Monte-Carlo Tree Search (MCTS) for Computer Go

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Outline

- The game of Go: a 9x9 game
- The « old » approach (*-2002)
- The Monte-Carlo approach (2002-2005)
- The MCTS approach (2006-today)
- Conclusion

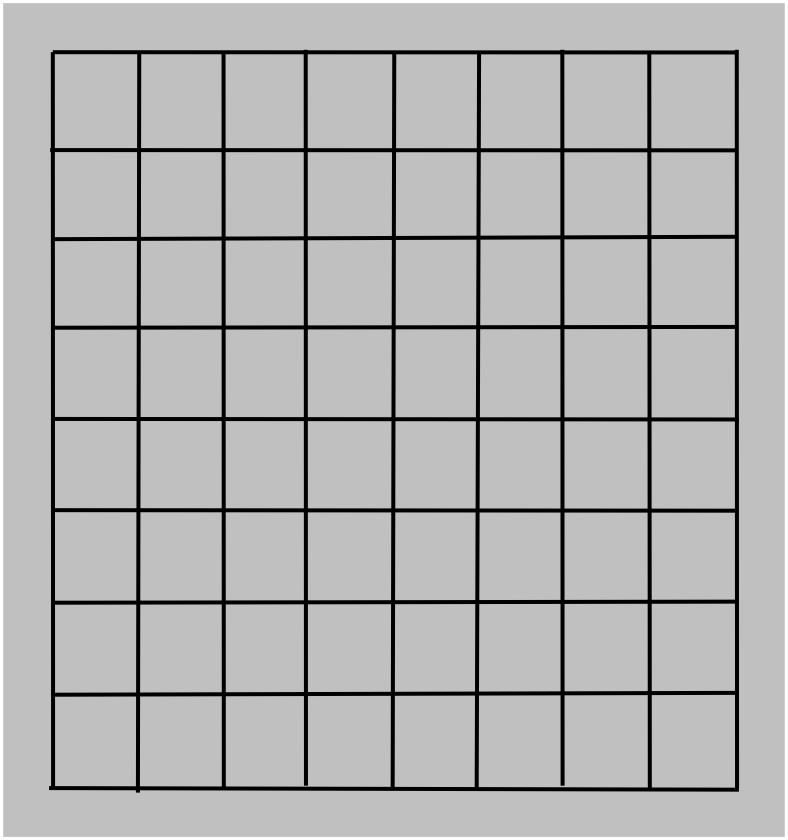
The game of Go

The game of Go

- 4000 years
- Originated from China
- Developed by Japan (20th century)
- Best players in Korea, Japan, China
- 19x19: official board size
- 9x9: beginners' board size

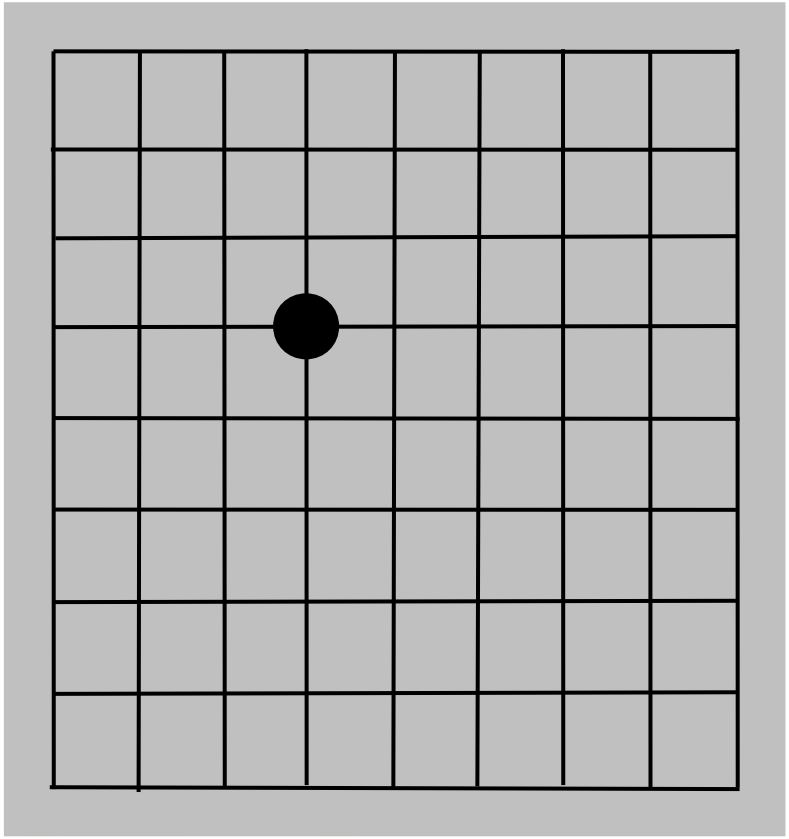
A 9x9 game

- The board has 81 « intersections ». Initially,it is empty.



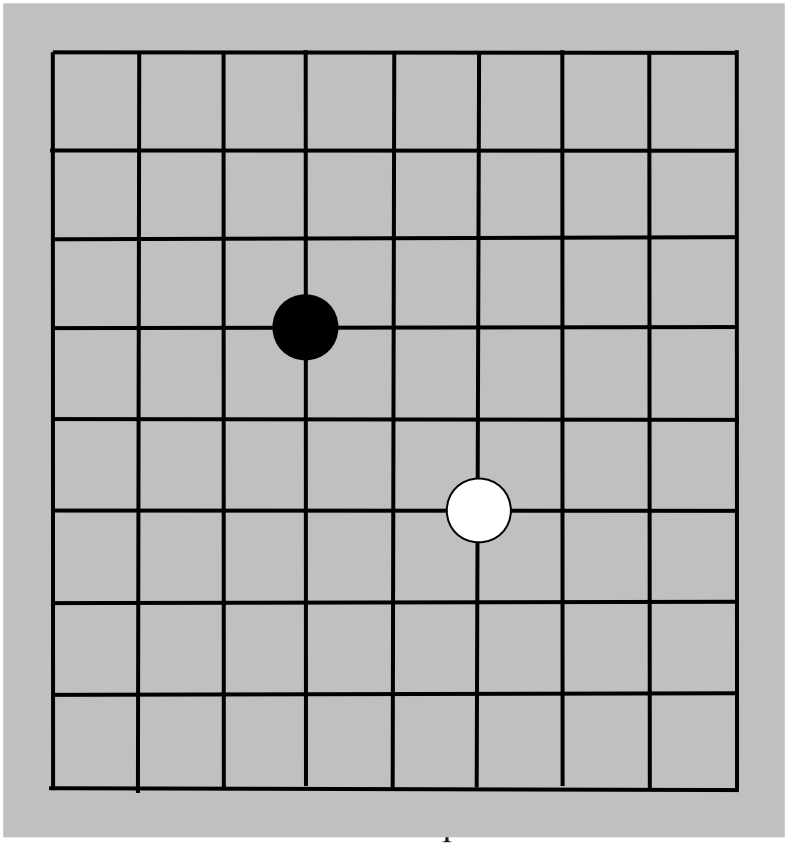
A 9x9 game

- Black moves first. A « stone » is played on an intersection.



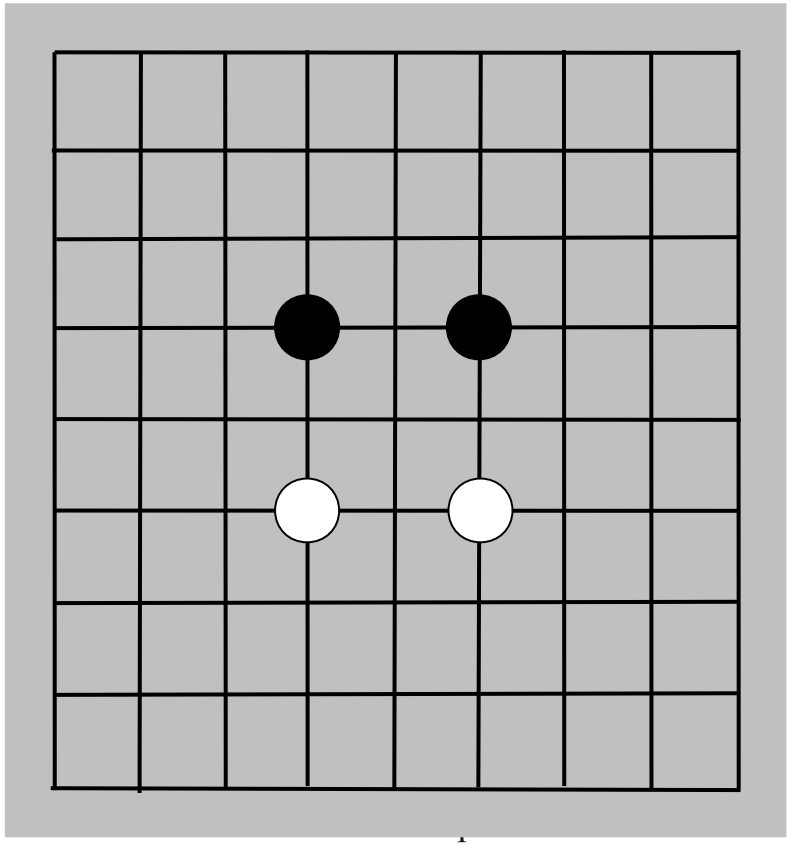
A 9x9 game

- White moves second.



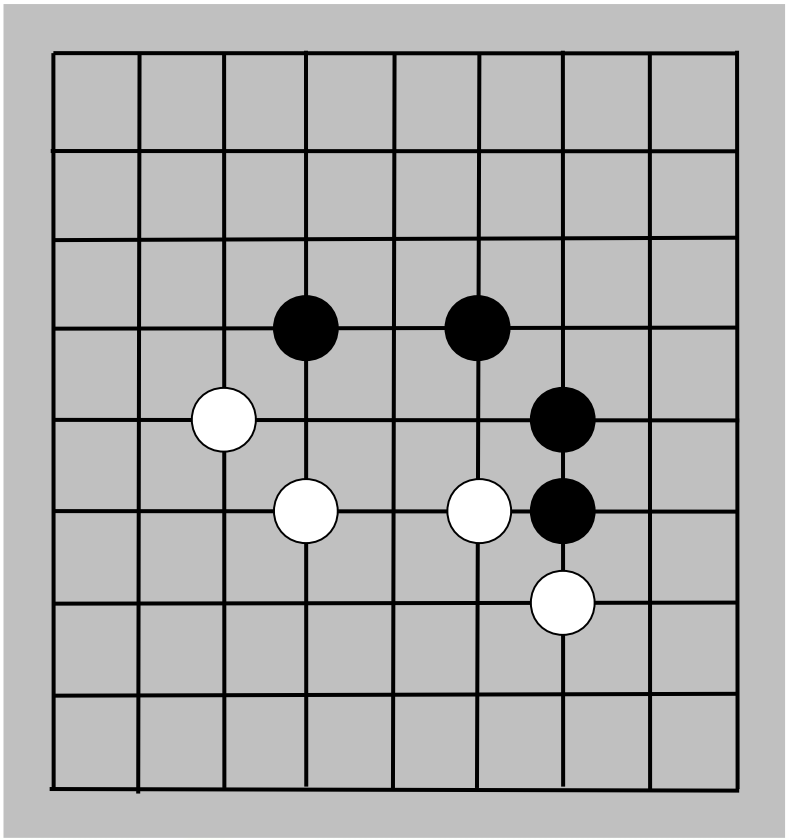
A 9x9 game

- Moves alternate between Black and White.



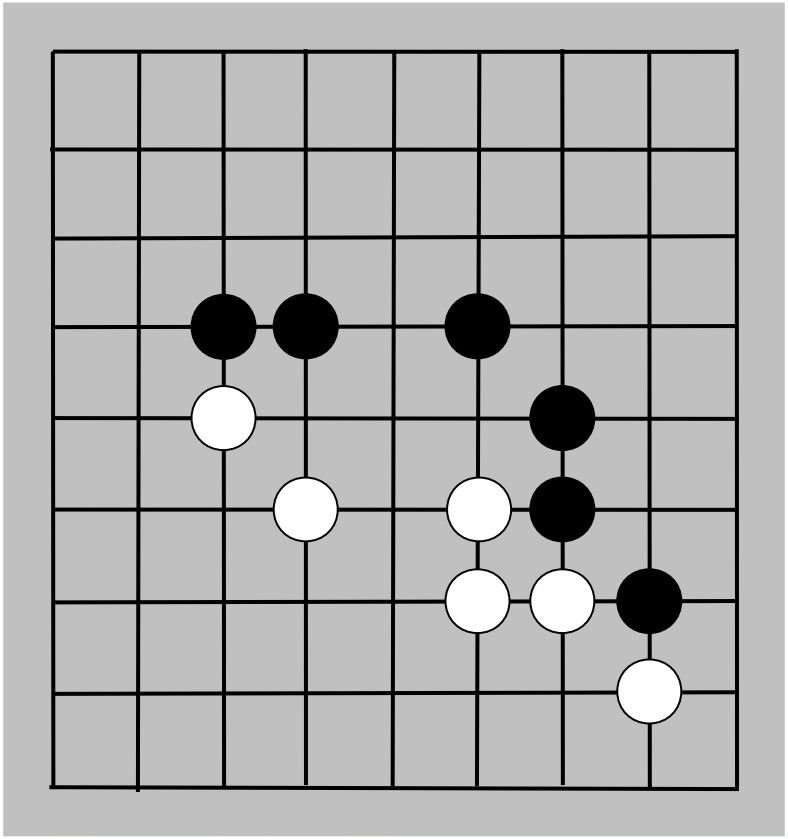
A 9x9 game

- Two adjacent stones of the same color builds a « string » with « liberties ».
- 4-adjacency



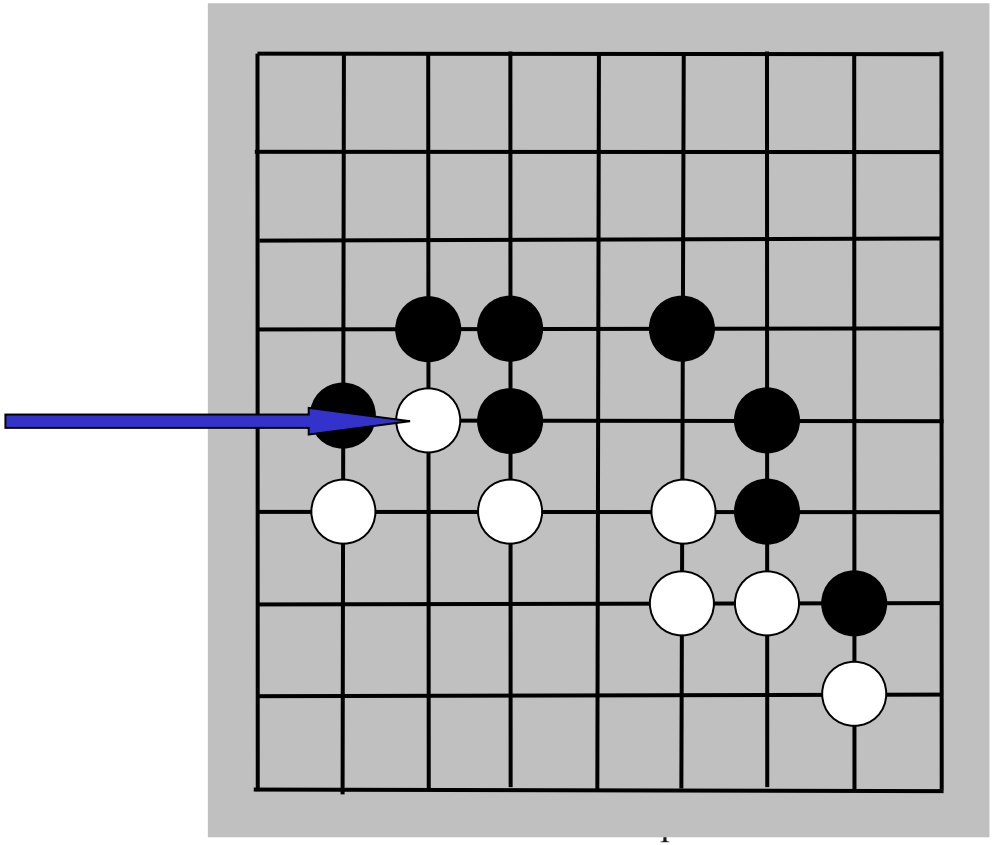
A 9x9 game

- Strings are created.



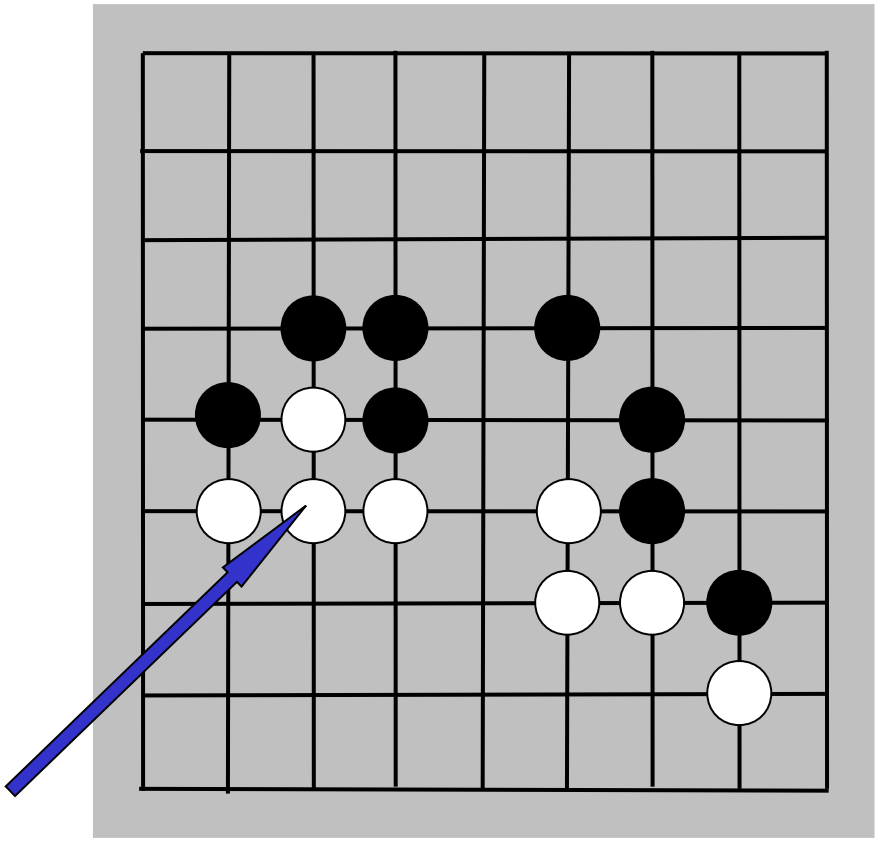
A 9x9 game

- A white stone is in « atari » (one liberty).



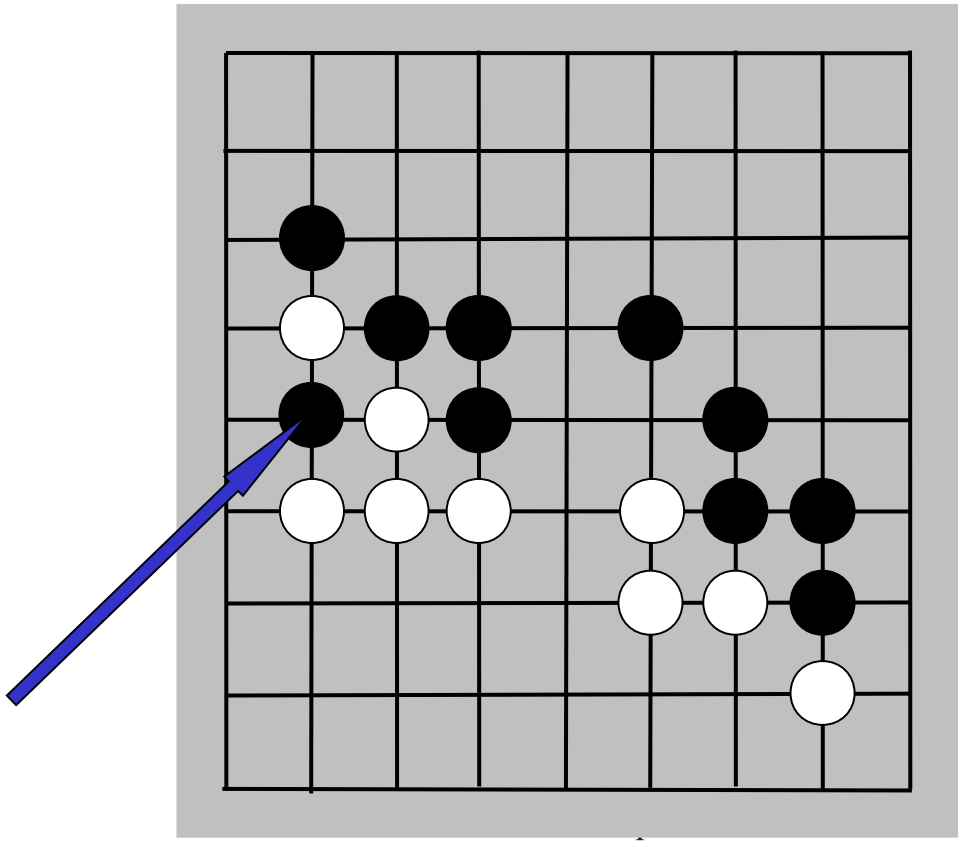
A 9x9 game

- The white string has five liberties.



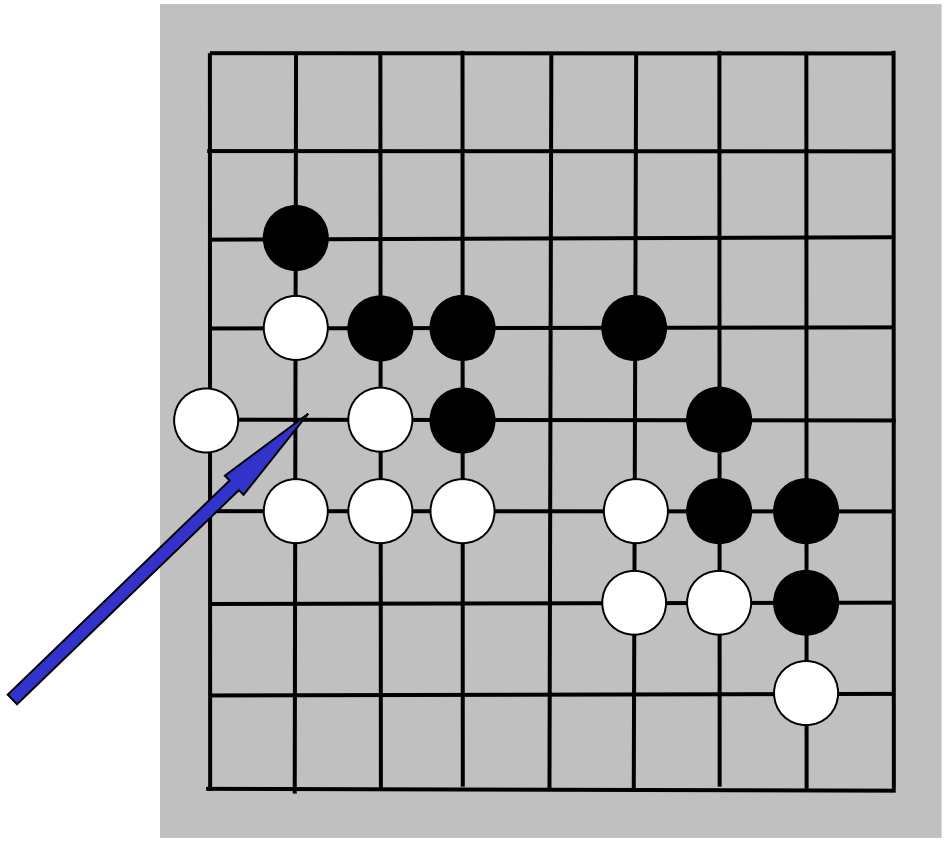
A 9x9 game

- The black stone is « atari ».



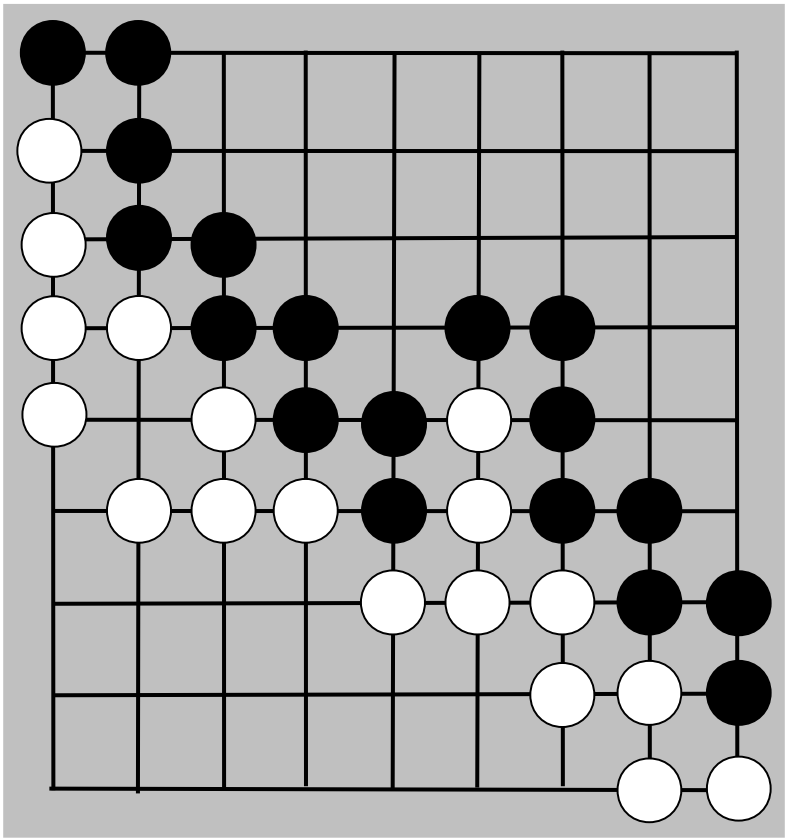
A 9x9 game

- White « captures » the black stone.



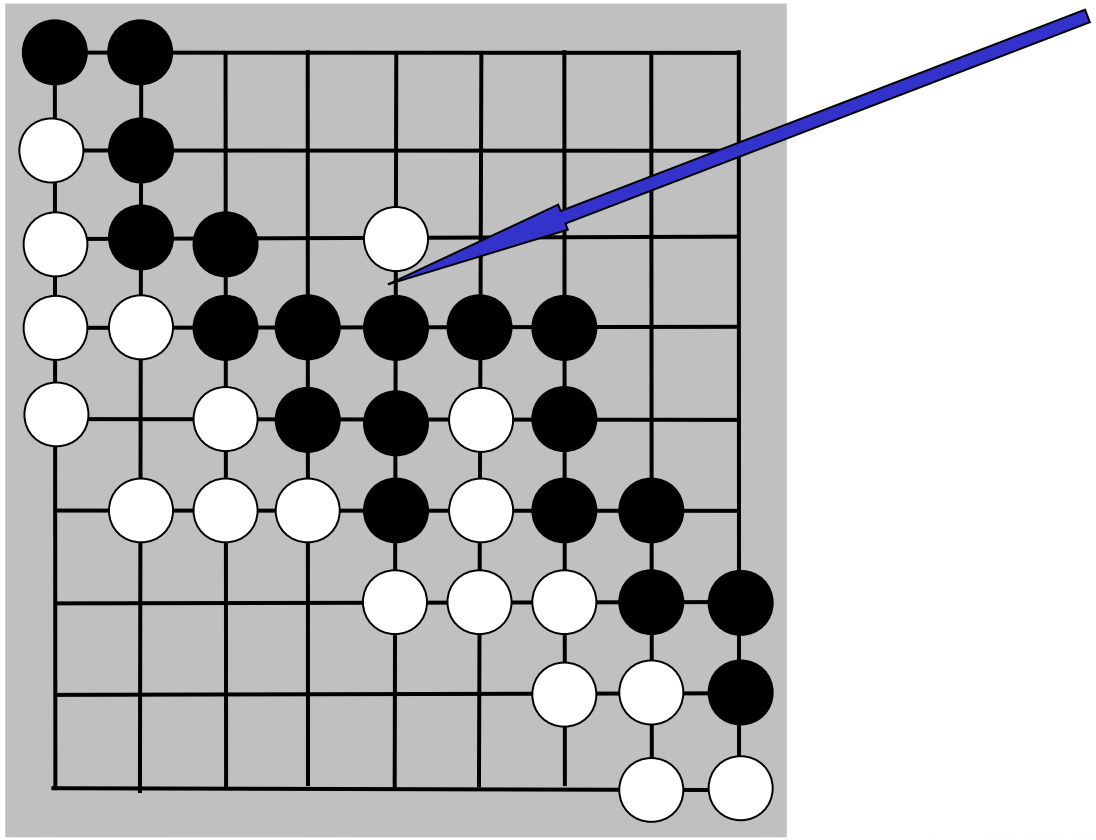
A 9x9 game

- For human players, the game is over.
  - Hu?
  - Why?



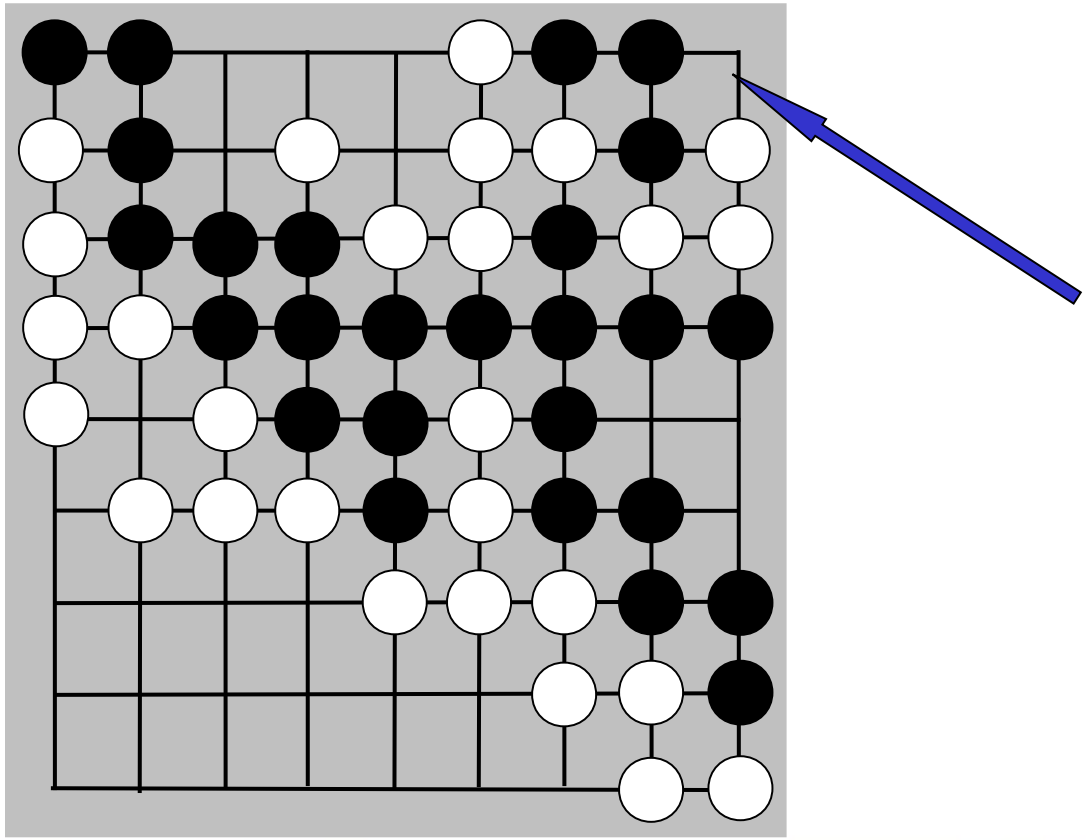
A 9x9 game

- What happens if White contests black « territory »?



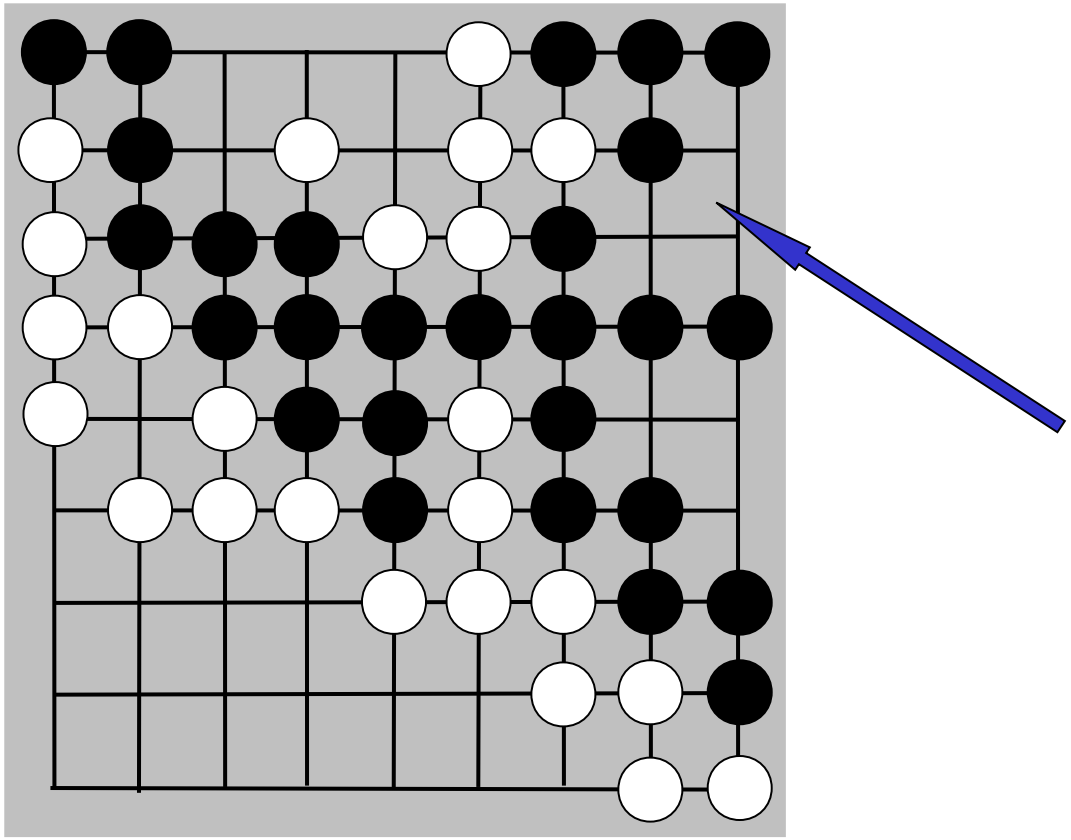
A 9x9 game

- White has invaded. Two strings are atari!



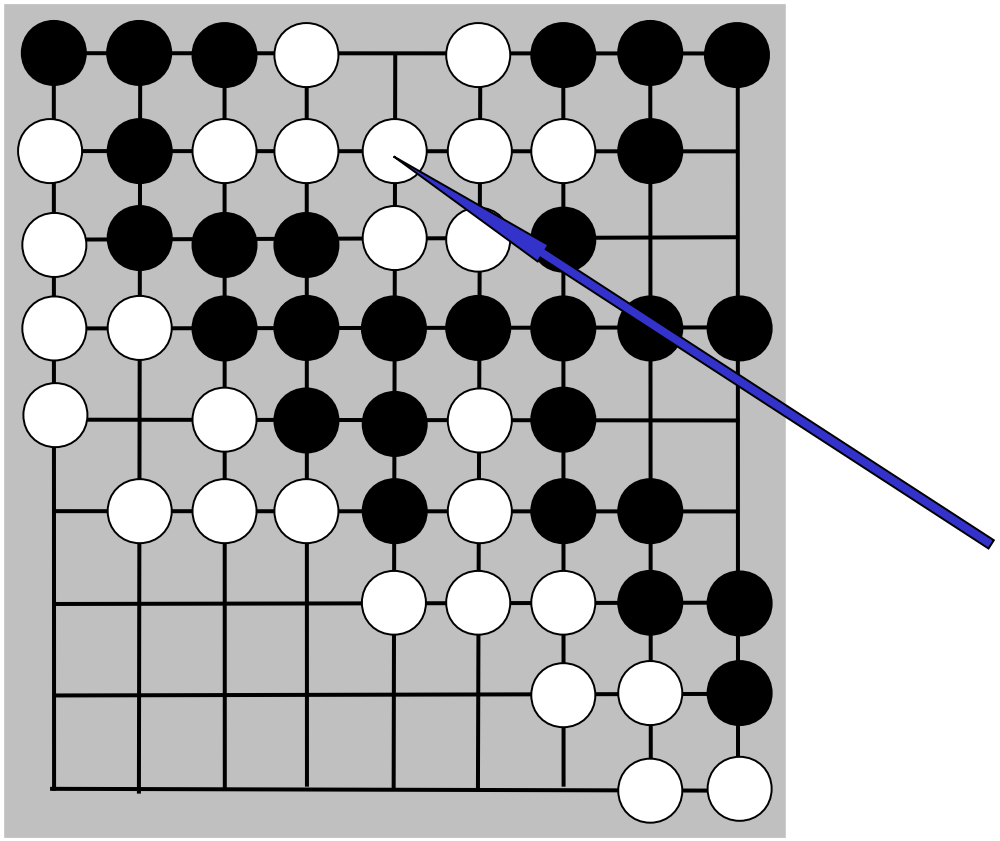
A 9x9 game

- Black captures !



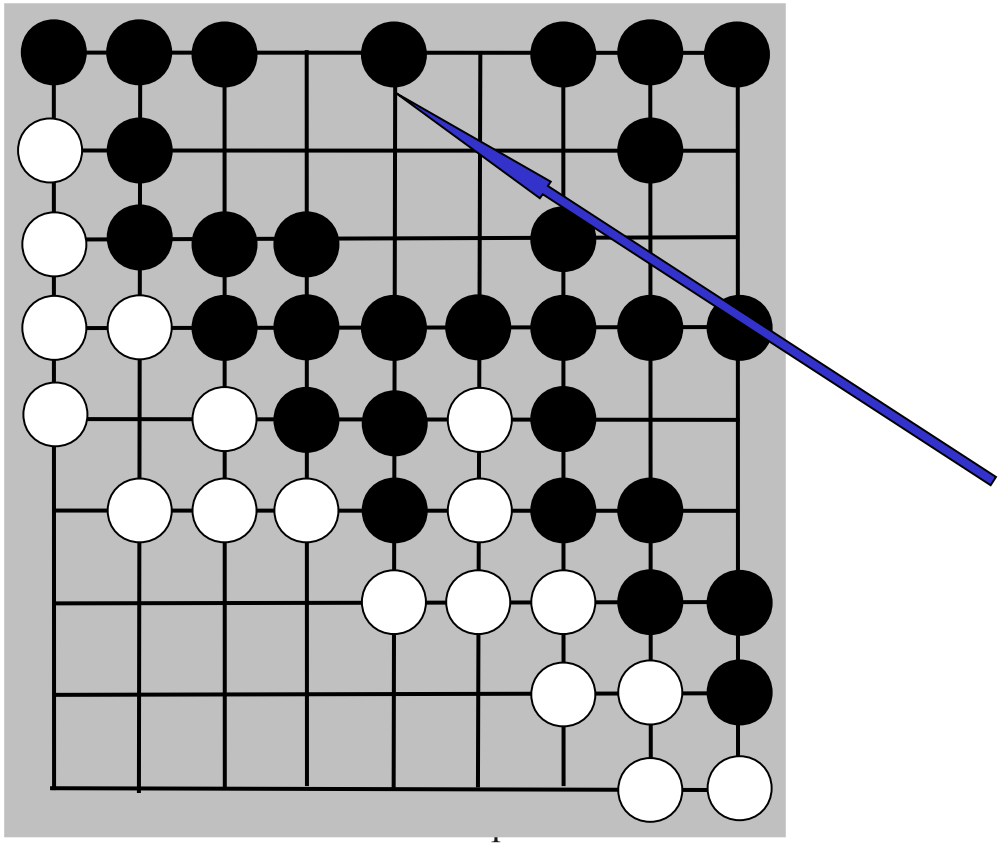
A 9x9 game

- White insists but its string is atari...



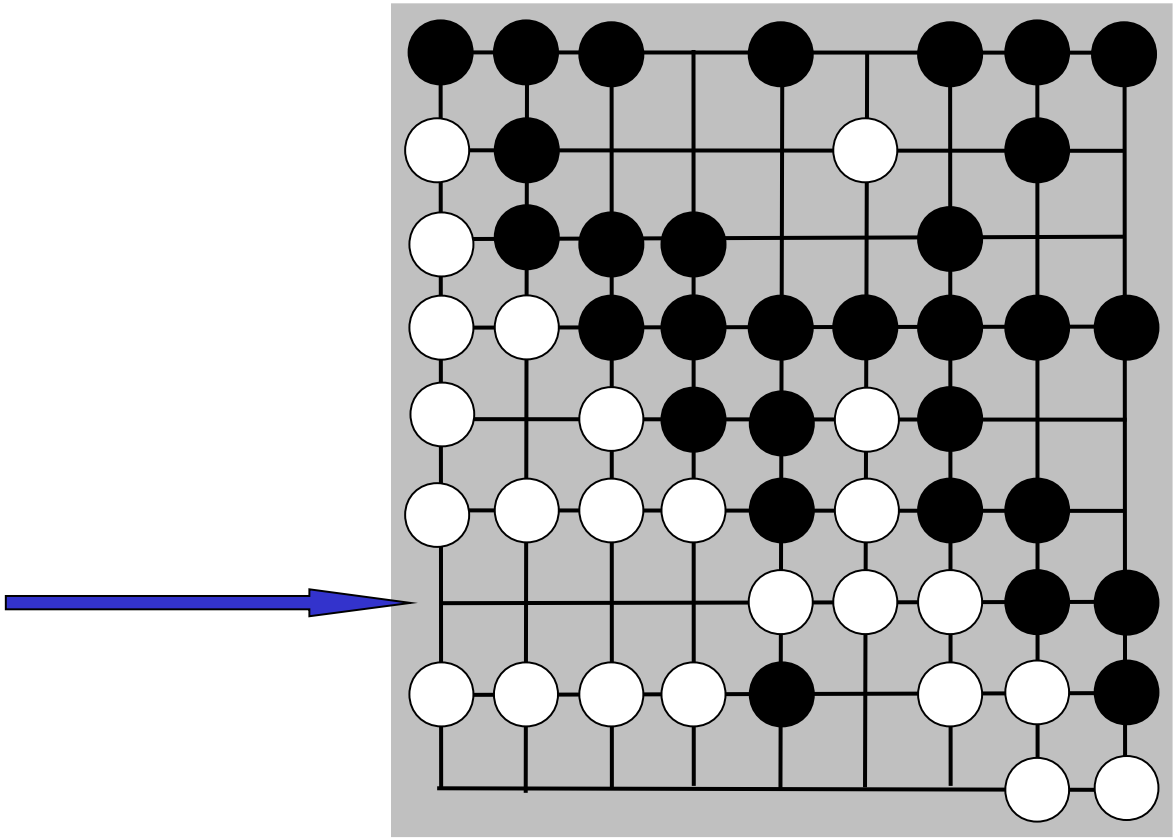
A 9x9 game

- Black has proved is « territory ».



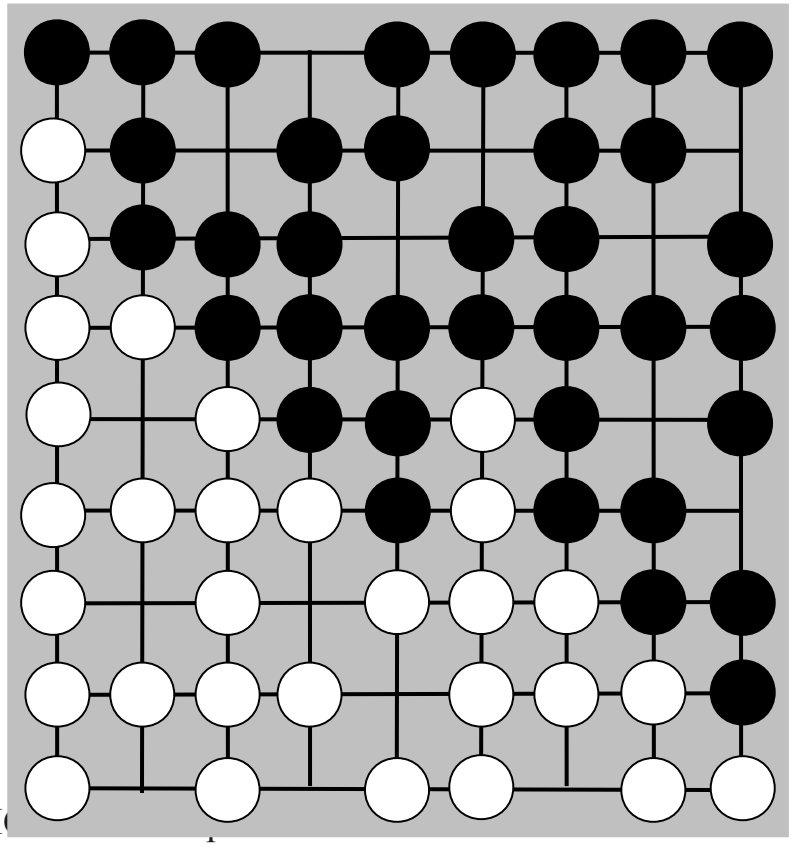
A 9x9 game

- Black may contest white territory too.



A 9x9 terminal position

- The game is over for computers.
  - Hu?
  - Who won ?

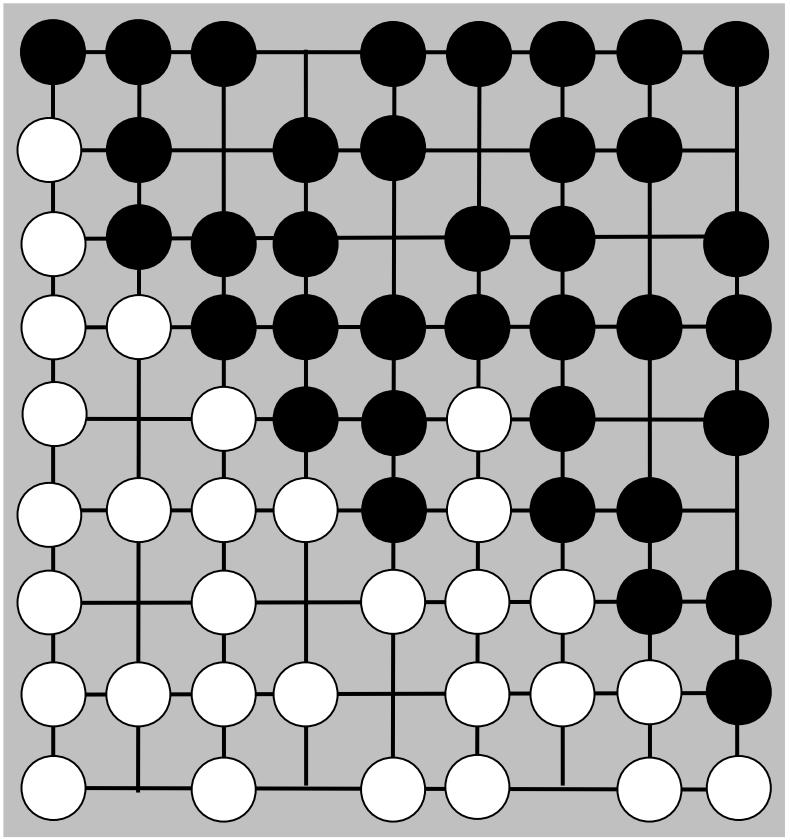


A 9x9 game

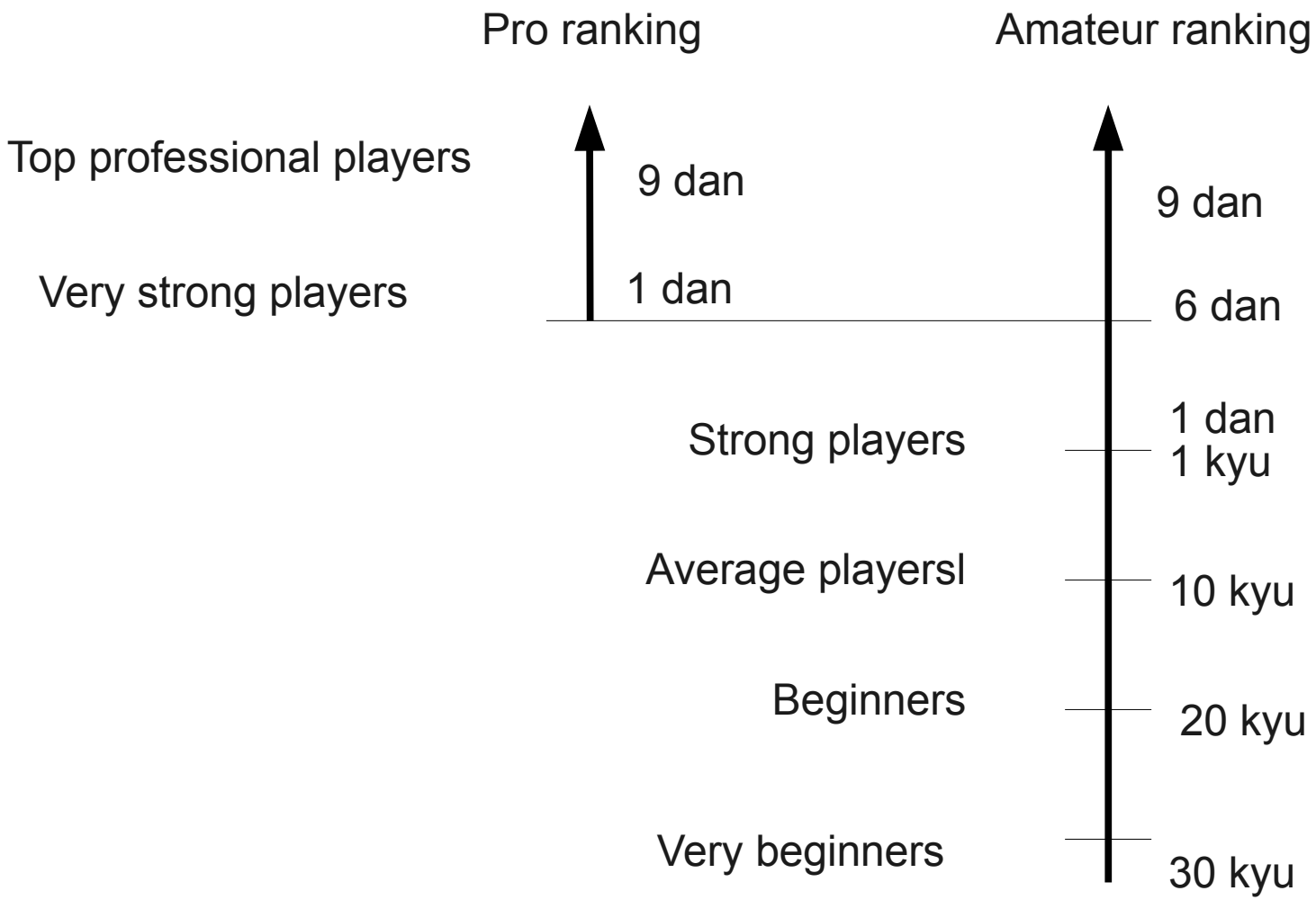
- The game ends when both players pass.
- One black (resp. white) point for each black (resp. white) stone and each black (resp. white) « eye » on the board.
- One black (resp. white) eye = an empty intersection surrounded by black (resp. white) stones.

A 9x9 game

- Scoring:
  - Black = 44
  - White = 37
  - Komi = 7.5
  - Score = -0.5
- White wins!



Go ranking: « kyu » and « dan »



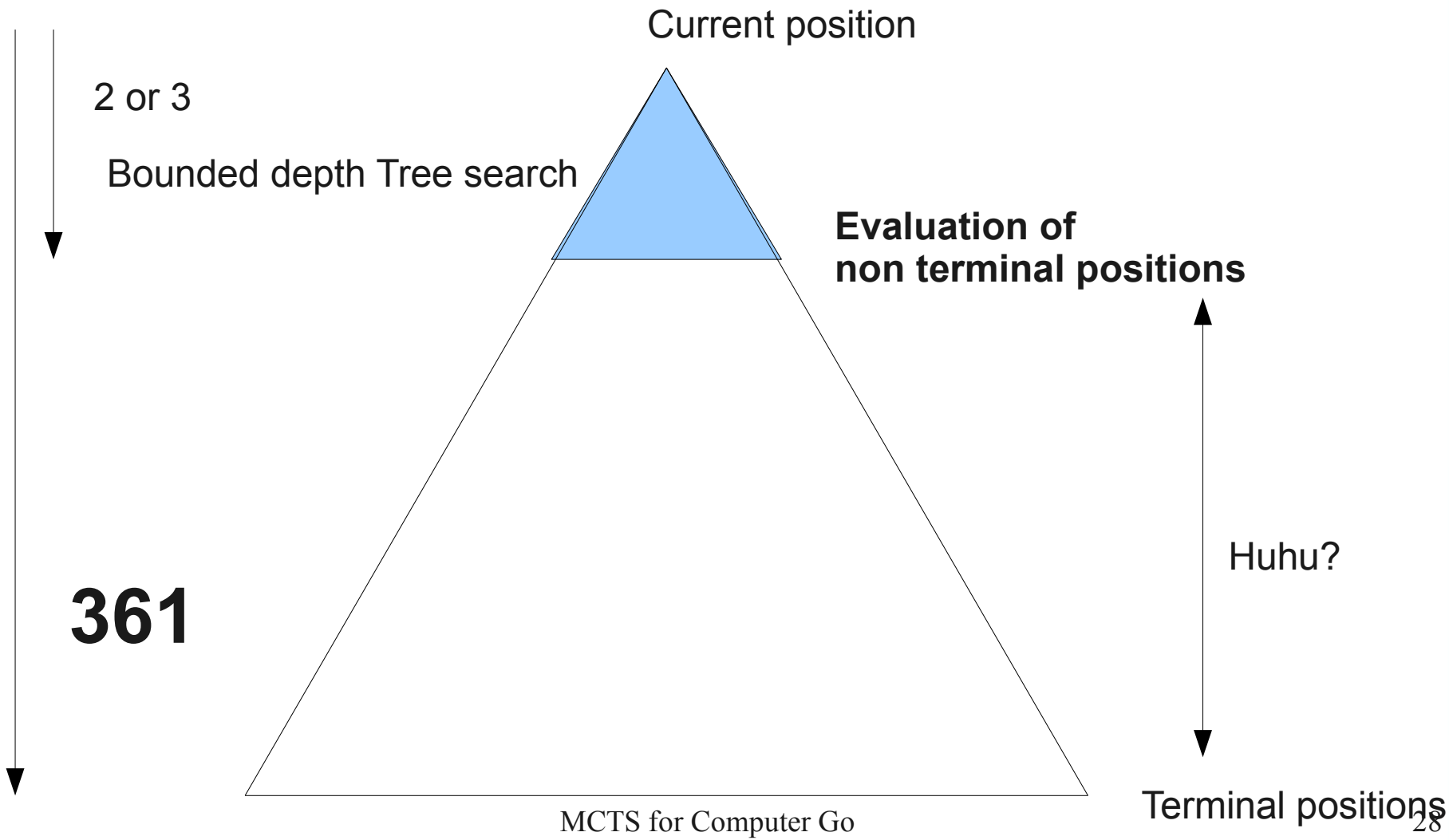
Computer Go (old history)

- First go program (Lefkovitz 1960)
- Zobrist hashing (Zobrist 1969)
- Interim2 (Wilcox 1979)
- Life and death model (Benson 1988)
- Patterns: Goliath (Boon 1990)
- Mathematical Go (Berlekamp 1991)
- Handtalk (Chen 1995)

The old approach

- Evaluation of non terminal positions
  - Knowledge-based
  - Breaking-down of a position into sub-positions
- Fixed-depth global tree search
  - Depth = 0 : action with the best value
  - Depth = 1: action leading to the position with the best evaluation
  - Depth > 1: alfa-beta or minmax

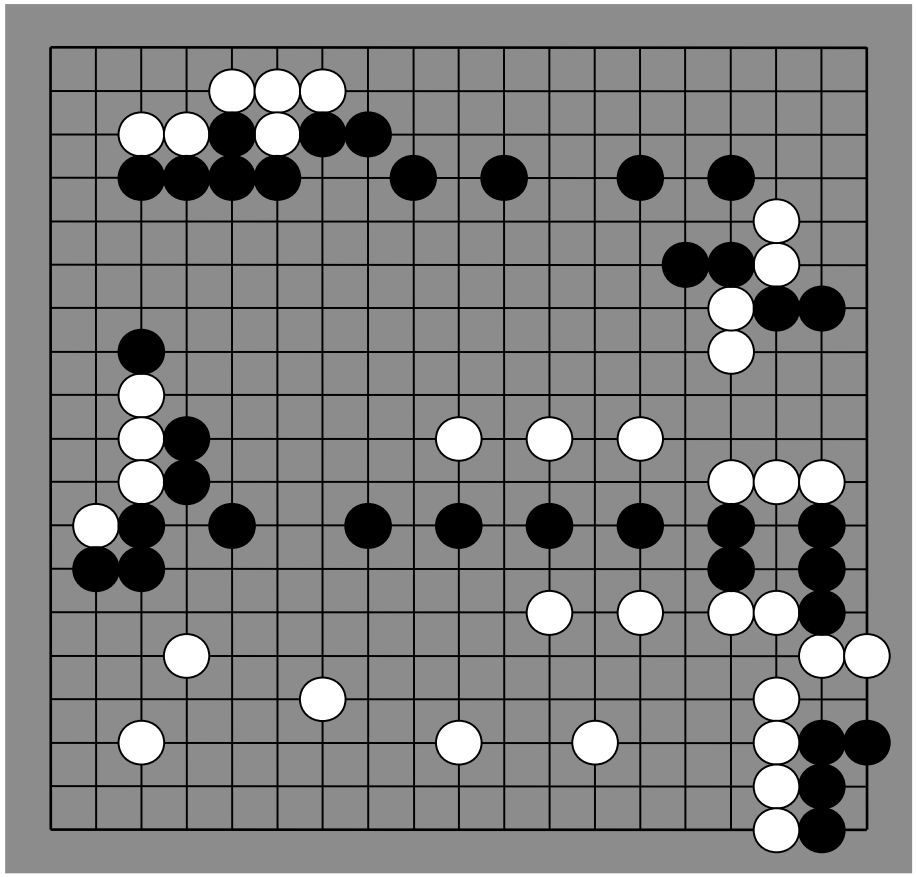
The old approach



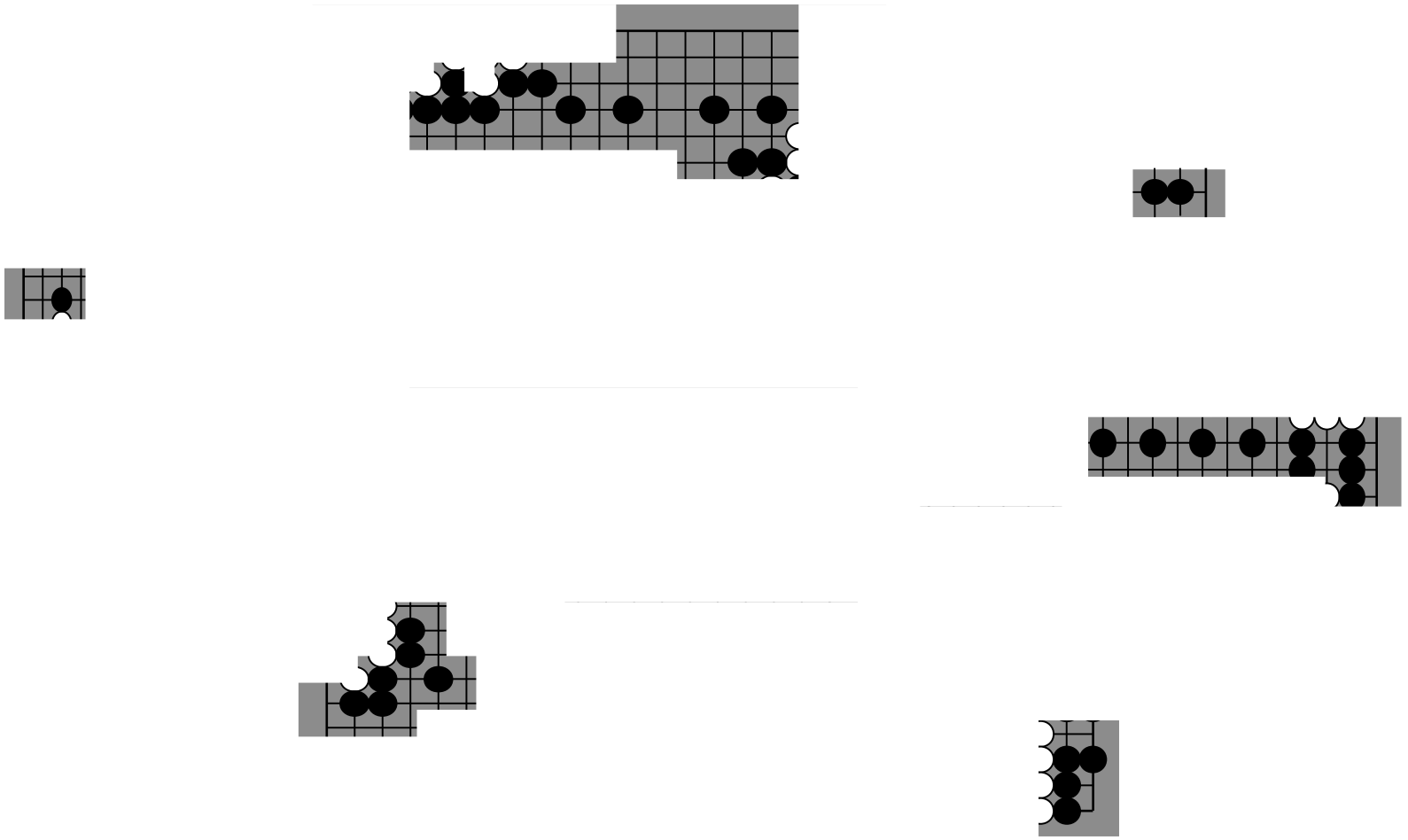
Position evaluation

- Break-down
  - Whole game (win/loss or score)
  - Goal-oriented sub-game
    - String capture
    - Connections, dividers, eyes, life and death
- Local searches
  - Alpha-beta and enhancements
  - Proof-number search

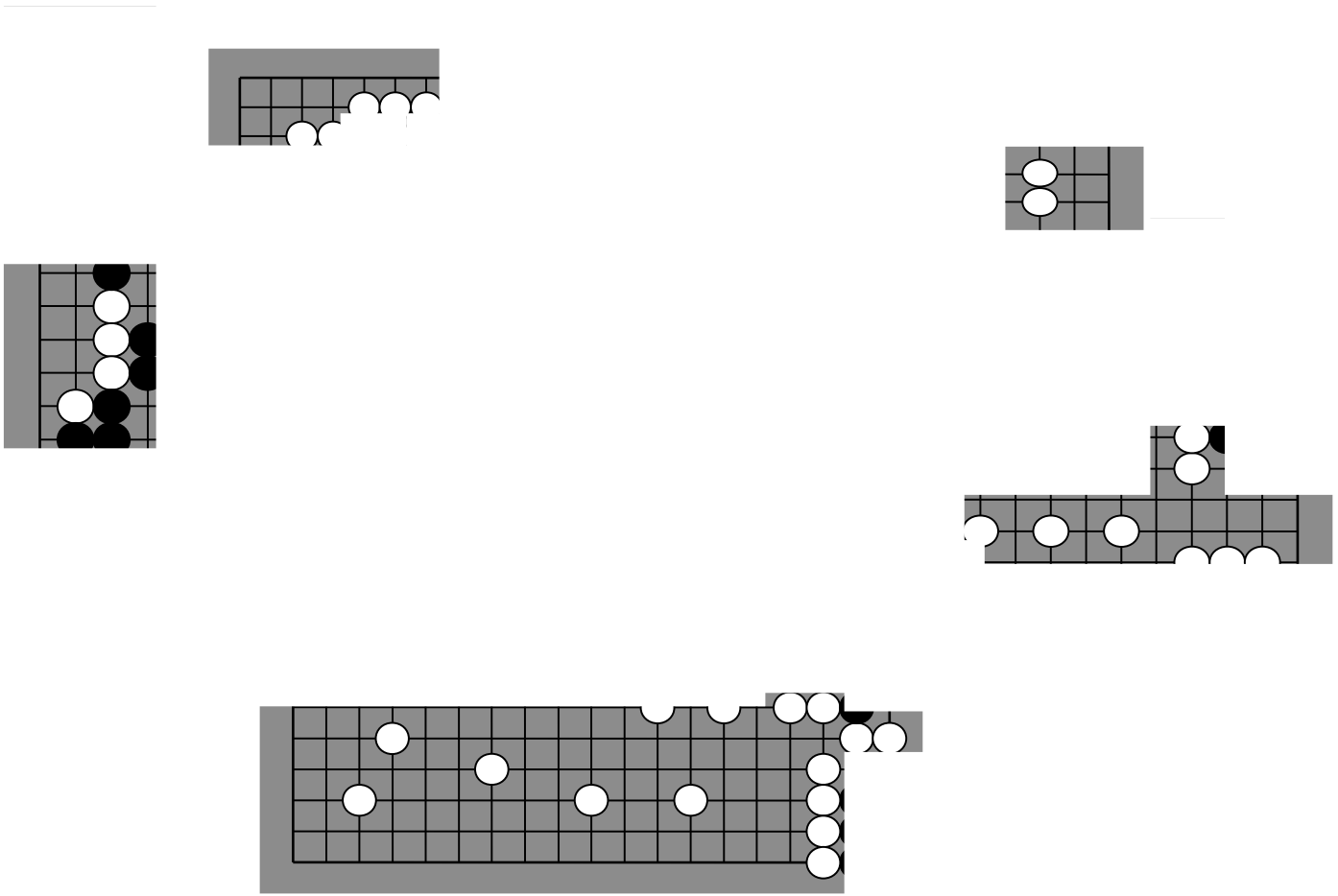
A 19x19 middle-game position



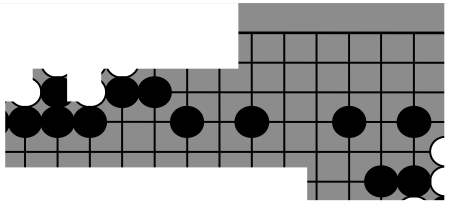
A possible black break-down



A possible white break-down



Possible local evaluations (1)

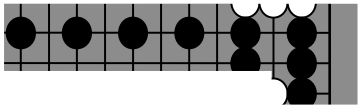


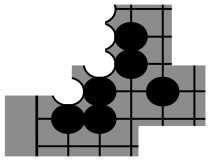
Alive and territory

unstable

Not important

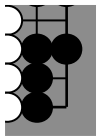
alive





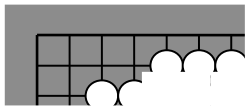
alive

dead

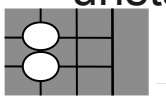


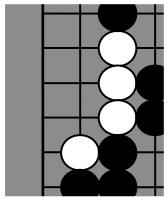
Possible local evaluations (2)

alive

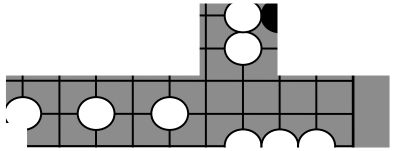


unstable

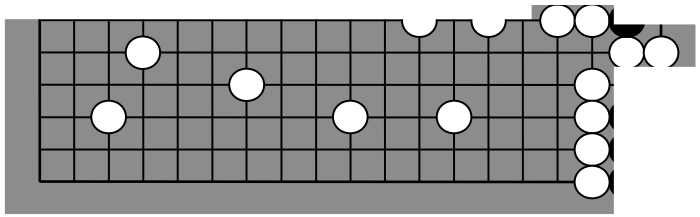




unstable



alive + big territory

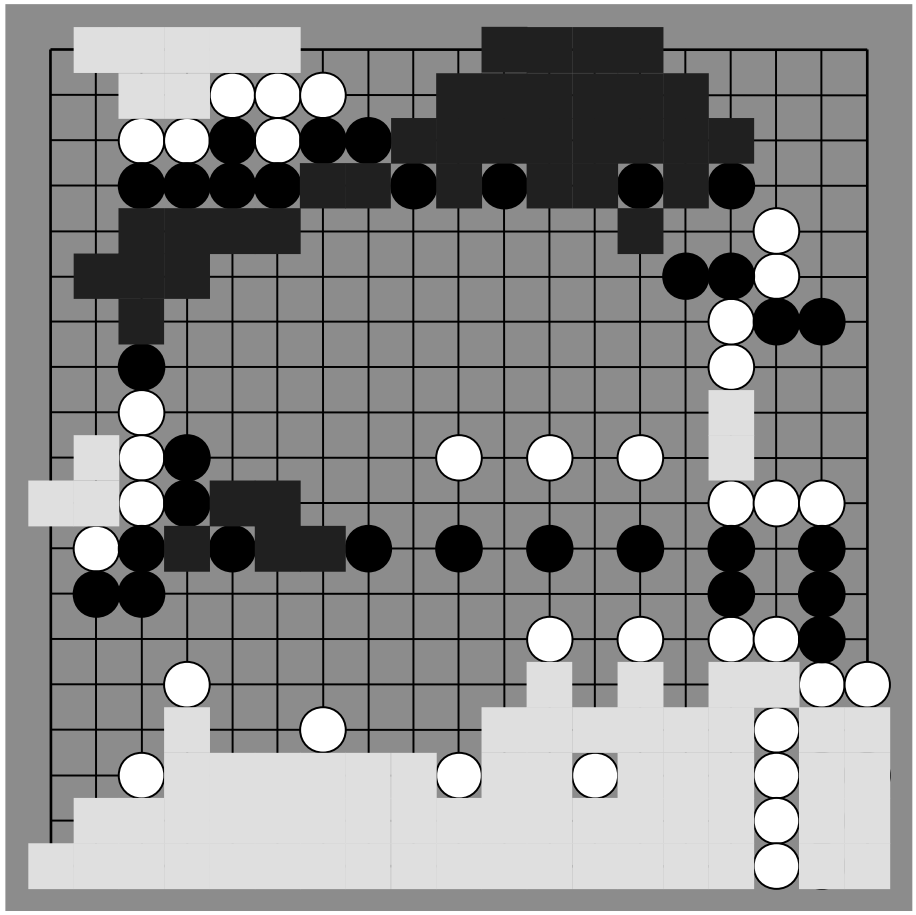


unstable

Position evaluation

- Local results
  - Obtained with local tree search
  - Result if white plays first (resp. black)
  - Combinatorial game theory (Conway)
  - Switches {a|b}, >, <, *, 0
- Global recomposition
  - move generation and evaluation
  - position evaluation

Position evaluation



Drawbacks (1/2)

- The break-down is not unique
- Performing a (wrong) local tree search on a (possibly irrelevant) local position
- Misevaluating the size of the local position
- Different kinds of local information
  - Symbolic (group: dead alive unstable)
  - Numerical (territory size, reduction, increase)

Drawbacks (2/2)

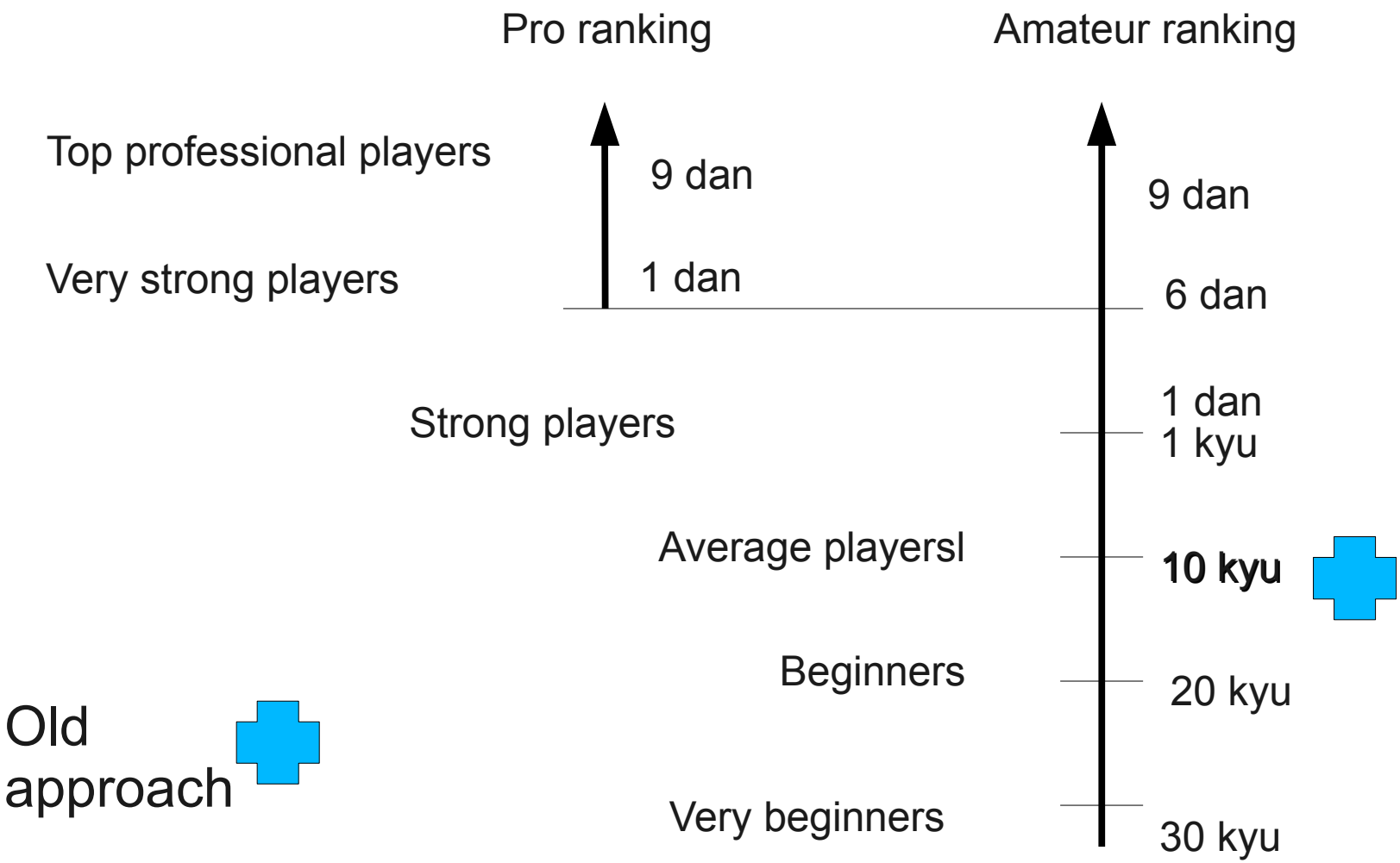
- Local positions interact
- Complicated
- Domain-dependent knowledge
- Need of human expertise
- Difficult to program and maintain
- Holes of knowledge
- Erratic behaviour

Upsides

- Feasible on 1990's computers
- Execution is fast

- Some specific local tree searches are accurate and fast

The old approach



End of part one!

- Next: the Monte-Carlo approach...

The Monte-Carlo (MC) approach

- Games containing chance
  - Backgammon (Tesauro 1989)
- Games with hidden information
  - Bridge (Ginsberg 2001)
  - Poker (Billings & al. 2002)
  - Scrabble (Sheppard 2002)

The Monte-Carlo approach

- Games with complete information
  - A general model (Abramson 1990)
- Simulated annealing Go
  - (Brügmann 1993)
  - 2 sequences of moves
  - « all moves as first » heuristic
  - Gobble on 9x9

The Monte-Carlo approach

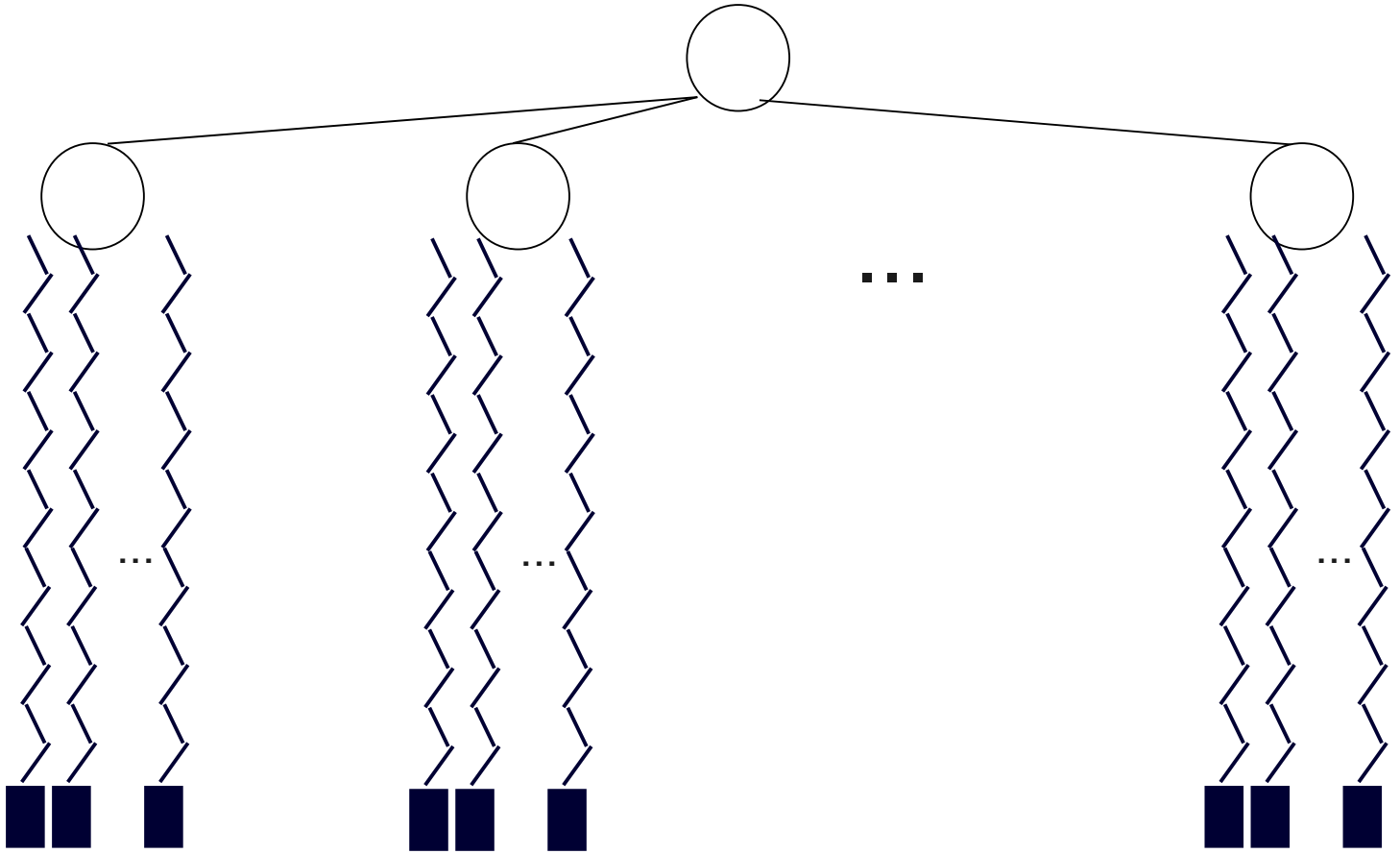
- Position evaluation:

```
Launch N random games
Evaluation = mean value of outcomes
```

- Depth-one MC algorithm:

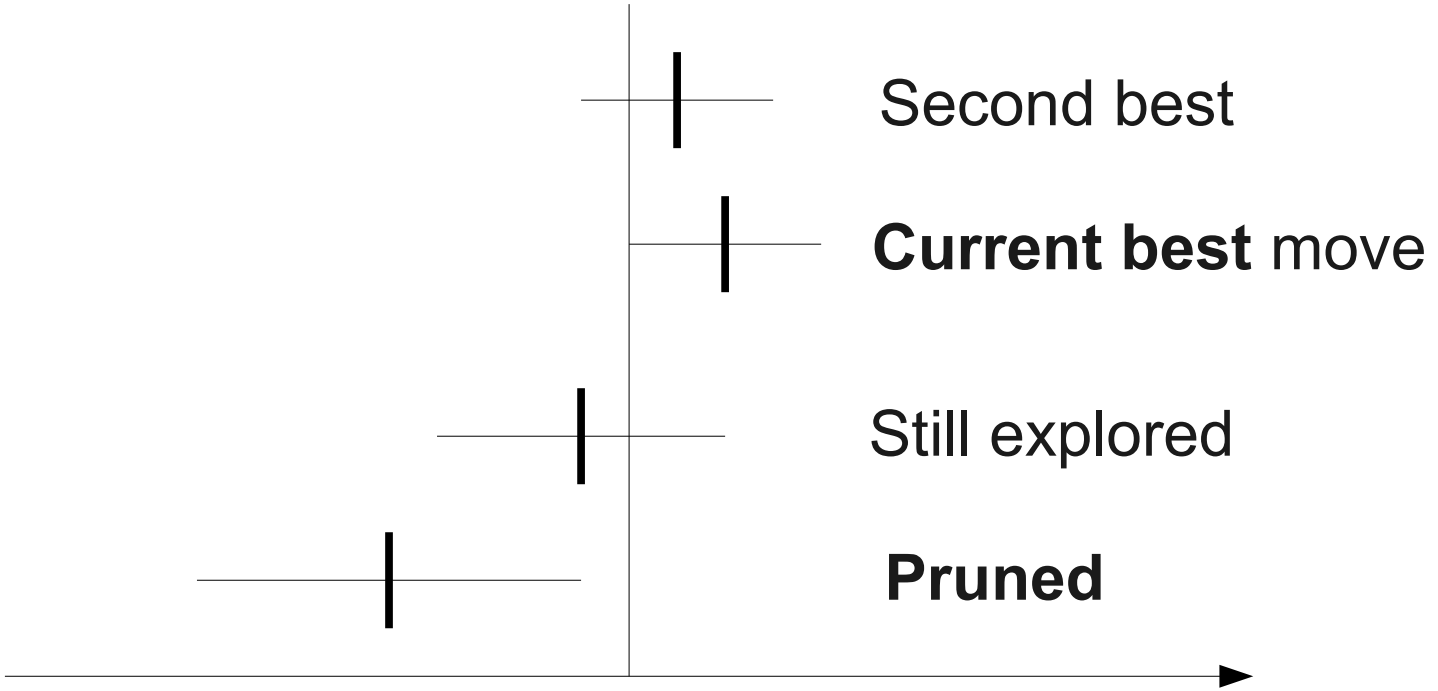
```
For each move m {
        Play m on the ref position
        Launch N random games
        Move value (m) = mean value
}
```

Depth-one Monte-Carlo



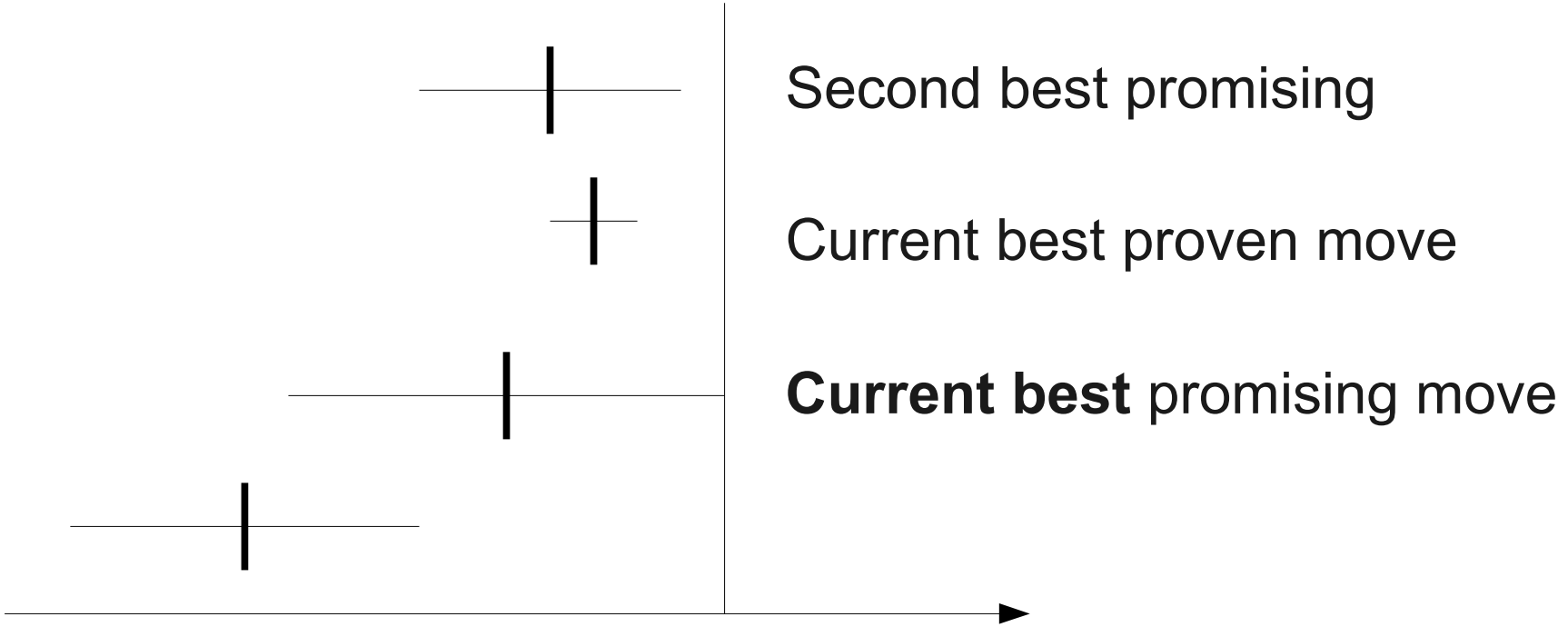
Progressive pruning

- (Billings 2002, Sheppard 2002, Bouzy & Helmstetter 2003)

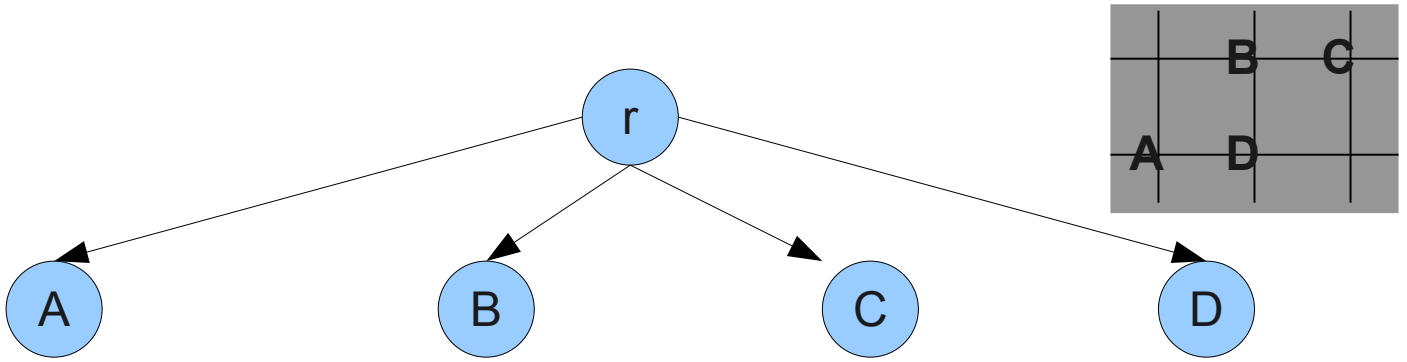


Upper bound

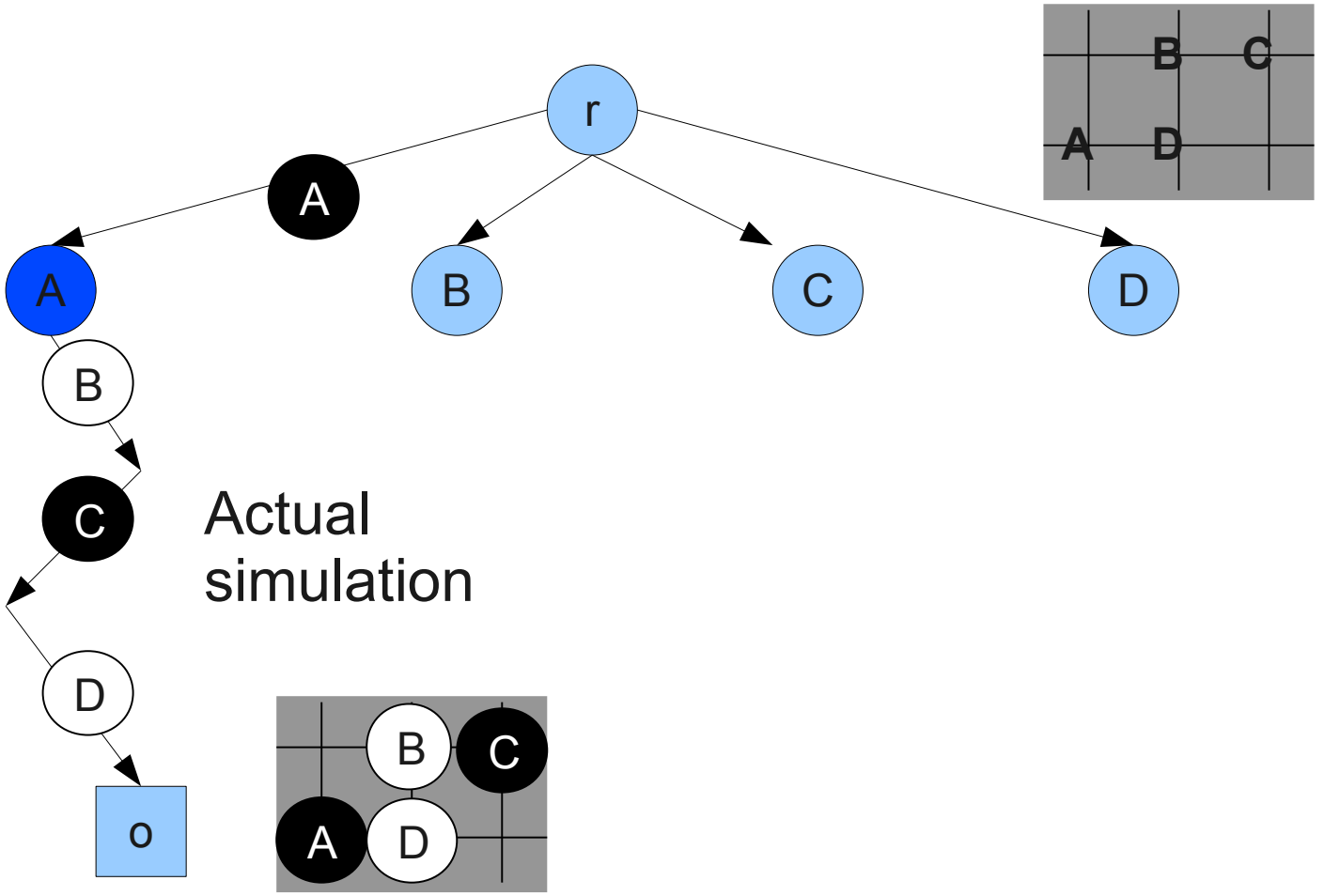
- Optimism in face of uncertainty
  - Intestim (Kaelbling 1993),
  - UCB multi-armed bandit (Auer & al 2002)



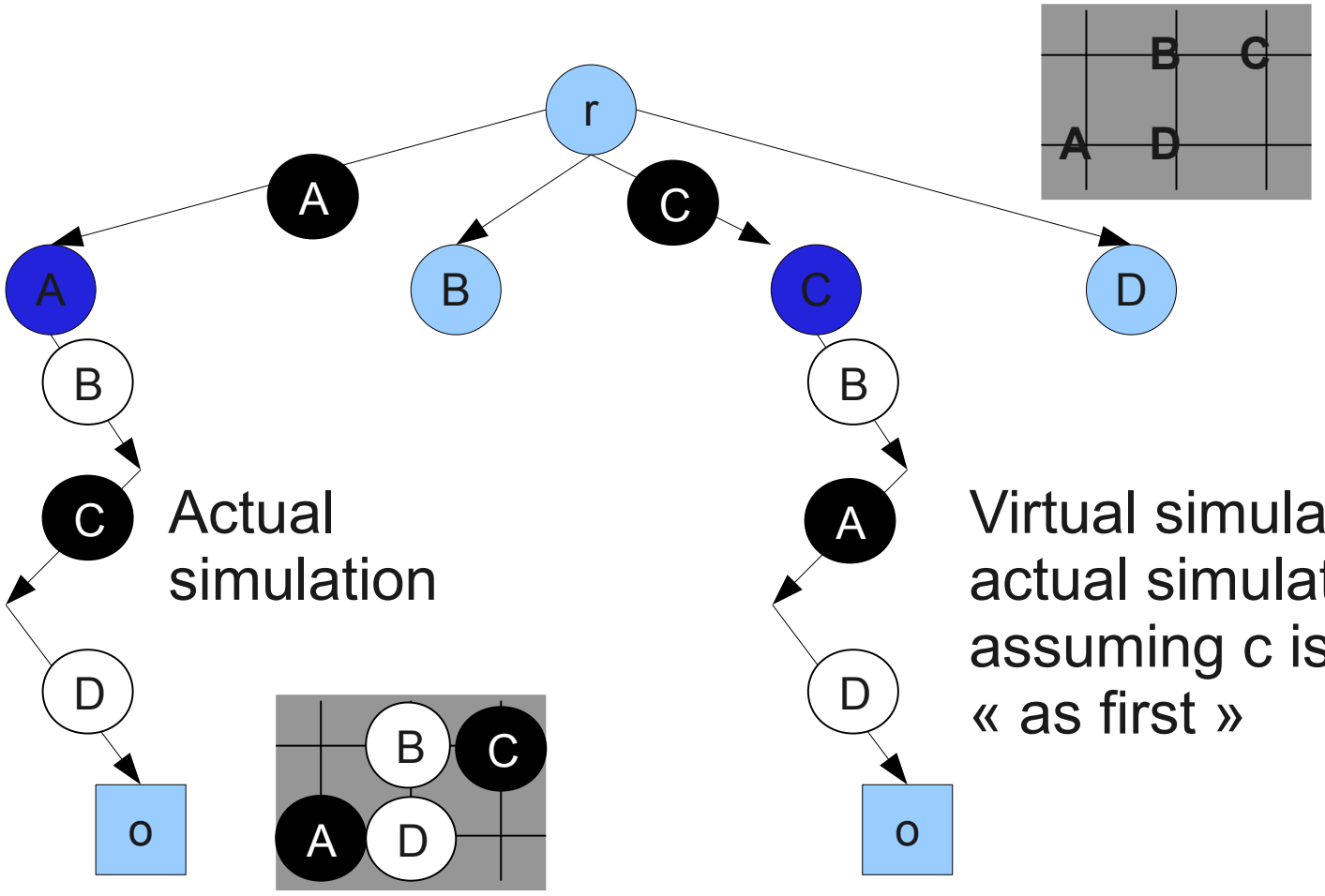
All-moves-as-first heuristic (1/3)



All-moves-as-first heuristic (2/3)



All-moves-as-first heuristic (3/3)



Actual simulation

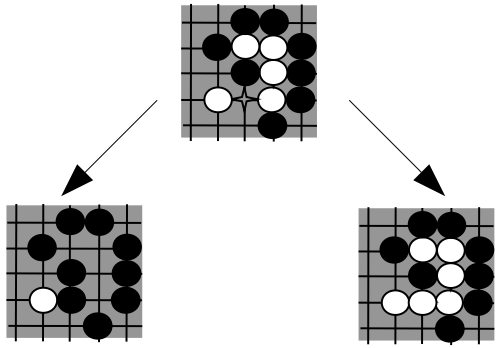
Virtual simulation = actual simulation assuming c is played « as first »

The Monte-Carlo approach

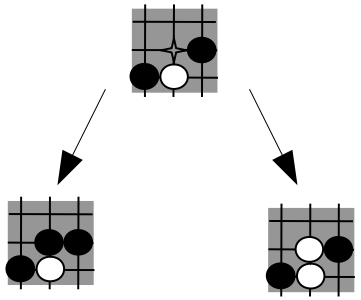
- Upsides
  - Robust evaluation
  - Global search
  - Move quality increases with computing power
- Way of playing
  - Good strategical sense but weak tactically
- Easy to program
  - Follow the rules of the game
  - No break-down problem

Monte-Carlo and knowledge

- Pseudo-random simulations using Go knowledge (Bouzy 2003)
  - Moves played with a probability depending on specific domain-dependent knowledge
- 2 basic concepts
  - string capture



3x3 shapes



Monte-Carlo and knowledge

- Results are impressive
  - MC(random) << MC(pseudo random)
  - Size 9x9 13x13 19x19
  - % wins 68 93 98
- Other works on simulations
  - Patterns in MoGo, proximity rule (Wang & al 2006)
  - Simulation balancing (Silver & Tesauro 2009)

Monte-Carlo and knowledge

- Pseudo-random player
  - 3x3 pattern urgency table with 3^8 patterns
  - Few dizains of relevant patterns only
  - Patterns gathered by
    - Human expertise
    - Reinforcement Learning (Bouzy & Chaslot 2006)
- Warning
  - p1 better than p2 does not mean MC(p1) better than MC(p2)

Monte-Carlo Tree Search (MCTS)

- How to integrate MC and TS ?
- UCT = UCB for Trees
  - (Kocsis & Szepesvari 2006)
  - Superposition of UCB (Auer & al 2002)
- MCTS
  - Selection, expansion, updating (Chaslot & al) (Coulom 2006)
  - Simulation (Bouzy 2003) (Wang & Gelly 2006)

MCTS (1/2)

```
while (hasTime) {
        playOutTreeBasedGame()
        expandTree()
        outcome = playOutRandomGame()
        updateNodes(outcome)
}
```

then choose the node with...

... the best mean value

... the **highest visit** number

MCTS (2/2)

```
PlayOutTreeBasedGame() {
      node = getNode(position)
      while (node) {
            move=selectMove(node)
            play(move)
            node = getNode(position)
      }
}
```

UCT move selection

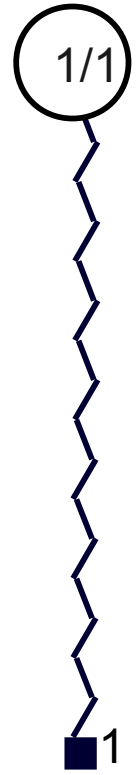
- Move selection rule to browse the tree:

  move=argmax (s*mean + C*sqrt(log(t)/n)

- Mean value for exploitation
  - s (=+-1): color to move
- UCT bias for exploration
  - C: constant term set up by experiments
  - t: number of visits of the parent node
  - n: number of visits of the current node

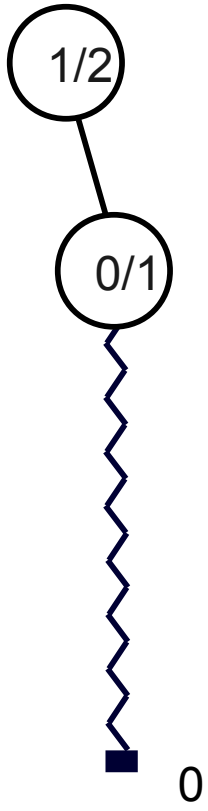
Example

- 1 iteration



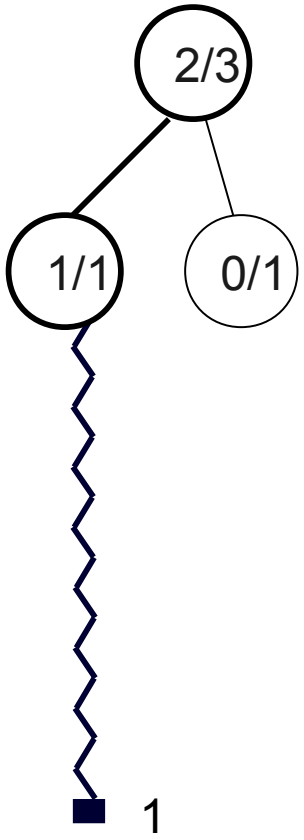
Example

- 2 iterations



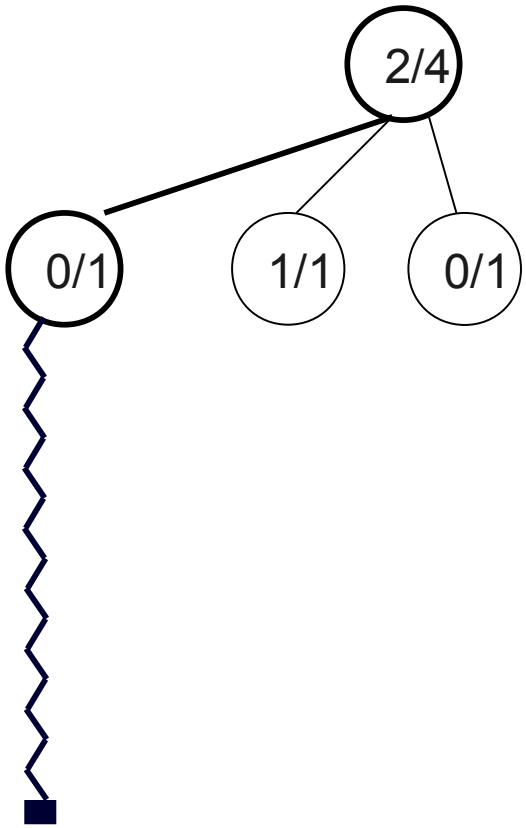
Example

- 3 iterations



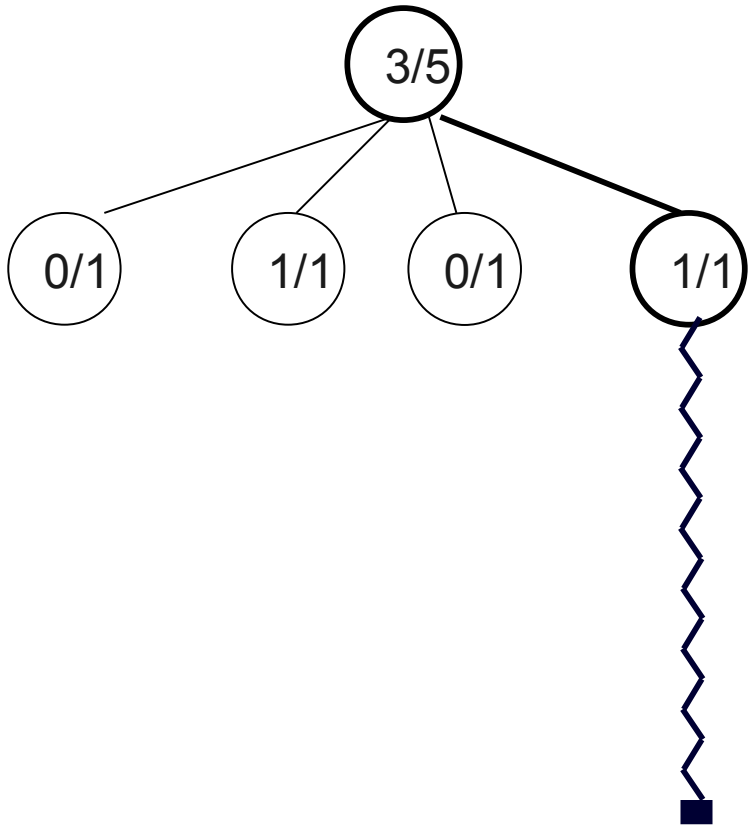
Example

- 4 iterations



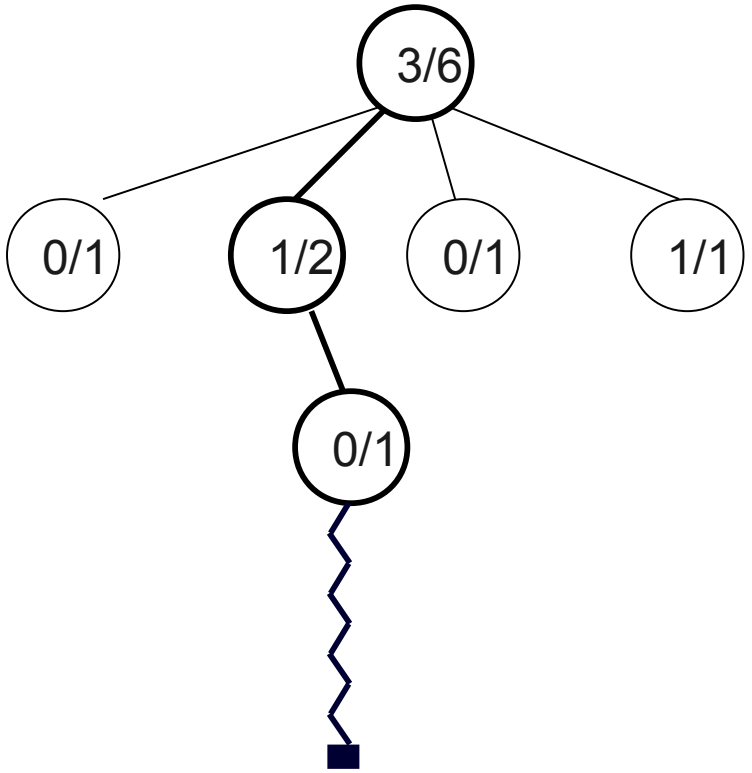
Example

- 5 iterations



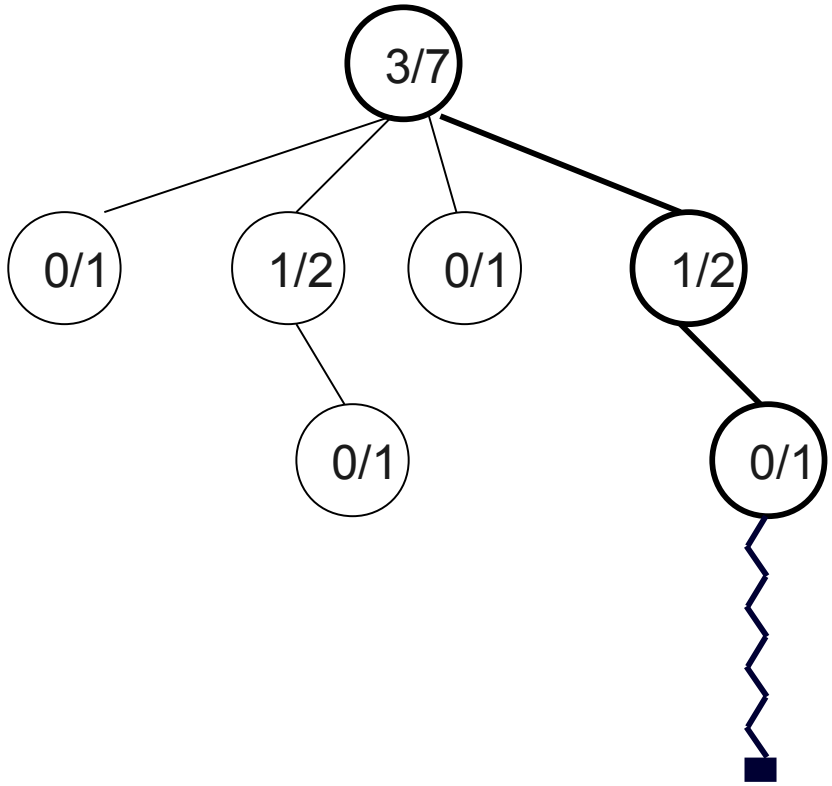
Example

- 6 iterations



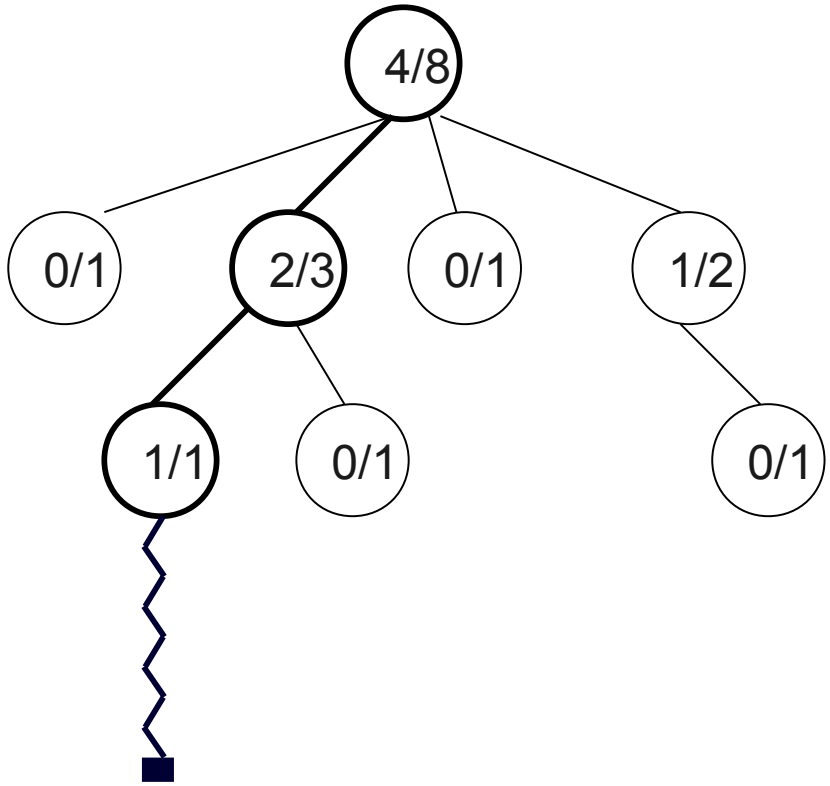
Example

- 7 iterations



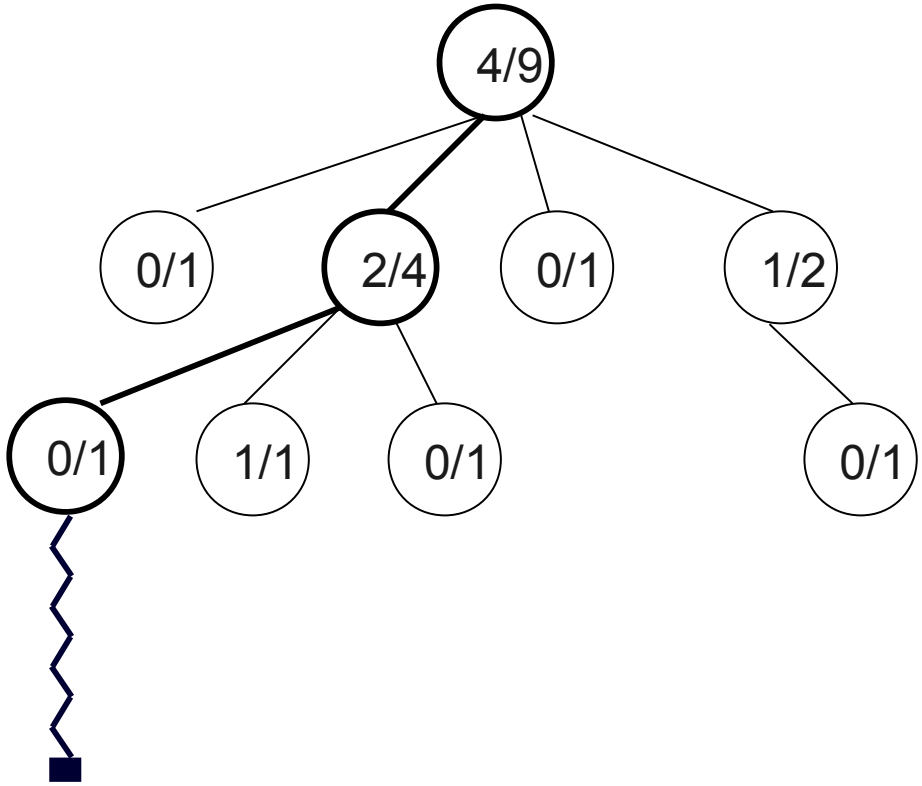
Example

- 8 iterations



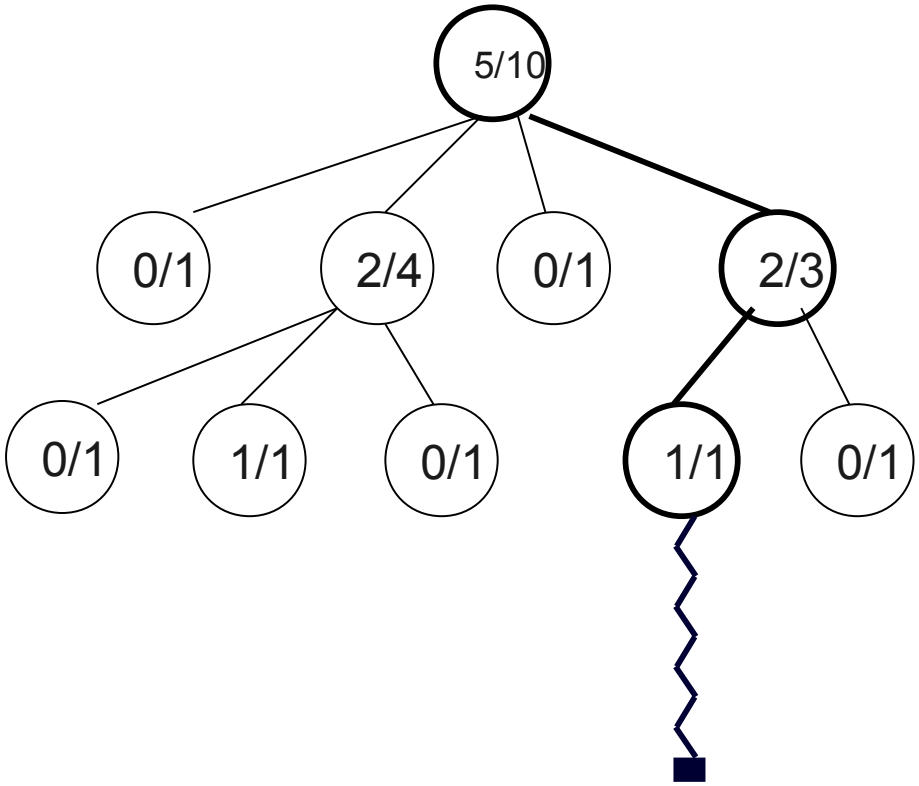
Example

- 9 iterations



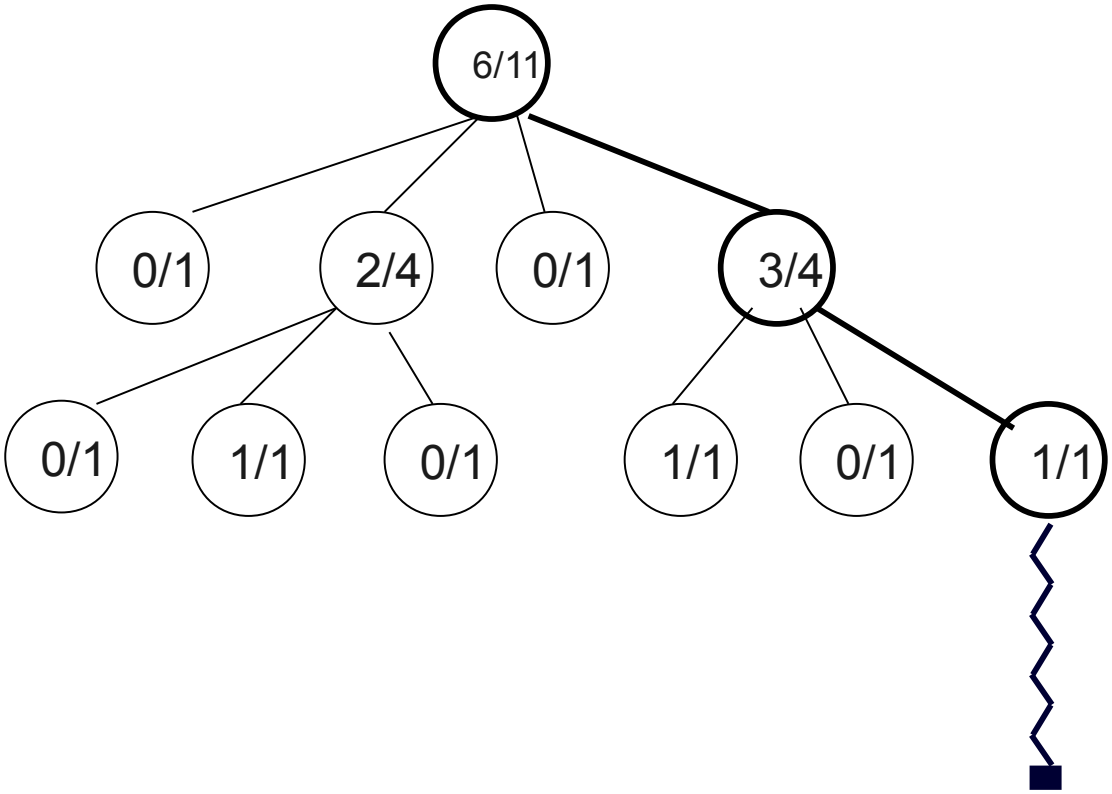
Example

- 10 iterations



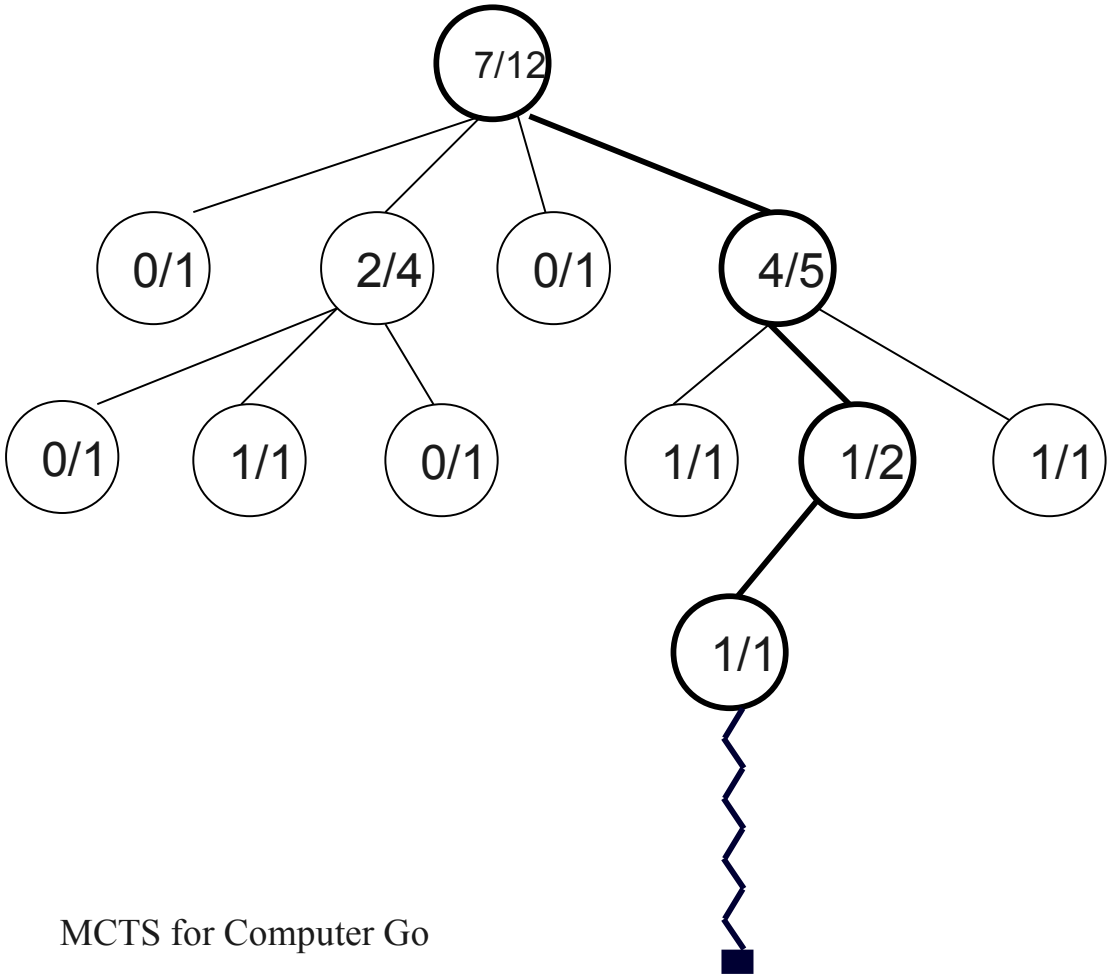
Example

- 11 iterations



Example

- 12 iterations



Example

- Clarity
  - C = 0
- Notice
  - with C != 0 a node cannot stay unvisited
  - min or max rule according to the node depth
  - not visited children have an infinite mean
- Practice
  - Mean initialized optimistically

MCTS enhancements

- The raw version can be enhanced
  - Tuning UCT C value
  - Outcome = score or win loss info (+1/-1)
  - Doubling the simulation number
  - RAVE
  - Using Go knowledge
    - In the tree or in the simulations
  - Speed-up
    - Optimizing, pondering, parallelizing

Assessing an enhancement

- Self-play
  - The new version vs the reference version
  - % wins with few hundred games
  - 9x9 (or 19x19 boards)
- Against differently designed programs
  - GTP (Go Text Protocol)
  - CGOS (Computer Go Operating System)
- Competitions

Move selection formula tuning

- Using UCB
  - Best value for C ?
  - 60-40%
- Using « UCB-tuned » (Auer & al 2002)
  - C replaced by min(1/4,variance)
  - 55-45%

Exploration vs exploitation

- General idea: explore at the beginning and exploit in the end of thinking time
- Diminishing C linearly in the remaining time
  - (Vermorel & al 2005)
  - 55-45%
- At the end:
  - Argmax over the mean value or over the number of visits ?
  - 55-45%

Kind of outcome

- 2 kinds of outcomes
  - Score (S) or win loss information (WLI) ?
  - Probability of winning or expected score ?
  - Combining both (S+WLI) (score +45 if win)
- Results
  - WLI vs S 65-35%
  - S+WLI vs S 65-35%

Doubling the number of simulations

- N = 100,000
- Results
  - 2N vs N 60-40%
  - 4N vs 2N 58-42%

Tree management

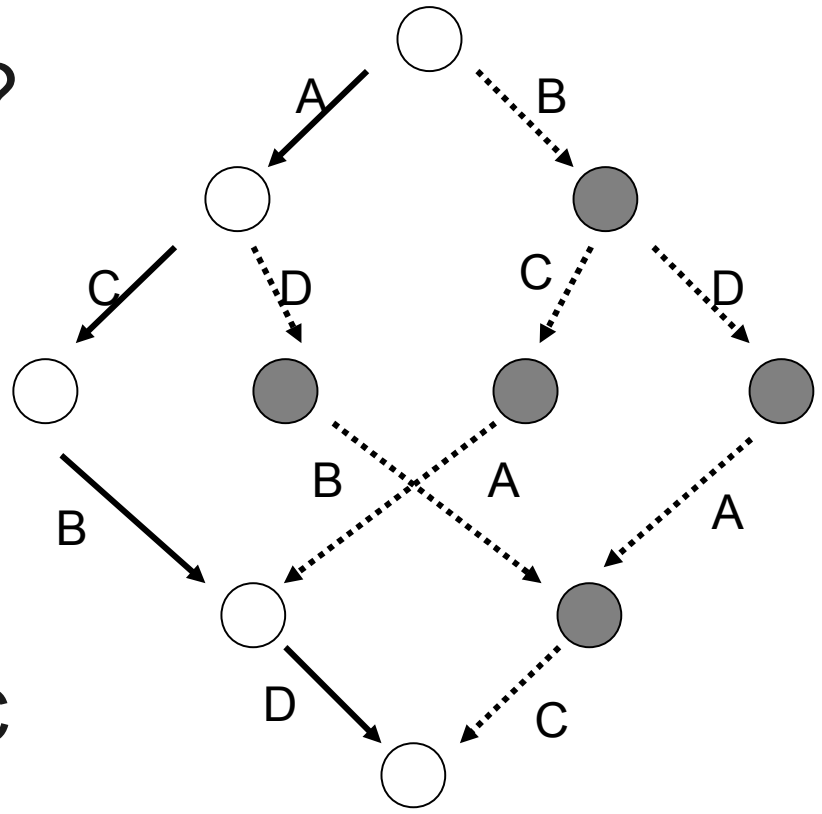
- Transposition tables
  - Tree -> Directed Acyclic Graph (DAG)
  - Different sequences of moves may lead to the same position
  - Interest for MC Go: merge the results
  - Result: 60-40%
- Keeping the tree from one move to the next
  - Result: 65-35%

RAVE (1/3)

- Rapid Action Value Estimation
  - Mogo 2007
  - Use the AMAF heuristic (Brugmann 1993)
  - There are « many » virtual sequences that are transposed from the actually played sequence
- Result:
  - 70-30%

RAVE (2/3)

- AMAF heuristic
- Which nodes to update?
- Actual
  - Sequence ACBD
  - Nodes ○
- Virtual
  - BCAD, ADBC, BDAC
  - Nodes ●



RAVE (3/3)

- 3 variables
  - Usual mean value M_u
  - AMAF mean value M_{amaf}
  - $M = \beta\ M_{amaf} + (1-\beta)\ M_u$
  - β = sqrt(k/(k+3N))
  - K set up experimentally
- M varies from M_{amaf} to M_u

Knowledge in the simulations

- High urgency for...
  - capture/escape 55-45%
  - 3x3 patterns 60-40%
  - Proximity rule 60-40%
- Mercy rule
  - Interrupt the game when the difference of captured stones is greater than a threshold (Hillis 2006)
  - 51-49%

Knowledge in the tree

- Virtual wins for good looking moves
- Automatic acquisition of patterns of pro games (Coulom 2007) (Bouzy & Chaslot 2005)
- Matching has a high cost
- Progressive widening (Chaslot & al 2008)
- Interesting under strong time constraints
- Result: 60-40%

Speeding up the simulations

- Fully random simulations (2007)
  - 50,000 game/second (Lew 2006)
  - 20,000 (commonly eared)
  - 10,000 (my program)
- Pseudo-random
  - 5,000 (my program in 2007)
- Rough optimization is worthwhile

Pondering

- Think on the opponent time
  - 55-45%
  - Possible doubling of thinking time
  - The move of the opponent may not be the planned move on which you think
  - Side effect: play quickly to think on the opponent time

Summing up the enhancements

- MCTS with all enhancements vs raw MCTS
  - Exploration and exploitation: 60-40%
  - Win/loss outcome: 65-35%
  - Rough optimization of simulations 60-40%
  - Transposition table 60-40%
  - RAVE 70-30%
  - Knowledge in the simulations 70-30%
  - Knowledge in the tree 60-40%
  - Pondering 55-45%
  - Parallelization 70-30%
- Result: 99-1%

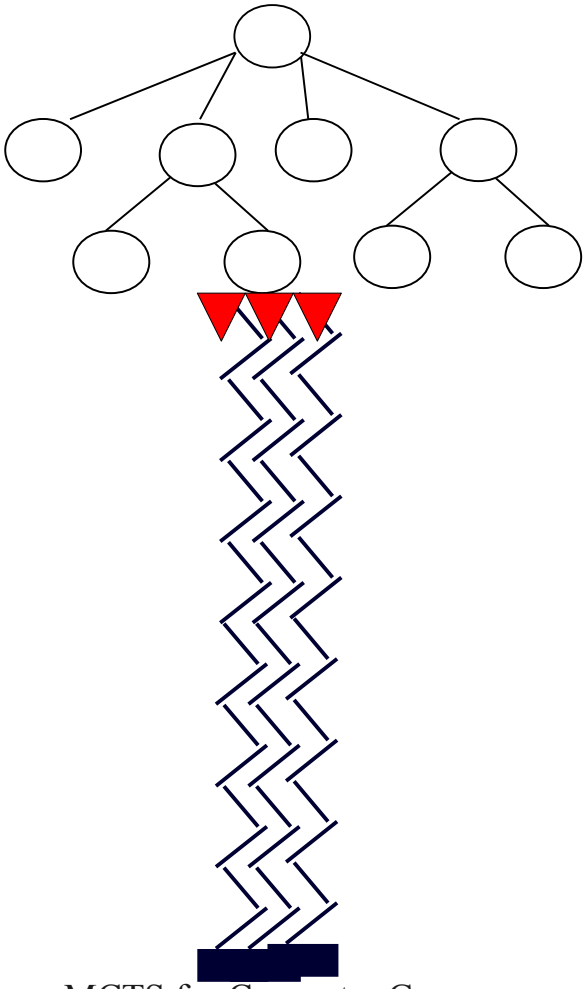
Parallelization

- Computer Chess: Deep Blue
- Multi-core computer
  - Symmetric MultiProcessor (SMP)
  - one thread per processor
  - shared memory, low latency
  - mutual exclusion (mutex) mechanism
- Cluster of computers
  - Message Passing Information (MPI)

Parallelization

```
while (hasTime) {
      playOutTreeBasedGame()
      expandTree()
      outcome = playOutRandomGame()
      updateNodes(outcome)
}
```

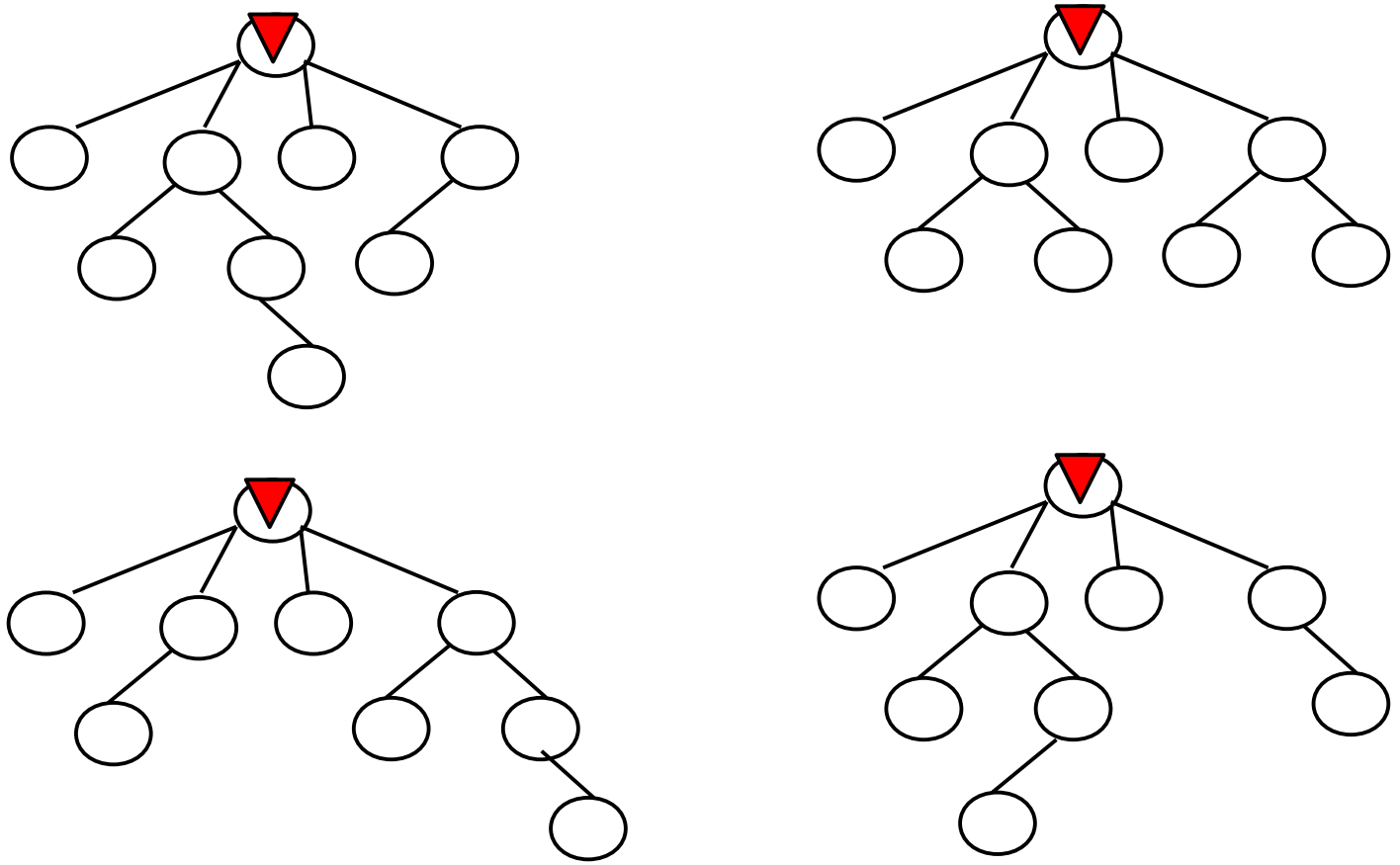
Leaf parallelization



Leaf parallelization

- (Cazenave Jouandeau 2007)
- Easy to program
- Drawbacks
  - Wait for the longest simulation
  - When part of the simulation outcomes is a loss, performing the remaining may not be a relevant strategy.

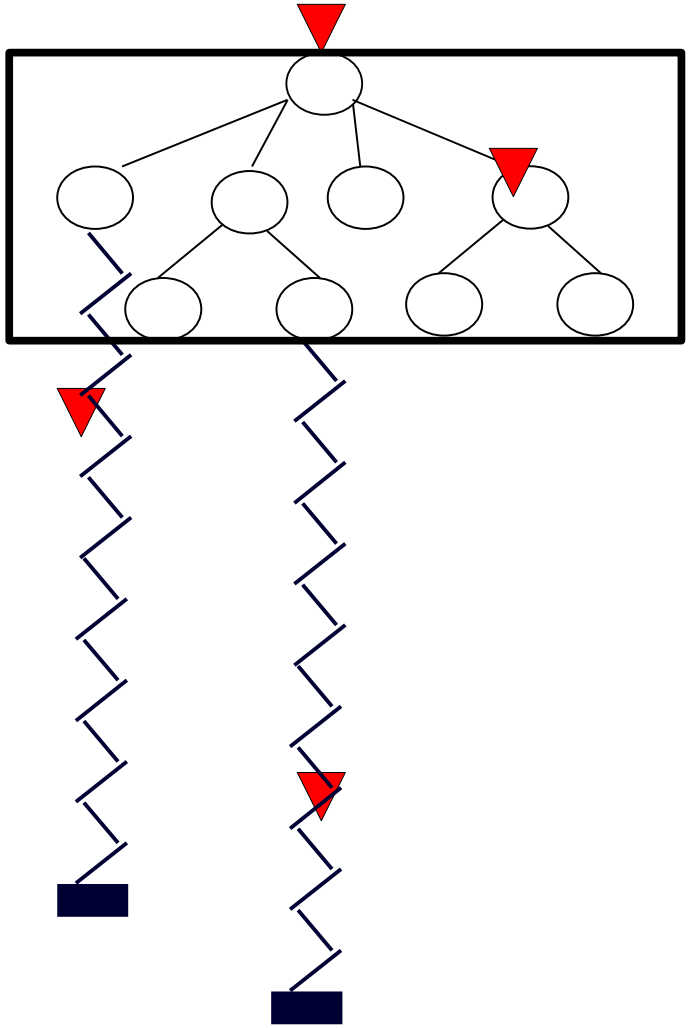
Root parallelization



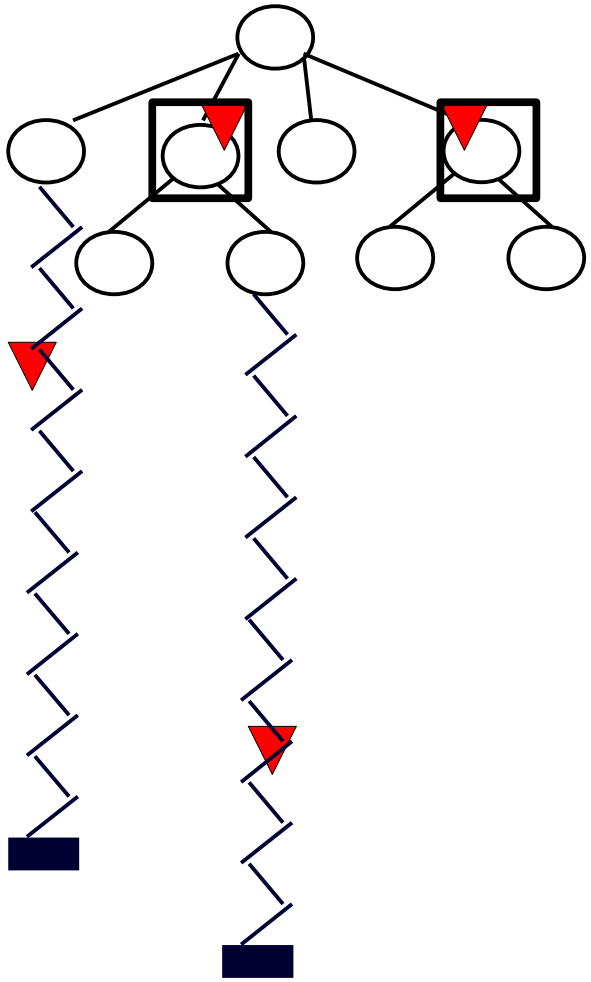
Root parallelization

- (Cazenave Jouandeau 2007)
- Easy to program
- No communication
- At completion, merge the trees
- 4 MCTS for 1sec > 1 MCTS for 4 sec
- Good way for low time settings and a small number of threads

Tree parallelization – global mutex



Tree parallelization – local mutex



Tree parallelization

- One shared tree, several threads
- Mutex
  - Global: the whole tree has a mutex
  - Local: each node has a mutex
- « Virtual loss »
  - Given to a node browsed by a thread
  - Removed at update stage
  - Preventing threads from similar simulations

Computer-computer results

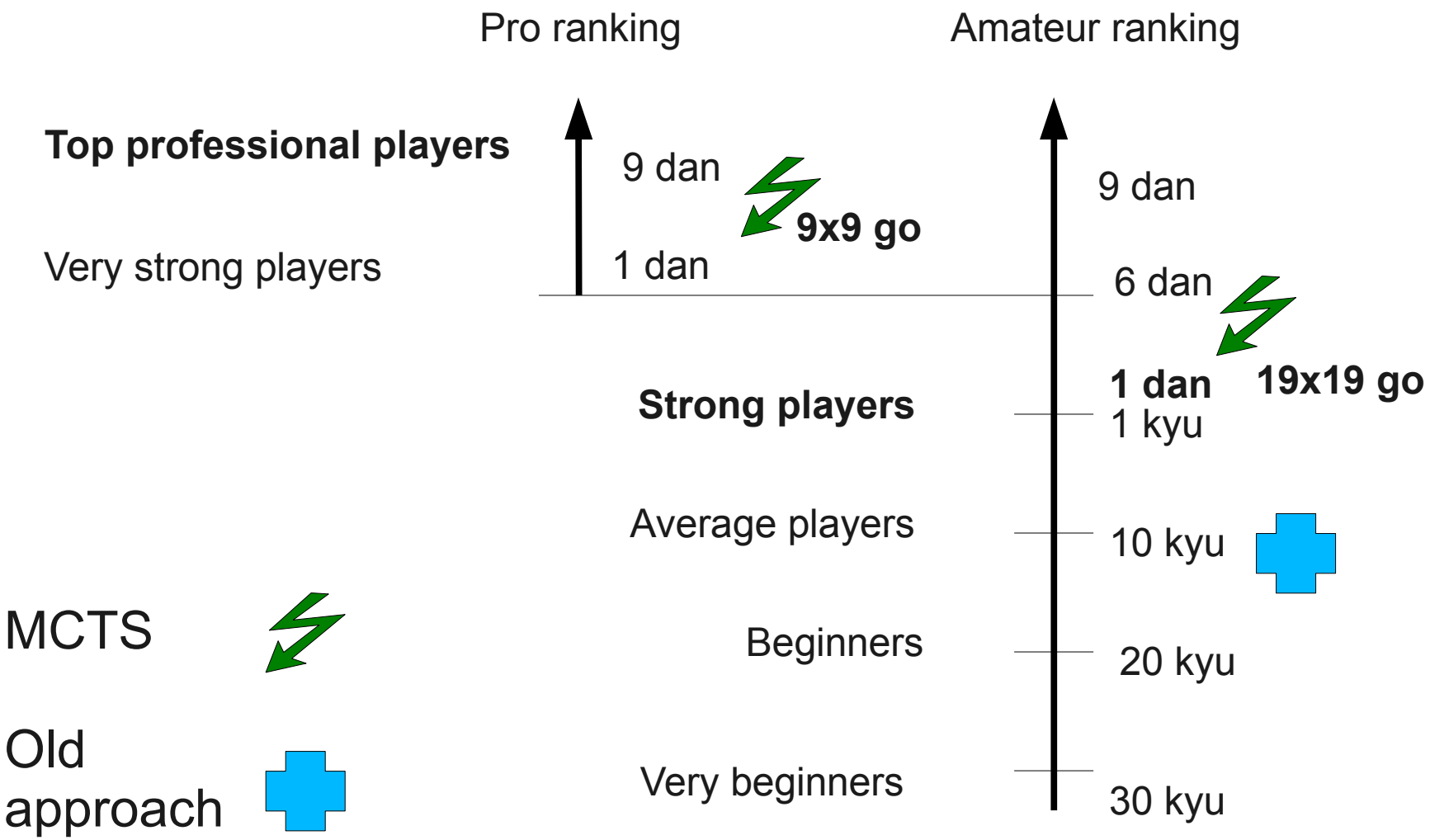
- Computer Olympiads

	19x19	9x9
– 2010	Erica, Zen, MFGo	MyGoFriend
– 2009	Zen, Fuego, Mogo	Fuego
– 2008	MFGo, Mogo, Leela	MFGo
– 2007	Mogo, CrazyStone, GNU Go	Steenvreter
– 2006	GNU Go, Go Intellect, Indigo	CrazyStone
– 2005	Handtalk, Go Intellect, Aya	Go Intellect
– 2004	Go Intellect, MFGo, Indigo	Go Intellect

Human-computer results

- 9x9
  - 2009: Mogo won a pro with black
  - 2009: Fuego won a pro with white
- 19x19:
  - 2008: Mogo won a pro with 9 stones
    Crazy Stone won a pro with 8 stones
    Crazy Stone won a pro with 7 stones
  - 2009: Mogo won a pro with 6 stones

MCTS and the old approach



Computer Go (MC history)

- Monte-Carlo Go (Brugmann 1993)
- MCGo devel. (Bouzy & Helmstetter 2003)
- MC+knowledge (Bouzy 2003)
- UCT (Kocsis & Szepesvari 2006)
- Crazy Stone (Coulom 2006)
- Mogo (Wang & Gelly 2006)

Conclusion

- Monte-Carlo brought a Big improvement in Computer Go over the last decade!
  - No old approach based program anymore!
  - All go programs are MCTS based!
  - Professional level on 9x9!
  - Dan level on 19x19!
- Unbelievable 10 years ago!

Some references

- PhD, MCTS and Go (Chaslot 2010)
- PhD, Reinf. Learning and Go (Silver 2010)
- PhD, R. Learning: applic. to Go (Gelly 2007)
- UCT (Kocsis & Szepesvari 2006)
- 1st MCTS go program (Coulom 2006)

Web links

- http://www.grappa.univ-lille3.fr/icga/
- http://cgos.boardspace.net/
- http://www.gokgs.com/
- http://www.lri.fr/~gelly/MoGo.htm
- http://remi.coulom.free.fr/CrazyStone/
- http://fuego.sourceforge.net/
- ...

Thank you for your attention!