# Network dynamics of the online chess platform Lichess: A social network analysis case study

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***Abstract*— This paper is interested in unraveling the dynamics of a network of chess players constructed by observing 20 000 online chess matches played on Lichess.com. A complex network of players is built based on match data and social network analysis techniques are applied. The results are compared to over-the-board chess and other previously studied online chess platforms, to determine if and how the differences in implemented matchmaking algorithms impact network structure and topological properties of the network models. We show that the Lichess social network follows a power-law degree distribution and is not a small world network. It is highly disassortative and clustering is weakly expressed, making Lichess.com more similar to other online chess platforms than over-the-board chess. We employ assortativity analysis to explore the correlations between the difference in player ratings and show that the matchmaking algorithm remains fair, matching players of vastly differing skill level in less than 3% of the matches.**

## I. Introduction

The recent COVID-19 lockdowns have led to an increased interest in online chess platforms and a rise in player numbers. Chess.com has seen 1.5 million new subscribers in April 2020, compared to only 670 000 in January of the same year, making it the online chess website with the largest player base of over 20 million.

Although core game rules remain the same, match formats, ranking systems, and matchmaking algorithms vastly differ between over-the-board and online chess. In over-the-board chess tournaments, ELO rating [1] is used as a proxy of player skills, to regulate matches and improve matchmaking. In sanctioned over-the-board tournaments players of similar ELO ratings meet. This, in theory, allows for fair games, which often end in a draw or the white player winning. A slight bias towards the number of victories achieved by the white player is offset by the multiple games played between the players, where the players alternate colors of their pieces.

In contrast to the fairness of matchmaking based on player skill which is being enforced in over-the-board chess, users of online chess platforms often play quicker chess variants during breaks in their everyday schedule and want to quickly find opponents for a chess match. Therefore, a priority on online platforms is short queue times, even at the expense of possibly larger disparity in player skill. Thus, when no suitable opponent of a similar skill level is available, users can be paired with an opponent with a vastly differing rating. This has been shown to yield differences in properties and structure in networks of chess players built from over-the-board and online chess data [2].

In addition to differences between over-the-board and online chess, online chess platforms also differ between themselves. There are several online chess platforms with a significant player base. Among them, Chess.com stands out based on popularity and player numbers. However, we chose to analyze Lichess.com, an alternative online chess platform, because it is unique and popular among players for its concept of teams. Users are allowed to join teams and teams can organize tournaments for the members, which could significantly impact network structure and dynamics by increasing the local clustering of players.

Previous attempts of applying social network analysis to the topic of chess have mostly involved over-the-board chess. A vast majority of the documented over-the-board chess matches have been played and recorded on tournaments organized and sanctioned by World Chess Federation (FIDE). Complex network theory and social network analysis have been successfully applied to FIDE chess data to identify patterns based on nationality, sex, and color of pieces used by the players during a chess game [3], howbeit without the deeper analysis of the correlation between player rankings. FIDE over-the-board tournaments use ELO rating to perform matchmaking and differ significantly from online chess, disallowing for the interpretation of online chess dynamics as conducted in [3].

The first goal of this paper was to check if and how the differing priorities in the matchmaking algorithm impact the network structure and fairness of matchmaking. Another goal was to explore the impact of the existence of teams on Lichess.com on network structure and topology, as they were expected to lead to more clustering and stronger node groupings.

To achieve this, several social networks of chess players were constructed and social networks analysis was performed. We prove that the matchmaking algorithm employed on Lichess.com remains fair, even while prioritizing for short queue times, by matching players of significantly differing ratings in less than 3% of cases. Furthermore, we show that the existence of teams on Lichess.com does not significantly change the network dynamics and that the system is very similar to other online chess platforms analyzed in [2]. Finally, we discuss our findings, give further insights into the problem of matchmaking fairness in chess and propose possible directions for future research.

## II. DATA SETS AND METHODOLOGY OF ANALYSIS

This section addresses the primary data set, data transformation used to obtain the constructed graphs from the primary data set. In addition, this section contains the methodology of analysis used to obtain the results and check our hypotheses. Finally, a short review of software tools used in our research is given.

### A. Data set

The primary data set [4] is available on Kaggle.com and consists of around 20000 matches played on Lichess.com. The data was collected by observing several teams and allows for analyzing the effects of teams on the structure and dynamics of the constructed social networks.

Secondary data set was obtained by cleaning the primary data set, according to the needs and research goals. For example, as the focus of our research lies on the fairness of matchmaking, information about the moves played during the chess matches, chess openings used by the players etc. is superfluous and thus ought to be removed.

### B. Network modelling

In order to capture the dynamics of the system, an undirected social network was build, with chess players (users of Lichess.com) represented as network nodes. The nodes were connected with an edge if there is a registered match between the corresponding players in teh secondary data set. Weight of the edge equals the number of matches played. We will refer to this network as Original network (O-Net). It visualized in Fig. 3a.

O-Net consists of multiple connected components and several nodes of degree 1. O-Net was pruned by extracting the dominant component and removing all nodes with a single neighbour.

To allow for analysis of matchmaking fairness, information about player ratings is needed. Average player ratings and rating volatility (absolute error of player's rating in observed matches) were calculated. Players were classified into three categories based on their ratings: low (less than 1500 rating), medium (rating between 1500 and 1800) and high (rating over 1800). The thresholds for rating categories were chosen based on the distribution of average player ratings, which can be seen in Fig. 1.

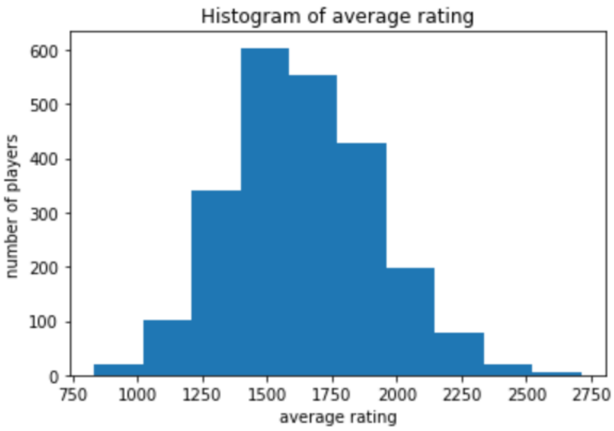


Figure 1. Histogram of average player ratings in Rating Enhanced Pruned network of chess players on Lichess.com (REP-Net)

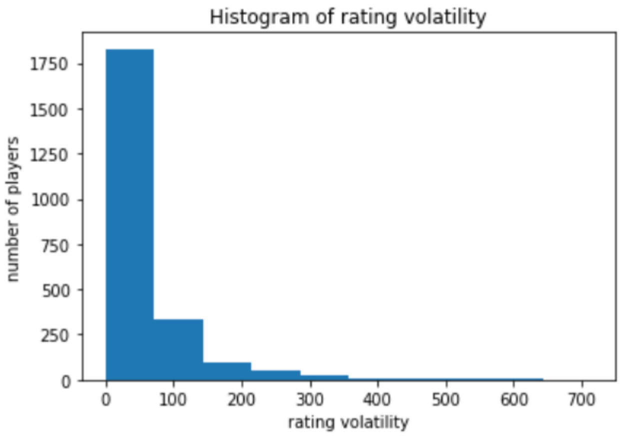


Figure 2. Histogram of rating volatility (absolute error from the player's average rating) in Rating Enhanced Pruned network (REP-Net)

Rating volatility histogram can be seen in Fig. 2 and shows that a majority of players have very low changes in rating in the observed matches, coming from the fact that all the matches come from a short time period. Additionaly, as shown later in Table I, average node degree in this pruned network is quite low, corresponding to a small average number of matches played, therefore lowering the possibility for a big change of player's rating.

The nodes of this pruned network of Lichess players are enhanced with metadata about player's average rating, rating volatility and rating category of the player. We will refer to this resulting network as Rating Enhanced Pruned network (REP-Net) (see Fig. 3b).

A sub-network of the most active and social players was extracted from REP-Net, by keeping only nodes with an unweighted degree of at least 20 and removing the rest. This network is called AS-Net, a short for Active and Social network and can be seen in Fig. 3c.

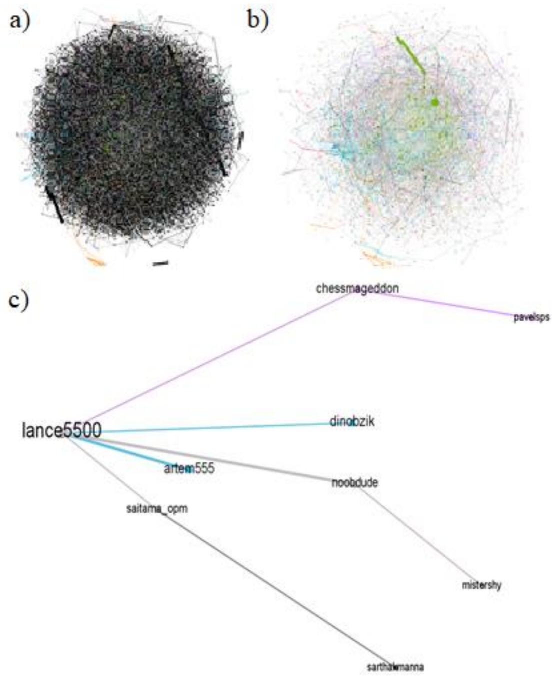


Figure 3. Visualization of constructed networks.
a) O-Net, b) REP-NET, c) AS-Net.

### C. Network analysis

Network statistics of O-Net and REP-Net, such as weighted and unweighted average node degrees, degree distributions, clustering coefficient, and diameter, were calculated. Further analysis was conducted on REP-Net.

Calculated degree distribution was used to fit REP-Net to a network model. Goodness of fit of several candidate distributions was compared.

Clustering coefficient and network diameter were used to check if REP-Net possesses the small-world property. To test if REP-Net expresses the rich-club phenomenon, the structure of AS-Net was observed and analyzed.

In order to evaluate the fairness of the matchmaking algorithm employed by Lichess.com, an assortative analysis based on the player's average rating was conducted. Matrices of assortative mixing and heatmaps were used to visualize the results.

### D. Software tools

Data cleaning and transformation, as well as analysis, were conducted using Python and its module for graphs and complex networks NetworkX [5]. Network model fitting was accomplished using powerlaw [6]. Visualizations were performed using NetworkX [5] and Gephi [7].

## III. RESULTS

### A. Properties of constructed networks

Measured network metrics of O-Net and REP-Net are shown in Table I. Properties of AS-Net are not included in the table, as it contains only 9 nodes and can be explored and analyzed visually, by looking at Fig. 3c.

As seen in Table 1, O-Net and REP-Net are exceedingly weakly clustered and have diameters much higher than 7, meaning neither is a small-world network.

Testing for the existence of a rich-club structure in REP-NET is trivial due to the structure of AS-Net. To clarify, as AS-Net contains the most social and active players, if REP-Net were to express a rich-club structure, all the nodes in AS-Net would belong to the rich club and therefore have to be tightly connected. However, as seen in Fig. 3c, AS-Net is a tree. That is the polar opposite of complete connectedness which would occur in case of the existence of a rich-club structure in REP-Net. Therefore, REP-Net does not conform to the rich-club structure. This result is in agreement with the analysis performed in [2].

TABLE I
METRICS OF THE CONSTRUCTED SOCIAL NETWORKS

| | **O-Net** | **REP-Net** |
|---|---|---|
| Players (nodes) | 15635 | 2352 |
| Edges | 16384 | 3510 |
| Avg. weighted degree | 2.511 | 3.541 |
| Avg. unweighted degree | 2.096 | 2.683 |
| Avg. shortest path length | 8.925 | 7.425 |
| Diameter | 22 | 20 |
| Avg. clustering coefficient | 0.007 | 0.009 |

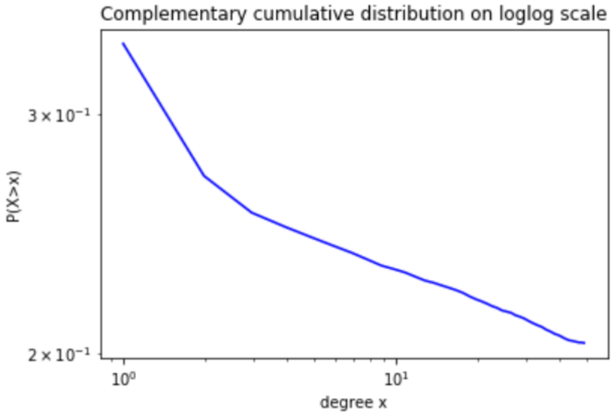


Figure 4. Complementary cumulative distribution of unweighted node degree in REP-Net on loglog scale. Degree distribution follows power law with exponent α=2.34, starting from $x_{min}$=2.

To check if REP-Net follows the power law, a complementary cumulative distribution of unweighted node degree was calculated. It can be seen in Fig. 4. Python package powerlaw was used to fit the degree distribution to all possible candidate distributions, namely power-law distribution, exponential distribution and truncated power-law distribution. Statistical significance of pairwise tests showed that power law distribution is the best fit for node degree distribution in REP-Net, which is in concert with findings reported in [2].

To explore the homophilic properties of REP-Net with regards to node degree, assortativity with respect to weighted ($r_u$) and unweighted ($r_w$) node degree were calculated. As $r_u = -0.605$ and $r_w = -0.607$, REP-Net is highly disassortative, which makes it similar to other online chess platforms [2][1].

### B. Fairness of matchmaking algorithm

Low average changes in player rating, as seen in Fig. 2, validate looking at correlations between average ratings of opponents in order to estimate the fairness of the matchmaking algorithm. Therefore, an assortative mixing analysis with respect to player's average rating was performed.

As a player's average rating is a numeric variable with vastly differing values, it was transformed into a categorical variable. The players were classified into three categories. These categories are the same as the three player rating categories used to label the nodes of REP-Net. Matrix of assortative mixing between the categories and a heatmap visualization of assortativity based on player's average rating are shown in Table II and Fig. 5.

TABLE II
MIXING MATRIX BASED ON PLAYER'S AVERAGE RATING

| | **Low** | **Medium** | **High** |
|---|---|---|---|
| **Low** | 0.202 | 0.091 | 0.027 |
| **Medium** | 0.091 | 0.212 | 0.072 |
| **High** | 0.027 | 0.072 | 0.205 |

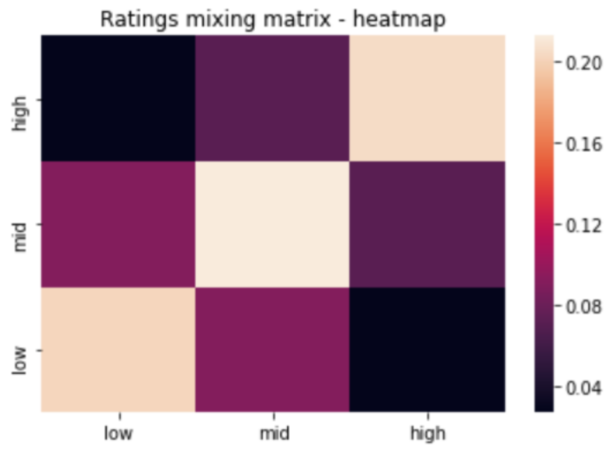


Figure 5. A heatmap of mixing based on player's average rating. Rating categories are low (below 1500 rating), medium (rating between 1500 and 1800) and high (rating over 1800). As mixing between players with low and high rating occurs rarely, the matchmaking algorithm is fair.

It should be noted that the ratings used by Lichess.com are not official ELO ratings and do not follow the same update procedure. Therefore, even though a difference in rating of around 300 between the top-rated players in the low rating category and the lowest-rated players in the high rating category might seem steep, the actual interpretation of the difference is milder than if it were a 300 ELO rating difference in over-the-board chess. Looking through such a lens makes 2.7% of pairings between low-rated and high-rated players even slightly fairer than if those were the players' ELO ratings.

## IV. Discussion and Conclusion

Social networks analysis approach worked well to answer the main research questions. A social network of chess players on Lichess.com was shown to largely follow the same network structure as other previously analyzed online chess platforms, not following a small world model nor expressing a rich-club structure, but following a power-law degree distribution while being weakly clustered and strongly disassortative.

Unintuitively, the existence of teams on Lichess.com yields negligible impact on network structure and it remains largely the same as on other online chess platforms which lack them. The clustering coefficient shows us that player grouping is not stronger and the node degree assortativity coefficient tells us that the network remains highly disassortative. However, the amount of matches observed is possibly not high enough for the concept of teams to materialize in the network structure – after all, the average node degree is a little over 2 in the case of the original network. Therefore, there is a high possibility that many players did not partake in any team-organized tournaments.

The topic of matchmaking fairness was tackled through assortative mixing patterns by transforming the player's average rating node feature into a categorical variable with three categories. Interpretation of the resulting matrix of assortative mixing shows that the matchmaking algorithm does not jeopardize fairness to achieve shorter queuing times. Classification of players into categories was performed somewhat intuitively, by observing the distribution of the player's average ratings. However, it is somewhat in correspondence with the rating system employed by FIDE for their online chess platform FIDE Online Arena, which brackets players into rating categories spanning 300 ELO rating points.

A more complete way to interpret matchmaking fairness would include looking into how up-to-date player ratings are. On Lichess.com and other online chess platforms, the digital nature of the platform allows for rating updates to be made immediately. However, in over-the-board chess tournaments, it sometimes takes several months for the results of the tournament matches to be reported back to FIDE. This leads to a scenario where a player could lose several matches in a tournament organized in June, possibly lowering their ELO rating by a large amount, falling under a threshold that should not allow them to qualify for a tournament organized in July. However, if the results of the first tournament do not reach FIDE before July, the player will be allowed to compete in the tournament. Similarly, increasing a player's ELO rating after winning matches, which would ideally take place immediately, could take months, again impacting the player's ability to participate in the tournaments. To make matters more complicated, besides the problem of qualification for a tournament, it is easy to see that the aforementioned players could meet based on their outdated ELO ratings. Even though it would seem they are of a similar skill level, their current abilities estimated by their real ELO rating should differ quite a lot in reality. In this regard, Lichess.com and other online chess platforms are much more fair and unbiased, so this topic should be further addressed in any future research on the topic of fairness of chess matchmaking algorithms.

## Acknowledgment

This work has been partially funded by the Ministry of Education, Science, and Technological Development of the Republic of Serbia. Grant numbers III44009 and TR32047.

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