# Streaky Good Models

## Incorporating Short-Run Trends into NBA Predictions

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**Abstract**

This paper proposes a senior project for Yale's Computer Science and Mathematics major based around the study of streaks in NBA basketball. In particular, it outlines some background information and inspiration for the idea, along with potential avenues for research and model implementation, a list of deliverables, and a timeline for completing the project. Ultimately, it describes a project based around creating NBA prediction models strongly correlated with a team's recent performance, making them far more responsive to streaks than most popular models used today.

## Contents

# 1 Background

*"The streak has become my identity;*
*it's who I've become."*

– Cal Ripken, Jr. [2]

The above quote from famed baseball "Iron Man" Cal Ripken, Jr. serves as an apt introduction to the core topic of my proposal: streaks in sports. From Ripken's legendary 2,632 consecutive games played to Caltech basketball's 207 consecutive losses to Jahangir Kahn 555 straight squash match victories, nothing captures the imagination of fans and athletes alike more than the idea of a streak [3].

While often viewed the perspective of superstitions and luck, streaks can also reveal changes in form that may have useful predictive value. As Ripken explains so eloquently, streaks are not just an aspect of sports but an encapsulation of their identity, and thus they serve as an obvious avenue for analytical analysis.

## 1.1 Streaks in the NBA

While there are certainly streaks of various kinds in each and every sport, one sport whose streaks are particularly explanatory of a team's form is basketball, in particular the NBA. As explained by FiveThirtyEight, "NBA data is subject to relatively little randomness," as there are less than 10 players in a typical rotation, all of whom play a fairly regular distribution of minutes when uninjured [5]. Moreover, there are no major differences in positions from game to game, unlike baseball with starting pitchers, and the large amount of games (82 in the regular season, as much as 28 in the postseason) provides ample time for variable short-run trends to emerge across a season.

As a result of these characteristics, an extended streak of good or bad performance in the NBA is more likely to represent a true change in the performance of a team, rather than some fluky trend due to randomness. This is often due to changes like a new scheme or lineup, poor or good health of important players, or even just an establishment of better chemistry within a team (as was the case with the 2021-22 Boston Celtics, who started the season 18-21 and finished 51-31). Thus, recent performance has strong predictive power with regards to NBA games, something acknowledged implicitly by fans, journalists, and coaches alike when assessing the probability of success for a given team.

## 1.2 Predictive NBA Models

In terms of mathematical models predicting NBA games, there has been consistent and continual development, with several methods emerging to prominence in recent years. Most of them build on a staple of more casual game predictions: power ratings.

Whereas most traditional power ratings merely rank teams from 1 to 30, modern models are typically structured to allow precise predictions for a theoretical game between any two teams. In order to do so, there are two main strategies: a mathematical metric that can be used to calculate win probabilities, or a direct measure of how many points a team would be expected to score "relative to average."

### 1.2.1 Elo Ratings

The first type of model is typified by the now ubiquitous Elo rating system, a method for calculating the relative skill levels and win probabilities for games with two opponents (most often thought of with regards to chess). These types of ratings assume that each participant's performance in a random variable that is normally distributed, which represents the uncertainty natural in any competitive game while also providing a predictor of the outcome of the match based on the difference in Elo scores. Then, when an actual game is played, the scores the teams or participants update, with larger adjustments in the case of an "upset" [4].

The aforementioned FiveThirtyEight provides the most popular rendition of Elo-based ratings for NBA teams, expanding on the typical Elo model with NBA-specific adjustments. In particular, given teams $A$ and $B$ with ratings $R_A$ and $R_B$ (which average about

1500), the probability that team $A$ wins is

$$E_A = \frac{1}{10^{\frac{-(R_A - R_B + Adj)}{400}} + 1} \qquad [6]$$

where $Adj$ represents adjustments from aspects of the game like home-court advantage. Then, after a game in which team $A$ has win probability $E_A$ and has actual result $S_A$ (1 for a win and 0 or a loss), their score is updated to $R'_A$ according to

$$R'_A = R_A + K(S_A - E_A) \qquad [4]$$

where the $K$-factor determines how responsive the ratings are to each result (20 for FiveThirtyEight's model). Overall, this strategy has proven to be highly effective with regards to win probabilities, essentially providing a dynamic rating for each team that consistently updates with every result.

#### 1.2.2 Adjusted Point Differentials

On the other hand, there are a variety of popular models that instead provide something more in line with a betting spread, i.e. by how many points would a team be expected to win on average. One prominent ranking of this sort is ESPN's NBA Basketball Power Index (BPI) [7], with Basketball Reference's Simple Rating System utilizing a similar technique [8].

While the precise methods are far more opaque than the well-known Elo ratings, they usually involve some Bayesian framework with priors according to statistics like offensive and defensive efficiency, schedule strength, days of rest, and preseason expectations [9]. They also update in real time with new game results, though these equations are also typically proprietary.

## 2 Motivation

While the various predictive models described in the previous section naturally update according to new results, they are designed under the assumption that the expected performances of a team changes *slowly* over time [4]. However, this assumption naturally breaks down in the wake of a significant winning or losing streak.

As mentioned in the background on streaks, the somewhat deterministic behavior of NBA games means that significant streaks often reflect equally significant changes in performance. Thus, a model that properly incorporates streaks should be very responsive to these changes.

While Elo ratings do update every game and theoretically compound during a streak, they only adjust a set amount based on the result of a single game and the $K$-factor. They will thus take a while to properly adjust to a team's short-run performance, potentially only truly reacting once a streak is over. Likewise, the predicted point differential models typically depend strongly on prior assumptions about a team from previous years, roster construction, etc. So while these assumptions can be updated based on team changes like injuries, they are also slow to react to recent form.

From the "sticky" title favorite whose odds never seem to fall enough with their poor performances to the hot young team that just can't move up the BPI rankings, the explosion of mathematical models of the NBA has been coupled with an understatement of the importance of streaking teams. This is the core discrepancy this project will seek to address.

## 3 Method

With this disconnect between predictive models and short-run trends established, this project aims to create unique methods of calculating NBA win probabilities that are strongly influenced by a team's current form. Doing so will involve significant research into the mathematical underpinnings of Bayesian statistics, machine learning, and more, along with mining data, defining "significant streaks," and creating models based on them.

### 3.1 Potential Techniques

In terms of the actual techniques for creating a "more responsive" model, the most obvious direction is to modify the Elo ranking algorithm to be more dependent to recent team performance, perhaps by dynamically setting the $K$-factor. This could be done in a variety of ways, but the most promising idea at the moment is to utilize a Bayesian framework similar to BPI and SRS but with more weight towards streaking teams. Alternatively, some method of machine learning could be utilized to "train" the $K$-factor based on a team's recent performance.

Beyond this modification of Elo ratings, which will direct the initial research of this project, there are a variety of alternative models which could be more tailor-made to streak-based prediction. Some promising possibilities based on other research [10] include

- Logistic regressions
- Neural networks
- Random forests

along with techniques more closely matching those of BPI and SRS. At the moment, there is no clear type of model that obviously fits this problem best, so determining this will be the basis of most of the initial mathematical research.

### 3.2 Deliverables

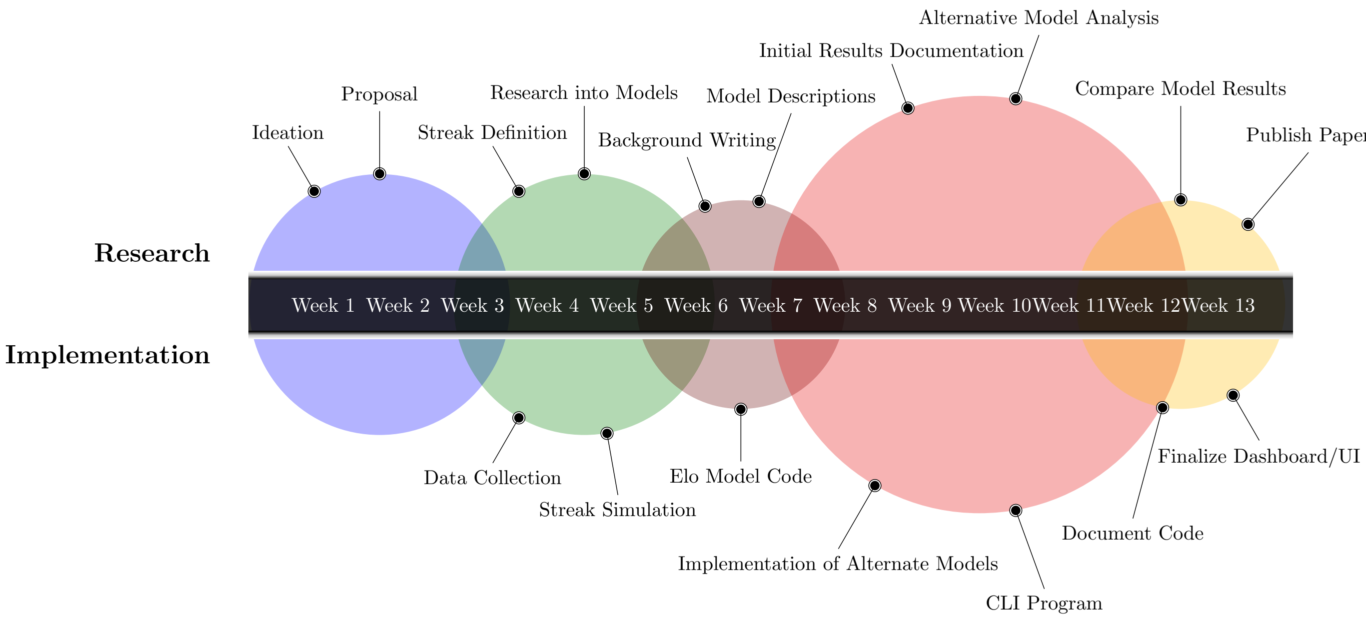
As with any project, there will be a great variety of work on several different aspects of the problem, all of which should be encompassed by the following deliverables presented at the end of it.

- A database of relevant NBA results and data, including:
  - Game results and team statistics from the past 5-10 years
  - Elo scores and other model results for documentation and use as prior assumptions
- A GitHub repository of Python code for parsing the data and creating the model(s), including:
  - Data mining code to create the database
  - Streak simulations to characterize what streaks are significant
  - Code to emulate established models
  - Implementation of models adjusted for streaks
- An interactive program for displaying or obtaining win probabilities or power rankings, including:
  - A CLI for determining win probabilities
  - A dashboard for viewing the results, predictions, and power rankings of the model
- A final report documenting the mathematical research and results of the model(s), including
  - Background research on the different types of models
  - Theoretical mathematics behind my ultimate solution
  - Comparison of the results with existing models and each other

### 3.3 Plan

In terms of a plan for actually completing the project, there are a few main tasks, which I have divided up into smaller tasks spread across five "phases" (outlined below in text with keys to the graphic on the next page), each of which contains some element(s) of research/writing and some element(s) of implementation/coding.

- **Phase 1 (Blue, Weeks 1-3):** Conceptual Ideation and Organization
- **Phase 2 (Green, Weeks 3-6):** Streak Modeling/Simulation, Data Collection, and Research
- **Phase 3 (Brown, Weeks 6-8):** Elo Model Implementation and Outline of Alternative Models
- **Phase 4 (Red, Weeks 8-12):** Alternative Model Implementation and Analysis
- **Phase 5 (Yellow, Weeks 12-13):** Documentation and Presentation

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