

9. Odds and Ends

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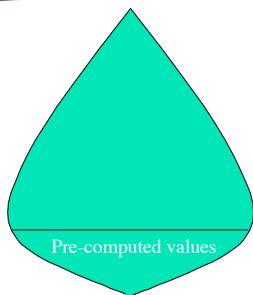
Endgame Databases

- Pre-compute known values in the search
- Start with the goal state(s)
- Work backwards as far as time and space permits
- Retrograde analysis [1,2]

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Using an Endgame Database



Normal search here until the search reaches the endgame databases.

Whenever search reaches here, can treat it as a terminal node.

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Advantages

- Many more terminal nodes
- Terminal nodes are now closer to the root
- Reduces the amount of heuristic error in the search
- Effective search depth is deeper along some lines of play
- Can be used to solve a game

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Endgame Databases

- Search benefits
 - Improves the quality of the evaluations
 - Perfect information with no error
 - Cuts off the search
- Less search, more accuracy
 - Cost in storage
 - Program slows down because of I/O accesses
- Benefits usually far out-weigh the costs
- Unfortunately, not possible for all games (e.g., Ataxx)

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Databases in Chinook

- Pre-computed all positions with 8 or fewer pieces on the board
 - 444,000,000,000 positions
 - compressed into 6 gigabytes of data organized for real-time decompression
- Most game-playing programs are compute-bound; Chinook is I/O-bound
- Made a massive difference in quality of play
- Working on the 10-piece databases
 - 12 trillion positions.

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Opening Databases

- Most games have a single starting state
- Pre-compute the initial moves of the game, saving time for later moves
- In the past, this has been done using expert knowledge
 - Belle, Chinook books constructed from human literature
 - Human literature is full of errors!

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Opening Databases

- Want to automatically build an opening database
 - Save a tree on disk
 - Have processors expand leaf nodes
 - Update tree with new values
 - Search tree identifying leaf nodes to expand
 - Buro [3] ; Lincke [4]

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Alpha-Beta Alternatives

- Many algorithms have been proposed as replacements to alpha-beta
- Most look good on paper, but fail in practice; usually have far too much overhead
- Min-max approximation...
- Mega-greedy search...
- BPIP...

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B* [5]

- Prove that a move is best at the root, but not necessarily its value
- Evaluation function has two values: an upper bound and a lower bound on the true value
- Two search strategies: prove best or disprove rest

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B*

- Prove best
 - Try to raise one move's lower bound to be \geq than the upper bound of alternatives
- Disprove rest
 - Lower the upper bound of alternatives to \leq that of the best move

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B* Reality

- Need to have accurate upper/lower bounds for the algorithm to converge
 - In practice, this is very hard to do
- PBA* -- evaluation function is a (simple) probability distribution [6]
 - Values obtained using null-move searches
- Only one known application where B* has been effective (Scrabble)

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Conspiracy Numbers [7]

- Alpha-beta returns a value, but no measure of our confidence in that value
- Conspiracy number -- the number of child nodes that have to change their value ("conspire") to cause a change in the root parent

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Conspiracy Numbers

- Assume a range of values from 1 to 6
- Leaf node with value 4
 - (1, 1, 1, 0, 1, 1)
 - 0 nodes have to conspire to achieve 4
 - 1 node must conspire to achieve any other value
- Terminal node with value 4
 - (∞ , ∞ , ∞ , 0, ∞ , ∞)

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Conspiracy Numbers

- Max node: to increase a value requires only one child to change its value; to decrease requires all children with higher values to lower theirs
- $\uparrow(T,v) = 0$ for all $v \leq m$ and $\text{MIN } \uparrow(T,v)$ for all $v > m$
- $\downarrow(T,v) = 0$ for all $v \geq m$ and $\sum \downarrow(T,v)$ for all $v < m$

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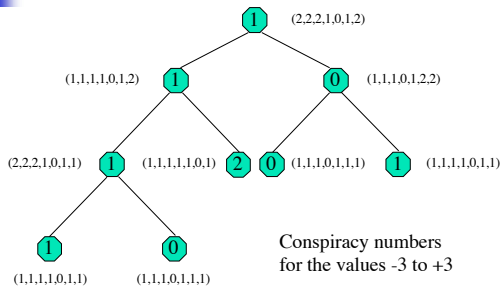
Conspiracy Numbers

- Min node: to decrease a value requires only one child to change its value; to increase requires all children with lower values to raise theirs
- $\uparrow(T,v) = 0$ for all $v \leq m$ and $\sum \uparrow(T,v)$ for all $v > m$
- $\downarrow(T,v) = 0$ for all $v \geq m$ and $\text{MIN } \downarrow(T,v)$ for all $v < m$

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Example



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Conspiracy Numbers

- Search to increase “confidence” in the root value
- Expand node that promises to give the most information on the root value
- Use iterative search
 - Prove root with a CN of 1
 - Then try and prove with CN of 2
 - Iterate until time expires

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Conspiracy Numbers

- Excellent for tactics
 - Automatically searches forced lines of play (low conspiracy numbers)
- Generally not used in practice
- PN (proof number search) variant [8]
 - Win, loss, unknown values
 - Successfully used to solve several games

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References

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- [8] V. Allis, M. van der Muelen, and J. van den Herik. “Proof-number Search”, *Artificial Intelligence*, vol. 66, pp. 91-124, 1994.

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