Monte Carlo Tree Search and Computer Go

Cmput 366 Guest Lecture

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Contents

- Limits of alpha-beta search
- The Game of Go
- What is Monte Carlo Tree Search?
- The *Fuego* project

Alphabeta Search

- Minimax principle
  - My turn: choose best move
  - Opponent's turn: they choose move that's worst for me
- Alphabeta ($\alpha\beta$): prune irrelevant parts of tree

αβ Successes (1)

- Full search: solve the game
  - checkers (Schaeffer et al 2007)
  - Nine men's morris (Gasser 1994)
  - Gomoku (5 in a row) (Allis 1990)
  - Awari, 5x5 Go, 5x5 Amazons,.....

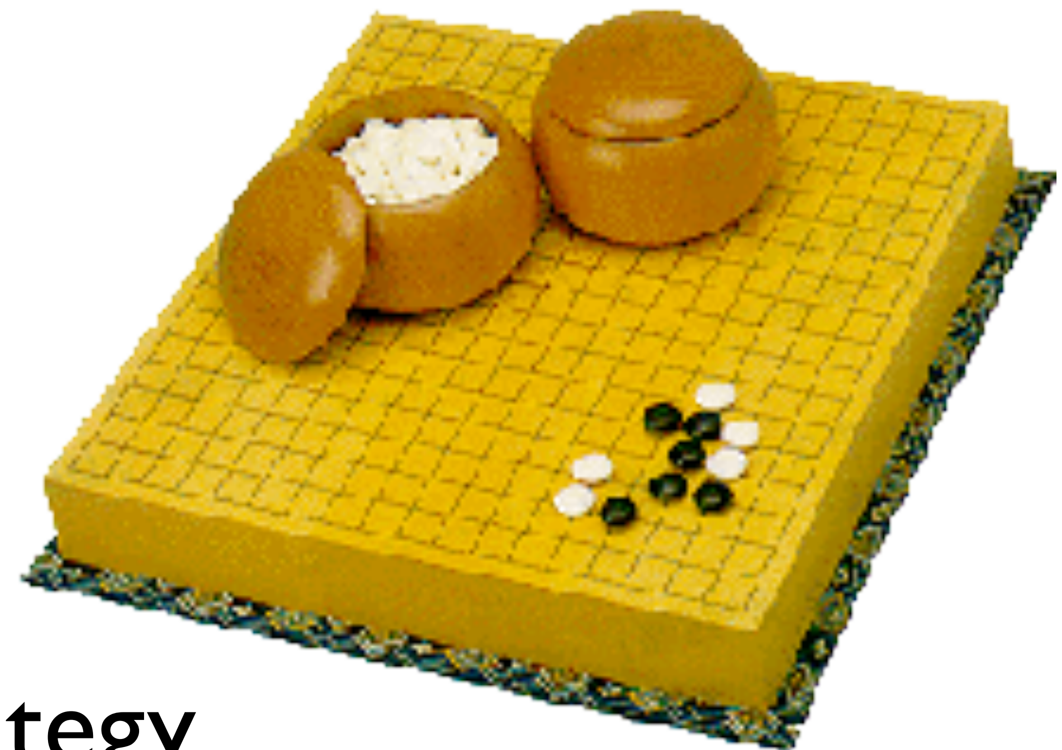
αβ Successes (2)

- Not solved, but super-human strength:
  - chess (Deep Blue team, 1996)
  - Othello (Buro 1996)
- Grandmaster strength:
  - shogi (Japanese chess)
  - xiangqi (Chinese chess)

αβ Failures

- Go
- General Game Playing (GGP)
- Why fail?
  - Focus on Go here

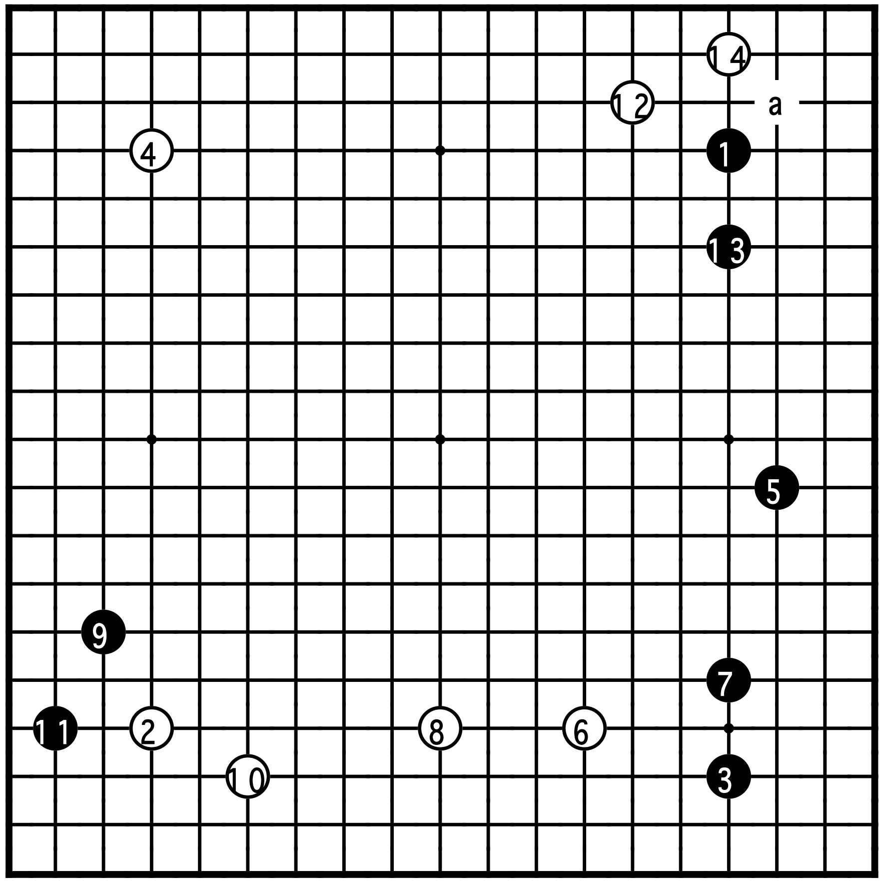
Go



- Classic Asian board game
- Simple rules, complex strategy
- Played by millions
- Hundreds of top experts - professional players
- Until recently, computers much weaker than humans

Go Rules

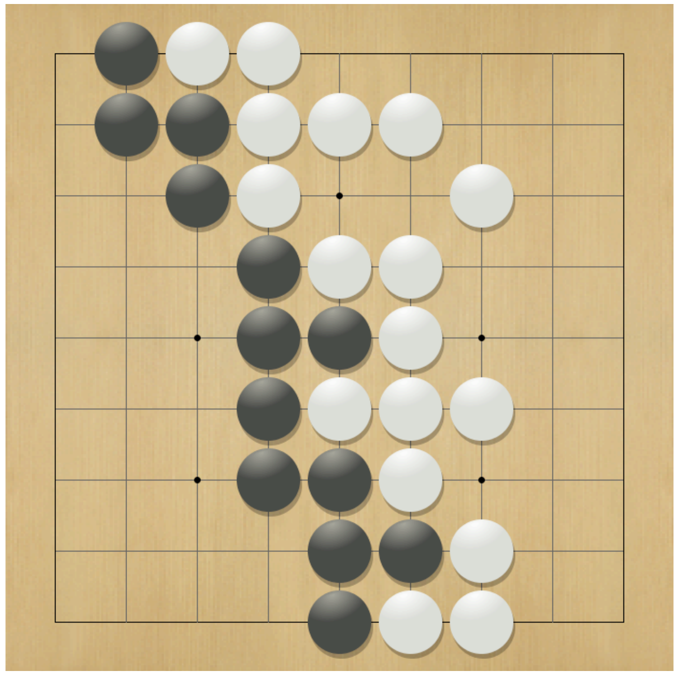
- Start: empty board
- Goal: surround
  - Empty points
  - Opponent (capture
- Win: control more th
  half the board

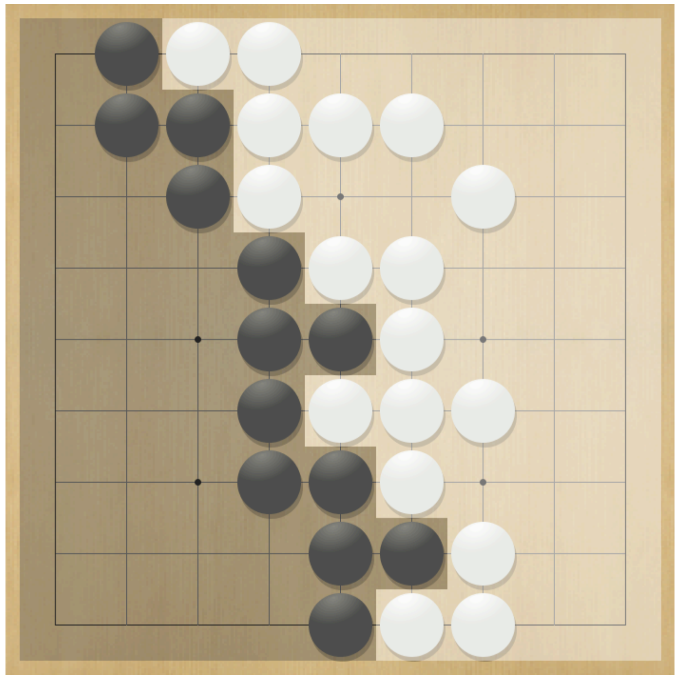


- *Komi*: compensation for first player advantage

End of Game

- End: both players pass
- *Territory* - intersections surrounded by one player
- The player with more (stones+territory) wins the game
- *Komi*: adjustment for first player advantage (e.g. 7.5 points)





Why does αβ Fail in Go?

- Depth and width of game tree
  - 250 moves on average
  - game length > 200 moves
- Lack of good **evaluation function**

Monte Carlo Methods

- Recently popular (mainly last 5 years)
- Hugely successful
  - Backgammon (Tesauro)
  - Go (many)
  - Amazons, Havannah, Lines of Action, ...

Monte Carlo Simulation

- No evaluation function? No problem!
- Simulate rest of game using random moves (easy)
- Score the game at the end (easy)
- Use that as evaluation (hmm, but...)

The GIGO Principle

- **G**arbage **i**n, **g**arbage **o**ut
- Even the best algorithms do not work if the input data is bad
- How can we gain any information from playing random moves?

Well, it Works!

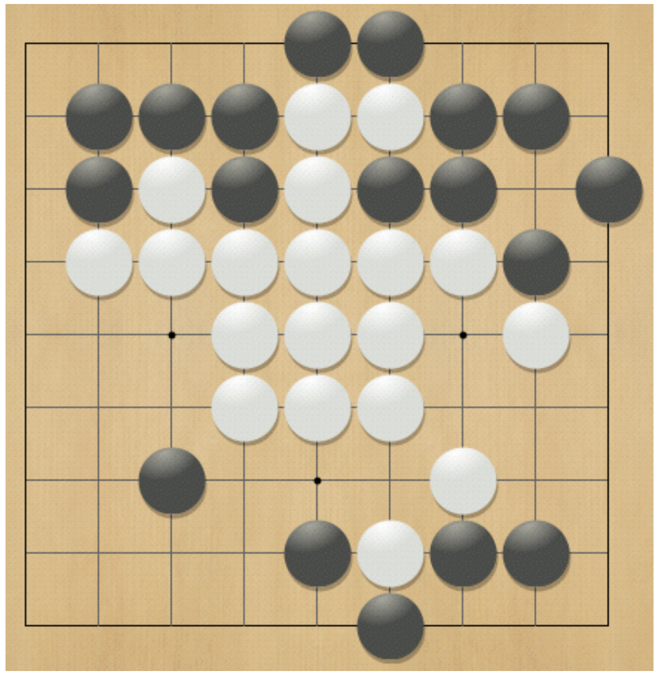
- For some games, anyway
- Even random moves often preserve some difference between a good position and a bad one
- The rest is statistics...
  - ...well, not quite.

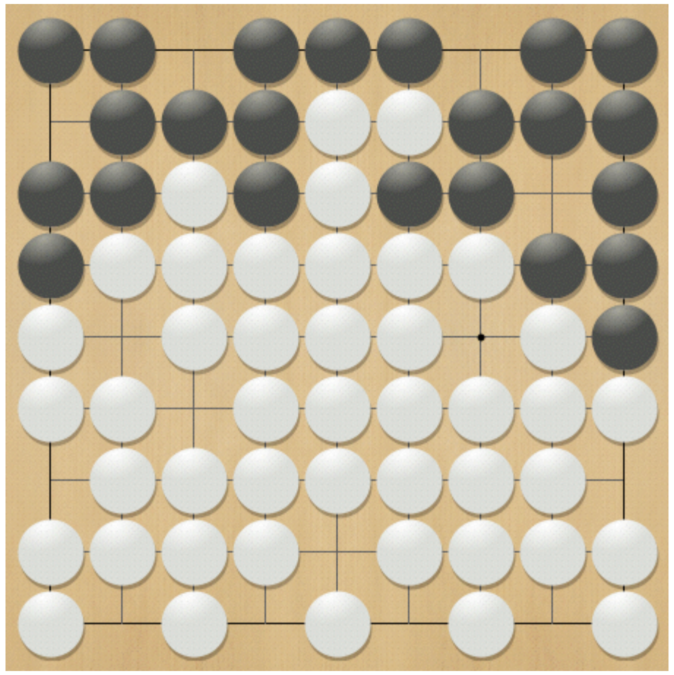
Basic
Monte Carlo Search

- Play lots of random games starting with each possible move
- Keep winning statistics for each move
- Play move with best winning percentage

Simulation - Example

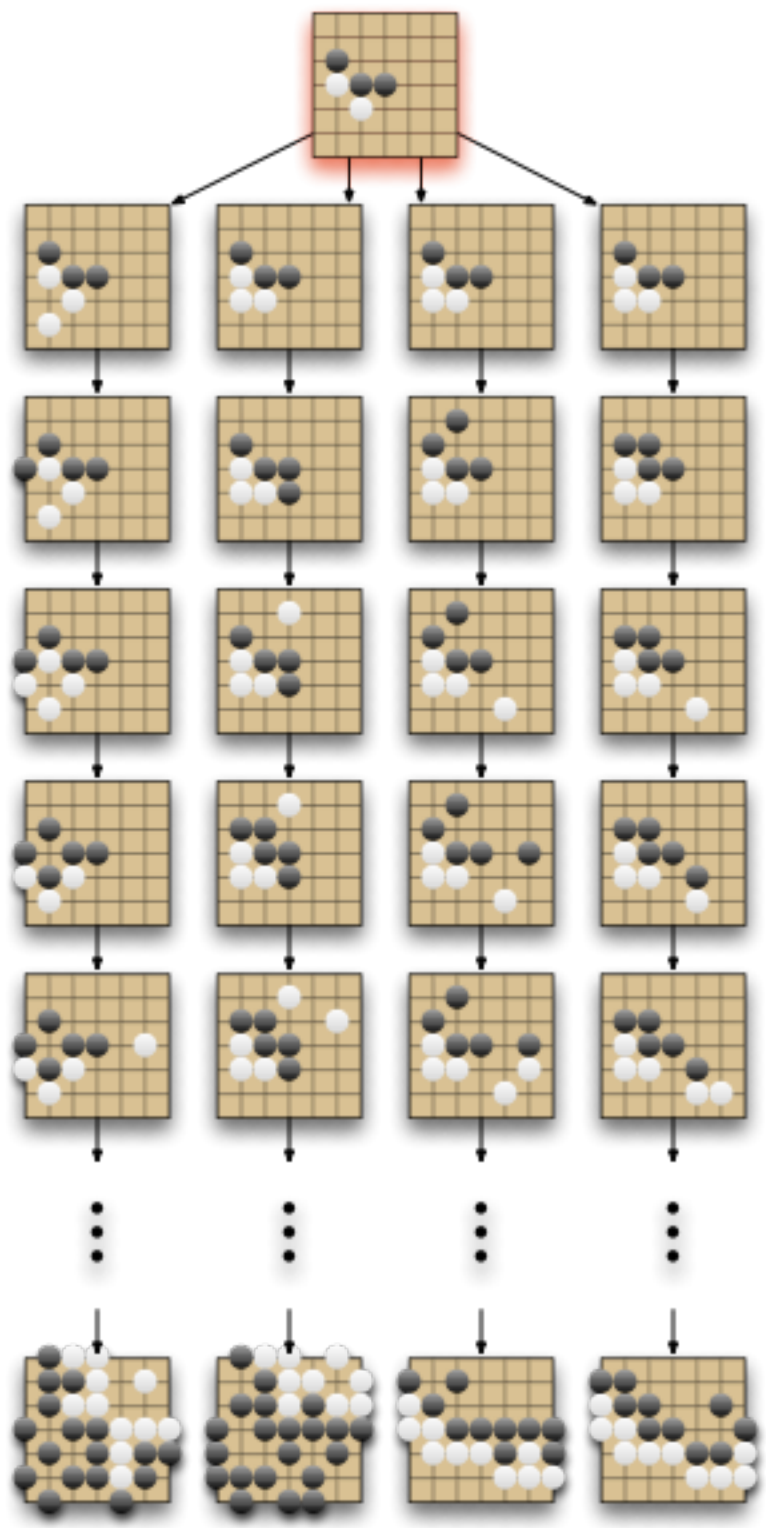
- Random legal moves, but…
- …do not fill one point eyes
- End of game after both pass
- Evaluate by Chinese rules:
  +1 for win
  0 for loss





valkyria-ExBoss-randomgame.sgf

Example (for one move)



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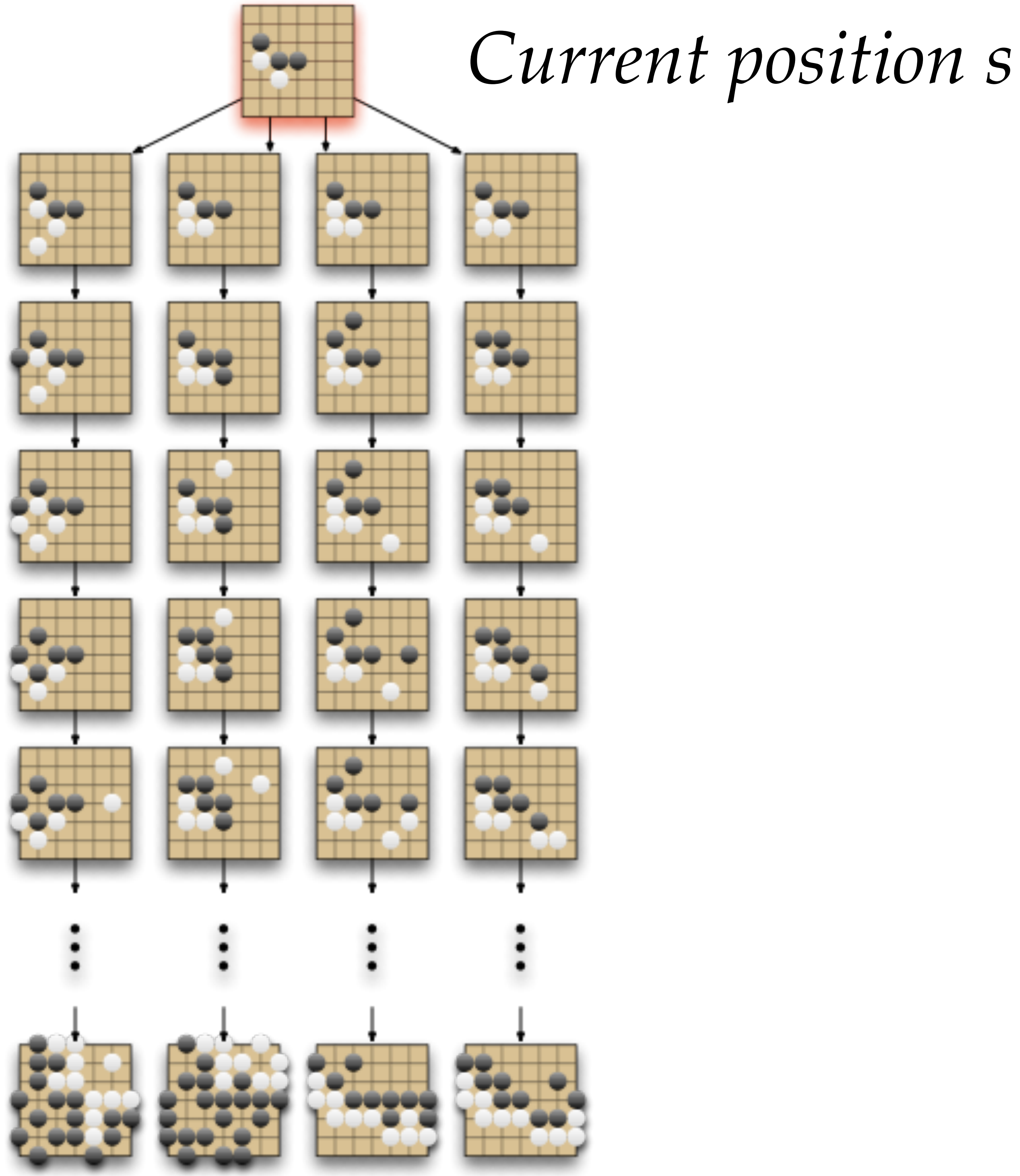

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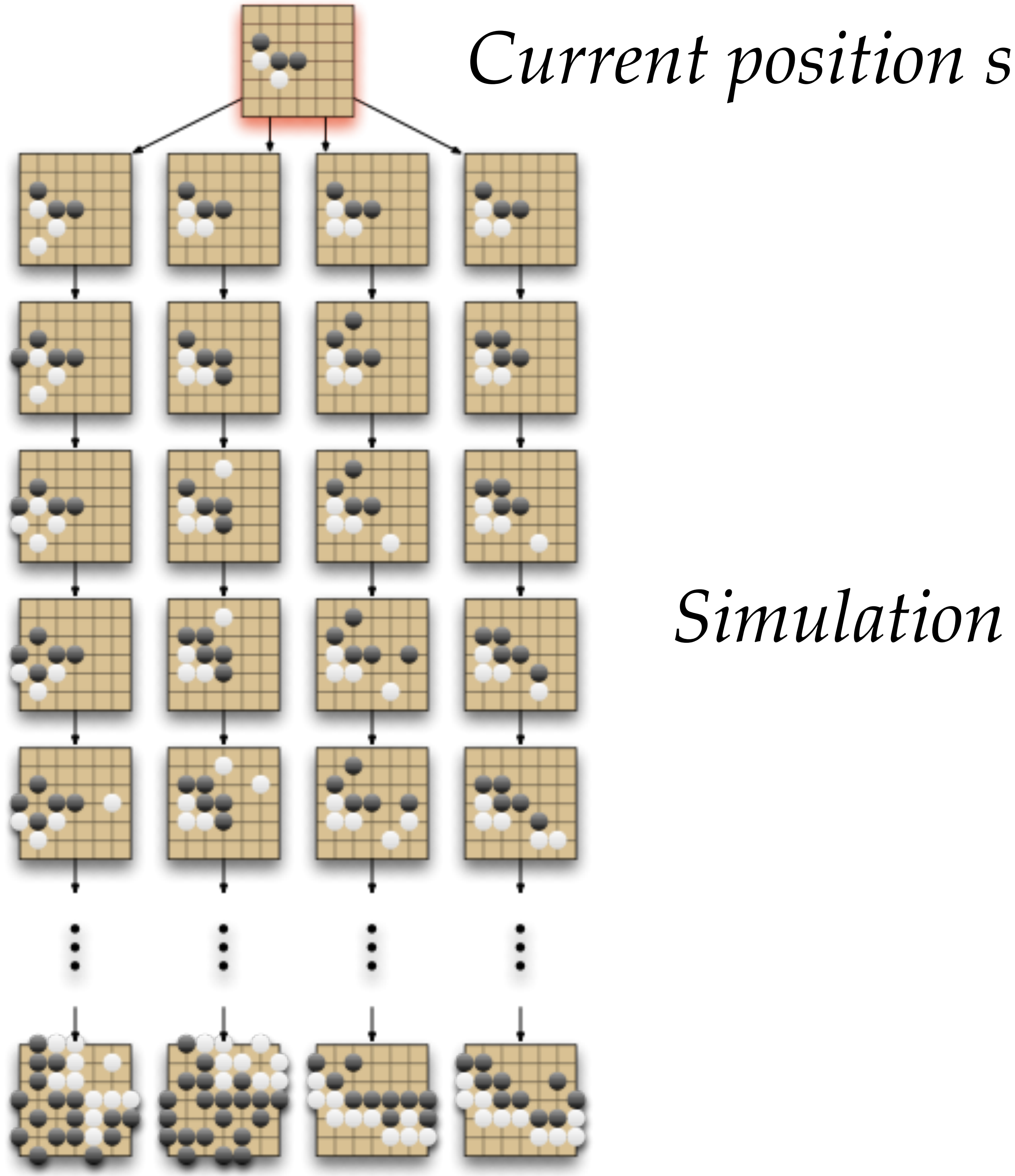

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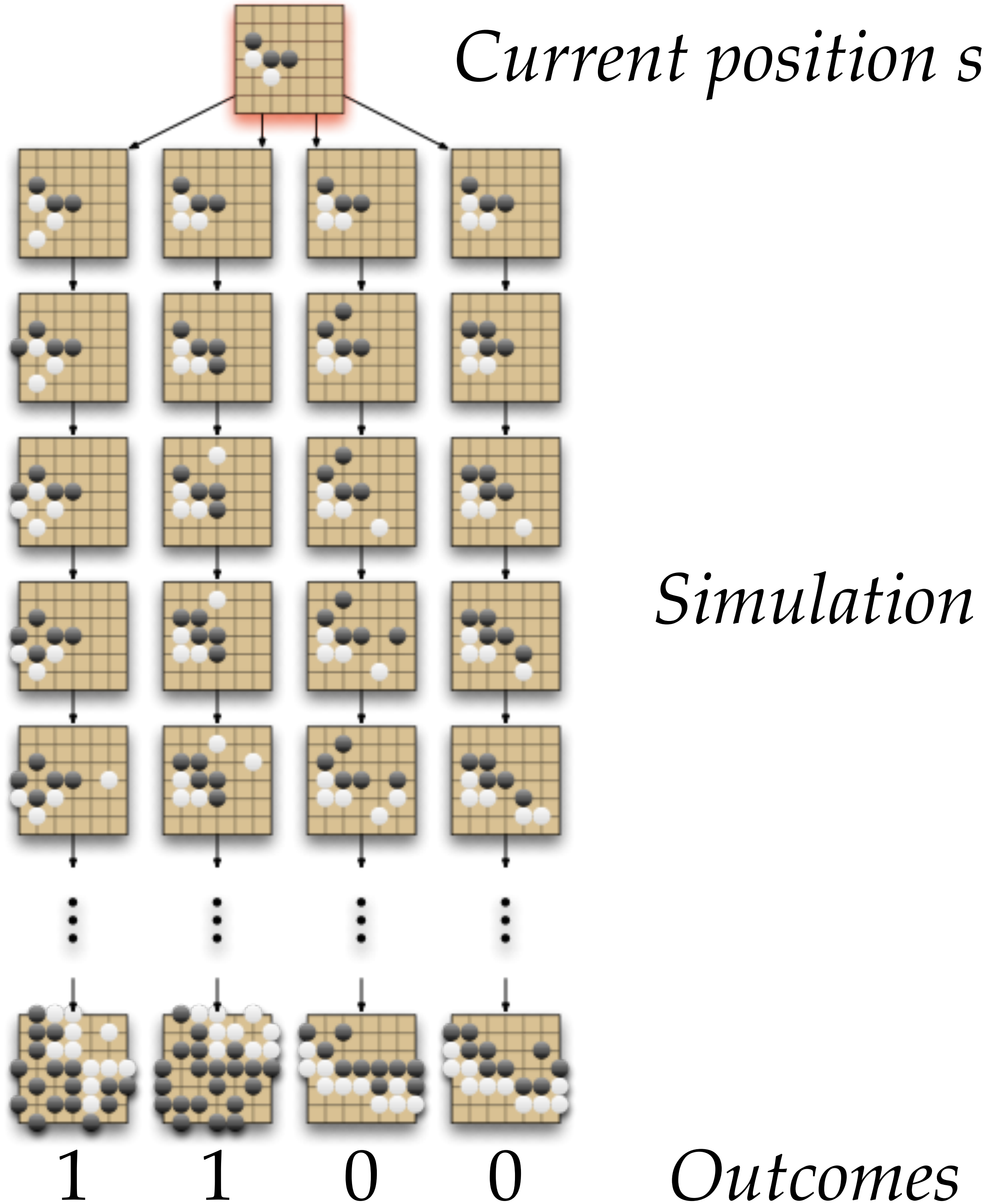

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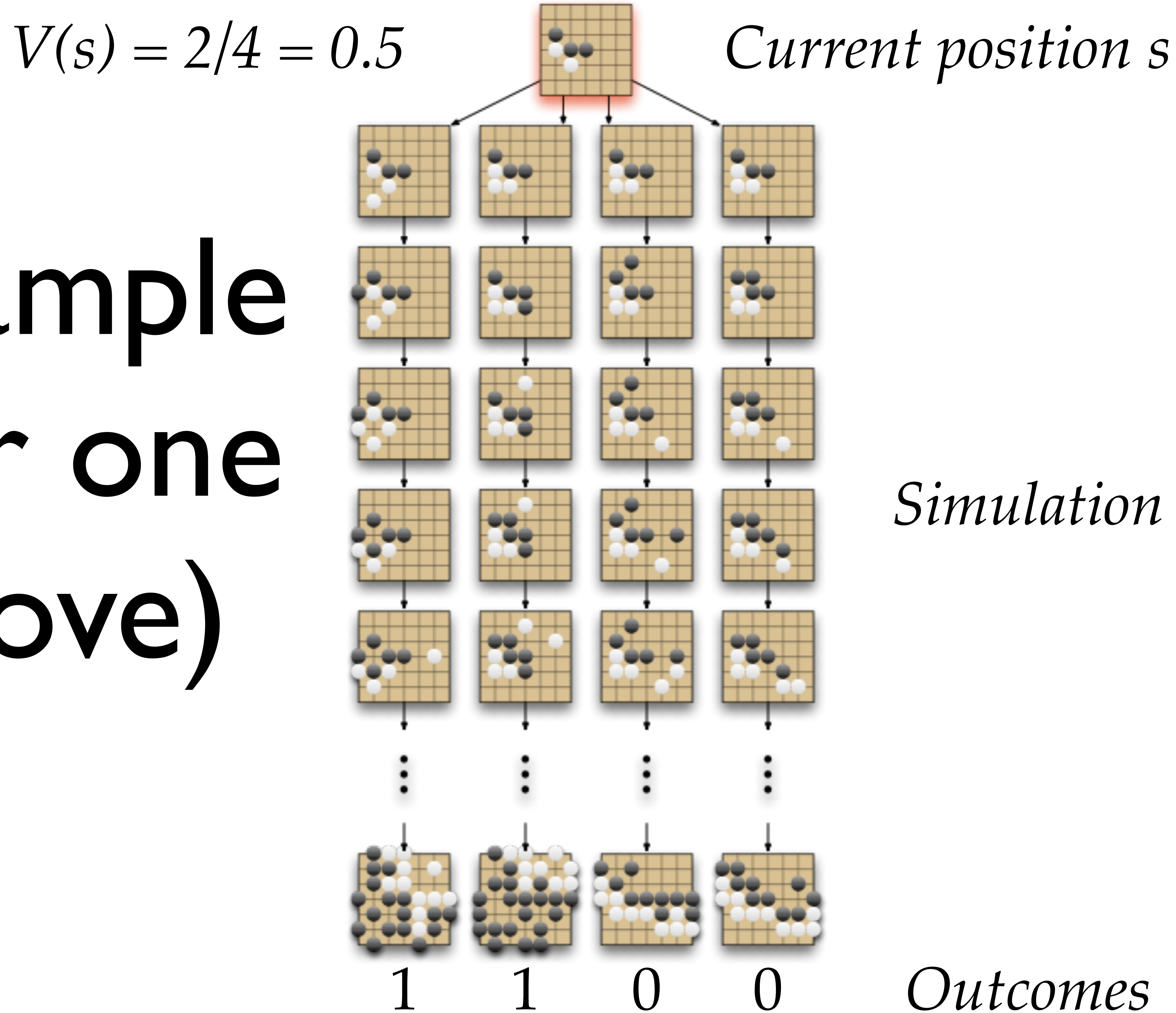


Evaluation

- Surprisingly good e.g. in Go - much better than random or simple knowledge-based players
  - Still limited
    - Prefers moves that work "on average"
    - Often these moves fail against the best response
    - "Silly threats"

How to Improve?

1. Better-than-random simulations
2. Add game tree (as in $\alpha\beta$)
3. Add statistics over move quality (RAVE, AMAF) - not today
4. Add knowledge in the game tree - not today
    1. human knowledge
    2. machine-learnt knowledge

1. Better Simulations

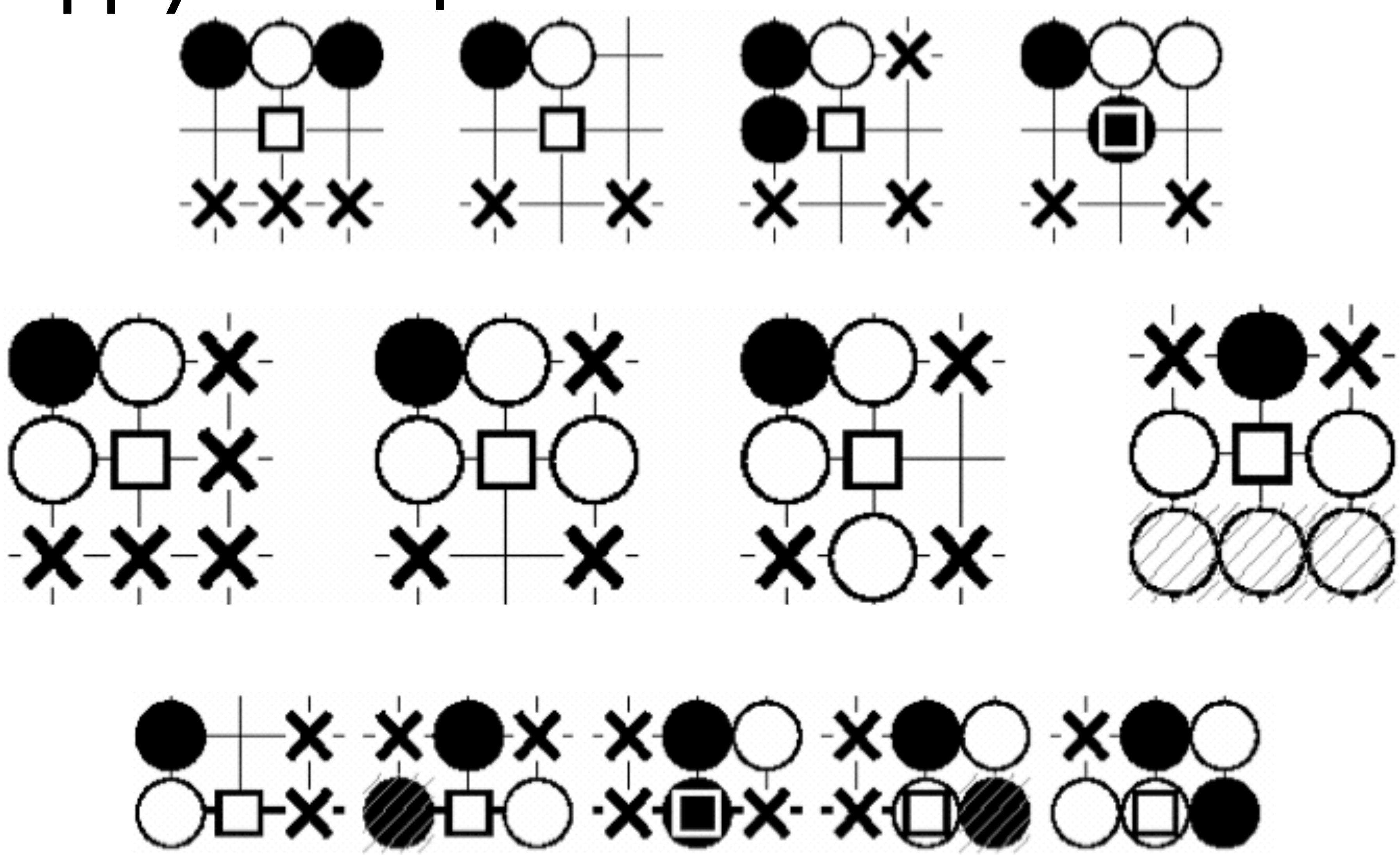
- Goal: strong correlation between initial position and result of simulation
- Preserve wins and losses
- How?

Knowledge in Simulations

- MoGo-style patterns
- Tactical rules

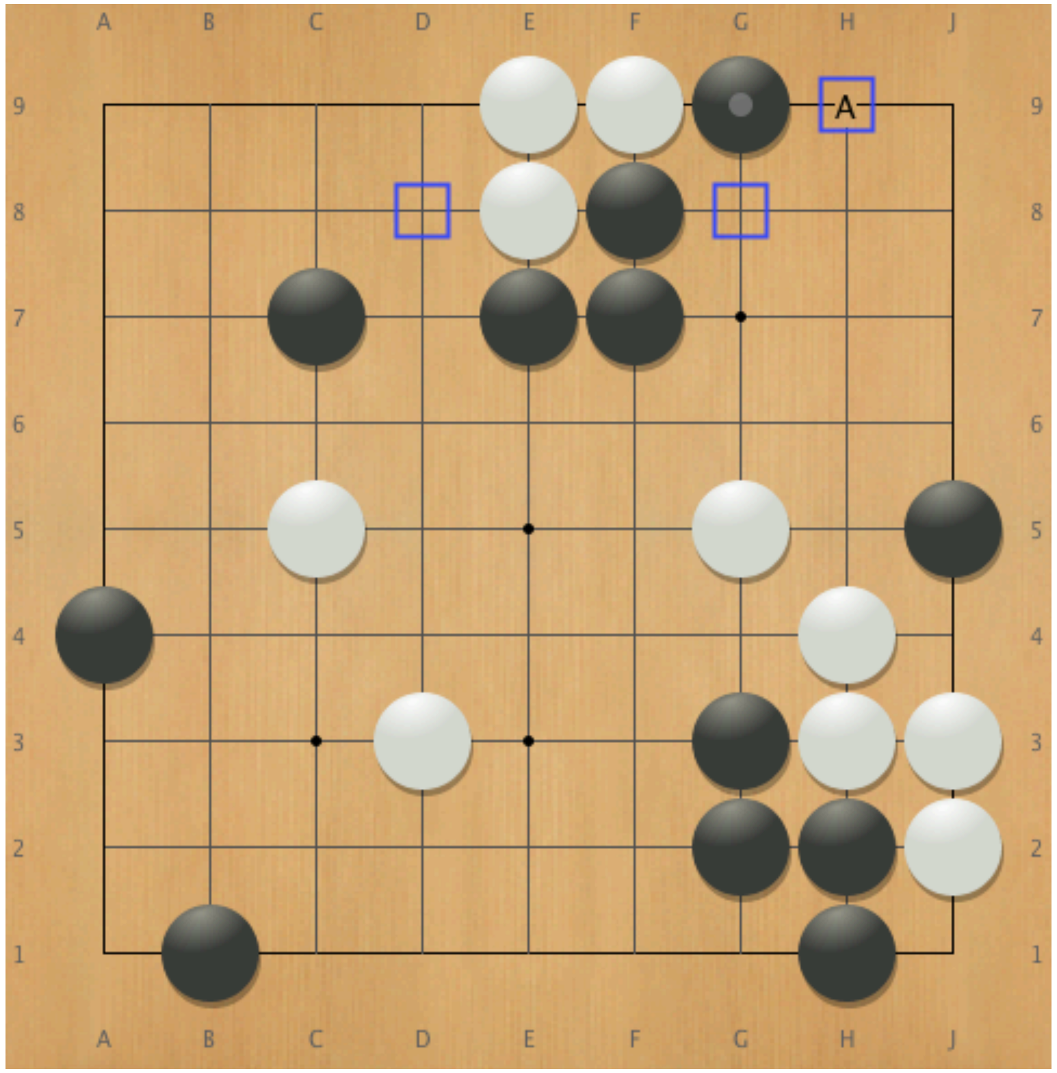
MoGo-Style Patterns

- 3x3 or 2x3 patterns
- Apply as response near last move

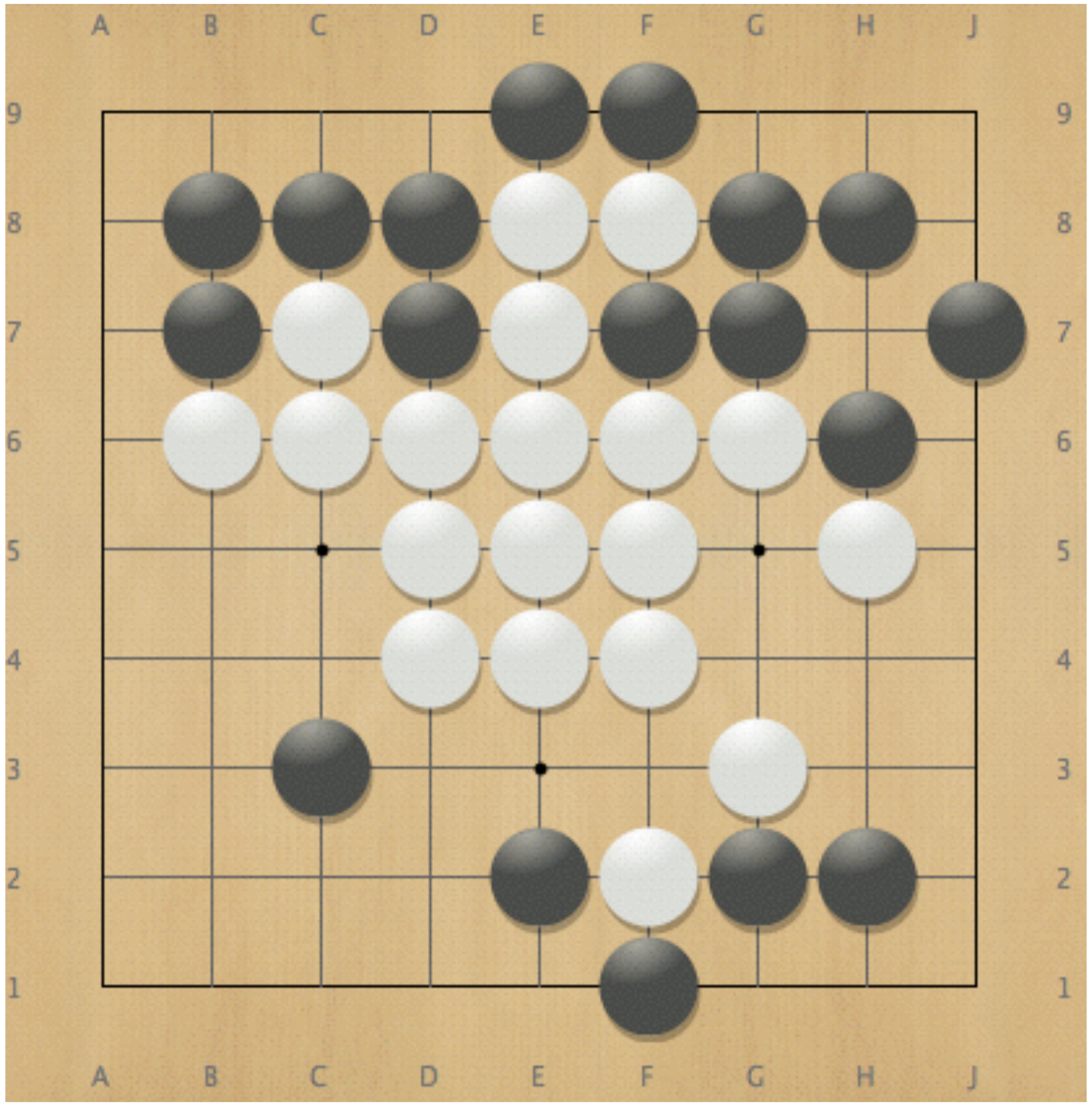


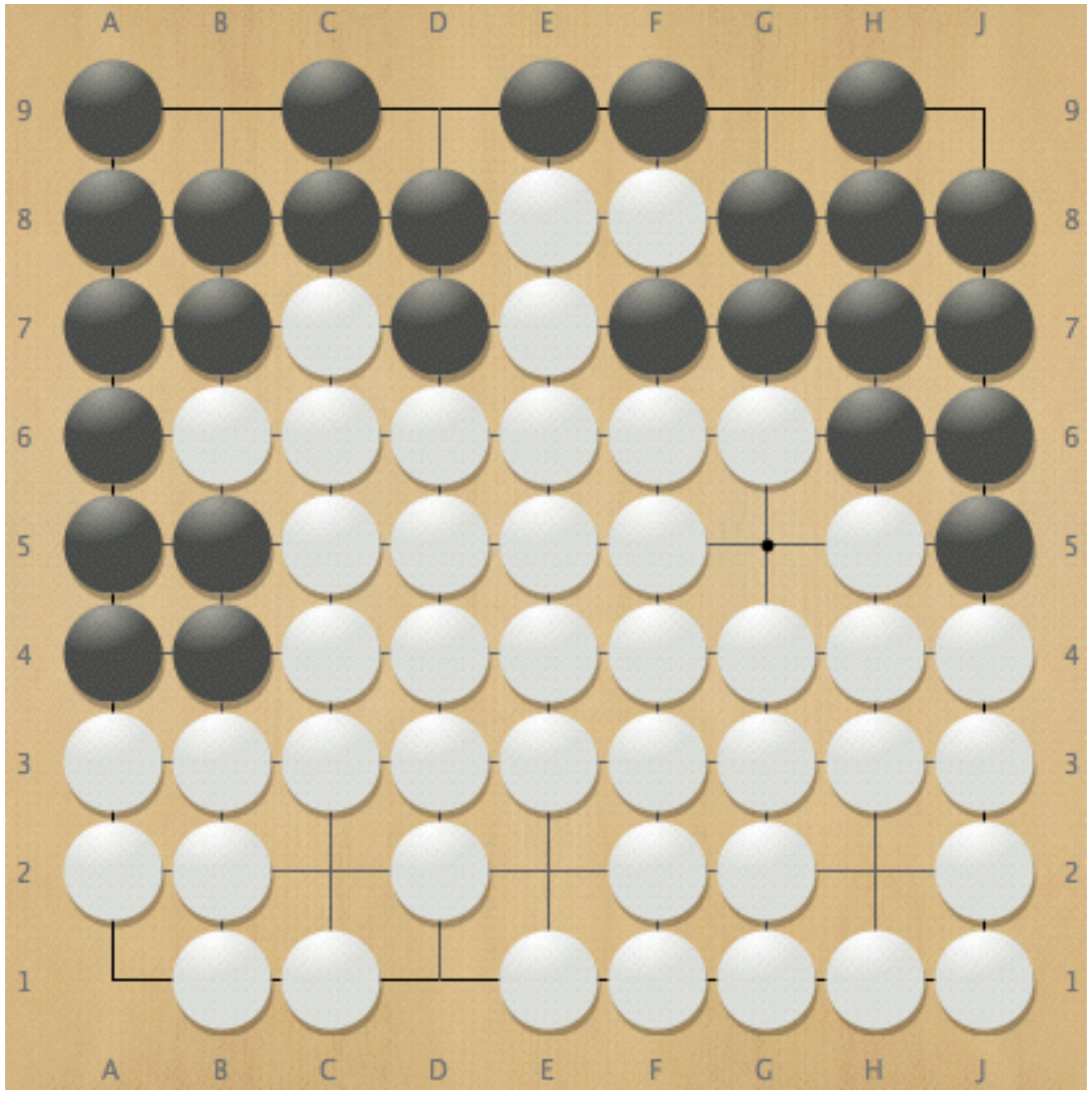
Tactical rules

- Escape from threats
- Stabilize/attack weak stones



Example of Biased Simulation





valkyria-ExBoss-biased-random-game.sgf

Building a better Random Policy

- Two main approaches
  - Crazy Stone: use rules, patterns to set probabilities for each legal move
  - MoGo, Fuego: hierarchy of rules
    - Find set of highest priority rules
    - Choose randomly from this (often small) set

2. Add Game Tree

- Using simulations directly as an evaluation function for $\alpha\beta$ fails
  - Too much noise, or too slow if running many simulations per state
- Result: Monte Carlo was ignored for over 10 years in Go

Monte Carlo Tree Search

- Idea: use results of simulations to guide growth of the game tree
- **Exploitation**: focus on promising moves
- **Exploration**: focus on moves where uncertainty about evaluation is high
- Two contradictory goals?

UCB Formula

- Multi-armed bandits (slot machines in Casino)
  - Which bandit has best payoff?
  - Explore all arms, but:
    - Play promising arms more often
  - Minimize *regret* from playing poor arms

UCT Algorithm

- Kocsis and Szepesvari (2006)
- Apply UCB in each node of a game tree
- Which node to expand next?

- Start at root (current state)
- While in tree, choose child *n* that maximizes

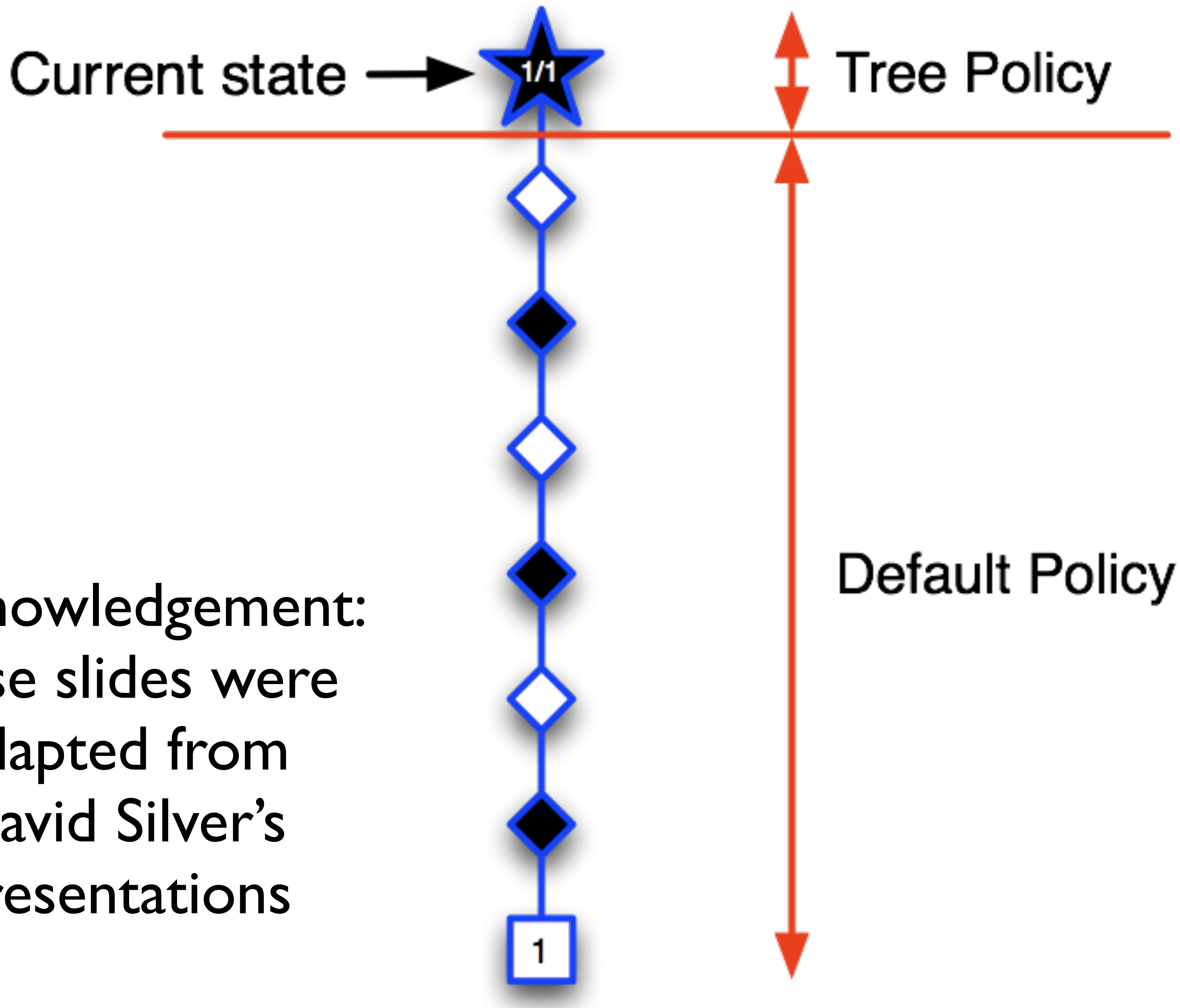
  UCTValue(*parent*, *n*) =

  winrate(*n*) + C*sqrt(ln(*parent.visits*)/*n.visits*)

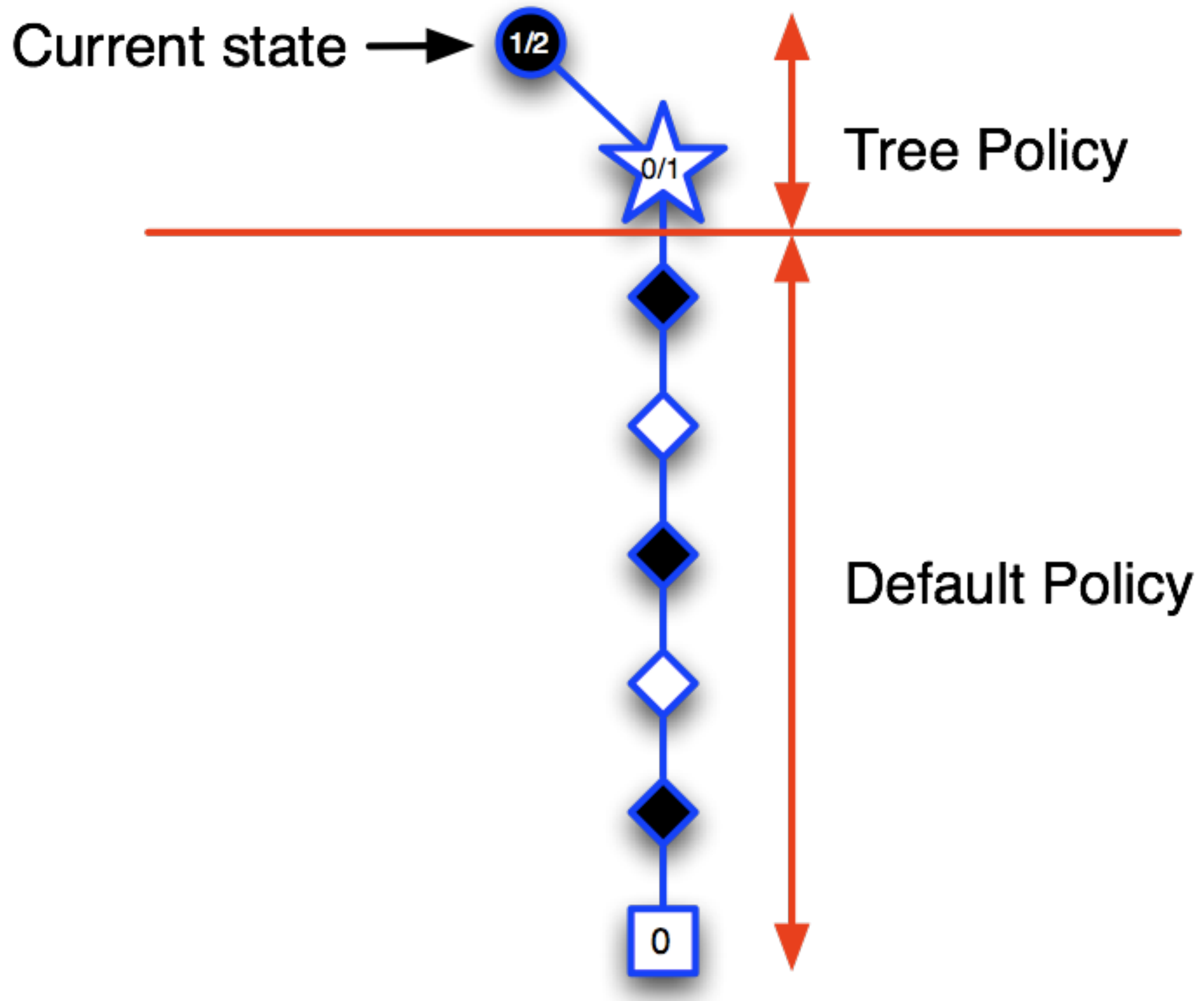
- UCTValue(*parent*, *n*) =

winrate(*n*) + C * sqrt(ln(*parent.visits*)/*n.visits*)

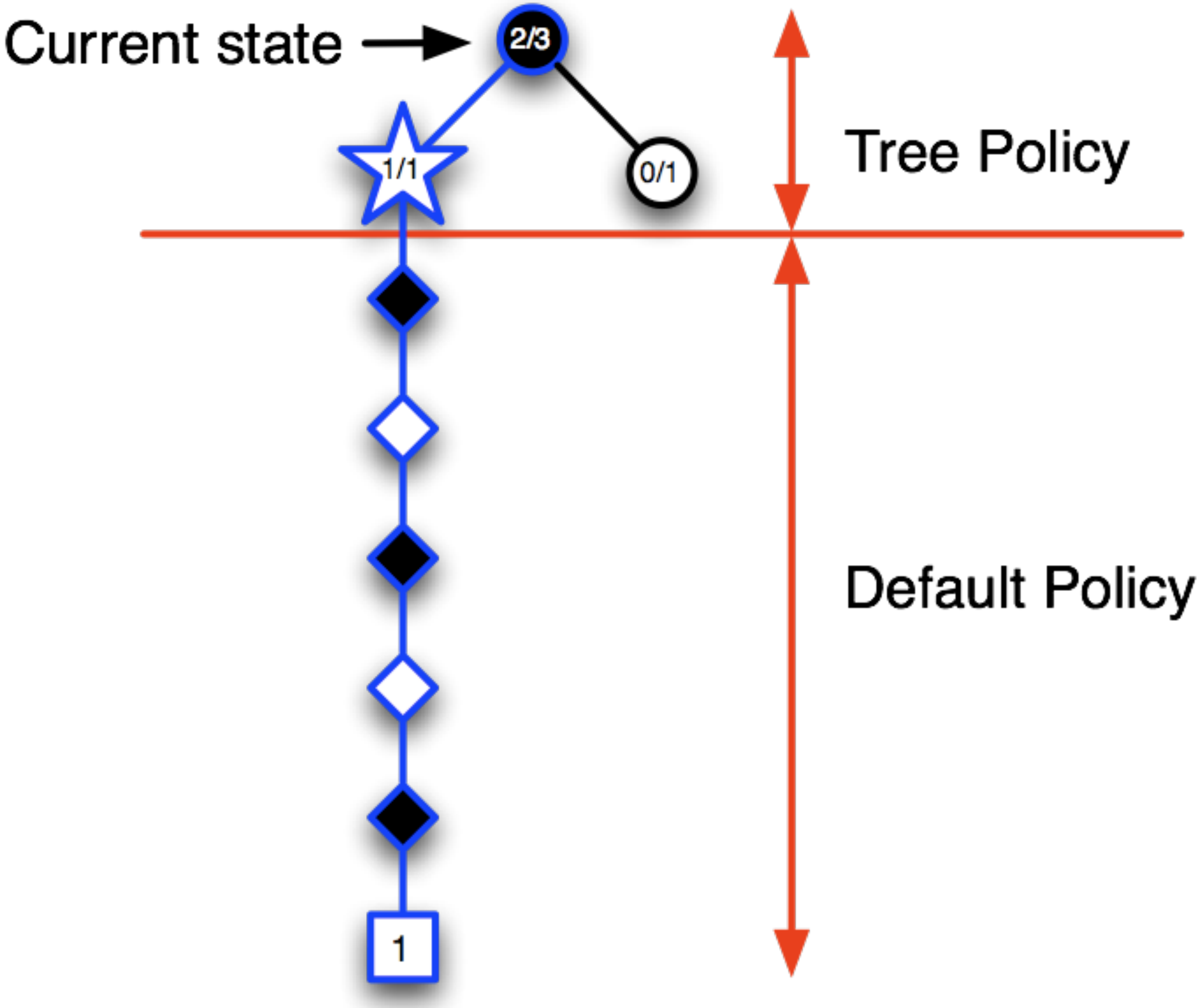
- winrate(*n*) .. *exploitation* term - average success of *n* so far
- 1/*n.visits* .. part of *exploration* term - explore nodes with very few visits - reduce uncertainty
- ln(*parent.visits*) .. part of *exploration* term - explore all nodes at least a little bit
- C .. *exploration constant* - how important is exploration relative to exploitation?



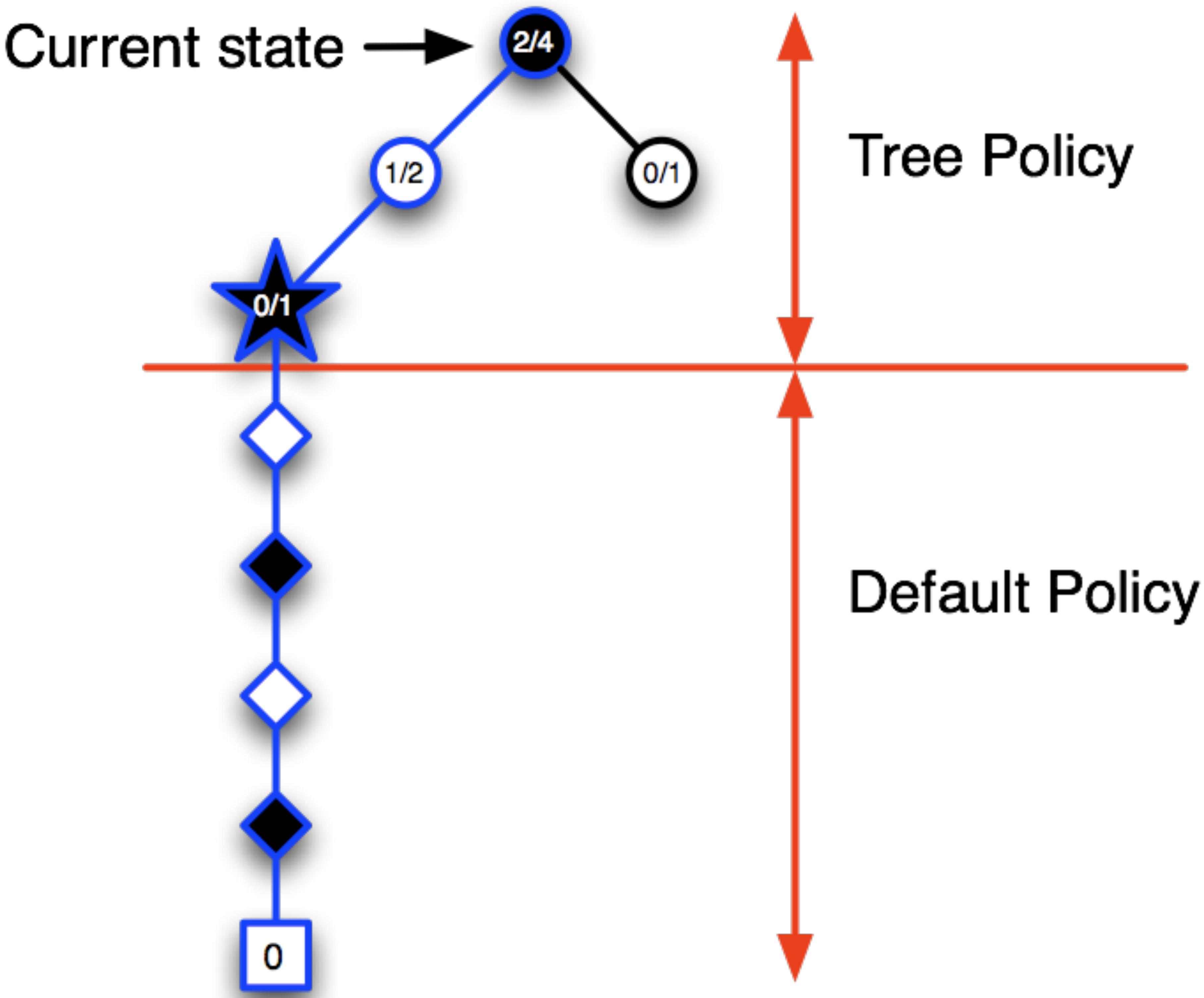
Acknowledgement: these slides were adapted from David Silver's presentations

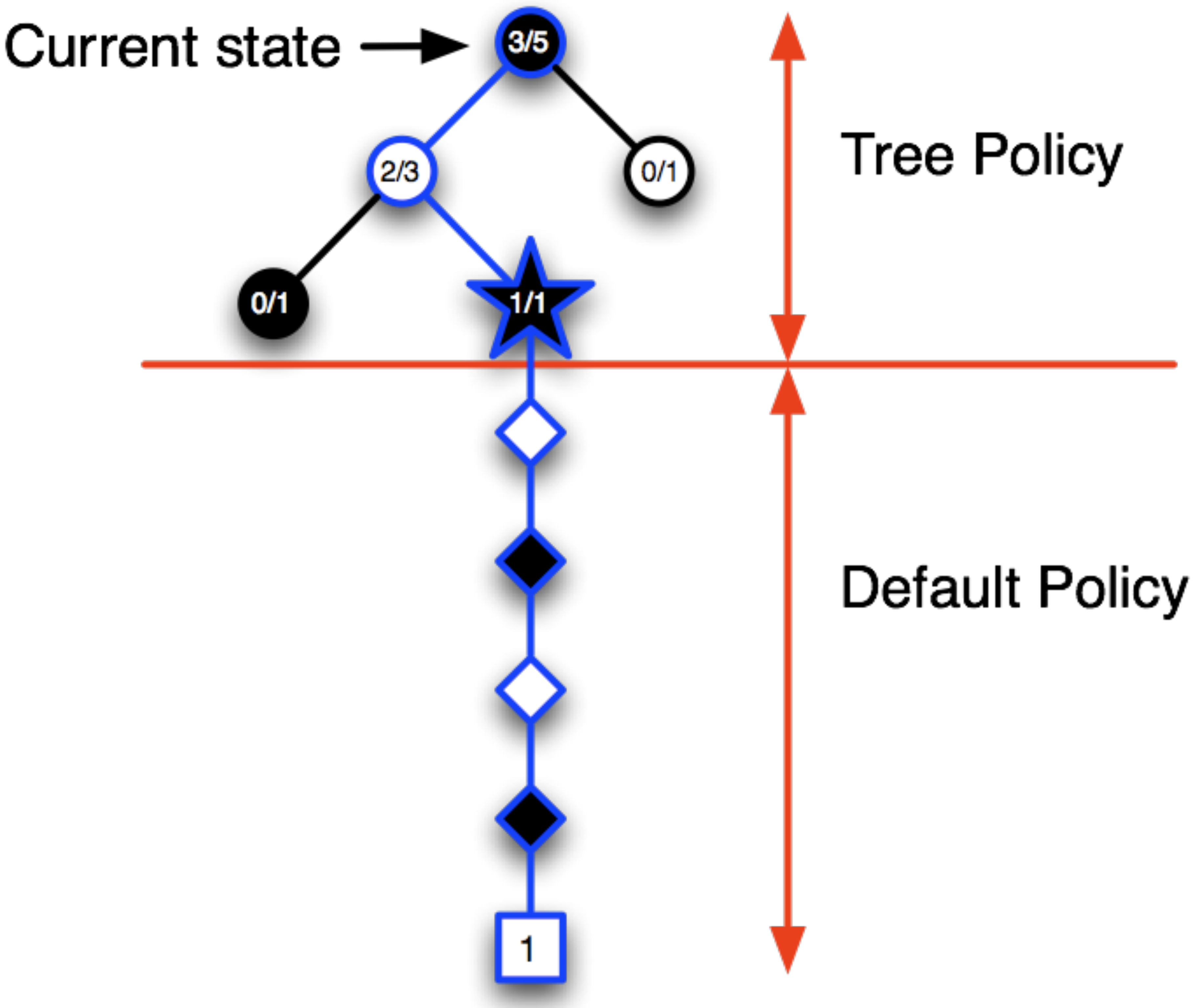


Current state
1/2
0/1
Tree Policy
Default Policy
0



Current state
2/3
1/1
0/1
1
Tree Policy
Default Policy


Current state
2/4
1/2
0/1
0/1
0
Tree Policy
Default Policy



Current state
3/5
2/3
0/1
0/1
1/1
1
Tree Policy
Default Policy

Summary - Monte-Carlo Tree Search

- Amazingly successful in games where alphabeta failed
  - Top in Backgammon, Go, General Game Playing, Hex, Amazons, Lines of Action, Havannah,...
  - Similar methods work in multiplayer games (e.g. card games), planning and puzzles

Summary(2)

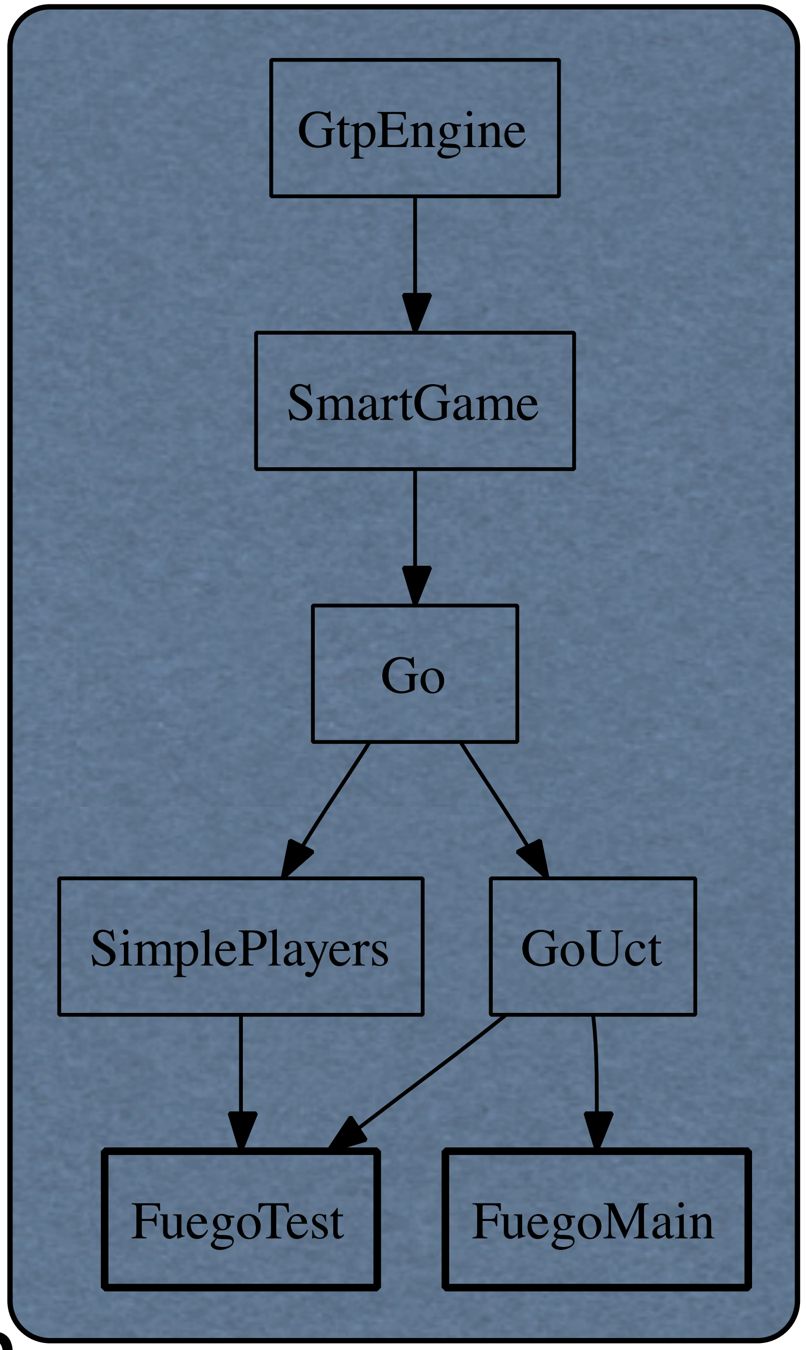
- Very successful in practice
- Scales OK to parallel machines
- Reasons for why and how it works still poorly understood
- Some limitations (see later)

The Fuego Project

- Developed at UofA (Enzenberger, Müller, Arneson,...)
- Open-source program hosted on *sourceforge*
- *http://fuego.sourceforge.net/*
- Goals:
    - General game-independent framework
    - Strong programs, e.g. Go, Hex, Amazons

Fuego Structure

- Game-independent kernel: smartgame library
  - MCTS, alphabeta, common data structures, utility classes
- General Go engine
  - Go board, rules, blocks, static safety algorithms
- Fuego - Monte Carlo Go program



Fuego Go Successes

- 2009: First program to beat top human professional Chou Chun-Hsun in 9x9 game with no handicap
- Won 2009 Computer Olympiad 9x9 Go, 2010 UEC cup (19x19)
- 2nd places in Olympiad: 2009 (19x19), 2010 (9x9 and 13x13)
- This year: 3rd(9x9), 4th(13x13), 5th(19x19)
- Fuego ranked 1st on 9x9 CGOS all-time

Projects using Fuego(1)

- **Bluefuego**: MPI library for Fuego
  - Developed by IBM
  - Scales to hundreds of cores
- **MoHex**: world's strongest Hex program
  - Developed by Ryan Hayward's group in Alberta
  - Uses SmartGame kernel, MCTS engine
  - Won Olympiad 2009, 2010, 2011

Projects using Fuego(2)

- **Explorer**: ``classical” Go program
  - Strong solvers for Tsume Go, safe territory, endgame
  - Uses Fuego’s SmartGame, Go libraries
- **FuegoEx**: add Explorer knowledge to Fuego
  - Tactical search (block capture)
  - Pattern matching - 4000 handmade large irregular patterns
  - Filter: prune blunders from MCTS

Projects using Fuego(3)

- **RLGO** (Dave Silver)
  - Reinforcement-learning based Go program
  - Uses SmartGame, Go, GoUct
- **TsumeGo Explorer** (Kishimoto + Müller)
  - World's best Life and Death solver for enclosed areas
  - Uses SmartGame, Go
- **Arrow** (Müller) Amazons-playing program
  - uses classical alpha-beta search other basic functionality from SmartGame
  - Arrow2 (Huntley, VanEyck) MCTS-based - third in 2011 Olympiad

Parallel Search

- Shared memory parallelization (Enzenberger)
  - Good speedup up to about 8 cores
  - Lockfree shared game tree
  - Memory-limited
- Distributed memory - BlueFuego (IBM)

Research Challenges

- How to improve simulations?
  - offline
  - online (during a game)
- How to achieve “locally strong” play?
  - Global search cannot see enough
- How to scale to massively parallel systems?

AI Planning

- Related idea: Monte Carlo random walks
- Add exploration into the search
- Arvand planner (Nakhost)
- Strong in finding plans
- Weaker in plan quality
- Strong for problems with limited resources
- Recent work: add local search tree (Xie)

Summary

- Monte Carlo methods have revolutionized search and games
- Still not well understood
- Lots of good research to be done
- General method, promising for many other applications