# Winning By Chance: Can Chess Be Predicted?

**By Michaela Okporokpo**

At first glance, chess appears to be a simple game where every move follows fixed rules. However, as many players quickly realise, winning is far from simple and predicting the outcome of a game is even more complex. To illustrate this unpredictability, I want you to imagine this scenario:

You're a few moves into a chess game. You and your opponent have equal positions. It's your turn to move and you decide to capture a piece from your opponent. ...Suddenly you've gained question marks in your Chess.com game analysis. This blunder (for those who don't play chess) has turned your position into a losing one and may cost you the game, your honour, and later your life.

In all seriousness, chess is a game of strategy, but its outcomes can still seem unpredictable. This raises the question: if every move can change the outcome so drastically, can the outcome of a chess game truly be predicted? But a better question is to focus on the nature of chess itself: if chess is governed by such strict rules can it really be as unpredictable as it seems?

**Scores Across the Board -**

Instead of trying to predict exact moves we can focus on the wider positions across the board. A simple way of classifying positions is through material advantage, as all pieces (except the king) have point values tied to them.

| Piece | Value |
|---|---|
| Pawn | 1 |
| Knight | 3 |
| Bishop | 3 |
| Rook | 5 |
| Queen | 9 |

*A table showing common piece values*

These values help players make strategic exchanges, and having more pieces may suggest an advantage. However, this is misleading, as a player can be ahead in material and still losing due to weak positioning. A more accurate approach is using overall evaluation, considering both material and positioning.

For simplicity we can categorise these positions into winning, losing or roughly equal. To make this model more precise, we can use a numerical evaluation, measuring in centipawns. As shown in the table, pawns have a piece value of 1, and this is equivalent to 100 centipawns. Centipawns are used to evaluate advantage, as a worsening of the position can be compared to losing a pawn.

A score of +100 means that white has a single pawn advantage. Conversely, a score of –100 shows that black has a single pawn advantage. Other numbers such as +50 can be used to show advantage as a fraction of a pawn advantage (+50 shows that white has a half-pawn advantage). So, we can specify the positions through the following ranges (from white's perspective):

$Let\ centipawns\ be\ denoted\ by\ cp$

$$Winning\ position\ is\ shown\ by\ cp > +100$$

$$Losing\ position\ is\ shown\ by\ cp < -100$$

$$Equal\ position\ is\ shown\ by -100 \leq cp \leq +100$$

Individual moves do not determine the outcome of the game outright but instead shift the balance of the game, showing that certain moves can be more significant than others. Centipawns therefore offer a more effective model than using material advantage alone, as they allow for analysis of the changing positions throughout a changing game.

Since positions can be classified into these three states, chess can be modelled as a system that moves between them over time. From any given position, there is a chance that the next move will improve the overall position, worsen it or leave it relatively unchanged. This reflects move evaluation where a strong move will increase evaluation and a blunder will decrease it significantly.

**Play Prediction -**

But where's the maths? Well here comes Andrey Markov – or Andrey the Furious - with his chains!

Interestingly, Andrey "The Furious" was also an avid chess player and his eponymous work, Markov chains, were proven solely to disprove the work of Pavel Nekrasov, "The Tsar of Probability". (A fascinating pair of mathematicians they were).

The state-based system we created earlier can be modelled using Markov chains, which describe transitions between state spaces. The states in this context are the position classifications (winning, losing or equal), and transitions are the moves that cause shifts between states.

A key feature of this model is the *Markov property*: the probability of transitioning depends **only** on the current position not on earlier positions. This is called the memoryless assumption (don't forget it!). These transitions can be represented using a transition matrix, which shows the probability of moving between each state.

$$P = \begin{pmatrix} 0.7 & 0.2 & 0.1 \\ 0.3 & 0.4 & 0.3 \\ 0.1 & 0.2 & 0.7 \end{pmatrix}$$

*States are in the order winning, equal, losing both top to bottom and left to right*

These probabilities are not exact but are chosen to reflect typical behaviours in chess. Each row horizontally is used to represent the current state, and shows the probability of moving to a winning, equal and losing position, after the next move.

For example, if a player is currently in a winning position, using the top row, there is a 70% chance that after the next move they will remain in a winning position, a 20% chance that the position will become equal, and a 10% chance that it becomes a losing position. This reflects the idea that strong positions are more likely to remain favourable, but a mistake can still cause a significant shift.

The exact probabilities depend on player skill, but estimates can be made based on how stable each state is. As shown by the matrix, winning positions are likely to remain winning, but inaccuracies can reverse this advantage. Generally, for stronger players, the probability of staying in a winning position will be higher and the transition probability to a losing position will be lower. Similarly, losing positions are likely to remain losing, with weaker players generally having a higher probability of remaining in this state. Equal positions however are less stable, as all probabilities are close to each other.

This matrix can be used to model how positions evolve over time by repeatedly multiplying the current distribution by the matrix. By doing this, the system may begin to stabilise, and the probability of each state will eventually converge reaching a *stationary distribution* $\pi$, where the probability no longer changes significantly, and this represents the long-term probability of being in each state, all of which must sum to 1.

$$\pi = (\pi_1, \pi_2, \pi_3)$$

$$\pi_1 + \pi_2 + \pi_3 = 1$$

$$\pi P = \pi$$

After many moves, this distribution stabilises and further transitions and no longer changes, showing the long-term trend.

**A Knight's Journey -**

Even though individual moves are unpredictable, Markov chains can predict the paths of certain pieces over time. For example, we can use them to evaluate a classic problem: how many moves does it take a knight, moving in random directions, to return to its starting position on average? To evaluate this, we can treat each square of the board as a state and assume that there are no other pieces on the board for simplicity. The knight can only make legal moves so we can write the number of possible moves from each square as shown:

| *8* | **2** | **3** | **4** | **4** | **4** | **4** | **3** | **2** |
|---|---|---|---|---|---|---|---|---|
| *7* | 3 | 4 | 6 | 6 | 6 | 6 | 4 | 3 |
| *6* | 4 | 6 | 8 | 8 | 8 | 8 | 6 | 4 |
| *5* | 4 | 6 | 8 | 8 | 8 | 8 | 6 | 4 |
| *4* | 4 | 6 | 8 | 8 | 8 | 8 | 6 | 4 |
| *3* | 4 | 6 | 8 | 8 | 8 | 8 | 6 | 4 |
| *2* | 3 | 4 | 6 | 6 | 6 | 6 | 4 | 3 |
| *1* | 2 | 3 | 4 | 4 | 4 | 4 | 3 | 2 |
| | *a* | *b* | *c* | *d* | *e* | *f* | *g* | *h* |

*A board showing all of the legal moves of a knight from each square*

The transition probabilities to any legal square from a given position will always be equal as they are all random. So, picking one of the possible starting positions b1, the knight has a 1/3 probability of making one of its legal moves. To answer this question, it is easier to model these possible moves as multiple knights:

1) Given that from a square there are N legal moves, place N knights onto that specific square.

2) Repeat this for all the squares and then move every knight one square randomly.

3) A given square now has N knights, and the probability of moving in any direction is 1/N. So, it is likely that over time from each square, one knight will move in each direction.

This means that the distribution of the knights will not change probabilistically, even if this process is repeated. Therefore, we can infer that this distribution shows the stationary distribution of the knight's movement, and the specific distribution can be calculated by dividing the number of legal moves by the total number of legal moves.

$$\Sigma(Legal\ Moves) = 336, \qquad Original\ Number\ of\ Legal\ Moves = 3$$

$$Stationary\ distibution = \frac{3}{336} = \frac{1}{112}$$

This can then be used to calculate the average unit "time" that it will take to return to the original square, by calculating the inverse of this distribution. The unit "time" is the number of moves here, so this gives us a final value of 112 moves on average.

$$Number\ of\ Moves = \left(\frac{1}{112}\right)^{-1} = 112$$

Both Markov chain models can be applied together to each phase of chess: in the opening phase of a game, most positions are close to equal, as pieces have limited movement options, so position transitions here will usually remain in the equal state. Progressing into the midgame, leads to greater instability as pieces in the centre generally have the highest number of legal moves. In turn, the probability of transitioning between states is significantly higher. This results in an endgame where advantages are more exploitable, so winning and losing states remain stable.

I’ve gone on this slight detour (there is a point – I promise!) to show the uses of Markov chains in analysing both long-term piece movements, as well as long-term position shifts throughout chess games, and this may immediately demonstrate a limitation of these models. These models become more accurate with more movements and therefore have limited effectiveness in predicting the outcome of shorter games such as Blitz games.

**The Problem -**

Real chess is not random! The Markov property means that only the current positioning of pieces will be considered, in a game where successive moves can form long term strategies for winning games.

Chess in reality is underpinned by game theory, a framework for analysing situations where decisions are also reliant on those of others. Chess players have perfect information, so they are fully informed about all the moves that have taken place and all the potential moves that can be made.

This means that chess itself is not Markovian, as the wider context is important to each move. This is arguably the greatest limitation of the Markov property, when used to model chess, as the model lacks the foresight that a real player would have (don’t tell Markov – he’d be furious).

But these models still have their benefits, as it means that a complex game can be simplified and analysed quickly. Over time, models become more accurate using both textbook moves as well as data from players, especially since positions often repeat themselves across games. This provides players with quick answers which can be used for game analysis.

**So, Can Chess be Predicted? –**

The answer is kind of…

Markov chains won't provide you with a 100% accurate model of every player's chess game, but it does offer an elegant way to turn them into a probabilistic system. They provide clear advantages in terms of modelling simplicity, but this simplicity also limits their ability to capture the strategic nature of chess. So, although you might be able to predict common tendencies using Markov chains, they may not be enough to predict all ten duodecillion possible chess games.

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