Following Soccer Fans from Geotagged Tweets at FIFA World Cup 2014

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Motivations and goals (1/2)

- In the past, understanding people behavior in a large-scale event was extremely difficult to catch
- Today, using geo-localized services of social media, we can analyze the behavior of large groups of people attending popular events
- Example: geotagged tweets can be used to understand users' mobility behaviors that are useful in travel route discovery
- **Goal** of this work: monitoring the attendance of **Twitter** users during the **FIFA World Cup 2014** matches to discover the most frequent movements of fans

Motivations and goal (2/2)

- **Data source:** more than half million geotagged tweets posted from inside the stadiums during the 64 matches of the World Cup from June 12 to July 13, 2014

- **Trajectory pattern mining** was carried out to identify the most frequent movement patterns of **Twitter** users attending the **World Cup matches**

- **Original results:**
  - **Number of matches attended** by fans
  - **Most frequent sequences of matches** attended by fans, either in the same stadium or to follow a given soccer team
  - **Most frequent movement patterns** obtained by grouping matches based on the phase in which they were played

Outline

- Trajectory pattern mining
- Definitions
- Analysis process
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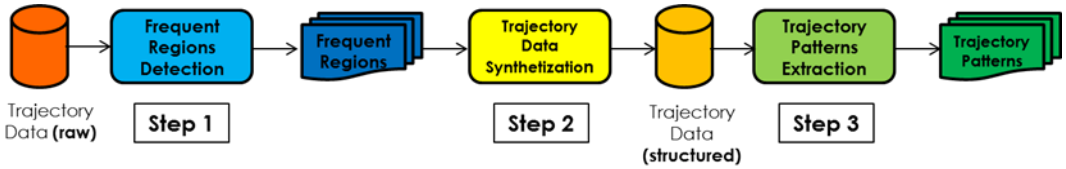
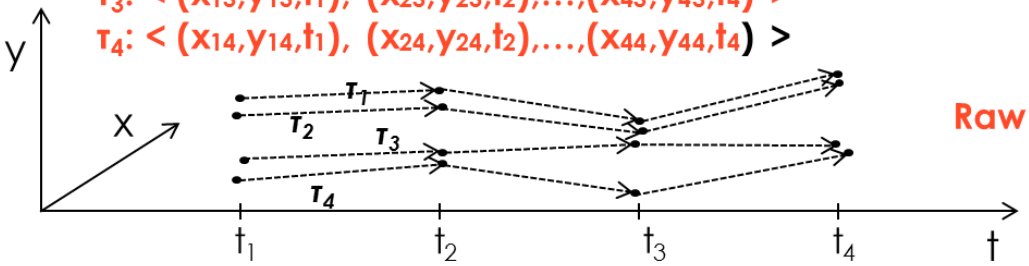
  - *Data pre-processing*
  - *Data mining*
  - *Results visualization*
- Results
  - *Number of Matches Attended*
  - *Frequent Sequences*
  - *Aggregate Analysis*
- *Conclusions*

Trajectory pattern mining

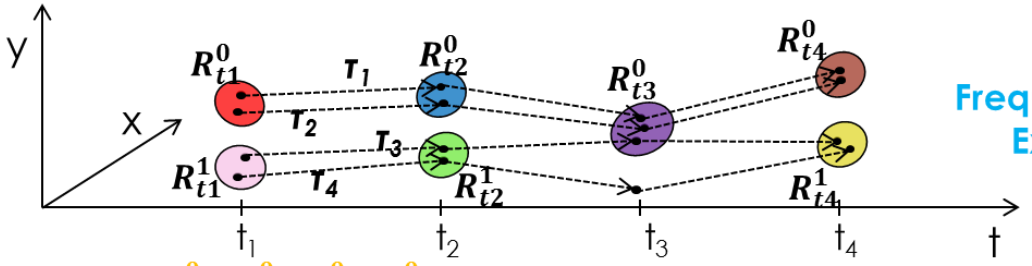


τ_1: < (x_{11},y_{11},t_1), (x_{21},y_{21},t_2),…,(x_{41},y_{41},t_4) >
τ_2: < (x_{12},y_{12},t_1), (x_{22},y_{22},t_2),…,(x_{42},y_{42},t_4) >
τ_3: < (x_{13},y_{13},t_1), (x_{23},y_{23},t_2),…,(x_{43},y_{43},t_4) >
τ_4: < (x_{14},y_{14},t_1), (x_{24},y_{24},t_2),…,(x_{44},y_{44},t_4) >

Raw Trajectory Data



Raw Trajectories



Frequent Region Extraction

τ_1: < R^0_{t1}, R^0_{t2}, R^0_{t3}, R^0_{t4} >
τ_2: < R^0_{t1}, R^0_{t2}, R^0_{t3}, R^0_{t4} >
τ_3: < R^1_{t1}, R^1_{t2}, R^0_{t3}, R^0_{t4} >
τ_4: < R^1_{t1}, R^1_{t2}, R^1_{t4} >

Structured Trajectory Data

$R^0_{t1} \wedge R^0_{t2} \wedge R^0_{t3} \rightarrow R^0_{t4}$
$R^0_{t1} \wedge R^0_{t2} \rightarrow R^0_{t3}$
…

Trajectory Patterns

Definitions

- $S=\{s_1,\ldots,s_{12}\}$: set of **stadiums**, where for each stadium s_i are known the four corner coordinates of the rectangle containing it

- $TW=\{tw_1, \ldots, tw_N\}$: set of **geotagged tweets**, where each tweet tw_i is described by the following properties:
  - *user* who posted tw_i
  - *latitude* and *longitude* (of the place from where tw_i was sent)
  - *source* (device or application used to generate tw_i)
  - *date* and *text*

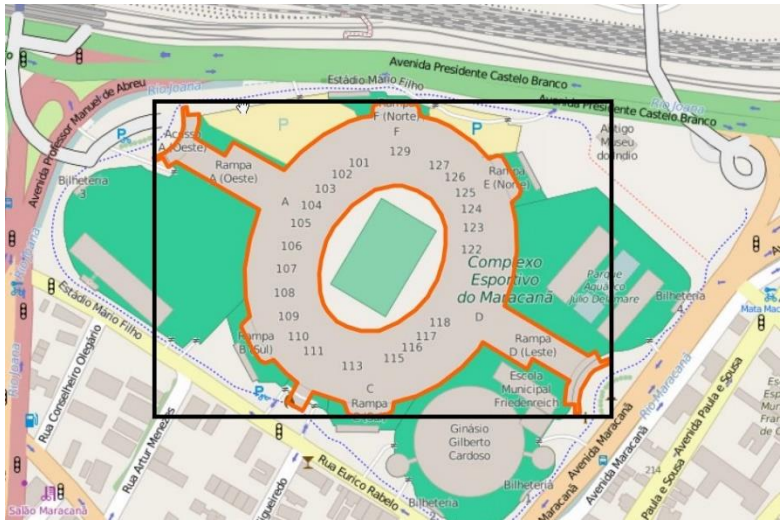
- $M=\{m_1, \ldots, m_{64}\}$: the 64 **matches**, where each match m_i is described by the following properties:
  - *stadium*
  - *date*
  - $team_1$ and $team_2$ (the two teams playing the match)

Analysis process

- The analysis process is composed of four steps:
  - ***Data acquisition***, collecting the geotagged Twitter data
  - ***Data pre-processing***, cleaning, selection and transformation of data to make it suitable for analysis
  - ***Data mining***, analyzing pre-processed data to infer trajectory patterns
  - ***Results visualization***, making results readable and usable

Data acquisition

- **Twitter REST APIs** used to collect all the geotagged tweets posted during the World Cup matches
- Only **tweets** whose coordinates fallen **within the area of stadiums during the matches**



- About **526,000 tweets** collected from June 12 to July 13, 2014

Data pre-processing

- A three-step task:
  1. **Cleaned** data by removing tweets with unreliable positions (e.g., tweets with coordinates manually set by users or applications)
  2. **Selected** only tweets written by users present at the matches, by removing *re-tweets* and *favorites* posted by other users
  3. **Transformed** data by keeping one tweet per user per match, as we were interested to know only if a user attended a match or not
- Final dataset ***D*** with about 10,000 transactions, each one containing the list of matches attended by a single user:

$$D=\{T_1,T_2,\ldots,T_n\}$$

where $T_i=<u_i,\{m_{i1},m_{i2},\ldots,m_{ik}\}>$ and $m_{i1},m_{i2},\ldots,m_{ik}$ are the matches attended by a Twitter user u_i

Data mining (1/2)

- Trajectory pattern mining to extract the most frequent movements of fans starting from ***D***
- **Trajectory pattern:** sequence of geographic regions that emerge as frequently visited in a given temporal order
- The ***support*** of a trajectory pattern ***p*** (# of transactions containing ***p***) is a measure of its reliability
- In our case, a ***frequent pattern fp*** with support ***s***:

$$fp=<m_i, m_j,.., m_k>(s)$$

is an ordered sequence of matches $m_i, m_j,.., m_k$ where ***s*** is the percentage of transactions in ***D*** containing ***fp***

Data mining (2/2)

- Pattern extraction algorithm:
  - Compute the support of each match in ***D***
  - *Iteratively:*
    - Generate new candidate ***k*-match-sets*** and compute their support, using the frequent **(*k*-1)-match-sets** found in the previous iteration
    - Delete all the candidate match-sets whose support is lower than a given minimum support
  - Terminate when no more frequent match-sets are generated

k-match-set = set of matches of cardinality ***k***

Results visualization

- Creation of **Infographics** for presenting the mobility patterns

- Main design guidelines:
  - Visual representation of quantitative information
  - Minimising the efforts necessary to decoding symbols

- **Result**: a visualization model helping readers to easily catch the key meaning of extracted knowledge

Results

- Three main categories:
  - **Number of matches attended** by fans during the competition
  - **Most frequent sequences of matches** attended by fans, either in the same stadium or to follow a given soccer team
  - **Most frequent movement patterns** obtained by grouping matches based on the phase in which they were played

Results: Number of matches attended

No. of matches	Spectators
1	71.3%
2	16.0%
3	6.0%
4	3.0%
5 or more	3.7%

- 3.7% of the spectators attended **five or more** matches during the whole World Cup
- Twitter profiles of those who attended several matches, show that many of them were journalists

Results: Frequent sequences (1/4)

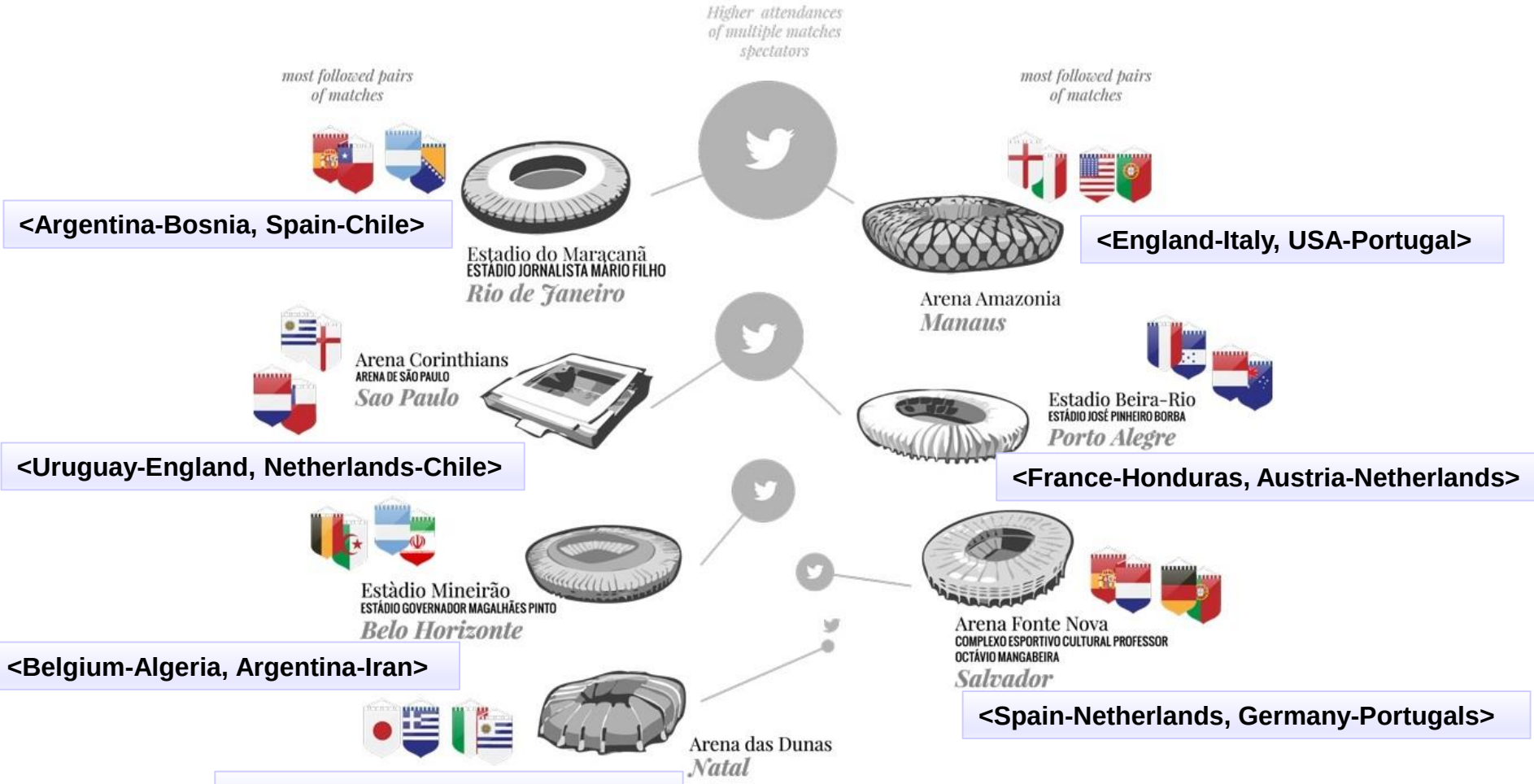
- General classification of the paths followed by fans who attended at least two matches:

No. of matches	Same stadium	Same team
2	62.9%	22.2%
3	48.8%	11.8%
4	41.0%	7.2%
5	37.0%	8.4%
6	33.7%	4.8%

- Results show that **most of who attended multiple matches did it staying in the same city**

Results: Frequent sequences (2/4)

- Most frequent **2-match-sets** observed during the **group stage**, from June 12 to June 26, 2014



Results: Frequent sequences (3/4)

- Most frequent paths of fans who attended **two** or **three** matches of the same team during the group stage

Most frequent 2-match sets:

<***Colombia***-Greece, ***Colombia***-Cote d'Ivoire>

<Brazil-***Mexico***, Croatia-***Mexico***>

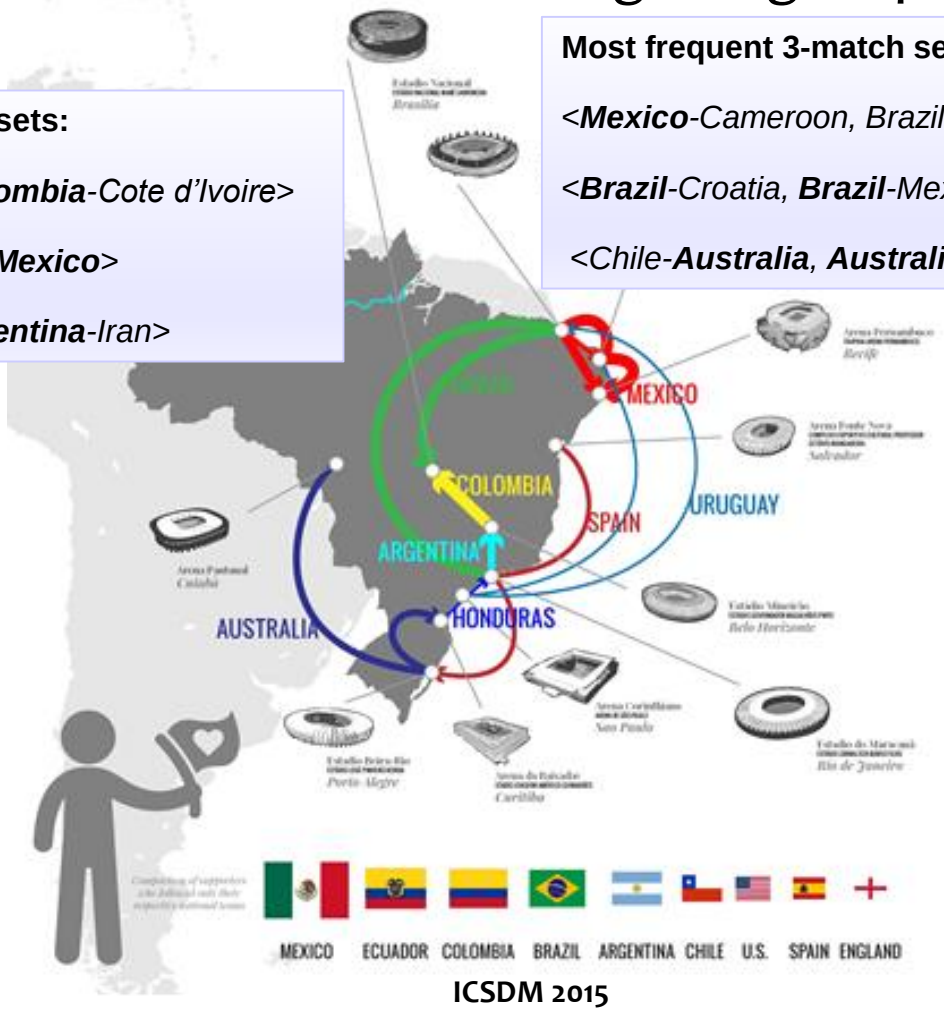
<***Argentina***-Bosnia, ***Argentina***-Iran>

Most frequent 3-match sets:

<***Mexico***-Cameroon, Brazil-***Mexico***, Croatia-***Mexico***>

<***Brazil***-Croatia, ***Brazil***-Mexico, Cameroon-***Brazil***>

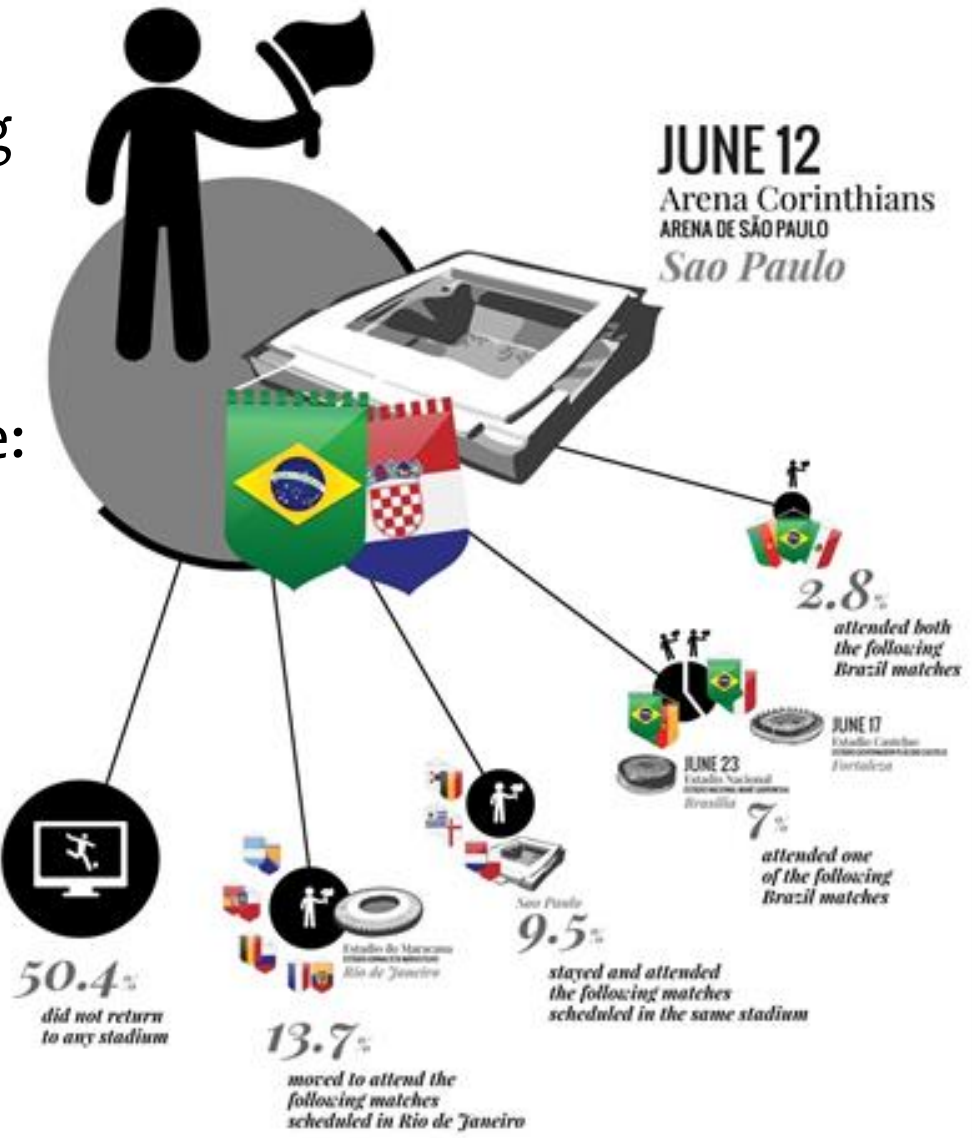
<Chile-***Australia***, ***Australia***-Netherlands, ***Australia***-Spain>



Results: Frequent sequences (4/4)

- Specific analysis on the spectators of the opening match <*Brazil-Croatia*> played on in São Paulo

- At the end of group stage:
  - **50.4%** did not attend other matches
  - **13.7%** moved to Rio de Janeiro to attend other matches
  - **9.5%** attended other matches in the same stadium



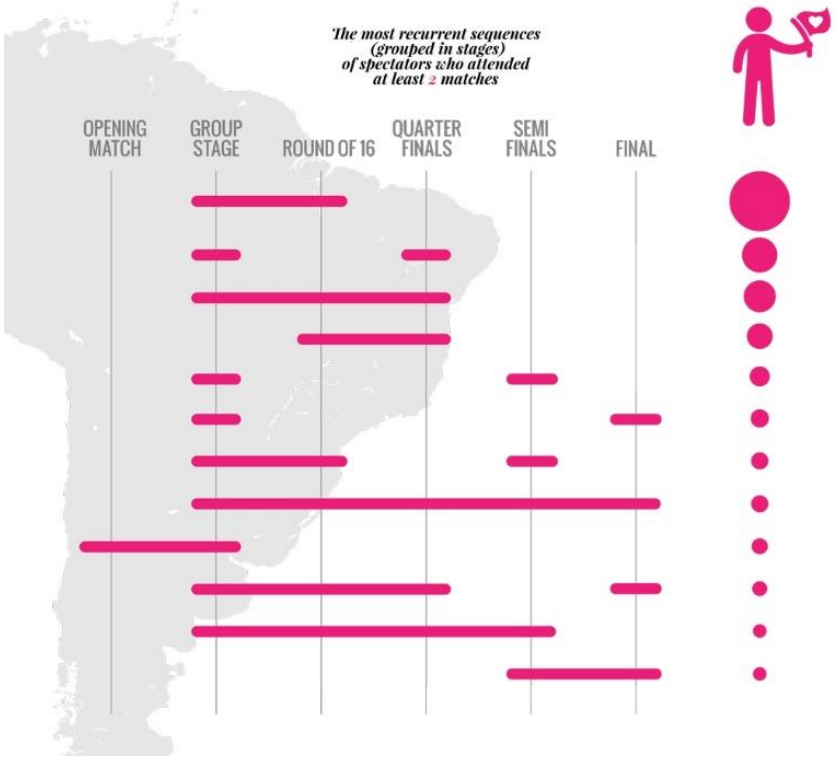
Results: Aggregate analysis (1/2)

- *Goal*: studying the movements of fans during the different phases of the competition

- Matches were grouped into the following phases:
  - *Opening match* (match no. 1)
  - *Group stage* (matches no. 2-48)
  - *Round of 16* (matches no. 49-56)
  - *Quarter finals* (matches no. 57-60)
  - *Semi-finals* (matches no. 61-62)
  - *Final* (match no. 64)

Results: Aggregate analysis (2/2)

- Patterns of movements based on the grouping above, and the relative frequency (support) of these patterns



Most frequent:

Group stage and **Round of 16**

2nd most frequent:

Group stage and **Quarter finals**

3rd most frequent:

Group stage and **Group of 16** and **Quarter finals**

Least frequent:

Semi-final and **Final**

- The relative frequency of each pattern is represented by a circle: the larger the circle, the higher the frequency

Conclusions

- Analysis of fans' movements during the FIFA World Cup 2014: An example of how social data analysis can be used to know how people behave in big events
- Social data applications can help the organization of future events, e.g. monitoring and management of key services like transports, security, logistics, and others
- This methodology can be re-used in similar scenarios to understand collective behaviours that are very hard to discover with traditional social analysis techniques

Questions?

Thank you!