Opponent Modeling in Poker

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Outline

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3 Features
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An Interesting Problem

- Games of complete information
  - Chess
  - Go
- Games of incomplete information
  - Poker
  - Backgammon
- We chose No-Limit Hold’em
- Best game of incomplete information to study
  - Currently popular ($$)
  - Challenging
  - Active research area
Motivation

Opponent Modeling

- Current poker AI is not competitive
  - Just becoming competitive in 2-player setting
  - Multiplayer largely unsolved
- Opponent modeling may be the answer
  - Following a match against U of A’s pokerbot, one of the best online players said: “You have a very strong program. Once you add opponent modeling to it, it will kill everyone.”
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Game Structure

- **Blinds**
  - Forced bets that create something to play for
  - Similar to antes

- **4 Rounds of betting**
  - **Hole** – 2 private cards
  - **Flop** – 3 community cards
  - **Turn** – 1 more community card
  - **River** – final community card

- **Bets** – any size
  - ”Check”
  - ”Bet”
  - ”Call”
  - ”Raise”

- Best 5 card hand wins at showdown
Cash Game
- Players may come and go at any time
- May purchase any amount of chips at any time
- Static Blinds

Tournaments
- Set buy-in
- Payouts based on place finished
- Increasing blinds

All-In
- A player who has run out of chips is allowed to continue to the end of the hand and only vies for the portion of the pot he can match
Basic Strategy Elements

- Position
  - "Behind"
  - "In front"

- Playing Styles
  - "Poker is not a people game played with cards, but rather a card game played with people"

- Pot Odds

- Image
All-in or Fold

- Simple Tournament Strategy
- Only requires modeling of call or fold during first betting round
- Blunts all of the best poker weapons, forcing your opponents to either accept tremendous risk or fold away their chips.
  - World Series of Poker purportedly won this way
- Avoids Multi-armed Bandit
- Allows learning with a smaller dataset
Defining the Problem

- Opponent Modeling, not a poker bot
- We are attempting to learn how players react to someone going all-in
  - $p(\text{call}|\text{an all-in bet})$
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Overview of Features

- Players in pot
- Players yet to act
- Aggressiveness of all-in player
- Looseness of all-in player
- Looseness of caller
- Pot odds
- Blinds to pot ratio
- Previous all-in behavior
- Previous hand strength shown
Players Involved

- The number of players who have willfully entered the pot
- Exponentially increases expected strength of best hand [1]
- The more players already in the pot, the stronger your hand should be to enter the pot.
Players Left to Act

- Number of players who remain to act.
- The more players there are behind you, the greater the probability that someone behind you has a strong hand.
- A player who pays attention to this feature can be said to be aware of his or her position at the table.
Pot Odds

- Represents the cost/benefit ratio of calling
- With poor pot odds, you need a very good hand to justify a call
Aggressiveness of All-in Player

- Ratio of money put in pot proactively to reactively
- A passive player is likely to have a strong hand when going all in
- A player who realizes should call be more apt to call an aggressive player
Features

Looseness of potential caller

- Percentage of chips this player has contributed to all pots he played in
- A loose player is more likely to call an All-in
- This is a common stat used in player tracking software (VPIP)
- Might be a number a strong player is actually looking at
Blinds to Pot Ratio

- Portion of pot contributed as blinds
- A high ratio may indicate that the all-in player has a mediocre hand
- Higher value should make a call more likely
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Text based hand Histories

- Played about 50 hours of All-In or Fold
- Extensive parsing to get data out of histories
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Online Learning Setting

- Each trial is a hand of poker where an all-in bet has already been made.
- At each trial, the player being modeled must decide whether to call an all-in bet or fold.
- Each expert returns an estimated conditional probability that the player will call the bet given the current state of the game.
- Our algorithm is weighted majority with a square loss.
- Weights represent factors an individual player is currently paying attention to.
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Experimental results

How Data Influences our Approach

- We have hand histories for 19 tournaments and 347 distinct players.
- Because of the setting, we get very few data points per player.
  - Largest number of hands for a player: 18.
  - Mean number of hands per player: 4.
- With convergence bounds proportional to $\log N$, we should have very few experts.
- Best expert is too easy a comparator to beat, so we decided to consider aggregate data.
  - Uses all data by combining all players into a single aggregate player.
  - Models an "average" player.
  - For a given player, we compare the weight vector computed on aggregate data to weight vector computed for that player.
Experimental results

Loss vs. Comparator 1

![Graph showing opponent model for Player 136 vs. Comparator]

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Opponent Modeling in Poker
Experimental results

Loss vs. Comparator 2

Opponent Model for Player 304 v. Comparator

Cumulative Loss

Hand

player weight vector
aggregate weight vector
Per Player Weights

Weight Vector for Player 136
Per Player Weights

![Weights](image)

Weight Vector for Player 303
Per Player Weights

Weight Vector for Aggregate Data

Expert

0 2 4 6 8 10 12 14 16 18

Weight

0 0.05 0.1 0.15 0.2 0.25 0.3 0.35
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Future Work

- Bot?
- More specialized experts
  - Some features are "advanced"
  - Experts based on overall averages will not capture these well
- Estimate Hand Strength of All-in player
Clement Sire.
Universal statistical properties of poker tournaments, 2007.