Learning Personalized Models of Human Behavior in Chess

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Abstract

Even when machine learning systems surpass human ability in a domain, there are many reasons why AI systems that capture human-like behavior would be desirable: humans may want to learn from them, they may need to collaborate with them, or they may expect them to serve as partners in an extended interaction. Motivated by this goal of human-like AI systems, the problem of predicting human actions — as opposed to predicting optimal actions — has become an increasingly useful task. We extend this line of work by developing highly accurate personalized models of human behavior in the context of chess. Chess is a rich domain for exploring these questions, since it combines a set of appealing features: AI systems have achieved superhuman performance but still interact closely with human chess players both as opponents and preparation tools, and there is an enormous amount of recorded data on individual players. Starting with an open-source version of AlphaZero trained on a population of human players, we demonstrate that we can significantly improve prediction of a particular player’s moves by applying a series of fine-tuning adjustments. Furthermore, we can accurately perform stylometry — predicting who made a given set of moves — indicating that our personalized models capture human decision-making at an individual level.

1. Introduction

The advent of machine learning systems that surpass human ability in various domains raises the possibility of humans learning from and productively interacting with them. However, such human-AI collaboration is made difficult by the fact that many machine learning systems behave very differently from humans. The actions, techniques, or styles that work well for AI may not translate to how humans operate. To bridge this gap, a natural idea is to focus on characterizing human behavior — instead of approximating optimal policies in a given domain, learning to approximate human policies. Developing an ability to model human behavior in this way could provide a path toward building algorithmic learning tools that can effectively guide people to performance improvements, or machine learning systems that humans can more easily collaborate with to achieve a shared goal.

In recent work, researchers have made progress towards this objective in an ideal model system: chess (Anderson et al., 2017; McIlroy-Young et al., 2020). Chess has a number of attractive properties as a domain to pursue these questions in. First, chess AI definitively surpassed human chess-playing ability in 2005, yet millions of people still play it. There are billions of games played online each year, in each of which people face dozens of decision-making situations, and the actions they take and how long they take to make them are digitally recorded. And it has been a leading indicator in AI and machine learning for decades; most recently, AlphaZero revolutionized algorithmic game-playing with a novel deep reinforcement learning framework. In (McIlroy-Young et al., 2020), McIlroy-Young et al. trained an AlphaZero-like framework on millions of human games to characterize human behaviour in chess, where the objective is to predict which move the player will make. By training several models, each on a subset of games limited to a coarse skill level, this approach captures human behavior in chess at different levels of strength.

Although this was an important step, the ultimate realization of human behavior characterization would be the ability to emulate at the individual level. A model that could faithfully capture a particular person’s actions would be of clear use for automating different forms of interaction with them, and potentially for teaching them how to improve. However, in chess, just as in other domains such as medical diagnosis and text generation, extremely strong performance is often achieved by aggregating data over many people; it is far from clear whether the variation among individuals provides sufficiently distinctive signals to enable individualized models to do significantly better than these aggregate models. Indeed, our hypothesis was that this would not be true.
In this paper, we build models of individual human behavior in chess that outperform the coarse skill-level models in (McIlroy-Young et al., 2020) by a significant margin, raising the move prediction accuracy for the individual player by 10 percentage points on average above the highest-performing coarse model.

We achieve this by taking the open-source AlphaZero-like framework of (McIlroy-Young et al., 2020) and applying recent fine-tuning and transfer learning methods to personalize move predictions to individual players. We thus use chess as an application domain to demonstrate how to fine-tune a deep neural network to an individual person when there are hundreds of thousands of examples per person, a property that has traditionally not been present in other domains.

We demonstrate that our models capture individual decision-making to such an extent that we can use them to perform a version of the “author attribution” task, i.e., stylometry. Here, we are given a game or set of games, and the goal is to predict who played it. Given one side of 100 games, we can correctly identify the player who was playing 94.5% of the time out of a pool of 400 players. We achieve similar results even when we only consider the latter parts of the game (which only contain unseen positions), suggesting that our models capture unique features of a player’s decision-making style.

2. Related Work

Transfer Learning. Our work applies methods that were mainly developed in the transfer learning literature, but are also closely related to imitation learning, domain adaptation, meta-learning, and multitask learning. In particular, we experiment with fine-tuning our model by freezing its bottom layers (Zoph et al., 2016; Tajbakhsh et al., 2016; Oquab et al., 2014), initializing the top layers randomly versus starting from a pre-existing model (Donahue et al., 2014), and varying the pre-existing model that we start with (Kornblith et al., 2019; Chatfield et al., 2014). We derive inspiration from computer vision tasks that specialize a pre-existing model (e.g. Resnet-50 (He et al., 2019; George et al., 2018)) to a specific task (Yosinski et al., 2014; Raghu et al., 2019b; Huh et al., 2016; Pan & Yang, 2009; Litjens et al., 2017), a method that has also been extended to many other domains, such as natural language processing (Zoph et al., 2016; Dai & Le, 2015; Radford et al., 2018; Yang et al., 2017; Peters et al., 2018; Howard & Ruder, 2018) and speech recognition (Huang et al., 2016; Kunze et al., 2017; Deng et al., 2013; Wang & Zheng, 2015).

Many developments in transfer learning are geared towards dealing with data scarcity by minimizing the number of samples required (Kunze et al., 2017; Rohrbach et al., 2013; Sun et al., 2019). One of our contributions is to map out which techniques work best when even personalized models are relatively data-rich, a less well-studied setting (Raffel et al., 2019). Other approaches include adding additional layers (Tan et al., 2018) or additional inputs (Kawahara & Hamarneh, 2016).

Several other machine learning tasks are closely related to our problem. It could be cast as a meta-learning task (Finn et al., 2017; Raghu et al., 2019a;b; Andrychowicz et al., 2016), with the goal of picking the closest model to each individual. Our goal of training a model on human behavior is reminiscent of imitation learning, although a key difference is that in our setup we are starting from already-superhuman AI and aiming to design more human-friendly models, whereas imitation learning models are generally aiming to improve by emulating a human expert (Ding et al., 2019; Ho & Ermon, 2016; Torabi et al., 2019; Schaal, 1999).

Finally, our results on identifying players draw on some of the earliest uses of neural networks in handwriting recognition (LeCun et al., 1998) and performing stylometry (Graves et al., 2008; Plamondon & Srihari, 2000; Tappert et al., 1990; Pham et al., 2014; Revow et al., 1996).

Our application domain, chess, has been used as a model system for artificial intelligence (McCarthy, 1990; Newell et al., 1958; Anderson et al., 2017) and understanding human behavior (Chase & Simon, 1973; Simon, 1977; Biswas & Regan, 2015; Charness, 1992; Gobet & Simon, 1996) for decades. A period of fervent work on computer chess culminated in Deep Blue defeating Garry Kasparov in 1997, but more recently the introduction of AlphaZero, a system using deep residual networks, revolutionized the state of the art (Silver et al., 2018; McIlroy-Young et al., 2020; Czech et al., 2019). While AlphaZero is designed to approximate optimal play in chess even more perfectly than its predecessors, we adapt it to characterize human play at an individual level. Work done before AlphaZero to capture style in chess was much more limited in scope; for example one attempt using GANs considers only the first few moves and a single player’s style (Chidambaram & Qi, 2017). More recent papers have pursued similar goals in competitive game-playing (Carroll et al., 2019), card-playing (Baier et al., 2018), and chess (McIlroy-Young et al., 2020). There are also commercial products (such as Play Magnus and Chess.com’s personalized bots) that attempt to mimic specific players. Their methods are not publicly disclosed, but are thought to be simple attenuated versions of existing chess engines (Longe, 2020).

3. Data and Background

Lichess. We use data from the largest open-source online chess platform, Lichess (liccess.org) (Duplessis, 2021).
With almost 100 million games played per month and almost 2 billion games played in total, Lichess provides us with a large number of diverse chess players, some of whom have played tens of thousands of games each. Games are played at a variety of set durations ranging from long games, where each player has an hour or more, to extremely quick games, where each player has only 15 seconds for the entire game. For our work we ignore the fastest games, as players tend to make many more mistakes, sometimes intentionally, in order to not run out of time. We analyze games from the Blitz category, where players have between 3 to 8 minutes per game. Each player has a rating (Glickman, 1995) that represents their skill level, and is derived from their results against other players on the platform. The rating system is calibrated such that a player who outrates their opponent by 200 points is expected to win 75% of the time. As most players are rated between 1100 and 2000 on Lichess, we restrict our attention to these players only. Lichess also has a robust community with impressive capabilities to detect bots and cheaters who use chess engine assistance. Players are also encouraged to maintain a single continuous account. As a result, we are able to train models on hundreds of human players with over 20,000 games played each.

**Dataset construction.** To assemble a specific set of players to train personalized models on, we first collected a dataset containing all rated games played on Lichess between January 2013 and December 2020. We then defined a set of criteria to select players: at least 20,000 games played, mean rating between 1000 and 2000 (for consistency with (McIlroy-Young et al., 2020)), low variance in rating, at least one game played in December 2020, and account older than one year; see Supplement for full details. We then grouped players by the number of games they have played, and randomly assigned players from these groups into exploration (10%), evaluation (80%), and holdout (10%) sets. The exploration set is used to configure the training parameters and architecture of our fine-tuning methodology (Section 4). This methodology is then applied to the evaluation set to train and test personalized models for those players (Section 5). The median rating of players in the exploration and evaluation sets is 1750 and 1739 respectively. The holdout set was never used for this work and is reserved for future analysis. Table 1 shows the composition of the player sets.

<table>
<thead>
<tr>
<th># Games</th>
<th>Exploration</th>
<th>Evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,000</td>
<td>3,852**</td>
<td>30,821*</td>
</tr>
<tr>
<td>5,000</td>
<td>662**</td>
<td>5,298*</td>
</tr>
<tr>
<td>10,000</td>
<td>233*</td>
<td>1,866*</td>
</tr>
<tr>
<td>20,000</td>
<td>36</td>
<td>295</td>
</tr>
<tr>
<td>30,000</td>
<td>10</td>
<td>86</td>
</tr>
<tr>
<td>40,000</td>
<td>10</td>
<td>19</td>
</tr>
</tbody>
</table>

Table 1. The number of players in each of our sets, grouped by the minimum number of games played. (The unused holdout set is identical in size to the exploration set). In the 40,000+ group the maximum was under 60,000. * 40 random players were selected from these sets. ** No players were used from these sets.

**Leela and Maia.** Our work builds on two chess engines projects. The first, Leela Chess Zero, is an open source implementation of the deep reinforcement learning system AlphaZero Chess (Silver et al., 2018), and provides the code infrastructure that we leverage to build our models. The second, Maia Chess, is a supervised learning adaptation of Leela that attempts to predict the next move the average human player at a particular rating level will make in given a specific chess position (McIlroy-Young et al., 2020). Maia is the most human-like chess engine to date, significantly outperforming the previous state of the art, attenuated versions of strong chess engines such as Stockfish and Leela. There are 9 versions of Maia, one trained on each rating level between 1100 and 1900 (inclusive).

**4. Methodology**

Our high-level approach is to take existing Maia models, which are designed to predict human moves at a particular skill level, and specialize them to predict the moves of an individual player. This type of transfer learning can be carried out in myriad ways, which we organize through a logical sequence of design decisions that we explore in turn. The end result is a transfer learning methodology for creating a personalized model for any player, given a sufficient number of the player’s games.

Since we start from an existing Maia model and fine-tune it on an individual player’s data, we first explore parameters required to define the mechanics of training, e.g., learning rate, batch size, and training steps. Then, instead of taking the entire Maia architecture verbatim, we explore which parts of it to copy, which parts to reinitialize, and which parts we allow the training process to adapt. Finally, we experiment with different starting Maia models to see if they influence the final accuracy of the personalized model; in the extreme case, we train the Maia architecture from scratch solely using the individual player’s data.

To train our models, we used a heavily modified version
of the Maia Chess training pipeline, which is in turn based on the one used by Leela Chess Zero. This allows us to load existing Maia models and have over 99.99% agreement with them. As Leela-based models are based on a series of residual connections (He et al., 2016) between convolutional layers with ReLU activations and squeeze layers (Hu et al., 2018), but without pooling layers, the core model design is not limited by this decision (see Figure 1 for a visualization of our architecture). The input representation is a 112-channel 8 × 8 board image representation, and there are two outputs: the predicted move (policy) and the probability of the active player winning the game (value). The predicted move is represented as a 1858-dimensional vector, and we ignore the win prediction output in this work (our initial experiments showed it had no effect on our results). We keep the value head in our architecture for full compatibility with Leela Chess Zero so that it is accessible to the broader research and chess engine communities.

4.1. Model Parameter Selection

Training parameters. To understand the impact of various hyperparameter choices and design decisions, we conducted exploration in two main phases. We first performed an initial, broad set of analyses on a set of 10 exploration players with over 40,000 games each—we refer to these players as the initial set. Then, we performed our deeper methodological experiments on the full set of 96 exploration players: 10 with over 40,000 games each, 10 with over 30,000 games each, 36 with over 20,000 games each, and a random sample of 40 players with over 10,000 games each. We evaluated both accuracy and cross-entropy loss on the initial set using the players’ validation games (and checked training dataset loss at frequent intervals). We then used the players’ testing datasets for the final evaluation.

We explored, in line with previous work, were freezing the top layers of our deep residual network, and either initializing weights randomly or with a preexisting model. We tested freezing our network at every reasonable location (all the white layers in Figure 1), and generally found that the deeper the gradients flowed the better performance we achieved (see full results in the Supplement). Our initial experiments also generally showed that initializing our model with Maia’s weights also tended to give a boost at deeper stopping locations.

Depth of gradient flow. The two most important strategies we explored, in line with previous work, were freezing the top layers of our deep residual network, and either initializing weights randomly or with a preexisting model. We tested freezing our network at every reasonable location (all the white layers in Figure 1), and generally found that the deeper the gradients flowed the better performance we achieved (see full results in the Supplement). Our initial experiments also generally showed that initializing our model with Maia’s weights also tended to give a boost at deeper stopping locations.

Initial model choice. Previous work found that the Maia models best predict players near the rating level they were trained on (e.g. Maia 1500, the version trained on 1500-rated players, best predicts players that are rated 1500 and 1600) (McIlroy-Young et al., 2020). Because of this fact, we expected the choice of which Maia we start with to also show this pattern—for example, that developing a personalized model for a 1500-rated player would benefit from starting with Maia 1500 as opposed to Maia 1900. Surprisingly, however, our experiments showed that our move prediction accuracy for a particular player doesn’t vary much with the choice of Maia we start with. We also tried randomly initializing weights, which had a significant negative effect scaling with the depth of the stop. Introducing small amounts of Gaussian noise to the weights before training also had no effect or negative effects, depending on the amount of noise. Therefore, for the rest of the paper we start from Maia 1900, the model trained on the highest-rated population of players.

Number of steps. In the initial exploration we ran the models for a large number of steps (150,000) and observed the validation loss curve. This suggested that most improvement occurred in the first 12,000 steps (3 million board-move pairs). For our final models we used 30,000 steps with drops in learning rate at 15,000, 20,000 and 25,000 each by a factor of 10. In the final exploration we did still include a
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### Table 2. Move-matching accuracy of exploration player set during final tuning. \( LR = .0001 \) is the final configuration used in Section 5

<table>
<thead>
<tr>
<th># Player’s Games</th>
<th>Maia 1100</th>
<th>Maia 1500</th>
<th>Maia 1900</th>
<th>Maia nearest</th>
<th>LR = .00001</th>
<th>LR = .0001</th>
<th>LR = .001</th>
<th>LR = .01</th>
<th>150,000 Steps</th>
</tr>
</thead>
<tbody>
<tr>
<td>10,000</td>
<td>0.490</td>
<td>0.526</td>
<td>0.526</td>
<td>0.535</td>
<td>0.538</td>
<td>0.570</td>
<td>0.578</td>
<td>0.507</td>
<td>0.573</td>
</tr>
<tr>
<td>20,000</td>
<td>0.480</td>
<td>0.516</td>
<td>0.519</td>
<td>0.524</td>
<td>0.546</td>
<td>0.574</td>
<td>0.580</td>
<td>0.538</td>
<td>0.575</td>
</tr>
<tr>
<td>30,000</td>
<td>0.475</td>
<td>0.517</td>
<td>0.529</td>
<td>0.530</td>
<td>0.553</td>
<td>0.581</td>
<td>0.590</td>
<td>0.555</td>
<td>0.582</td>
</tr>
<tr>
<td>40,000</td>
<td>0.494</td>
<td>0.528</td>
<td>0.540</td>
<td>0.544</td>
<td>0.553</td>
<td>0.580</td>
<td>0.593</td>
<td>0.565</td>
<td>0.582</td>
</tr>
</tbody>
</table>

longer training configuration which showed the same effect.

**Sampling function.** As noted earlier, during our initial exploration we observed that earlier moves are more predictable, since players repeatedly encounter some opening positions. To emphasize the middlegame and endgame, we switched from sampling positions with uniform probability across the game to sampling moves using a scaled \( \beta(2, 6) \) distribution over plies (dividing by 150 to normalize them to \([0, 1]\)). Although this change showed a minor uplift in validation accuracy for the initial set, it showed no effect during our exploration over the full set.

**Final tuning.** Our initial analyses narrowed our search for a suitable model architecture; as a result of these explorations we decided to initialize from base Maia models instead of random initialization, we realized always starting with Maia 1900 is best, we determined that freezing layers only hurts performance, and we optimized the number of steps and sampling function. In our deeper exploration over the full set of 96 exploration players, we optimized the learning rate. We found that for all data regimes from 10,000 to 40,000 games, a learning rate of 0.0001 is optimal. Table 2 show the complete results. Adding this learning rate to the design decisions above results in our final architecture, which we will refer to as “Transfer Maia” for the rest of the paper. We now turn to presenting our results.

**5. Results**

We apply our transfer learning methodology to specialize the baseline Maia model (Maia 1900) to the 400 different players in our evaluation player set. We use 80% of each player’s games to train their personalized models, and evaluate them on a 10% test dataset and the future dataset (the 10% holdout dataset remains untouched). Here, we show the results for the original task of predicting the target player’s moves, as well as a different stylometry task of identifying the player given only a subset of their moves. Since all of our results on the test and future datasets are qualitatively identical, we report results for the test datasets only.

**5.1. Move Prediction Accuracy**

We evaluate how accurately our personalized models predict the moves of their target players on their testing datasets. Since the early part of the game is often repeated, we ignore the first 10 plies of each game. For comparison, we also evaluate the Maia models on the testing dataset; as we observed, these models represent the state-of-the-art in human move prediction, but they can only predict at coarse skill levels (chess ratings). Thus we expect the Maia model whose training level is closest to a target player’s rating, which we call the “nearest” Maia, to have the highest baseline accuracy. Figure 2 shows the results, where the target players are color-coded by their rating and ordered from left (lower rating) to right (higher rating). As expected, Maia’s accuracy increases as its training level approaches the target player’s rating, which for example explains the downward tilt of Maia 1100 and the upward tilt of Maia 1900. This replicates the main result of McIlroy-Young et al. (McIlroy-Young et al., 2020). The “Nearest Maia” column combines the top performing Maia models per player. In contrast, our personalized models outperform all Maia models by a sizable margin, achieving 10% higher accuracy on average than the top performing Maia model, per player. That we can achieve significantly higher move prediction accuracy through personalization is a result that is neither implied by nor expected based on the performance of Maia, which has enough difficulty predicting moves at coarse rating levels.

**Game phases.** A plausible explanation for the higher accuracy of our models is that they are memorizing formulaic patterns in the opening play, or other easily predictable aspects of the target player’s style. To investigate this, we perform a finer analysis of model accuracy along different dimensions. Figure 3 shows how model accuracy varies as the move number in the game increases. While both the personalized models and Maia models benefit from the higher predictability of the opening play, the benefit quickly diminishes as more moves are played. Positions seen during training are predicted with higher accuracy than unseen positions. The bottom panel shows the ratio of number of training positions to new positions. Plies 0–4 (including the opening board) were seen in the training dataset 100% of the time, but by ply 30 only 0.02% positions were seen in the training dataset. Despite these dynamics, personalized models achieve consistently superior accuracy by a significant margin throughout the entire game.

**Move quality.** One of our driving motivations behind developing personalized models of human behavior is to inform
Figure 2. Move-matching accuracy of our personalized models versus Maia models on target players’ test set games. Target players are color-coded by Rating level from left (lower rating) to right (higher rating). Nearest Maia is the Maia whose training level is closest to the target player’s rating. Error bars show one standard deviation (the standard error is microscopic). The personalized model achieves higher accuracy than the best Maia model on every player.

Figure 3. Move-matching accuracy as a function of move ply, comparing positions that were encountered in the training data versus unseen positions. While Nearest Maia was run on all positions. The bottom panel shows the ratio of number of training positions to new positions in each ply.

Figure 4. Move-matching accuracy of our personalized models versus Maia models as we vary the quality of the move played. Our personalized model, Transfer Maia, outperforms unpersonalized baseline Maias across the entire spectrum of move quality.

The future design of algorithmic learning tools. As such, characterizing the errors that people make is of primary interest. Figure 4 shows how prediction accuracy varies with the quality or “goodness” of the move being predicted. The quality of a move is measured by the change in estimated win probability before and after the move, where win probability is calculated via an empirical procedure based on evaluation of the position (who is ahead in material, strategic considerations, etc.) following the method of McIlroy-Young et al. (McIlroy-Young et al., 2020). The change is always non-positive because it is measured against optimal play—the optimal move changes the win probability relative to optimal play by 0, and every worse move lowers the win probability. As the figure shows, both the personalized models and Maia models can predict better moves with higher accuracy than worse moves, but the personalized models are consistently more accurate across all move qualities by a significant margin.

Training data size. Although in this work we are mainly concerned with demonstrating the possibility of transfer learning to capture individual decision-making style, another advantage of chess as a domain is that we can measure how training data size affects performance at predicting individual decisions. In Figure 5, we show how personalized move matching accuracy varies as a function of base Maia performance, grouped by how many games each player has played. There are two main insights that result from this analysis. First, there is a strong correlation between the two—some players are more predictable than others. Second, personalization performance increases with training data size. Our architecture produces significant uplift over base Maia for players who have played at least 5,000 games played. However, our model is ineffective on play-
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Figure 5. Personalized move-matching accuracy as a function of best baseline Maia move-matching accuracy, grouped by training set size.

<table>
<thead>
<tr>
<th># Player’s Games</th>
<th>Nearest Maia</th>
<th>Transfer Maia</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,000</td>
<td>0.527</td>
<td>0.497</td>
</tr>
<tr>
<td>5,000</td>
<td>0.532</td>
<td>0.550</td>
</tr>
<tr>
<td>10,000</td>
<td>0.528</td>
<td>0.556</td>
</tr>
<tr>
<td>20,000</td>
<td>0.524</td>
<td>0.564</td>
</tr>
<tr>
<td>30,000</td>
<td>0.520</td>
<td>0.567</td>
</tr>
<tr>
<td>40,000</td>
<td>0.528</td>
<td>0.580</td>
</tr>
</tbody>
</table>

Table 3. Move-matching accuracy for players with differing numbers of games.

Figure 6. Stylometry accuracy for moves after 10 ply in 100 games, over a set of 400 players. Players are ordered using Ward clustering (Müllner, 2011), so players with similar accuracy vectors are closer together. The dark diagonal line indicates that for most players, their moves are best predicted by their personalized models.

5.2. Stylometry

Having created personalized models that achieve higher accuracy than non-personalized baselines, a natural question to ask is how unique these models are. To what extent are we really characterizing the idiosyncrasies and signatures of individual players? Concretely, can the personalized model of one player be used to predict the moves of another player? Figure 6 shows the after-ply-10 accuracy of each personalized model (columns) on 100 randomly sampled games from each of the 400 evaluation players (rows). The players are ordered using Ward clustering (Müllner, 2011), so that players with more similar model accuracy vectors are closer together. As the dark diagonal line shows, we can uniquely identify the target player 94.5% of the time by picking the model with the highest accuracy on their moves. This result has profound implications, because it means that we can uniquely identify a player by simply inspecting a small sample of their games. The method is simple: given a player’s games, test each personalized model on those games and output the one with the highest move prediction accuracy. Since we know the personalized models perform poorly on games outside of the player set, we can also identify when a game has not been played by any of the players by using a simple accuracy threshold. Our personalized models indeed capture individual style.

Skill levels. A distinguishing property of the personalized models compared to Maia is that their accuracy is largely independent of the target player’s rating in the range we examine (1100–1900 Elo). The $R^2$ of an ordinary least squares regression of accuracy against player rating is 0.089, which is minor. This property may not hold across all rating levels, however: our preliminary attempts to create personalized models for Grandmasters did not yield the same accuracy gains as above. We conjecture that at the highest levels of play, it is more difficult for human-oriented models such as Maia and ours to achieve higher accuracy than chess engines like Stockfish or Leela, because the strongest players tend to play near-optimal moves which traditional chess engines are designed to predict.
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<table>
<thead>
<tr>
<th># games</th>
<th>ply</th>
<th>Stylometry accuracy (P@1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>all</td>
<td>0.86</td>
</tr>
<tr>
<td>10</td>
<td>10+</td>
<td>0.47</td>
</tr>
<tr>
<td>10</td>
<td>30+</td>
<td>0.11</td>
</tr>
<tr>
<td>30</td>
<td>all</td>
<td>0.94</td>
</tr>
<tr>
<td>30</td>
<td>10+</td>
<td>0.81</td>
</tr>
<tr>
<td>30</td>
<td>30+</td>
<td>0.26</td>
</tr>
<tr>
<td>100</td>
<td>all</td>
<td>0.983</td>
</tr>
<tr>
<td>100</td>
<td>10+</td>
<td>0.945</td>
</tr>
<tr>
<td>100</td>
<td>30+</td>
<td>0.552</td>
</tr>
</tbody>
</table>

Table 4. Stylometry accuracy at differing numbers of games used. The accuracy is top 1, so the correct player is who the model is most accurate on.

Stylometry performance among the 400 evaluation players varies with ply cutoff and number of games considered (see Table 4). The later the ply cutoff, the fewer opening positions are considered, and thus the harder the prediction task is. On the other hand, accuracy increases as we consider more games. Stylometry accuracy—recovering the target player’s identity from the set of 400 players with a single guess—ranges from 98.3%, using all moves from 100 games, to 11%, using only moves after ply 30 from 10 games. In all cases, our personalized models substantially outperform random guessing (0.25%). As a baseline for stylometry, we train a Naive Bayes classifier (one for each game length) on the vector of centipawn losses incurred by each player on their training set games, and use this classifier to identify the most likely player given a game (and its associated centipawn loss vector). Though a reasonable style marker, this baseline achieves very poor accuracy compared to our personalized models, peaking at 1.4%, which is only slightly better than random guessing. Other style markers may achieve better results, but finding a good style marker is difficult in general (Gatys et al., 2016). In effect, our personalized models serve as a proxy for style markers: by abstracting the differences between players through the move prediction task, we can perform stylometry without the need for explicit style markers.

6. Discussion

This work takes the next step towards learning human policies by building on the coarse skill-level models of prior work to create personalized models for individual players. Our models can predict a player’s moves more accurately than any prior baseline, regardless of when the move occurs in a game. Furthermore, the gains we see from personalizing to individual players are significant: 10% higher accuracy on average than the top performing Maia model, per player. Finally, our models capture enough individual behavior to allow us to perform near-perfect stylometry. Given a sample of games, we can uniquely identify who played them from among a set of 400 players.

An interesting challenge is to scale up our methodology along different dimensions: e.g., more players, more skill levels, and more time periods. For example, as we mentioned, creating accurate personalized models for the strongest players (Grandmasters) remains an elusive goal.

Machine learning systems that capture human behavior in a personalized way will open the door to algorithmic learning tools and training aids. Using chess as a model system, we have shown that predicting granular behavior at an individual level is possible. We hope this inspires others to advance human learning and facilitate collaboration with AI systems in a variety of domains.

Ethical implications. Chess has traditionally been an open, public ecosystem, with both online and offline games documented, uploaded, and made easily searchable to the public. Our work relies entirely on this public data. Anyone can use our code and model architectures to reproduce any of our results. Although it would not increase their exposure, we anonymize the usernames and other identifying information of all players for whom we develop personalized models.

The presence of superhuman chess engines has led to the occurrence of cheating during online game play. Our personalized models do not increase the overall effectiveness of cheating, because predicting an opponent’s next move is not as effective as knowing the optimal move to play, but they could be used to circumvent cheating detection systems. The incentive to cheat using our personalized models are not significantly greater than the baseline Maias developed in previous work. However, our personalized models could be used to target practice training with a specific player in mind, so as to increase the likelihood of defeating that player in a game.

Unlike our move prediction accuracy, our stylometry accuracy is extremely high (in some cases, approaching 100%). This has interesting implications. For example, our personalized models could be used to identify when an individual’s playing style has unexpectedly or sharply changed, which could help identify cases of cheating.
References


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7. Supplement

7.1. Dataset Creation

7.1.1. Player Inclusion Criteria

We constructed our player selection as a SQL query (see Listing 1). It implements the following logic: we required each player to have played over 1000 games in blitz, with a mean rating between 1000 and 2000 and a per-game rating variance under 75, have played at least one game before 2020 and one game after the first of December 2020, and we excluded titled players. Titles are given for having an official FIDE title or being a bot. We also excluded players with high or low win rates and high or low numbers of games played as White. These are simple filters to exclude color cheating (playing one color disproportionately often, usually White) and other types of manipulation.

```
SELECT * FROM player_stats
WHERE game_count > 1000
AND game_type = 'Blitz'
AND mean_elo < 2000
AND mean_elo > 1000
AND std_elo < 75
AND last_game > '2020-12-01'
AND first_game < '2020-01-01'
AND white_count / game_count < .55
AND white_count / game_count > .45
AND lost_count / game_count > .4
AND lost_count / game_count < .6
AND title IS NULL;
```

Listing 1. Selection Criteria for players in analysis

Figure 7 shows the number of games as a function of rating for each player with 20,000 or more games in the final analysis.

![Figure 7. Distribution of players by rating and count](image)

7.1.2. Final Player Splits

We include the final number of games used for each player’s partitions, which are given in Table 5. The median dates are also provided (see Table 6), which demonstrate the temporal separation between the future set and other 3 sets.

7.2. Methods appendix

7.2.1. Training Data Format

The Leela/Maia training pipeline normally does not consider which player it is loading and requires full games for its data format, a compressed protocol buffer based binary. To enable training on only one side’s moves, we use a custom format that encodes additional metadata, such as player ID and game ID. Our final models are still available in the Leela Chess model file format.
Learning Personalized Models of Human Behavior in Chess

<table>
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Table 5. Median number of games in each dataset per player partition

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<td>2020-12-16</td>
<td>2020-12-17</td>
<td>2020-12-19</td>
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<td>2020-02-10</td>
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<td>2020-12-16</td>
<td>2020-12-17</td>
</tr>
</tbody>
</table>

Table 6. Median date from each game in each dataset per player partition

7.2.2. Depth of Flow

On the final model training procedure Figure 8 shows the effects of changing the gradient flow depth on final accuracy.

7.2.3. Future Accuracy

As we mention in the main text, there is no significant difference between the future and test set accuracy. Accuracy on the future set is very slightly higher than on the test set, as shown in Table 7.

7.2.4. Computational Resources

We primarily trained our models on 6 core virtual machines with Tesla V100 GPUs. The training time for one model was 40 minutes when run alone. As the models are relatively small (using \( \sim 300 \text{MB} \) of vRAM), our training procedure should be feasible on most GPUs.

<table>
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<tr>
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</tr>
<tr>
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</tr>
<tr>
<td>40000</td>
<td>0.0045</td>
</tr>
</tbody>
</table>

Table 7. Increase in accuracy between the testing set and future set for the different player categories.
7.3. Additional Plots

7.3.1. Model Calibration

Our models function by outputting a probability for each move\(^3\). Instead of only examining the most likely move, we can also consider the top \(k\) moves. Figure 9 shows the accuracy versus predicted probability of the move occurring for both our transfer models and Maia 1900. All models are good at predicting their own accuracy. Figure 10 shows the number of positions each model has a given probability for.

7.3.2. Alternate Accuracy Criteria

As we discuss in the main text, the move-matching accuracy depending on which parts of the game we include, since the opening is much more repetitive, and thus easily predictable, than the later parts of the game. We include here versions of Figure 2 using alternative ply cutoffs.

Figure 11 shows the accuracy comparison using all moves in each game.

Figure 12 shows the accuracy comparison using the moves after the 30th ply in each game.

\[^3\] The output is an unnormalized distribution over all possible moves that is then normalized with a softmax to only legal moves.
Figure 10. Distribution of model certainties across all games per player, log Y axis

Figure 13 shows the top 3 accuracy comparison using the moves after the 10th ply of each game.

7.3.3. Stylometry by Ply

Instead of looking at the stylometry accuracy of our ensemble models on some number of games whole games, we also considered it with when limited to some range of ply within those games.

7.4. Code

The code for training and evaluating the models will be provided when published.

7.5. Example Games

One important factor to creating the personalized models is that the resulting models feel human and differ noticeably from the initial weights. To this end a skilled chess player played some of the models. The player was familiar with the base model (Maia 1900) and when playing it won 4 games, lost 2 and had 1 tie. We had them play the model trained on the player in our exploration set with over 40,000 games and a high mean rating (1942). The model has 59.8% accuracy on moves after the first 10 ply. The two games are provided in listings 2 and 3 with Stockfish evaluations provided by Lichess:
Figure 11. Move-matching accuracy of our personalized models versus Maia models on target players’ test set games, using all positions encountered by the target player in each game. Target players are color-coded by Rating level from left (lower rating) to right (higher rating). Nearest Maia is the Maia whose training level is closest to the target player’s rating. Error bars show one standard deviation (the standard error is microscopic). The personalized model achieves higher accuracy than the best Maia model on every player.

Figure 12. Move-matching accuracy of our personalized models versus Maia models on target players’ test set games, using positions encountered after ply 30 by the target player in each game. Target players are color-coded by Rating level from left (lower rating) to right (higher rating). Nearest Maia is the Maia whose training level is closest to the target player’s rating. Error bars show one standard deviation (the standard error is microscopic). The personalized model achieves higher accuracy than the best Maia model on every player.
Figure 13. Move-matching top 3 accuracy of our personalized models versus Maia models on target players’ test set games, using positions encountered after ply 10 by the target player in each game. Target players are color-coded by Rating level from left (lower rating) to right (higher rating). Nearest Maia is the Maia whose training level is closest to the target player’s rating. Error bars show one standard deviation (the standard error is is microscopic). The personalized model achieves higher accuracy than the best Maia model on every player.
1. e4 {[eval 0.25] [clk 0:06:00]} 1... a6 {[eval 0.62] [clk 0:06:00]} 2. d4 {[eval 0.36] [clk 0:06:04]} 2... b5 {[eval 0.56] [clk 0:06:10]} 3... Nf3 {[eval 0.77] [clk 0:06:16]} 4. Nc3? { (0.68 -> -0.39) Mistake. Bd3 was best. } {[eval -0.39] [clk 0:06:22]} 4... b4 { [eval -0.75] [clk 0:06:19]} 5. Nfd5 { [eval -0.92] [clk 0:06:24]} 6. Bd3 { [eval -0.97] [clk 0:06:34]} 7... Ne5 { [eval -0.72] [clk 0:06:28]} 8. 0-0 { [eval -0.31] [clk 0:06:40]} 8... Bxe4 { [eval -0.51] [clk 0:06:22]} 9. Bg5 { [eval -0.58] [clk 0:06:26]} 10. Nbd2 { [eval -0.72] [clk 0:06:34]} 11. Nxc4 { [eval -0.96] [clk 0:06:45]} (11... a5 12. a3
{ (-0.96 -> -1.61) Inaccuracy. d5 was best. } { [eval -0.16] [clk 0:07:04]} (12... d5) 12... a5? { (-1.61 -> -0.43) Mistake. Bd6 was best. } {[eval -0.43] [clk 0:06:52]} (12... Bd6 13... c4 bxc3 14. bxc3 Rb8 15. Bc1 a5 16. c4 Bb4 17. Rf1 d5 18.
Ne5 dxc4 19. Qxc4) 13. c4? { (-0.43 -> -1.81) Mistake. d5 was best. } { [eval -1.81] [clk
0:07:10]} (13... d5 Nbd8 13... bxc3 { [eval -1.43] [clk 0:06:57]} 14. Bxc3? { (-1.43 -> -2.84) Mistake. bxc3 was best. } { [eval -2.84] [clk 0:07:16]} (14... bxc3
d5 15. Ng5 Bd6 16. Nh5 g6 17. Nf4 Re8 18. Qh4 Rb8 19. Nd3 e5 20. Nxe5 Nxe5) 14... Re8
?! { (-2.84 -> -2.12) Inaccuracy. Nb4 was best. } { [eval -1.22] [clk 0:06:59]} (14... Nb4) 15. d5 { [eval -1.97] [clk 0:07:22]} 15... exd5?? { (-1.97 -> -0.07) Blunder. Nb4 was best. } { [eval -0.07] [clk 0:07:03]} (15... Nb4 16. Bxc4 axb4 17. dxe6 fxe6 18. Qc4 Bd6 19. Nd3 Nbd5 20. Nde5 c6 21. Re2 Rf8 22. g3) 16. Nxd5 { [eval
0.0] [clk 0:07:28]} 16... Rxd5 { [eval -0.03] [clk 0:07:07]} 17. Qxd5 { [eval -0.04] [clk 0:07:34]} 17... Bd6?? { (0.04 -> 4.77) Blunder. h6 was best. } { [eval
4.77] [clk 0:07:04]} (17... h6 18. Ne5 Nxe5 19. Qxe5 Bf6 20. Qxe8+ Qxe8 21. Rxe8+ Rxe8 22. Bxa5 Bxb2 23. Rxd7 Ra8 24. Bxc7) 18. Rxe8?? { (4.77 -> 0.52) Blunder. Ng5 was best. } { [eval -0.52] [clk 0:07:39]} (18... Nb4 19. Qe4 20. Qe7 21.
Ne7 22. Qd4 23. Ne5 Ng7 24. Qd7 25. Nb8 26. Rd8 27. Qxe6+) 19. Rf1 { [eval 0.37] [clk 0:07:45]} 19... Qf8? { (0.37 -> -0.95) Inaccuracy. Ne7 was best. } { [eval -0.95] [clk 0:07:12]} (19... Ne7) 20. Ng5? { (0.95 -> -0.32) Mistake. Qf5 was best. } { [eval -0.32] [clk 0:07:51]} (20... Qf5 Ne7 21. Qd7 a4 22. a3 Nd5
23. Ba5 Nb6 24. Qc6 Bc5 25. Bxb6 cxb6 26. Re4 Qd8) 20... h6 { [eval -0.12] [clk
0:07:15]} 21. Ne4 { [eval 0.0] [clk 0:07:57]} 21... Re8 { [eval 0.0] [clk 0:07:08]} 22... Qh4
(0.00 -> -0.77) Inaccuracy. Kf1 was best. } { [eval -0.77] [clk 0:08:03]} (22... Kf1 Re6 23. a3 Qb8 24. Nxd6 Rxd6 25. Qc4 Re6 26. Rxe6 fxe6 27. Qd3
Qe8 28. Qd6 Qh8 29. Nb4?! { (-0.77 -> 1.00) Blunder. Re7 was best. } { [eval 1.0] [clk
0:07:06]} (22... Re7 23. Kf1) 23. Qd4?! { (1.00 -> 0.00) Inaccuracy. Qxa5 was best. } { [eval 0.0] [clk 0:08:05]} (23... Qxa5) 23... Be5 { [eval -0.08] [clk
0:06:48]} 24. Qxd7 { [eval 0.1] [clk 0:08:15]} 24... Bxc3?? (DiaW# 0.10 -> 2.55)
Blunder. Re7 was best. } { [eval 2.55] [clk 0:06:51]} (24... Re7 25. Qd2 Bxc3 26.
Nxe5 Rxe1+ 27. Qxe1 Qd8 28. Qe4 c6 29. a3 Nd3 30. Qxc6 Nxb2 31. Qe4) 25. bxc3?? { (5.25 -> 1.04) Blunder. Nf6+ was best. } { [eval 1.04] [clk 0:08:20]} (25... Rd8
25... Nd3 { [eval 1.44] [clk 0:05:59]} 26. Qxc7 { [eval 1.73] [clk 0:08:26]} 26... Nb1?? { (1.78 -> -0.04) Blunder. Rd1 was best. } { [eval -0.04] [clk 0:08:32]} (27... Rd1) 27... Rc8?? { (-0.04 -> 2.12)
Blunder. f5 was best. } { [eval 2.12] [clk 0:05:56]} (27... f5 28. Nd2 Nfx2 29. Nf3 Nh3+ 30. Kg2 Ng5 31. Nc4 Rc8 32. Qd7 Rxc3 33. Rb7 Qf6 34. Qxf5) 28. Qxa5 { [eval
2.46] [clk 0:08:38]} 28... Ra8? { (2.46 -> 4.63) Mistake. Qe7 was best. } { [eval 4.63] [clk 0:05:58] }
(28... Qe7 29. Qf5) 29... Qd5?! { (4.63 -> 3.09) Inaccuracy. Qb5 was best. } { [%eval 3.09] [%clk 0:08:44] } (29. Qb5 Rd8 30. Rd1 Qe8 31. Qxe8+ Rxe8 32. Nd6 Nb3 33. Nxe8 Nxd1 34. a4 Nxc3 35. a5 Nb5) 29... Rd8 { [%eval 2.63] [%clk 0:05:59] } 30. Qf5 { [%eval 3.27] [%clk 0:08:50] } 30... Qa3 { [%eval 3.22] [%clk 0:05:55] } 31. Rb7?? { (3.22 -> 0.54) Blunder. Rd1 was best. } { [%eval 0.54] [%clk 0:08:55] } (31. Rd1 Qxa2 32. Nc5 Qa5 33. Rxd3 Rxd3 34. Qxd3 Qxc5) 35. Qd4 Qc6 36. c4 g6 37. Qd5 Qxd5) 31... Qxa2 { [%eval 2.63] [%clk 0:05:59] } 32. Nd6?! { (0.88 -> 0.19) Inaccuracy. Re7 was best. } { [%eval 0.19] [%clk 0:09:01] } (32. Re7 Qb1+ 33. Kg2 Re8 34. Nd6 Ne1+ 35. Kf3 Qf5+ 36. Nxf5 Nd3 37. Kg2 Ra8 38. Re3 Nc5) 32... Qxf2+ { [%eval 0.32] [%clk 0:05:48] } 33. Qxf2 { [%eval 0.17] [%clk 0:09:07] } 33... Qxh6 { [%eval 0.13] [%clk 0:05:54] } 34. Kxf2 { [%eval 0.14] [%clk 0:09:13] } 34... Rxd6 { [%eval 0.19] [%clk 0:05:59] } 35. c4 { [%eval 0.16] [%clk 0:09:19] } 35... Rd2+ { [%eval -0.06] [%clk 0:06:03] } 36. Kg1 { [%eval 0.0] [%clk 0:06:08] } 36... Rc2 { [%eval 0.0] [%clk 0:06:12] } 38. c5 { [%eval 0.0] [%clk 0:09:37] } 38... Kg7 { [%eval 0.0] [%clk 0:06:17] }

1. e4 { [%eval 0.25] [%clk 0:06:00] } 1... e6 { [%eval 0.13] [%clk 0:06:00] } 2. d4 { [%eval 0.0] [%clk 0:06:04] } 2... d5 { [%eval 0.0] [%clk 0:06:06] } 3. Nc3 { [%eval 0.0] [%clk 0:06:13] } 3... Be7 { [%eval 0.32] [%clk 0:06:18] } 5. e5 { [%eval 0.09] [%clk 0:06:19] } 5... Nf6 { [%eval 0.0] [%clk 0:06:24] } 6. h4 { [%eval 0.12] [%clk 0:06:28] } 6... c5?! { (0.12 -> 0.70) Inaccuracy. Bxg5 was best. } { [%eval 0.7] [%clk 0:06:30] } { C13 French Defense: Alekhine-Chatard Attack, Breyer Variation } (6... Bxg5 7. hxg5 Qxg5 8. Nh3 Qh4 9. g3 Qe7 10. Qg4 g6 11. O-O-O 7. Nh5??? (0.70 -> -1.72) Blunder. Bxe7 was best. ) { [%eval -1.72] [%clk 0:06:28] } (7. Bxe7 Kxe7 8. f4 Nc6 9. dxc5 Nxc5 10. a3 a5 11. Qd4 7... O-O? ( -1.72 -> 1.16) Blunder. f6 was best. ) { [%eval 1.16] [%clk 0:06:59] } 16... Bd7! { (2.29 -> 3.55) Inaccuracy. c4 was best. } { [%eval 3.55] [%clk 0:07:30] } (16... c4 17. Re1) 17. Nc7 { [%eval 3.55] [%clk 0:07:03] } 17... Qd6 { [%eval 4.12] [%clk 0:07:36] } 18. Nb5 { [%eval 4.38] [%clk 0:07:07] } 18... Qb8 { [%eval 3.92] [%clk 0:07:42] } 19. Bd3 { [%eval 3.53] [%clk 0:06:57] } 19... a6 { [%eval 3.61] [%clk 0:07:47] } 20. Na3 { [%eval 3.12] [%clk 0:07:02] } 20... Nxe4 { [%eval 3.31] [%clk 0:07:53] } 21. Nq5 { [%eval 2.68] [%clk 0:07:03] } 21... h6 { [%eval 2.87] [%clk 0:07:59] } 22. Nf3?! { (2.87 -> 1.90) Inaccuracy. Bh7+ was best. } { [%eval 1.9] [%clk 0:07:04] } (22... Bh7+2) 22... b4 { [%eval 1.7] [%clk 0:08:05] } 23. cxb4?! { (1.70 -> 1.08) Inaccuracy. Nc2 was best. ) { [%eval 1.08] [%clk 0:07:09] } (23. Nc2 c4) 23... Nxb4 { [%eval 1.36] [%clk 0:08:11] } 24. Bb1 { [%eval 1.09] [%clk 0:07:11] } 24... e5 { [%eval 1.52] [%clk 0:08:17] } 25. Rhei?? { (1.52 -> -2.75) Blunder. g3 was best. } { [%eval -2.75] [%clk 0:06:55] } (25. g3) 25... e4 { [%eval -1.95] [%clk 0:08:23] } 26. Ng1? { (-1.95 -> -3.75) Mistake. Qc3 was best. } { [%eval -3.75] [%clk 0:06:47] } (26. Qc3) 26... Qe5? { ( -3.75 -> -2.32) Blunder. Bg4 was best. } { [%eval 2.32] [%clk 0:06:29] } (26... Bg4) 27. Nh3 Bxd3+ 28. Bxd3 Nxd3+ 29. Kbl Bxd1 30. Rxd1 c4 31. Qc2 Kh8 32. Kaf1 Qe5 33. Nb1) 27. Qc3?? { (2.32 -> -0.87) Blunder. g3 was best. } { [%eval -0.87] [%clk 0:06:34] } (27. g3 Ne6 28. Nc4 Qc7 29. Rxe4 dxe4 30. Qxd7 Nhd3+ 31. Rxd3 Rf1+ 32. Kd2 exd3 33. Qxe6+ Qf7=27... Qxc3?? { (0.87 -> -1.39) Blunder. Qb8 was best. } { [%eval 1.39] [%clk 0:08:34] } (27... Qb8 28. Nc4) 28. bxc3 { [%eval 1.3] [%clk 0:06:39] } 28... Nbd3+ { [%eval 1.38] [%clk 0:08:40] } 29. Bxd3 { [%eval 1.14] [%clk 0:06:43] } 29... Nxd3+ { [%eval 1.08] [%clk 0:08:46] } 30. Kd2 { [%eval 0.82] [%clk 0:06:37] } 30... Rf2?? { (0.82 -> -1.86) Inaccuracy. Bg4 was best. } { [%eval 1.86] [%clk 0:08:52] } (30... Bg4 31. Ke3) 31. Re2 { [%eval 2.34] [%clk 0:06:38] } 31... Bg4?? { (2.34 -> 5.38) Blunder. Rf4 was best. ) { [%eval 5.38] [%clk 0:08:58] } (31... Rf4 32. Nh3) 32. Rxf2 { [%eval 5.4] [%clk 0:06:37] } 32... Nxf2 { [%eval 5.25] [%clk 0:09:04] } 33. Rbl { [%eval 5.31] [%clk 0:06:38] } 33... d4 { [%eval 5.57] [%clk 0:09:09] } 34. Rb8+ { [%eval 5.4] [%clk 0:06:42] } 34... Kh7 { [%eval 5.79] [%clk 0:09:15] } 35. cxd4 { [%eval 5.77] [%clk 0:06:46] } 35... cxd4 { [%eval 5.73] [%clk 0:09:21] } 36. Nc4 { [%}
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eval 4.55] [eval 0:06:47] 36... e3+?! (4.55 -> 6.26) Inaccuracy. Be6 was best. ) {
[eval 6.26] [eval 0:09:27] ) (36... Be6 37. Ne5 Bxa2 38. Rd8 e3+ 39. Ke2 Ne4 40.
Rxd4 Ng3+ 41. Ke1 Nf5 42. Rf4 Nd6 43. Ra4) 37. Nxe3 ( [eval 5.82] [eval 0:06:52] )
37... dxe3+ {
[eval 6.24] [eval 0:09:33] ) 38. Kxe3 ( [eval 6.15] [eval 0:06:58] ) 38...
Nd1+ {
[eval 6.52] [eval 0:09:39] ) 39. Kd2 ( [eval 6.24] [eval 0:07:00] ) 39...
Nf2 ( [eval 6.1] [eval 0:09:45] ) 40. Re8 ( [eval 5.45] [eval 0:06:57] ) 40...
Kg6 ( [eval 5.96] [eval 0:09:51] ) 41. Nf3 ( [eval 6.05] [eval 0:07:00] ) 41...
Kf7 ( [eval 6.41] [eval 0:09:57] ) 42. Re2 ( [eval 5.79] [eval 0:07:03] ) 42...
Nh1 {
[eval 7.18] [eval 0:10:03] ) 43. Ne5+ ( [eval 7.36] [eval 0:07:01] ) 43...
Kf6 ( [eval 7.54] [eval 0:10:09] ) 44. Nxf4+ ( [eval 7.6] [eval 0:07:07] ) 44...
Kf5 ( [eval 7.91] [eval 0:10:15] ) 45. Ne3+ ( [eval 7.51] [eval 0:07:11] ) 45...
Kf4 ( [eval 7.43] [eval 0:10:21] ) 46. Nd5+ ( [eval 7.46] [eval 0:07:15] ) 46...
Kg3 ( [eval 7.55] [eval 0:10:27] ) 47.
Re7 ( [eval 5.45] [eval 0:07:19] ) 47... Kxh4?? (6.71 -> Mate in 9) Checkmate is now unavoidable. Kxg2 was best. ) {
[eval #9] [eval 0:10:33] ) (47... Kxg2 48. Rxg7+) 48. Rxg7 ( [eval #10] [eval 0:07:24] ) 48...
Ng3 ( [eval 68.71] [eval 0:10:39] ) 49. Rg6 ( [eval #10] [eval 0:07:20] ) 49...
h5?? (60.47 -> Mate in 15) Checkmate is now unavoidable. Nf5 was best. ) ( [eval #15] [eval 0:10:45] ) (49...
Nf5 50. Ne3) 50. Rxa6? ( Mate in 15 -> 9.32) Lost forced checkmate sequence. Ne3 was best. ) {
[eval 9.32] [eval 0:10:50] ) (50. Ne3 Ne4+ 51. Ke3 Ng5 52. a4 Kg3 53. Rfx5+ Kf4 54. Rf5+ Kg3 55. Rfx6 a5 56. Rf5 Kh4) 50...
Kg4 ( [eval 74.21] [eval 0:10:50] ) 51. Ne3+ ( [eval 17.94] [eval 0:07:28] )
51...
Kf4 ( [eval #9] [eval 0:11:25] [eval 0:10:56] ) 52. Ra4+ ( [eval 16.3] [eval 0:07:32] ) 52...
Ke5 ( [eval 60.68] [eval 0:11:02] ) 53. Ra5+ ( [eval 12.36] [eval 0:07:36] ) 53...
Kf4 ( [eval 71.45] [eval 0:11:08] ) 54. a4 ( [eval 59.31] [eval 0:07:39] ) 54...
Ne4 + ( [eval 67.67] [eval 0:11:14] ) 55. Ke2 ( [eval 11.22] [eval 0:07:43] ) 55...
Nc3+ ( [eval 66.7] [eval 0:11:20] ) 56. Kd3 ( [eval 60.67] [eval 0:07:47] ) 56...
Ne4? (60.67 -> Mate in 9) Checkmate is now unavoidable. Na2 was best. ) ( [eval #9] [eval 0:11:26] ) (56...
Na2 57. Rf5+ 57. Rfx5+! (Mate in 9 -> 76.34) Lost forced checkmate sequence. Rfx5+ was best. ) ( [eval 76.34] [eval 0:07:47] ) (57. Rfx5+ Kg3 58. Kxe4 Kh4 59. a5 Kg3 60. a6 Kh4 61. a7 Kg3 62. a8=Q Kh4 63. Qa1 Kg3) 57...
Ng3? (76.34 -> Mate in 12) Checkmate is now unavoidable. Na6 was best. ) ( [eval #12] [eval 0:11:32] ) (57...
Nd6 58. a5 Kg3 59. Nf5+ Kg4 60. Nxd6 Kh5 61. a6 Kg5 62. a7 Kf6 63. a8=Q Ke6 64. Ne4) 58. Rh4+ ( [eval #10] [eval 0:07:52] )
58...
Ke5 ( [eval #11] [eval 0:11:38] ) 59. a5 ( [eval #9] [eval 0:07:55] ) 59...
Nf5 ( [eval #9] [eval 0:11:44] ) 60. Rh5 ( [eval #9] [eval 0:07:59] ) 60...
Ke6 ( [eval #8] [eval 0:11:50] ) 61. Rfx5 ( [eval #7] [eval 0:08:05] ) 61... Kd6 ( [eval #7] [eval 0:11:56] ) 62. a6 ( [eval #6] [eval 0:08:10] ) 62...
Kc7 ( [eval #6] [eval 0:12:02] ) 63. a7 ( [eval #5] [eval 0:08:16] ) 63...
Kb7 ( [eval #5] [eval 0:12:08] ) 64. Rf7+ ( [eval #9] [eval 0:08:21] ) 64...
Ka8 ( [eval #9] [eval 0:12:14] ) 65. Rf6 ( [eval #8] [eval 0:08:19] ) 65...
Kxa7 ( [eval #8] [eval 0:12:20] ) 66. Kc4 ( [eval #6] [eval 0:08:25] ) 66...
Kb7 ( [eval #7] [eval 0:12:26] ) 67. Kd5 ( [eval #6] [eval 0:08:31] ) 67...
Kc7 ( [eval #6] [eval 0:12:32] ) 68. g4 ( [eval #6] [eval 0:08:35] ) 68...
Kd7 ( [eval #6] [eval 0:12:38] ) 69. g5 ( [eval #5] [eval 0:08:41] ) 69...
Ke7 ( [eval #3] [eval 0:12:44] ) 70. Ke5 ( [eval #5] [eval 0:08:46] ) 70...
Kd7 ( [eval #5] [eval 0:12:50] ) 71. Nd5 ( [eval #4] [eval 0:08:50] ) 71...
Kf8 ( [eval #2] [eval 0:12:56] 72. Kd6 ( [eval #1] [eval 0:08:55] ) 72...
Kd8 ( [eval #1] [eval 0:13:02] ) 73. Rf8# ( [eval 0:08:54] ) {White wins by checkmate.} 1-0

Listing 3. Example game, transfer mode is white