Artificial Intelligence & Cognitive Processes:

Pattern recognition of the unique characteristics of the playing styles of chess world champions

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Abstract

As the computing and programming abilities of technology evolve, interest in the concept of an artificial intelligence has grown exponentially. "Smart" machines such as automobiles, household appliances, and digital assistants are developing at a rapid pace, yet the production of a complete artificial intelligence seems to still lack a certain core functionality. This project proposes the idea that what these various ideals of AI lack is a concept of cognitive abilities which are inherent in humans yet are not currently reproduced through the coding methods in use today, and develops the system of a convolutional neural network for a chess engine that recognizes the unique world champion involved in a particular chess match rather than the optimal moves in the game.

1. Introduction

Chess has a lengthy history as a model for both studies in cognitive science and artificial intelligence. Vaci and Bilalić (2016) eloquently described its application in the psychological sciences:

> The game of chess has often been used for psychological investigations, particularly in cognitive science. The clear-cut rules and well-defined environment of chess provide a model for investigations of basic cognitive processes, such as perception, memory, and problem solving, while the precise rating system for the measurement of skill has enabled investigations of individual differences and expertise-related effects. (p. 1227, Abstract)

Levinson et al. (1991) gives an equally strong explanation of the role of chess in artificial intelligence research:

> Chess has been fertile because it provides a complex reasoning problem from a simple domain with a built-in performance criterion. The simple domain permits research to progress with little initial overhead. Having a hostile adversary adds complexity to the reasoning. In many domains (natural language understanding comes to mind), progress can be hindered by lack of performance criteria - it can be hard to tell whether the latest thesis is an improvement on the current state of the art. Chess, by contrast, provides precise answers to performance questions. (p. 159, Sec. 3.5)

This game's application in each different discipline provides a unique opportunity to perform an analysis which applies to both disciplines, especially with the intent to further the study and development of artificial intelligence to create a system or machine with more closely resembles a true intelligence – one with cognitive capabilities such as intuition, insight, reasoning, and memory which are not readily explained or created by computer science.

Although current machine learning techniques are adequate for creating an application that can repeatedly cycle through a task in order to build an understanding of the data and problem to consistently increase its accuracy, no design has – as of yet – produced an application that can be given a new and unrelated problem to solve simply by reasoning on its own with its own understanding. True intelligence, however, has this capability, whether the intelligence is human or animal; this concept has been proven time and again throughout history, and should be the example of what research in artificial intelligence is trying to achieve – not simply a non-biological machine that learns, but one that grows in the same manner as a child as it develops.

While this concept has been the focus of frequent fearmongering in the last few decades in many forms – from entertainment to political discourse – and for many reasons – from the removal of opportunities for people to the enslavement of humankind by machines – this concept of childlike development is the core focus and belief of this research. Humanity has no fear that the opportunities available to its future progeny will have grave consequences for its current population, nor that its descendants will attempt to impose tyrannical control over it in the future; in like manner, the development of a true artificial intelligence will bring new and greater opportunities of knowledge, understanding, and growth for all the populace of Earth.

1.1 Delving into the Mind of Champions

As a first step to attempt to achieve this development of true intelligence, this project seeks to bridge the gap between the studies of cognitive science and artificial intelligence through study of chess matches involving chess masters as well as championship events, then training of a machine to predict which player(s) are involved in the match by analyzing the patterns of different play styles and matching them to one of ten specific World Chess Champions, namely José Raúl Capablanca, Alexander Alekhine, Machgielis "Max" Euwe, Mikhail Moiseyevich Botvinnik, Vasily Vasilyevich Smyslov, Mikhail Nekhemyevich Tal, Tigran Vartanovich Petrosian, Boris Vasilievich Spassky, Anatoly Yevgenyevich Karpov, and Garry Kimovich Kasparov. It should be noted that while the preceding list is ordered according to the timeline where each of the listed champions held the title, the remainder of this project handles all future ordering of this list in alphabetical order for ease of computing.

Due to the international popularity and challenge of chess, acquiring adequate data on these players for this purpose is readily available. The World Chess Federation (French: *Fédération Internationale des Échecs*), also known as FIDE, maintains and regulates the record-keeping of chess matches, particularly of those matches where at least one player has international acclaim. Most of these records are maintained in a computer format known as Portable Game Notation or PGN (filename extension .pgn), which has the unique capability of being easily read by both computers and humans. PGN gives details such as the event, site, date, and round where a particular match occurred, the two players of the match by name and connected to their appropriate color, and the end score of the match. After these tags are given, the format provides the details of the game through the use of the movetext which details every move of the game as denoted by the letter abbreviations for each piece and the algebraic notation of the board denoted by the file (letter a though h) and rank (number 1 through 8).

While the approach of this project is similar to many projects and research designed around movement prediction, its goal in this design is to not predict the best or most likely piece movement, but rather determine if the machine can be taught to recognize how a particular player makes their choices based on the options available – the goal is not to determine the *best* or *winning* strategy in a particular situation, but rather the *player's* most-likely strategy developed from that player's own experiences, perception, and intuition. While a particular player may be known to take certain gambles, to predict their opponent's plans in specific ways, or to attempt plans which are unorthodox in order to confound their opponent, current chess engines are incapable of doing the same – this project aims to help the system recognize and develop these traits by repeatedly subjecting the system to these factors to develop its understanding of their presence and application.

1.2 Research of the Cognitive Science of Chess

Many studies have been performed in the field of how a chess player (particularly an expert chess player) perceives the position of a chess board at any one time. One of the first researchers of note on this concept was Adriaan de Groot. De Groot (1965) researched extensively on this topic, analyzing verbal reports by subjects about their thoughts, plans, calculations, and other considerations leading to the move decision of the subject based on the presentation of an unfamiliar position from an actual tournament game – these verbal reports were produced by experimental sessions from 1938 to 1943 (p. V).

These insights received further review by future researchers as they attempted to delve deeper into the techniques for isolating and studying the perceptual structures that the chess players perceive – Chase and Simon (1973), for example, applied two techniques to subjects of three differing degrees of mastery (master, Class A, and beginner) in their research on this topic: one by giving a *perception task* where they asked their subjects to reconstruct a chess position while it remains in plain view; the other entailing a *memory task* where the subjects were asked to reconstruct a position from memory after a brief exposure of 5 seconds to the position (p. 57). These experiments had the purpose of analyzing both the mind's capability to perceive and to remember the positioning of the pieces on a board, while comparing the effect of skill and experience on the subjects' abilities to perform in these areas.

While these analyses served to demonstrate some of the ways in which the human mind studies and responds to chess positions through recognition and looking ahead to possible moves, the conclusion of the relative importance of each mechanism to one another is not one where different researchers agree (Gobet and Simon, 1996, pp. 5-6), which produces a distinct problem in the development of a chess engine as the code must be split between these two concepts to produce an active and responsive machine opponent.

1.3 Chess Engines and Machine Learning

As mentioned previously, most machine learning projects which involve chess are designed for the creation of an engine that can play chess as well as a human opponent at varying levels – these specialized chess engines are programed with the rules of the game and various strategies, and the best motors provide authoritarian judgment that can be used in many applications such as detecting cheats, calculating internal force, evaluating abilities, or studying human decision-making. An important problem for the research community is to collect a large set of chess games with engine judgments. Unfortunately the analysis of each move can take an enormous amount of time, since any machine learning system would need to learn from and account for a total of $(8^2)^2 = 4096$ possible positions and moves to be scored and considered. To reiterate the fact and purpose of this project, a human player does not memorize the best move for every situation of a game of chess, but rather draws on past experiences and intuition to choose a move – whatever the outcome of that move, the player has made the decision based on their own intelligence and not dictated through a structured series of strict commands from which the player cannot deviate.

2. Project Design and Initial Process

This project's data was acquired through the collections of the website pgnchessbook.org/pgn/, which houses numerous chess matches in various collections. In particular, the collections of matches played by various world champions and the world championship match collections from 1886 to 2018 were considered for this project – the final decision was made to use the collections of matches played by various world champions because that data provided more examples for both training and testing the data as well as larger subsets of data for the individual world champions which were reviewed.
Unfortunately, there was an error produced with the Fischer file which was available on that site due to a mismatch in the number of lines of the data while being read which prevented that data from being used for this project. With the remaining ten world champion collections available, the collection for Alekhine contained 1661 matches, the collection for Botvinnik contained 996 matches, the collection for Capablanca contained 590 matches, the collection for Euwe contained 1122 matches, the collection for Karpov contained 1049 matches, the collection for Kasparov contained 1798 matches, the collection for Petrosian contained 1893 matches, the collection for Smyslov contained 2627 matches, the collection for Spassky contained 1805 matches, and the collection for Tal contained 2499 matches, for a grand total of 16039 matches which were supplied in the data for this project.

This project made use of a Convolutional Neural Network for the purpose of building and running the tests, which was founded upon the work of Oshri and Khandwala (2015) – the neural network design that Oshri and Khandwala used was based on a concept of training both from the starting coordinates of each move and to the ending coordinates, which each type of piece trained in separate secondary neural networks (see pp. 2-3).

In lieu of establishing individual secondary networks for each piece, this project has applied the same logic to each champion in place of each piece, along with the change of connecting the y-value in each training set with the matching champion player, with all other players placed under the general heading of "Other" – in those games where two champions were playing each other, the black player was favored due to the fact that it would result in more reactionary responses, thus showing the champion's more intuitive mindset.

The pgn files were prepared and joined into one file using the R programming language, while the actual applications of the training and testing of the data used the Python programming language. Due to the similarities in the design of this project with that of Oshri and Khandwala, many of the same considerations which were used in their project were applied in this one. All eleven networks in this project also make use of a three-layer convolutional neural network for the same reasons – networks with more layers resulted in no learning while less layers did not produce significant information. Likewise, using a rectified linear unit (ReLU) for the activation function produced improved results when compared to the hyperbolic tangent (tanh) function. Pooling, weight initialization, regularization, and dropout were all minimized to preserve the data in the best format to supply the information for the project.

The original data was divided into one training set of 12000 matches and one testing set of 4000 matches, which allows for some variation in each set since the total is less than the full 16039 matches of the data. In order to attempt to find the best models, each network was trained on a series of 15 epochs separated into a number of iterations of 250 – due to the differences in the sizes of each set the total number of iterations performed in training in each of the epochs varied widely for each network, as shown in the following chart:

Net	Iterations per Epoch	Net	Iterations per Epoch
Other	40	Kasparov	435
Alekhine	441	Petrosian	430
Botvinnik	268	Smyslov	663
Capablanca	154	Spassky	79
Euwe	286	Tal	19
Karpov	293		

The primary reason why Oshri and Khandwala's work was chosen as the foundation of this project is due to the due to their unique approach to the challenge of chess reasoning and pattern recognition – as their work (2015) states:

> Critics of CNNs argue that neural networks cannot adequately explain such tactical advantages because the forms of these conditions are too global across the board and affected by extraneous variables... However, we claim that these shortcomings are mostly a result of the ill-formed task of training to binary labels of win and loss. Such an algorithm labors at developing an oracle intuition for whether small local patterns correspond to a winning or losing state, the association of which is likely weak in most chess situations. (p. 2, Sec. 1.3)

Since this project is applying the same idea of training a chess engine not for the goal of winning a game, but rather on recognizing the style and characteristics of the individual players, this different design purpose was one of the best possible matches for this project.

3. Processing and Validation

The baseline training set for this project is the "Other" category, which is the full combination of all the player data. Since this is a combination of varied players with both known and unknown skill sets, the predicted results for this subset was an accuracy of 0.50 in accordance with a "true" expected average. The validation value for the network's classification in this subset found this middle mark immediately, with the fluctuation in the training classification deviating closely around that center line except at the ends, as shown in Figure A, below:

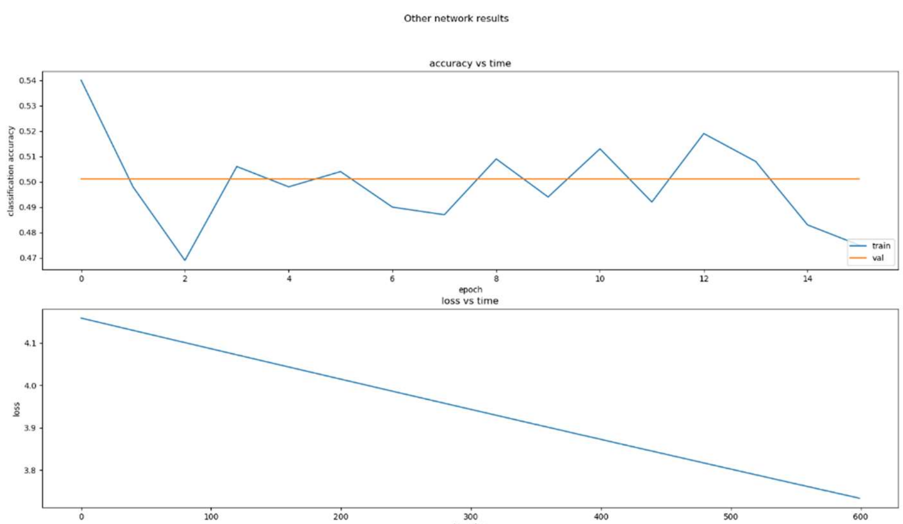

Figure A: Validation and training accuracy for baseline neural net ("Other")

As we evaluate the results of the other neural networks, we see similarities to this design as shown in Figure B below:

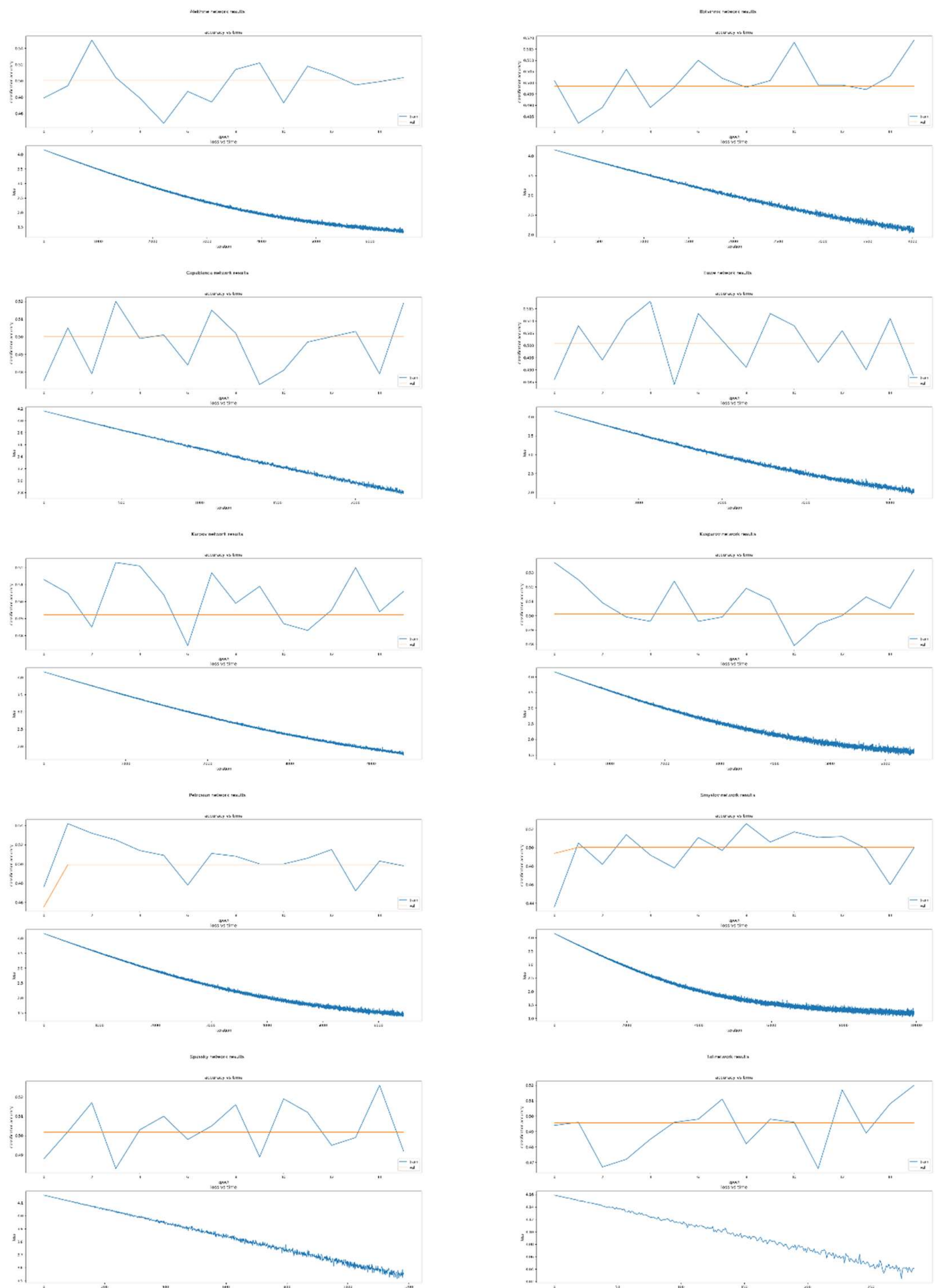

Figure B: Validation and training accuracy for secondary neural nets – Alekhine, Botvinnik, Capablanca, Euwe, Karpov, Kasparov, Petrosian, Smyslov, Spassky, Tal (from top left to bottom right)

The variability that can be seen with each secondary network is both striking and informative, as the results are not directly related to the total number of matches in the collection – as noted above, Botvinnik, Petrosian, and Smyslov had 996, 1893, and 2627 matches in their collections, respectively (which in comparison to the total number of matches in each collection places Botvinnik at the second smallest collection, Petrosian around the middling range, and Smyslov as the largest collection), yet these three collections produced the least variability of all of the sets, and Botvinnik produced generally better than average results with its iterations. On the other end of the spectrum, the collections for Alekhine, Capablanca, Euwe, Karpov, and Kasparov all show a wider degree of variability even though these collections span almost the entire range of possible number of matches (Capablanca's collection contained the least number of matches at 590, and Kasparov's collection contained the fourth largest total at 1798).

4. Challenges

The primary challenge which was faced by the project is found in the rapid progression of technology – since the creation of Oshri and Khandwala's original project, the base coding language for that project, Python, had developed from a version 2 to a version 3 with a plethora of changes to the style and rules dictated by the language. Additionally, due to these same changes, many of the core packages and modules used by the original code were either no longer in development or changed drastically enough that their current formats could not interact with modern code in the same manner as with the original project design. This resulted in significant issues as the code was rewritten and reformatted in order to properly design the project to conform with its goals.

5. Conclusions

As can be seen with the charts and values shown above, this project does show some promise as a template for development and creation of models and systems designed to respond to stimuli in a manner that is not dictated by standard rules of logic. Accuracy in pattern recognition is beginning to show in this system for the characteristics of games involving Kasparov and Petrosian, and would likely require an influx of more data and tweaking of the design of the convolutional neural networks to distinguish the unique details of each player. Further development through additional iterations and larger data sets would likely produce more accuracy and improved results for further analysis.

6. Possible Further Development

If this project were to receive the support to continue this process, a logical next step would be to produce a larger pool of candidates for comparison – introducing matches with additional World Champions as well as renowned grandmasters for observation will help produce more variety in the psychology behind the various playstyles. In so doing, observations on relationships between mentors and students can help to broaden the system's ability to recognize particular variations styles and characteristics and possibly refine its ability to choose the correct player. Depending on the time periods from which the additional subjects are chosen, another layer of challenge and opportunity could be introduced to the project – namely the changes in rules and trends of chess over time. Once again, this would help to broaden the capabilities of the project as it progresses further toward the development of a complete and true artificial intelligence.

Another set of options would be to introduce quantifying aspects of risks and preferences to the moves and pieces themselves, as dictated by the matching player's characteristics. Building a profile of preferred movements helps solidify the pattern recognition of the individual players and provides a foundation for the creation of a system that identifies choices which are not solely dictated by precisely dictated, logical responses which are restricted only to known situations.

In like manner, a system that recognizes differences in risk with the various moves can begin to not only develop profiles based on the personality and development of a player, but also recognize particular emotional or mental states of the player in different matches and at different timeframes within the matches – perhaps a particular player uses aggressive and risky moves to intimidate their opponents, or makes such moves when faced with the likelihood that they will lose as a way to distract their competition and stall for time as they rebuild their defenses. Once again, these patterns and their results can help to produce a better and broader recognition of the possibilities available to the system above and beyond any strictly defined set of rules.

As can be surmised from the preceding paragraphs, a possible result of the development of this project further could produce an artificial opponent which could be programmed to play and respond in a manner which is specified as a particular, unique opponent, allowing human players to choose to challenge specific champions and grandmasters in a virtual setting with no limitations on availability in either a temporal or spatial domain – further studies could be performed on matches between modern champions and those of hundreds of years past, or allow a poor college student in the United States to play against the current world champion without needing to find a way to transport themselves to Norway. In this way new projects and studies could be developed which could begin to remove issues of bias that can easily be caused by the temporal and spatial restrictions which were mentioned previously.

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