Theory of Computer Games: Concluding Remarks

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Abstract

- **Introducing practical issues.**
  - **The open book.**
  - **The graph history interaction (GHI) problem.**
  - **Smart usage of resources.**
    - ▷ *time during searching*
    - ▷ *memory*
    - ▷ *coding efforts*
    - ▷ *debugging efforts*
  - **Opponent models**
- **How to combine what we have learned in class together to get a working game program.**

The open book (1/2)

- **During the open game, it is frequently the case**
  - **branching factor is huge;**
  - **it is difficult to write a good evaluating function;**
  - **the number of possible distinct positions up to a limited length is small as compared to the number of possible positions encountered during middle game search.**
- **Acquire game logs from**
  - **books;**
  - **games between masters;**
  - **games between computers;**
    - ▷ ***Use offline computation to find out the value of a position for a given depth that cannot be computed online during a game due to resource constraints.***
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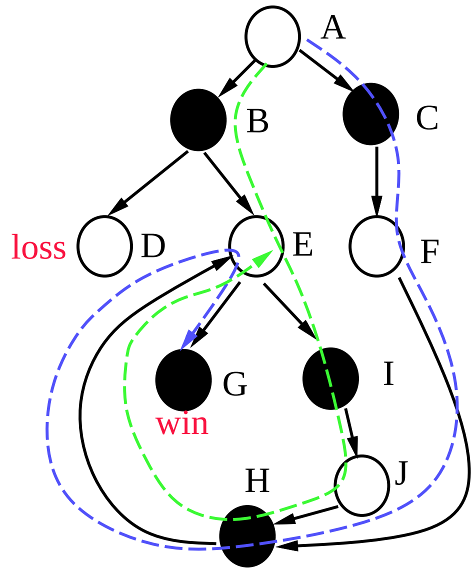
The open book (2/2)

- **Assume you have collected r games.**
  - **For each position in the r games, compute the following 3 values:**
    - ▷ *win: the number of games reaching this position and then wins.*
    - ▷ *$loss$: the number of games reaching this position and then loss.*
    - ▷ *$draw$: the number of games reaching this position and then draw.*
- **When r is large and the games are trustful, then use the 3 values to compute a value and use this value as the value of this position.**
- **Comments:**
  - **Pure statistically**
  - **You program may not be able to take over when the open book is over.**
  - **It is difficult to acquire large amount of "trustful" game logs.**
  - **Automatically analysis of game logs written by human experts. [Chen et. al. 2006]**

Graph history interaction problem

- **The graph history interaction (GHI) problem:**
  - **In a game graph, a position can be visited by more than one paths.**
  - **The value of the position depends on the path visiting it.**
- **In the transposition table, you record the value of a position, but not the path leading to it.**
  - **Values computed from rules on repetition cannot be used later on.**
  - **It takes a huge amount of storage to store the path visiting it.**

GHI problem – example



- $A \to B \to E \to I \to J \to H \to E$ **is loss because of rules of repetition.**
  - ▷ ***Memorized H is loss.***
- $A \to B \to D$ **is a loss.**
- $A \to C \to F \to H$ **is loss because H is recorded as loss.**
- A **is loss because both branches lead to loss.**
- **However,** $A \to C \to F \to H \to E \to G$ **is win.**

Using resources

- **Time**
  - **For human:**
    - *More time is spent in the beginning when the game just starts.*
    - *Stop searching a path further when you think the position is stable.*
  - **Pondering:**
    - *Use the time when your opponent is thinking.*
    - *Guessing and then pondering.*
- **Memory**
  - **Using a large transposition table occupies a large space and thus slows down the program.**
    - *A large number of positions are not visited too often.*
  - **Using no transposition table makes you to search a position more than once.**
- **Other resources.**

Opponent models

- **In a normal alpha-beta search, it is assumed that you and the opponent use the same strategy.**
  - **What is good to you is bad to the opponent and vice versa!**
  - **Hence we can reduce a minimax search to a negamax search.**
  - **This is normally true when the game ends, but may not be true in the middle of the game.**
- **What will happen when there are two strategies or evaluating functions f_1 and f_2 so that**
  - **for some positions p, $f_1(p)$ is better than $f_2(p)$**
    - ▷ ***"better" means closer to the real value $f(p)$***
  - **for some positions q, $f_2(q)$ is better than $f_1(q)$**
- **If you are using f_1 and you know your opponent is using f_2, what can be done to take advantage of this information?**
  - **This is called OM (opponent model) search.**
    - ▷ ***In a MAX node, use f_1.***
    - ▷ ***In a MIN node, use f_2***

Opponent models – comments

- **Comments:**
  - **Need to know your opponent model precisely.**
  - **How to learn the opponent on-line or off-line?**
  - **When there are more than 2 possible opponent strategies, use a probability model (PrOM search) to form a strategy.**

Putting everything together

- **Game playing system**
  - **Use some sorts of open book.**
  - **Middle-game searching: usage of a search engine.**
    - *Main search algorithm*
    - *Enhancements*
    - *Evaluating function: knowledge*
  - **Use some sorts of endgame databases.**

How to know you are successful

- **Assume during a selfplay experiment, two copies of the same program are playing against each other.**
  - **Since two copies of the same program are playing against each other, the outcome of each game is an independent random trial and can be modeled as a trinomial random variable.**
  - **Assume for a copy playing first,**

$$Pr(game_{first}) = \begin{cases} p & \textbf{if won the game} \\ q & \textbf{if draw the game} \\ 1-p-q & \textbf{if lose the game} \end{cases}$$

  - **Hence for a copy playing second,**

$$Pr(game_{last}) = \begin{cases} 1-p-q & \textbf{if won the game} \\ q & \textbf{if draw the game} \\ p & \textbf{if lose the game} \end{cases}$$

Outcome of selfplay games

- **Assume $2n$ games, $g_1, g_2, \ldots, g_{2n}$ are played.**
  - **In order to offset the initiative, namely first player's advantage, each copy plays first for n games.**
  - **We also assume each copy alternatives in playing first.**
  - **Let g_{2i-1} and g_{2i} be the ith pair of games.**
- **Let the outcome of the ith pair of games be a random variable X_i from the prospective of the copy who plays g_{2i-1}.**
  - **Assume we assign a score of x for a game won, a score of 0 for a game drawn and a score of $-x$ for a game lost.**
- **The outcome of X_i and its occurrence probability is thus**

$$Pr(X_i) = \begin{cases} p(1-p-q) & \textbf{if } X_i = 2x \\ pq + (1-p-q)q & \textbf{if } X_i = x \\ p^2 + (1-p-q)^2 + q^2 & \textbf{if } X_i = 0 \\ pq + (1-p-q)q & \textbf{if } X_i = -x \\ (1-p-q)p & \textbf{if } X_i = -2x \end{cases}$$

How good we are against the baseline?

- **Properties of X_i.**
  - **The mean $E(X_i) = 0$.**
  - **The standard deviation of X_i is**

$$\sqrt{E(X_i^2)} = x\sqrt{2pq + (2q + 8p)(1 - p - q)},$$

    and it is a multi-nominally distributed random variable.
- **When you have played n pairs of games, what is the probability of getting a score of s, $s > 0$?**
  - **Let $X[n] = \sum_{i=1}^{n} X_i$.**
    - ▷ ***The mean of $X[n]$, $E(X[n])$, is 0.***
    - ▷ ***The standard deviation of $X[n]$, σ_n, is $x\sqrt{n}\sqrt{2pq + (2q + 8p)(1 - p - q)}$,***
  - **If $s > 0$, we can calculate the probability of $Pr(|X[n]| \leq s)$ using well known techniques from calculating multi-nominal distributions.**

Practical setup

- **Parameters that are usually used.**
  - $x = 1$.
  - **For Chinese chess,** q **is about** 0.5, $p = 0.3$ **and** $1 - p - q$ **is** 0.2.
    - ▷ ***This means the first player has a better chance of winning.***
  - **The mean of** $X[n]$, $E(X[n])$, **is** 0.
  - **The standard deviation of** $X[n]$, σ_n, **is**

$$x\sqrt{n}\sqrt{2pq + (2q + 8p)(1 - p - q)} = \sqrt{0.98n}.$$

Results

$Pr(\|X[n]\| \leq s)$	$s = 3$	$s = 4$	$s = 5$	$s = 6$	$s = 7$	$s = 8$	$s = 9$
$n = 10, \sigma_{10} = 3.1$	0.737	0.850	0.922	0.963	0.984	0.994	0.998
$n = 20, \sigma_{20} = 4.4$	0.571	0.691	0.786	0.858	0.910	0.946	0.969
$n = 30, \sigma_{30} = 5.4$	0.481	0.593	0.690	0.770	0.834	0.883	0.921
$n = 40, \sigma_{40} = 6.3$	0.424	0.528	0.620	0.701	0.769	0.826	0.871
$n = 50, \sigma_{50} = 7.0$	0.383	0.480	0.568	0.647	0.716	0.775	0.825

$Pr(\|X[n]\| \leq s)$	$s = 10$	$s = 12$	$s = 14$	$s = 15$	$s = 18$	$s = 21$	$s = 24$
$n = 10, \sigma_{10} = 3.1$	0.999	1.000	1.0000	1.000	1.000	1.000	1.000
$n = 20, \sigma_{20} = 4.4$	0.983	0.996	0.999	1.000	1.000	1.000	1.000
$n = 30, \sigma_{30} = 5.4$	0.948	0.979	0.993	0.996	0.999	1.000	1.000
$n = 40, \sigma_{40} = 6.3$	0.907	0.954	0.980	0.987	0.997	1.000	1.000
$n = 50, \sigma_{50} = 7.0$	0.867	0.926	0.962	0.973	0.992	0.998	1.000

Statistical behaviors

- **Hence assume you have two programs that are playing against each other and have obtained a score of $s+1$, $s>0$, after trying n pairs of games.**
  - **Assume $Pr(|X[n]| \leq s)$ is say 0.95.**
    - ▷ ***Then this result is meaningful, that is a program is better than the other, because it only happens with a low probability of 0.05.***
  - **Assume $Pr(|X[n]| \leq s)$ is say 0.05.**
    - ▷ ***Then this result is not very meaningful, because it happens with a high probability of 0.95.***
- **In general, it is a very rare case, e.g., less than 5% of chance that it will happen, that your score is more than $2\sigma_n$.**
  - **For our setting, if you perform n pairs of games, and your net score is more than $2\sqrt{n}$, then it means something statistically.**
- **You can also decide your "definition" of "a rare case".**

Concluding remarks

- **Consider your purpose of studying a game:**
  - **It is good to solve a game completely.**
    - ▷ *You can only solve a game once!*
  - **It is better to acquire the knowledge about why the game wins, draws or loses.**
    - ▷ *You can learn lots of knowledge.*
  - **It is even better to discover knowledge in the game and then use it to make the world a better place.**
    - ▷ *Fun!*

References and further readings

- M. Buro. Toward opening book learning. *International Computer Game Association (ICGA) Journal*, 22(2):98–102, 1999.
- David Carmel and Shaul Markovitch. Learning and using opponent models in adversary search. Technical Report CIS9609, Technion, 1996.
- R. M. Hyatt. Using time wisely. *International Computer Game Association (ICGA) Journal*, pages 4–9, 1984.
- M. Campbell. The graph-history interaction: on ignoring position history. In *Proceedings of the 1985 ACM annual conference on the range of computing : mid-80's perspective*, pages 278–280. ACM Press, 1985.
- B.-N. Chen, P.F. Liu, S.C. Hsu, and T.-s. Hsu. Abstracting knowledge from annotated Chinese-chess game records. In H. Jaap van den Herik, P. Ciancarini, and H.H.L.M. Donkers, editors, *Lecture Notes in Computer Science 4630: Proceedings of the 5th International Conference on Com-*

puters and Games, pages 100–111. Springer-Verlag, New York, NY, 2006.