

# Machine Learning for Time Series

## Presentation - Mini-Project

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SoccerCPD: Formation and Role Change-Point Detection in Soccer  
Matches Using Spatiotemporal Tracking Data

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## Context and Problem Statement

- **Context:** Analyzing team formation is crucial for interpreting tactics in fluid sports like soccer.
- **The Challenge:** Tracking data is noisy; players frequently switch positions temporarily.
- **Limitation of existing methods:** Often assume constant formations or react too sensitively to frame-by-frame noise.
- **Objective:** Reproduce and extend **SoccerCPD** [Kim+22], an unsupervised framework that distinguishes:
  - **FormCPD:** Shifts in global spatial configuration.
  - **RoleCPD:** Long-term tactical changes in individual roles.

# Work Repartition and Contributions

## Work Repartition

- **FormCPD:** Implementation of Delaunay-based adjacency and formation change detection.
- **RoleCPD:** Synthetic role data generation, permutation analysis, and recursive segmentation.

## Implementation & Extensions

- Python package with R-backend for g-segmentation.
- **Novel Experiment:** "Player Stationarity" metric.

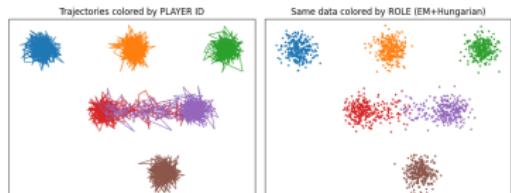


Figure: Role vs Player coloring

# Methodology: FormCPD (1/2)

## Role Assignment and Spatial Structure

### 1. Role Assignment

- Players assigned latent spatial roles via constrained EM.

### 2. Delaunay Triangulation

- Encodes local spatial relationships.
- Produces binary role-adjacency matrix  $A(t)$  invariant to permutations.
- Emphasizes *topological structure*.

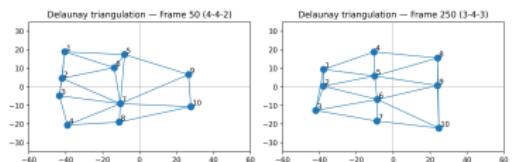


Figure: Delaunay Triangulation reconfiguration

## Methodology: FormCPD (2/2)

### Change-Point Detection and Adjacency

### 3. Discrete g-segmentation

- Applied to adjacency sequence  $\{A(t)\}$ .
- Distance:  $d_M(A(t), A(t')) = \|A(t) - A(t')\|_{1,1}$ .
- Constraints:  $p < 0.01$ , min duration 5 min.

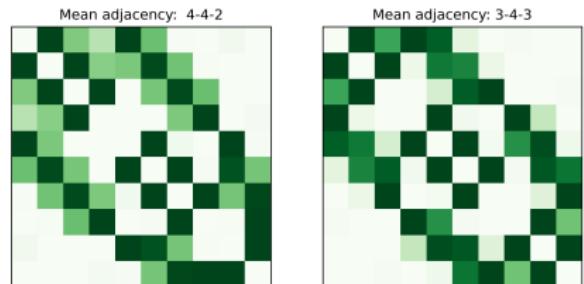


Figure: Mean Adjacency Matrices

# Methodology: RoleCPD

## Detecting Intraphasic Tactical Shifts

- **Goal:** Detect permanent role swaps within stable formation.
- **Metric:** Normalized Hamming Distance (Switch Rate):

$$d(\pi_t, \pi_{t'}) = \frac{1}{N} \sum_{p \in P} \mathbb{1}_{\pi_t(X_p) \neq \pi_{t'}(X_p)}$$

- **Process:**
  - ① Preprocessing: Exclude Switch Rate  $> 0.7$ .
  - ② Recursive g-segmentation.

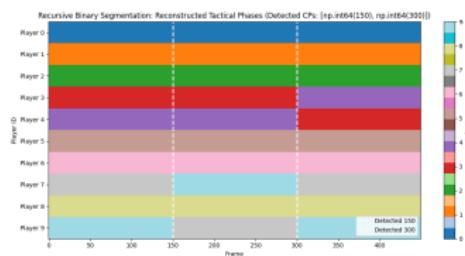


Figure: Recovered Tactical Phases

# Data Sources and Diagnosis

## High-Frequency Tracking (GPS)

- SkillCorner (10Hz) & Last Row (20Hz).
- Clean signals, suitable for Gaussian assumptions.

## Event-Stream (StatsBomb)

- **Challenge:** Extreme sparsity (< 10 pts/min).
- **Adaptation:** Pseudo-trajectories via temporal aggregation (5-min average).

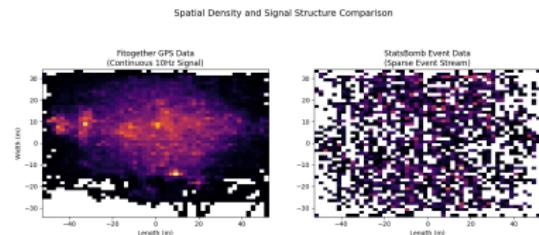


Figure: GPS vs Event Data Density

# Results: Sensitivity Analysis

## Sensitivity to `min_fdist`

- `min_fdist`: Threshold for formation distance.
- **Observation:** Increasing threshold reduces segment count but preserves stable change-points.
- **Conclusion:** Acts as a pruning mechanism for minor structural variations.

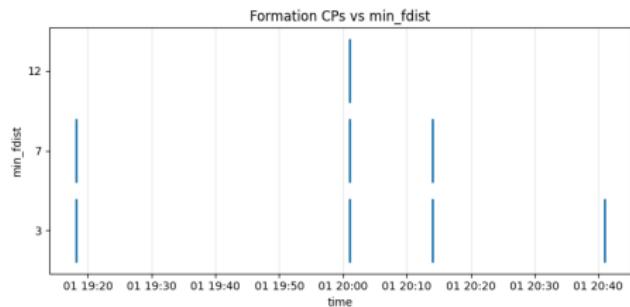


Figure: Timeline stability under varying thresholds

## Extension 1: Possession Context

### Refining Formation Analysis

- **Limitation:** Global average ignores game state.
- **Method:** Filter frames (Attack vs. Defense).
- **Result (Match 1925299):**
  - **Defending (Left):** Compact block.
  - **Attacking (Right):** Wider, advanced shape.

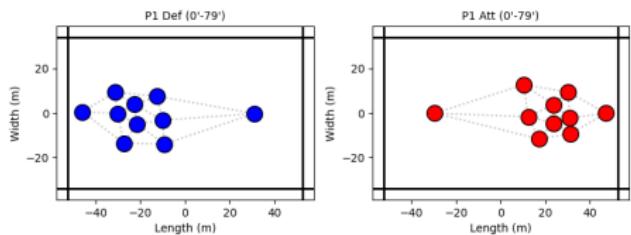


Figure: Defending vs Attacking Formations

## Extension 2: Player Stationarity Metric

### Quantifying Role Fluidity

- **Metric:** Std dev of Euclidean distance between player position and role center.
- **Findings (A-League):**
  - Captures variance in movement within a "stable" phase.
  - Distinguishes "Fixed" roles (CB) from "Roaming" roles (Wingers/Midfield).

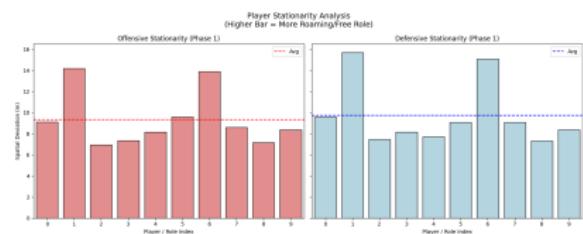


Figure: Player Stationarity (Phase 1)

## Conclusion

- **Successful Reproduction:** Implemented FormCPD and RoleCPD, validating the framework on synthetic and real matches.
- **Robustness:** Confirmed method stability via sensitivity analysis.
- **Key Extensions:**
  - ① **Possession Context:** Revealed distinct attacking/defensive shapes.
  - ② **Stationarity Metric:** Provided quantitative insights into player role adherence.
- **Versatility:** Demonstrated applicability to sparse event-stream data.

## Bibliography

- [Kim+22] Hyunsung Kim et al. “SoccerCPD: Formation and Role Change-Point Detection in Soccer Matches Using Spatiotemporal Tracking Data”. In: *The 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. ACM, 2022, pp. 3146–3156. DOI: 10.1145/3534678.3539150. URL: <https://doi.org/10.1145/3534678.3539150>.