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 off-line 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.*
  - $\cdots$

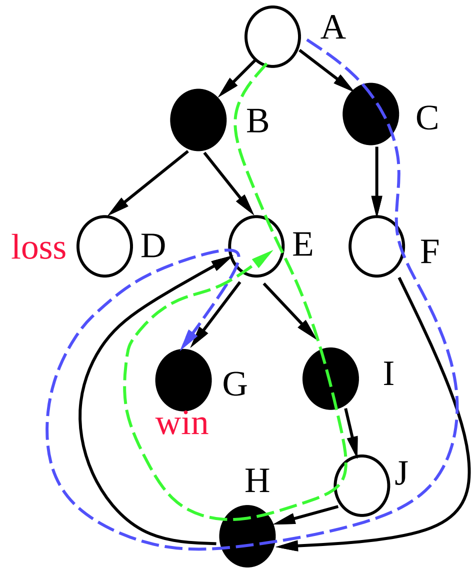
The open book (2/2)

- **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]**
  - **Using high-level meta-knowledge to guide the way in searching:**
    - ▷ ***Dark chess: adjacent attack of the opponent's Cannon. [Chen and Hsu 2013]***

Graph history interaction problem

- **The graph history interaction (GHI) problem [Campbell 1985]:**
  - **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 [Hyatt 1984] [Šolak and Vučković 2009]**
  - **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 [Carmel and Markovitch 1996].**
    - ▷ ***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** 0.3161**,** $p = 0.3918$ **and** $1 - p - q$ **is** 0.2920**.**
    - ▷ ***Data source: 63,548 games played among masters recorded at www.dpxq.com.***
    - ▷ ***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**

$$x\sqrt{n}\sqrt{2pq + (2q + 8p)(1 - p - q)} = \sqrt{1.16n}.$$

Results (1/3)

$Pr(\|X[n]\| \leq s)$	$s=0$	$s=1$	$s=2$	$s=3$	$s=4$	$s=5$	$s=6$
$n=10,\ \sigma_{10}=3.67$	0.108	0.315	0.502	0.658	0.779	0.866	0.924
$n=20,\ \sigma_{20}=5.19$	0.076	0.227	0.369	0.499	0.613	0.710	0.789
$n=30,\ \sigma_{30}=6.36$	0.063	0.186	0.305	0.417	0.520	0.612	0.693
$n=40,\ \sigma_{40}=7.34$	0.054	0.162	0.266	0.366	0.460	0.546	0.624
$n=50,\ \sigma_{50}=8.21$	0.049	0.145	0.239	0.330	0.416	0.497	0.571

Results (2/3)

$Pr(\lvert X[n]\rvert \le s)$	$s = 7$	$s = 8$	$s = 9$	$s = 10$	$s = 11$	$s = 12$	$s = 13$
$n = 10,\ \sigma_{10} = 3.67$	0.960	0.981	0.991	0.997	0.999	1.000	1.000
$n = 20,\ \sigma_{20} = 5.19$	0.851	0.899	0.933	0.958	0.974	0.985	0.991
$n = 30,\ \sigma_{30} = 6.36$	0.761	0.819	0.865	0.902	0.930	0.951	0.967
$n = 40,\ \sigma_{40} = 7.34$	0.693	0.753	0.804	0.847	0.883	0.912	0.934
$n = 50,\ \sigma_{50} = 8.21$	0.639	0.699	0.753	0.799	0.839	0.872	0.900

Results (3/3)

$Pr(\lvert X[n]\rvert \leq s)$	$s = 14$	$s = 15$	$s = 16$	$s = 17$	$s = 18$	$s = 19$	$s = 20$
$n = 10,\ \sigma_{10} = 3.67$	1.000	1.000	1.000	1.000	1.000	1.000	1.000
$n = 20,\ \sigma_{20} = 5.19$	0.995	0.997	0.999	0.999	1.000	1.000	1.000
$n = 30,\ \sigma_{30} = 6.36$	0.978	0.986	0.991	0.994	0.997	0.998	0.999
$n = 40,\ \sigma_{40} = 7.34$	0.952	0.966	0.976	0.983	0.989	0.992	0.995
$n = 50,\ \sigma_{50} = 8.21$	0.923	0.941	0.956	0.967	0.976	0.983	0.988

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 $2*\sqrt{1.16}*\sqrt{n} \simeq 2.154\sqrt{n}$, 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!***

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