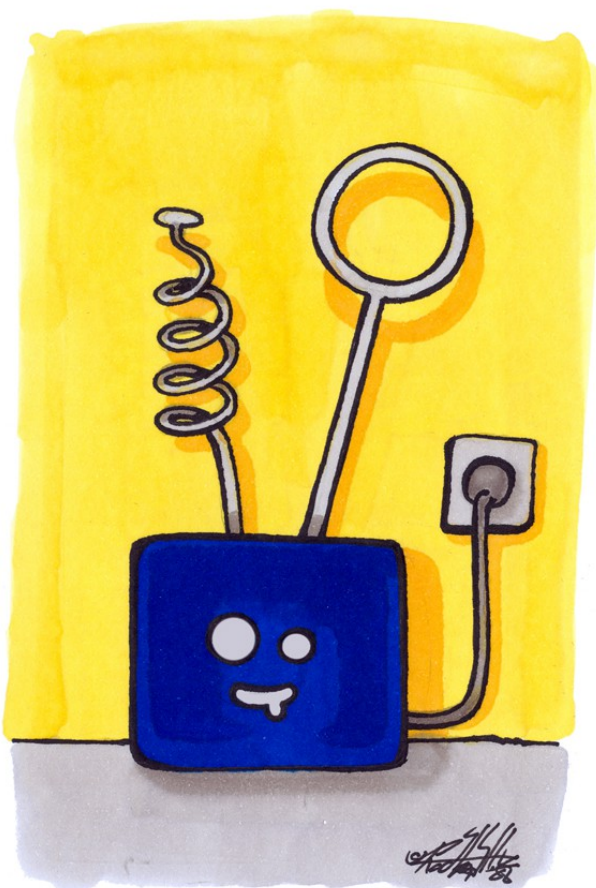
Elo Ratings

- 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* γ
  - $P(i \text{ beats } j) = \gamma_i / (\gamma_i + \gamma_j)$
- 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

- 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

- 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

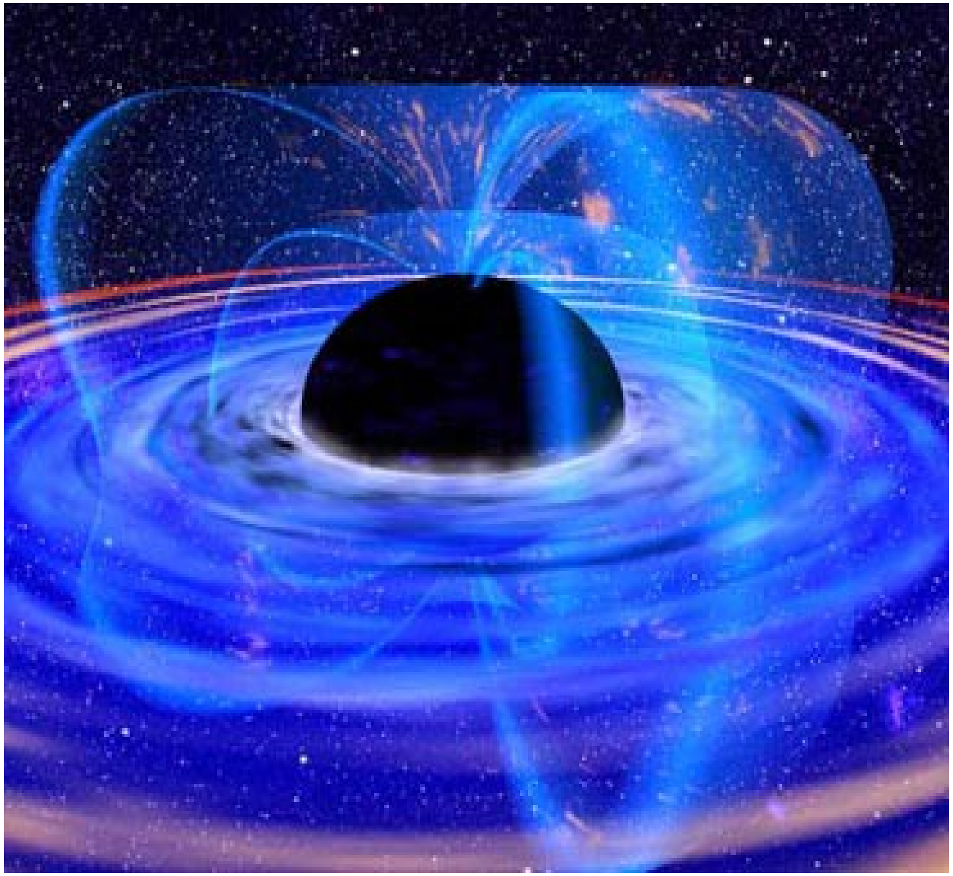
Unsolved Problems

Narrow sequences

HPC implementation

Aesthetically pleasing play

Abstract understanding of the board



Narrow Sequences

- 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

- 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?

- 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

- 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

- 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

- 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)

Thank you!

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