COMPLEXITY EMERGES IN MEASURES OF THE MARKING DYNAMICS IN FOOTBALL GAMES

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Paper:

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(1) INTRODUCTION

(2) MARKING DYNAMICS IN REAL GAMES

(3) MODELING. MARKING DYNAMICS IN SIMULATED GAMES

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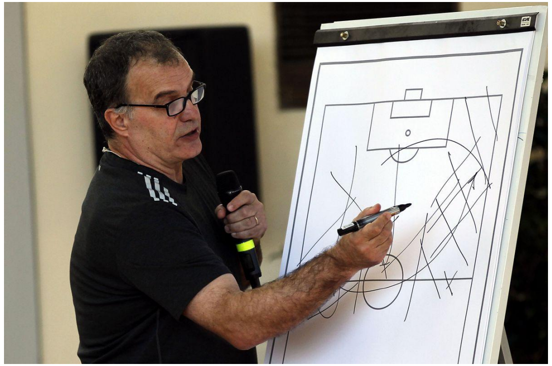
(1) INTRODUCTION

How do we define marking?

-It is the set of individual and **collective coordinated** actions oriented to cover/control the **opponents** and the **free space** during the game. (Castelo, 1986; Queiroz, 1983; López Ramos, 1995).



Note players mark
- In **defensive** and **offensive** situations
- **Close** and **far** from the ball

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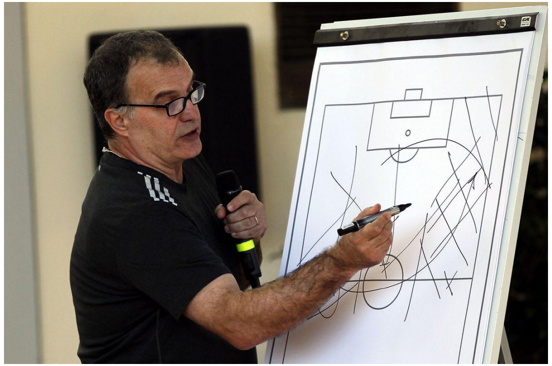

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How do players mark?

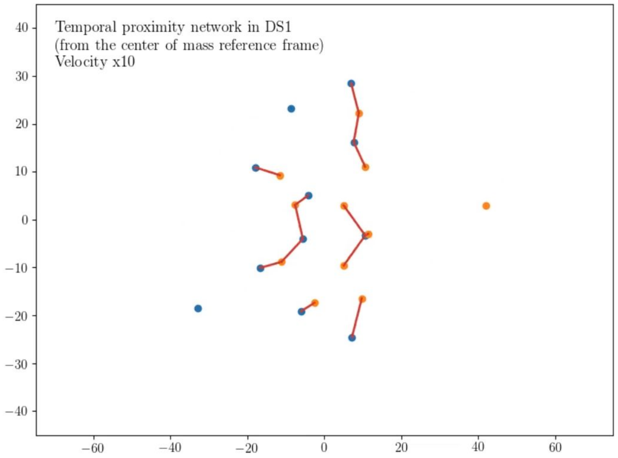
- Zonal marking
- Man to man
- Mixed, a combination of both

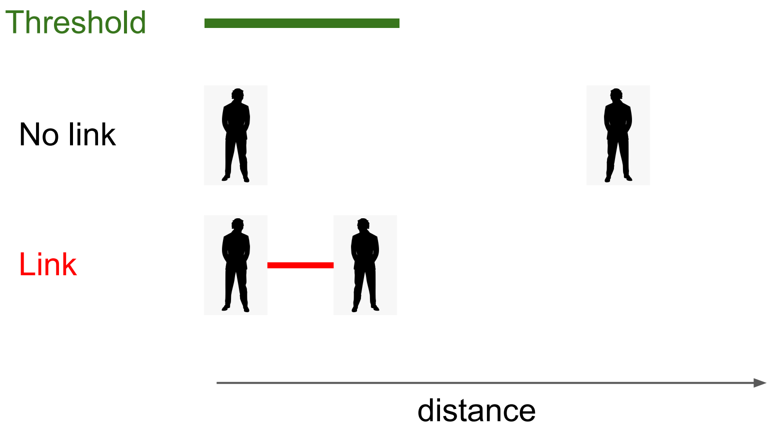
Note, the **proximity** among opponents **is key** to understanding the marking system.

(1) INTRODUCTION

How do we study the marking dynamics?

- At every second of the game, we define **temporal bipartite proximity network** representing the state of the marking.
- **Links** are established **only between opponents** if the distance between them is less than a **threshold**





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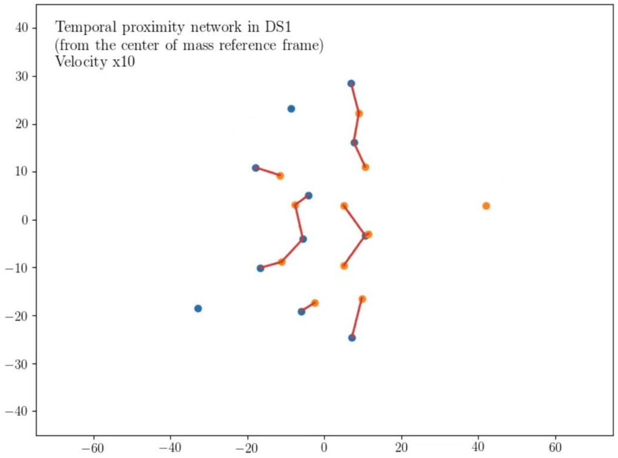


Data

-Three football games (male), provided by *Metrica Co.*

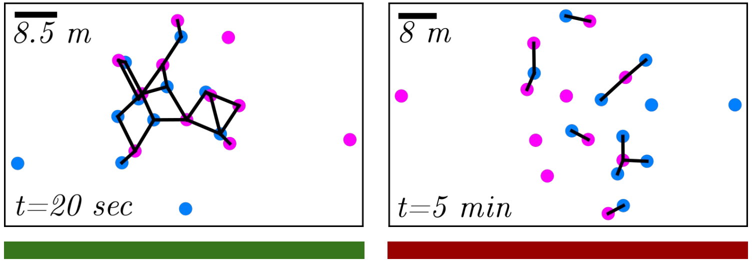
-Players' coordinates at every second of the game.

We observe

-Abrupt **changes** in the **network structure** during the game.

-Periods of **high clusterization** and **high fragmentation**.

-Changes in the network structure bear information on the evolution of the marking.



Time series analysis

-To analyze how this **structural change** evolves, we study the evolution of the **heterogeneity parameter**.

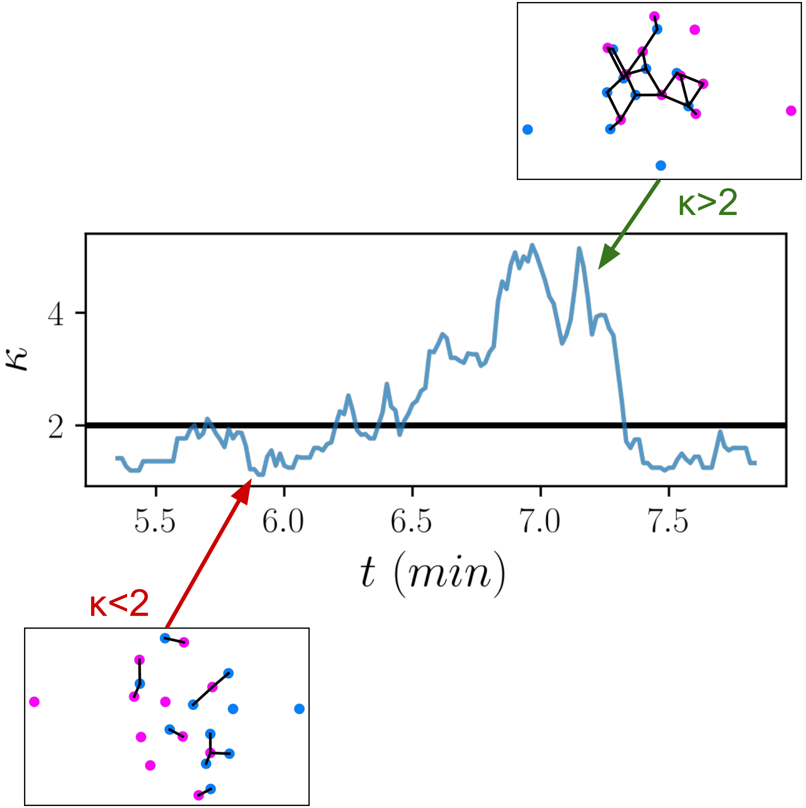
$$\kappa(t) = \frac{\langle \text{degree}^{2} \rangle}{\langle \text{degree} \rangle}$$

-When κ<2 the network is fragmented

-When κ>2 the network is clusterized

- Note, κ(t) is a **measure** of the evolution of the marking.

- The statistical properties of the **series** can be related to the statistical properties of the **marking dynamics**.



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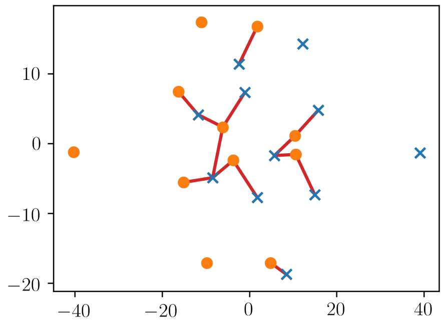
(2) MARKING DYNAMICS IN REAL GAMES

(3) MODELING. MARKING DYNAMICS IN SIMULATED GAMES

Tuning the threshold value

-Standardization: we tune the **threshold** value such that when the players are in their **average position→ κ≈2**

-In the three analyzed games the value of the threshold is similar: 8 m, 8.5 m, 9 m.



Network of players in their average position

In this game, Threshold: 8 meters

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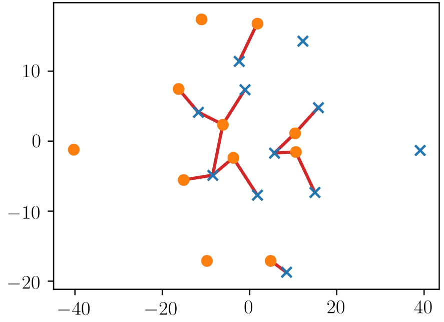
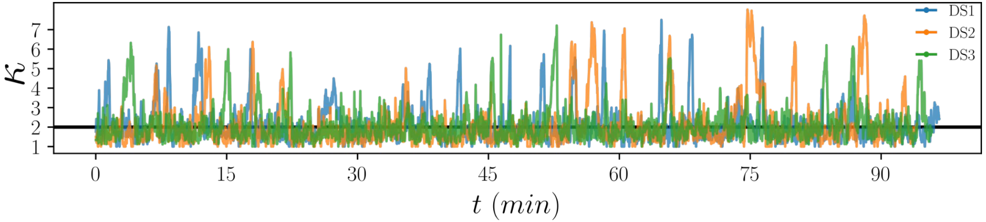


Network of players in their average position

The evolution of κ

-**<κ>≈2** in the three analyzed games, similar scale

-High peaks → big clusterization, special situations like corner kicks or free kicks



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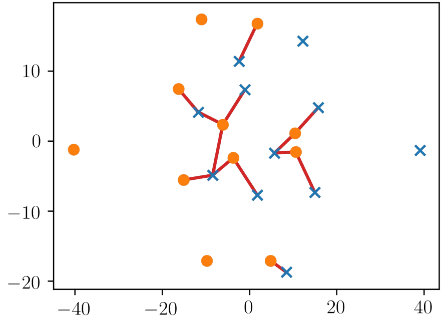

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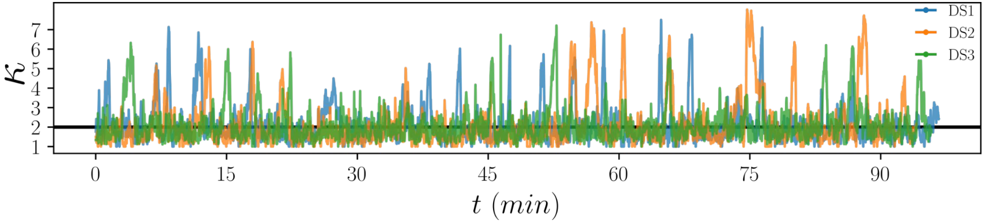
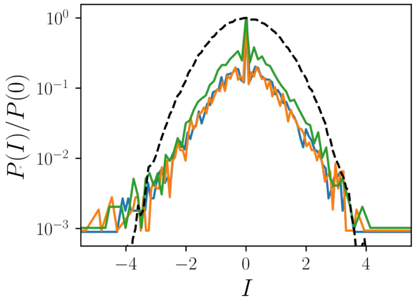
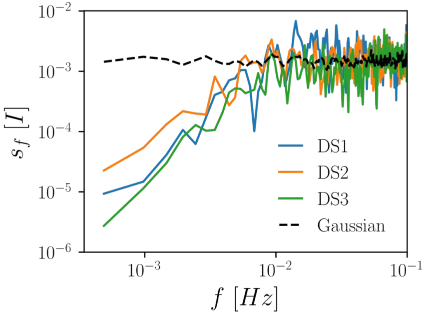


The successive increments: $I(t) = \kappa(t+1) - \kappa(t)$

-The data deviates from Gaussian behavior
-Presence of **heavy Tails**
-A **decay in the PSD** for low values of the freq.
-Hurst exponent **h≈0**

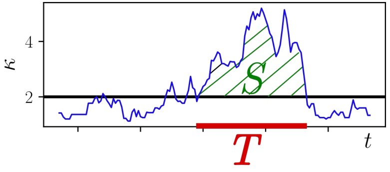
Anti-persistency → the players tend to return to their average position.





(2) MARKING DYNAMICS IN REAL GAMES

Avalanches in κ(t)



We define an event x as the consecutive points starting when κ>2 and ending when κ<2.

The event **lifetime T** as the duration of the event and the event **size S** as the integral under the curve.

We observe a power-law behavior in P(**T**), P(**S**), and <**S**> vs **T**.

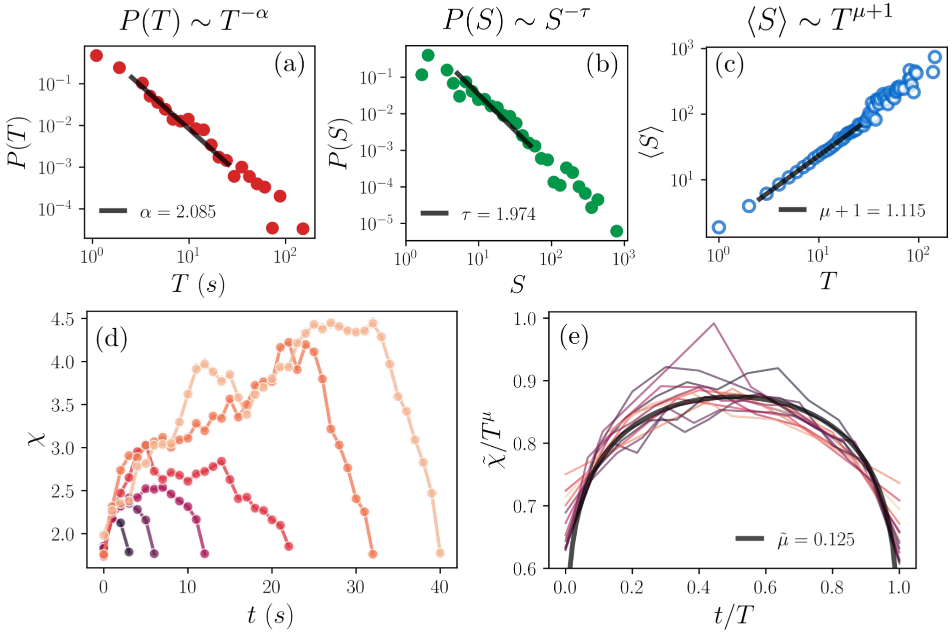
The following relation between the exponents holds,

$$\frac{\alpha - 1}{\tau - 1} = \mu + 1$$

The **average shape** of the events follows a **scaling law**

$$\chi = T^{\mu} \rho(t/T)$$

The collapse exhibits the non-trivial **self-similarity** in κ(t).



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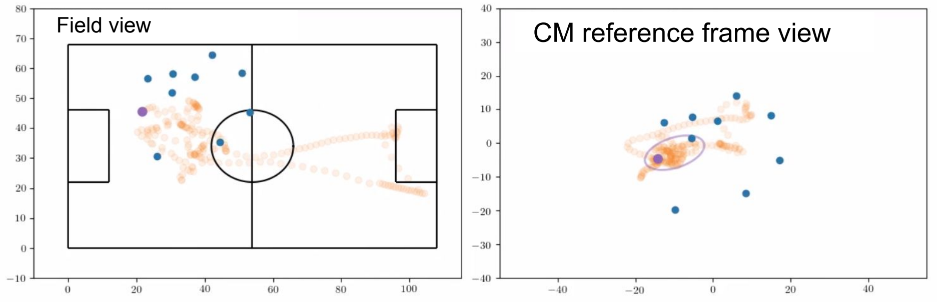
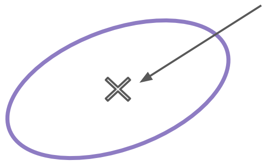
The bases

(1) The players have action zones in the tactical scheme.
Players are constraint to their action zones.

(2) The movement of one player may depends on the positions of their teammates and opponents.



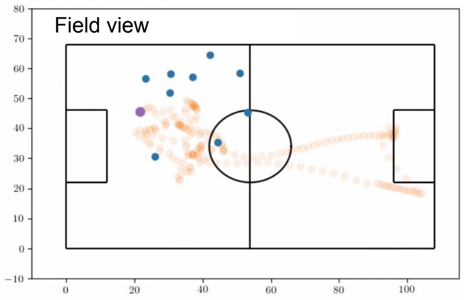
Player's action zone

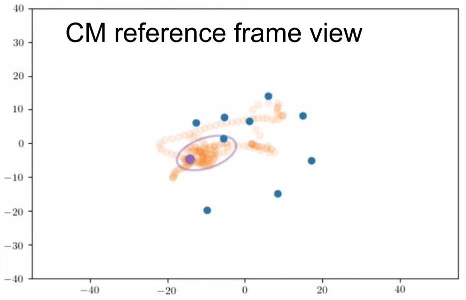


Center: Average position

Ellipse radii: standard deviation in principal directions

(3) MODELING, SIMULATIONS AND MARKING DYNAMICS IN SYNTETIC GAMES





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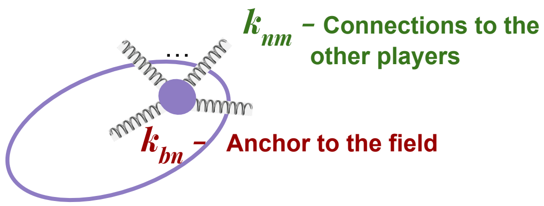
The model

-Linear interactions: spring-like forces among the players and an anchor to their positions in the field.

$$\vec{a}_n = -\gamma_n \vec{v}_n + k_{bn}(\vec{b}_n - \vec{r}_n) + {\sum_m}' k_{nm}(\vec{r}_m - \vec{r}_n)$$



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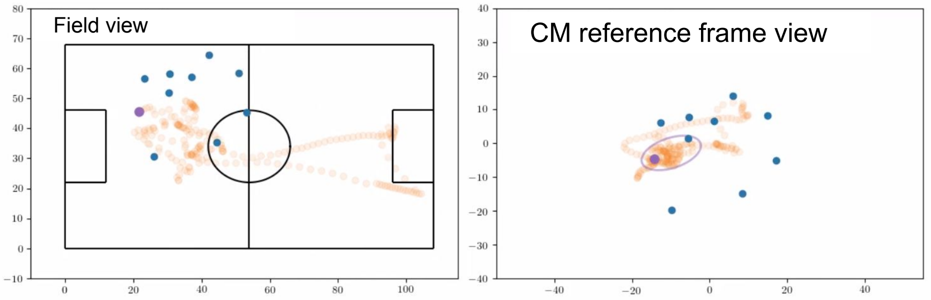

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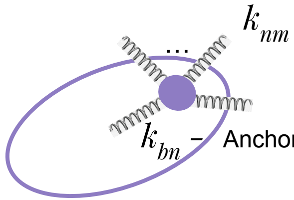
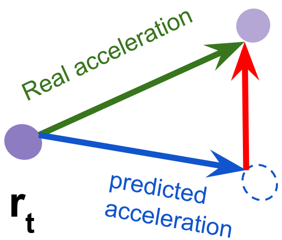


Fitting the model to the data

$$\vec{\xi}_n(t) := \underbrace{[\vec{v}_n(t+1) - \vec{v}_n(t)]}_{\text{Data}} - \underbrace{\vec{a}_n(t)]}_{\text{Model}}$$

We minimize $\sum_t \sum_n |\vec{\xi}_n(t)|$ via parameters: γ_n, k_{bn} ,k_{nm}



(3) MODELING, SIMULATIONS AND MARKING DYNAMICS IN SYNTETIC GAMES

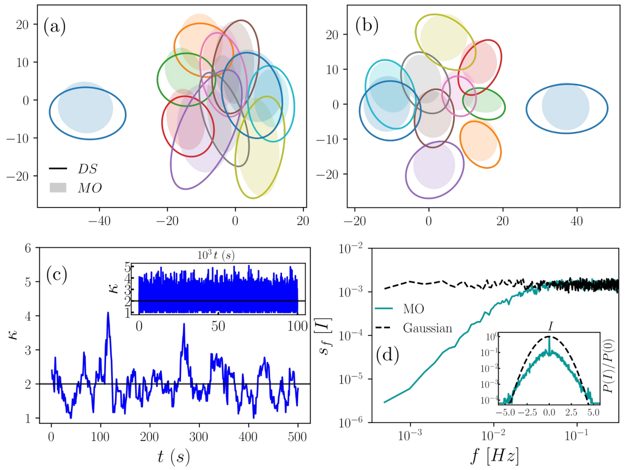
Simulating the collective players' movement

- Using the fitted parameters, we simulate a **system of stochastic differential equations** with Gaussian noise.

$$\begin{cases} d\vec{r}_n = \vec{v}_n dt \\ d\vec{v}_n = \left[-\left(k_{nb} + {\sum_m}' k_{nm}\right)\vec{r}_n + {\sum_m}' k_{nm}\vec{r}_m - \gamma_n \vec{v}_n + k_{nb}\vec{b}_n \right] dt + d\vec{W}_n \end{cases}$$

-The simulated actions zones, approximates well to the real

-We observe, like in the empirical case, **anti persistency** in the time series **K**(t)



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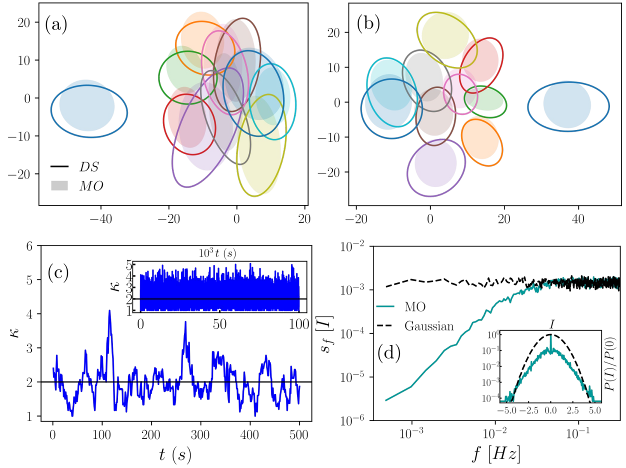
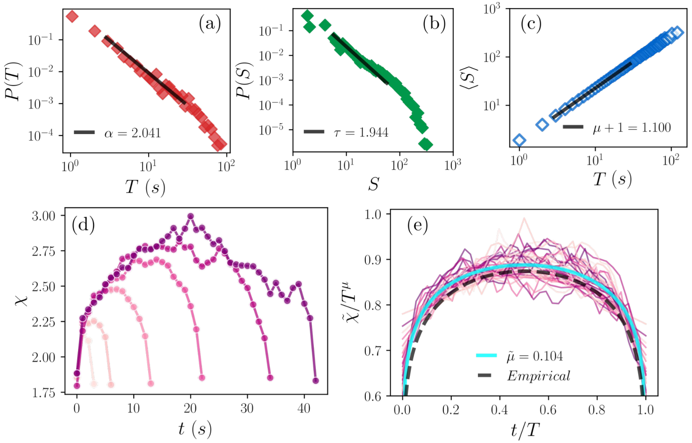


Avalanches

-We obtain statistical similarities between the empirical system and the model's outcomes.
-Stronger anti-persistency than the empirical case.



→ The model works well in capturing the phenomenology of the marking dynamics

Summary

- **Data analysis**. The use of the temporal network to describe the marking dynamics allowed us to reduce the system multidimensionality to a single variable: $\kappa(t)$. The statistical analysis of this variable was useful for unveiling and characterizing the complexity of the marking.

- **Modeling**. We proposed a parsimonious model for the players' motion equations based on two observations: (1) the existence of players' action zones; and (2) the interdependence of players' movements. We showed that the model's dynamics generate the statistical properties we observed in real football games.

- **Complexity and performance.** We know that when there is a lacking of complexity in the living system, something abnormal happens: the proliferation of cancer cells, the appearance of nervous system diseases, etc. In this sense, a lacking of complexity in the marking system may be related to a lacking of performance. We are currently working in this interesting topic.

THE END

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Strong link between Cuti Romero y Haaland