Enhancing Football Event Forecasting by Integrating Betting Odds into the SCORE Architecture

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Introduction

Football is characterized by a blend of skill and luck, making it difficult to predict. The SCORE [1] framework proposed a convolutional approach to forecast the next event (e.g., Goal, Corner, Card) based on event history.

A. The Limitation

While SCORE [1] effectively distinguishes between Home and Away entities, it is designed to be invariant to specific team identities. The model is unaware of the specific quality difference between opponents (e.g., a title contender vs. a relegation candidate).

B. The Solution

We propose SCORE-ODDS, which integrates betting odds representing the wisdom of the crowd. This allows the model to determine team strength based on external market data, distinct from generic home and away labels.

Original Architecture

SCORE [1] treats a match as a sequence of events.

- **Input:** A matrix $M^{(i)}$ representing the history of events (rows = time, columns = event types).
- **Mechanism:** Uses two convolution types:
  - $\mathcal{F}$ filters: Applied across the event dimension.
  - $\mathcal{G}$ filters: Applied across the time dimension.

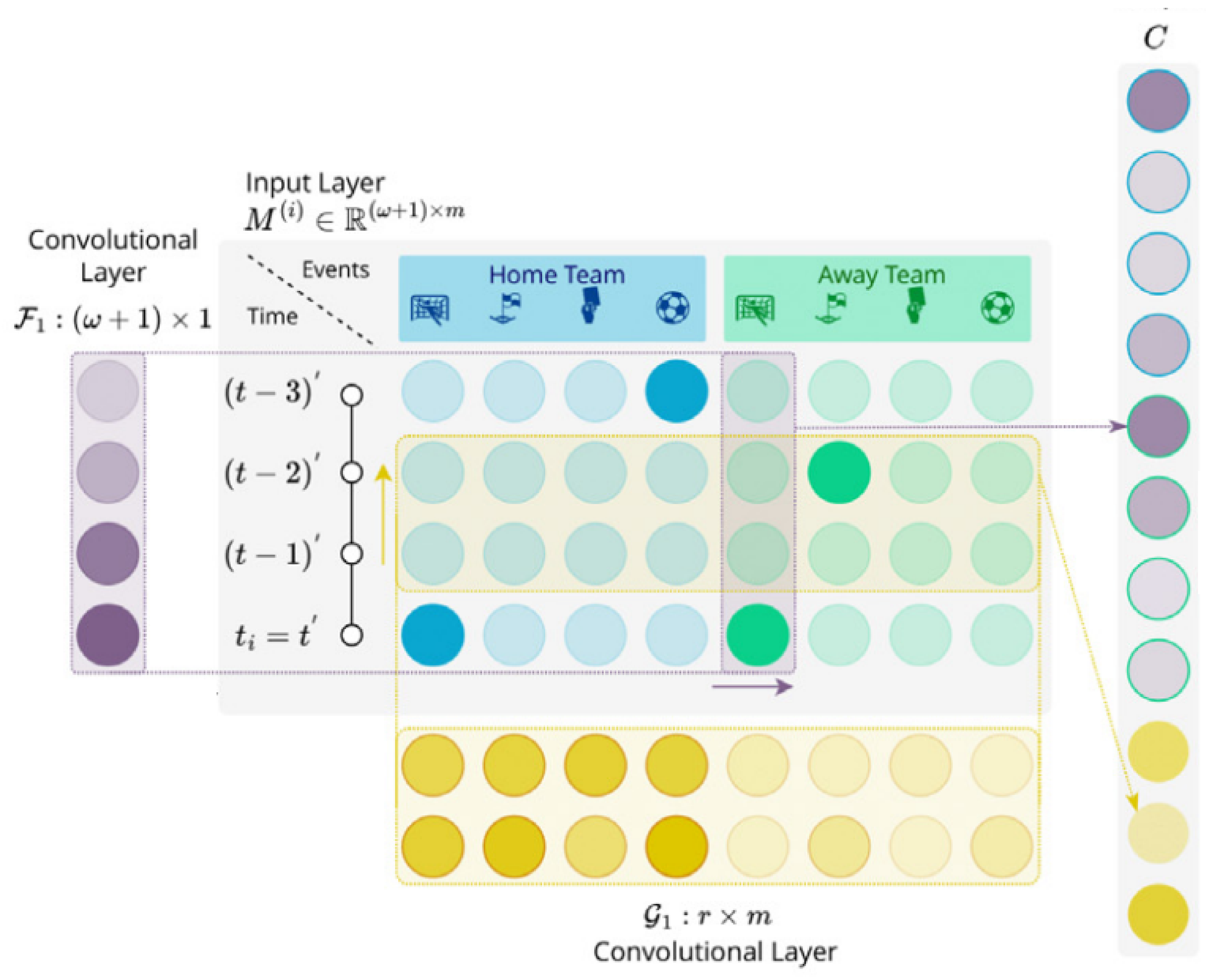

Figure 1. Schematic of the SCORE model architecture. Adapted from [1].

Proposed Methodology

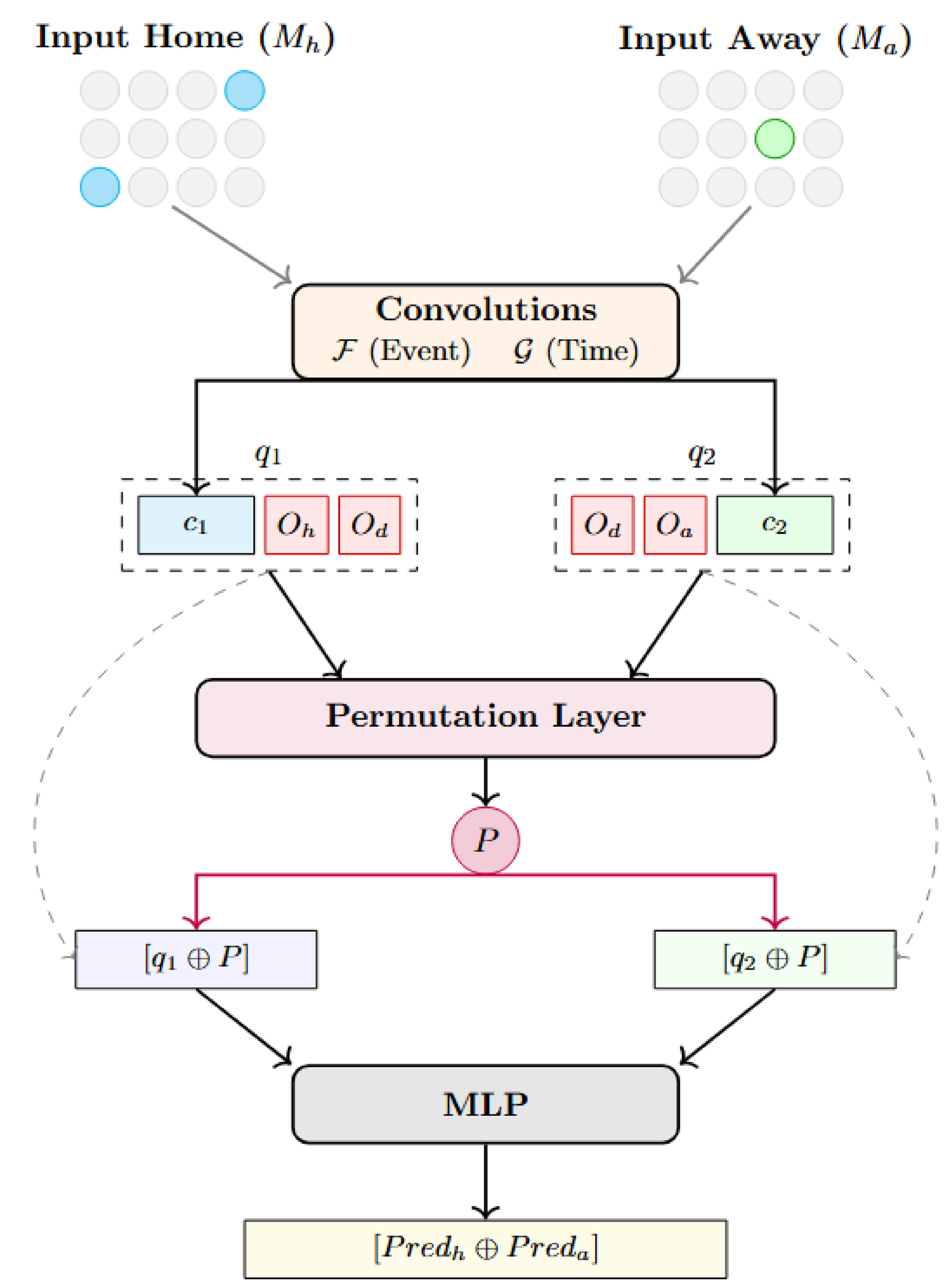

Figure 2. The proposed SCORE-ODDS architecture.

We introduce a permutationally equivariant architecture that integrates static betting odds (Home/Draw/Away) with event data.

A. Convolutions

Unlike SCORE [1], the input is split into distinct Home M_h and Away M_a matrices. We employ a shared convolutional layer (applying identical filters $\mathcal{F}$ and $\mathcal{G}$ to both inputs) to extract latent feature vectors c_1 and c_2 independently.

B. Odds Injection

We inject betting odds directly into these latent features to construct the augmented vectors q_1 and q_2. Note that the team-specific odds O_h and O_a are assigned to their respective counterparts, while the draw odd O_d is included in both.

C. Permutational Layer

To ensure the model learns match dynamics regardless of team ordering and determines team strength via external sources (such as betting odds) rather than home/away labels, we utilize a **Permutational Layer**. It computes a global context vector P derived from q_1 and q_2

D. Final Prediction

The global context P is concatenated back to each vector q_1 and q_2. These vectors pass through a shared MLP to generate scores, which are then concatenated and normalized via Softmax to get the final probability distribution.

Evaluation Metrics

We assess performance using two standard metrics:

- **Top-k Accuracy:** Measures the proportion of times the actual next event appears within the model's top k predicted probabilities.
- **Mean Reciprocal Rank (MRR):** Evaluates the quality of the probability ranking. It rewards the model for placing the correct event high on the list, even if not first.

$$\mathrm{MRR} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\mathrm{rank}_i}$$

Results

We evaluated SCORE-ODDS on a dataset comprising 5 major European leagues (EPL, La Liga, Bundesliga, Serie A, Ligue 1). The model was compared against the original SCORE [1] architecture. Additionally, we implemented a Markov chain baseline.

Performance was measured using **Accuracy (Top-1, Top-3)** and **MRR**.

Model	Acc (Top-1)	Acc (Top-3)	MRR
Random	0.056	0.166	0.194
Popularity	0.107	0.303	0.283
Markov	0.191	0.402	0.363
SCORE [1]	0.236	0.471	0.416
SCORE-ODDS	0.242	0.480	0.423

Table 1. Performance comparison on the test set. SCORE-ODDS outperforms the original architecture and other baselines.

Conclusions

1. Our results **confirm** that **pre-match betting odds** serve as a **valuable** external signal, **improving** both Accuracy and MRR metrics by distinguishing team quality beyond home and away labels.
2. The successful deployment of a SCORE-ODDS architecture demonstrates that **team strength** can be **decoupled** from **structural positioning** (Home/Away). This ensures the model relies on data (such as odds) rather than learning simple positional biases.

Future Work

The current architecture relies on a fixed-size input window representing recent history, but it is not time-aware.

- The model does not explicitly know the match time (e.g., minute 10 vs. minute 85) for a given input row.
- Future iterations should inject the necessary time information into the dense layers alongside the odds, allowing the model to learn time-dependent behaviors.

References

[1] Rodrigo Alves. Score: A convolutional approach for football event forecasting. *International Journal of Forecasting*, 41(4):1636–1652, 2025. ISSN 0169-2070. doi: https://doi.org/10.1016/j.ijforecast.2025.02.004. URL https://www.sciencedirect.com/science/article/pii/S0169207025000111.

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