

Rotated Bitboards and Reinforcement Learning in Computer Chess and Beyond

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Abstract

There exist several techniques for representing the chess board inside the computer. The straight-forward-approach of maintaining an array of the 64 squares has several drawbacks. In the first part of this paper, the concepts of the bitboard-representation and the advantages of (rotated) bitboards in move generation are explained. In order to illustrate those ideas practice, the concrete implementation of the move-generator in FUSc# is discussed, with code snippets in C#. Additionally, we explain a technique how to verify the move-generator of a chess programm with the “perft”-command - after the general concept is described, we show that the move-generator of FUSc# works 100% correct.

The second part of this paper deals with reinforcement learning in computer chess (and beyond). We exemplify the progress that has been made in this field in the last 15-20 years by comparing the “state of the art” from 2002-2008, when FUSc# was developed, with recent innovations connected to “AlphaZero”. We discuss how a “FUSc#-Zero” could be implemented and what would be necessary to reduce the number of training games necessary to achieve a good performance: While strong humans play about 10.000 up to 50.000 games of chess to achieve grand-master performance, AlphaZero needed between 20-40 million training games to do so. This can be seen as a test case to the general problem of improving “sample efficiency” in reinforcement learning.

In the final discussion, we move beyond computer chess, as the importance of sample efficiency extends far beyond board games into a wide range of applications where data is costly, difficult to obtain, or time consuming to generate. Moreover, in many real-world scenarios, AI systems must learn and adapt quickly to new situations with limited data, making sample efficiency a critical factor in their success. We review some application of the ideas developed in AlphaZero in other domains, i.e. the “other Alphas” like AlphaFold, AlphaTensor, AlphaGeometry and AlphaProof. We also discuss future research and the potential for such methods for ecological economic planning.

Abstract

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1 Introduction to bitboards

1.1 The basic idea of bitboard representations

The idea for the bitboard representation of the chessboard is based on the observation that modern CPUs are 64bit-processors, i.e. the length of a word in machine language is nowadays often 64bit. Those 64bit-words will correspond to the 64 squares on the chess board, and those “bitboards” (the name that is used for an unsigned int64) are used to represent various information about the position on the chessboard. The advantage of this representation lies in the availability of very fast bit-manipulating operations on modern CPUs: On 64bit-machines, operations like AND, OR, NOT etc. can be executed on a 64bit “bitboard” in only one cycle. It is therefore to construct very efficient chess programs on the basis of the bitboard-approach, because, roughly speaking, the CPU operates on all 64bit “in parallel”. Details how this works exactly will be given in sections 1.2 and 1.3.

In the history of computer chess, there were several authors who used variants of the bitboard-representation in their chess engines. As early as in the seventies, Slate and Atkin described the idea of using bitboards in their program “CHESS 4.5” (see [3], chapter 4). Another prominent program that used this technique successfully is the former computer chess champion “Cray Blitz”, written by Robert Hyatt, who continued to develop the program as an open-source project called “Crafty” ([9]). Another world-class chess engine using bitboards is DarkThought, developed at the university of Karlsruhe in the late 90s. Crafty and DarkThought were also the first programs that used an important refinement of the bitboard-representation called “rotated bitboards” (see section 1.4). The author of DarkThought Ernst A. Heinz gives an overview of rotated bitboards as used in DarkThought (see [2]), which inspired much of our own developments.

1.2 Bitboards to represent a chess positions

In each bitboard, a special information/property of the position can be encoded, where a “1” in the bitboard means the property is true for the given square, while a “0” means the property is not true. As an example, consider a bitboard “w_occ” that contains the information which square is occupied by a white piece - all squares corresponding to a “1” are occupied by a white piece, the others are not.

In order to represent a chess position, one “bitboard” is of course not enough - only the combination of several bitboards can contain the complete information of a position. Let’s consider the following bitboards:

- one bitboard for each type of piece: “pawns”, “knights”, “bishops”, “rooks”, “queens”, “kings”
- two bitboards “w_occ” and “b_occ” indicating which squares are occupied by which color
- a collection of bitboards encoding the occupied squares in a “rotated” manner (see 1.4)

In this representation, the white pawns can be obtained by “ANDing” the “pawns”-bitboard (in which the pawns of both colors are encoded) with the “w_occ”-bitboard:

```
white_pawns = pawns AND w_occ
```

Another example is computing the empty squares. For this, the white and black pieces are “ANDed”, and then the bitwise complement (“NOT”) is formed:

```
empty_squares = NOT (w_occ AND b_occ)
```

By following this idea and using the bitwise operations “AND”, “OR”, “NOT” etc., many more interesting information can be computed from the bitboards very efficiently.

1.3 The bitboard-approach towards move-generation

The move-generation is used many times during the search-algorithms used in chess programs. Therefore, an efficient move-generation is needed. Based on the bitboard-approach, there exist different strategies for each of the piece-types in chess. One important concept is to compute bitboards of all possible moves (e.g. of a knight) from all the squares beforehand during the initialisation of the program, and store this information in a data-structure that provides efficient access to these pre-computed moves during the move-generation. For non-sliding pieces, this approach works straightforward, but for sliding-pieces some more tricks are needed, which are explained in the next section (1.4). But let's start with looking at generating moves for pawns, which uses a different but very elegant way of using the bitboard-representation.

1.3.1 Pawns

The idea for generating pawn moves using bitboards is based on the “shift”-operations that exist on all microprocessors: by shifting the bitboard containing the white pawns to the left by 8 positions, the non-capturing moves of all (up to 8) white pawns can be generated simultaneously (this shifted bitboard has to be “ANDed” with the empty_squares in order to be valid)! For pawn captures, just shift to the left by 7 and 9 respectively, and “AND” with the black pieces. Although this looks amazingly fast on first sight, in practice some of the advantage of the parallel generation is lost when the moves must be put into a move list separately (see section 2.2 for details). Maybe this could be avoided in some cases, and there are some ideas for future developments (see 3.4).

1.3.2 Non-sliding pieces

For non-sliding pieces like knight or king all possible moves from all the squares of a chess board are computed during the initialisation of the program and stored in arrays indexed by the from-field, i.e. there exist 2 arrays:

- knight_moves[from-field]
- king_moves[from-field]

In knight_moves[c1], for example, a bitboard that contains all possible “to-squares” for a knight standing on field “c1” is stored. During move generation, this bitboard can be “ANDed” with a bitboard containing the fields that are not occupied by own pieces (i.e. NOT(own_pieces)) to produce all knight moves from c1. But there are more possibilities: if knight_moves[c1] is “ANDed” with the opponents pieces, only capture-moves will be produced (this is needed very often e.g. during quiescence search). In general, very advanced move generation schemes are possible, e.g. “moves that attack the region of the opponent king” could be generated by “ANDing” the possible to-squares with a bitboard that encode the fields near to the opponent king. These examples show the flexibility of the bitboard-approach.

Although this technique works fine for non-sliding pieces, there are difficulties when starting to think about sliding pieces, which will be covered in the next section.

1.3.3 Sliding pieces

Computing “all possible moves from all squares” for sliding pieces is not as easy as for non-sliding pieces, because the possible moves for a sliding piece will depend on the configuration of the line/file/diagonal it is standing. For example, on a completely empty chessboard, a bishop standing in one of the corners will have plenty of moves, but in other positions with own pieces standing next to it and blocking its diagonal, there might be not even one move possible for the bishop. Therefore, the idea for bitboard-move-generation for sliding pieces is to compute all the possible moves for all squares **and** all configurations of the involved ranks/files/diagonals! For example, the rank-moves for a rook standing on a1 on an otherwise empty chessboard will be stored in “rank_moves[a1][00000001]”, with the second index of the array being the configuration

of the involved rank (i.e. 8 bits, with only “a1” being occupied as the rook is standing there itself). This works fine for rank-moves, because the necessary 8 bits for the respective rank can be easily obtained from the bitboard of the occupied pieces (this bitboard consists of 8 byte, and each of those corresponds to one rank). For file-moves of rooks and queens, and especially for the diagonal moves of bishops and queens, things turn out to be much more difficult: the necessary bits about the respective files/diagonals are spread all over the “occupied”-bitboard, they are not “in order”, as they are for rank-moves. Here the idea of rotated bitboards helps out.

1.4 Rotated bitboards

The idea of rotated bitboards is to store the bitboards that represents the “occupied squares” not only in the “normal” way, but also in a “rotated” manner. Therefore, the necessary bits representing files/diagonals are “in-order” in those rotated bitboards, as needed by the move-generation (see previous section). The “rotated bitboards” are updated incrementally during the search, i.e. when a move is done or undone. The following bitboards are maintained:

- `board.occ`, which represents the occupied squares in the “normal” representation
- `board.occ_l90`, the board flipped by 90° (for file moves)
- `board.occ_a1h8`, for diagonal moves in the direction of the a1h8-diagonal
- `board.occ_a8h1`, for diagonal moves in the direction of the a8h1-diagonal

A detailed description how these bitboards are used during move-generation can be found in sections 2.4.1 and 2.4.2. See the Appendix (6) for details about how the different rotated bitboards look like.

2 Move generation in FUSc#

FUSc# is the chess program developed by the “AG Schachprogrammierung” at the Free University in Berlin ([5]). It is written in C# and runs on the Microsoft .NET Framework ([11]). This section aims to give explain in details how the move generator of FUSc# works. At first an overview of move generation in FUSc# is given, then the generation of moves for the different pieces is explained. As explained in section 1.3, there are three main categories of piece-types for move generation:

1. Pawns
2. Non-sliding pieces (knight, king)
3. Sliding pieces (bishop, rook, queen)

For each of these categories, the steps involved in the move-generator of FUSc# are explained and illustrated by some snippets from the source-code of FUSc#. However, for these explanations, not the latest (fine-tuned, and therefore quite unreadable) version of the source-code of the FUSc#-move-generator will be used, but an earlier version where the concepts involved can be seen much clearer. Those concepts of course still form the basis of the move-generator of the latest versions of FUSc# and DarkFUSc# (our new engine, both can be downloaded from [6])

2.1 Overview of move generation in FUSc#

We will discuss now in detail how the move generator in FUSc# works. We will only deal with “movegen_w” that generates moves for white - there is a symmetrical routine for black, which is based on the same ideas and will not be treated here. The call for “movegen_w” is:

```
int movegen_w(Move[] movelist, ulong from_squares, ulong to_squares)
```

You can see that `movegen_w` expects 3 parameters:

- a “movelist” to store the generated moves in
- a bitboard (ulong is 64bit in .NET!) of “from_squares”, which is normally “board.w_occ”, i.e. all white pieces
- a bitboard of “to_squares”, which is normally “~board.w_occ”, i.e. the complement of all white pieces, but could also be e.g. “board.b_occ” to generate only capture moves

In the following sections we will discuss the move generation for the different pieces in detail.

2.2 Pawns

2.2.1 Non-capturing moves

Here is the code-snippet from the FUSc#-move-generator that generates (one step) non-capturing pawn moves for white:

```
1 // WHITE PAWNS (one step)
2 pawn_fields_empty = ( (board.pawns & from_squares) << 8) & (~board.occ.ll);
3 tos = pawn_fields_empty & to_squares;
4 froms = tos >> 8;
5 while (from = GET_LSB(froms))
6 {
7   board.w_attacks |= from;
8   movelist[movenr].from = from;
9   movelist[movenr].to = GET_LSB(tos);
10  movelist[movenr].det.ll = 0;
11  movelist[movenr].det.ail.piece = PAWN;
12  movelist[movenr].det.ail.flags = 0;
13  movenr++;
14  CLEAR_LSB(tos);
15  CLEAR_LSB(froms);
16 };
```

In line 2, the idea is to compute a bitboard of all the “empty squares in front of white pawns”. To get this, the pawns (standing on the “from_squares”) are shifted to the left by 8 bits, and the result is “ANDed” with the complement of the “occupied” squares (found in “board.occ.ll”). Then, this “pawn_fields_empty” is “ANDed” with the “to_squares” in order to get the destination squares (“tos”) for all the desired moves. The from-squares (“froms”) for those moves can be obtained by shifting back the “tos” by again 8 bits. After line 4, all one-step non-capturing pawn moves (that origin from “from_squares” and head to “to_squares”) have been generated and are encoded in the two bitboards “froms” and “tos”. In the while-loop in lines 5-16 those moves are put into the movelist individually. Therefore, the individual moves that correspond to the bits in the bitboard “froms” and “tos” must be obtained one-by-one. In line 5, the “Least Significant Bit” (LSB) of “froms” is extracted and saved in the bitboard “from”, and in line 9 the same is done for the LSB in “tos” (it is saved in the bitboard “to”). These two bitboards, together with some additional information (like the piece that is moving) is then saved in the movelist (lines 7-12). In lines 13 and 14, the “Least Significant Bits” of “froms” and “tos” are cleared, as this was the move that has just been processed. If there are bits left in “froms”, then the next iteration of the while-loop will extract them, otherwise the generation of one-step non-capturing pawn moves is finished.

Two-step non-capturing pawn moves are generated similarly.

2.2.2 Pawn captures

Here is the code-snippet from the FUSc#-move-generator for generating white pawn captures (to the right side):

```
1  // WHITE PAWNS (captures right)
2  tos = ( (board.pawns & NOT_RIGHT_EDGE & from_squares) << 9) & board.b_occ & to_squares;

3  froms = tos >> 9;
4  while (from = GET_LSB(froms))
5  {
6  board.w_attacks |= from;
7  movelist[movenr].from = from;
8  movelist[movenr].to = GET_LSB(tos);
9  movelist[movenr].det.ll = 0;
10 movelist[movenr].det.ail.piece = PAWN;
11 movelist[movenr].det.ail.flags |= NORMAL_CAPTURE;
12 movenr++;
13 CLEAR_LSB(tos);
14 CLEAR_LSB(froms);
15 };
```

Pawn captures are generated similar to non-capturing pawn moves, although there are some differences: in the code-snippet above, the pawn-captures “to the right side” are generated, that’s why the pawns standing on the right edge may not be included in the bitboard that is shifted (this time by 9 positions) in order to generate the moves. To achieve this, a bitboard the bitboard “NOT_RIGHT_EDGE” is “ANDed” to the pawns before the shift (line 2). Another difference is that now the destination squares must contain black pieces, as we generate pawn captures. Lines 4-15 work like the respective lines for pawn non-capturing moves.

2.2.3 Special moves

To explain the section for en-passant and promotion moves lies beyond the scope of this article. The techniques used base on the concepts introduced in the previous two paragraphs about pawn moves. If you are interested in the concrete implementation, you can download the source of FUSc# at our homepage ([5]) and have a look yourself!

2.3 Non-sliding pieces

2.3.1 Knights

Here the a code-snippet from the FUSc#-move-generator that generates moves for the white knight:

```
1  // WHITE KNIGHT
2  froms = board.knights & from_squares;
3  while (from = GET_LSB(froms))
4  {
5  from_nr = get_LSB_nr(from);
6  tos = knight_moves[from_nr] & to_squares;
7  while (to = GET_LSB(tos))
8  {
9  board.w_attacks |= from;
10 movelist[movenr].from = from;
11 movelist[movenr].to = to;
```

```

12 movelist[movenr].det.ll = 0;
13 movelist[movenr].det.ail.piece = KNIGHT;
14 movelist[movenr].det.ail.from_nr = from_nr;
15 movelist[movenr].det.ail.flags |= FROM_NR_COMPUTED;
16 if (board.b_occ & to) movelist[movenr].det.ail.flags |= NORMAL_CAPTURE;
17 movenr++;
18 CLEAR_LSB(tos);
19 };
20 CLEAR_LSB(froms);
21 };

```

Generating moves for the white knight starts in line 2, where “board.knights” (containing the knights of both colors) is “ANDed” with the “from_squares” (which normally contain all the white pieces). The result (a bitboard containing the white knights) is saved in “froms”. In line 3 the LSB of “froms” is extracted and saved in the bitboard “from”, which then only contains one bit set (at the position where the first white knight resides). Then, in line 5, the number of the bit set in “from” is computed by the routine “get_LSB_nr(from)” and saved in “from_nr”. The “from_nr” is needed to index the array “knight_moves” in line 6 (this array contains all ever possible knight moves from the square that is given as index, see section 1.3.2). The destination squares for knight-moves (“tos”) are computed by “ANDing” the “knight_moves[from_nr]” with the “to_squares”, which could be all empty squares or all black pieces, e.g., if only the generation of certain types of moves is desired (capturing/non-capturing). After that, the generated moves are put in the movelist in lines 7-21.

2.3.2 Kings

The move-generation for the king is analog to the move-generation for knights, using “king_moves[from_nr]” instead of “knight_moves[from_nr]”, of course. Like in many other engines, assuring that the king is not left in check after a move is not done inside the move-generator, but inside the search-routine, i.e. the FUSC#-move-generator produces only pseudo-legal moves that possibly leave the own king in check.

2.4 Sliding pieces

2.4.1 Rooks

Here the a code-snippet from the FUSC#-move-generator that generates moves for the white rook:

```

1 // WHITE ROOK
2 froms = board.rooks & from_squares;
3 while (from = GET_LSB(froms))
4 {
5   from_nr = get_LSB_nr(from);
6   rank_pattern = board.occ.byte[from_nr >> 3];
7   file_pattern = board.occ_l90.byte[l90_to_normal[from_nr] >> 3];
8   tos = (rank_moves[from_nr][rank_pattern] | file_moves[from_nr][file_pattern])
& to_squares;
9   while (to = GET_LSB(tos))
10  {
11    board.w_attacks |= from;
12    movelist[movenr].from = from;
13    movelist[movenr].to = to;
14    movelist[movenr].det.ll = 0;
15    movelist[movenr].det.ail.piece = ROOK;

```



```

16 movelist[movenr].det.ail.from_nr = from_nr;
17 movelist[movenr].det.ail.flags |= FROM_NR_COMPUTED;
18 if (board.b_occ & to) movelist[movenr].det.ail.flags |= NORMAL_CAPTURE;
19 movenr++;
20 CLEAR_LSB(tos);
21 };
22 CLEAR_LSB(froms);
23 };

```

For generating rook-moves, the idea of “rotated biboards” (section 1.4) comes into play. But at first, the white rooks are computed and extracted in lines 2-3, and the number of the square where the rook is standing is computed in line 5 and stored in “from_nr” (see previous sections for details). In lines 5 and 6 patterns of the rank and the file on which the rook is standing is saved in “rank_pattern” and “file_pattern” respectively. These patterns are 8-bit variables that are used to index the “rank_moves” and “file_moves”-arrays in line 8, in addition to “from_nr”, containing the square where the rook is standing (see section 1.3.3 for details). In line 7, you can see how the idea of accessing the “rotated” representations of the occupied squares works in practice: The desired file-pattern is found in

```
“board.occ_l90.byte[l90_to_normal[from_nr] >> 3]”
```

Let’s look at the individual parts of this expression:

- “board.occ_l90” contains a bitboard of the occupied squares, shifted by 90iœ to the left
- this bitboard consists of 8 bytes (i.e. 64bits), that can be accessed individually by “board.occ_l90.byte[0]” to “board.occ_l90.byte[7]”
- in order to get the correct byte-number, the “from_nr” is converted to the “l90”-square-nr by accessing the array “l90_to_normal” with index “from_nr” and shifted to the right by 3 bits
- this last shift can also be seen in line 6. When shifting “from_nr” (a number from 0...63) to the right by 3 bits, you will get the number of the byte where the bit corresponding to the “from_nr” resides

Thus, after line 6 and 7, you have the correct patterns stored in “rank_pattern” and “file_pattern”. These are used to access the pre-computed “rank_moves” and “file_moves” arrays in line 8, where the bitboard of the possible destination squares for rook-moves (“tos”) is computed. The individual moves are put in the movelist in lines 9-23 as described above.

2.4.2 Bishops

Here the a code-snippet from the FUSc#-move-generator that generates moves for the white rook:

```

1 // WHITE BISHOP
2 froms = board.bishops & from_squares;
3 while (from = GET_LSB(froms))
4 {
5   from_nr = get_LSB_nr(from);
6   a1h8_pattern = board.occ_a1h8.byte[a1h8_to_normal[from_nr] >> 3];
7   a8h1_pattern = board.occ_a8h1.byte[a8h1_to_normal[from_nr] >> 3];
8   tos = (a1h8_moves[from_nr][a1h8_pattern] | a8h1_moves[from_nr][a8h1_pattern])
& to_squares;
9   while (to = GET_LSB(tos))
10 {

```

```

11 board.w_attacks |= from;
12 movelist[movenr].from = from;
13 movelist[movenr].to = to;
14 movelist[movenr].det.ll = 0;
15 movelist[movenr].det.ail.piece = BISHOP;
16 movelist[movenr].det.ail.from_nr = from_nr;
17 movelist[movenr].det.ail.flags |= FROM_NR_COMPUTED;
18 if (board.b_occ & to) movelist[movenr].det.ail.flags |= NORMAL_CAPTURE;
19 movenr++;
20 CLEAR_LSB(tos);
21 };
22 CLEAR_LSB(froms);
23 };

```

The move generation for bishops is quite similar to the move generation for rooks. In line 6 and 7 the needed patterns (this times for the two diagonal directions) are computed, whereas the arrays with the pre-computed moves are accessed in line 8. Note that for bishop moves, the corresponding rotated bitboards are called “board.occ_alh8” and “board.occ_a8h1”. For details on how these rotated bitboards look like, please have a look at the Appendix (6). Again, the individual moves are put in the movelist in lines 9-23, as described earlier.

2.4.3 Queens

The queens moves are generated in the same way as the rook and bishop moves. Basically, the idea is to generate bitboards for all rank/file/diagonal moves from the square the queen is standing on, and “ORing” all of those bitboards in order to get a bitboard with all the queen moves. Again, the individual moves are then put in the movelist, as described earlier.

3 Verifying the move-generator in FUSc# and Discussion

Constructing a basic move-generator is not too hard, since the basic rules for piece-movements in chess are manageable both in number and complexity. However, when also considering special moves like castling, promotion and en-passant and the huge number of possible chess positions there are some really tricky cases to handle - and the question arises how to make sure that the move-generator of one’s chess program works 100% correct, even in awkward and seldom occurring yet possible positions. “Manually” checking the move-lists of the program is possible for only a very limited number of positions - nevertheless it should of course be done in the process of developing a chess program, although it can always only be a first step. A more advanced method to verify the move-generator of a chess engine have been developed is to use the command “perft”.

3.1 The “perft”-idea

The basic idea is to implement a “perft”-command to the chess engine which will construct a minmax-tree untill a fixed depth and count all the generated nodes. This number can be compared to the number of nodes generated by the “perft”-command of other chess engines, and there exist Web-Sites with both a collection of chess positions and the corresponding correct “perft”-numbers for several depths (see [10]). Of course, special attention should be given to positions involving “special moves” like castling, en-passant and promotion. One important point is that the search conducted by the “perft”-command must construct a plain minmax-tree without alpha-beta, transpositions tables, quiescence search, search extensions or any forward pruning techniques like null-moves.

3.2 Test positions

3.2.1 The start position

The correct results for the “perft”-command at the start position are given in the following table. It is clear that for depth 1 (i.e. “move generation for white and counting the nodes”) the result is 20, as there are 20 legal moves for white in the start position in chess:

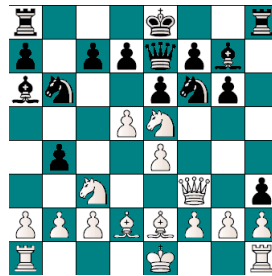
Depth	Perft(Depth)
1	20
2	400
3	8,902
4	197,281
5	4,865,609
6	119,060,324
7	3,195,901,860
8	84,998,978,956
9	2,439,530,234,167
10	69,352,859,712,417

3.2.2 A middlegame position

The following position involves castling, en-passant and promotion (at least in higher depths) for both sides.

The FEN-Code is `r3k2r/p1ppqpb1/bn2pnp1/3PN3/1p2P3/2N2Q1p/PPPBPPPP/R3K2R w KQkq`

-

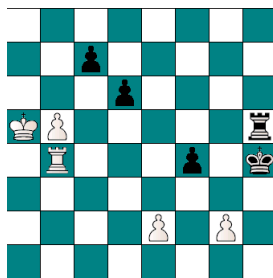


The correct results are:

Depth	Perft(Depth)
1	48
2	2039
3	97,862
4	4,085,603
5	193,690,690
6	8,031,647,685

3.2.3 An endgame Position

Here is an endgame-position with FEN-code `8/2p5/3p4/KP5r/1R3p1k/8/4P1P1/8 w - -`



The correct results are:

Depth	Perft(Depth)
1	14
2	191
3	2,812
4	43,238
5	674,624
6	11,030,083
7	178,633,661

3.3 Results of Crafty and FUSc#

In order to test the move-generator of FUSc#, the three positions described above were loaded into the program and the “perft”-command was executed. In order to re-check the results, the experiment was also done with Crafty (version 1919p3, see [9]). See the Appendix (6.2) for the detailed output of both programs in the three positions.

3.4 Discussion of rotated bitboards in FUSc#

In the first 3 chapters of this paper, the ideas behind the rotated bitboard board representation was explained and illustrated at the chess program Fusch#, which uses this technique in order to construct an efficient the move-generator. When we introduced this concept to our chess program, we observed a huge speedup compared to the old version of FUSc#, which used the array-representation. However, when it comes to speed, other chess programs like “Crafty” perform much better in terms of “nodes per second”, which is closely related to the speed of the move-generator (this can also be seen at the execution time of the “perft”-command, which is also much faster in Crafty than in FUSc#). FUSc# is written in C# and runs on Microsoft Framework .NET, which means that the source-code of FUSc# is not compiled into machine language directly, but into the “Microsoft Intermediate Language” (MSIL), which is translated into machine language by the JIT-compiler (“Just in Time”) of the .NET-Framework **at execution time**. Crafty, on the contrary, was written in C, is compiled directly into machine language, and uses compilers that makes intensive use of optimizations **at compiling time** (like gcc, see). That’s why a big part of the difference in performance can be explained by the use of different programming frameworks - .NET was not made for low-level high-performance applications in the first place, but for distributed computing, web services etc. Additionally, FUSc# was in the past mainly a research project not with the aim of fine-tuning the move-generator or the search function of chess programs, but to experiment with new ideas in chess programming like machine learning, neuronal networks (see [7]). That’s why it is understandable that it can not compete with professional programs that were developed and tuned for many years by professional programmers and/or chess players. Nevertheless, the performance and chess skill of FUSc# have improved steadily over the last three years although the development of FUSc# was done by students in their free time, the team was changing often etc. It is was successfully playing at the FUSc#-servers, and has all features of modern uci-engines as well as some interesting additions like a self-learning opening book.

4 Reinforcement Learning in Computer Chess

4.1 The Paper “Reinforcement Learning in Chess Engines” (2008)

4.1.1 Introduction and Context

In order to give some “historical” context, we quote from the Introduction of the paper [14]:

“The complexity of chess makes it impossible for computers to explore every possible move throughout the whole space of possible variants and pick the best one. Most chess engines therefore focus on a brute force strategy to search in the space of the next possible moves up to a certain depth only. Many pruning-processes are used, as well as linear position evaluation which incorporates knowledge based approaches in order to evaluate a special position. However, the main problem still lies in the correct tuning of the coefficients used in these functions. The method presented in this paper optimizes the evaluation functions and its coefficients by automating the use of temporal differences and thereby increasing it’s own understanding of chess after each game.”

Back then, the understanding was that “the main problem lies in the correct tuning of the coefficients” of the evaluation functions, and the idea of MCTS was not yet developed.

4.1.2 NeuroChess and Temporal Difference (TD)-based methods in computer chess

In the “related work”-section of the same paper [14], a paragraph on NeuroChess is interesting to read from the perspective of today:

“The chess program NeuroChess, developed by Sebastian Thrun, also uses a neuronal network as position evaluation and a TD-method based on the root nodes to modify the coefficients. In contrast to SAL, NeuroChess only learns from itself. Games from a grand master database have mostly been used as entry points of the learning process (90%), while only 10% of the training games where played from the initial positioning. Later experiments with other programs showed that a learning strategy based on playing against oneself, does not yield satisfying results. In an experiment against GNUChess, where both programs where calculating a move depth of 2 and using the same evaluation, 316 out of 2400 games could be won by NeuroChess and the learned coefficients. Thrun, the main developer of NeuroChess admitted two fundamental problems of his approach: the large training time and the incompleteness of the evaluation coefficients. Thrun concludes that it is unclear whether TD-based solutions will ever find usage in chess programming.”

So in 2008, “experiments with other programs showed that a learning strategy based on playing against oneself, does not yield satisfying results”, which changed dramatically with AlphaZero. Only about 10 years later, its general reinforcement learning algorithm, “starting from random play, and given no domain knowledge except the game rules, achieved within 24 hours a superhuman level of play”. So the game of chess was mastered “by tabula rasa reinforcement learning from games of self-play”, in contrary what seemed possible a decade ago. More details on AlphaZero will be given in the next chapter.

4.2 The “AlphaZero”-Revolution

In December 2017, a paper was uploaded to arxiv with the title “Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm” [13]. In the abstract, it is stated that:

“The game of chess is the most widely-studied domain in the history of artificial intelligence. The strongest programs are based on a combination of sophisticated search techniques, domain-specific adaptations, and handcrafted evaluation functions that have been refined by human experts over several decades. In contrast, the AlphaGo Zero program

recently achieved superhuman performance in the game of Go, by tabula rasa reinforcement learning from games of self-play. In this paper, we generalise this approach into a single AlphaZero algorithm that can achieve, tabula rasa, superhuman performance in many challenging domains. Starting from random play, and given no domain knowledge except the game rules, AlphaZero achieved within 24 hours a superhuman level of play in the games of chess (...)

4.2.1 Introduction / Background

In the introduction to the AlphaZero-paper [13], it is stated:

“A long-standing ambition of artificial intelligence has been to create programs that can instead learn for themselves from first principles (26). Recently, the AlphaGo Zero algorithm achieved superhuman performance in the game of Go, by representing Go knowledge using deep convolutional neural networks (22, 28), trained solely by reinforcement learning from games of self-play (29). In this paper, we apply a similar but fully generic algorithm, which we call AlphaZero, to the games of chess and shogi as well as Go, without any additional domain knowledge except the rules of the game, demonstrating that a general-purpose reinforcement learning algorithm can achieve, tabula rasa, superhuman performance across many challenging domains.” (references from the quoted paper, see the reference-section of [13])

4.2.2 Relative Performance of AlphaZero compared to traditional chess programmes

The approach of AlphaZero is very different to classical chess programs and FUSc#: Instead of an “alpha-beta search with domain-specific enhancements”, it uses “a general-purpose Monte-Carlo tree search (MCTS) algorithm. Each search consists of a series of simulated games of self-play that traverse a tree” from root to leaf (compare p.3). Concerning the relative Performance of AlphaZero compared to traditional chess programmes, it is stated (p. 5):

“We also analysed the relative performance of AlphaZero’s MCTS search compared to the state-of-the-art alpha-beta search engines used by Stockfish and Elmo. AlphaZero searches just 80 thousand positions per second in chess and 40 thousand in shogi, compared to 70 million for Stockfish and 35 million for Elmo. AlphaZero compensates for the lower number of evaluations by using its deep neural network to focus much more selectively on the most promising variations – arguably a more “human-like” approach to search, as originally proposed by Shannon (27). “

4.2.3 Conclusion

In the end, the chess knowledge discovered by AlphaZero is analysed, including the most common human openings (those played more than 100,000 times in an online database of human chess games. Concerning that, it is stated that

“Each of these openings is independently discovered and played frequently by AlphaZero during self-play training. When starting from each human opening, AlphaZero convincingly defeated Stockfish, suggesting that it has indeed mastered a wide spectrum of chess play.

The game of chess represented the pinnacle of AI research over several decades. State-of-the-art programs are based on powerful engines that search many millions of positions, leveraging handcrafted domain expertise and sophisticated domain adaptations. AlphaZero is a generic reinforcement learning algorithm – originally devised for the game of Go – that achieved superior results within a few hours, searching a thousand times fewer positions”

That is an impressive achievement, however the “sample size” needed to achieve it is quite large, which is the topic of the next chapter.

5 Sample efficiency in reinforcement learning in chess and beyond

5.1 “FUSc#-Zero” and Sample Efficiency

5.1.1 Sample Size for AlphaZero

According to the AlphaZero paper [13], millions of self-play training games were used for the training:

- about 20 million games (approx. 4 hours of training time) were necessary to achieve super-human performance
- about 44 million games (approx. 9 hours of training time) were necessary to beat Stockfish, the best available computer chess programm

5.1.2 (Rotated) Bitboards as a Domain Specific Language for chess

A new idea is to use the already existing bitboard-structure (e.g. in FUSc#) as a basis for a DSL (Domain Specific Language) for chess. One example could be to introduce the concept of “ranks” and “files” in relation to “rook moves”. By introducing “more structure”, i.e. the bitboard-DSL, our approach aims at learning useful “evaluation heuristics” of chess positions, which we hope needs much less training games than “learning good positions for all pieces with no structure at all”, like AlphaZero did:

- by e.g. introducing the concept of “ranks” and “files” in relation to “rook moves” (see above), we hope to “rediscover” simple heuristic rules that humans use, like “put rooks on open ranks”...
- ... as a start, we will look at a few such heuristics that already exist in chess engines like FUSc#, and try to “reproduce” them by:

1. Self-Play
2. with a “sparring partner”, i.e. a strong chess program (much like a human would not learn much by “just playing against oneself”, but typically will learn from stronger players, which we could mimic)...
3. ... however it might be useful/fair to use a “Zero Human Chess Knowledge” engine like lc0 as a sparring partner, because otherwise, we will arguably just “rediscover the chess knowledge that the other programmers invested in their chess engines”. Note that this is not the case for lc0, as just “self-play” made it strong, and we will use this strength to investigate which “simple heuristics of piece positioning” can be learnt by a “Zero-FUSc#” with as few training games as possible.

5.1.3 Position classification in FUSc# and sample efficiency

To further improve sample efficiency, it could make sense to relate the “piece evaluation heuristics” to “position type” (e.g. opening, middle game, endgame), because the former will greatly vary with the latter (e.g. “king safety” in the middle game vs. “active king play” in the endgame). At first we could “give” such a structure to our programm, the question is if a “Zero-FUSc#” could “re-discover” such “position-types” itself in a second step, maybe with even more “position types” that just 3 (in FUSc# 33 were used).

Observation: Some of these ideas/questions are related to concepts that “FUSc#” used nearly two decades ago, with much less computing power available at the time.

We could do an “update” and maybe use the experiences of FUSc# as a basis. In “Conclusion”-Section of the 2008-paper on “Using reinforcement learning in chess engines”, it is stated that FUSc# considerably improved performance only after 119 (!) games, and “We estimate that FUSc# requires more than 50.000 training games ...” (p.9) - so in a way, this was a much higher “sample efficiency” (of course with limitations w.r.t the performance/chess playing strength, which peaked only at about 2000 ELO), but it could serve as an interesting starting point.

5.1.4 Concrete Implementation of FUSc#-Zero and testing with lc0

Steps to be done:

- Get lc0 running on a (reasonably capable) machine, s.t. it can serve as a sparrings-partner to “Zero-FUSc#”. Do you happen to know anyone who has experimented with lc0
- Get the FUSc#-code running again, find out what the last “well-tested” version was and verify that it plays reasonably and that all things work as they should (e.g. the bitboard-structures that could be used as the basis for a DSL).
- Develop a concrete setup s.t. our engine can play against Lc0 and learn from it.
- Create the “DSL based on bitboards” - check if that can that be done “step by step”, e.g. “piece by piece” (e.g. starting with knights or rooks), or if it is necessary/useful to first develop an elaborated “DSL for all pieces/situations”, and only then start to implement things.

5.2 The “other Alphas”

We review the application of the ideas developed in AlphaZero in other domains, , i.e. the “other Alphas” (all created by DeepMind) like AlphaFold [19], AlphaTensor [18]and AlphaProof. [20].

5.2.1 AlphaFold (1, 2 and 3)

AlphaFold [19] had spectacular success applying the ideas of AlphaZero to predictions of protein structure. While AlphaFold 1 originated from 2018 and the improved AlphaFold arrived in 2020, the most recent AlphaFold 3 was announced in May 2024. It can predict the structure of complexes created by proteins with DNA, RNA, various ligands, and ions. Demis Hassabis and John Jumper of Google DeepMind shared one half of the 2024 Nobel Prize in Chemistry, awarded "for protein structure prediction" with AlphaFold (for more details see e.g. [19]).

5.2.2 AlphaTensor

In 2022, Deepmind announced AlphaTensor [18], a “first extension of AlphaZero to mathematics” that unlocks new possibilities for research:

“Algorithms have helped mathematicians perform fundamental operations for thousands of years. During the Islamic Golden Age, Persian mathematician Muhammad ibn Musa al-Khwarizmi designed new algorithms to solve linear and quadratic equations. In fact, al-Khwarizmi’s name, translated into Latin as Algoritmi, led to the term algorithm. But, despite the familiarity with algorithms today – used throughout society from classroom algebra to cutting edge scientific research – the process of discovering new algorithms is incredibly difficult, and an example of the amazing reasoning abilities of the human mind.

In our paper, published today in Nature, we introduce AlphaTensor, the first artificial intelligence (AI) system for discovering novel, efficient, and provably correct algorithms for fundamental tasks such as matrix multiplication. This sheds light on a 50-year-old open question in mathematics about finding the fastest way to multiply two matrices.” (from [18])

5.2.3 AlphaProof and AlphaGeometry

AlphaProof and AlphaGeometry2 [20] solved four out of six problems from the 2024 International Mathematical Olympiad (IMO), achieving the same level as a silver medalist in the competition. Here is a short description of both systems from [20]:

“AlphaProof is a system that trains itself to prove mathematical statements in the formal language Lean. It couples a pre-trained language model with the AlphaZero reinforcement learning algorithm (...).

AlphaGeometry 2 is an improved version of AlphaGeometry. It’s a neuro-symbolic hybrid system in which the language model was based on Gemini and trained from scratch on an order of magnitude more synthetic data than its predecessor. This helped the model tackle much more challenging geometry problems, including problems about movements of objects and equations of angles, ratio or distances.”

5.3 Outlook and Discussion - RL for Ecological Economic Planning

As an outlook, we discuss future research and the potential to use AI methods for economic planning, e.g. referring to [16]. In the following, we propose a research project in that direction that could be called “Critical Mathematical Economics and Progressive Computer Science for Ecological Economic Planning”, extending the ideas developed in [21].

5.3.1 The Hype around “AI” and the Strategic Triangle

Since a few years, there is a hype around „Artificial Intelligence“ (AI), and the amount of digital data about products that is available increases steadily, including ecological data e.g. for so-called “lifecycle assessment”. We propose to have a closer look on the role that digital product data and AI (in a broad definition, see below) can play for democratic economic planning. One focus lies naturally on ecological questions, such as those arising in order to „close the loops“ of material flows and achieving a „circular economy“, while also the role of care work and “male role models” is very important and should be considered from the start, as also discussed in the “Outlook”-Section of [21]. For the transition to a post-capitalist economic system and the role AI can play in it, we propose to map three different strategic aspects in the corners of a „strategic triangle“, namely „protest against how capitalism uses AI“, „mitigation of the worst consequences of capitalist AI“ and „use the potential of AI for the transition to a post-capitalist economy“. For the later, we elaborate how the complexity of coordinating production requires to use the latest available technologies. Given the current attention that AI receives (for a mix of right and wrong reasons), we propose to use this hype in order to gain space in society for debates about democratic economic planning.

5.3.2 Circular Economy and AI

In the EU, a “Circular economy Action Plan” was adopted, and one central part of it is to improve the availability of digital product data. The so-called “EU digital product passport” is designed to provide information about each product’s origin, materials, environmental impact, and disposal recommendations. In addition, there are a number of further EU initiatives like “Gaia-X” that intends to enable trusted decentralised digital ecosystems or the “AI-Act”, regulating AI on a European Level. Although of course all of this is currently embedded into capitalist economic structures, the data infrastructure and technology that will be created in the coming years in the EU can arguably play an important role when designing a post-capitalist economy. The following three strategies can be employed:

- a) „protest against how capitalism uses AI to increase profit“

Under capitalism, the driver for introducing AI is increasing profit, and this has often disastrous consequences for the environment (among others, e.g. surveillance). Power consumption and resource usage will increase dramatically to fuel the AI boom. Massive protest is necessary, which is already articulated in civil society and many progressive organisations.

b) „mitigation of the worst consequences of capitalist AI by proposing concrete alternatives/regulation“

Although maybe a (small) first step in the right direction, the EU regulation of both AI and the transition towards a circular economy is far from enough. Proposing concrete improvements of this regulation is necessary (“reform proposals”), although far-reaching regulation that massively limits profits is difficult to achieve in capitalism.

c) „use the potential of AI and digital product data for the transition to a post-capitalist economy“.

5.3.3 The The Problem With AI Is the Problem With Capitalism

The “third corner of the triangle” is absolutely essential: Only in combination with the fight for a post-capitalist economy, the “protest” and “reform” of AI and digital product data will be part of a promising strategy.. Fighting for such a “fundamental change” is essential to complement the necessary protest on how AI is used currently under capitalism. Arguably AI and other “state of the art”-technologies from computer science are an important pillar in order to construct a post-capitalist economy that works “in the real world”. From this perspective it does not make sense to see “AI” mostly as “the problem”, it depends how it is used, and it is even essential for the “solution”.

Put in a nutshell, “The Problem With AI Is the Problem With Capitalism”, which was the title of a recent article in Jacobin [15]. It states in my view correctly that “most of the problems AI could cause really boil down to problems of the way power and wealth are apportioned in our existing society.” To extend these ideas, we will have a closer look to what “Artificial Intelligence” actually means.

5.3.4 Definitions of AI, Hegemony and Post-Capitalism

The current hype of AI was fuelled by the introduction of large language models (“LLMs”) like ChatGPT, and nowadays “AI” and “LLMs” are often used interchangeably. However, for our purpose, AI can and should be defined much more broadly: A classic definition by Marvin Minsky from the 1960s defined AI as “the science of making machines do things that would require intelligence if done by humans”, and in a recent article on artificial intelligence and modern planned economies [17], Spyros Samothrakis noted that historic debates and proposals on computerised economic planning (CEP) “have been inspired by and/or have touched upon other numerate disciplines like cybernetics, game theory, optimisation, complex systems, machine learning, and statistics. Arguably, the applied cutting edge of the fields that have partially contributed to the debate is currently being studied under the broad umbrella of artificial intelligence (AI).”

Given the obvious complexity of organizing let’s say the economy of the EU (ca. 450 million inhabitants), it is necessary to do fundamental research on how digital product data and AI can be used for economic planning. Even if 99% of the (about 600 million) products listed on amazon are useless and won’t be produced in a post-capitalist economy, we are definitively looking at millions of products (and their pre-products) that more than half a trillion Europeans (if we look beyond the EU member states) would probably like to keep in some form even in a post-capitalist economy. Again quoting from the article by S. Samothrakis, “one of the major issues modern work on CEP suffers from is that it tries to link itself to outdated (but excellent) ideas from the 1960s”, so an “update” of technological methods is necessary.

If “it is easier to imagine the end of the world than the end of capitalism”, as a famous quote says, maybe the hype on AI can contribute to a hegemonic view that “technologically, a post-capitalist economy is possible”, which could prove very helpful for political fight to transcend capitalism. We propose to use this dynamics for the purpose of popularising democratic and ecological economic planning for a post-capitalist circular economy.

6 Appendix

6.1 Rotated bitboards in detail

This section should illustrate how the chess-board looks like in the “rotated bitboards”. After the “normal” bitboard, the flipped bitboard (rotated to the left by 90°) as well as the two bitboards needed for move generation in direction of the two diagonals (the “a1h8” and the “a8h1”-bitboard) will be shown. For more information, please have a look at [2].

6.1.1 The normal bitboard

This is the “normal” bitboard, as used in many places in the program:

```
a8 b8 c8 d8 e8 f8 g8 h8
a7 b7 c7 d7 e7 f7 g7 h7
a6 b6 c6 d6 e6 f6 g6 h6
a5 b5 c5 d5 e5 f5 g5 h5
a4 b4 c4 d4 e4 f4 g4 h4
a3 b3 c3 d3 e3 f3 g3 h3
a2 b2 c2 d2 e2 f2 g2 h2
a1 b1 c1 d1 e1 f1 g1 h1
```

6.1.2 The flipped bitboard (“l90”)

The “flipped” bitboard is stored in “board.occ_l90” and used to generate moves along files for rooks and queens:

```
a8 a7 a6 a5 a4 a3 a2 a1
b8 b7 b6 b5 b4 b3 b2 b1
c8 c7 c6 c5 c4 c3 c2 c1
d8 d7 d6 d5 d4 d3 d2 d1
e8 e7 e6 e5 e4 e3 e2 e1
f8 f7 f6 f5 f4 f3 f2 f1
g8 g7 g6 g5 g4 g3 g2 g1
h8 h7 h6 h5 h4 h3 h2 h1
```

6.1.3 The a1h8 bitboard

The a1h8 bitboard is stored in “board.occ_a1h8” and used to generate diagonal moves in direction of the “a1h8-diagonal” for bishops and queens. Note that in this “compressed” representation, it must be assured that a piece can not “jump over the edge” of the chessboard and re-enter it on the other side because this would allow illegal moves. This must be taken care of during the initialisation of the bitboards, where all the legal diagonal moves in the direction of the a1h8-diagonal are encoded into the “a1h8_moves”-array. The edge of the board is marked with the symbol “|” in the following figure:

```
a8 | b1 c2 d3 e4 f5 g6 h7
a7 b8 | c1 d2 e3 f4 g5 h6
a6 b7 c8 | d1 e2 f3 g4 h5
a5 b6 c7 d8 | e1 f2 g3 h4
```

```

a4 b5 c6 d7 e8 | f1 g2 h3
a3 b4 c5 d6 e7 f8 | g1 h2
a2 b3 c4 d5 e6 f7 g8 | h1
a1 b2 c3 d4 e5 f6 g7 h8

```

6.1.4 The a8h1 bitboard

The a1h8 bitboard is stored in “board.occ_a1h8” and used to generate diagonal moves in direction of the “a1h8-diagonal” for bishops and queens. The edge of the board is again marked with the symbol “|” in the following figure (see above):

```

a8 b7 c6 d5 e4 f3 g2 h1
a7 b6 c5 d4 e3 f2 g1 | h8
a6 b5 c4 d3 e2 f1 | g8 h7
a5 b4 c3 d2 e1 | f8 g7 h6
a4 b3 c2 d1 | e8 f7 g6 h5
a3 b2 c1 | d8 e7 f6 g5 h4
a2 b1 | c8 d7 e6 f5 g4 h3
a1 | b8 c7 d6 e5 f4 g3 h2

```

6.2 “perft”-output for FUSc# and Crafty

As a prove for the correctness of the FUSc# move generator, the position described in section 3.2 are loaded into FUSc# and Crafty. Then the “perft”-command is executed. All the computed numbers turn out to be correct for both FUSc# and Crafty! For reference, you find the original output in the following two sections.

6.2.1 FUSc#

In FUSc#, the “perft”-command is implemented as “debug counodes”, in order to be consistent with the other debugging commands (that can be obtained by entering “debug help” at the command prompt). Here is the output up to depth 5:

```

debug countnodes 1
Minmax-Suche bis Tiefe 1
Besuchte Knoten: 20
debug countnodes 2
Minmax-Suche bis Tiefe 2
Besuchte Knoten: 400
debug countnodes 3
Minmax-Suche bis Tiefe 3
Besuchte Knoten: 8902
debug countnodes 4
Minmax-Suche bis Tiefe 4
Besuchte Knoten: 197281
debug countnodes 5
Minmax-Suche bis Tiefe 5
Besuchte Knoten: 4865609

```

Now the middlegame-position:

```

position fen r3k2r/p1ppqpb1/bn2pnp1/3PN3/1p2P3/2N2Q1p/PPPBPPPP/R3K2R w KQkq -
debug countnodes 1

```

```

Minmax-Suche bis Tiefe 1
Besuchte Knoten: 48
debug countnodes 2
Minmax-Suche bis Tiefe 2
Besuchte Knoten: 2039
debug countnodes 3
Minmax-Suche bis Tiefe 3
Besuchte Knoten: 97862
debug countnodes 4
Minmax-Suche bis Tiefe 4
Besuchte Knoten: 4085603

```

And now the endgame-position:

```

position fen 8/2p5/3p4/KP5r/1R3p1k/8/4P1P1/8 w - -
debug countnodes 1
Minmax-Suche bis Tiefe 1
Besuchte Knoten: 14
debug countnodes 2
Minmax-Suche bis Tiefe 2
Besuchte Knoten: 191
debug countnodes 3
Minmax-Suche bis Tiefe 3
Besuchte Knoten: 2812
debug countnodes 4
Minmax-Suche bis Tiefe 4
Besuchte Knoten: 43238
debug countnodes 5
Minmax-Suche bis Tiefe 5
Besuchte Knoten: 674624
debug countnodes 6
Minmax-Suche bis Tiefe 6
Besuchte Knoten: 11030083

```

6.2.2 Crafty

Here is the output of Crafty in the start-position:

```

White(1): perft 1
total moves=20 time=0.00
White(1): perft 2
total moves=400 time=0.00
White(1): perft 3
total moves=8902 time=0.00
White(1): perft 4
total moves=197281 time=0.26
White(1): perft 5
total moves=4865609 time=6.66
White(1): perft 6
total moves=119060324 time=283.79

```

Now the middlegame-position:

White(1): setboard r3k2r/p1ppqpb1/bn2pnp1/3PN3/1p2P3/2N2Q1p/PPPBPPPP/R3K2R w
KQkq -

White(1): perft 1
total moves=48 time=0.00
White(1): perft 2
total moves=2039 time=0.00
White(1): perft 3
total moves=97862 time=0.10
White(1): perft 4
total moves=4085603 time=4.52

And now the endgame-position:

White(1): setboard 8/2p5/3p4/KP5r/1R3p1k/8/4P1P1/8 w - -
White(1): perft 1
total moves=14 time=0.00
White(1): perft 2
total moves=191 time=0.00
White(1): perft 3
total moves=2812 time=0.00
White(1): perft 4
total moves=43238 time=0.04
White(1): perft 5
total moves=674624 time=0.86
White(1): perft 6
total moves=11030083 time=22.34

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