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PREDICTING GIVE-UP DECISIONS BASED ON OBJECTIVE INDICATORS

Holubets T., Medykovskyy M. Predicting give-up decisions based on objective indicators. Despair and loss of control are critical moments in a person’s state. Despite the importance of such emotions, this issue has not been sufficiently studied. The challenge is that each person is unique, and our behavior depends on a large number of factors. Chess is one of the few domains that allows us to analyze a person’s desire to stop a certain activity. This sport discipline allows players to resign and clearly defines several key factors: the time available for decision-making, the complexity or hopelessness of the position the player is in, and the skill level of the opponents. This work aims to identify the features of admitting defeat by players of different skill levels and under different time constraints, using an LSTM model to predict resignation based on the sequence of moves. This approach allows us to predict the player's decision not only based on the situation at a specific moment, but also taking into account previous steps. While the trained model does not reach high accuracy, it shows the limit of prediction based only on objective factors. The results also demonstrate behavioral differences across skill levels: professional players resign about 15 percentage points more often than beginners, but they usually make about five more moves before making this final decision. The study is limited to considering events within only one game and does not take into account the possible influence of the results of previous matches. The general mood and internal state of the person at the time of decision-making are also not taken into account, the prediction is made only on the basis of clearly measured chess parameters.
Keywords: LSTM neural network, chess data analysis, sequence of decisions, behavioral modeling, resignation prediction.

Голубець Т. Р., Медиковський М. О. Прогнозування рішень про відмову на основі об'єктивних показників. Одним із критичних проявів стану людини є відчай і відчуття втрати контролю. Незважаючи на важливість таких емоцій, це питання досліджене недостатньо. Проблема аналізу стану людини полягає в унікальності кожного з нас і тому, що наша поведінка залежить від багатьох факторів. Шахи є однією з небагатьох сфер, що дозволяє проаналізувати бажання людини припинити виконання певної дії. Цей вид спорту передбачає можливість визнати поразку і чітко визначає кілька основних факторів, що можуть впливати: час на прийняття рішення, складність чи безнадійність позиції, в якій знаходиться гравець, та рівень навичок опонентів. Робота має на меті визначити особливості визнання поразки гравцями з різним рівнем майстерності та за різних часових обмежень. Для прогнозування визнання поразки на основі послідовності ходів навчено модель на основі рекурентної нейронної мережі LSTM. Цей підхід дозволяє передбачити рішення гравця не лише на основі обставин у конкретний момент, але й врахувати попередні ходи. Прогнозування на основі лише об’єктивних шахових показників є обмеженим, що підтверджено помірною точністю навченої моделі. Також аналіз показав різницю в поведінці між гравцями з різним рівнем гри: професіонали визнають поразку приблизно на 15 відсоткових пунктів частіше, ніж початківці, але роблять приблизно на 5 ходів більше перед цим фінальним рішенням. Дослідження обмежене врахуванням подій лише в межах однієї партії і потенційний вплив результатів попередніх поєдинків не розглядається. Вплив настрою та внутрішнього стану людини в момент прийняття рішення також не оцінено, прогнозування виконувалося виключно на основі тих шахових параметрів, що чітко вимірюються.
Ключові слова: нейронна мережа LSTM, аналіз шахових даних, послідовність рішень, моделювання поведінки, прогнозування рішення про визнання поразки.

Statement of the scientific problem. Modern automated systems already replace humans in some decision-making tasks or, at least, provide support for a responsible operator. Although the main focus is on improving the system itself, understanding the features of the human decision-making process is essential for effective combination of software and manual work. For example, the significant change in human behavior when we interact with decision support systems, especially systems with AI, was already highlighted by multiple scientists [1-3]. Another direction of possible performance enhancement could be detecting moments when people are no longer ready to continue, lose control, motivation or belief in the ability to solve the problem. The decision to stop an activity or admit defeat is one of the critical forms of human decision-making.

Predicting moments of critical decline in confidence or motivation could prevent possible loss of control during work duties, declining interest during studies or premature withdrawal in competitive activities, like professional sports. The main challenge of human behavior analysis is inconsistency, dependence on personality, mood and inner state. At the same time decisions are not always comparable or objectively measurable.

Although there are many domains in which people could choose to give up, a consistent recording of human decisions is relatively rare. Sports matches stand out in decision documenting, especially the ones that are held online. Special websites or systems save each stage of the contest, for example the moves of chess games. Clear rules, the ability to resign, and the availability of sequential data make chess a good domain for analysis of human behavior. Each match can be described by objective parameters: experience of opponents, time control, result, evaluation of each move and time spent on it. At the same time, a game lasts dozens of moves, which makes it possible to consider not only a single decision and its outcome, but a sequence of them.

The scientific problem lies in the limited understanding of human decision-making processes and in determining the upper limits of prediction accuracy achievable using only measurable and comparable factors. The research is focused on resignations in chess games and this decision is presented not as a random whim, but as a result of changes in position evaluation, mistakes measured through changes in engine evaluation, the complexity of finding the best move and time pressure.

The aim of the study is to formalize the process of resignation decision-making in chess, analyze the influence of objective factors across different groups of players, and train a predictive model for estimating the probability of resignation based on a sequence of moves.

Research analysis. The problem of understanding human decision-making is relevant for the current state of information technologies, especially for decision support systems and research of our collaboration with AI. There are many studies that demonstrate how time pressure, motivation, level of confidence in a system and the way of presentation influence human reaction to the suggestion. At the same time these studies indicate that human behavior cannot be explained only by objective task parameters [1-3].

Chess data is a good domain for analysis of human decisions, because of strict rules and the amount of collected data. In the [4] article data of chess games were used for research on human error. The authors highlighted such factors as skill of the decision-maker, time available to make the decision and difficulty of the situation. One of the main discussions in the study was the choice of objective indicator for description of difficulty of the decision. Anderson et al. [4] chose only positions with limited number of pieces, which has calculated scenarios and could be undoubtedly evaluated. However, Acher et al. [5] used the engine-based approach. They analyzed 270 million unique positions by the Stockfish chess engine with depth 20 [5] . Therefore, previous studies support the use of chess data as a source of human decisions that are recorded, evaluated and compared.

While chess provides a list of decisions the order of them matters as well. Dreżewski and Wątor [6] described chess as sequential data and used LSTM-based models to predict the result of the game. The achieved accuracy close to 69% shows the importance of considering the order of moves. Studies in other domains also show that individual differences in behavior are easier to capture in sequential decision-making data, as each choice is not isolated, but usually is the result of previous actions. Abbaszadeh et al. [7] analyzed the behavior of 1001 participants in a restless three-armed bandit task and showed that individual differences in decision-making become visible through sequential behavior, especially through the tendency to explore new options or exploit already known ones.

The [8] research is focused on reaction to a loss during chess tournaments. It is highlighted that men play less accurately, start with riskier options and more often are ready to leave the tournament, while women usually keep the same level or even improve their performance. The [8] paper demonstrates the use of chess data as a source of failure analysis, although the comparison of genders is described the most. Dilmaghani [9] also showed the difference between male and female reactions to a loss to a specific opponent. This study demonstrates that resignation or agreed draw is a very common outcome of the game and our decisions could be influenced not only by the position of the pieces, but by social and psychological factors, such as competitiveness, overconfidence, risk tolerance or stereotypes.

The mentioned articles show that chess could be used for research of human behavior in general and the nature of resignation in particular. They also support the importance of analyzing moves as a sequence to be able to capture additional patterns. However, the specific problem of predicting resignation based only on objective chess indicators is not sufficiently studied. Since the choice to give up determines the end of the game, the approach of deep recurrent survival analysis can be used. Ren et al. [10] described this method for time-to-event data. The survival analysis allows researchers to model the probability of an event during a certain period of time, so the task can be described as discrete-time hazard problem - predicting resignation within the next K plies in the chess game.

Presentation of the main material and substantiation of the obtained research results. The source of chess games used in this study is Lichess Open Database [11], which contains all games played on the Lichess platform and makes them publicly available. The first step of data preparation is transforming data into a tabular form, because Lichess stores games in Portable Game Notation (PGN) format. Each match is divided into multiple rows, where each row corresponds to one ply - half-move made by one player. For standardization of input sequences only games with 20 to 200 plies were used. Discarding a small portion of the shortest and longest matches allows the model to use at least 20 previous decisions and remove potentially unrepresentative cases.

Each ply is described by player-related, game-related and move-related features that are presented in Table 1.

Table 1. Objective parameters of each ply

Category	Feature	Units of measurement
Experience	ELO rating of white player	rating points
Experience	ELO rating of black player	rating points
Complexity	Change in engine evaluation	centipawns
Complexity	Engine evaluation after the ply	centipawns
Time pressure	Time spent on the ply	seconds
Time pressure	Time left after the ply	seconds
Auxiliary parameter	Current ply index	ply number
Auxiliary parameter	Piece color of the side to move	binary categorical variable

The decision to resign occupies a special place in chess because it is not a separate move, but it determines the end of the game. Because of this each move is also assigned a label indicating whether resignation would occur soon. However, the resignation was not treated as an immediate fact, but was framed as a discrete-time hazard problem. With the aim to use the trained model for estimation of the probability of resignation within the next K=5 plies of the mover, data is labeled in this horizon of 5 plies. This approach creates an indicator of near-future concession and allows us to predict the risk of critical decision based on current situation, not only classify the finished game. After conducting experiments for all values from 1 to 10 for K, the best results were obtained at K=5 - optimal number of plies for hazard framing. It is harder to catch resignation early enough with smaller K, but the label is too broad with bigger K.

The tendency to give up during a match varies from player to player and depends on the circumstances of the day or mood. Despite inability to consider all factors, it is possible to analyse dependence on multiple measurable parameters, for example skill level. Three categories of players are chosen using their ELO rating at the time of the game: beginner, amateur and professional. Table 2 shows that beginners resign the least often across the three groups and the most experienced players are the most likely to admit defeat.

Table 2. Resignation Statistics Across ELO Skill Groups

Skill level	ELO range	Resignation rate, %	Average moves before resignation	Resignations % on low time (< 10 seconds)
Beginner	0-1399	35.03	27.63	1.91
Amateur	1400-1999	45.88	30.81	3.08
Pro	2000+	50.22	32.87	8.26

The comparison also demonstrates the impact of time pressure - time pressure appears to have a weaker effect on players with low ELO ratings, but has a stronger influence on professionals. Another metric of resignation choice is an average number of moves before making a decision to admit defeat - game duration is growing with the increase of average experience level of opponents as shown in Table 2 and Figure 1.

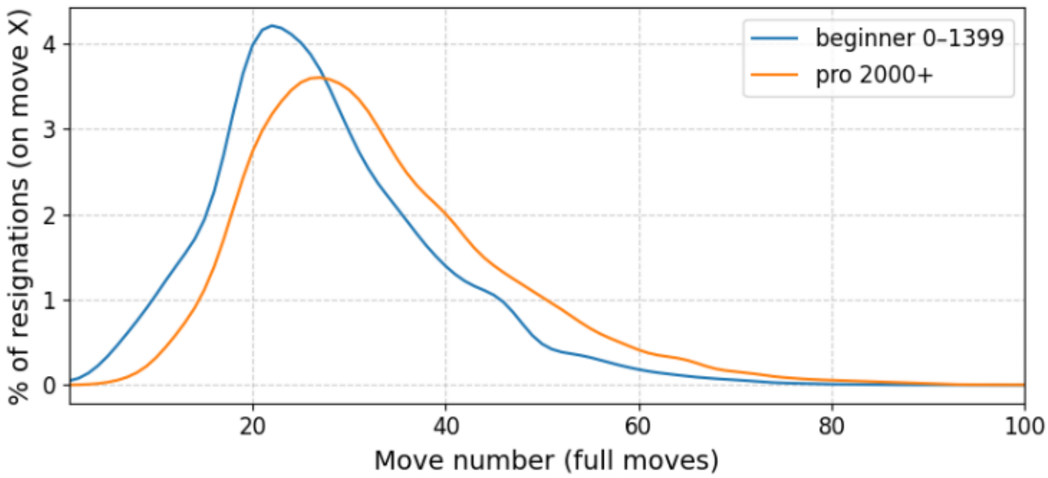

Fig. 1. Proportion of games resigned on move X, grouped by skill level

Additionally the analysis revealed correlation between blunders (more than 300 centipawns) and willingness to admit defeat. Large mistakes sharply increase the probability of resignation, but the chances are approximately 5% lower in games when both players make at least one blunder during the first dozen moves.

Since a game can be presented as a sequence of decisions, the resignation may depend not only on the final position, but also on the trajectory of previous moves. The use of Long Short-Term Memory (LSTM) network is a good fit to understand long-term patterns. The proposed LSTM model accepts a sequence of ply-level features, has 32 hidden dimensions, followed by an 8-unit dense layer with ReLU activation, and a sigmoid output layer. The model is trained using the binary cross-entropy loss function and optimized with the Adam optimizer. Batch size for training is set to 32. The model with these hyperparameters achieved convergence in approximately 10 epochs as early stopping was applied to prevent overfitting.

The trained model achieves an ROC-AUC of 0.746 and an accuracy of roughly 68% within the horizon of 5 plies. The values of precision and recall are close to balanced for both resignation and non-resignation scenarios. The exact validation results of the model are shown in Table 3.

Table 3. Model metrics

Class	Precision	Recall	F1-score
No resignation	0.7213	0.6816	0.7009
Resignation	0.6306	0.6737	0.6515

The ROC-AUC value of 0.746 is significantly higher than a random baseline of 0.5 - the difference is shown in Figure 2. This result highlights that objective indicators are informative but insufficient for explaining all patterns of resignation behaviour.

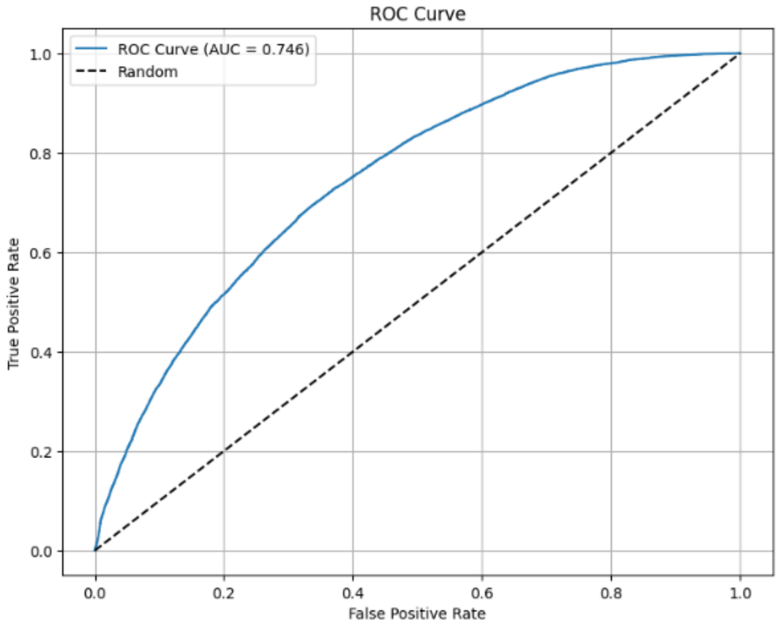

Fig. 2. Receiver Operating Characteristic (ROC) Curve

While the model is not able to classify all situations correctly, it is expected as the decision to admit defeat could not always be explained by objective indicators only. At the same time, the distribution of predicted resignation probabilities, shown in Figure 3, highlights that the model is able to find most of the sequences that lead to game continuation and identify history of moves that ended in a concession with higher confidence.

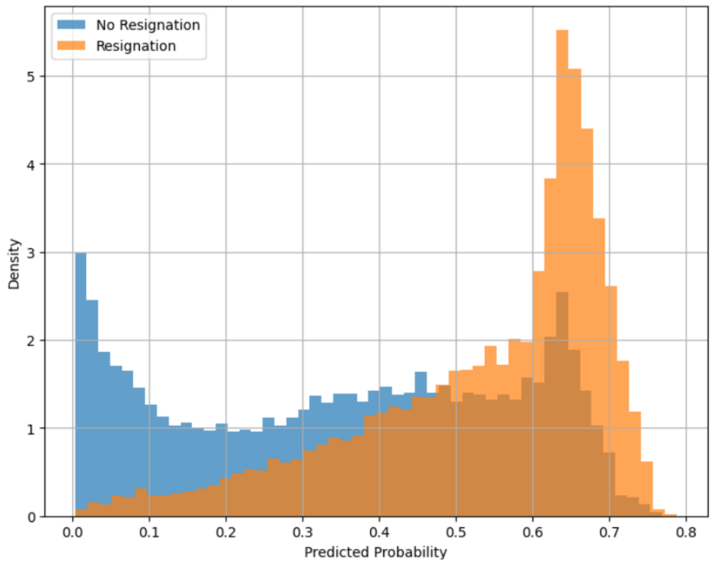

Fig. 3. Model Output Distribution for Resignation vs. Non-Resignation

The distribution of model output demonstrates the model's ability to separate situations from chess games, as most of the plies marked as non-resignation have low probability of defeat admission and vice versa. As the behavior of players varies for different skill groups the comparison of results shows whose decisions are more likely to be predictable. Figure 4 highlights that the model often assigns very low resignation probabilities (less than 10%) for games of beginners, but the density in the mid-probability range is lower than for professional players. On the other hand, sequences from beginner games still produce a larger share of false positives, as players at this level make more mistakes, so the chance of comeback is higher and it may be more reasonable for them to continue playing until the end.

Situations in which stronger players resign are less straightforward as even a small mistake could be enough to lead to a decisive defeat at this level. Distribution of probabilities in Figure 4 demonstrates that the model uses a wider range for professionals - from 0 to 0.8.

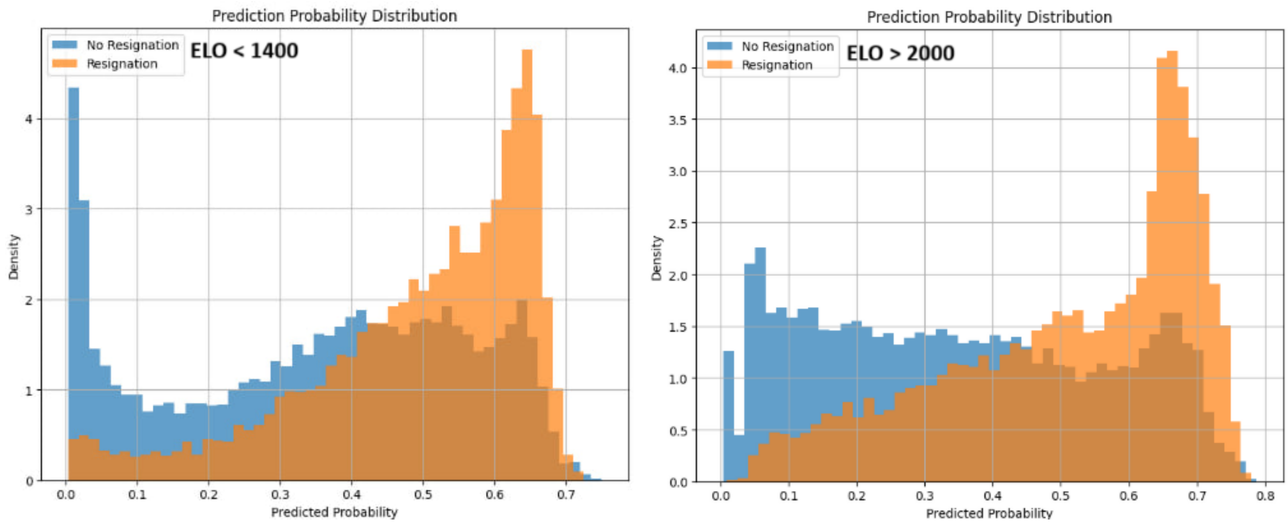

Fig. 4. Predicted resignation probability distributions by player skill level:
(a) beginner group (ELO < 1400) and (b) expert group (ELO > 2000)

These results indicate that resignation is formed not only by the evaluation of the board position, but by the sequence of decisions, accumulated mistakes, difference in experience and time pressure. The calculation of the saliency of all plies except the last 5 revealed that in less than half of the games last 5 plies account for more than 50% of total saliency. This fact emphasizes that it is important to analyze move history to catch more patterns, especially working with a limited number of measurable parameters.

Conclusions and prospects for further research. This research investigated resignation decisions in chess, as a domain that enables formalized modeling of human give-up behavior. There are a lot of factors that influence a person's choice, but in most cases it is a complicated task to collect and compare indicators of a cognitive state. For this reason only objective parameters were used to estimate the practical limits of prediction accuracy that can be achieved without information about general character traits and current mood.

The theoretical contribution of the research lies in the formalization of resignation decision in chess, the analysis of tendencies of various groups of players and estimation of the accuracy that can be achieved in prediction of human behavior-related tasks. The practical results could be used in live broadcasts of chess matches as an additional indicator of a possible outcome - resignation. On the other hand, conclusions from this research could be used for describing human behavior in other spheres after domain-specific validation.

This study presents an approach for preprocessing chess data and transforming it from a PGN-formatted game records to ply-level features in tabular form. The statistical analysis showed noticeable differences between beginners and professional players in fraction of games that end in resignation, the number of moves a player usually makes before this critical decision and impact of significant time pressure. The comparison of players by skill groups revealed that more experienced people are more likely to recognize an irreversible disadvantage and admit it in more than 50% of matches, but they tend to do so later.

The LSTM model was trained using different hazard horizons and it showed the best results with K=5. The achieved ROC-AUC of 0.746 and 68% of overall accuracy demonstrate that the model performs above a random level, but it has moderate accuracy as objective indicators cannot fully explain the nature of human decisions. The benefit of using sequential data and the LSTM model as a method that can capture patterns in the history of moves was supported by saliency analysis. This check showed that in 53% of analyzed sequences, more than half of the total saliency was attributed to plies other than the last five.

The main limitation of this research was considering only measurable and comparable parameters and ignoring character traits, emotions, mood or level of motivation to win. Additionally, each game was treated as a separate event, so the influence of previous results could not be analyzed. The recent comeback or a desire to prove one’s own strength against a certain opponent obviously could be the reason for making different decisions in the same positions, so the use of some factors of inner state could be an essential future improvement. Several directions for further research can be identified, for example analysis of the impact of winning or losing streaks and considering decisions made in previous games. Another way of chess-specific improvement is the comparison of different types of match ending: resignation, checkmate, timeout, draw by stalemate or insufficient material. On the other hand, the evaluation of different methods of predictions could be done. Moreover, the future challenge is testing the transfer of conclusions from the chess domain to other spheres, where data collection is more complicated.

The obtained results show that objective indicators have a measurable impact on human decisions and it is possible to predict some aspects of our behavior based only on these factors. At the same time, models trained on such limited data should be considered not as perfect tools, but as an instrument for early identification of risky situations. The uncertainty of the proposed model only highlights the human component and reflects the variability of individual decision-making.

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