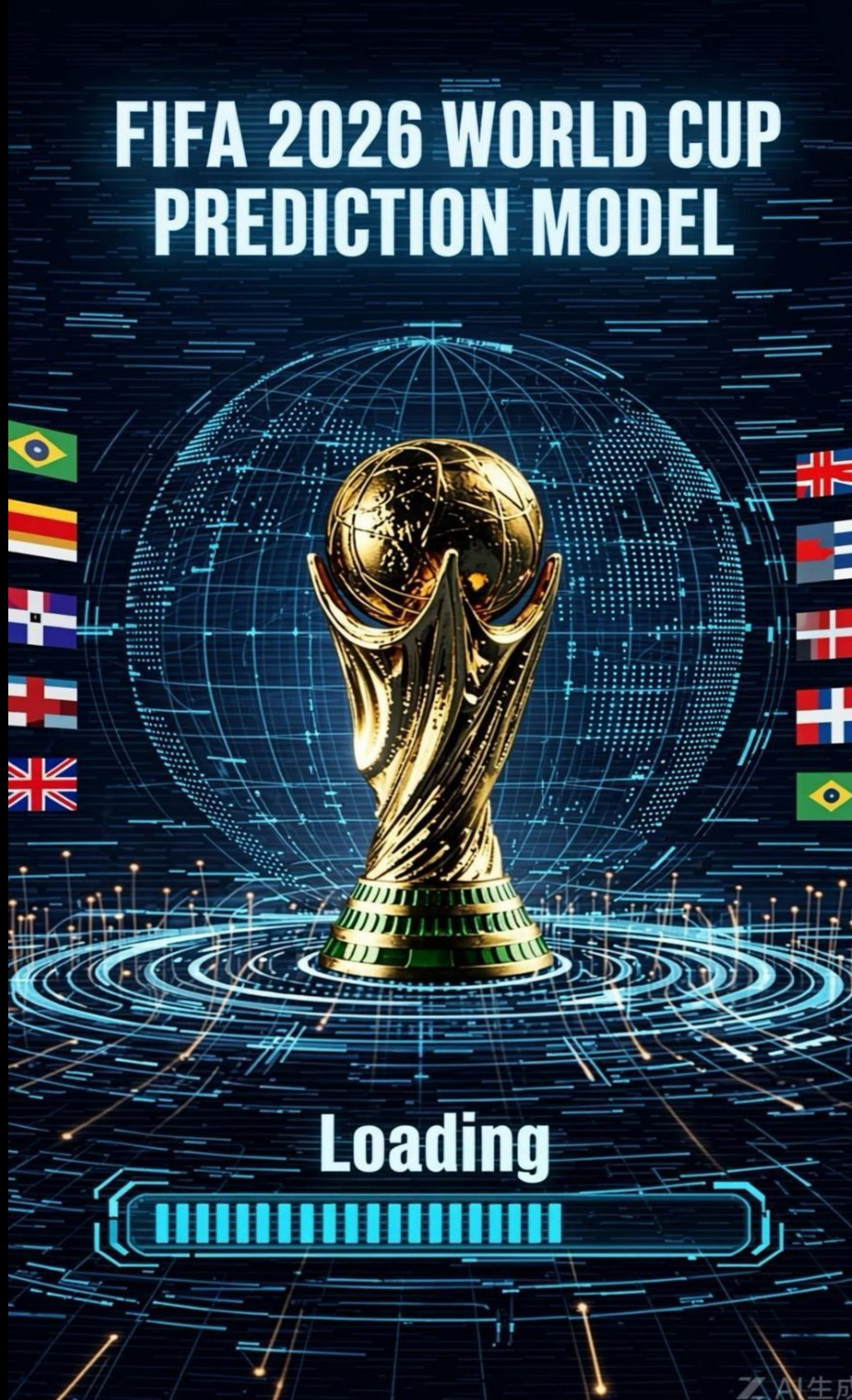
FIFA 2026 WORLD CUP
PREDICTION MODEL
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Predicting FIFA World Cup 2026 Outcomes

Probabilistic Modelling of Goals and Tournament Outcomes Using Statistical and Machine Learning Methods

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Core Questions

Who will win the tournament?

Who will win individual matches?

How many goals will be scored?

How far will teams advance?

Datasets

International Match Results

- Source: Public, community maintained dataset (Kaggle)
- Historical men's international matches
- Match date, teams, full-time score, venue
- 49,000 observations before processing

Official FIFA ranking releases

- Source: Fifa website
- Historical team strength ratings
- 68,000 observations before processing

Cleaning and Preparing Data

Preparation Steps

- Cleaned, removed and standardized missing values
- Removed friendly matches
- Merged nearest prior FIFA rankings to avoid look-ahead bias
- Filled missing ranking values using average
- Selected top 48 teams according to FIFA ranking points for 2026 world cup simulation

Key Features

- Fifa ranking difference
- Home advantage (only when not neutral)
- Neutral indicator
- Attack (team)/defence (opponent) relative strengths
- Recency weighting

$$\text{attack\_advantage} = \log\left(\frac{\text{team avg goals / global avg}}{\text{opponent avg conceded / global avg}}\right)$$

Two Modelling Approaches

1. **Goal-Based Model**
   Models expected goals using a GLM (Poisson/Negative Binomial)
   → Determine W/D/L from simulated goal counts

2. **Outcome-Based Model**
   Directly estimates W/D/L probabilities using ML classifiers
   → Sample match outcomes

Both approaches:
Run full tournament simulation with all 48 teams

Tournament Simulation

2026 Format Simulated

- 48 teams
- 12 groups of 4
- Top 2 groups + best 6 $\longrightarrow$ Round of 32
- Knockout to champion

Two simulation pipelines

- Goal-based (Negative Binomial sampling)
- ML-based (sample W/D/L from probabilities)
- We ran 2000 simulations and took averages

Why This Is Hard

- **Low-Scoring, High Variance Sport**
  - Goals are rare count events
  - Variance often exceeds the mean
  - One goal can flip outcome
  - Poisson assumptions may fail

- **Outcomes Are Inherently Probabilistic**
  - Upsets are common (a lot of games close to 50:50)
  - Draws are frequent
  - Home / neutral effects matter
  - Deterministic prediction is unrealistic

- **Tournament Structure Amplifies Noise**
  - 48 teams
  - Group + knockout stages
  - Small probability differences cascade
  - We must simulate distributions, not single outcomes

First Statistical Model

Poisson GLM (Count Model)

$$Y_i \approx Poisson(\mu_i)$$

$$\log(\mu_i) = \beta_0 + \beta_1 \cdot \text{points\_diff}_i + \beta_2 \text{ home\_adv}_i + \beta_3 \text{ neutral}_i + \beta_4 \text{ attack\_advantage}_i$$

$$\mu_i = \exp\left(\begin{pmatrix} \beta_0 + \beta_1 \text{points\_diff}_i + \beta_2 \text{ home\_adv}_i \\ + \beta_3 \text{ neutral}_i + \beta_4 \text{ attack\_advantage}_i \end{pmatrix} \right.$$

where: Y_i : goals scored
μ_i : expected goals

Fitted via maximum likelihood

Poisson assumption!
Variance ≈ Mean

Goal-based Model Diagnostic

Dispersion Ratio = Residual Deviance / Residual Degrees of Freedom
Overdispersion ratio ≈ **1.88** > 1

Interpretation

- Variance > Mean
- Poisson assumption violated

Solution

- Upgraded to **Negative Binomial GLM**
- Alpha ≈ 0.669
- Deviance dropped from 7,888 to 4556 - observed goal counts explained better
- (Alpha quantifies the degree of overdispersion, allowing the variance to grow faster than the mean, which better reflects the variability observed in goal counts)

$$\mathrm{Var}(Y_i) = \mu_i + \alpha\mu_i^2$$

This model was used for tournament goal simulation.

Model Results

- The explanatory variables ‘***points_diff***’, ‘***home_adv***’, ‘***attack_advantage***’ and ‘***neutral***’ were all strongly significant
- Higher ranking teams score more
- Home advantage and neutral venues increase goals scored
- Interestingly ‘***attack_advantage***’ DECREASES goals, possible explanations:
  - Collinearity with points_diff? Investigated and found unweighted correlation of 0.016
  - Attacking teams cancelling out?

Coefficient Estimates

Variable	Coef	Std Err	z	p-value	95% CI
Intercept	0.0119	0.031	0.383	0.701	[-0.049, 0.073]
points_diff	**0.0008**	4.84e-05	16.15	<0.001	[0.001, 0.001]
home_adv	**0.4608**	0.041	11.20	<0.001	[0.380, 0.541]
attack_advantage	**-0.1575**	0.028	-5.70	<0.001	[-0.212, -0.103]
neutral	**0.3057**	0.042	7.32	<0.001	[0.224, 0.388]

Machine Learning Statistical Model

Outcome Classification Model
Target: Win / Draw / Loss

Models

- Random Forest
- HistGradientBoosting
- Ensemble (average probabilities)

Training

- Stratified 5-fold CV
- RandomizedSearchCV
- Optimized for log-loss

Model metrics

Overall Performance

- Accuracy
- Macro F1 (treats all classes equally)

Probability Quality

- Log-loss (probability quality)
- Multiclass Brier score

Diagnostic Checks

- Confusion matrices
- Calibration plots

Key Model Findings

Probability Quality > Raw Accuracy

- Models optimized for log-loss, not just accuracy
- Ensemble delivered best log-loss (~1.025) and best Brier (~0.614)
- Calibration improved vs single models

Modest Predictive Signal

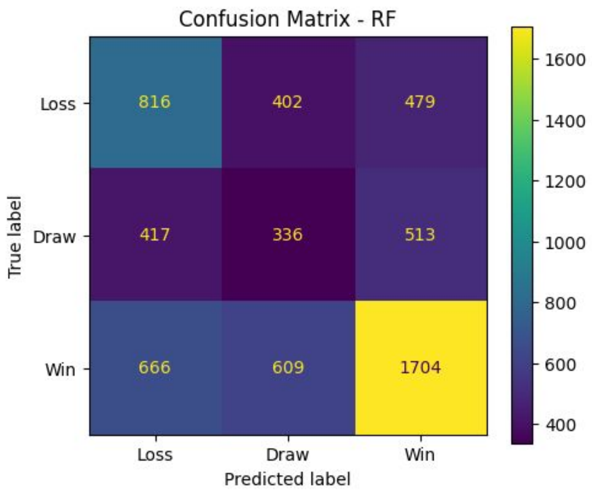
- Many matches close to 50:50 → inherent uncertainty
- Accuracy only moderately above baseline

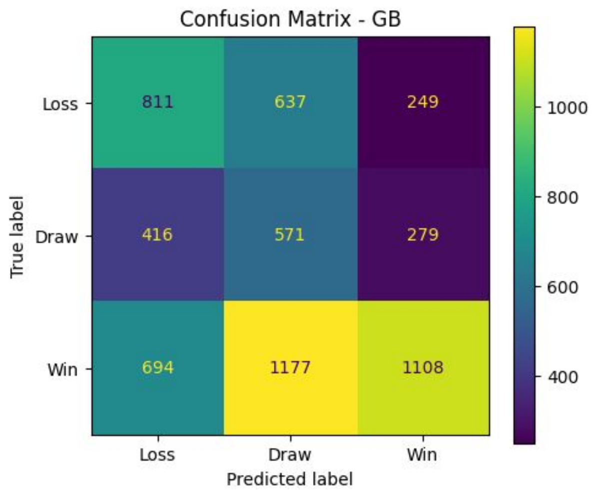
Feature Importance

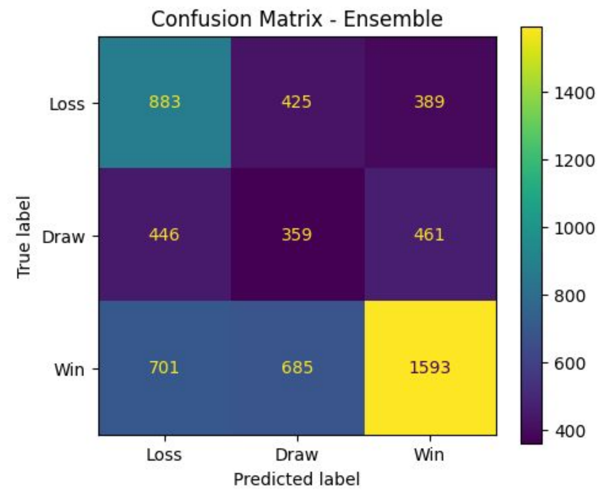
- FIFA points difference strongest predictor
- Home advantage meaningful
- Attack advantage smaller marginal impact
- Attack advantage had weak and non-monotonic effects in the ML models, consistent with it being a secondary signal rather than a dominant driver.

Draws Remain Hard to Predict

- Confusion matrices show draws most misclassified - reflects real-world parity and noise

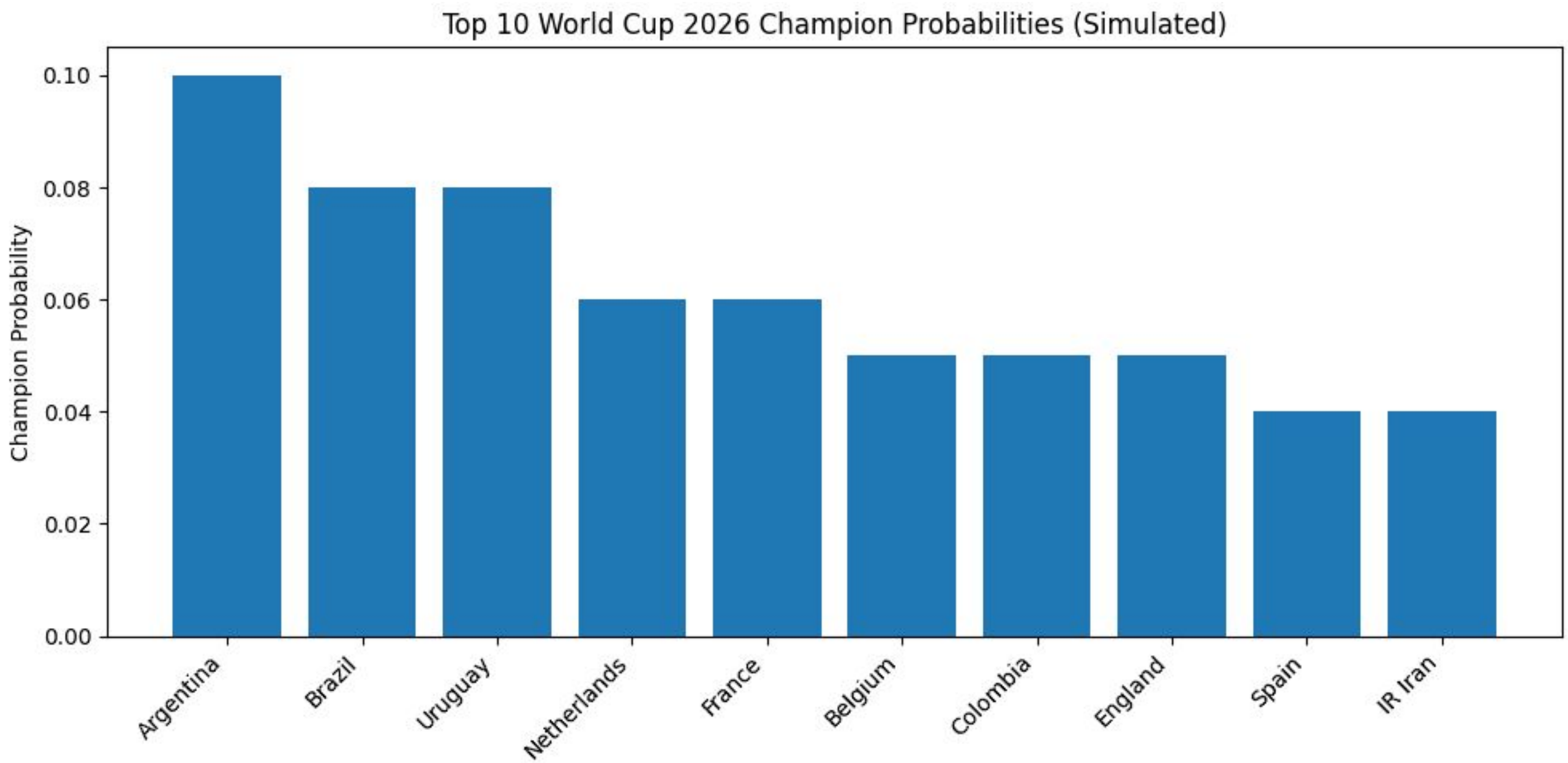






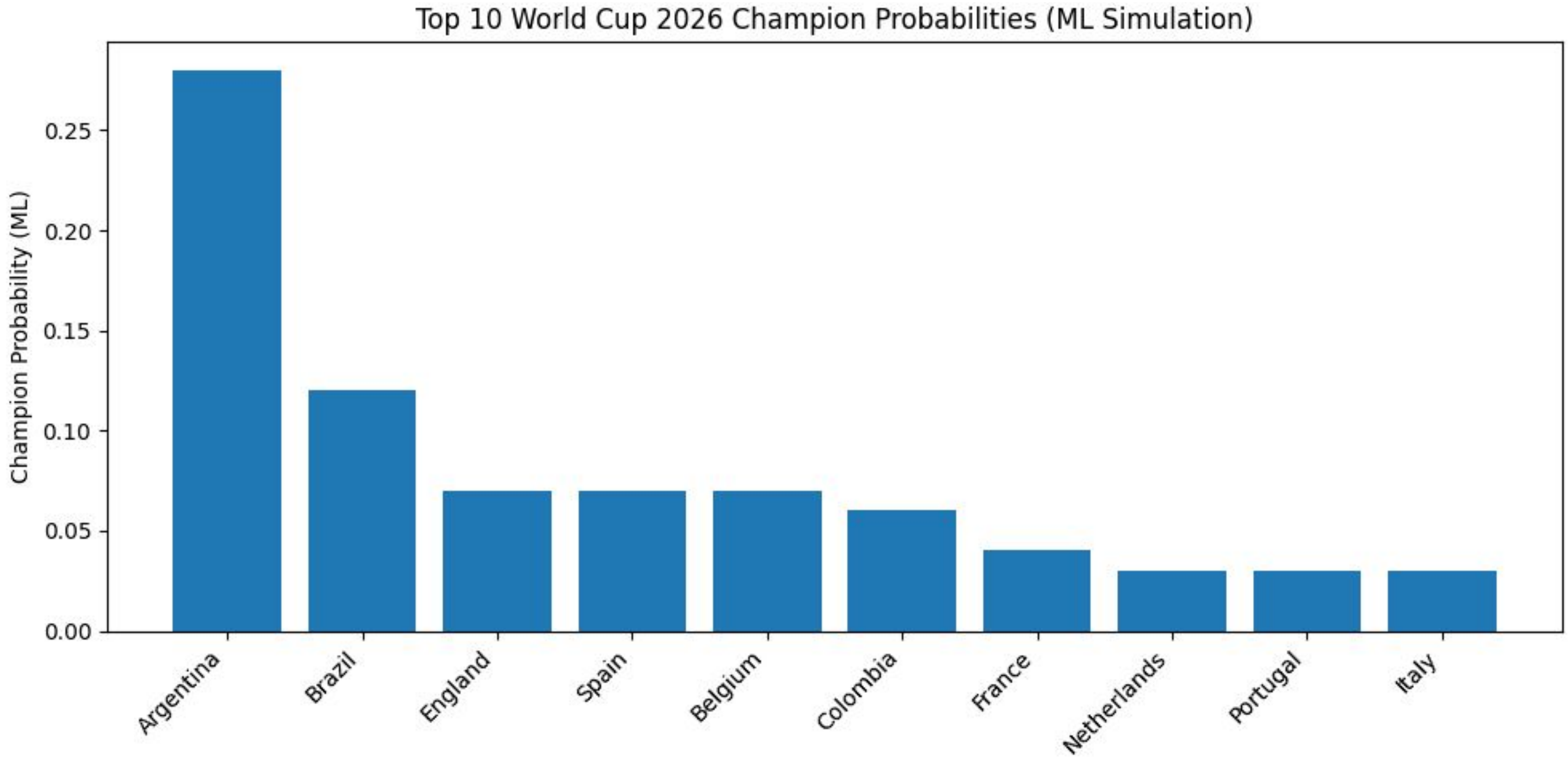
Simulation Results

Goal Model (GLM) Champions



Simulation Results

ML Model Champions (sample runs)



Assumptions & Limitations

- Results were plausible - but unstable
- FIFA rankings imperfect proxy for strength
- No injuries, tactics, or player-level data
- Simplified scorelines in ML simulation
- Potential temporal leakage if not time-split

Future Improvements

High-impact upgrades:

- Increase simulations (5,000–50,000)
- Time-based train/test splits
- Better score generation in ML simulation
- Take into account player rankings and penalties
- Team fixed effects ratings
- Calibrate the ensemble probabilities better

Thank you!
Any Questions?

2026

FIFA WORLD CUP

UNITED STATES - CANADA - MEXICO