An Introduction to Poker Opponent Modeling

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It is not my aim to surprise or shock you - but the simplest way I can summarize is to say that there are now in the world machines that think, that learn and that create. Moreover, their ability to do these things is going to increase rapidly until - in a visible future - the range of problems they can handle will be coextensive with the range to which the human mind has been applied.
It is not my aim to surprise or shock you—but the simplest way I can summarize is to say that there are now in the world machines that think, that learn and that create. Moreover, their ability to do these things is going to increase rapidly until—in a visible future—the range of problems they can handle will be coextensive with the range to which the human mind has been applied.

Herbert Simon - 1957 [1]
Goals

- Basic Knowledges of General Approaches to Opponent Modeling (OM)
- Ability to Implement the Simple OM System Used in Loki
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Outline

1. Motivation
2. General Approaches
3. Loki Opponent Modeling
Opponent Modeling

Goals:
Understanding the internal state of the opponent
Predicting the opponent's future actions
Opponent Modeling

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- Predicting the opponent’s future actions
"There is no psychology at work" in Deep Blue, says IBM research scientist Murray Campbell. Nor does Deep Blue "learn" its opponent as it plays. Instead, it operates much like a turbocharged "expert system," drawing on vast resources of stored information (For example, a database of opening games played by grandmasters over the last 100 years) and then calculating the most appropriate response to an opponent’s move.
Scrabble

- **Rack**
- **Board**

**Move generation**
- Output: A list of all possible moves

**Static Evaluation**
- Output: 23 moves most likely to be best

**Simulation**
- Output: Hypothetical 2-move-lookahead sequences for each play

**Win percentage estimation**
- Output: 10 moves ordered by estimated win %

Additional inputs:
- Game score
- Number of tiles left
As well as RPS, you might be interested in online poker; you can find the best sites for us players as well as which poker sites accept MasterCard deposits and where to find the best: Party bonus code.

Home
How to Beat Anyone at Rock Paper Scissors

'Rising of a Titan' Stops 2010 World Championship Event

It is our sad duty to announce the passing of Wojek Smallsola, Chairman of the World RPS Society Steering Committee. After a life-long battle with living, Chairman Smallsola's mortal Paper was snipped short at the age of 87. No details have been given as to the manner of his passing, nor are details of the funeral yet available. Due to the gravity of the situation, a period of mourning within the Society will be recognized which forces the cancellation of the 2010 World Championships of RPS.

Graham Walker, Director of Management, of the World RPS Society called Wojek's departure "devastating to our Society and society as a whole - the passing of a titan." Graham's brother Douglas the Managing Director of the Society, made the final decision.
The Second International RoShamBo Programming Competition

And the winner is:

*** Greenberg *** by Andrzej Nagorko
The Second International RoShamBo Programming Competition

And the winner is:

*** Greenberg *** by Andrzej Nagorko
int getComputerInput() {
    int total = seenPaper + seenRock + seenScissors;
    int choice = rand() % total;

    if (choice < seenPaper)
        return _SCISSORS;
    else if (choice < seenRock)
        return _PAPER;
    else
        return _ROCK;
}
```c
int henny() {
    return ((opponent_history ? opponent_history[random()] : opponent_history + 1) + 1) % 3;
}
```
Optimality and Maximality

Optimal Play
- Nash Equilibrium

Maximal Play
- Making non-optimal moves in order to increase expected value
Poker opponent modeling is hard.
Difficulties of Poker Opponent Modeling

Fundamental Uncertainties [2]

- Each hand is completely different
- Difficult to extract a “signal” through the noise.
Difficulties of Poker Opponent Modeling

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Time to Learn [3]
- Need to get a good model working in less than 100 hands
Difficulties of Poker Opponent Modeling

Missing Information [2]

- A fold does not reveal opponent’s hand
- Few games make it the showdown
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Different Criteria for Different Players \[2\]
- Position at the table
  - Generally better to have loose player on the right and tight player on the left \[4\]
- Stack size, blind size and position, previous actions of other players
- Mood of the game and players
- Player skill
- Hand strength
The past is not necessarily a good predictor of the future \[5\]
- Looking only at the recent history does not work
- Humans have emotions
- Good opponents change strategies
- Your opponent is modeling you
Rational Opponent

- The implicit model in Minimax search
- Variations possible
Simple Prepared Strategy
- Come up with some poker strategy that works against everyone

Categorical Prepared Strategy
- Loose, tight, passive, aggressive, etc.
Statistical Approach

Simple
- Percentage of time opponent sees the flop
- Percentage of time caught bluffing

Complex
- Frequency opponent goes for the straight
Figure 4.2: A neural network predicting an opponent’s future action.
### Neural Networks

<table>
<thead>
<tr>
<th>#</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>real</td>
<td>immediate pot odds</td>
</tr>
<tr>
<td>1</td>
<td>real</td>
<td>bet ratio: ( \frac{bets}{bets + calls} )</td>
</tr>
<tr>
<td>2</td>
<td>boolean</td>
<td>committed (has put money in the pot this round)</td>
</tr>
<tr>
<td>3</td>
<td>boolean</td>
<td>one bet to call</td>
</tr>
<tr>
<td>4</td>
<td>boolean</td>
<td>two or more bets to call</td>
</tr>
<tr>
<td>5</td>
<td>boolean</td>
<td>betting round = turn</td>
</tr>
<tr>
<td>6</td>
<td>boolean</td>
<td>betting round = river</td>
</tr>
<tr>
<td>7</td>
<td>boolean</td>
<td>last bets called by player &gt; 0</td>
</tr>
<tr>
<td>8</td>
<td>boolean</td>
<td>player’s last action was a bet or raise</td>
</tr>
<tr>
<td>9</td>
<td>real</td>
<td>( 0.1 \times \text{numPlayers} )</td>
</tr>
<tr>
<td>10</td>
<td>boolean</td>
<td>active players is 2 (heads-up)</td>
</tr>
<tr>
<td>11</td>
<td>boolean</td>
<td>player is first to act</td>
</tr>
<tr>
<td>12</td>
<td>boolean</td>
<td>player is last to act</td>
</tr>
<tr>
<td>13</td>
<td>real</td>
<td>estimated Hand Strength for opponent</td>
</tr>
<tr>
<td>14</td>
<td>real</td>
<td>estimated Hand Potential for opponent</td>
</tr>
<tr>
<td>15</td>
<td>boolean</td>
<td>expert predictor says they would call</td>
</tr>
<tr>
<td>16</td>
<td>boolean</td>
<td>expert predictor says they would raise</td>
</tr>
<tr>
<td>17</td>
<td>boolean</td>
<td>Poki is in the hand</td>
</tr>
</tbody>
</table>

**Table 4.1:** Neural network inputs.
Loki

Predecessor to Poki and Norse God or Jötunn or Both. [6]
Figure 1. The architecture of Loki-1.
Keep in mind Loki’s OM only tries to figure out opponents cards.
Hand Strength (HS)

- Pre-flop strength is calculated through offline random simulation.
- After the flop, the strength is the percentile ranking of the current hand in relation to all the other (1081) possible dealt pairs.
  - $A\spadesuit - Q\clubsuit$ with the flop $3\spadesuit - 4\clubsuit - J\diamondsuit$
  - 444 better hands, 9 equal hands, and 628 worse hands
  - $\frac{628 + \frac{9}{2}}{1081} = 58.5\%$
Hand Potential

- Positive Potential ($P_{pot_N}$): The probability of improving to the best hand after $N$ more cards
- Negative Potential ($N_{pot_N}$): The probability of falling behind after $N$ more cards
- For each 1,081 hands, look at 990 combinations of the two cards after the flop

Effective Hand Strength (EHS)

- Hands where player is ahead or have a positive potential
Opponent Modeling

- Calculate a weight for each of the 1,081 possible opponent hands
- Assumes "reasonable" behavior, seems vulnerable to bluffing
- Can include specific opponent history to increase accuracy
Opponent Modeling

Initial Weights

- Opponent Plays 30% of Hands
- 1000 Hands
- Income of +200

1,081 Hands

\[ \frac{i + \sigma - \mu}{2 \sigma} \]

- Income
  - +100
  - +300

- Weights
  - 0.01
  - 0.5

- 1
Opponent Modeling

Re-weighting

<table>
<thead>
<tr>
<th>Hand</th>
<th>Weight</th>
<th>HR</th>
<th>HS₁</th>
<th>~PP₂</th>
<th>EHS</th>
<th>Rwt</th>
<th>Nwt</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1♥ 4♥</td>
<td>0.01</td>
<td>0.993</td>
<td>0.990</td>
<td>0.04</td>
<td>0.99</td>
<td>1.00</td>
<td>0.01</td>
<td>very strong, but unlikely</td>
</tr>
<tr>
<td>A♠ J♣</td>
<td>1.00</td>
<td>0.956</td>
<td>0.931</td>
<td>0.09</td>
<td>0.94</td>
<td>1.00</td>
<td>1.00</td>
<td>strong, very likely</td>
</tr>
<tr>
<td>5♥ 2♥</td>
<td>0.20</td>
<td>0.004</td>
<td>0.001</td>
<td>0.35</td>
<td>0.91</td>
<td>1.00</td>
<td>0.20</td>
<td>weak, but very high potential</td>
</tr>
<tr>
<td>6♠ 5♠</td>
<td>0.60</td>
<td>0.026</td>
<td>0.006</td>
<td>0.21</td>
<td>0.76</td>
<td>0.90</td>
<td>0.54</td>
<td>weak, good potential</td>
</tr>
<tr>
<td>5♠ 5♥</td>
<td>0.70</td>
<td>0.816</td>
<td>0.736</td>
<td>0.04</td>
<td>0.74</td>
<td>0.85</td>
<td>0.60</td>
<td>moderate, low potential</td>
</tr>
<tr>
<td>5♠ 3♠</td>
<td>0.40</td>
<td>0.648</td>
<td>0.671</td>
<td>0.10</td>
<td>0.70</td>
<td>0.75</td>
<td>0.30</td>
<td>mediocre, moderate potential</td>
</tr>
<tr>
<td>A♥ Q♦</td>
<td>1.00</td>
<td>0.585</td>
<td>0.584</td>
<td>0.11</td>
<td>0.64</td>
<td>0.60</td>
<td>0.60</td>
<td>mediocre, moderate potential</td>
</tr>
<tr>
<td>7♣ 5♠</td>
<td>0.60</td>
<td>0.052</td>
<td>0.012</td>
<td>0.12</td>
<td>0.48</td>
<td>0.20</td>
<td>0.12</td>
<td>weak, moderate potential</td>
</tr>
<tr>
<td>Q♣ T♣</td>
<td>0.90</td>
<td>0.359</td>
<td>0.189</td>
<td>0.07</td>
<td>0.22</td>
<td>0.01</td>
<td>0.01</td>
<td>weak, little potential</td>
</tr>
</tbody>
</table>

Table 2. Re-weighting various hands after a 3♥-4♠-J♥ flop (μ = 0.6, σ = 0.2)
Knowledge is power, if you know it about the right person.

Erastus Flavel Beadle (1821-1894)
References


M. Salim and P. Rohwer, “Poker opponent modeling.”

Input interpretation:

\[
\begin{align*}
\text{solve} & \quad \mu x + y = 0.5 \\
(\mu + \sigma) x + y &= 1
\end{align*}
\]

for \(x, y\)

Result:

\[
\begin{align*}
x &= \frac{1}{2\sigma} \quad \text{and} \quad \sigma \neq 0 \quad \text{and} \quad y = \frac{\sigma - \mu}{2\sigma}
\end{align*}
\]