Computer Go :
Monte Carlo Search and Statistical Learning

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History

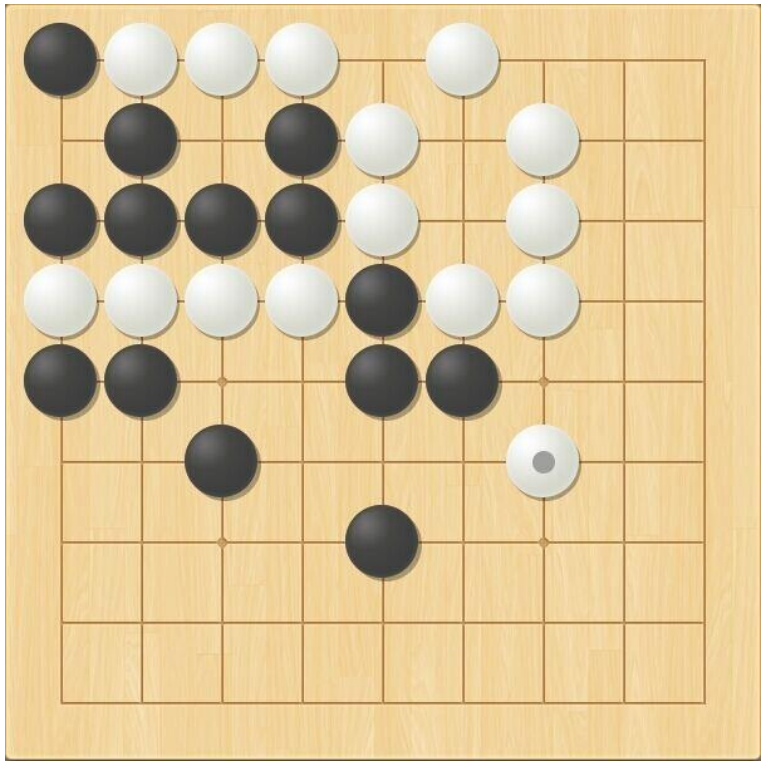
- **Event**
  - 1988 Othello Won Master (Kai-Fu Lee)
  - 1997 DeepBlue Won Kasparov (IBM)
  - 2007 Top 10 Breakthrough (Alberta)
  - 2011 Watson Jeopardy Challenge (IBM)
- **Progress**

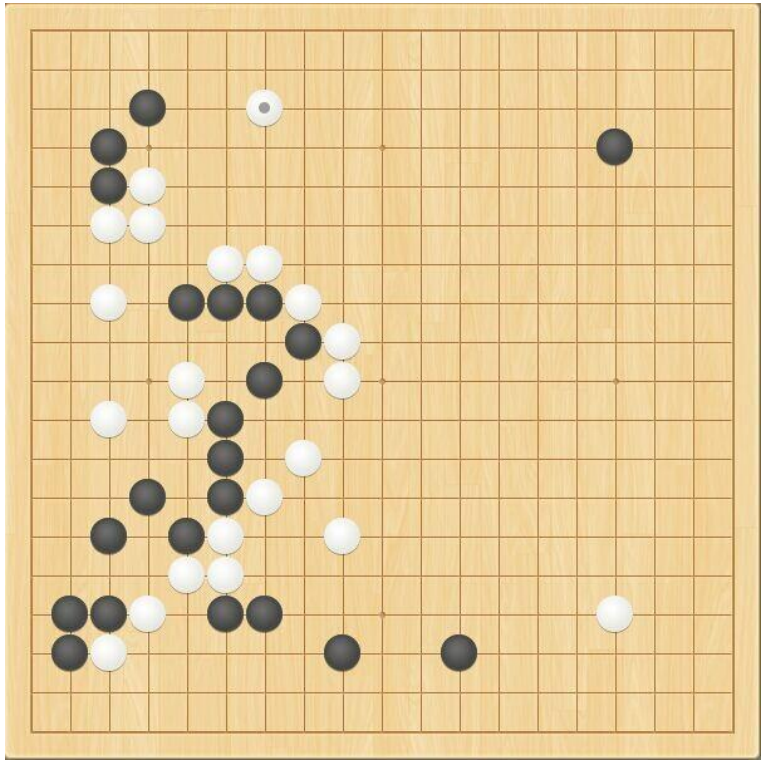
Computer Go

- Introduction
  - Go rule
    - 1) Who Has More Area Wins 2) Alive and Dead
  - One Of Most Difficult Challenges In AI
  - Drosophila Of AI ?
    - a) Fermat's Last Theorem b) Four Color Theorem
    - Biostatistics, Classical Planning, Active Learning
    - Page Search, Personalized Recommend, Natural Language
- Challenge
  - 1) Super Large Space 2) Unknown Evaluation
  - Alpha-Beta Search Totally Fails !

Computer Go

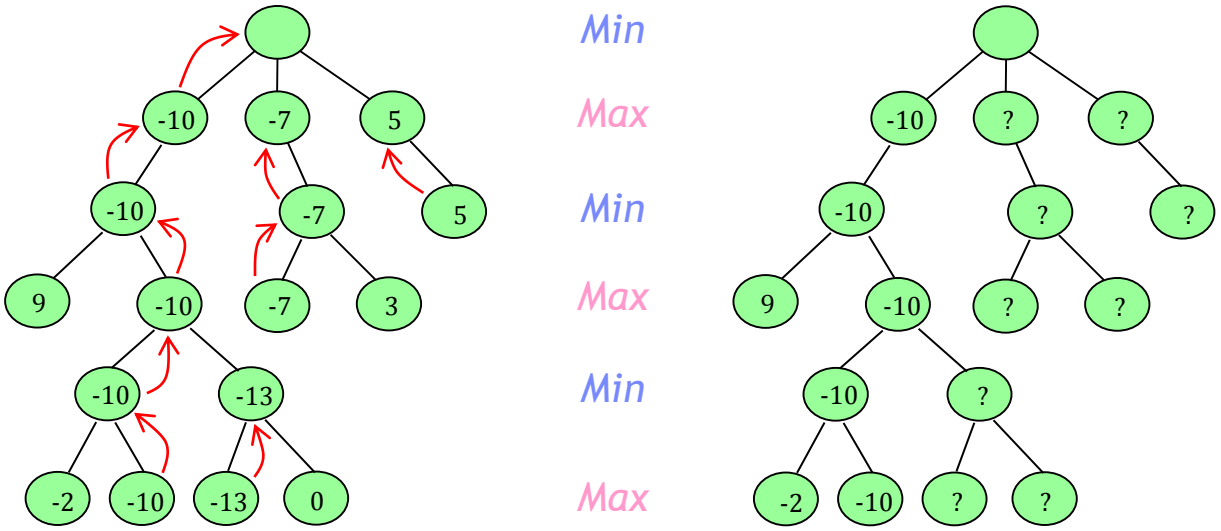
- BINGO!
  - 9x9: 6 Dan (Pro) 19x19: 1-2 Dan
  - Country: Top 1 World: Top Level





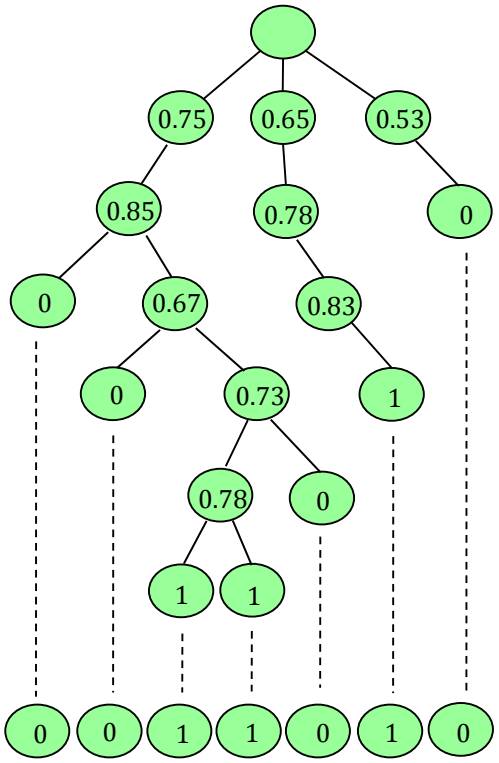
Mini-Max Search

- Principle
  - Solution To Zero-Sum Game
  - Max Player Maximize The Chances Of Winning
  - Min Player Minimize The Chances Max Player Winning
- Example



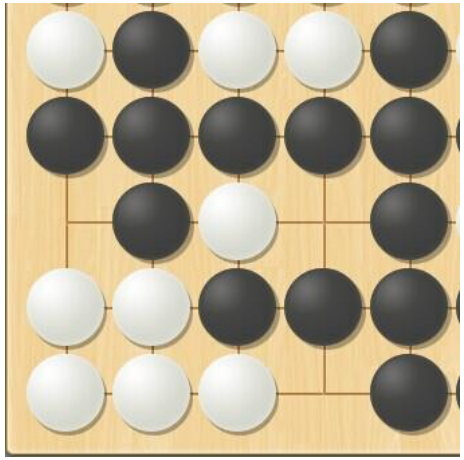
Monte Carlo Search

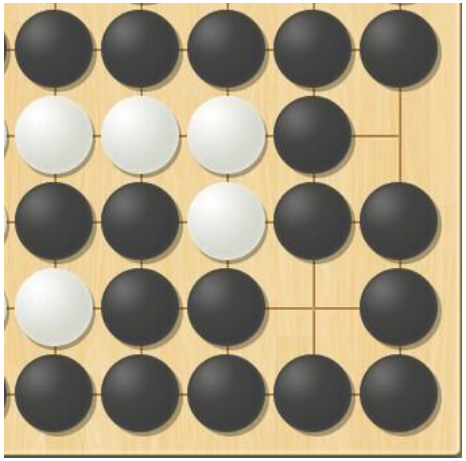
- Introduction
  - Brugmann Applied In Go (1993)
  - Seemingly Ridiculous Idea
  - Necessarily Bad or Slow ?
- In-Tree Part
  - Best First Search
  - Mean-Value Comparison
- Out-Tree Part
  - Randomly Playing Moves
  - Until Terminal State



Monte Carlo Search

- Descend Process
  - In-Tree Part And Out-Tree Part
  - Until When Each Block Has Only Simple Eyes
- Backup Process
  - Evaluate The Score Accurate And Fast
  - Backup The Score Along The Path Reversely





Multi-Armed Bandit

- Problem
  - Each Arm Provide Reward From Distribution
  - Independent Distribution Associated To Each Arm
  - Gambler Has No Initial Knowledge About Arms
  - Objective: Maximize Reward Sum By Iterative Plays
- Background
  - Extensively Studied Problem In Statistics
  - Fundamental In Reinforcement Learning
  - Exploration Vs. Exploitation Dilemma
  - What Is Good Policy ?

UCB Algorithm

- Introduction
  - UCB = Upper Confidence Bounds
  - Auer Proposed (2002)
- UCB1
  - Initialization: Play Each Arm Once
  - Loop: Play k^{th} Arm That Maximizes This Formula

$$R_k / t_k(n) + \text{sqrt}\,(2\log(n) / t_k(n))$$

Where n Is Overall Number Of Plays

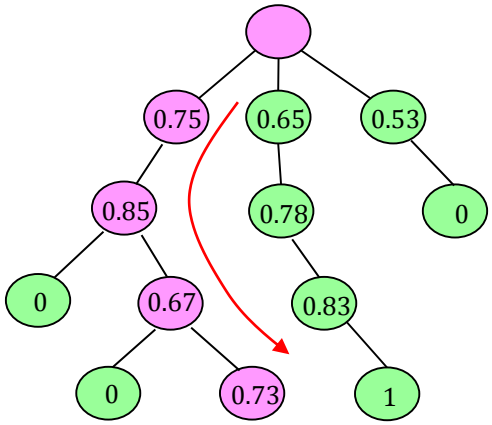
- UCB1-Tuned

$$R_k / t_k(n) + \text{sqrt}\,(\log(n) / t_k(n) \cdot \min\{1/4,\ T_k(t_k(n))\})$$

  - Auer Declares UCB1-Tuned Substantially Better Than UCB1

UCT Algorithm

- Principle
  - UCT = UCB Applied To Tree
  - Consider Each Node As A Bandit
  - Play Sequences Of Bandits
  - Begin From Root And End At Leaf



- Formula

$$w/v + \mathrm{sqrt}\,(2\log(n)/v) \qquad (1)$$

$$w/v + \mathrm{sqrt}(\log(n)/v \cdot \min\{1/4,\ T(v)\}) \qquad (2)$$

  - (2) Substantially Better Than (1) In Auer's Experiments
  - Correspond To Our Early Results

UCT Algorithm

- How Does Tree Grow
  - Expand Some Node After Each Simulation
  - Expand Nodes With Threshold T
  - Expand Nodes Gradually (Progressive Widening)
- How To Backup Values
  - Optimal Arm Is Played Exponentially More Often Than Any Arm

    When Rewards Are In [0, 1]
  - Not Return Real Score
  - Only Return Win =1 Or Lose=0

UCT Algorithm

- Advantage
  - Highly Selective Best First Search
  - Only Require Black Box Simulator
  - Usually Works Without Any Knowledge
  - Converge To Optimal Policy With Appropriate Exploration
  - Anytime, Computationally Efficient And Highly Parallelizable

Rapid Action Value Estimation

- UCT's Weakness
  - Initially Every Action Samples Once
  - For Low Variance Every Action Samples Multi Times
  - Slow Learning In Super Large Space
- Rapid Action Value Estimation
  - Brugmann (1993) Gelly (2007)
  - Consider Every Subsequent Action As First One

Let $Rave(s,a)$ be rapid action value

For episode $s_1, a_1, s_2, a_2, \ldots, s_t$

$Rave(s_m,a_n)$ is updated when

$\forall s_m \in S, a_n \in A(s_m), m \leq n$ and $\forall r < n, a_r \neq a_n$

Rapid Action Value Estimation

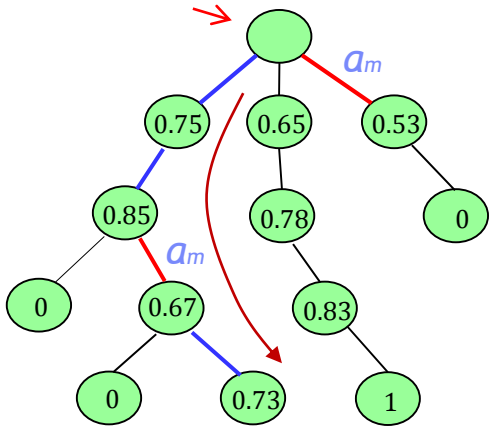
- *Rapid Action Value Estimation*
  - *Linear Combination To UCB Formula*

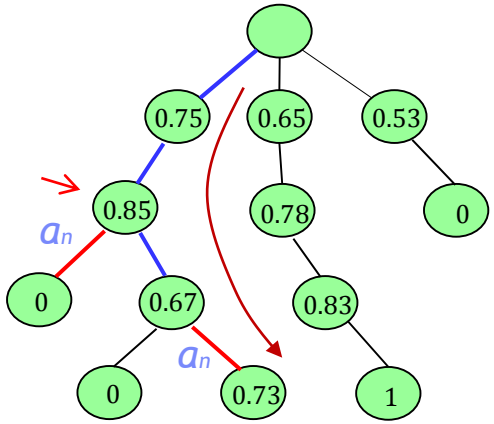
$$a \cdot (w/v) + b \cdot (rw/rv) \qquad (3)$$

Initially b≈1, RAVE Value ominates

Later b Decreases, a Increases

Eventually a≈1, b≈0, UCT Value Dominates





Rapid Action Value Estimation

- Advantage And Disadvantage
  - Learn Quickly With More Statistics (78%)
  - Extensible To Partially Transposed Sequences
  - Tricky, Empirical And Tuning

Supervised Learning

- Learn What
  - Is 5x5 Pattern OK ?
  - 3x3 Pattern And Other Rules
- How To Learn
  - Generalized Bradley-Terry Model

    For Players, $P(i \text{ win}) = y_i / (y_1 + y_2 + \ldots + y_n)$

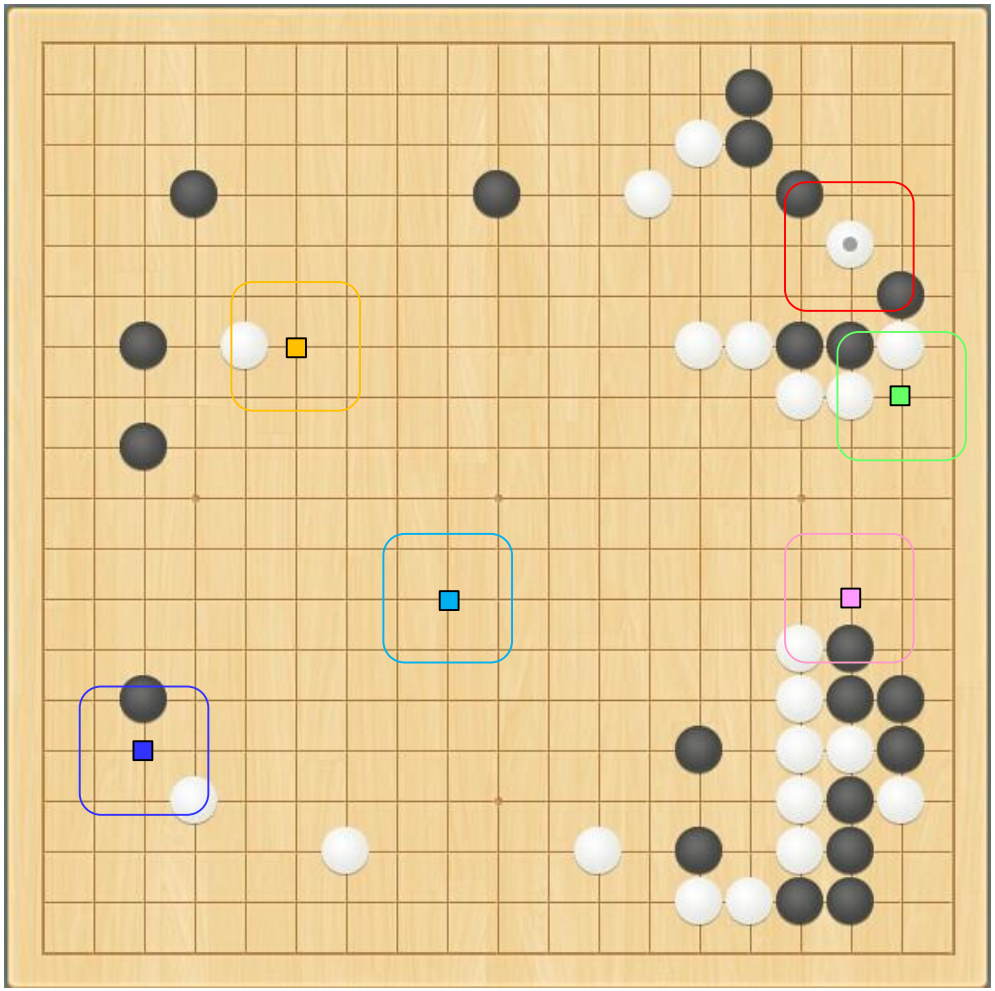
    For Teams, $P(1\text{-}2\text{-}3 \text{ win}) = y_1y_2y_3 / (y_1y_2y_3 + y_2y_4 + \ldots + y_1y_4y_5y_7)$

    Is Linearity Hypothesis Right ?
  - How to Use Pro Manual

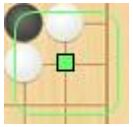
    Consider $(y_1, y_2, \ldots, y_n)$ $(R_1, R_2, \ldots, R_N)$

    $L = P(R_1)\cdot P(R_2)\cdots P(R_N)$, $P(R_i) = y_{i1}y_{i2}\ldots y_{in} / (y_{i1}y_{i2}\ldots y_{in} + \ldots)$

Supervised Learning

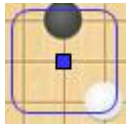


γ = 4.296



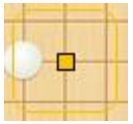
γ = 2.389

γ = 1.048



γ = 0.981

γ = 0.396



γ = 0.057

Biasing Search With γ

- Combination To (1)
  - Easily And Straightforward
  - γ's Impact Decreases Rapidly

$$w/v + \mathrm{sqrt}\,(2\log(n)/v) + H(p)/v$$

- Combination To (3)
  - Not Straightforward Combination
  - Worse Results Initially But Much Better Eventually

$$a\cdot(w/v) + b\cdot(rw/rv) + c\cdot H(p)$$

Initially $c\approx 1$, $H(p)$ Value Dominates

Later c Decreases, b Increases, RAVE Value Dominates

Eventually $a\approx 1$, $b\approx 0$, $c\approx 0$, UCT Value Dominates

Back to tree-growth

Thank You !

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