Causal Models for Evaluating Combinations of Patterns in Chess

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Abstract

In most algorithms for game playing, evaluation is based on a linear combination of features. We argue that this is insufficient in complex games like chess. We hypothesize that the influence of a feature or pattern on the game result is completely determined by a limited number of advantageous effects. These relations follow the markov condition. The evaluation of a pattern in a certain context should be made by testing if the effects of the pattern can be attained during the continuation of the game. A causal model captures all information for this evaluation. This is demonstrated for combinatorial situations and for game analysis.

1. Introduction

Although the big developments in computer chess and the defeat of World Champion Kasparov against Deep Blue, it is questionable if these computer algorithms are good models for the way humans play. All successful chess programs use a tree expansion that represent all possible move sequences to scan the search space for the move that will lead to a position with the highest probability of winning. Other algorithms use concepts or patterns, try to learn these (Furnkranz 1996), but are not at competition level. The positions at the leaves of the tree are evaluated by a weighted combination of features measuring *P(winning| position)*. The min-max path gives the best move sequence. The features can be direct advantages, like material, but also indirect, like positional advantages. Several algorithms exist to ensure an optimal estimation of *P(winning|move)*. Other algorithms prune the search tree by deciding upon some features which positions should be explored deeper than other, in order to look further into the future in situations with high uncertainty.

It is widely believed that the power of human chess players lies in their ability to very efficiently prune the search tree. Humans are better in describing, recognizing and learning patterns. We believe there are reasons to believe that this is not the whole story. Human players can reason about the game, analyze it, explain why one won, indicate the good, decisive moves and pinpoint where one lost the game. As opposed to the computer's state-space search, humans tend to follow a goal-driven search, they make strategic plans, by defining subgoals to pursue. Finally, humans have a good capacity of learning in an active and passive way, while the only successful machine learning is by tuning the weights. Despite the fact that Kasparov could not analyze games of Deep Blue before the tournaments, he was quickly finding out ways to exploit the computer's weaknesses.

Recent developments brought causality in the picture again (Pearl 2000 & Spirtes 1993). Pearl argues that cause-effect relations are close to the human way of thinking. Causal models represent relational information by a directed acyclic graph. The nodes represent variables and the edges the relations among them. The relations have a dependency and a modularity interpretation (Pearl 2000).

This paper will defend the hypothesis that the influence of patterns on the games termination can be represented by a causal model, in which a pattern has a limited number of effects that affect the game result. By this assumption, it will be possible to evaluate a pattern more accurate, since in complex games, *P(gain|pattern)* is heavily dependent on the context. Secondly, the modularity assumption makes it possible to construct an analysis by adding patterns and only having to reevaluate the nodes with which they interfere.

The next section explains why effects of patterns cannot be easily estimated. Section 3 introduces Bayesian models for reasoning about effects of patterns. Then, in section 4, causal models are used for evaluating patterns in a context. Finally, section 5 shows how a chess game analysis can be represented by a causal model.

2. Evaluation of Pattern Combinations

The starting-point is that chess is a complex game for which an evaluation cannot be reduced to a linear combination of the weights of features or patterns. There will always be exceptions that contradict the evaluation. In chess for example, the most important evaluation factor is the material (defined in pawn-equivalents), but in many games the victory can only be attained by sacrifying material for gaining other advantages like effective attacking positions.

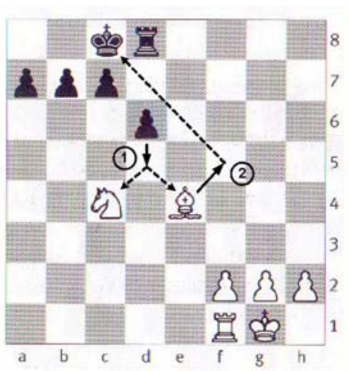

Figure 1: Fork situation, the move is with black

The example of Fig. 1 represents a position where black can make a *fork*, in which a player threatens to capture two pieces, not all of which can be blocked. This is advantageous for black, since one of the two white pieces will be lost. On the other hand, white has an advantageous move to its disposal, like making chess with the bishop on *f5* (Fig. 1). Then it is not immediately clear which player can improve its situation. It depends on the specific combination of both patterns. If the white player can move a piece out of the fork position by making chess, black is obliged to protect his king and white will be able to retreat the other piece too. But situations can be more complex, maybe black can react on the chess by threatening another piece, so that he keeps a double threat. We argue that for a pattern indicating a good move, there are many patterns that could interfere and counter the advantage. In the fork example, it could be possible that even after the retreat of white pieces, black still got a positional advantage, because of having chased both pieces from their positions.

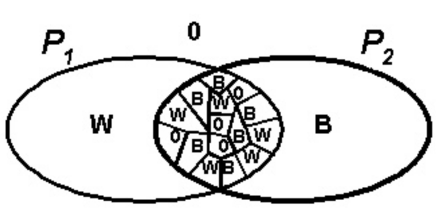

Figure 2: Evaluation of a combination of patterns P_1 and P_2, with W advantageous for white, B for black and 0 for none

Fig. 2 shows the possible situations. A pattern can be classified as beneficial if the other player has no alternative moves ($P_1 \setminus P_2$ or $P_2 \setminus P_1$). On the other hand, the evaluation of the intersection set ($P_1 \cap P_2$) depends on the specific context of the patterns. Evaluation by a weighted sum of both advantages is clearly inadequate. In a rule-based system we would have to classify all possible situations in the intersection. As we illustrated with two simple patterns, the number of combinations increases in an exponential way. We will show that there is a more powerful way of evaluating these combinatorial situations more accurately.

This shows that linear evaluation functions of computer algorithms are inaccurate. It is therefore indispensable that the algorithm expands the game tree as deep as possible. This can explain why Deep Blue went back to basics. It uses a light-weight evaluation function with only 4 features to be able to evaluate more positions, namely the material, the position of the pieces, the position of the king and the number of possible moves.

Note that in the end phase of a chess game, when there are only a limited a number of pieces left, the game becomes reducible and a limited number of rules can define the winning move sequence.

3. Bayesian Models for Evaluation

Causal models are in the first place Bayesian models, which represent the relations among a set of variables. These relations are based on the concepts of correlation and conditional independencies (Tian 2002). The fork-situation of Fig. 1 can be described by a causal model shown in Fig 3. The fork can lead to a better situation, a worse or a status quo. If the fork leads to gain in material, it will probably lead to a winning game, due to successful attack on the king or a winning end game. The relations are probabilistic (*P(material gain| fork)=0.8*) and indicate dependencies between the variables (*P(material gain| fork)>P(material gain)*). The relations are asymmetric, since the node material gain can also be attained in other situations.

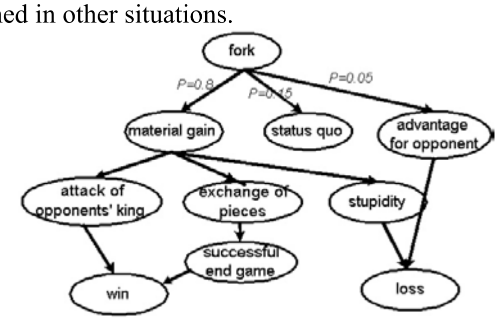

Figure 3: simplified Bayesian model of a fork situation

The second property of Bayesian network is based on conditional independencies. Without going into detail, it can best be understood by the Markov condition. This condition states that for a model $A \rightarrow B \rightarrow C$, A and C are also correlated, but become independent by conditioning on B. In other words, if B is known, A has no more information about C. Here, the model states that the advantage of the fork is determined by node 'material gain', *P(gain|fork, material) = P(gain|material)*. The probabilities can than be factorized and *P(gain|fork) = P(material|fork).P(gain|material)*. This is a very useful reduction of the analysis, since the relations fork – material and material – gain can be analyzed separately.

This brings us to the working hypothesis on which the rest of the text is based. We postulate that a pattern has a limited number n of effects that influence the result of the game:

$$P(gain|pattern) = SUM\ P(gain|effecti).P(effect_i|pattern) \quad (1)$$

The influence of a pattern is completely described by its positive and negative effects, where $P(effect_i|pattern) > P(effect_i)$.

We have no proof for this reduction. It is motivated by observation of the human way of thinking. The model answers typical human questions like 'why is a fork good?', 'why is material gain good?'. The rest of the text will demonstrate that this assumption adds a kind of information to the ones used in traditional gaming algorithms.

Note that a pattern can have accidental effects. The pawn moved to *d5* in Fig. 1 could be of great influence on the rest of the game. However, such situations are random coincidences or depend on other patterns. Secondly, a pattern incorporates other patterns having their own specific effects, like a 'fork' also is a 'threat' or an 'attack' pattern. These accidental and other effects have nothing to do with the fork pattern as such.

Besides the Bayesian properties, a causal model adds a causal interpretation to the relations. This interpretation will be used in the next section for solving the combinatorial problem of the previous section.

4 Causal Models for Evaluating Combinatorial Situations

Due to the property of Eq. 1, it is now possible to evaluate a pattern in a certain context. It is only necessary to analyze if one of the positive effect of the pattern can be attained/reached in the game tree by a path. A fork without alternatives for the opponent would lead to material gain. On the other hand, if the opponent has an alternative move that can counter the threat, the desired effect will not happen. Then there exists a better path for the opponent in the game tree. The model of Fig. 3 changes into a new model shown in Fig. 4, incorporating the influence of the new 'chess' pattern.

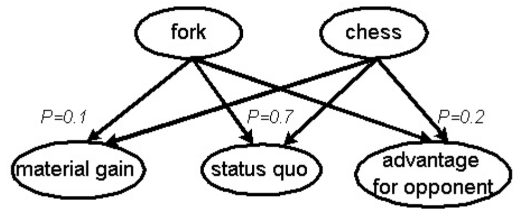

Figure 4: Mutilated model by adding the chess node

Extending the original model by locally adding nodes and changing probabilities, is based on the modularity assumption. Causal relations represent independent mechanisms that can be modified by so-called interventions without affecting other parts of the models (Pearl 2000).

The reasoning process we propose consists of two parts, there is the game tree with the exact information and there is the causal model containing patterns with the generalizing information. The causal model grows dynamically as more patterns are evaluated and added. This is done by combining new patterns with all patterns it interact and recalculating the probabilities. Humans immediately recognize if 2 patterns interfere or not. The advantage of this is that fewer nodes have to be evaluated. This is similar to tree pruning. On the other hand, we know when the effect of a pattern is attained, so how deep the tree should be explored. A brute-force algorithm that goes deep enough will come to the same conclusions. But we will show in the next section that only by knowing the effects of patterns, it is possible to pinpoint the essential choices in the game.

5 Chess Game Analysis

We will now demonstrate that a chess game analysis fits into the model as explained in the previous section. All analysis share the same ingredients. In the beginning, a specific opening is chosen, with its specific advantages for both sides. At a certain point, one player chooses a move that leaves the well-known variants. From that point, both players have to try to turn their specific advantages into a success and try to block the others advantages. The winner will be the one that is able to carefully accumulate small advantages. The analysis discusses alternative paths, to explain why certain moves are chosen or not. Furthermore, the analysis tries to pinpoint where it went wrong for the looser, where he should have an alternative move and why.

The example we will use is the decisive 16^{th} game of the famous match Karpov – Kasparov, Moskou 1985, after which Kasparov became the new world champion:

(K=King; Q=Queen; R=Rook; B=Bishop; N=Knight)
1. e2-e4 c7-c5 2. Ng1-f3 e7-e6 3. d2-d4 c5xd4 4. Nf3xd4 Nb8-c6 5. Nd4-b5 d7-d6 6. c2-c4 Ng8-f6 7. Nb1-c3 a7-a6 8. Nb5-a3 d6-d5 9. c4xd5 e6xd5 10. e4xd5 Nc6-b4 11. Bf1-e2 Bf8-c5 12. O-O O-O 13. Be2-f3 Bc8-f5 14. Bc1-g5 Rf8-e8 15. Qd1-d2 b7-b5 16. Ra1-d1 Nb4-d3 17. Na3-b1 h7-h6 18. Bg5-h4 b5-b4 19. Nc3-a4 Bc5-d6 20. Bh4-g3 Ra8-c8 21. b2-b3 g7-g5 22. Bg3xd6 Qd8xd6 23. g2-g3 Nf6-d7 24. Bf3-g2 Qd6-f6 25. a2-a3 a6-a5 26. a3xb4 a5xb4 27. Qd2-a2 Bf5-g6 28. d5-d6 g5-g4 29. Qa2-d2 Kg8-g7 30. f2-f3 Qf6xd6 31. f3xg4 Qd6-d4 32. Kg1-h1 Nd7-f6 33. Rf1-f4 Nf6-e4 34. Qd2xd3 Ne4-f2 35. Rf4xf2 Bg6xd3 36. Rf2-d2 Qd4-e3 37. Rd2xd3 Rc8-c1 38. Na4-b2 Qe3-f2 39. Nb1-d2 Rc1xd1 40. Nb2xd1 Re8-e1. Result: 0-1.

The analysis is by the Dutch chess master Jan Timman (Timman 1997). The game starts with a variant on the Sicilian opening. In this opening, it's whites' purpose to dominate the center. Kasparov plays a surprising move by *8. ... d5*, where he sacrifices a pawn to damage the white pawn wall and to get an active position (its pieces on strong positions with a high attacking potential). This can be seen by the position after the *11th* move, as shown in Fig. 5.

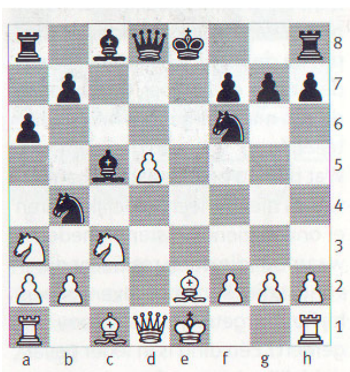

Figure 5: Karpov-Kasparov 1985, after 11th move

White has an extra pawn at *d5*, but black has already three pieces strongly positioned on the battlefield and his other pieces are ready to follow soon. This situation can be evaluated by the causal model of Fig. 6. Black will win if he can start a decisive attack, white wins if he can neutralize the threats.

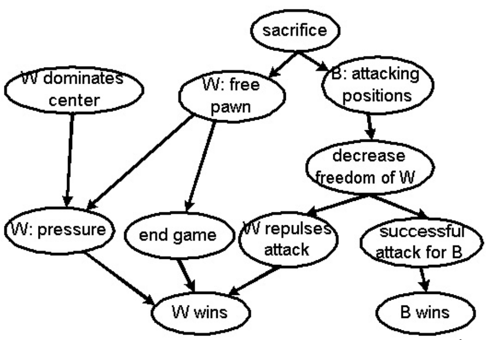

Figure 6: Causal model of situation after the 11th move.

At this point Karpov played *12. 0-0*. He should have played *12. Be3* that neutralizes both the bishop on *c5* and the rook on *b4*, since *12. ... Bxe3* is answered with *13. Qa4+* chess and the rook on *b4* is attacked without a cover. In a later match it was shown that this move contradicts Kasparovs' sacrifice and this opening was never played again among chess masters.

Figure 7: Karpov-Kasparov 1985, after 16th move

The plan of Kasparov is to limit the freedom of white pieces and get a good position with the knight on *d3*, after move *16* (Fig 7). He has chosen this continuation because he beliefs that the knight greatly limits the possibilities of white and that he can keep the knight there (otherwise the move would be in vain). Moreover, the knight will be decisive in the attack at move *34*. In the future, he is even prepared to sacrifices his rook to be able to keep the knight on that position (in order to attain the desired effect), if Karpov would have chosen *17.d6* and give up the pawn. Instead, he chose to defend the pawn and moved *17. Nab1*. Note that white is obliged to do this because of the threat of a successful fork with *b4*. Karpovs' choice of defending was a wrong estimation of the decisiveness of the subgoal.
The next step in Kasparovs' strategy is to chase whites' pieces to bad positions, before launching the final attack.

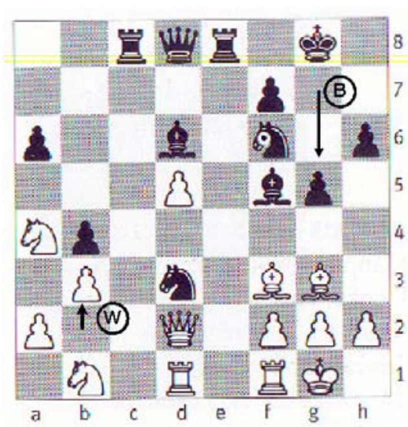

Figure 9: Karpov-Kasparov 1985, after 11th move

With move *21 b3*, Fig. 9, white wants to move his passive knight from *a3* to *c2* in order to attack the evermore dangerous knight at *d3*. However, after *21. ... g5*, this becomes impossible, because of the successful path for black *22… Nxb2 23. Qxb2 g5-g4 24. Be2 Rc2* after which the white bishop at *e2* is lost. Such explanations appear frequently in analysis. Their effectiveness of evaluating situations is possible due to the modularity property of the model. The whole analysis should not being recalculated again after each move. By the relational information, effect a move is known and it is known what has to be modified in the causal model.

The move *g7-g5* illustrates the proposition of the previous section. It would be evaluated negative by an evaluation function, because it weakens the black kings' defense. But in this context, black does not fear an attack. The advantage of the pawn lies far away in the future. It has only effect at the 30^{th} move, after *28. ... g5 - g4*. Note that at move *24*, black moves its queen to *f6*, preventing again the move *Na4-c2*.

The whole analysis is based on the assumptions that causes and effects can be pinpointed and that the analysis can be extended in a modular way.

6. Conclusions

This paper demonstrated that linear evaluations of features fail to capture all situations in complex games. The knowledge of the effects of a pattern is proposed as another kind of information. A causal model captures the properties of performing an evaluation of pattern combinations. This could be a promising new viewpoint on game playing, but does not solve the real difficulty of recognizing patterns, learning them and recognizing that patterns interfere.

Future work includes the design of experiments to proof the hypothesis.

7. References

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