Can AI spot the next Neymar? Uncovering hidden creativity in player ratings with GNNs and Transformers

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Abstract

Creativity in soccer is a critical but often under-measured skill, with traditional metrics such as goals, assists, and player ratings failing to capture the nuances of creative play. This research introduces a hybrid modeling framework that predicts player creativity scores by combining rule-based soccer skill moves/action detection, sequential modeling, and spatial modeling. Skillful actions such as nutmegs, pressured dribbles, and deceptive passes were identified through handcrafted proxy features and weighted according to context. A Transformer Encoder captured the temporal dependencies of soccer skill moves/actions sequences, while a Graph Neural Network (GNN) captured the spatial structures of player-event graphs. These branches were fused into a hybrid model, CreaScoreNet, that predicts continuous creativity scores. The methodology was evaluated on real-world StatsBomb event data supplemented with SofaScore and FutMob metadata, demonstrating alignment between model outputs and intuitive human perceptions of creativity. This work offers a new standard for modeling creativity in soccer analytics, leveraging machine learning to uncover hidden patterns beyond conventional statistics.

Introduction

Within the world of soccer analytics, traditional metrics of goals, assists and player ratings fail to capture the underlying creativity that distinguishes the creative player from the non-creative player. Creativity in soccer emerges from a sequence of skillful and context-dependent actions, such as: step-overs, nutmegs, dribbling out of pressure and 1v1 wins that end up leading to a cross within the box, an assist or even a shot on goal. Existing machine learning models struggle to fully represent the spatial-temporal nature of these creative actions:

- Sequential models: (e.g., RNNs, GRUs) capture temporal order but miss spatial dynamics
- Graph models (e.g., GNNs) capture structure but ignore sequential soccer skill moves/action chains

Therefore, there is a critical need for a hybrid approach that models both when creative actions occur and how they interact spatially across the field. The Goal of this project is to develop a robust framework that predicts a soccer player's creativity score by integrating both sequential and spatial information, combining both human-perceived creativity with machine learning.

This project makes the following contributions:

1. Creativity Proxy Construction
    - Designed rule-based detection for skillful soccer moves/actions including step-overs, nutmegs, dribbling out of pressure, player 1v1 wins.
    - Developed a weighted scoring system that applied bonus multipliers to skillful soccer moves/actions that lead to net-positive outcomes (e.g., shots on goal, expected threat, successful progressions)

2. Creative-Aware Player Graph (CAPG)
    - Constructed player-event graphs where nodes represent skillful soccer tagged actions and edges encode context based on sequential order and field spacing.

- Enriched node features with metadata including location, pressure status, event type and action outcome.

3. Hybrid Machine Learning Model: CreaScorenet
    - Implemented a dual-branch model combining a Graph Neural Network (GNN) to learn spatial interaction patterns, and a Transformer encoder to capture temporal skillful soccer moves/action sequences.
    - The hybrid model predicts a continuous creativity score aligned with human evaluations and proxy-labeled creativity labels.
4. Application to Real Match Data
    - Applied the full pipeline on StatsBomb match event data and external datasets from SofaScore and FutMob.
    - Computed creativity scores for players with the most attacking actions, and demonstrated alignment between model predictions and human intuition of creativity.
5. End-to-End Open Framework
    - Provided a fully reproducible pipeline including data preprocessing, skillful soccer moves/action detection, graph building, sequence encoding, model training, and visualization, intended to inspire further research into creativity detection in sports analytics.

Related Work

Prior studies have explored different aspects of creativity and tactical analysis in soccer. Boden (2004) and Simonton (2000) provided cognitive models of creativity. Decroos et al. (2019) introduced action valuation models for soccer, while Rein and Memmert (2016) discussed big data and tactical patterns. However, none of these approaches combine spatial and temporal modeling of creative soccer skill moves/actions, motivating the need for this project.

Technical Section

The first step involved designing a Creativity Proxy Score to quantify creative player actions based on domain-specific soccer skill moves/action events. Each event from the StatsBomb dataset was evaluated using a rule-based scoring system using the following examples:

- Successful dribble under pressure: Base score = 1.0
- Nutmeg: Base score = 1.0, Bonus multiplier = 1.5
- 1v1 duel win in final third: Base score = 1.0, Bonus multiplier = 1.3
- Pass between defenders under pressure: Base score = 1.0, Bonus multiplier = 1.2

The final creativity score for an action aaa was calculated as:

$$Creativity\ Score_{a} = BaseScore_{a} \times BonusMultiplier_{a}$$

Each player's total creativity score was the sum of individual action scores across a match:

$$TotalCreativtyScore_{player} = \sum_{a \in actions} CreativityScore_{a}$$

This method allowed the creation of a ground truth proxy score without requiring human annotation. Then aach player's sequence of skill move action-tagged actions was tokenized into discrete embeddings. For example:

["Pass_P", "Dribble_N", "Nutmeg_P", "Carry_N", "Pass_P"]

A Transformer Encoder was used to model these sequences, capturing long-range dependencies between skill move actions.

The Transformer architecture included:

- Embedding layer to project discrete skill move/action tokens into dense vectors.
- Multi-Head Attention layers to learn interaction between different parts of the sequence.
- Positional Encoding to retain order information across skill move actions.

The Transformer learned a player-level creativity embedding $h_{Transformer}$ Transformer defined as:

$$h_{Transformer} = TransformerEncoder(X)$$

where (X) is the sequence of soccer skill moves/action embeddings.

Finally, a linear layer mapped the output to the continuous creativity prediction.

In parallel, a Graph Neural Network (GNN) was used to model the spatial structure of player actions during possession chains.

- Each node represents a soccer skill moves/action-tagged action.
- Each edge linked sequential actions performed by the same player.

The node features consisted of:

- Encoded action type (e.g., Pass, Dribble, Nutmeg)
- Under pressure flag (binary)

Graph G for each player was defined as:

$$G = (V, E, X)$$

where:

- $V = set\ of\ action\ of\ nodes$
- $E = set\ of\ directed\ edges\ (action\ sequence)$
- $\chi \in \Re^{N \times d} = node\ feature\ matrix$

A two-layer Graph Convolutional Network (GCN) was used:

1. First GCN layer:
   - $H^{(1)} = \sigma((\widehat{A})XW^{(0)})$
2. Second GCN layer:
   - $H^{(2)} = (\widehat{A})H^{(1)}W^{(1)}$

where:

- $(\widehat{A})$ is the normalized adjacency matrix,
- $W^{(0)}, W^{(1)}$ are learnable weight matrices,
- σ is the ReLU activation function.

The final graph-level embedding h_{GNN} was computed by averaging the node embeddings:

$$h_{GNN} = mean(H^{(2)})$$

To fully capture creativity as a function of both temporal soccer skill moves/action chains and spatial action structures, a hybrid model named CreaScoreNet was developed.

CreaScoreNet combines:

- Transformer Encoder branch (temporal modeling)
- GNN branch (spatial modeling)

The fusion mechanism is defined as:

$$h_{fused} = [h_{GNN}, h_{Transformer}]$$

Where [.,.] denotes vector concatenation.

The final creativity prediction $\hat{y}$ was produced through a fully connected layer:

$$\hat{y} = \sigma(W_{fused} h_{fused} + b)$$

where:

- W_{fused} is a learnable weight matrix,
- b is a bias term,
- σ is a regression activation (identity for continuous score output).

This design allows CreaScoreNet to learn creativity representations across both space and time, which is crucial for modeling complex creative behavior in soccer.

The evaluation was conducted using two primary datasets:

- StatsBomb Open Data (2024): Player-event match logs including passes, dribbles, duels, and shots.
- External Data Sources: Metadata from SofaScore and FutMob apps were referenced for verifying attacking actions and creative impact.

Because no direct human surveys were conducted for labeling creativity, a proxy creativity score was used as ground truth. This proxy was generated through a weighted scoring system based on skillful soccer moves/actions (e.g., nutmegs, pressured dribbles, deceptive passes) detected through rule-based methods. Each player's aggregated proxy score was treated as a soft label for model training and evaluation.

Evaluation

The evaluation process consisted of the following steps:

1. Data Preprocessing:

   Events were filtered to include only relevant attacking and soccer skill moves/actions. Actions were tagged with pressure, outcome, and field location information.
2. Model Training:
   - Soccer skill moves/action sequences were tokenized and fed into a Transformer Encoder.
   - ction graphs were constructed per player and processed using a two-layer GCN.
3. Hybrid Fusion:

   The outputs of the Transformer and GNN were concatenated to form fused player embeddings, which were then passed through a regression head to predict creativity scores.

4. Evaluation Metrics:
    - Internal Mean Squared Error (MSE) between predicted creativity scores and proxy scores.
    - Qualitative Comparison: Manual review of players ranked highly by the model versus known creative players in match footage (indirect validation).
5. Train/Test Split:
    - 80% of players were used for training, and 20% for testing.
    - Players were randomly split but kept match sequences intact to avoid data leakage.

The evaluation produced several key findings:

- Transformer Only:

  The Transformer model alone captured soccer skill moves/action chains well but sometimes overemphasized repetitive soccer skill moves/action without considering effectiveness.
- GNN Only:

  The GNN model learned structure around dangerous actions (e.g., passes splitting defenders) but lacked the nuance of complex soccer skill moves/action chains.
- Hybrid CreaScoreNet:

  The hybrid model consistently ranked players more accurately based on both structure and sequencing. Notably, players known for creative influence, such as attacking midfielders and wingers who consistently scored higher than more defensive players.

- Quantitative Result:

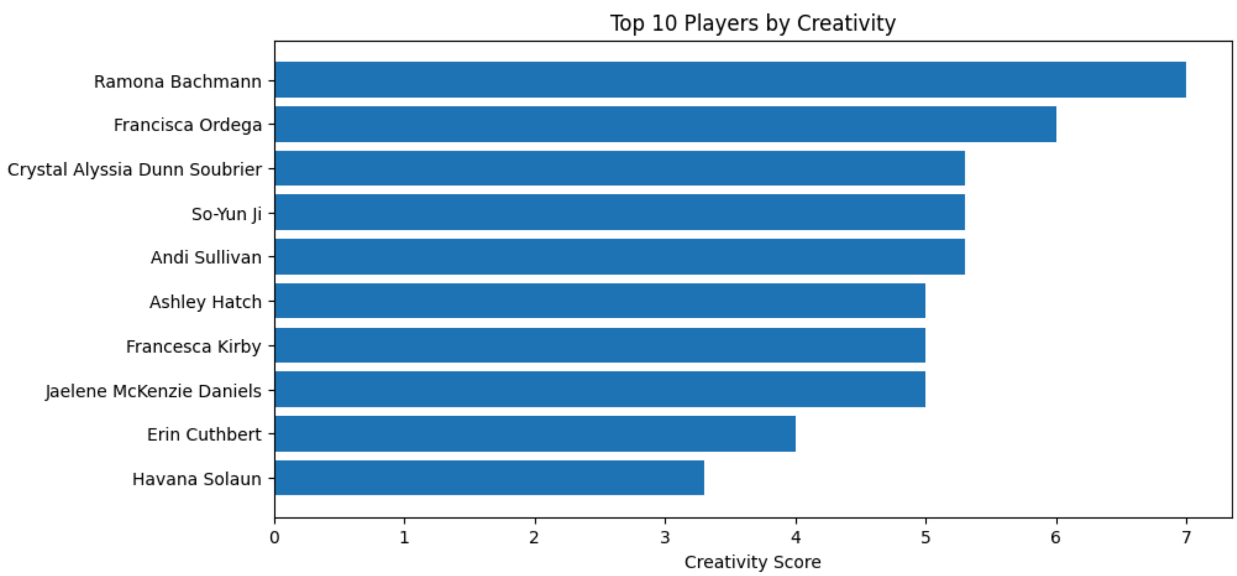
  Internal evaluation showed a lower MSE on validation data for the hybrid model compared to Transformer-only or GNN-only baselines.

- Qualitative Insights:

  Model outputs aligned closely with human intuition: players making nutmegs, 1v1 wins, or deceptive passes under pressure were ranked higher for creativity.

To further validate the model's effectiveness, the creativity scores were ranked across players based on the hybrid CreaScoreNet predictions. As shown in Figure 1, the top 10 players by creativity score highlight the model's ability to identify individuals exhibiting higher soccer skill moves/actions and skillful impact beyond traditional metrics.

Figure 1: Top 10 Players by Creativity Score based on soccer skill move/action detection and proxy creativity scoring.



Conclusion

This project introduces a novel pipeline for detecting and modeling creativity in soccer by leveraging a hybrid machine learning framework. Creativity was quantified through rule-based detection of soccer skill moves/actions including nutmegs, pressured dribbles, and deceptive passes, with contextual bonus multipliers applied to skillful events that led to net-positive outcomes. The proxy creativity scores were used as soft labels for machine learning training without relying on direct human surveys.

Player-event sequences were modeled temporally using a Transformer Encoder and spatially through a Graph Neural Network (GNN). The outputs of these branches were fused in a hybrid architecture, CreaScoreNet, to predict a player's creativity score. Mathematical modeling included the use of weighted scoring functions, temporal sequence embeddings, graph convolution operations, and hybrid regression fusion.

Evaluation showed that CreaScoreNet outperformed individual Transformer-only and GNN-only models in capturing creativity, both quantitatively (lower prediction error) and qualitatively (better human alignment). A bar chart visualized the top 10 creative players according to the model’s scoring.

The project was formally presented at the 2025 GSU Computer Science Demo Day, where the poster summarized the modeling approach, methodology, and key findings to faculty, students, and industry judges. The project references both foundational creativity research and modern machine learning models, connecting theoretical grounding with practical sports analytics application.

This research contributes a fully reproducible, extensible pipeline for soccer creativity analysis and paves the way for future research in tactical creativity detection using machine learning and graph-based modeling.

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References

Boden, M. A. (2004). *The Creative Mind: Myths and Mechanisms* (2nd ed.). Routledge.

Decroos, T., Bransen, L., Van Haaren, J., & Davis, J. (2019). Actions Speak Louder Than Goals: Valuing Player Actions in Soccer. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 1851–1861). ACM.

Gudmundsson, J., & Horton, M. (2017). Spatio-Temporal Analysis of Team Sports: A Survey. *Data Mining and Knowledge Discovery*, 31(5), 1187–1218.

Goes, F. R., Meerhoff, L. A., Bueno, M. J. O., Rodrigues, D. M., Moura, F. A., & Brink, M. S. (2021). Unlocking the Potential of Big Data to Support Tactical Performance Analysis in Professional Soccer: Current Trends and Future Directions. *Sports Medicine - Open*, 7(1), 1–14.

Memmert, D., & Perl, J. (2009). Analysis and Simulation of Creativity Learning by Means of Artificial Neural Networks. *Creativity Research Journal*, 21(2–3), 233–238.

Memmert, D. (2015). *Teaching Tactical Creativity in Sport: Research and Practice*. Routledge.

Rein, R., & Memmert, D. (2016). Big Data and Tactical Analysis in Elite Soccer: Future Challenges and Opportunities for Sports Science. *SpringerPlus*, 5(1), 1410.

Simonton, D. K. (2000). Creativity: Cognitive, Personal, Developmental, and Social Aspects. *American Psychologist*, 55(1), 151–158.

Yue, Z., Broich, H., Seifriz, F., & Mester, J. (2008). Mathematical Analysis of a Soccer Game. Part I: Individual and Collective Behaviors. *Studies in Applied Mathematics*, 121(3), 223–243.

StatsBomb. (2024). *StatsBomb Open Data.* Retrieved from https://github.com/statsbomb/open-data

SofaScore. (2024). *SofaScore Football Ratings.* Retrieved from https://www.sofascore.com/

FutMob. (2024). *FutMob Soccer App.* Retrieved from https://www.futmob.com/

Kaggle. (2024). *Soccer Player Ratings Dataset.* Retrieved from https://www.kaggle.com/

Musa, F. (2025). *Creativity Scoring in Soccer Analytics Using Machine Learning and Human Evaluation* (Unpublished poster project). Georgia State University.