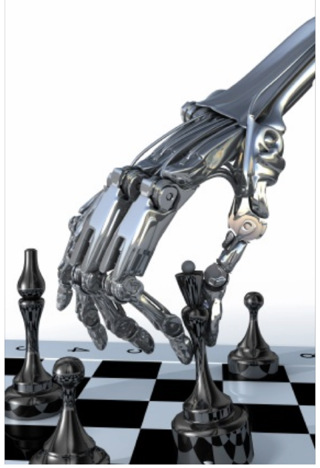


More on Games

Chapter 6

Some material adopted from notes by Charles R. Dyer, University of Wisconsin-Madison

Overview

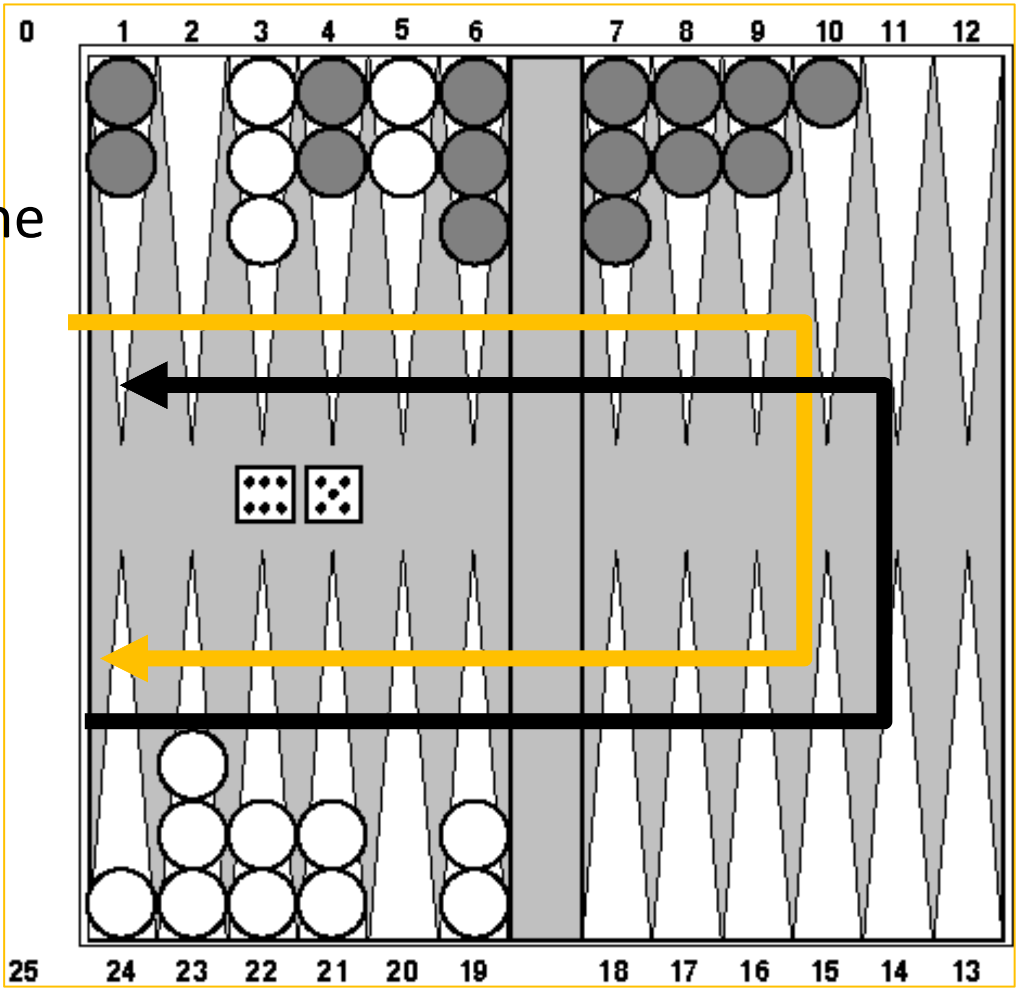
- Stochastic games
- Other issues
- AlphaGo Zero
- General game playing

Stochastic Games

- In real life, unpredictable external events can put us into unforeseen situations
- Many games introduce unpredictability through a random element, such as the throwing of dice
- These offer simple scenarios for problem solving with adversaries and uncertainty

Example: Backgammon

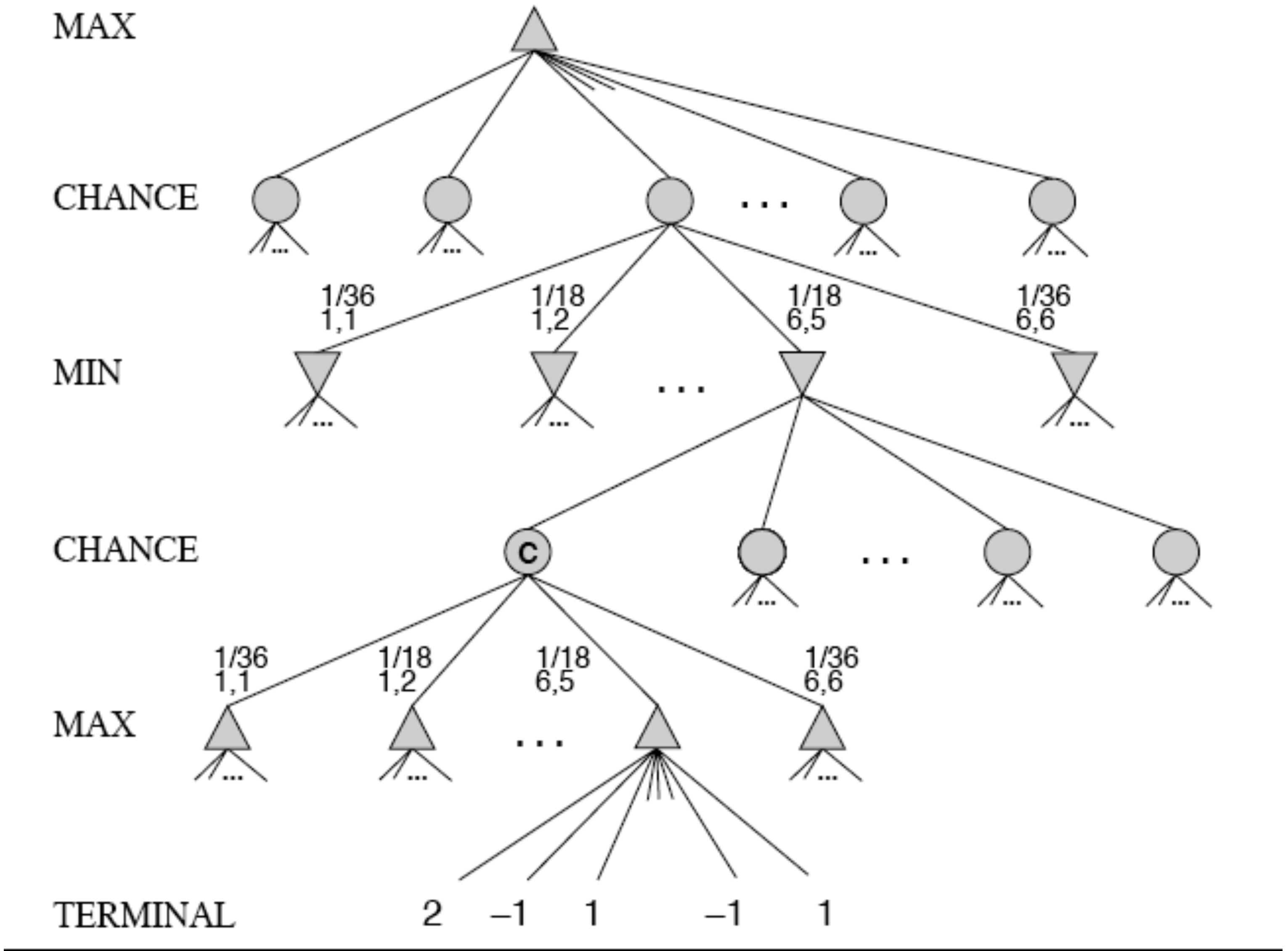
- Popular two-player game with uncertainty
- Players roll dice to determine what moves can be made
- White has just rolled 5 & 6, giving four legal moves:
  - 5-10, 5-11
  - 5-11, 19-24
  - 5-10, 10-16
  - 5-11, 11-16
- Good for exploring decision making in adversarial problems involving skill **and** luck



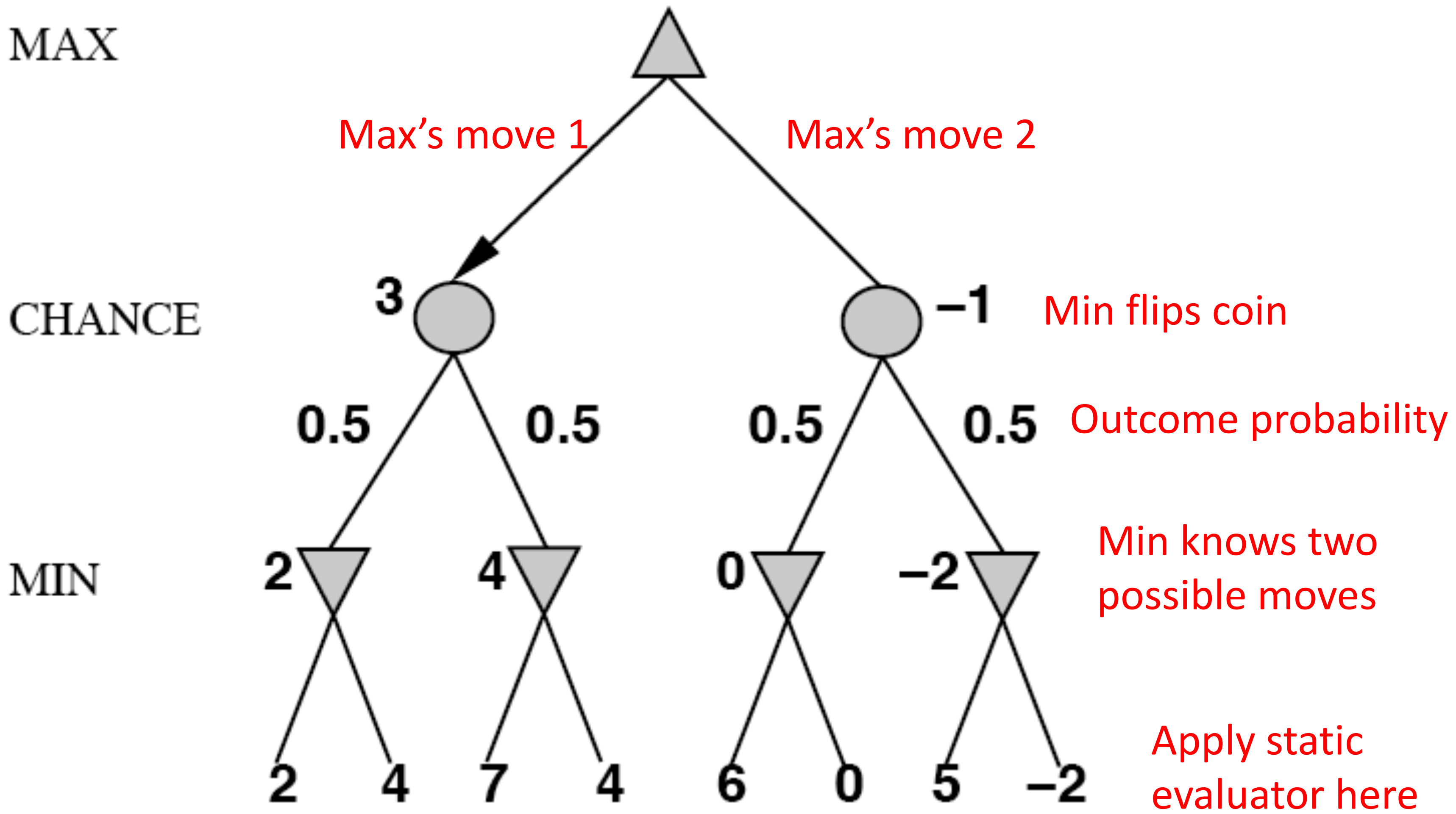
Why can’t we use MiniMax?

- Before a player chooses her move, she rolls dice and then knows exactly what they are
- The immediate outcome of each move is also known
- But she does not know what moves her opponent will have available in the future
- Need to adapt MiniMax to handle this

MiniMax trees with Chance Nodes



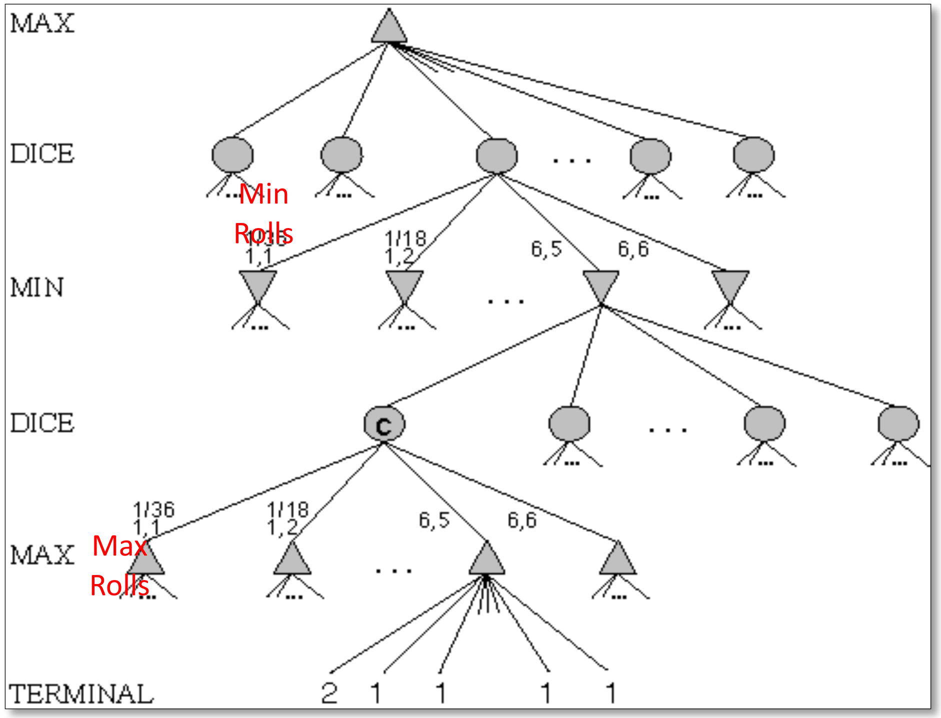
Understanding the notation



Board state includes chance outcome determining available moves

Game trees with chance nodes

- Chance nodes (circles) represent random events
- For random event with N outcomes, chance node has N children, each with a probability
- 2 dice: 21 distinct outcomes
- Use minimax to compute values for MAX and MIN nodes
- Use expected values for chance nodes

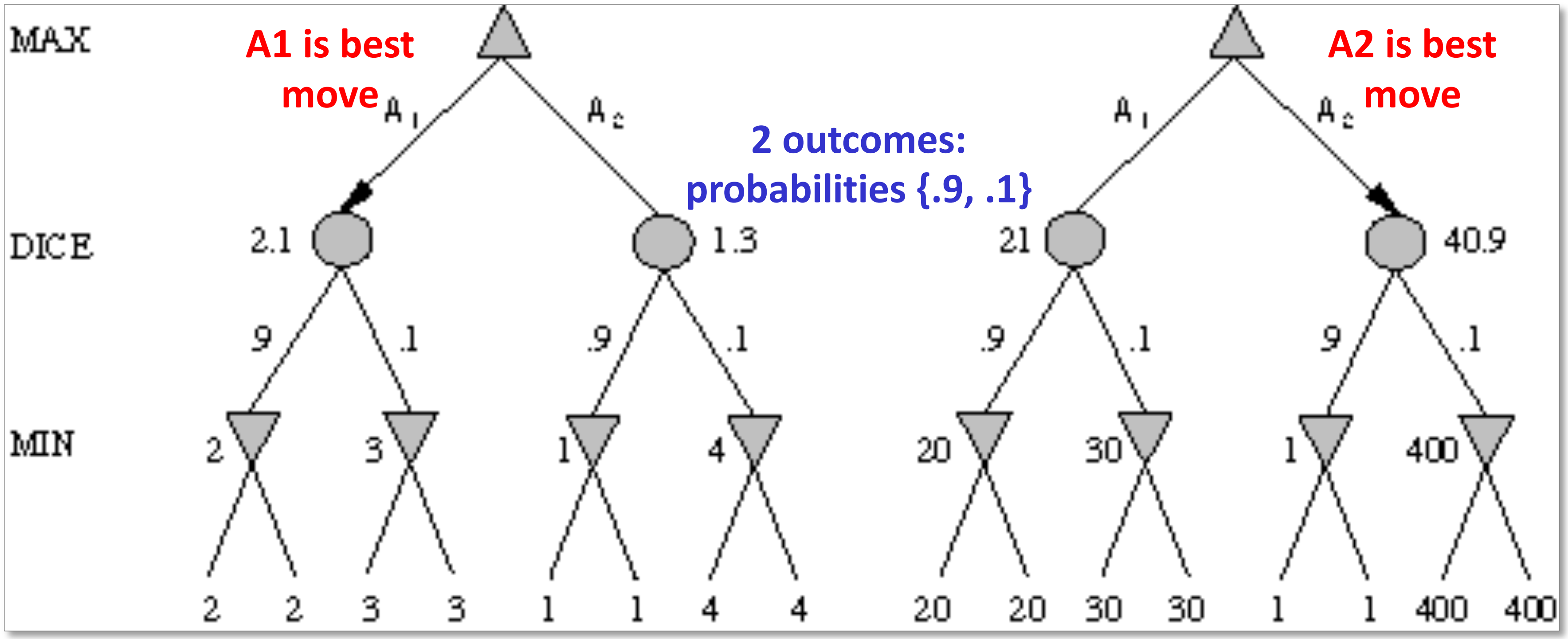


- Chance nodes over max node: expectimax(C) = $\sum_i (P(d_i) * \text{maxval}(i))$
- Chance nodes over min node: expectimin(C) = $\sum_i (P(d_i) * \text{minval}(i))$

Impact on lookahead

- Dice rolls **increase branching factor**
  - There are 21 possible rolls with two dice
- Backgammon: ~20 legal moves for given roll
  ~6K with 1-1 roll (get to roll again!)
- At depth 4: 20 * (21 * 20)**3 ≈ 1.2B boards
- As depth increases, probability of reaching a given node shrinks
  - lookahead's value diminished and alpha-beta pruning is much less effective
- TDGammon used depth-2 search + good static evaluator to achieve world-champion level

Meaning of the evaluation function



- With probabilities & expected values we must be careful about meaning of values returned by static evaluator
- Relative-order preserving change of static evaluation values doesn’t change minimax decision, but could here
- Linear transformations are OK

Games of imperfect information

- E.g. card games where opponent's initial hand unknown
  - Can calculate probability for each possible deal
  - Like having one big dice roll at beginning of game
- Possible approach: minimax over each action in each deal; choose action with highest expected value over all deals
- Special case: if action optimal for all deals, it's optimal
- GIB bridge program, approximates this idea by
  1. Generating 100 deals consistent with bidding
  2. Picking action that wins most tricks on average

High-Performance Game Programs

- Many programs based on alpha-beta + iterative deepening + extended/singular search + transposition tables + huge databases + ...
- Chinook searched all checkers configurations with ≤ 8 pieces to create endgame database of 444 billion board configurations
- Methods general, but implementations improved via many specifically tuned-up enhancements (e.g., the evaluation functions)

Other Issues

- Multi-player games, no alliances
  - E.g., many card games, like Hearts
- Multi-player games with alliances
  - E.g., Risk
  - More on this when we discuss game theory
  - Good model for a social animal like humans, where we must balance cooperation and competition

AI and Games II

- AI also of interest to the video game industry
- Many games include agents controlled by the game program that could be
  - Adversaries, in first person shooter games
  - Collaborators, in a virtual reality game
- Some game environments used as AI challenges
  - 2009 Mario AI Competition
  - Unreal Tournament bots

General Game Playing

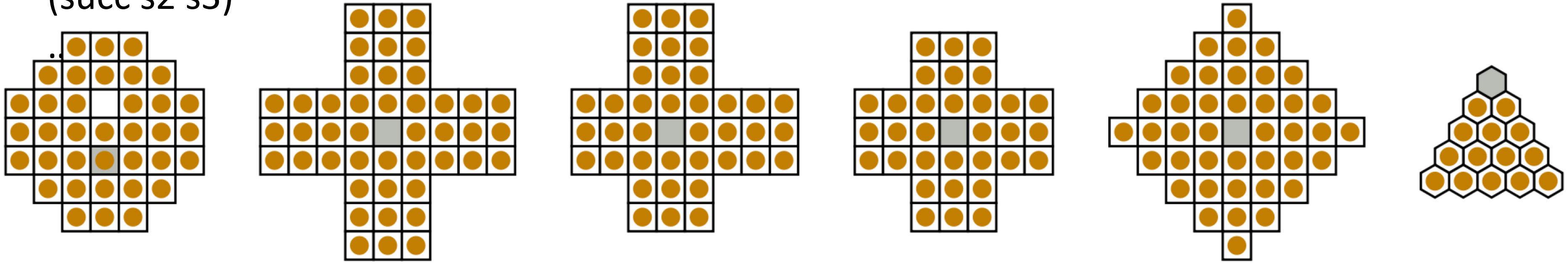
- General Game Playing is an idea developed by Professor Michael Genesereth of Stanford
- See his site for more information
- Idea: don’t develop specialized systems to play specific games (e.g., Checkers) well
- Goal: design AI programs to be able to play more than one game successfully
- **Work from a description of a novel game**

GGP

- Input: logical description of a game in a custom game description language
- Game bots must
  - Learn how to play legally from description
  - Play well using general problem solving strategies
  - Improve using general machine learning techniques
- Regular completions 2005-2016, $10K prize
- Java General Game Playing Base Package

GGP Peg Jumping Game

```
; http://games.stanford.edu/gamemaster/games-debug/peg.kif
(init (hole a c3 peg))
(init (hole a c4 peg))
…
(init (hole d c4 empty))
…
(<= (next (pegs ?x)) (does jumper (jump ?sr ?sc ?dr ?dc)) (true (pegs ?y))
      (succ ?x ?y)) (<= (next (hole ?sr ?sc empty)) (does jumper (jump ?sr ?sc ?dr ?dc)))
…
(<= (legal jumper (jump ?sr ?sc ?dr ?dc)) (true (hole ?sr ?sc peg))
      (true (hole ?dr ?dc empty)) (middle ?sr ?sc ?or ?oc ?dr ?dc) (true (hole ?or ?oc peg)))
…
(<= (goal jumper 100) (true (hole a c3 empty)) (true (hole a c4 empty))
      (true (hole a c5 empty))
…
(succ s1 s2)
(succ s2 s3)
…
```



Tic-Tac-Toe in GDL

```
(role xplayer)
(role oplayer)
;; Initial State
(init (cell 1 1 b))
(init (cell 1 2 b))
...
(init (control xplayer))
;; Dynamic Components
(<= (next (cell ?m ?n x))
  (does xplayer (mark ?m ?n))
  (true (cell ?m ?n b)))

(<= (next (cell ?m ?n o))
  (does oplayer (mark ?m ?n))
  (true (cell ?m ?n b)))
```

```
...
...
(<= (next (control xplayer))
  (true (control oplayer)))
(<= (legal ?w (mark ?x ?y))
  (true (cell ?x ?y b))
  (true (control ?w)))
(<= (legal xplayer noop)
  (true (control oplayer)))
(<= (legal oplayer noop)
  (true (control xplayer)))
...
(<= (goal xplayer 100) (line x))
...
(<= (goal oplayer 0) (line x))
...
```

See ggp-base repository: http://bit.ly/RB49q5

A example of General Intelligence

- Artificial General Intelligence describes research that aims to create machines capable of general intelligent action
- Harkens back to early visions of AI, like McCarthy's Advise Taker
  - See Programs with Common Sense (1959)
- A response to frustration with narrow specialists, often seen as "hacks"
  - See On Chomsky and the Two Cultures of Statistical Learning

Perspective on Games: Con and Pro

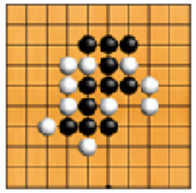
"Chess is the Drosophila of artificial intelligence. However, computer chess has developed much as genetics might have if the geneticists had concentrated their efforts starting in 1910 on breeding racing Drosophila. We would have some science, but mainly we would have very fast fruit flies."

John McCarthy, Stanford

"Saying Deep Blue doesn't really think about chess is like saying an airplane doesn't really fly because it doesn't flap its wings."

Drew McDermott, Yale

AlphaGO



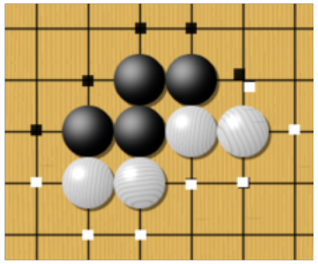
- Developed by Google's DeepMind
- Beat top-ranked human grandmasters in 2016
- Used Monte Carlo tree search over game tree

  expands search tree via random sampling of search space
- *Science* Breakthrough of the year runner-up

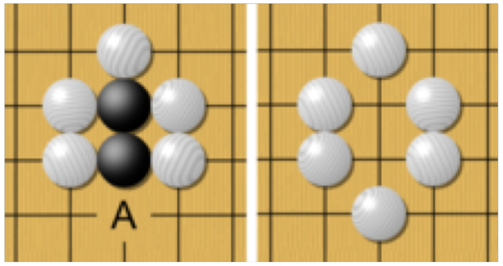
  Mastering the game of Go with deep neural networks and tree search, Silver et al., *Nature*, 529:484–489, 2016
- Match with grandmaster Lee Sedol in 2016 was subject of award-winning 2017 film

Go - the game

- Played on a 19x19 board, black vs. white stones
- Huge state space O(b^d): chess:~35^{80}, go: ~250^{150}
- Rule: Every stone on board must have an adjacent open point ("liberty") or be part of a connected group with a liberty. Groups of stones losing their last liberty are removed from the board.



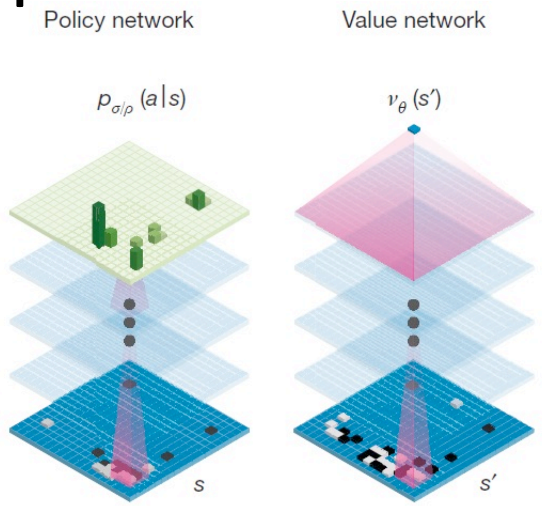
liberties

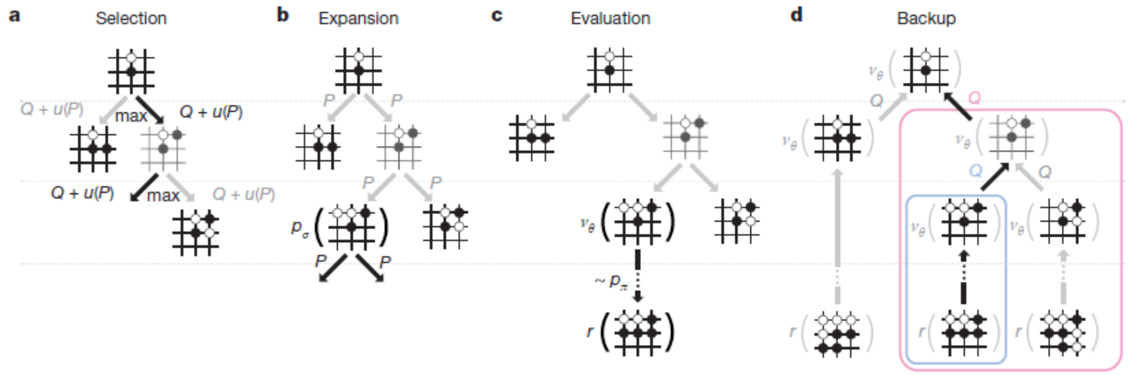


capture

AlphaGo implementation

- Trained deep neural networks (13 layers) to learn "value function" and "policy function"
- Performs Monte Carlo game search
  - –explore state space like minimax
  - –random "rollouts"
  - –simulate probable plays by opponent according to policy function





AlphaGo implementation

- Hardware: 1920 CPUs, 28O GPUs
- Neural networks trained in two phases
- **Phase 1:** supervised learning from database of 30 million moves in games with good human players
- **Phase 2:** play against self using reinforcement learning