



**Full Court Analysts**

# **Multi-Model Consensus: an Ensemble Approach to Basketball Predictions**

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# Introduction:

- Given a dataset with comprehensive game-level and team-level statistics from over 5,300 games with key metrics:
  - Create alternative women’s basketball team rankings within regions,
  - Predict outcomes of matchups in the Eastern region.
- Basketball outcomes are **notoriously difficult to predict** due to varying team strengths, home-court advantages, and contextual factors
- Single-model predictions rarely consider a sufficient number of factors to make accurate predictions

# Background:

- Traditional basketball analytics relied on simple win-loss records or point differentials, which neglected the influence of metrics like attendance, home-court advantage, and strength of schedule
- Modern approaches have evolved to include:
  - ELO ratings (popularized by FiveThirtyEight for sports predictions)
  - Advanced metrics like Dean Oliver Four Factors
  - Neural networks and time-series models for tournament predictions
- Despite these advances, **models rarely agree on exact win probabilities**, creating uncertainty

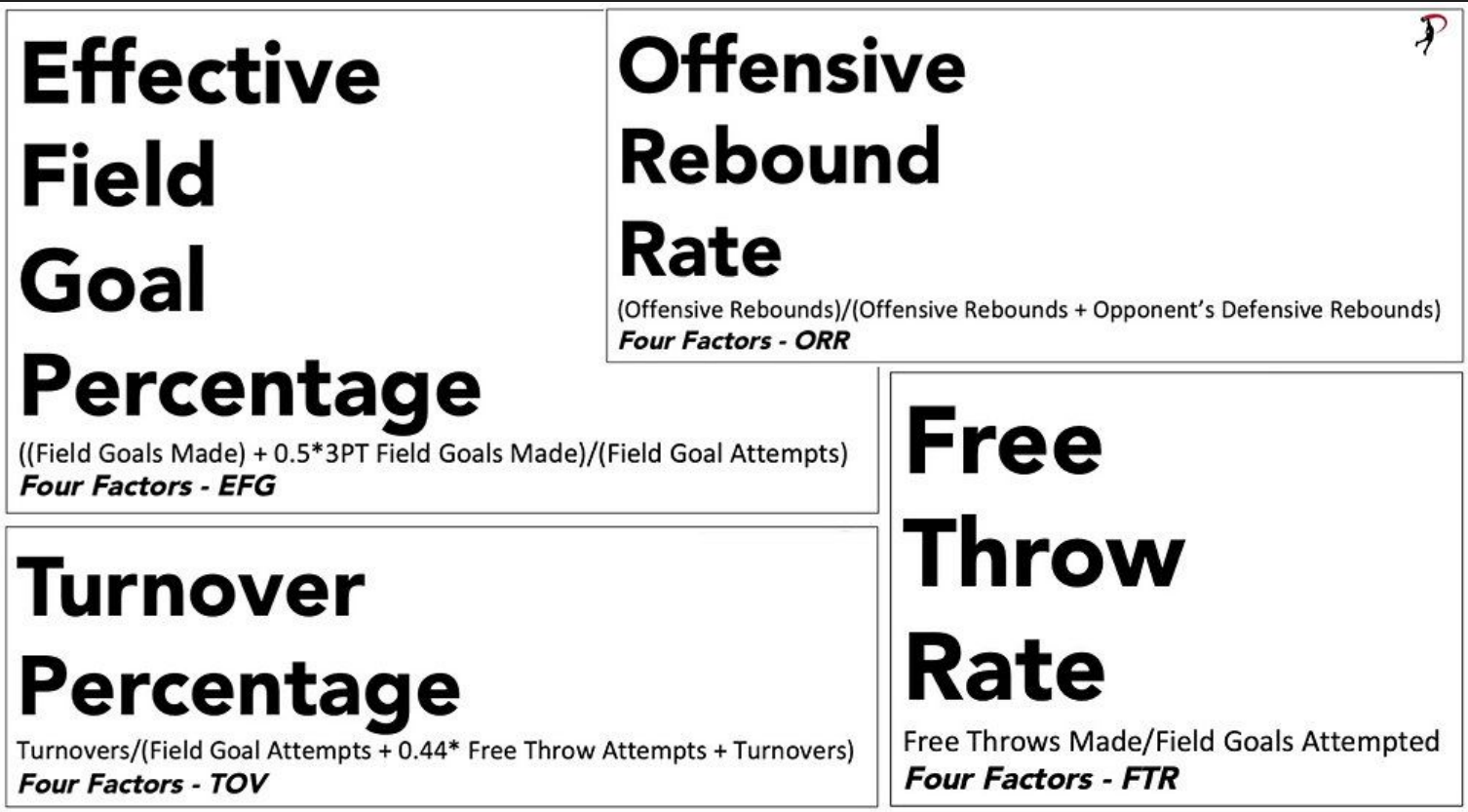


Figure 1

Source: Hvattum, L.M., & Arntzen, H. (2010). Using ELO ratings for match result prediction in association football. *International Journal of Forecasting*, 26(3), 460-470.

# Research Question: How does ranking teams based on win-loss records compare to ranking teams based on multiple metrics specific to the game?

## Goals

- Create **regional team rankings** based on simulated women’s basketball data
- Generate **accurate win probabilities** for regional tournament matchups

## Approach

- **Primary Method:** Dynamic ELO rating system with game-specific adjustments
- **Cross-Validation Strategy:** Implemented three independent models:
  - Dean Oliver’s Four Factors statistical framework
  - Time-aware Logistic Regression with rolling performance metrics
  - PageRank-inspired directed graph network analysis
- **Consensus Methodology:** Analyzed where models converged and to **establish robust ranking and probability bounds**

<b>ELO</b> <ul style="list-style-type: none"><li>• Easy to understand</li><li>• Responsive to recent performance</li><li>• Long-term view of team strength</li><li>• Useful for predicting direct matchups</li></ul>	<b>Four Factors</b> <ul style="list-style-type: none"><li>• Focuses on the key metrics of a game</li><li>• Easy to understand areas for growth</li><li>• Can be applied on both a team and player level</li></ul>
<b>Logistic Regression</b> <ul style="list-style-type: none"><li>• Used to predict binary outcomes</li><li>• Incorporates a variety of input variables</li><li>• Handles non-linear relationships</li></ul>	<b>PageRank</b> <ul style="list-style-type: none"><li>• Analyzing team networks</li><li>• Dynamic weighting of team’s statistics</li><li>• Highlights non-traditional statistics</li></ul>

Figure 2

Source: A normalized score-based weighted PageRank algorithm on ranking prediction of basketball games. Yang Chen, Yepeng Qiu, and Wei Ren. Modern Physics Letters B 2021 35:18.



# Data Prep

- Considered East region teams for Phase 1a rankings
- Combined both rows per game into one
- Imputed missing values through:
  - Rest days (**rest\_days**): replaced NAs with median (3 days)
  - Attendance (**attendance**): imputed with venue-specific averages
  - Technical fouls (**F\_tech**): zero-filled (rare events)
- Ensured chronological integrity by sorting all games by **game\_date** before processing

# Additional Variables

- Home court advantage indicator
- Modified margin of victory formula accounting for point differentials and elo differentials
- Rest differential: **rest\_days\_Home - rest\_days\_Away**
- Travel-induced fatigue metric based on **travel\_dist**

# Tools Used

- **Python 3.9** — Runtime
- **Pandas** — Data Manipulation
- **NumPy** — Calculations
- **SciPy** — Linear Algebra
- **scikit-learn** — Temporal Modeling

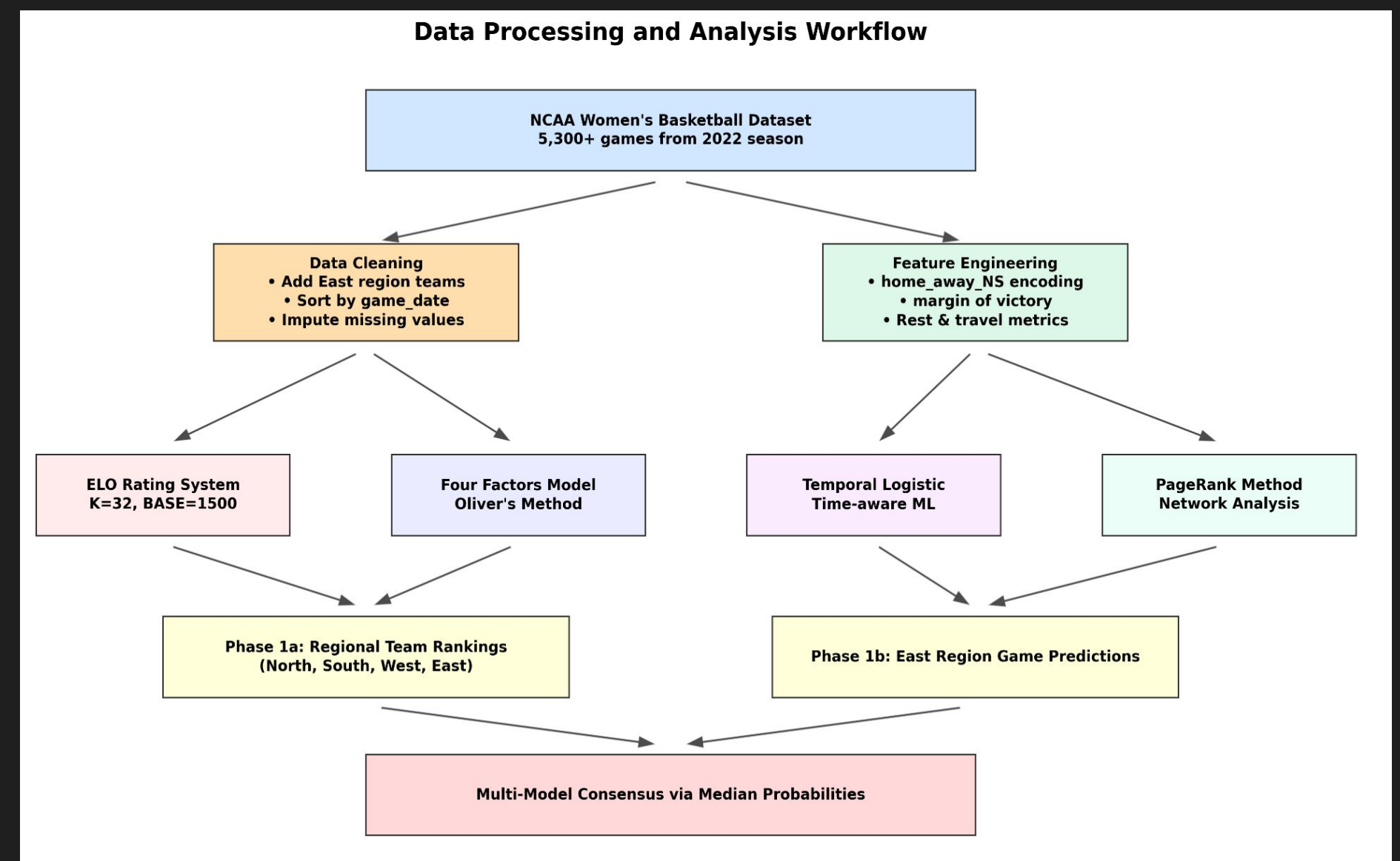


Figure 3

# Method

## Analysis System (Primary):

- Initialized all teams at **1500 base rating**
- Applied Adaptations:
  - K-Factor = 32 (controls rating update magnitude)
  - Home court advantage = 70 points (~10% win probability)
  - Margin of victory multiplier = 1.1 (rewards dominant wins)
  - Rest Day Adjustment - +7.2 points/rest day
  - Travel Distance Adjustment = -2.8 points/300 miles traveled

$$P(\text{win}) = \frac{1}{1+10^{-(\text{ELO}_A-\text{ELO}_B)/400}}$$

$$\text{MOV}_{\text{mult}} = \frac{(\text{point difference})^{0.8}}{7.5+0.006 \times |\text{ELO}_A-\text{ELO}_B|}$$

## Additional Validation Models:

- **Four Factors:** **Weighted combination** of shooting (35%), turnovers (30%), rebounding (25%), and free throws (10%)
- **Temporal Logistic:** Time-aware machine learning with **rolling team strength metrics** and L2 regularization
- **PageRank:** Directed network where wins create weighted edges between teams, with **eigenvector centrality** determining team strength

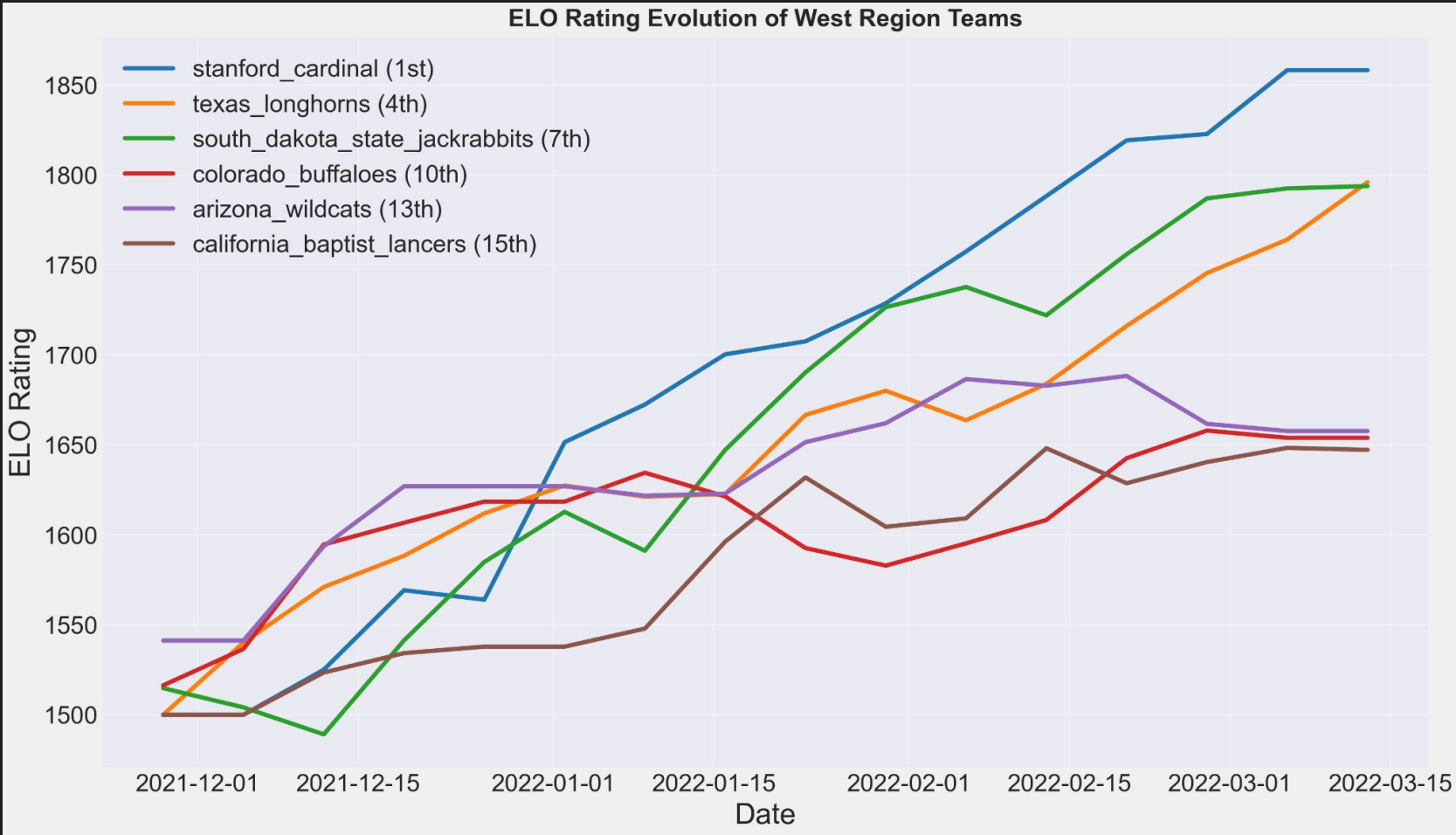


Figure 4

# Result 1: Regional Ranks & Predictions

## Regional Ranking Analysis:

- South Carolina Gamecocks (1907) emerged as the clear leader, with a 22-point gap to Florida Gulf Coast (1885)
- **Tightly clustered top teams** with Louisville Cardinals (1807) edging Iowa Hawkeyes (1798) by only 9 points
- Stanford Cardinal dominated with 1874 points, showing consistent performance against tough opposition
- Key Insight: Top 5 teams within each region separated by less than 100 ELO points (~14% win probability difference)

## East Region Prediction Analysis:

- High Confidence Games: NC State vs. Rhode Island (78.2%), UConn vs. Campbell (72.0%)
- Contested Matchups: Five games had ELO probabilities between 43-47%, indicating **near coin-flips**
- Liberty vs. Bucknell showed the **largest disagreement** (ELO: 68.1%, Temporal: 85.0%, Four Factors: 47.7%)

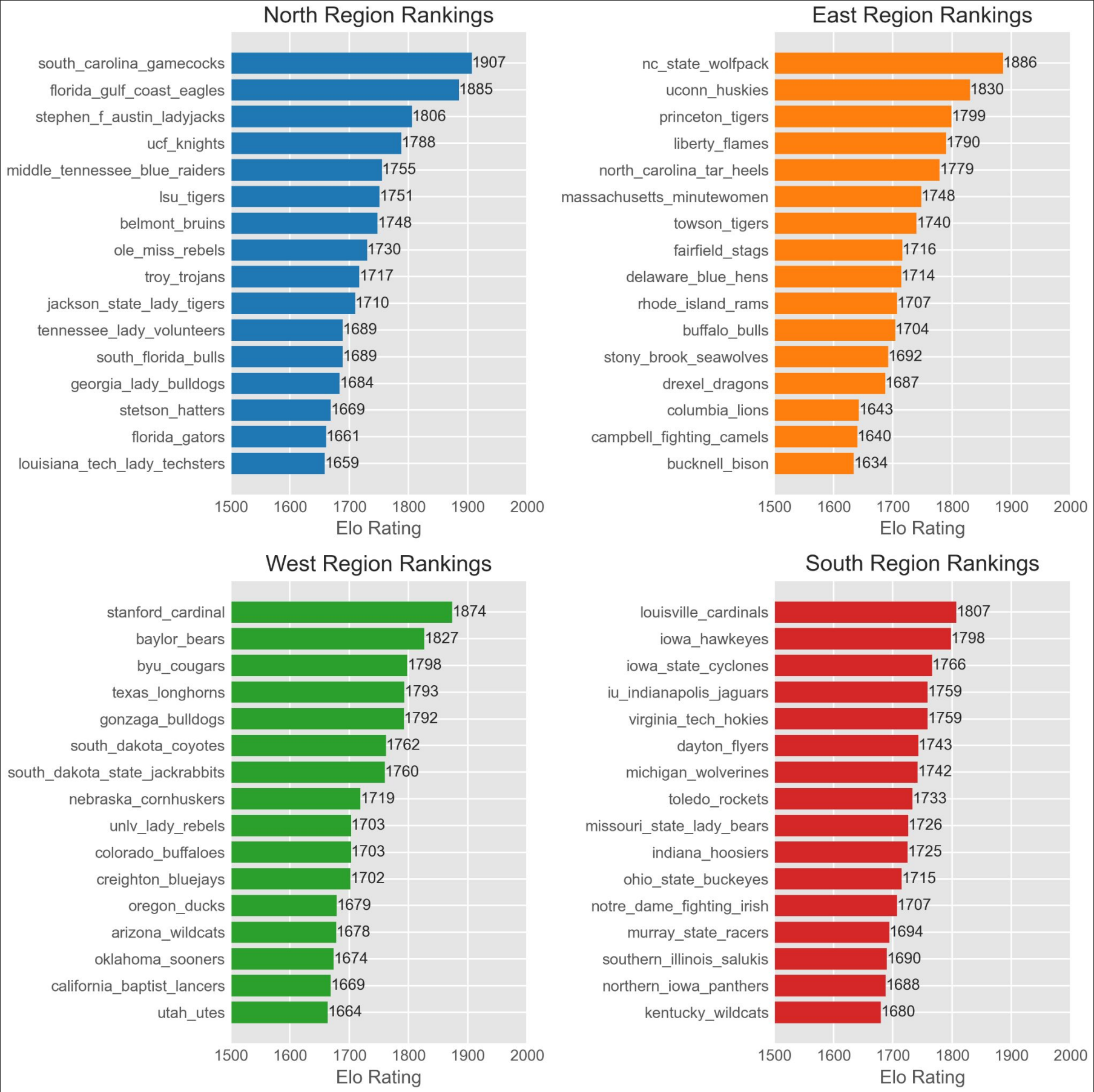


Figure 5



# Result 2: Cross-Validation for ELO

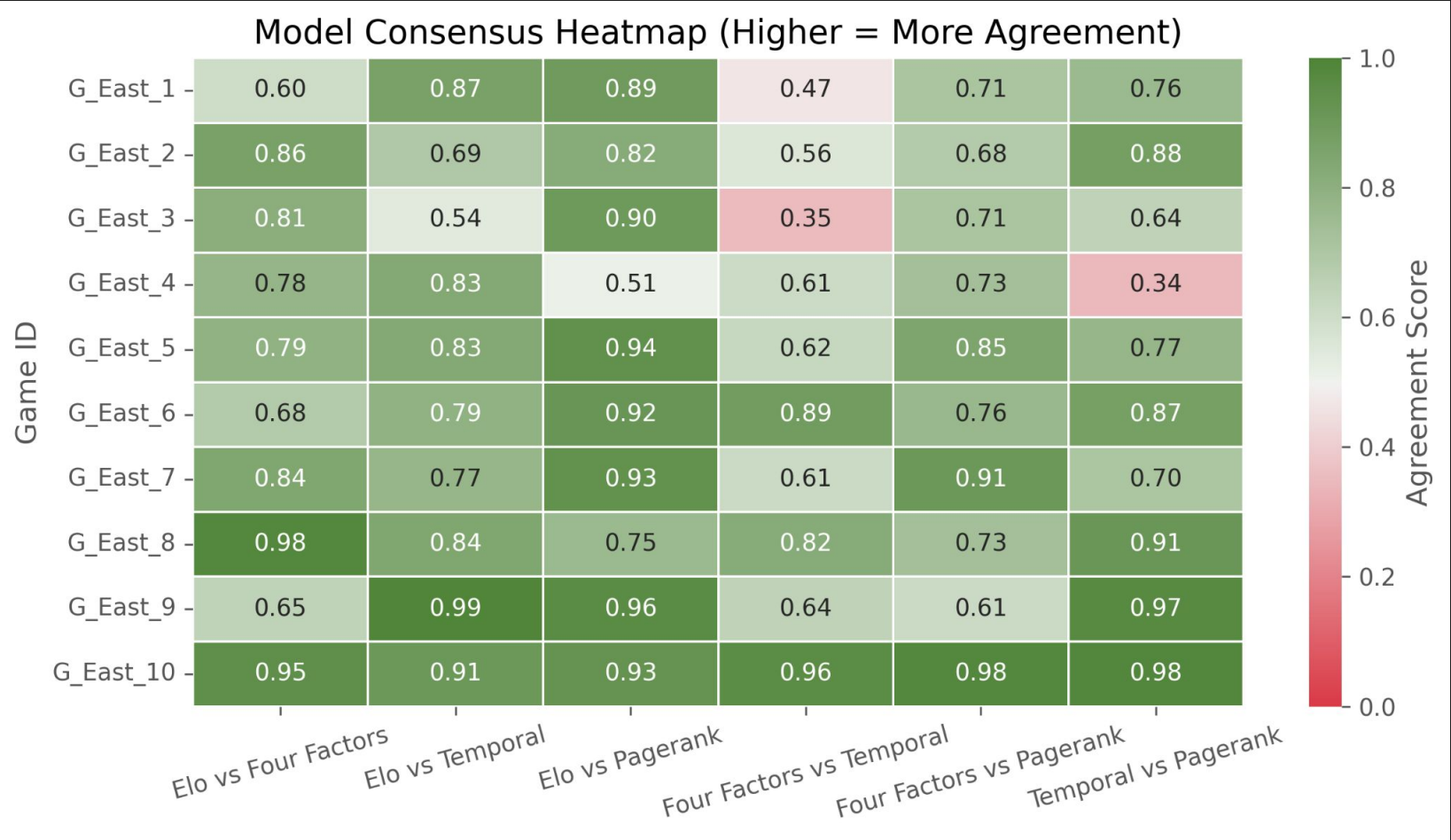


Figure 6

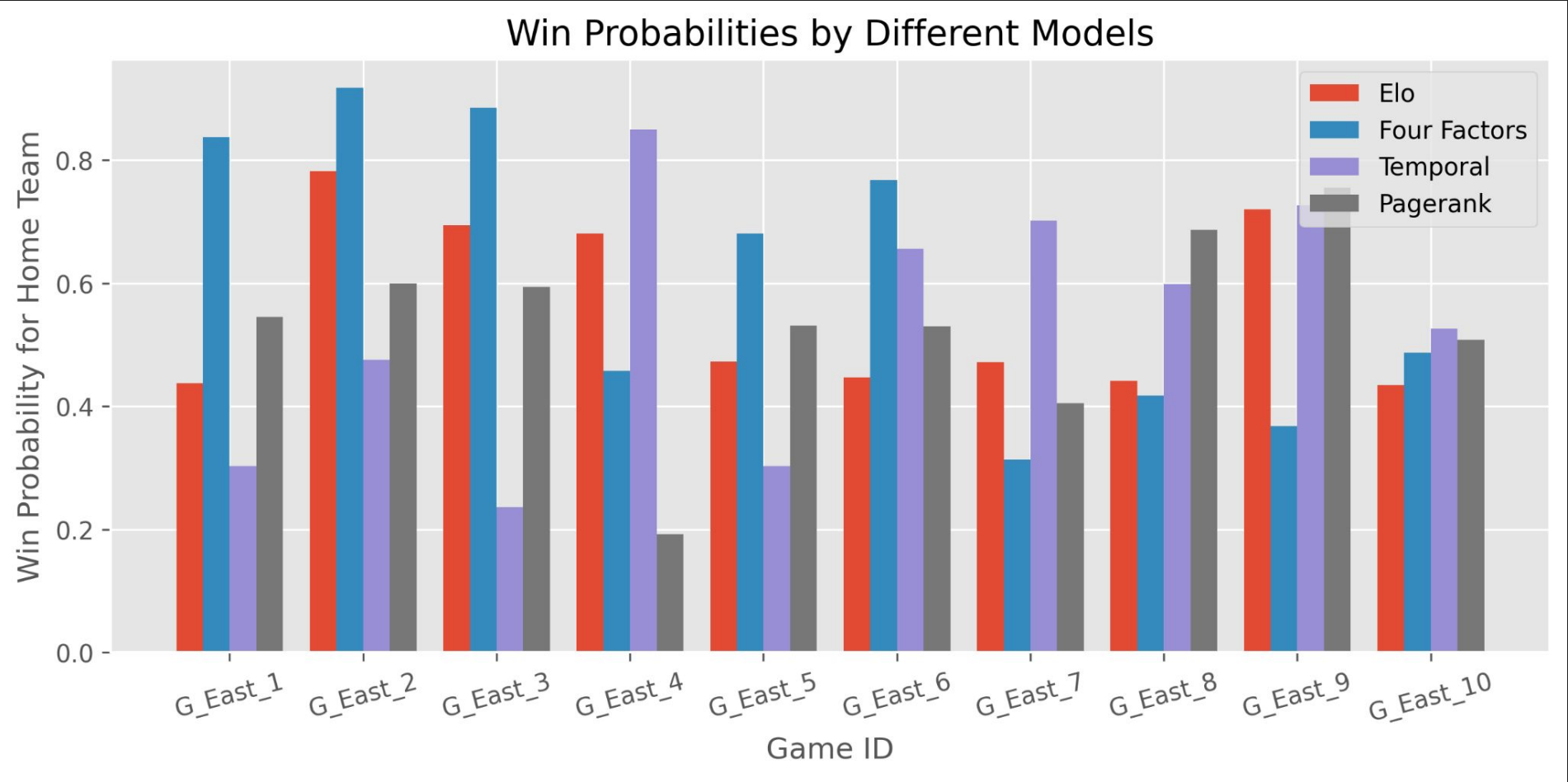


Figure 7

## Cross-Validation for Rankings:

- 68% agreement on top-10 teams across regions
- Jackson State Tigers ranked significantly higher in Four Factors (#1 in North) than in ELO (#10)
- West Region showed highest consistency between models (80% overlap in top 10)

## Cross-Validation for Probability:

- ELO provided the median probability in 7 of 10 games
- When models significantly disagreed, contextual factors explained differences:
  - Travel distance impact (Stony Brook's 3400-mile journey in Game 7)
  - Rest differential (NC State's 6-day advantage in Game 2)

# Conclusion

## General Findings

- **ELO provides reliable predictions** and typically fell between more extreme model outputs
- Multi-model consensus approach enabled confidence assessment: **70% probability agreement** within  $\pm 10\%$  across models
- Game-specific factors (ex. home advantage) are significant

## Considerations for Coaches

- Offensive index (FGA\_2, FGM\_2, FGA\_3, FGM\_3) found to be more significant than defensive index
- The specific environment & context of every game is crucial

## Limitations

- Limited historical data for some East region teams
- Long-term inflation of ELO scores
- Models cannot account for "tournament psychology" (pressure, experience factors)

## Improvements

- Incorporate neural networks to address highly non-linear variables
- Explore Bayesian updating for parameter optimization
- Finetune hyperparameters in existing four models

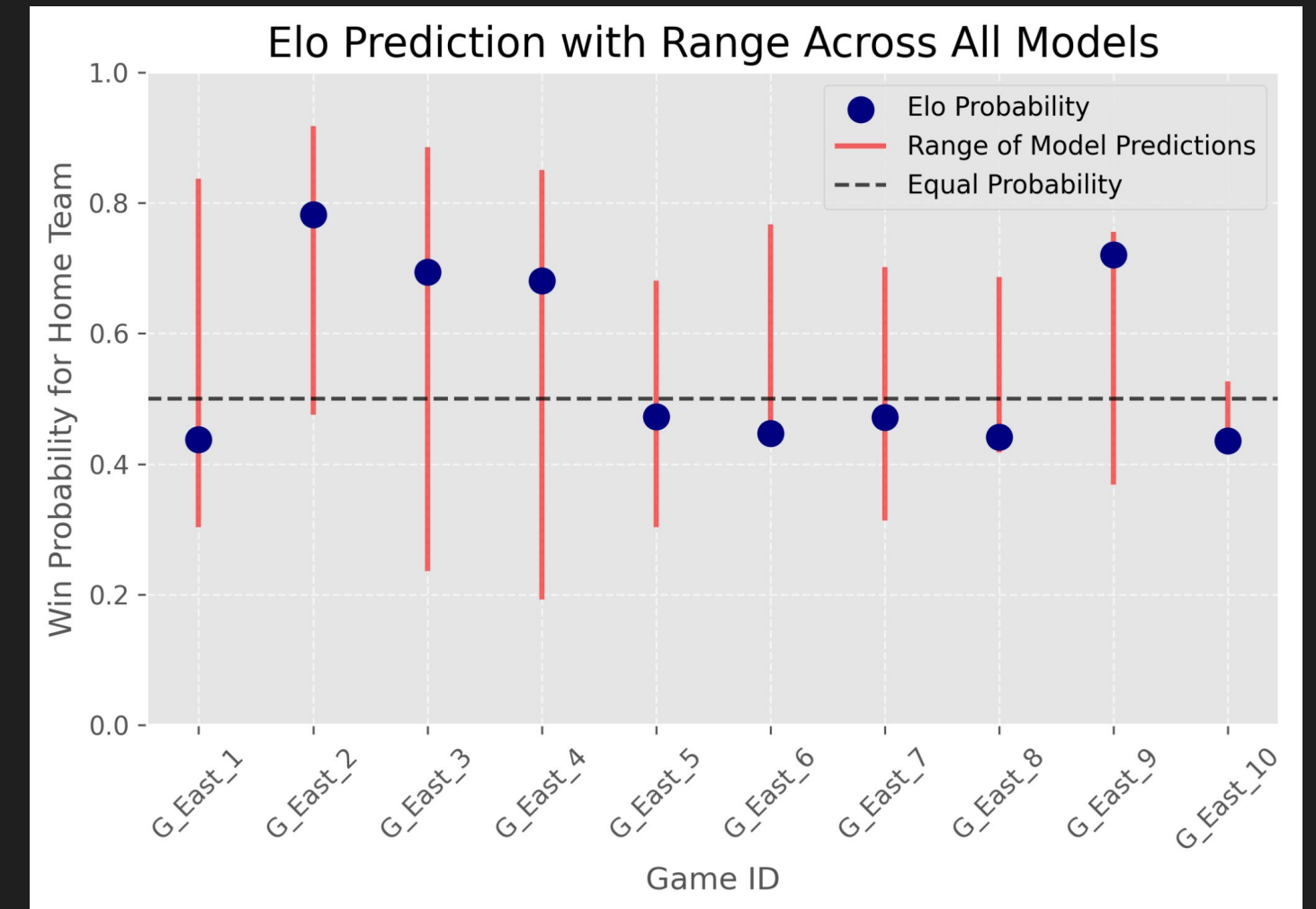


Figure 8