Temporal networks of human interaction

Petter Holme
Temporal networks
network
How can we measure them?

RFID tags
Smartphone Bluetooth
Hospital records
Public transportation
Sensor nodes
Wi-fi routers
Cell phone towers
.
Co-tagged in images
Sexual contacts
Internet dating
Temporal (proximity) networks

sociopatterns.org
# Temporal networks

## Contact sequences

<table>
<thead>
<tr>
<th>i</th>
<th>j</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>4</td>
<td>10</td>
</tr>
<tr>
<td>6</td>
<td>8</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>8</td>
<td>15</td>
</tr>
<tr>
<td>10</td>
<td>11</td>
<td>20</td>
</tr>
<tr>
<td>7</td>
<td>2</td>
<td>22</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>25</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
<td>30</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>30</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
<td>31</td>
</tr>
<tr>
<td>10</td>
<td>2</td>
<td>34</td>
</tr>
</tbody>
</table>
Temporal networks

Timelines of nodes
Temporal networks

Annotated graphs
Temporal network epidemiology
Step 1: Compartmental models
Temporal nwk. epidemiology

Step 1: Compartmental models

Susceptible meets Infectious
Temporal network epidemiology

Step 1: Compartmental models

With some probability or rate

Susceptible meets Infectious

Susceptible
meets
Infectious

Infectious

Infectious
Step 1: Compartmental models

Susceptible meets Infectious

With some probability or rate

Infectious

With some rate or after some time

Susceptible or Recovered
Temporal network epidemiology

Step 2: Contact patterns
Time matters
Time matters

A
B
C
D
E

11,20
14,8
3,8,10,17
11,15
16
Time matters


Escort/sex-buyer contacts:
16,730 individuals
50,632 contacts
2,232 days
Time matters

Time matters

Time matters

Simulated epidemics in an empirical spatiotemporal network of 50,185 sexual contacts

Luis Enrique Correa Rocha, Fredrik Liljeros, Petter Holme

Submitted on 14 Jun 2010

Small But Slow World: How Network Topology and Burstiness Slow Down Spreading


Submitted on 10 Jun 2010 (v1), last revised 22 Aug 2010 (this version, v3)
Time matters

Rocha, Liljeros, Holme

Fraction of infectious

Time (days)
Time matters

Rocha, Liljeros, Holme

Karsai, & al.
Time matters

Time matters


![Graphs showing the relationship between temporal network, static network, and fully mixed models](image)
Temporal networks

Petter Holme, Jari Saramäki

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   2.3. Physical proximity .................................. 101
   2.4. Cell biology ........................................ 101

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Abstract
A great variety of systems in nature, society and technology – from the web of sexual contacts to the Internet, from the nervous system to power grids – can be modeled as graphs of vertices coupled by edges. The network structure, describing how the graph is wired, helps us understand, predict and optimize the behavior of dynamical systems. In many cases, however, the edges are not continuously active. As an example, in networks of communication via e-mail, text messages, or phone calls, edges represent sequences of instantaneous or practically instantaneous contacts. In some cases, edges are active for non-negligible periods of time: e.g., the proximity patterns of inpatients at hospitals can be represented by a graph where an edge between two individuals is on throughout the time they are at the same ward. Like network topology, the temporal structure of edge activations can affect dynamics of systems interacting through the network, from disease contagion on the network of patients to information diffusion over an e-mail network. In this review, we present the emergent field of temporal networks, and discuss methods for analyzing topological and temporal structure and models for elucidating their relation to the behavior of dynamical systems. In the light of traditional network theory, one can see this framework as moving the information of when things happen from the dynamical system on the network, to the network itself. Since fundamental properties, such as the transitivity of edges, do not necessarily hold in temporal networks, many of these methods need to be quite different from those for static networks. The study of temporal networks is very interdisciplinary in nature. Reflecting this, even the object of study has many names—temporal graphs, evolving graphs, time-varying graphs, time-aggregated graphs, time-stamped graphs, dynamic networks, dynamic graphs, dynamical graphs, and so on. This review covers different fields where temporal graphs are considered, but does not attempt to unify related terminology—rather, we want to make papers readable across disciplines.

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Modern temporal network theory: a colloquium*

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Abstract. The power of any kind of network approach lies in the ability to simplify a complex system so that one can better understand its function as a whole. Sometimes it is beneficial, however, to include more information than in a simple graph of only nodes and links. Adding information about times of interactions can make predictions and mechanistic understanding more accurate. The drawback, however, is that there are not so many methods available, partly because temporal networks are a relatively young field, partly because it is more difficult to develop such methods compared to for static networks. In this colloquium, we review the methods to analyze and model temporal networks and processes taking place on them, focusing mainly on the last three years. This includes the spreading of infectious disease, opinions, rumors, in social networks; information packets in computer networks; various types of signaling in biology, and more. We also discuss future directions.

1 Introduction

To understand how large connected systems work, one needs to zoom out and view them from a distance. In other words, one needs a principled, consistent way of discarding irrelevant information. A common way of doing this is to represent the system as a network, where nodes are connected if they interact. For many systems one has more information that just about who interacts. Including that information into a temporal network, of course, goes against the idea of simplifying the system. Sometimes, however, it could be worth the effort in terms of increased accuracy of predictions, increased mechanistic understanding, etc. The drawback is that many of the methods and models developed for static networks could be unapplicable or could need significant generalizations.

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Randomization
Randomization

Fraction of infectious

Time (days)

0 100 200 300
Randomization

Contact sequences of links shuffled among links w. similar weight
Randomization

Temporal structures
History

Network

1. A power-law distribution is discovered.
2. It makes a difference for spreading dynamics.
3. It helps us to understand real epidemics.

Time

1. A power-law distribution is discovered.
2. It makes a difference for spreading dynamics.
3. It helps us to understand real epidemics.
**Interevent times**

Fat-tailed interevent time distributions

\[ \text{Poisson} \]

\[ \text{Power-law} \]

\[ \text{Time} \]

Incidence / \(N\)

But both the cell phone and the prostitution data are bursty. So why are they different w.r.t. spreading?

precursors:


Ongoing link picture
Link turnover picture
Reference models

Interevent times neutralized
Reference models

**Inter-event times neutralized**

**Beginning interval neutralized**
Reference models

- **Interevent times neutralized**

- **Beginning interval neutralized**

- **End interval neutralized**
SIR on prostitution data

- Duration of infection
- Per-contact transmission probability

Legend:
- 0.001
- 0.01
- 0.1
- 1
- 3
- 30
SIR on prostitution data
Interevent times neutralized
SIR on prostitution data
Beginning times neutralized
SIR on prostitution data
End times neutralized
SIR, average deviations

- E-mail 1
- E-mail 2
- Dating 1
- Conference
- Hospital
- Dating 2
- Film
- Facebook
- Forum
- Gallery
- Prostitution

beginning times
interevent times
end times

interevent times
SIR, average deviations

More temporal structures

...a no-brain (low-brain?) approach

P. Holme, 2016.
Temporal network structures controlling disease spreading.
Outbreak duration

- Prostitution
- Conference
- Hospital
- Reality
- School 1
- School 2
- Gallery 1
- Gallery 2

\[ \tau / T^{0.75} \]
vs static nwks

Prostitution

Conference

Hospital

Reality

School 1

School 2

Gallery 1

Gallery 2

-3 -2 -1 0 lg λ

-3 -2 -1 0 lg δ

-0.5 0 1 lg σ 0.5 1
vs fully-connected nwks
Ridiculograms (network)
Ridiculograms (network)
Ridiculograms (time)

Prostitution

Conference

Hospital

Reality

School 1

School 2

Gallery 1

Gallery 2
# Network structures

## Link activity
- link duration, mean
- link duration, s.d.
- link duration, coefficient of variation
- link duration, skew
- link interevent time, mean
- link interevent time, s.d.
- link interevent time, coefficient of variation
- link interevent time, skew

## Time evolution
- avg. fraction of nodes present when 50% of contact happened
- avg. fraction of links present when 50% of contact happened
- avg. fraction of nodes present at 50% of the sampling time
- avg. fraction of links present at 50% of the sampling time
- frac. of nodes present 1st and last 10% of the contacts
- frac. of links present 1st and last 10% of the contacts
- frac. of nodes present 1st and last 10% of the sampling time
- frac. of links present 1st and last 10% of the sampling time

## Node activity
- node duration, mean
- node duration, s.d.
- node duration, coefficient of variation
- node duration, skew
- node interevent time, mean
- node interevent time, s.d.
- node interevent time, coefficient of variation
- node interevent time, skew

## Degree distribution
- degree distribution, mean
- degree distribution, s.d.
- degree distribution, coefficient of variation
- degree distribution, skew

## Other network structure
- number of nodes
- clustering coefficient
- assortativity
Network structures

- Average life time of nodes:
  - \( x = 0.487 \)
  - \( x = 0.418 \)
  - \( x = 0.392 \)

- Fraction of nodes present after half of the contacts:
  - \( x = 0.392 \)

- Average life time of links:
  - \( x = 0.487 \)
  - \( x = 0.418 \)
  - \( x = 0.392 \)

- Nodes and their categories:
  - Prostitution
  - Conference
  - Hospital
  - Reality
  - School 1
  - School 2
  - Gallery 1
  - Gallery 2
Vaccination
Assume we can vaccinate a fraction $f$, then how can we choose the people to vaccinate? Using only local info?
Assume we can vaccinate a fraction \( f \), then how can we choose the people to vaccinate? Using only local info?
Chose a person at random.

Neighborhood vaccination
Ask her to name a friend.

Neighborhood vaccination
Vaccinate the friend.

Neighborhood vaccination
Vaccination

experience

vaccination
infection

disease simulation

Vaccination

Vaccination

The recent version

Vaccination

The weight version

Vaccination

A. Prostitution
- Weight
- Recent

B. Internet dating

C. Hospital

D. E-mail
Other temporal networks results & future outlook
Other results

**Spreading by threshold dynamics**

**Random walks**

**Review papers**
Future

Visualization.

Important temporal-network measures.*

Mesoscopic structures.*

Finite-size scaling (how to scale up results to populations).

Generative models.

New kinds of data.

*beyond generalizations from static networks
Thank you!

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