BDSports Big Data Analytics in Sports

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Sensor Analytics in basketball: analyzing spatio-temporal movements of players around the court

Rodolfo Metulini - March 15th, 2017

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Big & Open data Innovation Laboratory (BODaI - Lab)

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Aknowledgments

Big & Open Data Innovation (**BODaI**) laboratory BODaI

Big Data analytics in Sports (**BDS**) laboratory: BDS

Paolo Raineri (CEO and cofounder -**MYagonism** MYa)

Tullio Facchinetti (MYagonism, **Robotics Laboratory** RoLa, University of Pavia).

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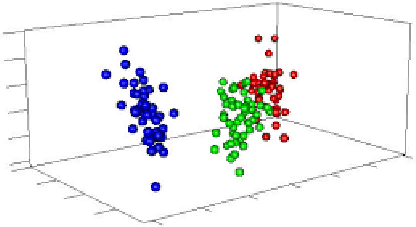
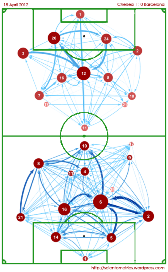
(Non exaustive) team sport literature

- **Data-driven techniques**: Carpita et al., 2013, 2015; Wasserman & Faust, 1994; Passos et al., 2011
- **Synchronyzed movements analysis**: Travassos et al., 2013; Araujo & Davids, 2016; Perin et al., 2013
- **Visualization tools**: Aisch & Quealy, 2016; Goldsberry, 2013; Polk et al. 2014; Pileggi et al. 2012; Losada et al., 2016

Data-driven techniques





- **Carpita et al.** (2013,2015) used cluster analysis and Principal Component Analysis (PCA) to identify the drivers that most affect the probability to win a football match
- From network perspective, **Wasserman & Faust** (1994) analysed passing network. **Passos et al.** (2011) used centrality measures to identify ‘key” players in water polo

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Synchronyzed movements analysis

Living things and their surrounds are not logically independent of each other. Together, they constitute a unitary planetary system - **Tuvey et al.** (1995)

- Borrowing from the concept of Physical Psychology, **Travassos et al.** (2013) and **Araujo & Davids** (2016) expressed players in the court as *living things* who face with external factors
- **Perin et al.** (2013) developed a system for visual exploration of phases in football

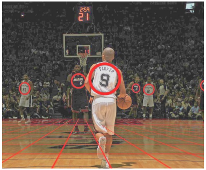
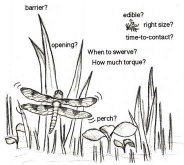
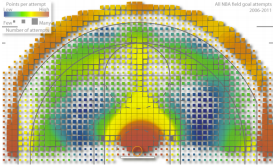


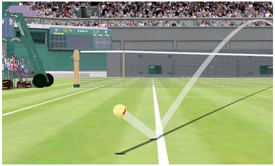
Figure 11.3. Controlled locomotion by a dragonfly is a very cognitive matter.

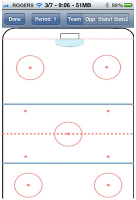


Visualization tools

Sports data tends to be hypervariate, temporal, relational, hierarchical, or a combination thereof, which leads to some fascinating visualization challenges - **Basole & Saupe** (2016)







- **Aisch & Quealy** (2016) ▸ A&Q and **Goldsberry** (2013) ▸ Gds use visualization to tell basketball and football stories on newspapers
- Notable academic works include data visualization, among others, in ice hockey (**Pileggi et al.** 2012), tennis (**Polk et al.** 2014) and basketball (**Losada et al.**, 2016)

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Aims and scope

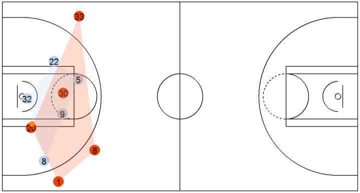
Experts want to explain why and how cooperative players movements are expressed because of tactical behaviour

Analysts want to explain movements in reaction to a variety of factors and in relation to team performance

External factors → Players' movements → Team performance

- **Aim 1**: To find and to demonstrate the usefulness of a visual tool approach in order to extract preliminar insights from trajectories (**fairly done**)
- **Aim 2**: To find any regularities and synchronizations in players' trajectories, by decomposing the game into homogeneous phases in terms of spatial relations (**in progress**)
- **Future aims**: to study cooperative players movements in relations to team performance (**future research**)

Global Positioning Systems (GPS)



- Object trajectories capture the movement of players or the ball
- Trajectories are captured using optical- or device-tracking and processing systems
- The adoption of this technology and the availability of data is driven by various factors, particularly commercial and technical

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Play-by-play

MIA Cantù	Min.	Grissin Bon Reggio Emilia
	1. min	
	0-2	**De Nicolao Andrea - Canestro da sotto**
Calathes Patrick - Tiro sbagliato da sotto		
Calathes Patrick - Stoppata Subita (1)		
Calathes Patrick - Rimbalzo offensivo (1)		
Calathes Patrick - Tiro sbagliato da sotto		
		Cervi Riccardo - Stoppata (1)
		Williams Jawad - Rimbalzo difensivo (1)
	0-4	**Cervi Riccardo - Canestro da sotto**
		De Nicolao Andrea - Assist (1)
	2. min	
Johnson JaJuan - Fallo subito (1)		
		Kaukenas Rimantas - Fallo commesso (1)
Dowdell Zabian - Canestro da sotto	2-4	
Pilepic Fran - Assist (1)		
	2-6	**Kaukenas Rimantas - Canestro da sotto**

Play-by-play (or 'event-log") reports a sequence of significant events that occur during a match

- Players events (shots, fouls)
- Technical events (time-outs, start/end of the period)
- Large amounts of available data
- Web scraping techniques (*R* and *Phyton* user-friendly routines)

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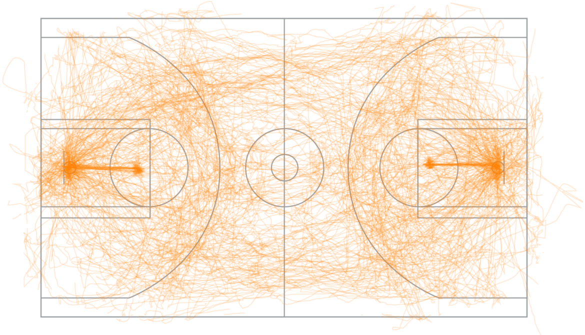
Data Visualization



▸ Metulini, 2016 *... a friendly and easy-to-use approach to visualize spatio-temporal movements is still missing. This paper suggests the use of gvisMotionChart function in googleVis R package ...*

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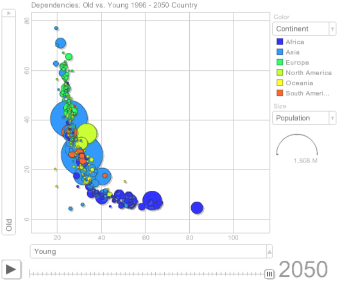
The use of motion charts



- A motion chart is a dynamic bubble chart expressing two values trough the *xy*-axes and a third value trough size
- Motion charts facilitate the interactive representation and understanding of (large) multivariate data
- Motion charts have been popularized by Hans Rosling in his TED talks ▸ TED

Applications of motion charts in other academic fields

- In students learning processes (**Santos et al., 2012**) and lingistic changes (**Hilpert, 2011**)
- In economics. **Heinz, 2014** visualizes sales data in an insurance context, **Saka & Jimichi, 2015** shed light on the inequality among countries and firms
- In medicine,**Santori, 2014** applied a new model to visually display aggregated liver transplantation
- **Bolt, 2015** explored stream and coastal water quality in space and time

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Motion charts providers

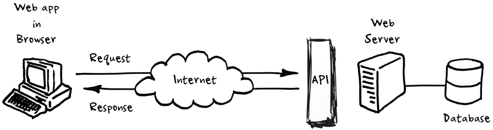

Table: List of tools to create Motion Charts

Name of tool	Format	Availability	Data input	Skill
Google charts	Software	Free	your own data	Low
Gapminder	Software	Free	included data	Low
Trend compass	Software	License	your own data	Low
JMP by SAS	Software	License	your own data	Low
Flash	Web	Varies	your own data	High
Google API	Web	Mostly free	your own data	High
Tableau Public	Web	Free	your own data	Low

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Objectives

Academic papers using motion charts in sport science disciplines do not exist

- To visualize the synchronized movement of players and to characterize the spatial pattern around the court
- To supply experts and analysts with an useful tool in addition to traditional statistics
- To corroborate the interpretation of evidences from other methods of analysis

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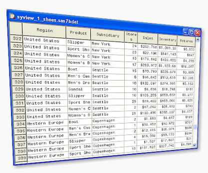
Data



- Data refer to a friendly match played on March 22th, 2016 by a team based in the city of Pavia (MYagonism MYa)
- Six players took part to the friendly match wearing a microchip in their clothings
- The microchip collects the position (in squares of 1 m^2) in both the x-axis, y-axis, and z-axis
- Players positioning has been detected at millisecond level
- The dataset records a total of 133,662 observations
- The positions are collected about 37 times every second (in average per player, every 162 milliseconds)

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gvisMotionChart

```
gvisMotionChart(data, idvar = "id", timevar =
"time", xvar = " ", yvar = " ", colorvar = " ",
sizevar = " ",date.format = "Y/m/d", options =
list(), chartid)
```

- data is a data.frame object that should contains at least four columns
- idvar represents the subject name
- timevar identifies the time dimension
- xvar and yvar correspond to the information to be plotted, respectively, in the *x*- and the *y*- axes
- colorvar and sizevar serve to fix, respectively, the colour and the dimension of the bubbles

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gvisMotionChart application

```
setwd("C:/Users/Rodolfo/Dropbox/Brescia/basket")

ds = read.delim("dataset_paper_MC.txt")

dim(ds)
names(ds)
summary(ds)

install.packages("googleVis")
library(googleVis)

ds = ds[ds$klm_y >=0 & ds$klm_z >= 0,]

MC = gvisMotionChart(ds[ds$time >=19555 & ds$time <=25000,], idvar = "tagid_new", timevar =
"time", xvar = "klm_y", yvar = "klm_z", colorvar = "", sizevar = "",
options=list(width=1200, height=600))

plot(MC)
```

Video on Youtube

Video from our youtube channel ‘bdssport unibs”

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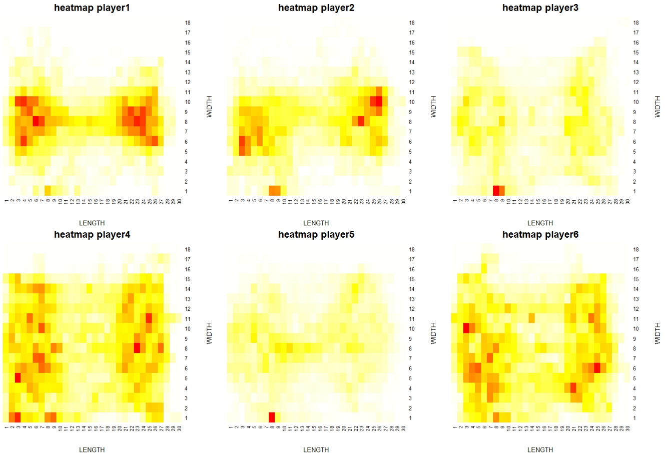
A static approach: heat maps



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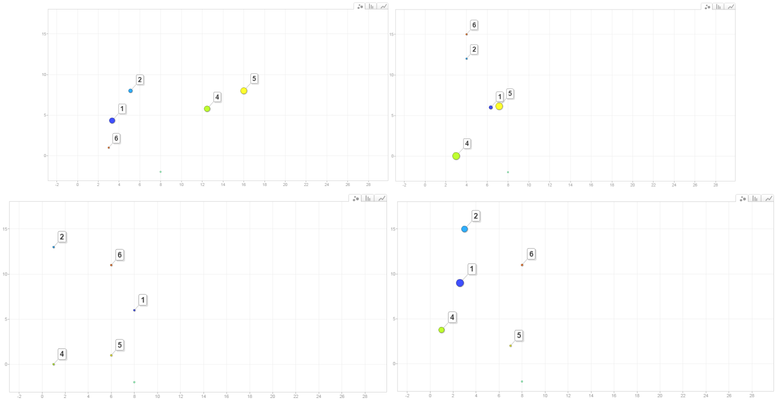
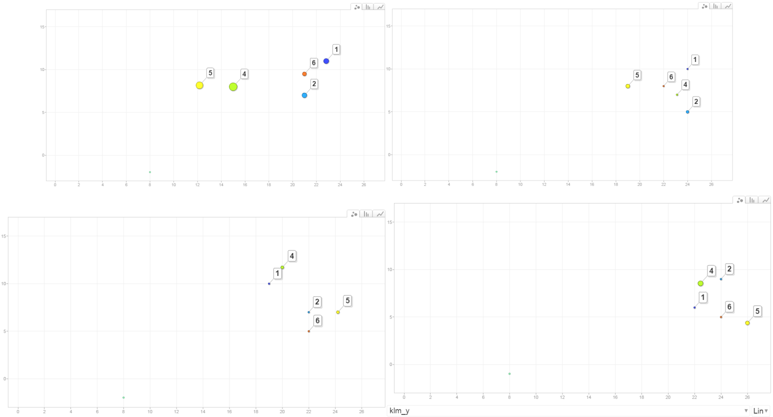
Snapshots - offensive play



Snapshots - defensive play



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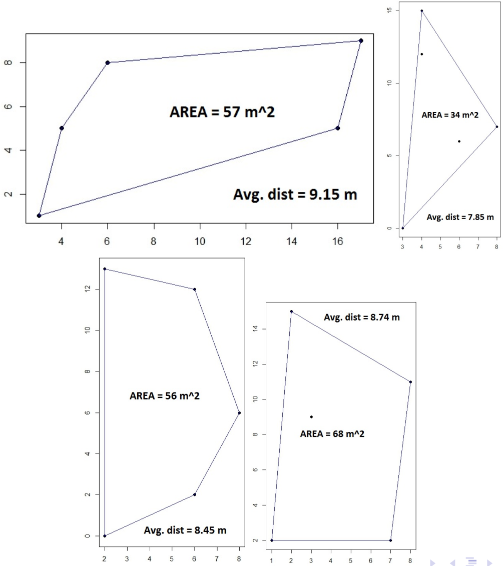
Convex hull - offensive play



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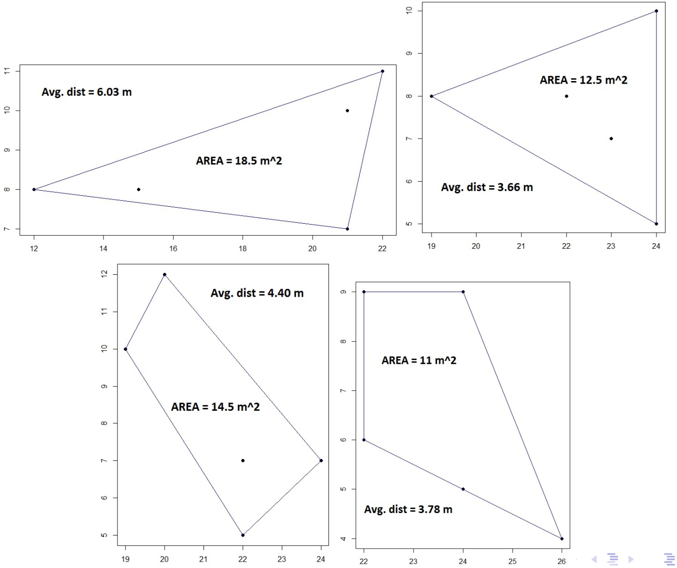
Convex hull - defensive plays



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Summary statistics

Table: Statistics for the offensive play and for the defensive play

	Average distance		Convex hull area	
	attack	defence	attack	defence
Min	5.418	2.709	11.000	4.500
1st Qu.	7.689	3.942	32.000	12.500
Median	8.745	4.696	56.000	18.500
Mean	8.426	5.548	52.460	32.660
3rd Qu.	9.455	5.611	68.500	27.500
Max	10.260	11.640	99.500	133.500

Future research in this direction

- To dynamically visualize team-mate and rivals movement together with the ball ▸ RPubs
- To extend the analysis to multiple matches

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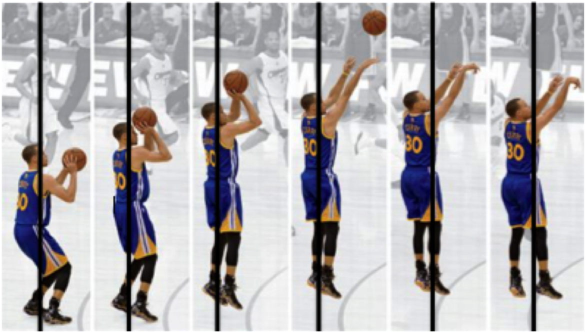
Phases decomposition



Objectives

A method to approach with complexity in team sport analysis consists on segmenting a match into phases

- To find, through a cluster analysis, a number of homogeneous groups each identifying a specific spatial pattern
- To characterize the synchronized movement of players around the court

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Analyses

- First, we characterize each cluster in terms of players position in the court
- We define whether each cluster corresponds to offensive or defensive actions
- We compute the transition matrices in order to examine the probabbility of switching to another group from time t to time $t+1$

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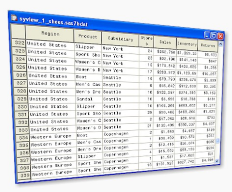
Data



- Data refers to a friendly match played on March 22th, 2016 by a team based in the city of Pavia. Data provided by MYagonism ▸ MYa
- Six players worn a microchip, collecting the position in both the x-axis, y-axis, and z-axis
- Players positioning has been detected at millisecond level, and the the dataset records a total of 133,662 observations
- After some cleaning and dataset reshaping, the final dataset count for more than 3 million records

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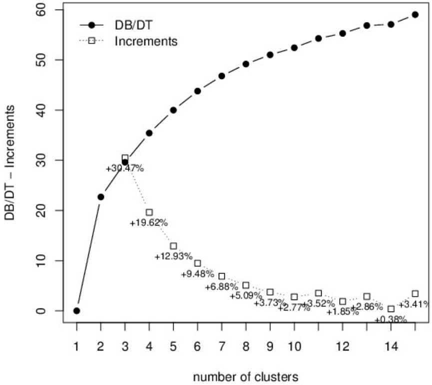
Methods

- We apply a k-means cluster analysis to group objects
- We group time instants
- The similarity is expressed in terms of players' distance
- We choose $k = 8$ based on the value of the between deviance (BD) / total deviance (TD) ratio for different number of clusters
- A multidimensional scaling is used to plot each player in a 2-dimensional space such that the between player average distances are preserved

Define k



Plot of the between deviance (BD) / total deviance (TD) ratio for different number of clusters

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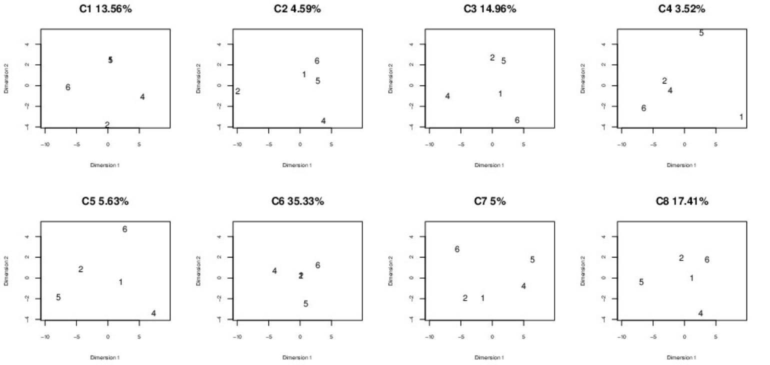
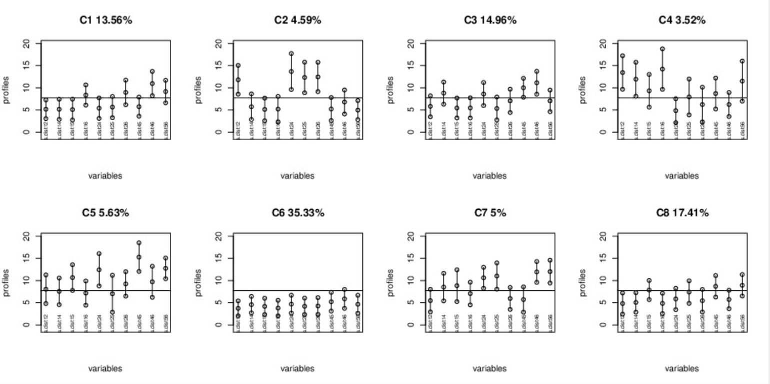
Multidimensional scaling



Map representing, for each of the 8 clusters, the average position in the $x - y$ axes of the five players, using MDS

Profiles plot



Profile plots representing, for each of the 8 clusters, the average distance among each pair of players

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Transition matrix

NA	1	2	3	4	5	6	7	8
1	0	10.71	23.53	47.83	0	20.83	31.25	20.23
2	0.77	0	9.15	0	1.85	2.08	8.33	2.89
3	31.54	42.86	0	8.7	44.44	20.83	18.75	20.23
4	6.15	3.57	1.96	0	7.41	0	10.42	1.16
5	0.77	3.57	16.99	17.39	0	0	16.67	8.09
6	27.69	7.14	18.95	0	1.85	0	0	43.93
7	15.38	21.43	3.92	4.35	18.52	0	0	3.47
8	17.69	10.71	25.49	21.74	25.93	56.25	14.58	0

D	A
14.12	85.88
14.09	85.91
26.07	73.93
15.38	84.62
57.98	42.02
85.07	14.93
39.53	60.47
39.08	60.92

Transition matrix reporting the relative frequency subsequent moments $(t,\ t+1)$ report a switch from a group to a different one

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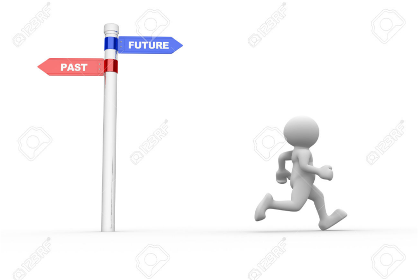
Future research in this direction



- To increase the complexity, by extending the analysis to multiple matches
- To match the play-by-play data with trajectories, to extract insights on the relations between particular spatial pattern and the team performance

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Future works and research challenges

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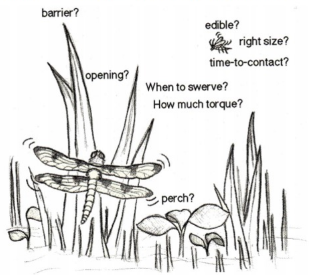
An example from Physical Psychology

A dragonfly feeds on small insects, such as mosquitoes. In seeking its prey, the dragonfly must perceive paths through the thicket. To do so, it must perceive obstacles to its forward locomotion and openings that permit it passage, given its size. Given the many objects within the thicket insects, birds, leaves, berries, flowers, and so on the dragonfly must perceive selectively those objects that are edible for it, commonly insects within a certain length scale and degree of softness. It must also perceive places that it can alight upon, places to rest between searches. In travelling through the thicket and in direct pursuit of a prey, the dragonfly must perceive when an upcoming twig or an upcoming prey will be contacted if current conditions (wing torques, forward velocity) continue, so that suitable adjustments can be made both with respect to the body as a unit and with respect to the most forward limbs that are used to effect a catch or a landing ...

- Turvey, M. T.,& Shaw, R. E. (1995). Toward an ecological physics and a physical psychology.ÂăThe science of the mind: 2001 and beyond, 144-169.

Figure 11.3. Controlled locomotion by a dragonfly is a very cognitive matter.



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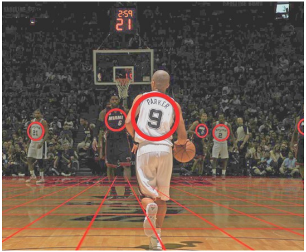
Generalizing the concept of physical Psychology to team sports

T. Parker starts an offensive plays for Spurs team in a match against Heat: while he is bouncing the ball he have to think how to convert that action in a 2- or 3- point. Without any obstacles, he will go straight to the basket and then shot the ball.

- However, he find obstacles (opposite team's players) he have to account for remaining time
- He have to think what the coach says to him
- Where all the other 4 team-mates are
- so on and so forth ...



Each player interact with each others, and players trajectories is the results of both **exogenous** (depending on T.Parker himself) and **endogenous** (external) factors

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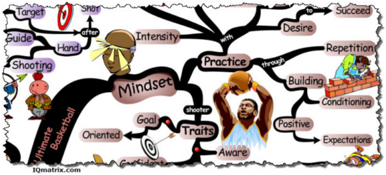
Exogenous vs. endogenous factors in team sports



Team Sports (the player have to decide where to go in the court)

- Short team equilibrium
- High level of interaction
- Exogenous (depending on the player himself) and endogenous (depending by external factors) are difficult to distinguish (sorrounding environment: movement of rivals, climatic factors, etc..)
- Opposition between predefined plays versus real time decision

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Exogenous vs. endogenous factors in other fields

- **Economics (firm location)**
  The decision is about where to locate the firm and depends on a mixture of exogenous and endogenous factors (Long-term dynamic)
  *Economists have studied the locational choices of individuals ... and of firms but generally treat the characteristics of locales as given. The purpose of much spatial work, however, is to uncover the interaction among (authorities of) geographic units, who choose, e g., tax rates to attract firms or social services to attract households ... An ideal model would marry the two; it would provide a model explaining both individuals' location decisions and the action of, say, local authorities (**Pinkse & Slade, 2010**). individual or collective decisions depend upon the decisions taken in other neighbouring regions or by neighbouring economic agents. thinking "of the economy as a self-organizing system, rather than a glorified individual (**Kirman, 1992**) ...* - Arbia, G. (2016). Spatial Econometrics: A Broad View. Foundations and Trends in Econometrics 8(3-4), 145-265
- **Medicine (disease contagion)**
  Temporal dimension: Average level of interaction among agents (medium-term dynamic)
- **Nature (dragonfly have to decide where to go)**
  There are both exogenous and endogenous factors for an high level of short-term interaction

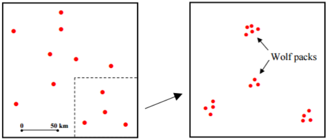
Space clustering vs. Space-time clustering

There is **space clustering** when events are close in space

When events are randomly distributed, we have spatial dispersion

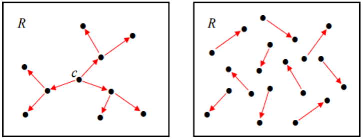
Whether events are clustered or dispersed depends on the scale

Example of wolf packs (from **Smith, T.E. , 2014**)

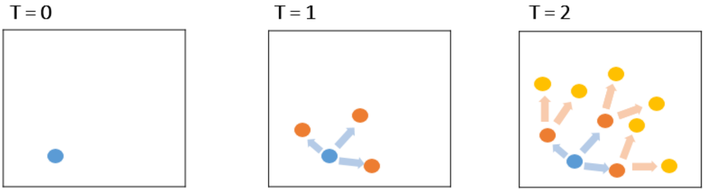


There is **space-time clustering** if events that are close in space tend to be closer in time than would be expected by chance alone

Example of epidemic contagion (from **Smith, T.E. , 2014**)



Epidemic space time clustering

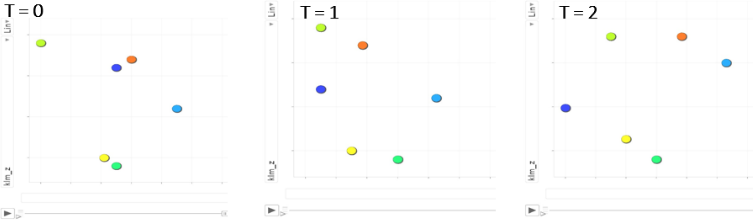


A case of *contagion*

Who start the contagion?

The person marked with the blue circle affects people marked with orange circles ar time t =1. People in Yellow are affected by people in orange circles at time t=2

Player space time clustering



A case of basketball players' movement:

- Who is the influencing player?
- How much each player influences the others? Are there more than one influencing players?
- Actually, it is likely that each player affects the others at every time t

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Potential research questions & proposed methods - I

- Who is the influencing player?
- How much each player influences the others?
- Are there more than one influencing player? How much trajectories are caused by external fact

1. Using GPS data on x-y coordinates at repeated moments, and analyzing the transition matrices from a multivariate markov chain (**Teugels, J. L., 2008**) of the type:

$$
\begin{aligned}
S_{x1,t1} &= S_{x2,t0} + S_{x3,t0} + S_{x4,t0} + S_{x5,t0} + \epsilon \\
S_{x2,t1} &= S_{x1,t0} + S_{x3,t0} + S_{x4,t0} + S_{x5,t0} + \epsilon \\
S_{x3,t1} &= S_{x1,t0} + S_{x2,t0} + S_{x4,t0} + S_{x5,t0} + \epsilon \\
S_{x4,t1} &= S_{x1,t0} + S_{x2,t0} + S_{x3,t0} + S_{x5,t0} + \epsilon \\
S_{x5,t1} &= S_{x1,t0} + S_{x2,t0} + S_{x3,t0} + S_{x4,t0} + \epsilon
\end{aligned}
$$

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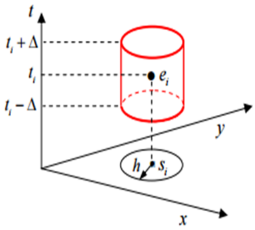
Potential research questions & proposed methods - II

Players clustering: If and how teammate (and rivals) are concentrated in the field.

- Are players equally dispersed in the field, or they are concentrated?
- At what extend, and at what distance h and what time t they are concentrated?

3. **Space time K-function**, that define a cylindrical neighborhoods, or **Bivariate Space time** K**-function** if we model the players of the two teams as two separate processes (**Dixon, P. M., 2002**)



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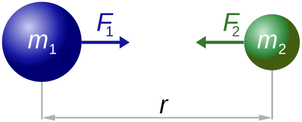
Spatial interaction models?



$$F_1 = F_2 = G\frac{m_1 \times m_2}{r^2}$$

$$F_{ij} = M_i * M_j * D_{ij}$$

Where F_{ij} is a flow (e.g. number of time player i passes the ball the player j), and depends on characteristics of both two players (M_i and M_j) and on the distance among them (D_{ij}). - **Tinbergen, J., 1962**

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Thank you!

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(... Pesaro, dating back to 1995)

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