CounterEval: A Deep Learning Framework for Performance Evaluation in Soccer Counterattacks Using Tracking Data

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1 Executive Summary

In modern soccer, counterattacking strategies are pivotal to scoring opportunities, yet quantifying individual player contributions within these fast-paced scenarios remains challenging. To address this, we introduce *CounterEval*, a deep learning framework that evaluates player performance during counterattacks by leveraging tracking data from 632 professional games, including MLS (2022), NWSL (2022), and international women's soccer (2020–2022).

The CounterEval framework integrates two core models:

- A **movement prediction model**, implemented as a Transformer-enhanced Variational Autoencoder (VAE), predicts players' next plausible locations under similar circumstances.
- A **tactical success model**, built using Graph Attention Networks (GATs), estimates the probability of counterattack success based on the current game context.

By comparing a player's actual movement to the predicted average movements of other players in similar scenarios, CounterEval generates **performance metrics** that quantify each player's influence on the success of the counterattack.

Key Results and Insights

1. Movement Prediction: The movement prediction model successfully captures realistic player movements, as shown in Figure 1. By predicting alternative positions for players, this model enables counterfactual comparisons to evaluate decision-making quality.

2. Tactical Analysis: The GAT-based tactical success model achieved a testing AUC of 0.62. While there is room for improvement, it provides meaningful tactical insights. For instance, Figure 2 shows how counterattack success probability evolves as the play progresses:

- Initially, the offense team struggles with no numerical advantage, leading to a low success probability.
- As the ball advances into the attacking third, the success probability rises, reflecting better positioning.

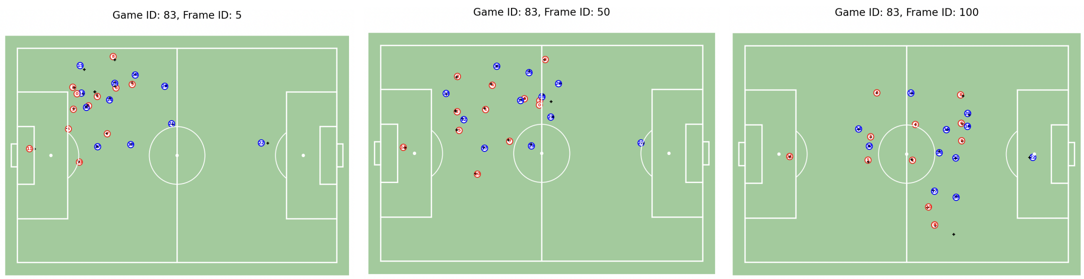

Figure 1: Movement prediction samples: Predicted player locations (black) closely align with actual observed movements.

- Near the penalty area, the probability fluctuates, driven by critical decision points such as dribbling or passing attempts.

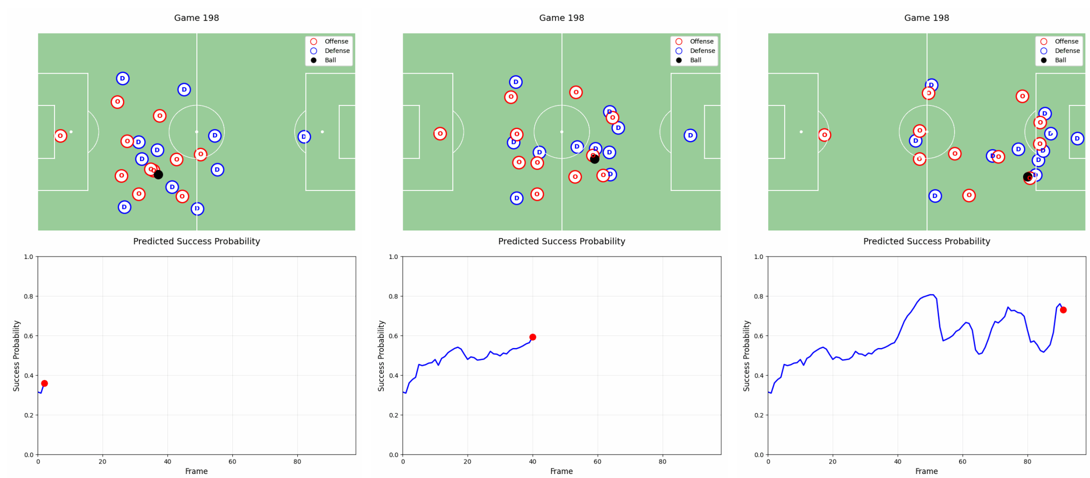

Figure 2: Tactical analysis of counterattack success probabilities over time.

3. Player Performance Metrics: Using the movement prediction and tactical success models, we compute player-specific performance scores that evaluate their contributions to counterattack success. Figure 3 illustrates the performance metrics for players in a specific game:

- Offensive players 1, 8, and 9 exhibit high scores due to effective off-ball movements and dribbling actions.
- Defensive players 17 and 20 receive positive scores for effectively marking key offensive players.
- Player 14, on the other hand, underperforms due to challenges in man-marking.

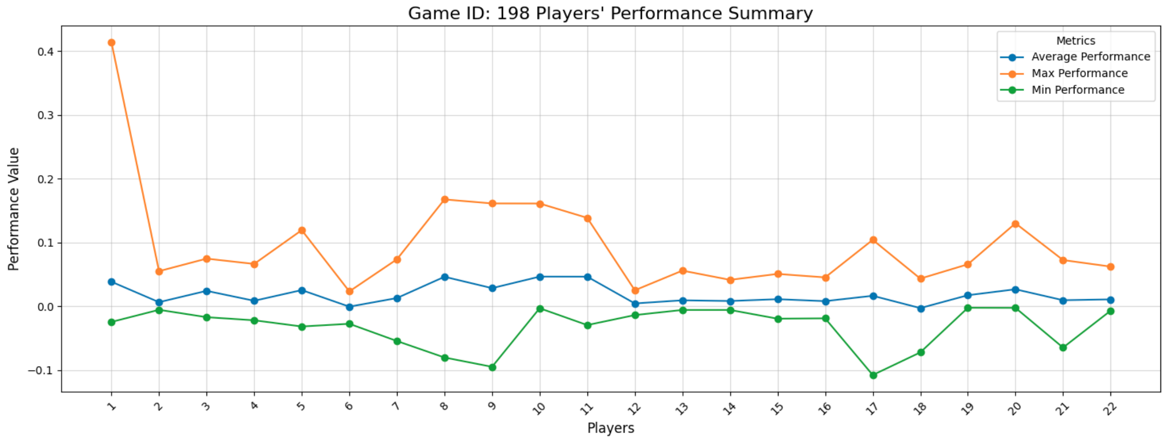

Figure 3: Player performance scores during a counterattack event.

Future Directions

The CounterEval framework provides a robust foundation for analyzing player performance in dynamic counterattack scenarios. However, several avenues for improvement and further research remain:

- **Counterfactual Paths:** Instead of evaluating single-step movements, incorporating entire movement paths could provide deeper insights into players' decision-making processes.
- **Time-Resolved Data:** Incorporating fixed time intervals would improve the accuracy of velocity and acceleration calculations.
- **Refined Event Definition:** A more rigorous and data-driven definition of a counterattack event would improve model consistency and accuracy.
- **Alternative Baselines:** Expanding beyond "average players" to include expert-defined baselines could enhance the evaluation framework.

Conclusion

CounterEval offers a scalable and interpretable framework for evaluating player performance during counterattacks. By combining movement prediction with tactical success analysis, it identifies key players and actions that influence success. While data quality and volume present challenges, the framework demonstrates promising results and offers actionable insights for coaches, analysts, and researchers in sports analytics. Future work will focus on refining the model and exploring its applications in other phases of play.