

TRANSFER LEARNING AND CHESS

READING CLUB KOGNITIVE SYSTEME

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Abstract

Playing chess has been on the forefront of AI research ever since Alan Turing and his students proposed chess playing machines. Lots of thinking have been put into creating better and better chess playing computer algorithms. Most of these programs use extensive databases and complicated algorithms for evaluating specific moments and positions in the game. Although this has proven to be very effective the way play machines play sometimes feels off to human players. Today's computer chess programs the likes of Deep Junior and Fritz just don't make the little mistakes that make watching or human chess game enjoyable.

One goal of AI chess has always been to better human players in their own domain. Now that the programs have become capable of beating even the best human players it may be the time that the student becomes the master.

With transfer learning evolving within the machine learning community the author proposes to reevaluate the ways we let machines play chess. With the input of a database of the current player's games the computer program may transfer the player's mistakes into new games and by making the mistakes itself challenging the human player to recognize them and learn from them.

1. AI CHESS – A BRIEF HISTORY

Chess has always been at the forefront of research considering artificial intelligence. Obviously playing chess is an activity that requires cognitive skill. So when Rationalism and the Age of Enlightenment were eminent and inventors and scientists were building all kinds of machines for performing tasks that only humans can do, chess machines were among the most notably wonders of that time. Although, from our point of view, being a hoax the chess playing machine the Turk was fooled many people, among them Mark Twain [BUCHANAN 2005].

So of course when the possibility of having huge computing machines really was more than a piece of fiction, again those at the forefront of research considered Chess to be among the most interesting fields of study. One of those researchers was Alan Turing who, with the help of his students, developed a chess playing program. Although he did not have the hardware to have a machine run it, it is considered to be one of the first real chess computers. With the emergence and abundance of first big mainframes and then personal computers, more and more researchers had the possibility of studying and implementing chess algorithms and programs.

The more advanced both the computers and the research became it was only a matter of time until computers could beat even the best human players.

In 1997 the program Deep Blue beat the World Champion at that time, Garry Kasparov in a close and heavily fought tournament. This may have been the first time Artificial Intelligence has made it to the front of newspapers and evening news alike.

After the big cut that marked the 1997 win of Deep Blue against Kasparov, AI Chess has continued to evolve and became better and better. What was considered to be “the holy grail”, positional play, now is in the repertoire of evolved programs such as Deep Junior and Deep Fritz. The best human chess players now acknowledge that the AI is capable of analyzing positional gain so well that it applies moves that, from a human perspective can only be categorized as taking chances. But it is not doing that. It sees an advantage and it is using it. [BUSHINSKY 2009]

Since AI chess evolved from human chess the next chapter will explain how humans learn chess and how transfer of learning plays a big role in that process.

2. LEARNING CHESS

HOW DO HUMAN PLAYERS LEARN CHESS?

Even more than for machines, that can calculate trillions of instructions per second, for the human mind it is impossible to “solve” the game of chess. It is simply beyond our capability of memorizing the perfect move for each and every possible position of the game.

That is why we need simplification, patterns and rules that we apply to our approximation of what we consider the best move. There are lots of these simple rules that we teach novices of the game. Rules that help tame the complexity of the game. Most of these rules fit in one sentence and that is why they work.

“Capture the center of the board.” “Don’t move a piece twice in the opening of the game.” “Get out your Knights and Bishops early.”

The more the game advances the more advanced these rules get. Some are just patterns of a particularly desirable position in the game. Along with lots and lots of opening moves learned by hard, it is these rules that help build a feeling for the game and differentiate a good player from a weaker opponent. The rules free “computing time” in the player’s mind to get creative. The combination and application of these rules even a well thought breaking of a certain rule. All these need one key ability, the ability to transfer them to different though similar games and positions.

TRANSFER OF LEARNING IN ANTHROPOLOGIC SCIENCES

In the last chapter I explained that chess can only be learned by transfer of learning. In this chapter I will explain what transfer of learning is and why it is so important to learning chess.

“Transfer of learning implies that previously acquired skills or knowledge are used in a novel setting[...][Gentile 2000]”

As Haskell [2001] points out „Transfer is a deceptively simple concept.” It simply implies that we take knowledge that we previously acquired and apply it to a similar but slightly different concept. But this is where it becomes difficult. How do we define similarity in a particular context? How do we define it in all contexts? Although the concept of similarity comes easy to the human mind, it is hard to grasp. Scientists have now been researching transfer (of learning) for over a century and the research is far from over. [GENTILE 2000]

Transfer comes naturally to humans. Most of the time we don’t even recognize it, when it is applied. It is deeply woven into our culture, language and minds so that we use it every day in our lives.

Without transfer we would have to assess each situation newly and would be find it impossible to accustom ourselves to new situations [HASKELL 2001]. If you have never used a subway system you will find it difficult to find your way through the London Tube. Whereas if you have lived in Berlin, Paris or Tokyo, you will find it easier to get around.

Transfer of learning is a subsection of the more general concept of Transfer. [HASKELL 2001] It exemplifies and analyzes Transfer in an educational context and applies it to certain tasks that can be more or less easily defined and limited. Sports have always been a field of research for Transfer of Learning. This research covers all areas of sports from football [HOLT ET AL. 2006] to Tennis [WILLIAMS ET AL. 2002]. Of course Chess has always been a well used example for Transfer of Learning, both from Chess to real world applications [PERKINS 1992] and within the game itself. Since no two games are exactly alike, chess players always have to transfer their set of rules and previous learning into the next game.

Of course the player always has to consider the possibility of negative transfer. Negative Transfer occurs when the transfer impairs performance in the target task and no transfer should have been done. [HASKELL 2001][CHEN 1989].

One way of approaching this problem in the domain of chess is that player learn a huge of number of preanalyzed openings, i.e. the first 10 to 15 move of a game by hard so that they play the best possible move and do not have to transfer knowledge. Still the capacity that a player can memorize is limited and since the game branches out almost infinitely the longer it is played general plans and concepts of a particular openings have then to be transferred onto the actual situation on the board.

So Transfer and Transfer of Learning has always been of great interest to a great variety of scientists and sciences. The next chapter will then go into detail how the concept of Transfer is used and understood in the machine learning context.

3. TRANSFER LEARNING IN MACHINE LEARNING

As with humans Transfer of Learning for machines and algorithms is about transferring the knowledge from one domain or task to another. As machines need a lot more detailed instructions to perform a task than humans do, the definition of Transfer of Learning is much more detailed and mathematical.

Sinno and Qiang[2010] define Transfer of Learning as follows:

Given a source Domain D_S and learning task T_S , a target domain D_T and learning task T_T , transfer learning aims to improve the learning of the predictive function $f_T(\bullet)$ in D_T using the knowledge in D_S and T_S , where $D_S \neq D_T$, or $T_S \neq T_T$.

In this definition, a domain D has two parts, its feature space X and a marginal distribution function $P(X)$. Within this domain a task again has two components: a label space Y and an objective predictive function $f(\bullet)$ that has been learned previously from training data.[SINNO & QIANG 2010]

The goal of Transfer of Learning in machine learning now is to identify what to transfer, how to transfer and when to transfer. [SINNO & QIANG 2010] Since the phenomenon of negative transfer occurs in machine learning, too, these are the most important decisions an algorithm or its creator has to consider.

One particular field of interest for AI research in general and transfer learning in particular has always been games. In the next chapter I will give a short overview on a few particularly interesting papers on transfer learning in games that have recently been published.

TRANSFER LEARNING IN GAMES

A lot of transfer learning research has been done in the domain of games and especially computer games. The research ranges from Strategy Games [RAY ET AL. 2011],[FORBUS 2011] to sports simulations [AHA ET AL. 2011]. All these share a common denominator. The player who simulated by the AI in these experiments has a range of actions that they can perform and has to chose from it in order to optimize the result. The result itself can be easily applied to a success function and has to transferred within the same domain. Some research has been done on far/deep transfer [E.G. FORBUS 2011] but does not extend to what we would consider far transfer if it were applied to anthropologic circumstances.

Also the games have a finite set of rules and states and if the set of the whole game is too complicated the researchers picked one particular subdomain of the game e.g. resources gathering.

The methods used for transfer and learning vary from case for case-based reasoning [FORBUS 2011],[AHA ET AL. 2011] to reinforcement learning [RAY ET AL. 2011]. Most of them try and build task hierarchies of smaller subtasks which are more easily transferrable since a certain amount of abstraction can be quite easily be achieved by pruning the hierarchy.

This way of dividing and subdividing goals to tasks and tasks to steps strongly correlates with the way human players play chess and plan ahead their movements. A typical such plan would consist of the goal “attack the king’s wing”, several subtasks such as “align knights and bishops to the king’s wing”, “get the rooks involved” and then divide to sets of moves “move knight there, then there”.

The next chapter will now lay out how the advances both in AI chess and transfer of learning in machine learning can be combined.

4. LEARNING FOR AI CHESS

As layed out in Chapter 1 it AI chess players are capable of beating any human competitor who challenges them. Although different from the human way of playing chess AI chess can find beautiful solutions humans did not even think of.

With this in mind one might say that AI chess is at the end of the road and there is no use of further development. Come a few more decades computing power and storage might be so vast that it might be possible to even solve the whole game as it has been done before with easier games as tic-tac-toe and recently even checkers [SCHAEFFER ET AL. 2007].

Learning and its transfer has been effectively applied to chess board evaluation before and thus could be applied to a broader context. Examples for Learning in Chess are [SAMADI ET AL 2007] who used a neural network for searching for ideal moves in chess endgames. Today chess endgames are mostly played by AI by searching through huge database with ideal moves for the current situation. Not only do these databases take time to search but they take a lot of space.

AI chess programs perform broad search when looking for a particular move. In endgames the search tree broadens exponentially since the pieces have more room and hence more opportunities to move. Elaborate techniques such as α - β -Pruning are used to cut off leaves from the search tree. α - β -Pruning is a depth first search algorithm that will only go as far as a predefined depth limit. The algorithm traverses the tree e.g. from left to right. For every node of the tree the successors are being evaluated. If the optima for the successors are inferior to the current optimum the search is cut off at that particular node and the search continues. [ERTEL 2011]

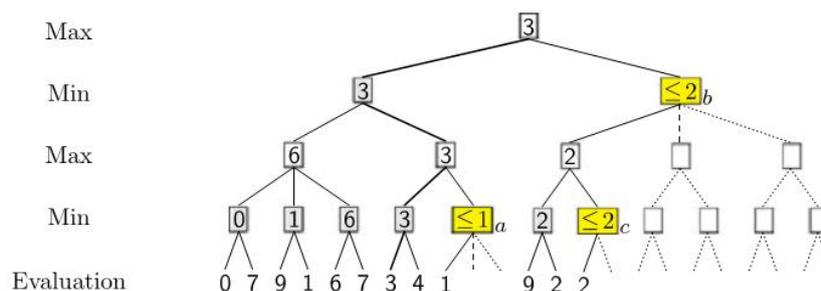


Figure 1: Alpha-Beta-Search tree after 4 half-moves [Ertel 2011]

But still this approach is far from efficient in chess endgames as the tree broadens very fast even at low depth. Human players perform a far more efficient algorithm: they have particular patterns to achieve and then perform a deep search only for moves that lead to that pattern. [SAMADI ET AL 2007]

That is why the endgame part of chess is particularly interesting for AI research. Along with [SAMADI ET AL 2007] who were using neural networks to improve the evaluation function of the α - β -Pruning algorithm, one can find many approaches of changing the inefficient way AIs play chess in the endgame.

Genetic algorithms are used to better the efficiency of particular end games such as King-Rook-King [IBA 2012] or endgames in general [HAUPTMAN, SIPPER 2005].

But all this research concentrates on learning and different approaches to do so. Transfer of learning has not been on the radar of researchers for AI chess. The next chapter will lay out one way of using transfer of learning for AI chess.

TRANSFER LEARNING FOR AI CHESS

What if we could use the frighteningly powerful play that modern AI chess players muster, to teach humans how to play chess better? And what if we teach not humans in general, but each individual, chess in their particular strength and pace.

This is where transfer learning comes of use. Even most amateur players have a vast database of their history of games played. AI players could analyze this data and find all the small and big mistakes a player made and still makes. Then this database of mistakes can be used by the AI to plant mistakes deliberately into its play.

Planting deliberate mistakes (and cutting computing power) is the way how computer chess programs adjust to a particular player strength. These mistakes are more or less random and although teaching the human how to capitalize on them they stay random.

Forcing you to analyze your own mistakes is the way how Chess is taught all over the world. The mistakes are dissected, put out into the open. This is how human trainers develop the play of their trainees. Hence letting the players capitalize on their own mistakes could better their play both in exploiting and avoiding mistakes, since the mistake will come to the players attention on both ends of the board.

I propose to adjust AI chess programs as described in *Figure 2: Process for adding deliberate mistakes*.

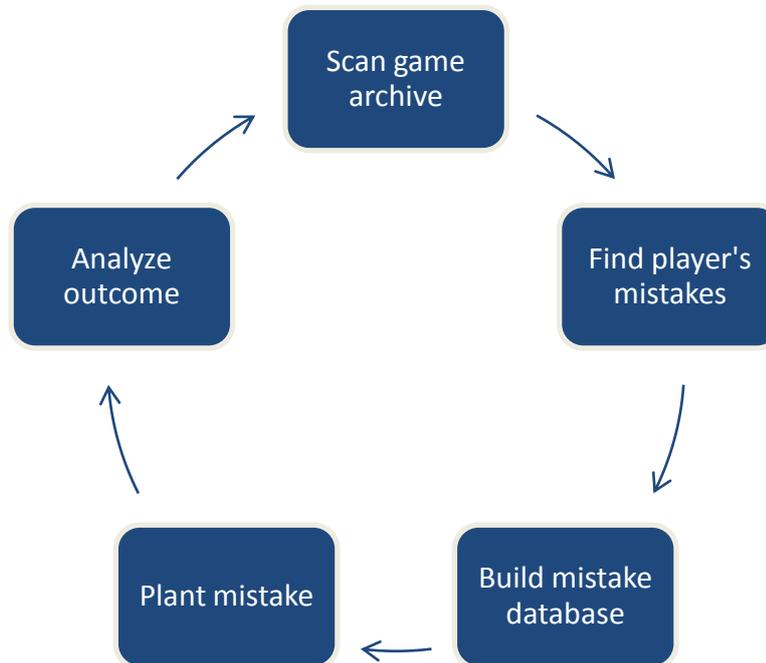


Figure 2: Process for adding deliberate mistakes

First the player enters their game archive into the database. This can come from the internet, databases from their team or previous plays with the AI. The AI then analyzes these games to find all mistakes made. Mistakes may as well be failure to capitalize on other's mistakes or making them themselves. Then the AI builds a database with these mistakes categorizing them in order to be able to apply them to a game played with the human player. This game will then be analyzed, too and then be added to the database as the circle commences again.

This circle needs not to be solely in the realm of the computer as human interaction is not to be left out when teaching humans something. A comprehensive output of the mistake database of a particular player could help their trainer to get a more complete understanding of what their trainee might be lacking.

5. CONCLUSION AND FUTURE WORK

I proposed a way of using the chess playing skills of today's AI to not only beat human players but teach them to become better. The approach was to analyze past of mistakes of the player and use transfer of learning techniques to plant similar mistakes into training games that the human player plays with the AI.

There are several future directions to pursue. Firstly a methodology has to be found to categorize mistakes in chess to make them applicable for future use. Since both finding and categorizing mistakes can be easy (lost a piece) or hard (positional disadvantage) some research has to be put here to be able to categorize mistakes automatically in a comprehensive way.

In addition to this future researchers may need to find and implement a useful algorithm to be able to transfer these mistakes into an ongoing game. This may be more difficult than it sounds at first hand since the planted mistake must not feel planted to the human player.

With this in mind it is safe to say that research on AI chess is far from at the the end of the road.

Since building AI is no means of its own and today's AI can beat any human player it is now that we have to think of new means for building stronger AI. We might also have to redefine what stronger means. In any way, there still is a lot to learn when advancing AI to the next level. This level may no longer be to be the better player but to be the better teacher.

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