# Raising the Stakes 

## Jonathan Schaeffer

Department of Computing Science University of Alberta
jonathan@cs.ualberta.ca

## GAMES Research Group

> Largest Al research group using games
> Classic Games

- Chess, checkers, go, hex

- Poker, hearts, spades
> Commercial games
- Role-playing (Bioware)
- Sports (Electronic Arts)
- Real-time strategy (Relic)



## Thank You

> Darse Billings
> Michael Bowling
> Neil Burch
$>$ Aaron Davidson
$>$ Rob Holte
> Morgan Kan

- Bryce Larson
- Carmelo Piccione
> Terrance Schauenberg
> Finnegan Southey
> Duane Szafiron


## Darse Billings



Poker player
Philosopher
Computer scientist
Perpetual graduate student

## Poker as a Test-bed for AJ

> Multiple agents (typically 10)
> Imperfect information (unknown cards)
> Stochastic (shuffiled deck)
> Risk management (betting)
> Partial observability

- Opponent modeling
> Unlike most other games-applied research, poker has many properties of real-world applications


## Applications

> Adversarial opponent modeling
$>$ Negotiation
$>$ Auctions
> Real-time strategy games

- Most of the techniques described her have been used for real-time planning in (military) strategy games


## Texas Hold'em

$>$ Hundreds of poker variants
$>$ Most strategically complex variant widely played
$>$ No-Limit Texas Hold'em used to determine the champion in the annual World Series of Poker
> Our research: Limit Texas Hold'em

- 10-player (ring game)
- 2-player (heads up)


## The Goal



## The Real Goal



Chris Ferguson


Stu Ungar


Annie Duke

## Texas Hold'em Rules

> 2-10 players
> Four rounds of play

- Pre-flop: Each player gets two private cards; bet
- Flop: Three community cards; bet
- Turn: One community card; bet
- River: One community card; bet
> Betting:
- fold (lose all you money)
- check/call (match what is in the pot)
- bet/raise (increase amount in the pot)
- Best five card poker hand wins


## Texas Holdlem Example



## Obstacle 1: Feeling Lucky?



## Obstacle 2: Does He Have It?

PLAY EP

VIDEO CALIBRATION

## Obstacles (3)

$>$ Imperfect Information

- Few data points
- Probabilistic strategies are essential
- Need to infer what the opponent is likely to have (modulo bluffing)
> Opponent Modeling
- Every opponent has a different style
- Opponents change style frequently
- One cannot be predictable!


## Building a Strong AJ 1991-2005

$>$ Rule-based (bad)

- Loki (1995-1997)
> Simulations (better but weak)
- Loki -> Poki (1997-present)
$>$ Game theory (good)
- PsOpti (2001-present)
$>$ Learning and adaptation (best?)
- Vexbot (2003-present)
- Bayesbot (2005-present)


## Rule-based Strategy

- Need a real domain expert (which we had)
> Poker knowledge is fragile
- Covered common cases reasonably well
- Unable to properly recognize and handle exceptions
> Poker expert quickly becomes the bottleneck, applying Band-Aid solutions to fix problems
- Easily exploitable by an experienced player
$>$ Loki could win at a good rate in Internet games
> The most knowledge-intensive strategy tried


## Simulations Strategy

> For each betting decision (f/c/r):

- "Deal" cards to the opponent
- Simulate hand to end of game
- Gather statistics on each decision
> Less reliance on expert knowledge
- Search is knowledge!
> Reliant on having a good model of the opponent
> Stronger than Loki in the laboratory, but not that much stronger against humans
> Less expert knowledge -> better play


## Game Theory

- Nash equilibrium
- Find an "optimal" answer
- Assumes both sides play perfectly
- Recipe for drawing matches against strong players



## Two-player Limit Hold'em



## Optimal Play

> Solve a linear programming problem for two-player Hold'em
$>$ An axis is all possible information sets for each player

- An information set is a set of states in the search tree where the player could be
- Can't know for sure because of hidden information


## Information Sets



## Abstraction



## Pseudo-optimal Solution

- Pretend that you and your opponent can have only one of 6 types of hands
- fantastic, very strong, strong, pretty good, so-so, weak
- This new game is 100 billion times simpler than real poker
- This new game looks like poker... and use its solution to play real poker.


## Bucketing

> Reduce branching factor at chance nodes
> Overlaying "strategically similar" sub-trees


## Abstraction Models



## Solving the LP

$>$ Generates a system of equations

- 10,000 to 100,000 entries per player
- Sparse; 100 non-zero entries per row/column
- Needs 24 hours to solve on an Athlon 1800 with 4 GB of RAM using CPLEX
$>$ Use 7 categories of hands? Gets too big very quickly!


## PsOpti2 versus "theCount"



## PsOptj

$>$ Pro:

- Quantum leap in playing ability
- Poker knowledge used in the abstraction (preprocessing), not in the program (during play)
- Irriproyed versiosi
$>$ Con
- It takes a while, but strong players can identify weaknesses and exploit them
- Program is oblivious to opponent's strategy
- Optimal is not maximal


## Human Opinion?

"You have a very strong program. Once you add opponent modeling to it, it will kill everyone."

Gautum Rao

## Rock, Paper, Scissors

$>1$ st \& 2nd International RoShamBo Championships

- Deceptively simple problem that illustrates the differences between optimal and maximal play



## locaine Powder



## Adaptive Play

$>$ Numerous standard machine learning attempts (genetic algorithms, neural nets, decision trees, etc.) but with no notable success
$>$ Gather data on opponent decisions and attempt to learn a model of their play

## Context Tree (1)

$>$ For each opponent, maintain a context tree of all possible betting sequences

- In a given betting context, keep track of how often the opponent did a $\mathrm{f} / \mathrm{c} / \mathrm{r}$
$>$ To compute a betting decision, search the tree and compute an expected value
$>$ Need:
- Assign a value to the leaf nodes
- Assign f/c/r frequencies to betting nodes


## Context Tree (2)

> Use a variation of Expectimax

- Value of a node is the sum of the weighted value of each of the children
> For opponent's decisions, use a mixed strategy
> For program's decisions, use a maximum or mixed strategy
$>$ Miximix and Miximax algorithms


## Using a Context Tree



## Obstacles

> Few data points for a given betting context

- Treat "similar" scenarios the same way, allowing one to abstract multiple contexts into one context
- Leaf node data is sparse
- Use empirical data when we have it, else infer a "reasonable" distribution based on the betting sequence
> Default seeding of the tree
- Defaults from a strong player or from PsOpti don't work; they are each skewed to a particular style


## Results

> Vexbot handily defeats PsOpti and all our other bots by large margins... over 40,000 hands
$>$ Results against humans are mixed, ranging from brilliant to mediocre
$>$ Vexbot needs to learn quickly and start winning within 50 hands

## Bayesbot

> Use a different model of a game based on probability distributions
> Accelerate learning by classification
> For each player (parameter space):

- Level 1 (4 options):
- Betting frequency, folding frequency, bluffing frequency, trapping frequency
- Level 2 (4 options):

Preflop, flop, turn, river

- Level 3 (4 options):

Bet level (bet, raise, re-raise, cap betting)

## Bayesbot

> Algorithm

- Start with a random model
- Play a hand
- Use Bayesian inference to a move to a model that better approximates the data seen
- Play a hand with the new model and repeat step above
- Simplifications
- Subset of the the complete abstraction model
- Use 10 values to approximate distribution
- Early stages, but results are very promising


## Conclusions

$>$ Poker is a challenging Al domain (if only I had realized this in 1991)
$>$ Optimal strategy is a misleading concept; maximal play will win more money
> Adaptive bots hold the key to world-class poker play
> Current program might be an even-money bet against a top player

## Play Online!

## http://games.cs.ual|berta.ca/poker/



## Better Yet... Buy it :)

## http://poki-poker.com

http://poker-academy.com


## Publicity!



