# Evolutionary dynamics of time-resolved social interactions


Alessio Cardillo

Department of Condensed Matter Physics – University of Zaragoza
&
Institute for Biocomputation and Physics of Complex Systems (BIFI), Zaragoza, Spain
http://bifi.es/~cardillo/


Thursday 6 June 2013, NetSci 2013, Copenhagen, Denmark

Universidad Zaragoza
1542

Instituto Universitario de Investigación Biocomputación y Física de Sistemas Complejos Universidad Zaragoza

# Acknowledgements

Cornell University Library

We gratefully acknowledge support from the Simons Foundation and member institutions

arXiv.org > physics > arXiv:1302.0558

Search or Article-id (Help | Advanced search) All papers Go!

Physics > Physics and Society

**Evolutionary dynamics of time-resolved social interactions**

Alessio Cardillo, Giovanni Petri, Vincenzo Nicosia, Roberta Sinatra, Jesús Gómez-Gardeñes, Vito Latora

(Submitted on 4 Feb 2013)

Cooperation among unrelated individuals is frequently observed in social groups when their members join efforts and resources to obtain a shared benefit which is unachievable

**Download:**

- PDF
- PostScript
- Other formats

Current browse context:
physics.soc-ph

http://arxiv.org/abs/1302.0558

## Collaborators

Giovanni Petri ISI Turin (Italy)

Vincenzo Nicosia Queen Mary University London (UK)

Roberta Sinatra Northeastern University (USA)

Jesús Gómez-Gardeñes University of Zaragoza (Spain)

Vito Latora Queen Mary University London (UK)
University of Catania (Italy)

# Outline

- Short Introduction on Evolutionary Game Theory

# Outline

- Short Introduction on Evolutionary Game Theory
- Time Varying Graphs

# Outline

- Short Introduction on Evolutionary Game Theory
- Time Varying Graphs
- Datasets

# Outline

- Short Introduction on Evolutionary Game Theory
- Time Varying Graphs
- Datasets
- Results

# Outline

- Short Introduction on Evolutionary Game Theory
- Time Varying Graphs
- Datasets
- Results
- Conclusions.

# Motivation

**Foreword**

Dynamical processes acting on time varying graphs behave differently than on static graphs.

P. Holme, & J. Saramäki, *T*emporal networks. Physics Reports, 519(3), (2012).

# Motivation

**Question:**

Does time resolution affects the classical results about the enhancement of cooperation driven by static networks?

# Short Introduction on Evolutionary Game Theory

## The game: Social Dilemma

Consider a pairwise interaction where individuals face a social dilemma between two possible strategies: *Cooperation* (C) and *Defection* (D). Such dilemmas can be encoded into a two-parameter game described by the payoff matrix:

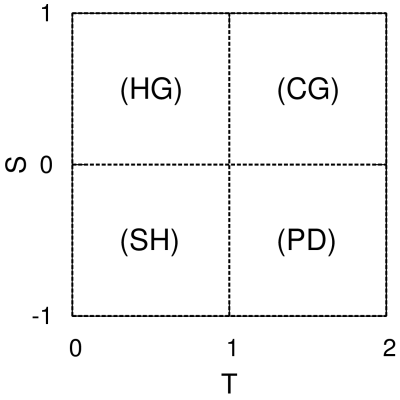
$$\begin{array}{c} \\ C \\ D \end{array}\!\!\begin{array}{c} \begin{array}{cc} C & D \end{array} \\ \begin{pmatrix} R & S \\ T & P \end{pmatrix} \end{array} = \begin{array}{c} \\ C \\ D \end{array}\!\!\begin{array}{c} \begin{array}{cc} C & D \end{array} \\ \begin{pmatrix} 1 & S \\ T & 0 \end{pmatrix} \end{array}, \tag{1}$$

# Short Introduction on Evolutionary Game Theory

## Mean field case

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} 1 & S \\ T & 0 \end{pmatrix} \end{array},$$

We consider three different kind of social dilemmas, namely:



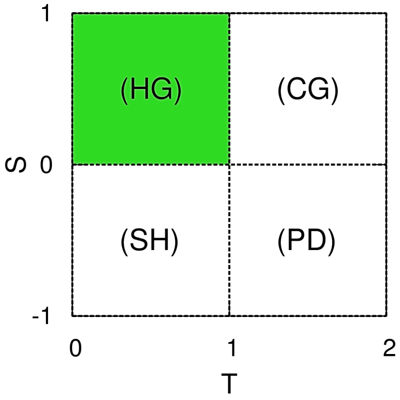
# Short Introduction on Evolutionary Game Theory

## Mean field case

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} 1 & S \\ T & 0 \end{pmatrix}, \end{array}$$

We consider three different kind of social dilemmas, namely:

- Harmony Game (HG)



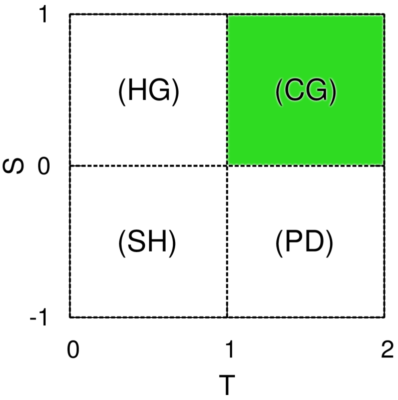
# Short Introduction on Evolutionary Game Theory

## Mean field case

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} 1 & S \\ T & 0 \end{pmatrix} \end{array},$$

We consider three different kind of social dilemmas, namely:

- Harmony Game (HG)
- Chicken Game (CG)



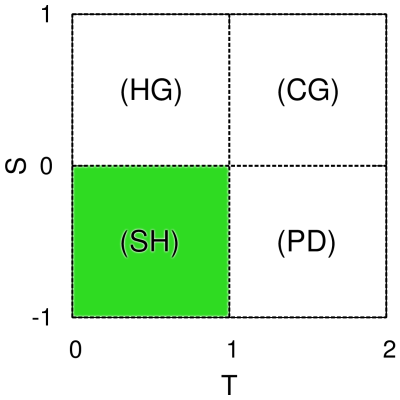
# Short Introduction on Evolutionary Game Theory

## Mean field case

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \left( \begin{array}{cc} 1 & S \\ T & 0 \end{array} \right), \end{array}$$

We consider three different kind of social dilemmas, namely:

- Harmony Game (HG)
- Chicken Game (CG)
- Stag Hunt (SH)



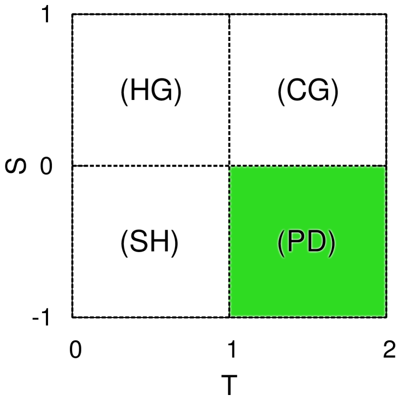
# Short Introduction on Evolutionary Game Theory

## Mean field case

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} 1 & S \\ T & 0 \end{pmatrix} \end{array},$$

We consider three different kind of social dilemmas, namely:

- Harmony Game (HG)
- Chicken Game (CG)
- Stag Hunt (SH)
- Prisoner's Dilemma (PD)



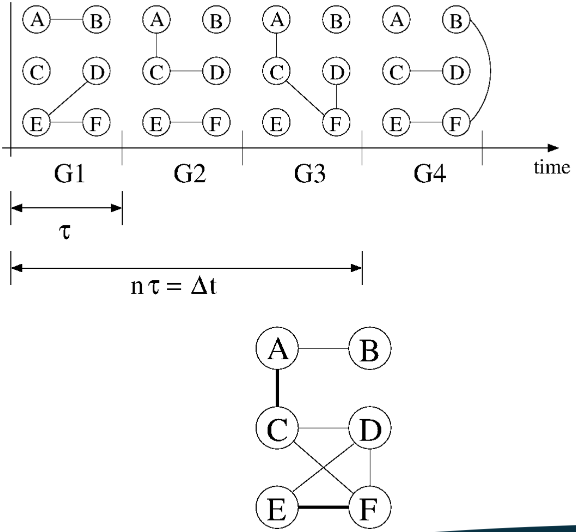
# Short Introduction on Evolutionary Game Theory

## Strategy Update

After all the individuals have played with all their neighbors in the network, they update their strategies as a result of an evolutionary process. To update the strategies of agents we consider the so-called Fermi Rule:

$$P_{i\to j} = \frac{1}{1 + e^{-\beta(p_j - p_i)}} \,, \qquad (1)$$

# Time Varying Graphs



# Datasets

## MIT Reality Mining

Data of proximity interactions collected through the use of Bluetooth-enabled phones distributed to a group of 100 users, composed by 75 MIT Media Laboratory students and 25 faculty members recorded over a period of about six months.

| $M$ | $N$ | $\tau$ | $E^\star$ | $\langle k \rangle_{agg}$ |
|---|---|---|---|---|
| 41291 | 100 | 5 min | 2114 | 42 |

N. Eagle, and A. Pentland, *"Reality mining: sensing complex social systems."* Personal and Ubiquitous Computing **10**, 255–268 (2006).

# Datasets

## INFOCOM'06

The data set consists of proximity measurements collected during the IEEE INFOCOM'06 conference held in a hotel in Barcelona between 23-rd and 29-th of April 2006.

| $M$ | $N$ | $\tau$ | $E^{\star}$ | $\langle k \rangle_{agg}$ |
|---|---|---|---|---|
| 2880 | 78 | 2 min | 2730 | 70 |


J. Scott *et al.* , "CRAWDAD Trace", INFOCOM, Barcelona (2006).

# Datasets

## Experimental setup:

1. A number $n$ of graphs corresponding to a time interval equal to $\Delta t$ is projected onto a single weighted one.

# Datasets

## Experimental setup:

1. A number $n$ of graphs corresponding to a time interval equal to $\Delta t$ is projected onto a single weighted one.
2. Each agent $i$ plays with all her $k_i$ neighbors and accumulate a payoff $p_i$.

# Datasets

## Experimental setup:

1. A number $n$ of graphs corresponding to a time interval equal to $\Delta t$ is projected onto a single weighted one.
2. Each agent $i$ plays with all her $k_i$ neighbors and accumulate a payoff $p_i$.
3. Agents update simultaneously their strategies.

# Datasets

**Experimental setup:**

1. A number $n$ of graphs corresponding to a time interval equal to $\Delta t$ is projected onto a single weighted one.
2. Each agent $i$ plays with all her $k_i$ neighbors and accumulate a payoff $p_i$.
3. Agents update simultaneously their strategies.
4. Apply points from 1 to 3 on the next time snapshots until stationary state is reached.

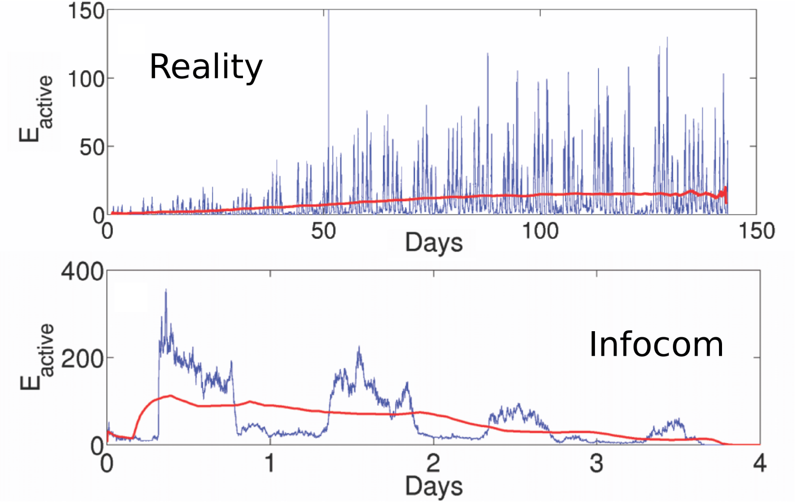
# Datasets

## Experimental setup:

1. A number $n$ of graphs corresponding to a time interval equal to $\Delta t$ is projected onto a single weighted one.
2. Each agent $i$ plays with all her $k_i$ neighbors and accumulate a payoff $p_i$.
3. Agents update simultaneously their strategies.
4. Apply points from 1 to 3 on the next time snapshots until stationary state is reached.

- Initial fraction of cooperators $f_c(0) = 0.5$ randomly distributed.
- Payoff parameters $T \in [1, 2] \quad S \in [-1, 1]$.
- Two kind of time sequence: the real one and a randomized version.
- Averaged over 50 different realizations.

# Time series

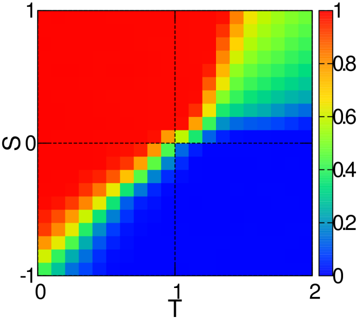


Reality
$E_{active}$
150
100
50
0
0
50
100
150
Days
Infocom
$E_{active}$
400
200
0
0
1
2
3
4
Days

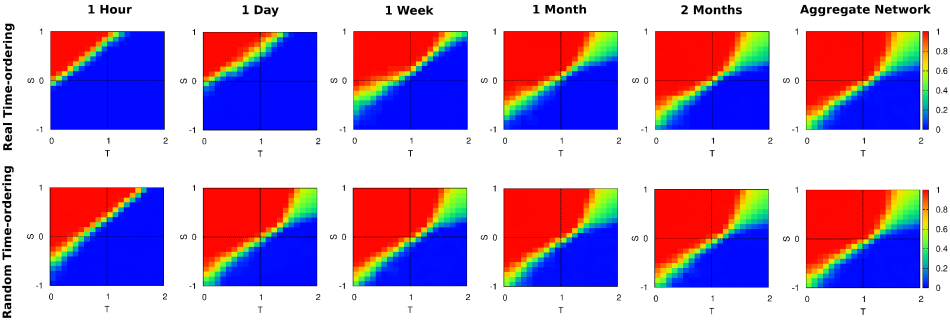
# Cooperation diagram I

We measure the cooperation level as:

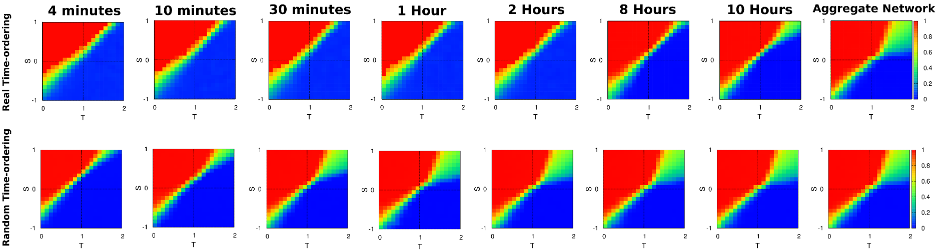
$$\langle C(T,S)_{\Delta t}\rangle = \frac{1}{Q}\sum_{i=1}^{Q}\frac{N_c^i}{N} \,,$$



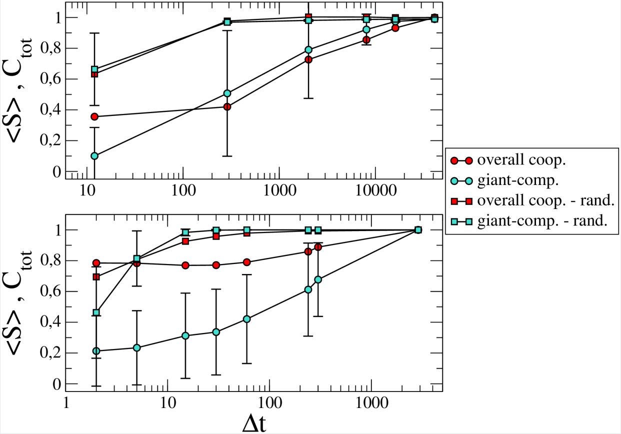
# Cooperation diagram I



# Cooperation diagram II



# Overall level of cooperation $C_{tot}(\Delta t)$




$$C_{tot}(\Delta t) = \frac{1}{C_{tot}(M_{\mathcal{T}})} \int_0^2 \mathrm{d}T \int_{-1}^1 C(T, S)\mathrm{d}S$$

# Summing up . . .

## Take home messages

- The level of cooperation achievable on time-varying graphs crucially depends on the temporal resolution, i.e. on the length of the aggregation interval used to construct each graph.

# Summing up ...

## Take home messages

- The level of cooperation achievable on time-varying graphs crucially depends on the temporal resolution, i.e. on the length of the aggregation interval used to construct each graph.
- The temporal ordering of interactions hinders cooperation, so that temporally reshuffled versions of the same time-varying graph usually exhibit a considerably higher level of cooperation.

# Summing up . . .

## Take home messages

- The level of cooperation achievable on time-varying graphs crucially depends on the temporal resolution, i.e. on the length of the aggregation interval used to construct each graph.
- The temporal ordering of interactions hinders cooperation, so that temporally reshuffled versions of the same time-varying graph usually exhibit a considerably higher level of cooperation.
- The average size of the giant component across different consecutive time-windows is indeed a good predictor of the level of cooperation attainable on time-varying graphs.

# Summing up . . .

## Take home messages

- The level of cooperation achievable on time-varying graphs crucially depends on the temporal resolution, i.e. on the length of the aggregation interval used to construct each graph.
- The temporal ordering of interactions hinders cooperation, so that temporally reshuffled versions of the same time-varying graph usually exhibit a considerably higher level of cooperation.
- The average size of the giant component across different consecutive time-windows is indeed a good predictor of the level of cooperation attainable on time-varying graphs.

## What's next? (Work in progress . . .)

- Trying to find bigger datasets.

# Summing up . . .

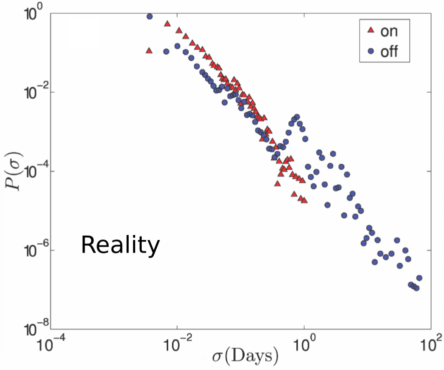
## Take home messages

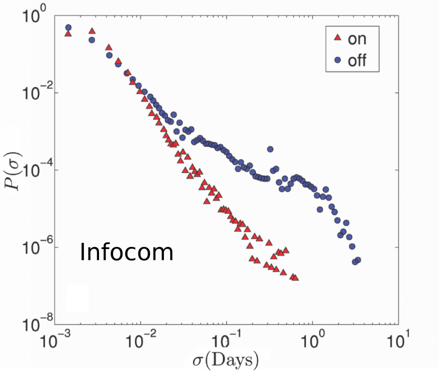
- The level of cooperation achievable on time-varying graphs crucially depends on the temporal resolution, i.e. on the length of the aggregation interval used to construct each graph.
- The temporal ordering of interactions hinders cooperation, so that temporally reshuffled versions of the same time-varying graph usually exhibit a considerably higher level of cooperation.
- The average size of the giant component across different consecutive time-windows is indeed a good predictor of the level of cooperation attainable on time-varying graphs.

## What's next? (Work in progress . . .)

- Trying to find bigger datasets.
- Use different randomization methodologies?

# Time series




- $\sigma_{on} \longrightarrow$ Contact duration.
- $\sigma_{off} \longrightarrow$ Inter-contact time.