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Last time

Game playing as search

- Assume the opponent will play optimally
- MAX is trying to maximize utility
 MIN is trying to minimize utility
 MINIMAX algorithm backs-up the value from the leaves by alternatively minimizing and maximizing action options
 plays "optimally", that is can play no better than
- Won't work for deep trees or trees with large branching factors •
- Pruning alleviates this be excluding paths
- Alpha-Beta pruning retains the optimality, by pruning paths that will never be chosen
- > alpha is the best choice down this path for MAX beta is the best choice down this path for MIN

Minimax example 2 MAX Aı A2 A3 MIN 37 27 prune!

Effectiveness of alpha-beta pruning

- > As we gain more information about the state of things, we're more likely to prune
- > What affects the performance of pruning? key: which order we visit the states
 - can try and order them so as to improve pruning

Effectiveness of pruning

- If perfect state ordering:
 - O(b^m) becomes O(b^{m/2})
 - We can solve a tree twice as deep!
- Random order:
- O(b^m) becomes O(b^{3m/4})
- still pretty good
- For chess using a basic ordering
- ▶ Within a factor of 2 of O(b^{m/2})

Evaluation functions

- O(b^{m/2}) is still exponential (and that's assuming optimal pruning)
 - for chess, this gets us ~10-14 ply deep (a bit more with some more heuristics)
 - > 200 million moves per second (on a reasonable machine)
 - 35⁵ = 50 million, or < 1 second</p>
 - hot enough to solve most games!
- Ideas?
 - heuristic function evaluate the desirability of the position
 - This is not a new idea:
 - Claude Shannon (think-- information theory, entropy), "Programming a Computer for Playing Chess" (1950)
 - http://vision.unipv.it/IA1/ProgrammingaComputerforPlayingChess.pdf
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Cutoff search

How does an evaluation function help us?

- search until some stopping criterion is met
- > return our heuristic evaluation of the state at that point

> When should we stop?

- as deep as possible, for the time constraints
- generally speaking, the further we are down the tree, the more accurate our evaluation function will be
- based on a fixed depth
 - keep track of our depth during recursion
 - if we reach our depth limit, return EVAL(state)

Cutoff search

- > When should we stop?
 - based on time
 - start a timer and run IDS
 - $\triangleright\,$ when we run out of time, return the result from the last completed depth
 - quiescence search
 - search using one of the cutoffs above
 - but if we find ourselves in a volatile state (for example a state where a piece is about to be captured) keep searching!
 - attempts to avoid large swings in EVAL scores

Heuristic EVAL

- > What is the goal of EVAL, our state evaluation function?
- $\,\triangleright\,$ estimate the expected utility of the game at a given state

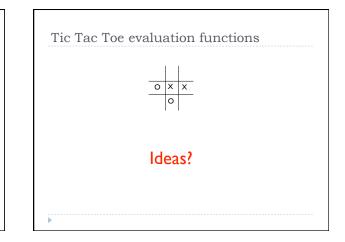
What are some requirements?

- must be efficient (we're going to be asking this about a lot of states)
- EVAL should play nice with terminal nodes
- $\,\,$ it should order terminal nodes in the same order at UTILITY
- a win should be the most desirable thing
- a loss should be the least desirable thing

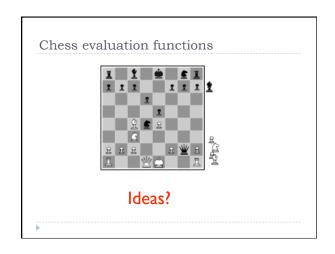
Heuristic EVAL

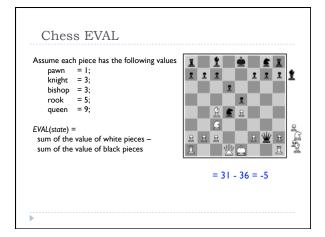
- > What are some desirable properties?
 - > value should be higher the closer we are to a win
 - and lower the closer we are to a lose
- The quality of the evaluation function impacts the quality of the player
 - Remember last time (De Groot), we expert players were good at evaluating board states!

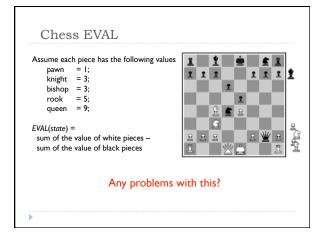
Simple Mancala Heuristic: Goodness of board = # stones in my Mancala minus the number of stones in my opponents.

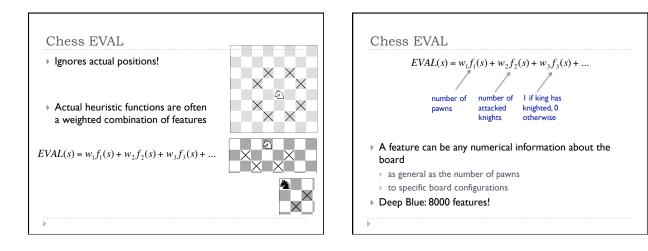


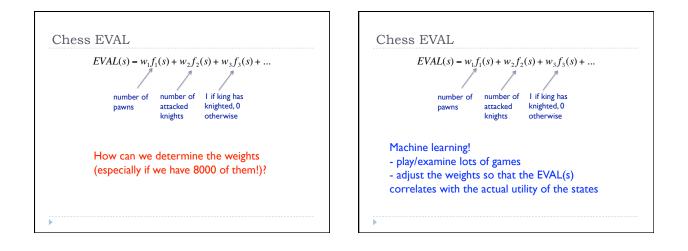
Tic Tac Toe			
Assume MAX is using "X"			
EVAL(state) =		х	0
if state is win for MAX:			
+ ∞			
if state is win for MIN:	= 6 -	4 =	2
- ∞			_
else:			
(number of rows, columns and diagonals available to MAX) -			
(number of rows, columns and diagonals available to MIN)			
		x	
	0	^	x
		0	

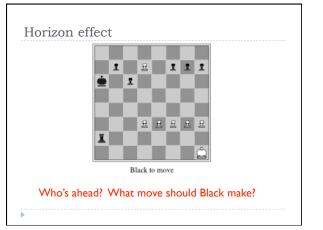


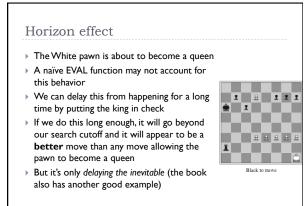












Other improvements

- Computers have lots of memory these days
- > DFS (or IDS) is only using a linear amount of memory
- How can we utilize this extra memory?
- transposition table
- history/end-game tables
- "opening" moves
- **،**...

Transposition table

- Similar to keeping track of the list of explored states
- Keeps us from duplicating work
- > Can double the search depth in chess!

history/end-game tables

- History
 - keep track of the quality of moves from previous games
 - use these instead of search

end-game tables

- do a reverse search of certain game configurations, for example all board configurations with king, rook and king
- ${\scriptstyle \flat}\,$ tells you what to do in any configuration meeting this criterion
- if you ever see one of these during search, you lookup exactly what to do

end-game tables

- Devastatingly good
- Allows much deeper branching
 - $\triangleright\,$ for example, if the end-game table encodes a 20-move finish and we can search up to 14
 - can search up to depth 34
- Stiller (1996) explored all end-games with 5 pieces
 one case check-mate required 262 moves!
- Knoval (2006) explored all end-games with 6 pieces
 one case check-mate required 517 moves!
- .
- Traditional rules of chess require a capture or pawn move within 50 or it's a stalemate

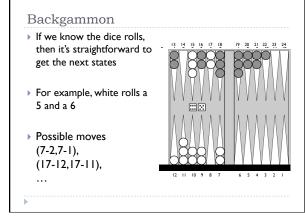
Opening moves

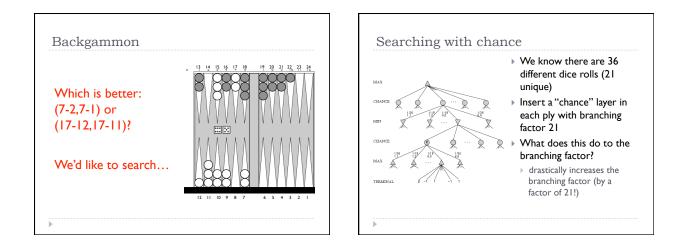
- At the very beginning, we're the farthest possible from any goal state
- People are good with opening moves
- > Tons of books, etc. on opening moves
- Most chess programs use a database of opening moves rather than search

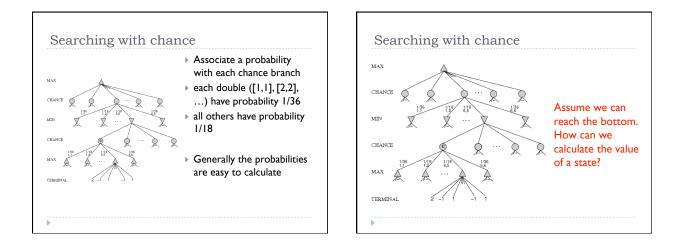
Chance/non-determinism in games

- All the approaches we've looked at are only appropriate for deterministic games
- Some games have a randomness component, often imparted either via dice or shuffling
- Why consider games of chance?
 - because they're there!
 - more realistic... life is not deterministic
- more complicated, allowing us to further examine search techniques

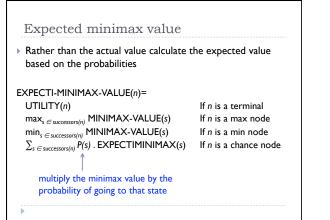


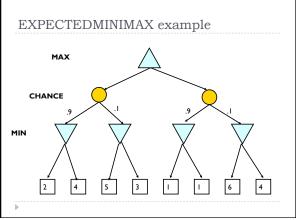


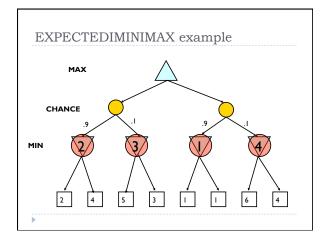


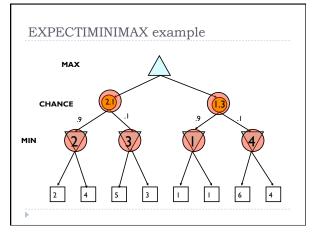


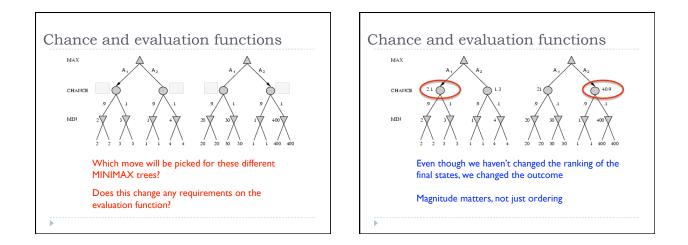
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Games with chance

- Original branching factor b
- Chance factor *n*
- What happens to our search run-time?
- ▶ O((nb)^m)
- ▶ in essence, multiplies our branching factor by n
- For this reason, many games with chance don't use much search
- backgammon frequently only looks ahead 3 ply
- Instead, evaluation functions play a more important roll
 TD-Gammon learned an evaluation function by playing itself
 - over a million times!

- Partially observable games
- In many games we don't have all the information about the world
 - battleship
- bridge
- poker
- scrabble
- Kriegspiel
- pretty cool game
- "hidden" chess
-
- How can we deal with this?



