An intelligent system for analyzing the dependence of a chess player's rating on inaccurate moves

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Abstract
This paper presents an intelligent system we developed to analyze the relationship between chess players' ratings and the mistakes they make during the game. To achieve the goal of this study, we used various techniques and algorithms of machine learning. With the help of big data tools, we analyzed thousands of chess games and received a large number of statistical insights about them. We created an algorithm that processes the obtained data and returns the results of the computations. Using different tools of information technologies, based on this algorithm, it will be possible to build numerous frameworks, such as human-like bots, in further development.

Keywords
chess, ACPL, Elo rating, correlation, FIDE, chess analysis, move evaluation, chess engines, rating prediction, machine learning.

1. Introduction

Information technologies play an important role in our lives. It brought people closer to collaborate and change this world for the better. With more and more new methods being created, it has transformed many industries, making processes more efficient. Now, it can help us to build tools and frameworks for collecting, processing, and analyzing huge datasets. To achieve the goal of our research, we merged different techniques of working with data to create an algorithm that accurately spots even the slightest mistakes made by chess players.

In chess, the main value that represents the strength of the player is their rating. But the rating depends not on the decisions that are made on the board but on the results of the games. That is why we need to build a system that captures players' performance and their actual moves for a deeper analysis of the connection between these two.

This exploration is intended to find out how strongly the rating correlates with different types of errors, such as blunders, mistakes, and inaccuracies that players make at different levels, from average to top grandmasters. The main tools that can help us achieve such a goal are Python, JupyterLab, ChessBase, and Stockfish.

We chose the Python programming language because it has many useful libraries for working with big data, data analysis, and machine learning. For our research, we used mostly Pandas, NumPy, and Seaborn. It is also convenient to work with chess data and manipulate it because it can work not

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only with CSV (Comma-Separated Values) files but also with PGN (Portable Game Notation), which is crucial for our research.

JupyterLab is a practical choice as a development environment for data science and scientific computing. It is a useful browser-based tool that allows you to interactively write the code, markdown commentaries, and create well-structured documents in one place. It is also handy to see the results of each cell immediately. An integration of data analysis with visualization makes it a good option for data scientists and researchers.

ChessBase is a powerful database that stores millions of games from beginners to top grandmasters, from the 15th century to the most recent ones. While primarily designed for storing the games, it also provides many additional features that help to analyze games, prepare for a tournament, study openings and endgames, implement engine analysis, create personal game databases, etc.

Stockfish is an engine that combines traditional algorithms with neural networks, making it the strongest among the others. It has a huge community of enthusiasts who help to make it stronger in many different ways, such as volunteering a computer's processing power or writing the code to make an evaluation function more accurate. Because it is being updated regularly and is an open-source project, it is a great tool for evaluating games precisely.

Combining all the tools, we were able to build an algorithm that fetches all the games, analyzes all the positions, and gives us statistical insights about players' decisions that we used for our research.

This study highlights the importance of information technologies in creating such software, where we were able to conduct this research. With the help of big data, machine learning, and statistical analysis, an intelligent system for analyzing chess games was built. Our approach can also be used in some other board games.

2. Analysis of literature and problem statement

One of the first researchers who tried to compare the quality of the games of the players was Guid and Bratko in 2006 [1]. Their research aimed to answer the question: 'Who is the most accurate world champion in the history of chess?' The question was complicated because the champions were from different eras, and most of them didn't play each other over the board. Furthermore, they had different playing styles. For that purpose, they analyzed all games played in World Championship matches using one of the strongest engines at that time – Crafty. They slightly modified the engine for their research, adding more depth for tactically sharp positions. Apart from using ACPL as the main value to rank the players, they also added the complexity of a position as a weighting factor to make the results more accurate.

The other attempt to rate the player's strength by the quality of moves played, rather than by the results of the games, was made by Regan and Haworth in 2011 [2]. When one of the players is far ahead in the evaluation, they can make suboptimal moves to safely converge their advantage. Also, the player who is behind can take much more risk, attempting to save a game. To penalize such moves less, the authors developed their formulas with intrinsic skill parameters for sensitivity and consistency, tested on large sets of games. One of the main points of the research was to find out whether a player with a certain current rating represents the same strength as one with the same rating several decades ago. For that purpose, they analyzed 150,000 games with the strongest engine at that time – Rybka 3.

More recent research in the field was done by Romero, Parra, Cuenca, and Lloret in 2019 [3]. They did a similar job to the first one but with a more recent and a lot stronger engine, Stockfish 10, and with much more powerful computers. It helped them to get more accurate results and find some new insights. They also compared their findings with the Guid-Bratko study, which showed similar results. However, the research of 2006 gave a bit higher average error because Crafty overestimated blunders and worked at a much lower depth. The authors added several new values to the ACPL, such as the percentage of best moves, the average of blunders, etc. Also, they added world championship runners-up to finalize their rankings.

The focus of the study conducted by McIlroy-Young, Sen, Kleinberg, and Anderson in 2020 was on modeling a human-like neural network [4]. There was always a possibility to weaken existing engines to make them play less precisely at a particular level before. It can be achieved by choosing suboptimal moves or by limiting the depth of a search tree. But the issue with that is they tend to choose the moves that a human player is unlikely to opt for. The authors aimed to build a bridge between human and artificial intelligence by introducing Maia – a customized version of the Alpha-Zero engine to achieve maximum accuracy in predicting human decisions at a specific level. They trained it on 12 million online games played on the free open-source chess platform Lichess. The games were played by players of all skill levels, from amateurs to the current world champion, Gukesh Dommaraju, and with several different time controls: HyperBullet, Bullet, Blitz, Rapid, and Classical.

The same team of researchers, together with Wang, concluded their exploration in 2022, aiming to characterize an individual human behavior of a chess player [5]. Instead of characterizing players by skill, rating, or performance, they intended the artificial intelligence systems to interpret humans as individuals and understand their strengths, weaknesses, and style. In addition to the already built model that could mimic a human player given its rating, which they did in previous research, they also developed a system that can capture the style of a specific player. They trained it on 63.7 million games played by 16,181 players. The results they achieved are remarkable: their model could correctly identify a player out of thousands of candidate players with 98% accuracy given only 100 games.

In our research, a similar approach to [1-3] was proposed to analyze errors of chess players in their games and to study their impact on the rating. We analyzed thousands of games played at different levels throughout two years. Apart from average centipawn loss, we also added several statistical insights, such as blunder, mistake, inaccuracy, etc. to estimate the value of errors and understand better what types of errors a player tends to make. Based on the results we received, in further studies, we could form more realistic images for the behavioral models of chess players. The obtained models can also be used to train artificial intelligence to increase accuracy in such studies, as well as to create a chess bot that can capture the human decision-making process and mimic the behavior of chess players, as in [4-5].

3. Methodology

The Elo rating system was originally invented by Arpad Emmerich Elo to predict chess game outcomes and is based on the results of the games. It was adopted by FIDE in 1970 and has been used till now. It is defined by the following formula [6-12]:

$$R_n = R_o + K(W - W_e)$$

where R_n is the new rating of the player after the event, R_o is the rating prior to the event, W is the number of wins, W_e is the expected number of wins, and K is a scaling factor that is higher for young and lower rated players.

Average centipawn loss is a measure of how accurately a player plays their moves during the game. It is defined as the difference between the best move according to the engine and an actual move that has been played. Then the sum of these differences divided by the number of moves in the game makes ACPL value [13-22]:

$$ACPL = \frac{1}{n}\sum_{i=1}^{n}|E_i - M_i|$$

where n is the number of moves made by the player in the game, E_i is an engine evaluation of the position after the optimal move, and M_i is an engine evaluation after the player's actual move.

Correlation is a statistical relationship between two variables. The Pearson correlation coefficient, often denoted as r, measures the strength and direction of the linear relationship between two continuous variables. It ranges from -1 to 1 and is defined by the following formula [23-27]:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

where n is the number of pairs of scores, x and y are the two variables being compared.

The games used for this study were collected from ChessBase 17. The code for fetching and processing the games was written in Python 3.12. We analyzed 8000 games using Stockfish 16, at depth 20 with Intel Core i7, at 2.5 GHz. There are 80 players here divided by 8 rating classes with their standard Elo rating on January 2024 [28]. For class A, we decided to have 7 players from Candidates 2024 Tournament (except Nijat Abasov who has the lower rating) and the 3 strongest players who didn't participate in the tournament. For all the other classes, we chose players that did not have big rating fluctuations during the last 2 years and represent all genders, all age groups and as many nationalities as possible. We took exactly 100 games with a standard time control for each player played during 2022 and 2023, excluding short games that lasted less than 15 moves. For several players who did not play enough games, we took games from 2021. The engine starts working after the end of the opening and stops after the 60th move to prevent the artificial lowering of ACPL [29-33].

4. Results

In the first two figures, we have a scatter plot and a box plot with the ACPL value of all games played by all players that we have analyzed. The players are sorted by their mean ACPL in descending order. According to our results, Wesley So has the lowest mean ACPL, meaning that he is the most accurate player. The classes in the plots represent the rating group of the player, such as class H stands for 2000-2099 Elo, class G stands for 2100-2199 and so on.

In Figure 1 we can see the ACPL of all the games we analyzed. There are only 4 games out of 8000 that ended with more than a 100 average centipawn loss. From a human perspective, it means that a player loses a pawn every move. But all these games were played by players under a 2200 rating, so it is quite normal for them to have one such game out of 100. If we take a look at stronger players, the most-catching eye observation is Nijat Abasov's pink dot with a very high for grandmaster ACPL value – 95. It was a game against Nikolas Theodorou in Saint Louis in 2022. Nijat played a rare move in Tarrasch Defence and the whole game was a total mess. Abasov is a very dangerous player who prefers to choose dubious moves and rare lines in the openings. And if we look at super grandmasters, we can find Magnus Carlsen's game with an ACPL value of 57, which is very strange for him. It was one of the most controversial games in chess history he played in the Sinquefield Cup in 2022 against Hans Niemann. After his loss with white pieces, Magnus immediately left the tournament for the first time in his career. Many interpreted his withdrawal as tacitly accusing Niemann of cheating.

According to our results, Wesley So has the lowest mean. The highest-rated player, Magnus Carlsen, has the second-lowest mean. And Nihal Sarin has third.

In Figure 2 we can see a box plot of the same games which gives us more statistical insights about the games. The horizontal lines that lie outside the box show the data minimum and maximum, excluding outliers. The lines of the box mark the first and third quartile of the data, meaning that half of the data lies inside the box. The line inside the box shows the median. And the dots above are outliers. According to our results, Wesley So also has the lowest median. The previous World Champion, Ding Liren, has the second-lowest median. And Fabiano Caruana has third.

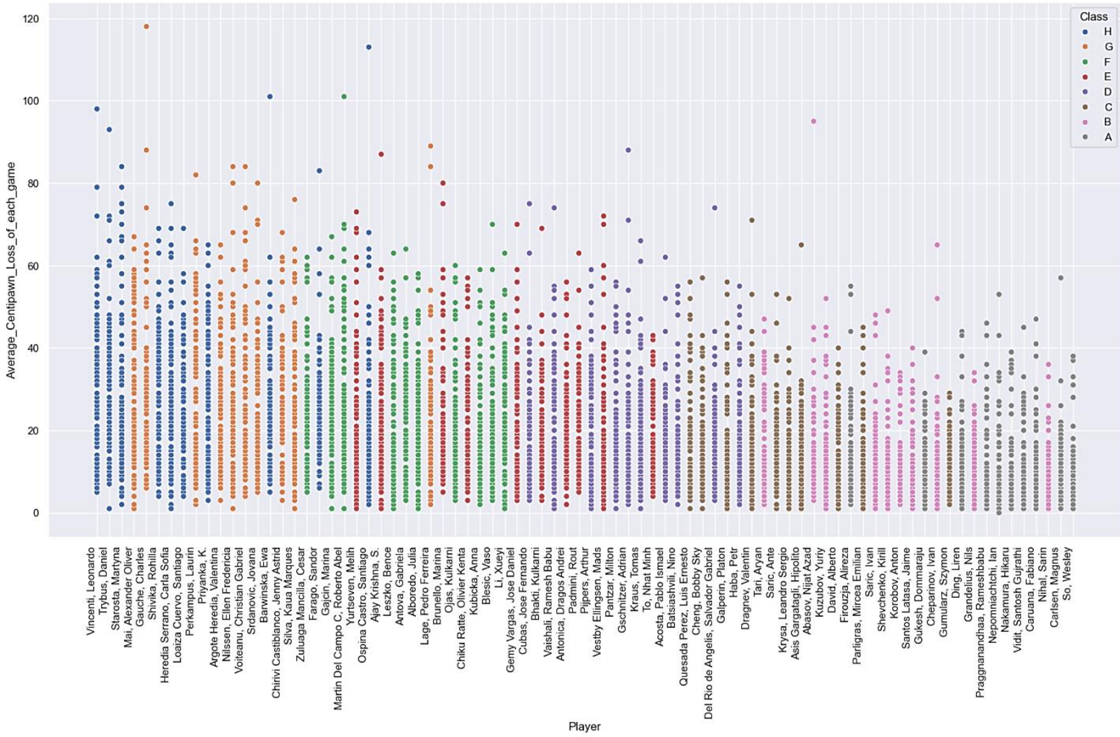

Figure 1. Scatter plot of each player's ACPL in every game.

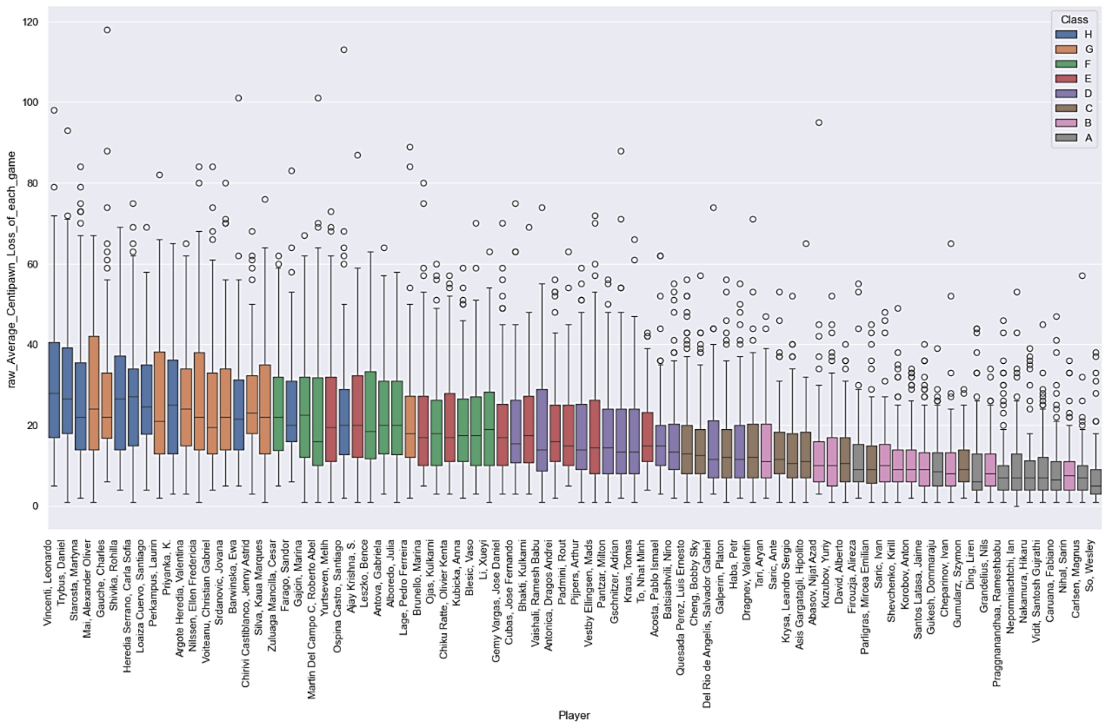

Figure 2. Box plot of each player's ACPL in every game.

Apart from using ACPL as the main value of the analysis, we decided to add several insights about the quality of the moves. In an equal position, for example, blunder means a big mistake and the position becomes lost. Mistake means that the position becomes worse but remains playable. Inaccuracy slightly worsens the position. Ok means that the move was good, but there was a better one. Missed win means that the player did not find a winning move.

According to our analysis, Wesley So is the most accurate player out of the players we analyzed. Wesley is known for his solid playing style. He takes very few risks but capitalizes on his opponents' mistakes. Many chess experts call him one of the best at pure calculation. The second accurate player is Magnus Carlsen. Magnus is the highest-rated player since 2011 and the World Chess Champion 2013-2023. Many people call him the best player in chess history. The third accurate player is a young rising Indian star, Nihal Sarin. All the other players with ACPL values lower than 15 can be seen in Figure 3.

Player	Class	Rating	blunder	mistake	innacuracy	ok	missed_win	mean_Average_Centipawn_Loss
So, Wesley	A	2757	0.09	0.42	1.70	15.14	0.04	7.48
Carlsen, Magnus	A	2830	0.08	0.49	1.96	16.61	0.06	8.54
Nihal, Sarin	B	2693	0.03	0.63	1.99	13.92	0.05	8.83
Caruana, Fabiano	A	2804	0.09	0.63	2.35	16.66	0.07	9.16
Vidit, Santosh Gujrathi	A	2742	0.05	0.78	2.10	14.86	0.06	9.45
Nakamura, Hikaru	A	2788	0.10	0.69	2.09	15.85	0.02	9.60
Nepomniachtchi, Ian	A	2769	0.10	0.71	2.25	15.05	0.02	9.61
Praggnanandhaa, Rameshbabu	A	2743	0.08	0.87	2.28	16.40	0.05	9.73
Grandelius, Nils	B	2673	0.06	0.67	2.16	14.36	0.10	9.83
Ding, Liren	A	2780	0.05	0.77	2.30	15.08	0.07	9.84
Gumularz, Szymon	C	2591	0.05	0.85	2.37	13.24	0.02	10.76
Cheparinov, Ivan	B	2638	0.06	0.79	2.36	15.02	0.11	10.76
Gukesh, Dommaraju	A	2725	0.12	0.90	2.72	13.99	0.07	10.80
Santos Latasa, Jaime	B	2615	0.13	0.72	2.28	14.88	0.07	10.98
Korobov, Anton	B	2663	0.09	0.83	2.59	14.00	0.05	11.30
Shevchenko, Kirill	B	2651	0.12	1.00	2.58	14.57	0.06	11.54
Saric, Ivan	B	2689	0.08	1.00	2.92	14.57	0.11	11.78
Parligras, Mircea Emilian	C	2539	0.10	0.93	2.60	14.76	0.08	11.81
Firouzja, Alireza	A	2759	0.08	1.37	2.92	16.19	0.06	12.52
David, Alberto	C	2525	0.13	1.01	2.53	12.96	0.10	12.54
Kuzubov, Yuriy	B	2605	0.14	1.00	2.40	13.72	0.02	12.78
Abasov, Nijat Azad	B	2641	0.15	1.04	2.23	13.65	0.05	12.96
Asis Gargatagli, Hipolito	C	2511	0.06	1.01	2.24	12.99	0.17	13.73
Krysa, Leandro Sergio	C	2541	0.13	1.02	2.62	13.20	0.13	13.75
Saric, Ante	C	2508	0.13	0.86	2.44	12.38	0.10	14.04
Tari, Aryan	B	2623	0.17	1.28	2.90	14.39	0.11	14.56
Dragnev, Valentin	C	2582	0.27	1.21	2.91	15.24	0.11	14.84
Haba, Petr	D	2437	0.12	1.23	2.57	12.37	0.13	14.99

Figure 3. Players with ACPL value lower than 15.

The value in the columns means how many times the player makes such type of mistake in one game. For example, Nihal Sarin made 3 blunders (big mistakes) in his 100 games, so on average he makes 0.03 blunders in one game. It is the lowest value in this column, so we can say that Nihal is the best at avoiding blunders. Wesley So is the best at making the least mistakes and inaccuracies.

Figure 4 shows the relationship between the Elo Rating and the mean ACPL of all players. There are no large residuals, as we can see. Of course, some players play better than the others in their rating class. And some players play worse. However, the distance of each player to the regression line is relatively small.

The bigger distances can be seen in the lower rating classes. It can be explained that the moves of weaker players are less consistent than the moves of stronger players. So that they are less predictable and can alternate good play with bad. Saying that we can make an assumption that the lower rating class, the bigger ACPL range.

If we take a look at super grandmasters, Class A, we can see Wesley So, who is a bit lower, and Alireza Firouzja who is much higher than the others.

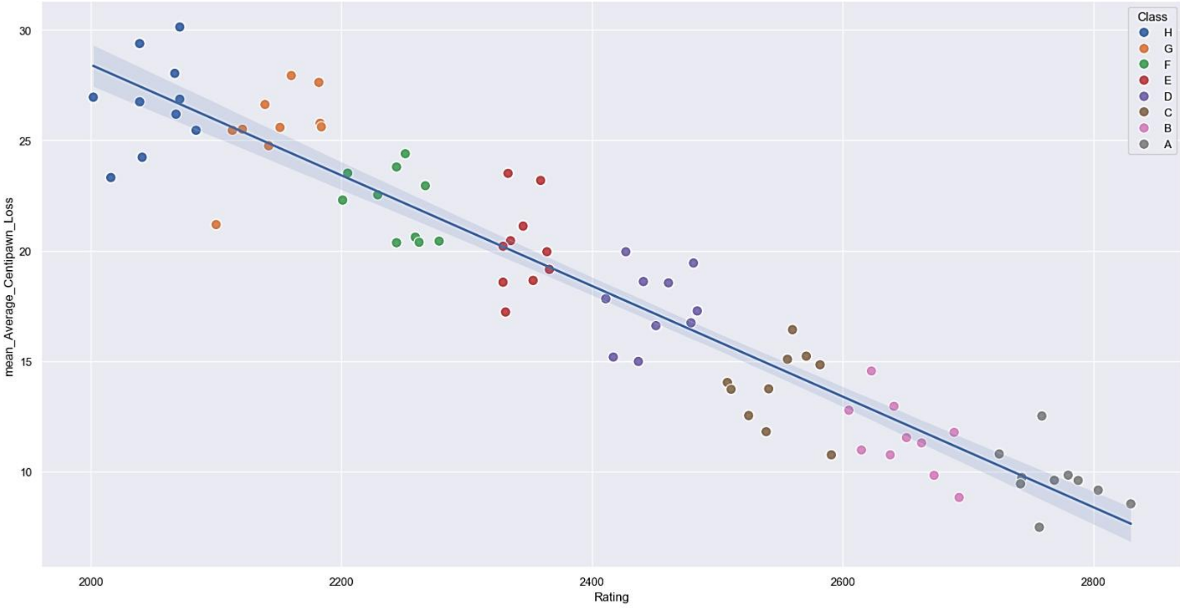

Figure 4. Scatter plot of player’s mean ACPL in all games with a regression line.

A correlation heatmap of all numerical features is pictured in Figure 5. The value with a minus sign means a negative correlation, so it can be interpreted that the higher the rating, the lower the ACPL. As we can see, Rating strongly correlates not only with ACPL but also with all types of mistakes made by the player. However, the correlation of -0.95 with ACPL seems very strong.

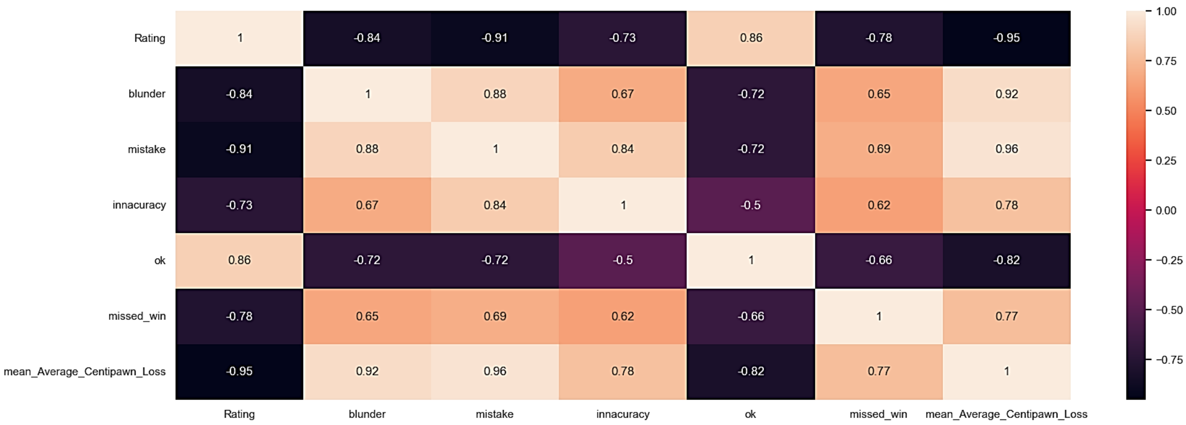

Figure 5. Correlation heatmap.

According to our findings, Wesley So is the most precise player. The highest-rated player and the former champion Magnus Carlsen is second. Nihal Sarin, who has not even reached a 2700 Elo rating yet, is third. Also, Wesley made the least mistakes and inaccuracies, while Nihal made the least blunders (big mistakes).

5. Discussion

The findings of this study clearly show a strong correlation not only between the rating of the player and the average centipawn loss but also between the rating and the types of mistakes made by the player. The exact ACPL can vary greatly depending on the level of play and the players involved. Generally, stronger players tend to make fewer mistakes. So, there definitely is a correlation between Average Centipawn Loss and Elo Rating.

But many factors that can affect a player's ACPL apart from their level, such as a style of play, the openings they choose, the types of positions they achieve, the strength of the opponent, psychological factors etc.

There are several outliers in our results. Most of them we can find in lower-rated classes. But if we talk about super grandmasters, we can point out a grandmaster, Alireza Firouzja, who has a higher ACPL than the players from his rating group. One explanation for this could be that he is the type of player who prefers an aggressive style of play, which leads to complicated positions where it is very hard to make precise moves.

This study was limited by the number of players and the depth of analysis. Our first intention was to compare all players starting from a 1000 Elo rating. But there were two main problems. The first one is that we could not find 100 games for the last 2 years of such players.

And the second one is that FIDE decided to change the rating minimum from 1000 to 1400 Elo. It affected all the players below 2000 Elo who got an increase in their rating by the following formula:

$$R_n = R_o + 0.4(2000 - R_o)$$

where R_n is the new rating of the player, and R_o is the old rating.

New rating regulations came into force from March 2024. Having that in mind, we decided to compare players starting from 2000 Elo.

The depth of the engine is another important question. The higher the depth, the more accurate the evaluation. We tried higher depths, up to 25, with several players, but the results were similar to depth 20. Considering analyzing 8000 games, increasing depth would lead to much more computing time. So, we think our choice of depth 20 is quite reasonable.

Furthermore, the next question is where to start and where to stop the engine. We started it after the end of the book because players tend to play the theory which is studied very well. And stopped it after move 60, because many long games end in a draw and don't change the ACPL much.

Many other features could be added in future work, such as the style of play or the complexity of the position. Moreover, there is also a question about the sensibility of using ACPL as a precision factor. The biggest chess online servers also added Accuracy to make it clearer and more understandable for players.

6. Conclusion

In this paper, we compared the quality of play of a wide range of players. It was proposed to use average centipawn loss as a main value for intellectual analysis of chess players' mistakes, which improved the accuracy of the analysis results.

Also, we added move classifications such as blunder, mistake, inaccuracy, etc. to show more statistical insights.

A high correlation was found not only between Elo rating and ACPL but also between Elo rating and different types of player errors. The correlation between Elo and ACPL is -0.95.

In future work, some other features, such as playing style or position complexity, will be added to more accurately model the behavior of real players for use in creating human-like chess bots.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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