

# Machine Learning for Time Series

## Presentation - Mini-Project

Adonis JAMAL   Fotios KAPOTOS

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

École Normale Supérieure Paris-Saclay - MVA

December 17th 2025

# Context: The Fluidity of Soccer

## The Challenge in Sports Analytics

- **Dynamic Formations:** Teams constantly reshape (e.g., 4-4-2 → 3-5-2) based on game state.
- **Noisy Data:** Players swap positions temporarily (overlap, pressing).
- **The Gap:** Standard methods often assume static formations or are too sensitive to noise.

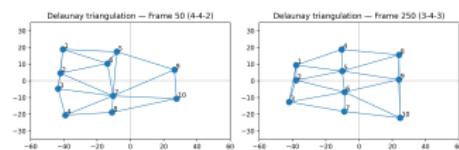


Figure: Formation shifts captured via Delaunay triangulation.

## Project Goal

- Reproduce and extend **SoccerCPD** [1], a change-point detection framework.

# Work Repartition & Novel Contributions

## 1. Reproduction & Implementation

- **Full Pipeline:** Python package with R backend (for g-segmentation).
- **FormCPD:** Delaunay-based spatial change detection.
- **RoleCPD:** Permutation-based role switch detection.

## 2. Novel Extensions (Beyond the Paper)

- **Possession Context:** Separating Attacking vs. Defensive shapes.
- **Player Stationarity Metric:** Quantifying role fluidity (Fixed vs. Roaming).
- **Event Data Generalization:** Adapting the framework for sparse StatsBomb data.

# FormCPD: From Trajectories to Graphs

## 1. Role Assignment

- Players assigned to latent roles (Gaussian Mixture Models).
- One-to-one mapping via Hungarian Algorithm.

## 2. Delaunay Triangulation

- Encodes spatial topology  $A(t)$ .
- Permutation invariant.
- Distance:  
$$d_M = \|A(t) - A(t')\|_{1,1}$$

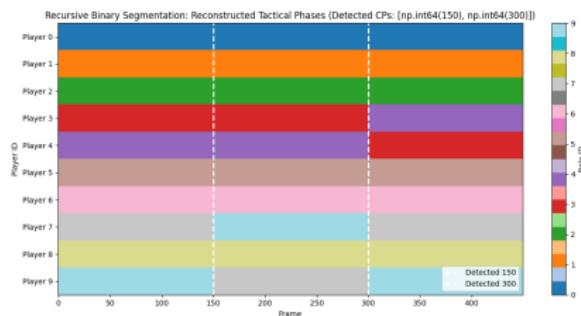


Figure: Topological changes trigger detection.

# RoleCPD: Detecting Intraphasic Swaps

**Objective:** Detect permanent role swaps (e.g., Wingers switching sides) within a stable formation.

## The Metric: Switch Rate

- Input: Sequence of role permutations  $\pi_t$ .
- **Hamming Distance:**

$$d(\pi_t, \pi_{t'}) = \frac{1}{N} \sum_p \mathbb{I}_{\pi_t(X_p) \neq \pi_{t'}(X_p)}$$

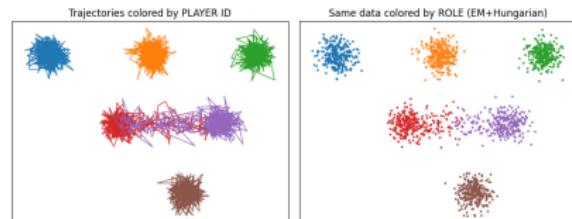


Figure: Synthetic Role Swap Data

- Measures deviation from the "Dominant Permutation".

# RoleCPD: Recursive Segmentation

## Discrete g-segmentation on Permutations

- ① **Pre-process:** Filter frames with Switch Rate  $> 0.7$  (temporary noise).
- ② **Recursive Search:**
  - Apply graph-based change-point detection on the sequence.
  - **Stopping Criteria:**  $p\text{-value} > 0.01$  or segment length  $< 5 \text{ min}$ .
- ③ **Result:** Identifies distinct tactical role configurations.

# High-Frequency vs. Sparse Event Data

## 1. Tracking Data (GPS)

- **Source:** Fittogether (10Hz) [1], SkillCorner (10Hz) [2].
- **Quality:** Dense, clean signals.
- **Prep:** Normalized to centered metric pitch.

## 2. Event Data (StatsBomb)

- **Source:** On-ball events only.
- **Challenge:** Extreme sparsity (< 10 pts/min vs 600+ for GPS).
- **Bias:** Spatial bias toward the ball.

## Novel Adaptation for Event Data:

- **Pseudo-Trajectories:** Aggregated events over 5-minute rolling windows.
- **Proxy Graph:** Average adjacency matrices instead of frame-by-frame Delaunay.

# Density Comparison

Spatial Density and Signal Structure Comparison

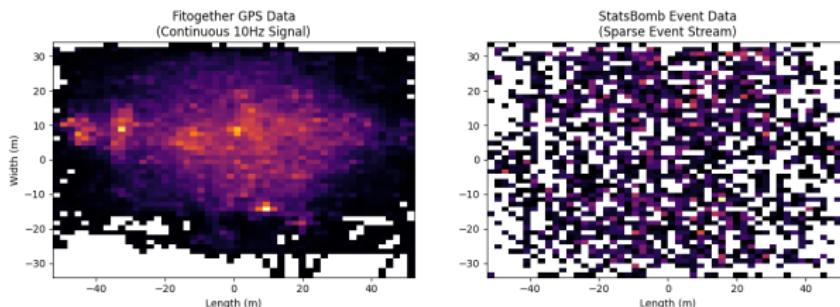


Figure: Heatmap: Dense GPS coverage vs. Sparse/Biased Event Data.

# Robustness: Sensitivity Analysis

## Parameter: min\_fdist

- Controls threshold for declaring a new formation.
- **Finding:** Higher threshold acts as a pruning mechanism.
- **Result:** Major tactical shifts remain stable; minor noise is filtered out.

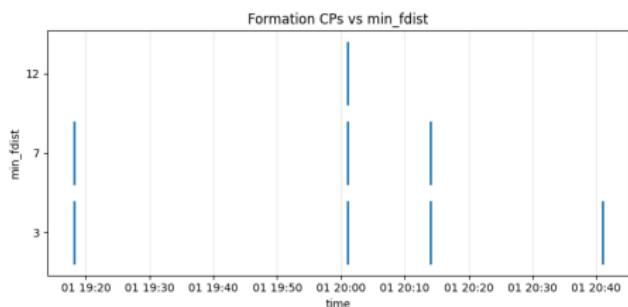


Figure: Timeline stability across thresholds.

# Contextualizing Formations (GPS)

**Problem:** A single "average" centroid formation ignores game state.

**Method:**

- Filter frames by possession status.
- Compute centroids separately.

**Insight:**

- **Defense:** Compact block.
- **Attack:** Wide, expansive shape.

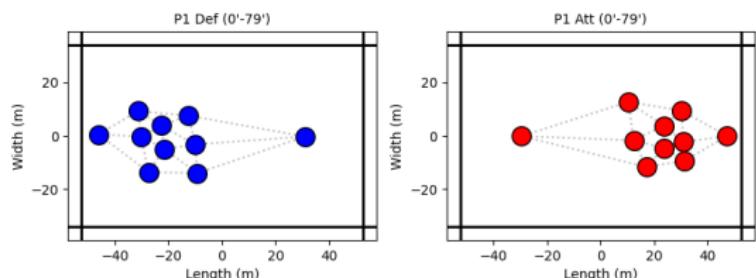


Figure: Match 1925299: Distinct shapes detected.

# Quantifying Role Fluidity ( $\sigma$ )

**Definition:** Standard deviation of Euclidean distance from the role center.  
**GPS Data Findings (A-League)**

- **Fixed Roles:** CBs show low  $\sigma$  (Stationary).
- **Roaming Roles:**  
Wingers/Midfielders show high  $\sigma$ .
- Validates tactical roles beyond simple coordinates.

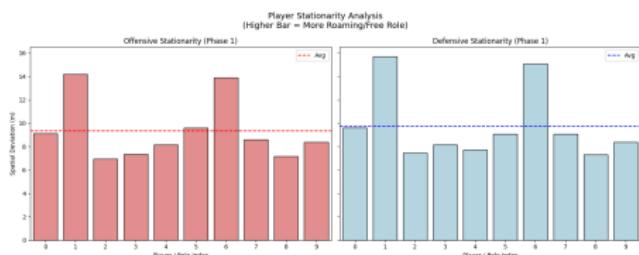


Figure: Stationarity profile (GPS Data).

# Offensive vs. Defensive Structures (FC Barcelona)

We extended the "Possession Context" analysis to sparse StatsBomb data.

## Tactical Shapes in Sparse Data

- Despite low data density, distinct shapes emerge when aggregated over time.
- **Defense:** High density in central zones (low width).
- **Attack:** Wingers push high and wide; full-backs overlap.

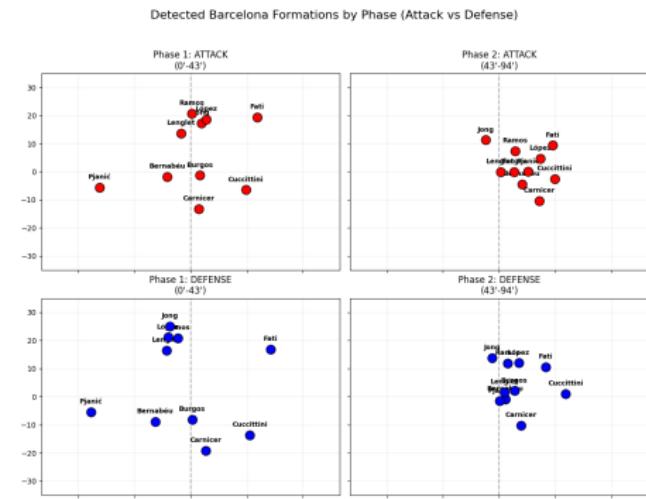


Figure: Barcelona: Attack (Red) vs Defense (Blue).

# Quantifying Fluidity in Event Data

Does the "Stationarity Metric" hold up with sparse event streams?  
**Comparison Results**

- **Consistency:** The "Fixed" vs. "Fluid" distinction persists.
- **Phase Analysis (Barcelona):**
  - *Attack Phase:* High deviation (Avg 12m) → Fluidity.
  - *Defense Phase:* Lower deviation (Avg 9.6m) → Rigidity.

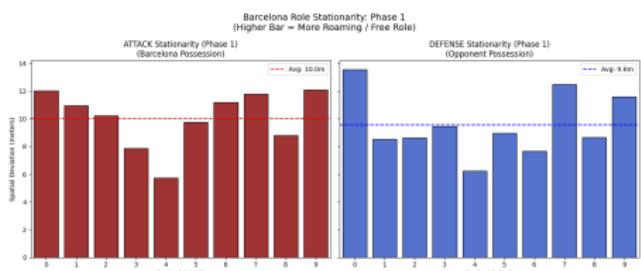


Figure: Stationarity: FC Barcelona (Event Data).

# 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 I

- [1] 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>.
- [2] SkillCorner. *SkillCorner Open Data: Broadcast tracking data*. <https://github.com/SkillCorner/opendata>. Accessed: 2025-01-04. 2020.

# RoleCPD: Hamming Distance Switch Rate

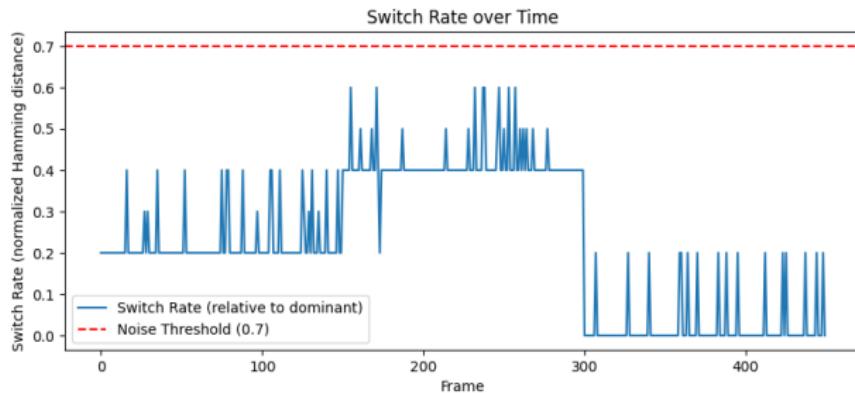


Figure: Hamming distance-based switch rate time series used for change point detection.

# RoleCPD: Formation Ground Truth

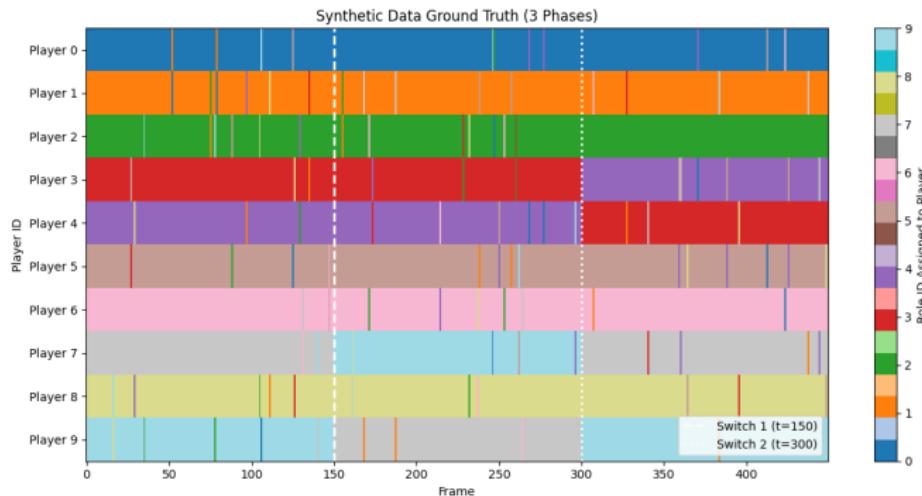


Figure: Ground truth role assignments over time with two tactical switches at frames 150 and 300.

# RoleCPD: Need for Recursive Segmentation

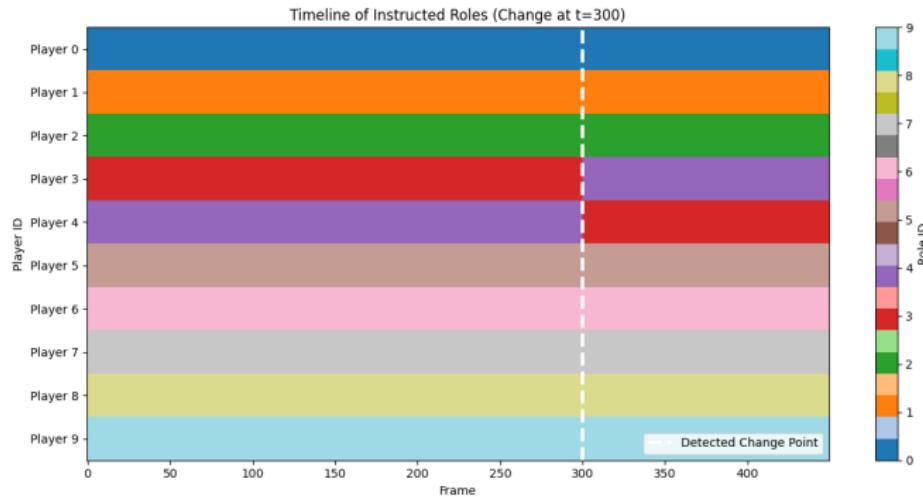


Figure: Visualization of one detected tactical phase with dominant role assignments. This shows the need for recursive segmentation to capture multiple phases.

# Stationarity: FC Barcelona Phase 2 (Event Data)

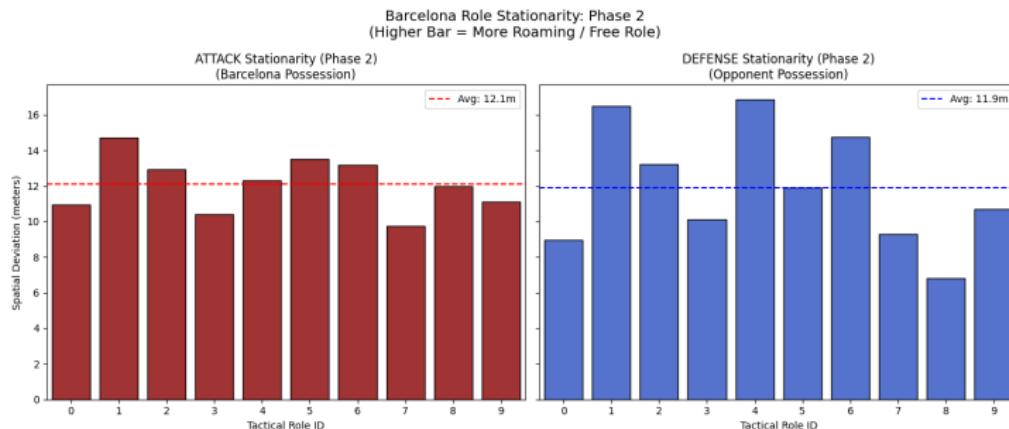


Figure: Stationarity: FC Barcelona (Event Data).