

# Adversarial Search Cont...

# Properties of $\alpha$ - $\beta$

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- Pruning **does not** affect final result
- However, effectiveness of pruning affected by...?

# Resource limits

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Suppose we have 100 secs, explore  $10^4$  nodes/sec  
→  $10^6$  nodes per move

Standard approach (Shannon, 1950):

- **evaluation function**  
= estimated desirability of position
- **cutoff test:**  
e.g., depth limit

# Cutting off search

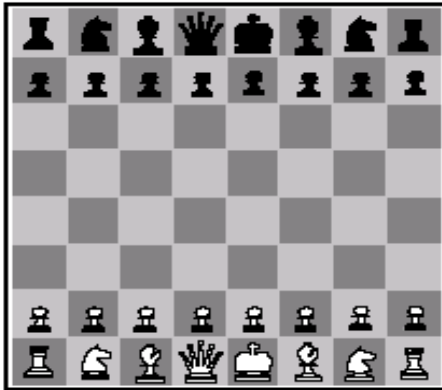
- Change:
  - ♦ if `TERMINAL-TEST(state)` then return `UTILITY(state)`
- into
  - ♦ if `CUTOFF-TEST(state,depth)` then return `EVAL(state)`
- Introduces a fixed-depth limit
  - ♦ Is selected so that the amount of time will not exceed what the rules of the game allow.
- When cutoff occurs, the evaluation is performed.

# Heuristic EVAL

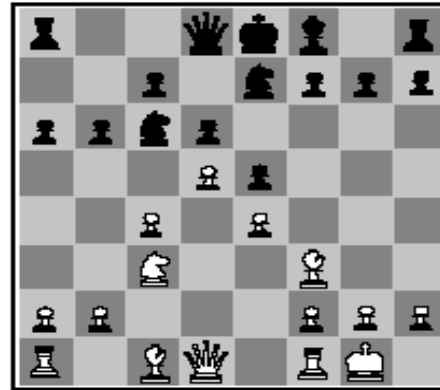
- Idea: produce an estimate of the expected utility of the game from a given position.
- Performance depends on quality of EVAL.
- Requirements:
  - ♦ EVAL should order terminal-nodes in the same way as UTILITY.
  - ♦ Computation may not take too long.
  - ♦ For non-terminal states the EVAL should be strongly correlated with the actual chance of winning.

Simple Mancala Heuristic: Goodness of board = # stones in my Mancala minus the number of stones in my opponents.

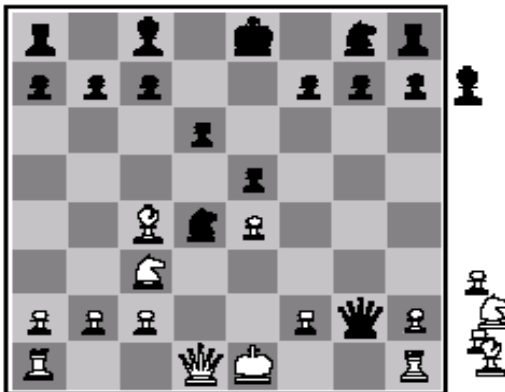
# Heuristic EVAL example



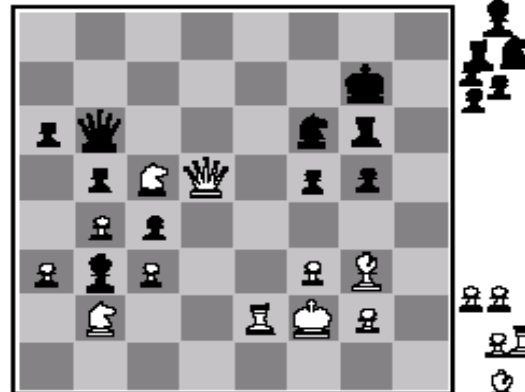
(a) White to move  
Fairly even



(b) Black to move  
White slightly better



(c) White to move  
Black winning

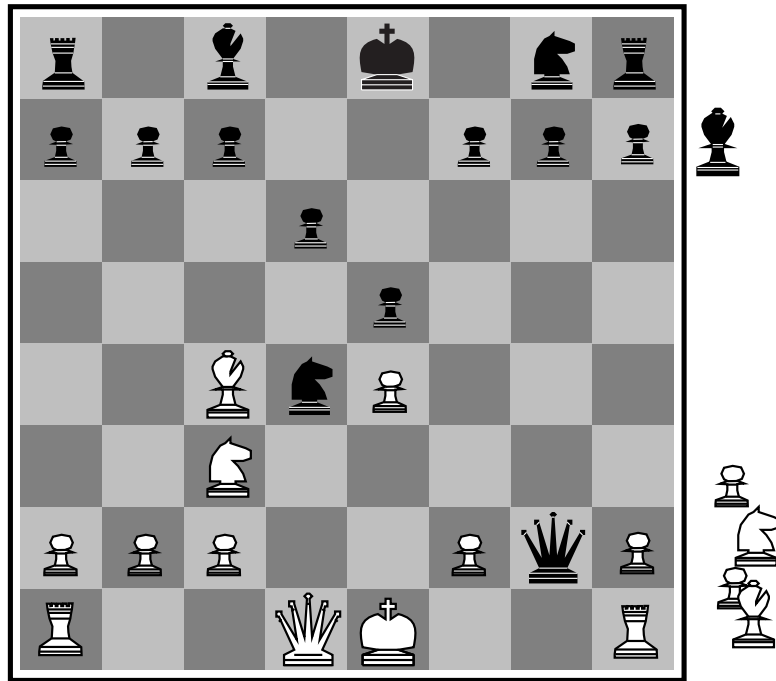


(d) Black to move  
White about to lose

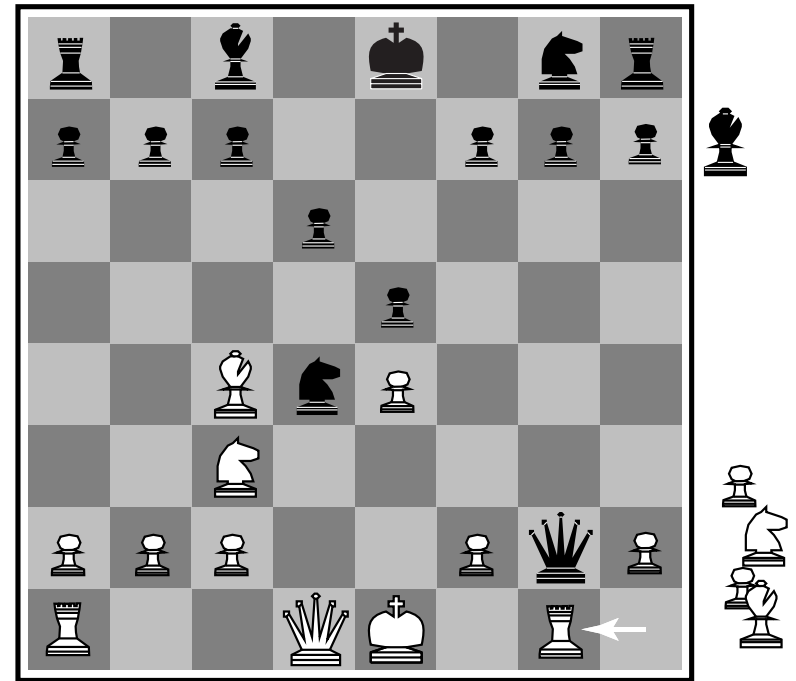
$$Eval(s) = w_1 f_1(s) + w_2 f_2(s) + \dots + w_n f_n(s)$$

# Heuristic difficulties

Simple heuristic - weighing the pieces by material value



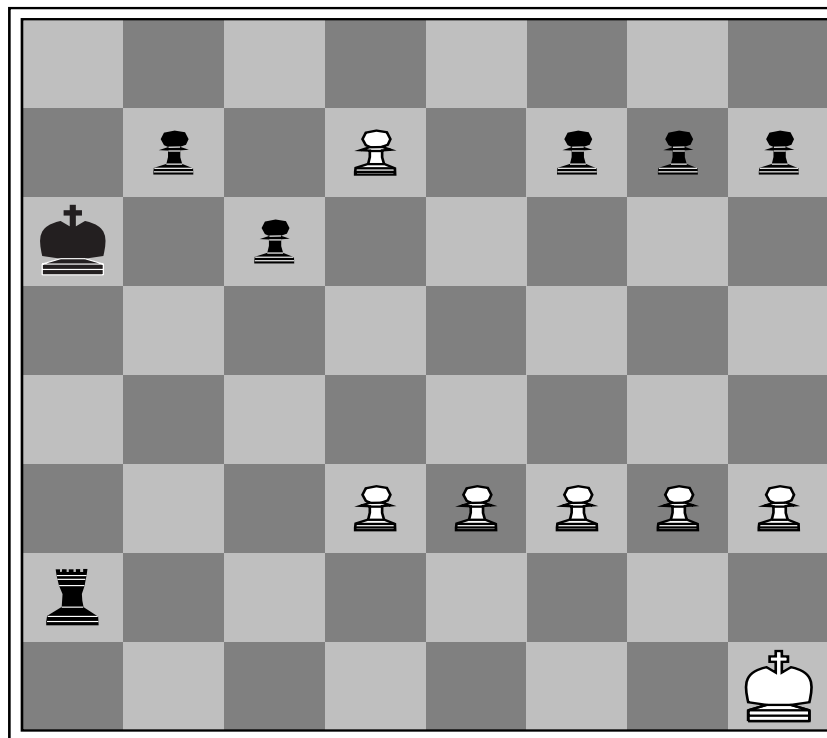
(a) White to move



(b) White to move

# Horizon effect

Fixed depth search  
thinks it can avoid  
the queening move

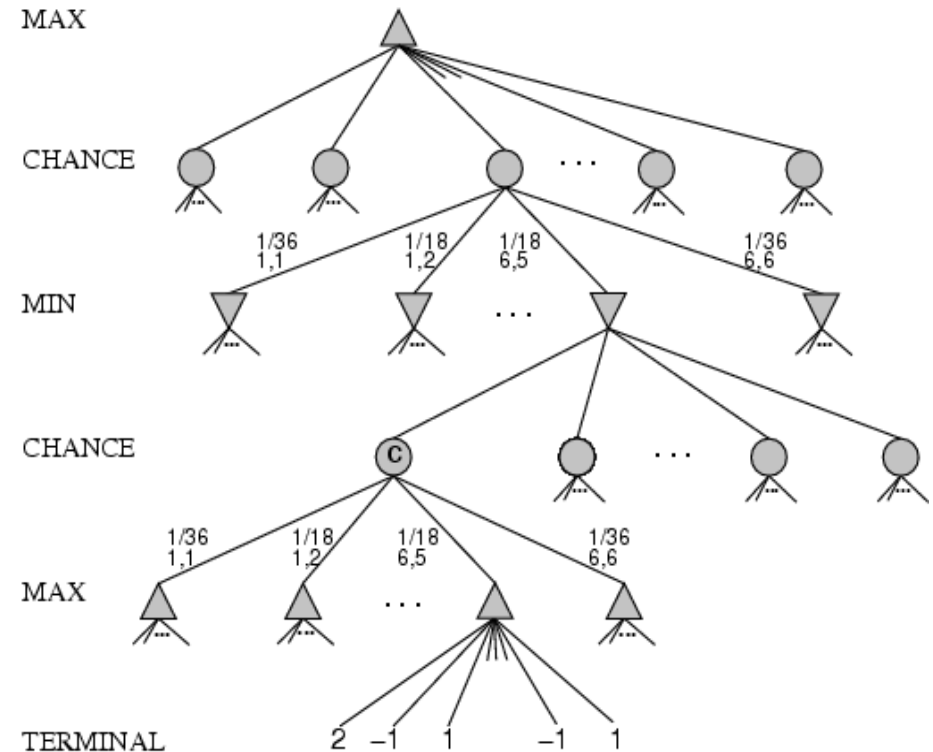
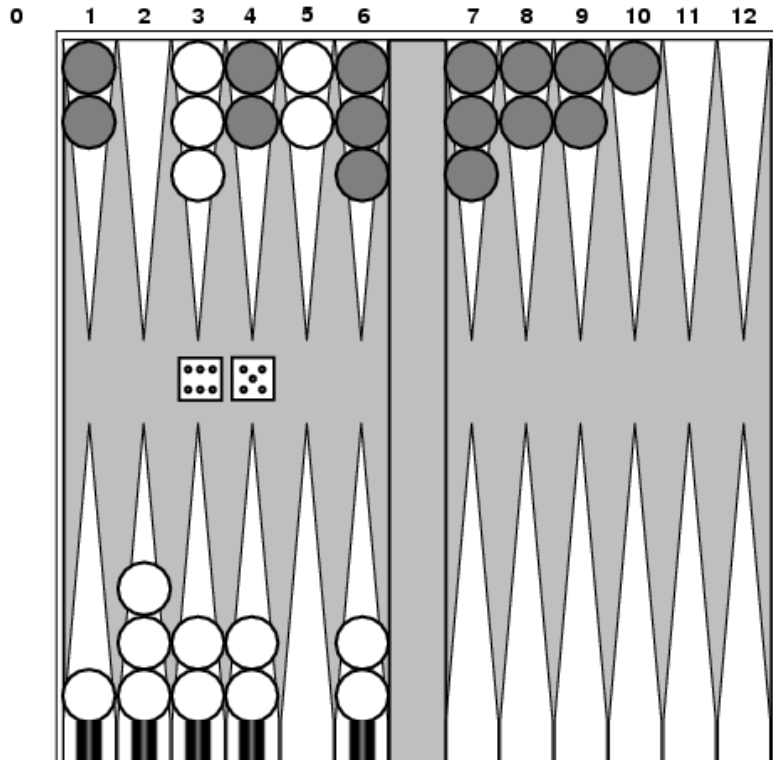


Black to move



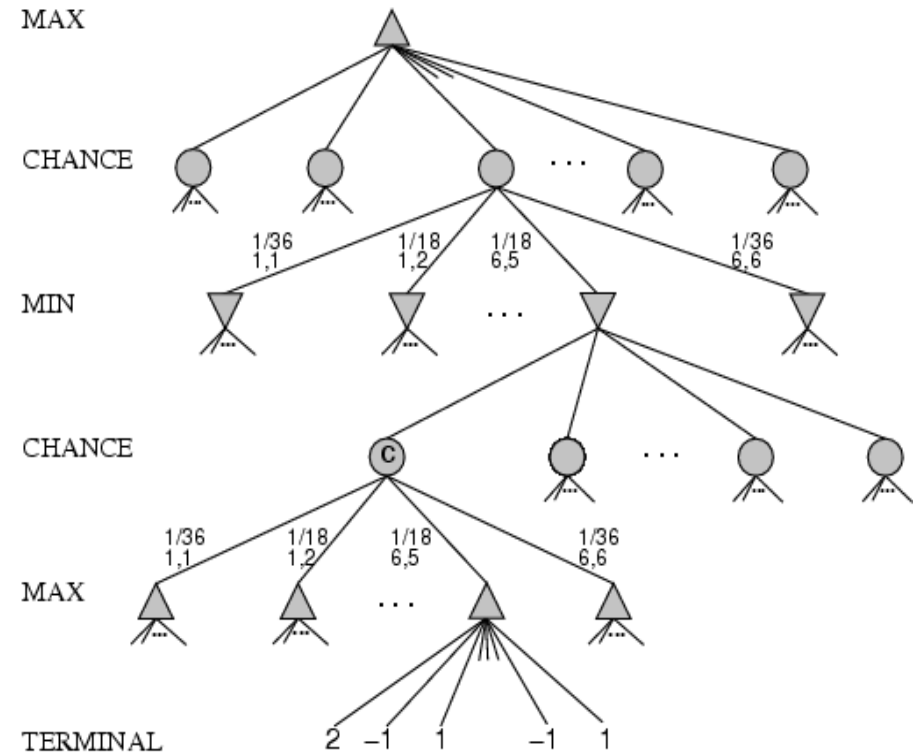
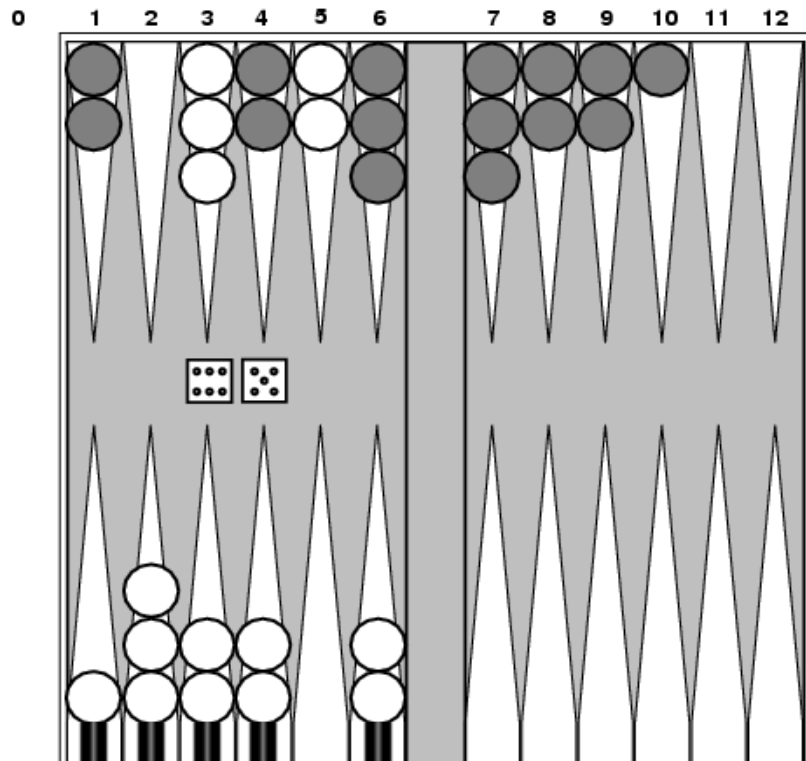


# Games that include chance



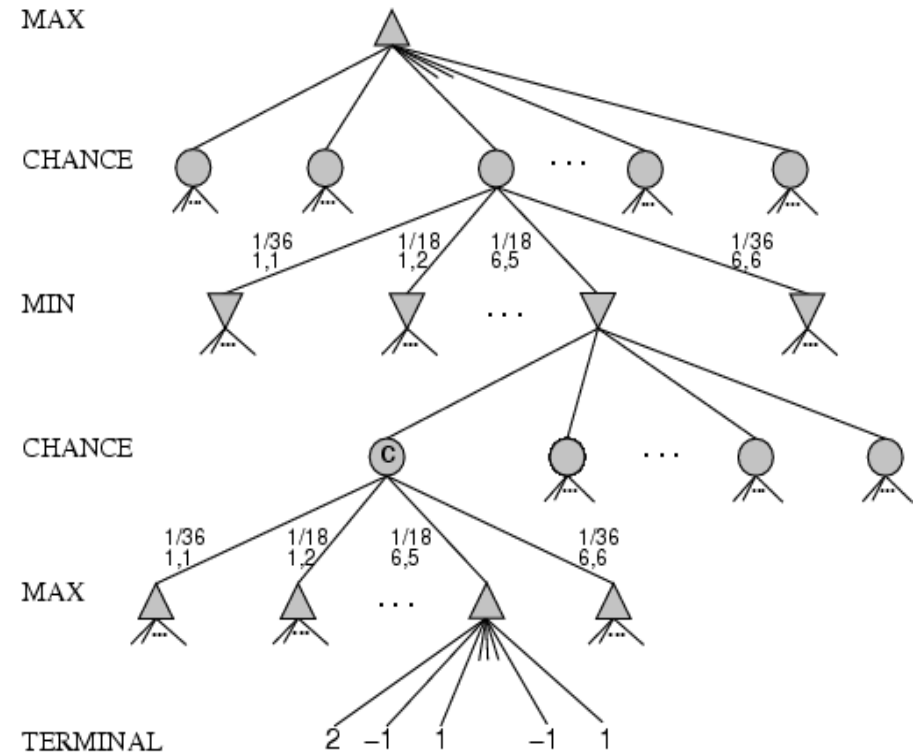
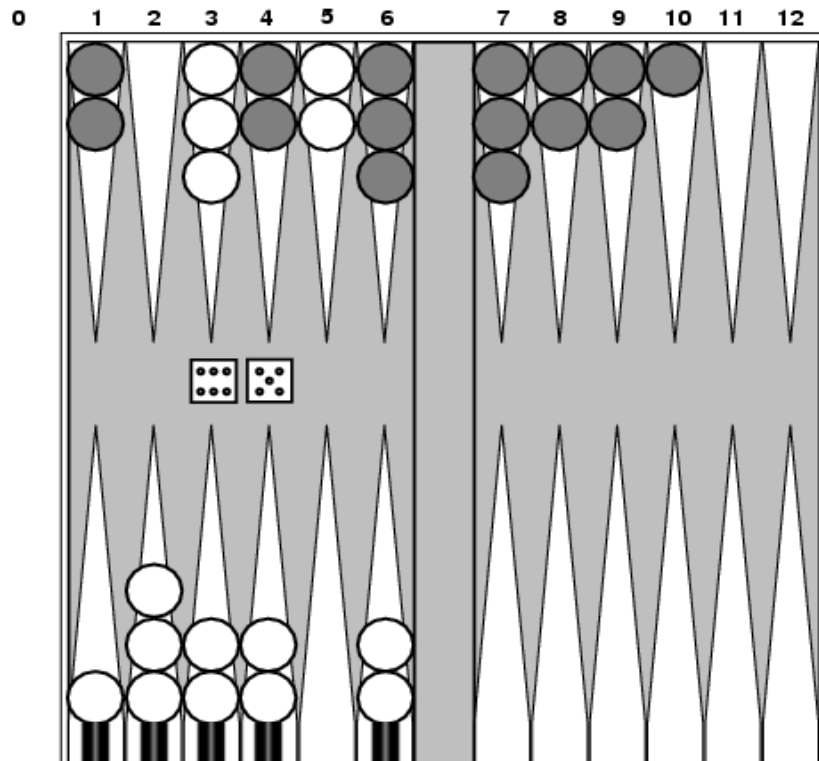
- Whites turn, After rolling a 5 and a 6
- Possible moves (5-10,5-11), (5-11,19-24), (5-10,10-16) and (5-11,11-16)

# Games that include chance



- Possible moves (5-10,5-11), (5-11,19-24), (5-10,10-16) and (5-11,11-16)

# Games that include chance



- [1,1], [6,6] chance 1/36, all other chance 1/18
- Can not calculate definite minimax value, only *expected* value

# Expecti minimax value

EXPECTI-MINIMAX-VALUE( $n$ )=

UTILITY( $n$ )

If  $n$  is a terminal

$\max_{s \in \text{successors}(n)} \text{MINIMAX-VALUE}(s)$

If  $n$  is a max node

$\min_{s \in \text{successors}(n)} \text{MINIMAX-VALUE}(s)$

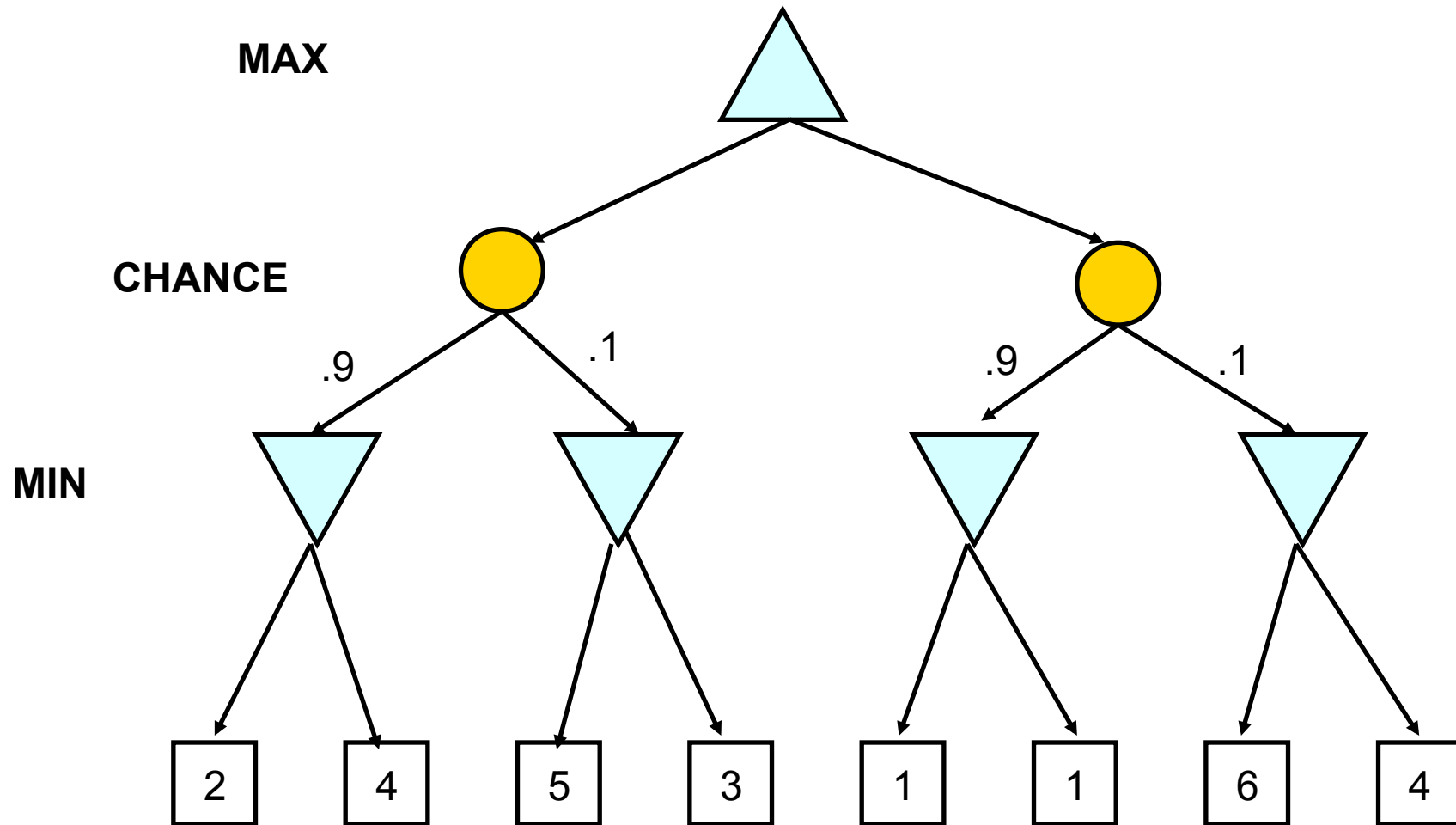
If  $n$  is a min node

$\sum_{s \in \text{successors}(n)} P(s) \cdot \text{EXPECTIMINIMAX}(s)$   
node

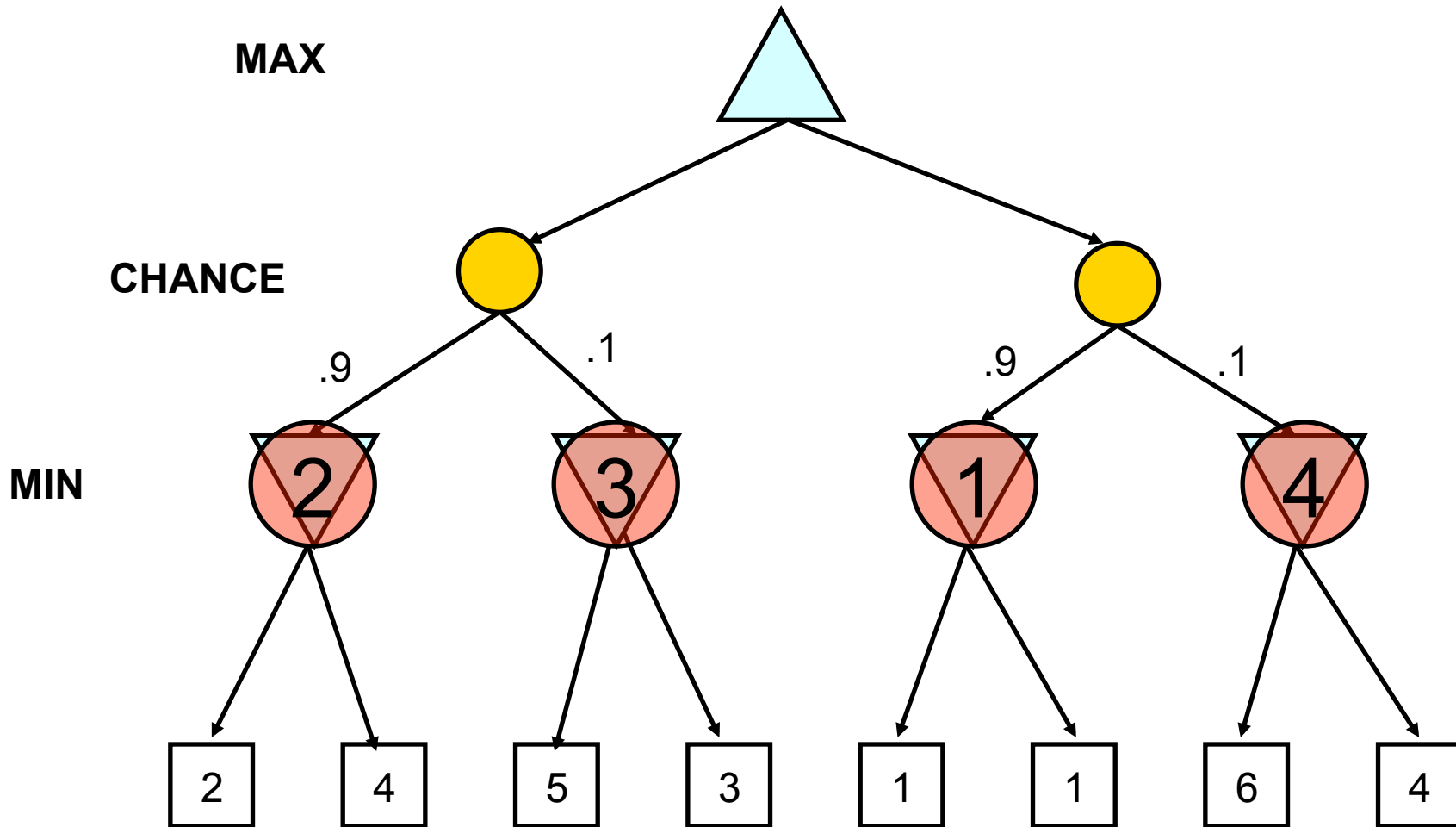
If  $n$  is a chance

These equations can be backed-up recursively  
all the way to the root of the game tree.

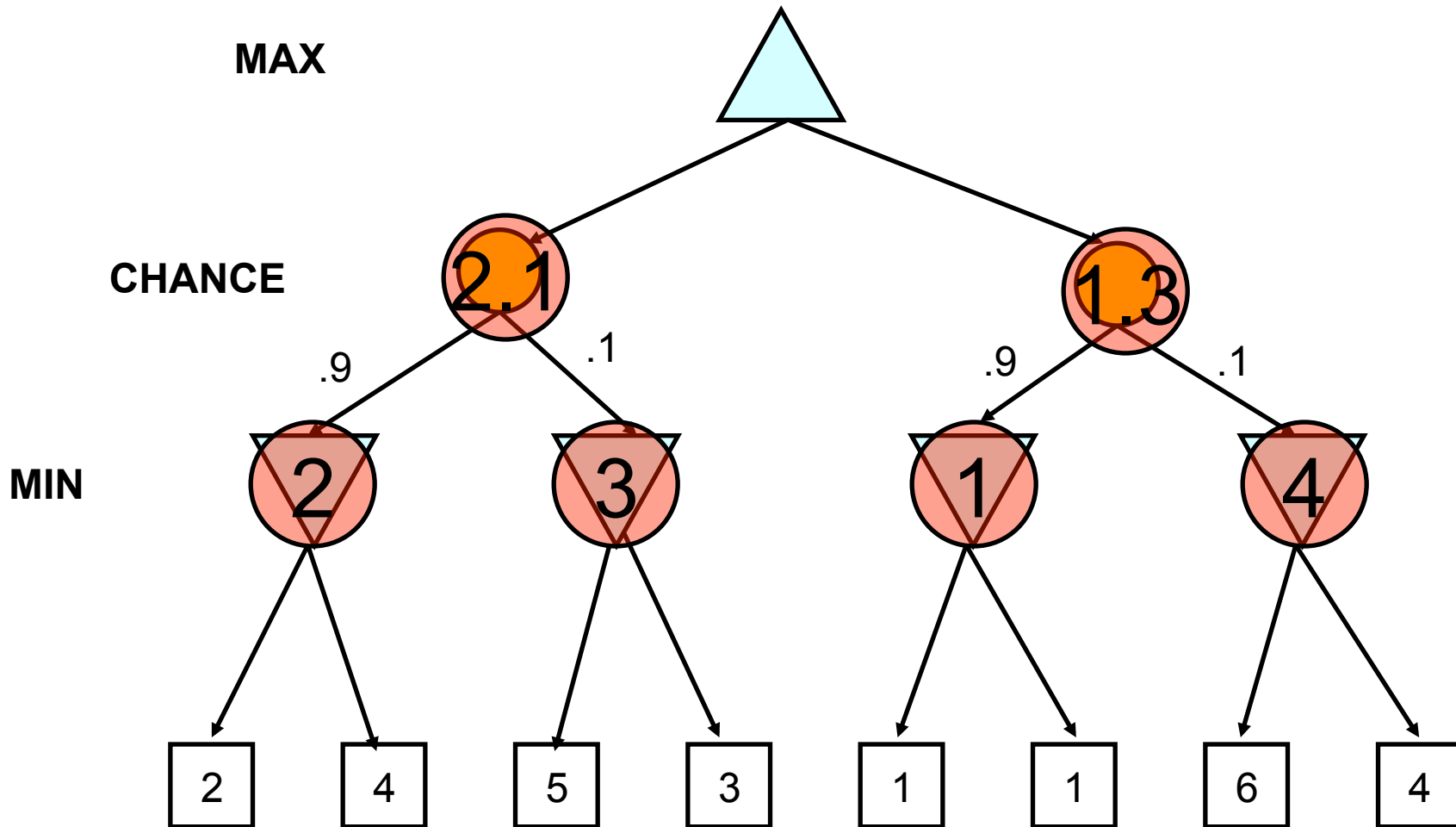
# EXPECTEDMINIMAX example



# EXPECTIMINIMAX example

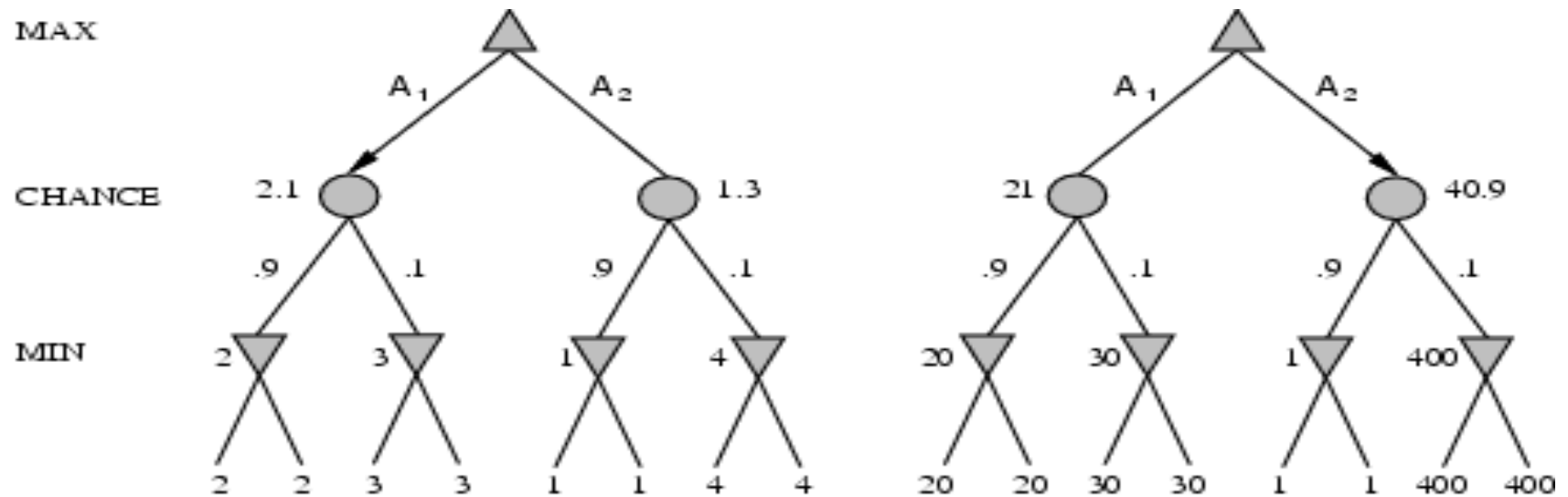


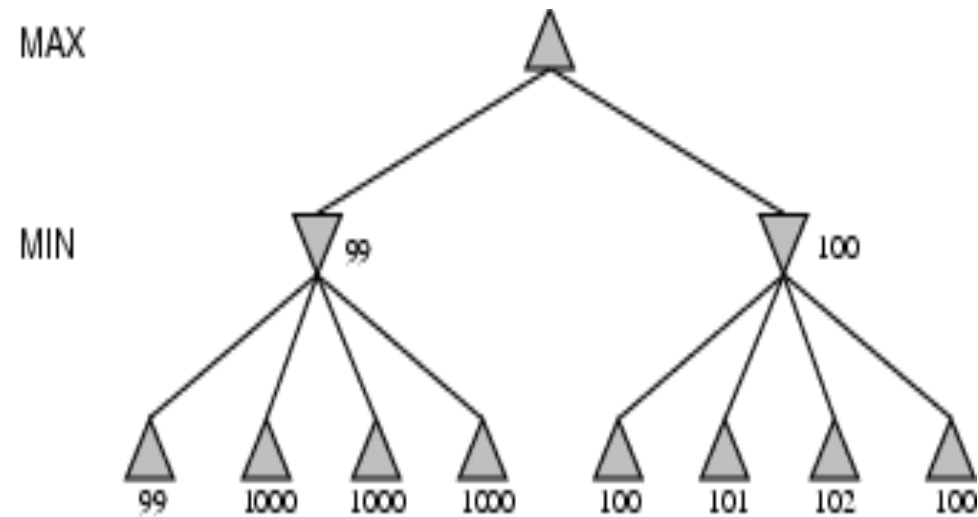
# EXPECTIMINIMAX example





# Position evaluation with chance nodes





- What will minimax do here?
- Is that OK?
- What might you do instead?

# Learning Types

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- Supervised learning:
  - ♦ (Input, output) pairs of the function to be learned can be perceived or are given.
- Unsupervised Learning:
  - ♦ No information about desired outcomes given
- Reinforcement learning:
  - ♦ Reward or punishment for actions

