Computer-Aided Go: Chess as a Role Model

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Abstract. Recently computers have gained strength in the Asian board game Go. The Chess community experienced some 15 to 30 years ago that teams with humans and computers may be much stronger than each of their components. This paper claims that time is ripe for computer-aided Go on a large scale, although neither most users nor the Go programmers have realized it. A central part of the paper describes successful pioneers in Go play with computer help. Progress in computer-aided Go may also lead to progress in human Go and in computer Go itself.

1 Introduction

As learned in Chess some decades ago (mainly between the years 1985 and 2000), humans and computers have teamed up to achieve levels of play that are much better than the single strengths of the agents involved [1]. A similar development is possible in Go. Progress in computer-aided Go may also lead to progress in computer Go as well as in the theoretical understanding of the game Go itself.

We present and discuss recent developments in computer-aided Go in different fields: we look both at over-the-board play and at (long-time) analysis. It is our expectation that computer-aided Go with commercial bots will surpass top human levels soon, in particular years before commercial bots alone will achieve this.

The paper is organised as follows. The first half deals with the histories of computer-aided Chess and Go: in Sect. 2 the Chess scene is discussed as a role model; Sect. 3 tells the stories of four pioneers in computer-assisted Go play. The second half is a sort of an opinion paper: Sect. 4 contains a wish list of six points for features in commercial Go bots; and the paper concludes with miscellaneous thoughts in Sect. 5.

2 Chess as a Role Model

In Chess, commercial bots became interesting as opponents and for analysis purposes around 1985. The approach of computer-assisted analysis made a great step forward, when PC-based Chess programs became popular in the late 1980's. In particular, the leading company ChessBase engaged world champion Garry Kasparov from 1987 on for several PR events where the champion demonstrated how Chess databases and analysis tools might be used to prepare for an opponent.

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The World Championship match from 1990 was the first where one of the teams (challenger Karpov) used a commercial Chess computer ("Fidelity Elite") for analysing adjourned games.

Already in 1988, one of the top Eastern German correspondence Chess players (Heinrich Burger) used several small commercial Chess bots around the clock to analyse positions from his games in the Correspondence Chess Olympiad. This helped East Germany to get a Bronze medal in that tournament. In the meantime, every serious correspondence Chess player is using intensive computer help.

In 1994, Chess programs for the PC with k-best analysis modes came up and made the machines interesting tools for testing new lines, refutations, and ideas [5,6] in openings. A recent interview with Matthias Wüllenweber (chief of the ChessBase company for 30 years already) [8] shows that even today more new analysis features and tools for Chess programs are just around the corner, both welcomed and are to be expected soon by strong Chess players. Currently, every Chess professional depends on computer analysis in his or her preparation for tournament games.

This author was successfully involved in early developments of interactive analysis tools. He used them in settings like 3-Hirn [1,4], where in realtime a human has the final choice amongst candidate moves provided by two different Chess bots. It turned out that 3-Hirn plays about 200 rating points stronger than the Chess bots involved, independently of the absolute Chess strength of the human controller [3,5].

3 Successful Pioneers in Computer-Assisted Go

So far, commercial Go bots are not really user-friendly for interactive analysis mode. Nevertheless, a handful of creative Go players found successful ways of interactive analysis. Here we portrait some of them.

3.1 Thomas Redecker and His Use of Komi Fans

MCTS bots do not give expected scores, but instead winning probabilities. In the analysis of positions (in particular endgame positions) a technique called "komi fan" helps to find the likely score for (score-)perfect play on both sides: the position under investigation is analysed for different values of (artificial) komi. Figure 1 shows a sample position.

Analysing this position with the bot CrazyStone2013 gives the winning probabilities of Table 1 for Black, depending on the komi value.

According to these data, the likely perfect score (without komi) seems to be about +5 for Black. We analysed the same position with another bot, Many Faces of Go, version 12.022. The outcomes are shown in Table 2. Again, the likely perfect score seems to be +5 for Black. Funnily, both bots have a slight anomaly at komi 3.5/4.5: Black achieved slightly better scores at komi 4.5. Each

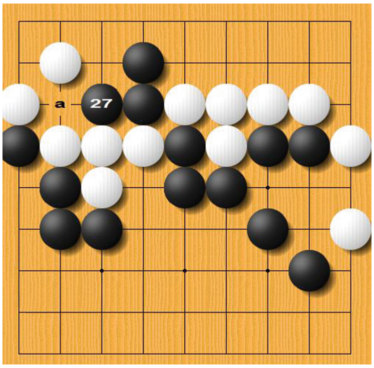

Fig. 1. Position on 9 × 9 board for a komi-fan test; White to move

Table 1. Winning percents computed by CrazyStone

komi	1.5	2.5	3.5	4.5	5.5	7.5	9.5
percent	72.7	68.1	61.6	62.3	46.4	34.5	22.6

Table 2. Winning percents computed by Many Faces of Go

komi	1.5	2.5	3.5	4.5	5.5	7.5	9.5
percent	69.9	69.2	54.4	57.1	44.2	30.4	22.4

of the searches in this example was performed with two minutes of computing time on a quad core notebook.

Thomas Redecker wrote a whole book on the analysis of one specific and very difficult Go position [9]. In several positions he used this komi fan technique with Many Faces of Go to find the "correct" value of the position.

3.2 Strong Correspondence Go with Computer Help on 9 × 9: Darren Cook

The internet game server www.LittleGolem.net is one of the few places where Go with very long thinking times (i.e., in correspondence mode) can be played with a western interface. In a typical tournament on LittleGolem the player has in average 36 h for each of his moves.

Between 2002 and 2011, Darren Cook was the operator/player behind the account "sm9" on LittleGolem. sm9 played only games on 9 × 9-board. In the paper [7] Cook revealed that he had used the help of strong Go bots to find moves for sm9. For several championship cycles on 9×9, sm9 was the dominating player, ahead of Valkyria9 and Gerhard Knop (see in the next subsection for more infos on them).

3.3 Strong Correspondence Go with Computer Help on 19 × 19: Gerhard Knop

Currently (on April 15, 2016), the highest-ranked Go account (9.7 dan) on LittleGolem is the Valkyria9_bot, the bot programmed by Magnus Persson which only plays games on 9 × 9-board. The second-highest rating has Gerhard Knop (9.4 dan), the player on rank 3 is 6.3 dan. Knop plays with intensive computer help (using Zen, CrazyStone and other bots).

In normal "over-the-board" Go, Knop was slightly active in tournaments some years ago (2008–2013) with a highest EGF rating around 1,700 (meaning 4 kyu). His 9.4 dan on LittleGolem is the more impressive when one takes into account that Knop mainly plays games on 19 × 19 whereas Valkyria9 with its 9.7 dan "works" only on 9 × 9-board. (Explanation: www.LittleGolem.net gives only one overall Go rating for each account. In this single number the performances for 9 × 9, 13 × 13, and 19 × 19-board are combined.)

3.4 Team "Crazy Manja" in "Over the Board"-Play

In Winter 2014/15, a team "Crazy Manja" played three games against 5-dan amateur Stefan Kaitschick (EGF rating 2,380). Crazy Manja consisted of top German female player Manja Marz (EGF rating 2,280) and bot CrazyStone_2013 in analysis mode (running on a standard quad core notebook; estimated strength around 2,300 on that hardware). Marz was free in her choice for a move but got all the information from CrazyStone's analysis screen.

After a loss in round 1, Crazy Manja won two games convincingly [2]. This author was involved in the experiment, operating CrazyStone without any influence on the move decisions. Two more games did not end so pleasantly: in late May 2015, Crazy Manja lost a single no-handicap game narrowly against FJ Dickhut (6-dan, EGF rating 2,537) and another exhibition match during the European Go Congress 2015 clearly against 5-dan pro player Guo Yuan (who gave 3 handicap stones).

It seems that it takes a lot of experience for the human in the team to read and interpret the analysis screen of CrazyStone properly. A similar statement will likely be true for future human players using DCNN-based Go bots in analysis mode.

4 A Wish List for Go Bot Features

The comparative look on Chess software makes clear that there is large space for improvement of interfaces in commercial Go bots. Here is a list of sic points we have in mind.

– Analysis modes have to be comfortable. The current situation where up to five mouse clicks are needed to undo and substitute a move is not satisfactorily.

– Programs need large score windows for possible komi values. Changing the komi value in a position should become a simple task, with only few mouse clicks.

– MCTS bots need something like a k-playout mode for small integers k. It is not sufficient that all candidate moves with their playout numbers and percents are shown. In particular this is not too helpful, when one candidate move gets more than 90 percent of the playouts in normal MCTS. Instead, it should be possible to force that each block of k playouts is distributed over k different moves. By such a spreading no move would get more than fraction $1/k$ of all playouts (rare exceptions may be positions with less than k feasible moves).

– Having in mind the analysis screen of CrazyStone 2013, it would be nice not only to have a single histogram where the results of all playouts are collected, but one such histogram for each (prominent) candidate move.

– Due to the probabilistic nature of MCTS and its variants, independent runs for the same position may lead to different results. As an example one can look at game 1 between Lee Sedol and AlphaGo in March 2016, at the position after move 101. In post-mortem analysis, Lee Sedol remarked that 102.R10 by AlphaGo was the winning move. Interestingly, CrazyStone 2013 proposes this move too in its analysis mode. However, a test with 30 independent runs (with about 3 min for each one) resulted in a first proposal of R10 for seven times, whereas in other twenty runs R14 became at rank 1. An analysis program should allow the "simultaneous" execution of m independent runs for a given position. The results should automatically be put together, showing frequencies for the (top) candidate moves.

– It would be nice to have simple switches between Japanese and Chinese rules during analysis mode. Sometimes play and analysis under the other rule set gives nontrivial insights into the difficulties of a position for a human controller.

Another experience from the history of computer-aided Chess is as following. As soon as Go bots become common tools in analysis, more features will surely be proposed by strong players. In particular, programs with neural nets should give insight into the proper values of certain "key neurons". It would then no longer be necessary that the programmers gave elaborate explanations what which value means. Instead, analysing players would soon learn by themselves to interpret neuron values in appropriate ways.

5 Miscellaneous Thoughts

This is no conclusion section in the traditional sense. The design of interactive systems for the game of Go (and also for other games) is a never-ending work in permanent progress. It will also remain a relevant task for the times when Go bots (without human help) will be stronger than all human players (without computer help).

In March 2016 a 5-game match was played between top human professional Lee Sedol and AlphaGo [10]. The games were transmitted to server KGS and commented live by hundreds of spectators. It turned out that for large sections of the games human estimates (those of professionals and amateurs) on the likely outcome of a game were far less accurate than the evaluations of the commercial bots CrazyStone and Zen. For many traditional Go players it will be a hard learning process to accept commercial Go bots as strong predictors and advisors.

As sequel to the above stories, we may conclude with our conviction: Advance in computer-aided Go is no one-way road! Progress in human+bot Go will also lead to progress in playing strength of autonomous bots and in the theoretical understanding of Go.

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