

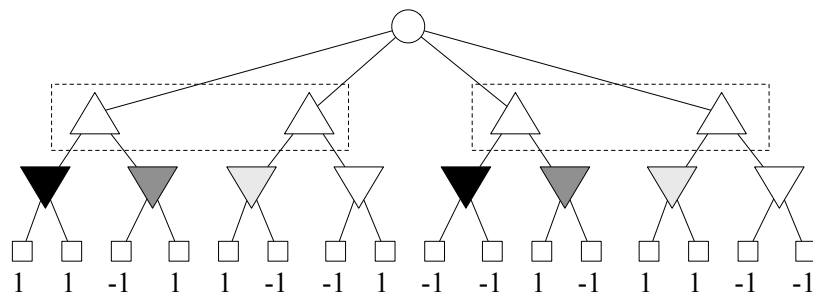
Lecture 10: Imperfect Information

AI For Traditional Games
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Imperfect Information

- So far, all games we've developed solutions for have perfect information
 - No hidden information such as individual cards
 - Hidden information often represented as chance nodes
 - Could be a play by one player that is hidden until the end of the game

Example Tree



What is the size of a game with ii?

- Simple betting game (Kuhn Poker)
 - Ante 1 chip
 - 2-player game, 3-card deck, 1 card each
 - First player can check/bet
 - Second player can bet/check or call/fold
 - If 2nd player bets, 1st player can call/fold
 - 3 hands each / 6 total combinations
 - [Exercise: Draw top portion of tree in class]

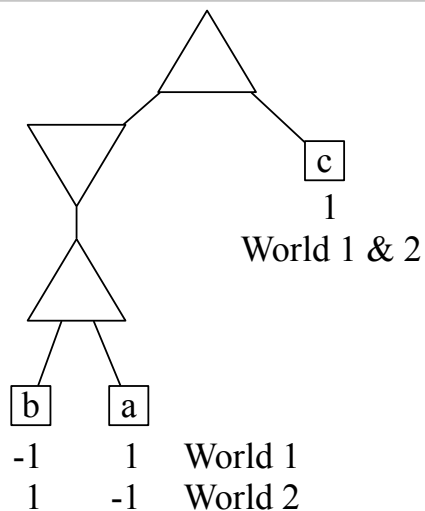
Simple Approach: Perfect-Info Monte-Carlo

- We have good perfect information-solvers
 - How can we use them for imperfect information games?
- Sample all unknown information (eg a world)
 - For each world:
 - Solve perfectly with alpha-beta
 - Take the average best move
- If too many worlds, sample a reasonable subset

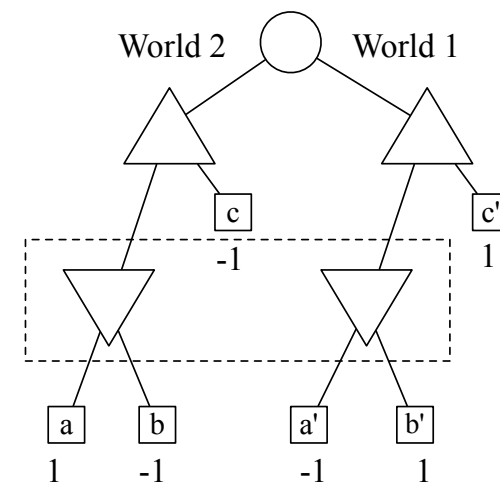
Drawbacks of Monte-Carlo

- May be too many worlds to sample
- May get probabilities on worlds incorrect
 - World prob. based on previous actions in the game
- May reveal information in actions
 - Good probabilities needed for information hiding
 - Program has no sense of information seeking/hiding moves
- Analysis may be incorrect (see work by Frank and Basin)

Strategy Fusion



Non-locality



Strengths of Monte-Carlo

- Simple to implement
 - Relatively fast
- Can play some games very well
 - Approximates some games better than others
- How can we measure this?
 - Abstract model of a game

Analysis of PIMC

- Understanding the Success of Perfect Information Monte Carlo Sampling in Game Tree Search
 - Jeffrey Long and Nathan R. Sturtevant and Michael Buro and Timothy Furtak

Leaf Correlation

- (lc) With probability lc , each sibling pair of terminal nodes will have the same payoff value (whether it be 1 or -1). With probability $(1 - lc)$, each sibling pair will be anti-correlated, with one randomly determined leaf having value 1 and its sibling being assigned value -1.

Bias

- b : At each correlated pair of leaf nodes, the nodes' values will be set to 1 with probability b and -1 otherwise. Thus, with bias of 1, all correlated pairs will have a value of 1, and with bias of 0.5, all correlated pairs will be either 1 or -1 at uniform random (and thus biased towards neither player). Note that anti-correlated leaf node pairs are unaffected by bias.

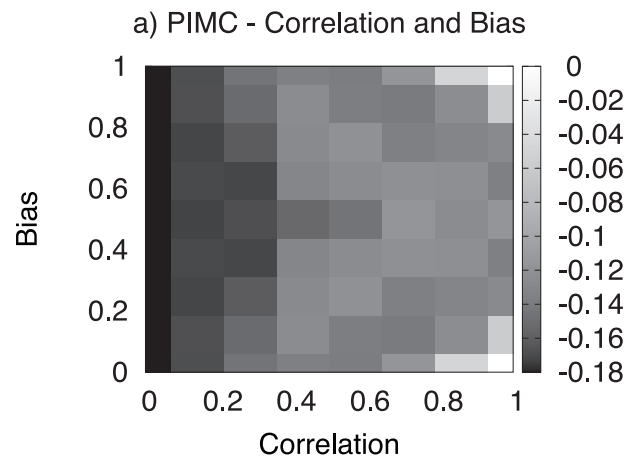
Disambiguation factor

- (df): Each time p is to move, we recursively break each of his information sets in half with probability df (thus, each set is broken in two with probability df ; and if a break occurs, each resulting set is also broken with probability df and so on). If df is 0, then p never gains any direct knowledge of his opponent's private information. If df is 1, the game collapses to a perfect information game, because all information sets are broken into sets of size one immediately.

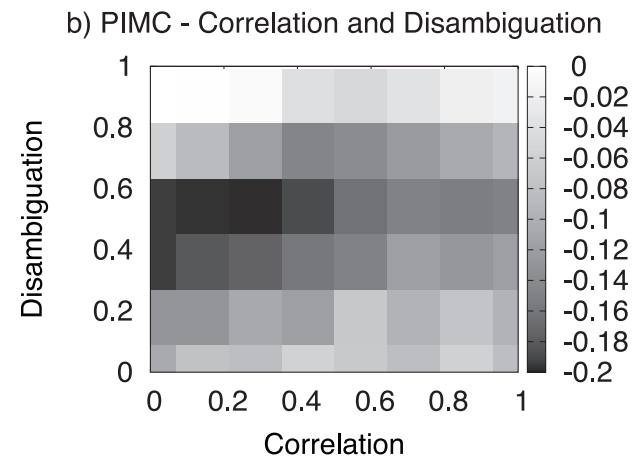
Measurements in practice

- Trick-based card games
 - Leaf-correlation: tends to be correlated
 - Bias: tend to have bias based on cards
 - Disambiguation: lots of disambiguation (each action provides some information)

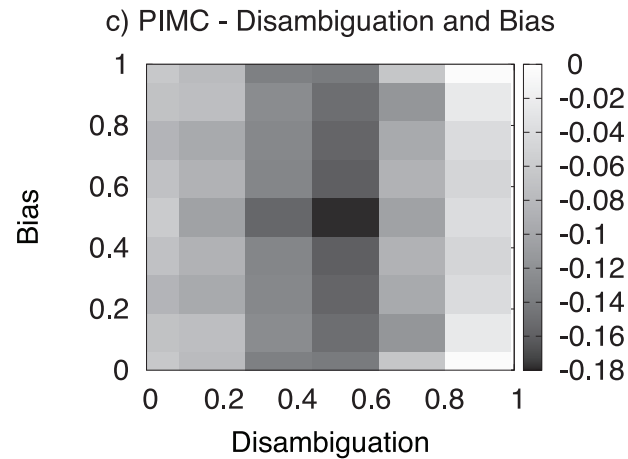
Abstract model results



Abstract model results



Abstract model results



Measurements in practice

• Kuhn Poker

- Leaf-correlation: mixed (0.5)
 - You can sometimes fold and give the payoff to the other player (anti-correlated)
- Bias: tend to have bias based on cards, but averages out over all cards (0.5)
- Disambiguation: no disambiguation (actions give no direct information about the cards you hold)

Kuhn Poker

Player:	Opponent	
	Nash	Best-Response
Random (p1)	-0.161	-0.417
Random (p2)	-0.130	-0.500
PIMC (p1)	-0.056	-0.083
PIMC (p2)	0.056	-0.166

Table 1: Average payoff achieved by random and PIMC against Nash and best-response players in Kuhn poker.