





COMPLEX SYSTEMS, NETWORKS AND SPACE

Cazabet Rémy

gopro2017 : Spatial Optimized Designs: from Cities to Natural systems

WHO AM I

- Maître de conférences (since September) in Computer Science (LIRIS, Lyon 1)
- Traditional topics:
 - "Network Science"
 - Network Analysis, Network Mining, "Community Detection", Dynamic Networks, etc.
 - "Data Science"
 - Learning knowledge from data
 - "Complex Systems"
 - Systems composed of multiple parts in interaction, non-linear behaviour, cannot be studied by reductionism:
 - Interactions between entities => Network

CITIES ? NATURAL SYSTEMS ?

- Cities and natural systems are complex systems
- 2015-2016: Working on Vél'innov ANR Project: understanding, characterising activity in Bike Sharing Systems (BSS)
- Currently: starting a collaboration with Claire Lesieur on the organisation of proteins

ORGANISATION OF COMPLEX SYSTEMS

- Usually, there is not **one** network of a complex system:
 - In cities:
 - Network of proximity between buildings
 - Network of trips using public transportations
 - Network of trips using bicycle
 - Network of roads
 - Network of socio-demographic similarities
 - Network of phone calls between neighbourhoods

- ...

- Each dataset can be modelled by countless networks, using thresholds, temporal aggregations, etc.
- I'm not working on a network in particular, just networks as models of interactions inside complex systems (Complex networks ?)

ORGANISATION OF COMPLEX SYSTEMS

- Complex Networks are not random. They have a particular **organisation**.
- My ultimate goal is to understand this organisation.
 - Find underlying rules explaining difference between observed and random networks
 - Spatial organisation is one potential candidate to explain the structure of networks

NETWORK & SPACE

- What is a spatial network model:
 - Nodes are characterised by a position, i.e an x-dimensional vector
 - The probability of observing an edge depends on the distance between nodes

NETWORK & SPACE

- Networks and spatial organisation have a complex history
 - First network models were often spatial-like:
 - Regular grids (nodes on a grid, edges at fix distance)
 - Watts-strogatz (nodes on a circle, most edges depends on distance)
 - Later models often have no spatial structure
 - Community-based
 - Dynamic models (preferential attachment, forest fire, ...)
 - Most network representations are based on 2D projections
 - The come back of spatial organisation: network embedding.
 - Given a network, which position of nodes better explain its organisation ?

AN EXAMPLE: VÉLO'V

VÉLO'V



Bicycle Sharing System (BSS) in Lyon

Dataset: trips (5y) + sociodemographic around stations



Nodes: station (2D position) Edges: number of trips over a period

- Random network
- #trips between any pair of station is the same

$$p_{ij}^{RR} = \frac{1}{m}$$

Model complexity:

Model precision: +

Evaluation of the model : diff between observed network and model

- Configuration model
- #trips between any pair of station depends on their "popularity"

$$p_{ij}^{Conf} = k_i k_j W$$

- Simple Gravity
- #trips between any pair of station depends on their
 "popularity" and their distance

Model complexity: n+2n

Model precision: ++++

$$p_{ij}^{Grav2} = W \frac{k_i k_j}{d_{ij}^2}$$

- Gravity with custom
 deterrence function
- #trips between any pair of station depends on their
 "popularity" and their distance.
- Distance influence learnt from data

 $p_{ii}^{Grav2} = Wk_i k_j f(d_{ij})$

Model complexity: n+2n+a

Model precision: ++++

DETERRENCE FUNCTION

Computation of a deterrence function: Impact of distance on edge probability

(Comparing observation with Configuration Model)



DETERRENCE FUNCTION



Distance d (meters)

DETERRENCE FUNCTION



Distance d (meters)

- Gravity with custom
 deterrence function
- #trips between any pair of station depends on their
 "popularity" and their distance.
- Distance influence learnt from data

 $p_{ii}^{Grav2} = Wk_i k_j f(d_{ij})$

Model complexity: n+2n+a

Model precision: ++++

- Gravity with custom deterrence function and conservation of degrees
- Same as before, but constraint to conserve node degrees

 $P_{ij}^{DCgrav} = n^{Oeis} n^{Ieis} f(d_{ij})$ $n^{Ieis} = \frac{deg^{out}(i)}{\sum_{i} n^{Oeis} f(d_{ij})}, n^{Oeis} = \frac{deg^{in}(i)}{\sum_{i} n^{Ieis} f(d_{ij})}$

Model complexity: n+2n+a

Model precision: +++++

MODEL EVALUATION



USEFUL MODEL ?



Geographic Potential Pi





IMPROVING THE MODEL ?

• Difference between observed network and model. Random errors ?

IMPROVING THE MODEL ?

Difference between observed network and model. Random errors ?



Yellow: well predicted

Red: overestimated

Black: Underestimated



MODEL OF IST MODEL ERRORS ?

- Incorrectly predicted trips constitute a new network
 - Cannot be modelled by geographical gravity model (flat deterrence func)
 - Socio-demographic gravity model ?
 - Community structure ?

NON-GEOGRAPHICAL GRAVITY MODELS

• Deterrence function can be computed on any distance function (here, on top of spatial effect)

- Community discovery (or graph clustering, SBM...)
 - Searching for groups of nodes with similar connections behaviours
 - Often dense groups less connected to the rest of the network, but not always

Community graph model:

Simple

 $p_{ij}^{SBM} = W p^{C}(c_i, c_j)$

Degree-Corrected

 $p_{ij}^{DC-SBM} = Wk_i k_j p^C(c_i, c_j)$

Community Structure Of trips Unexplained By Spatial Model

+ Junnel des States Andrew Page 12 Grann

Bron

Fort dell

Lyon Se prondissement

Same-roy-les-

Lyon

dell

Community Structure Of trips Unexplained By Spatial Model

(d) $f(x) = 1/x^2$, N/P Only (f) $f(x) = 1/x^{0.5}$, N/P Only

0,9

TAKE-HOME MESSAGE

- Complex systems organisation can often be modelled by networks
- Different network models exist
- Complex networks can probably be explained by a combination of factors, i.e. a combination of models

FUTURE WORK (HOPEFULLY)

Model complexity

FUTURE WORK (HOPEFULLY)

Model complexity

THANKYOU FORYOUR ATTENTION

PROPOSED NULL MODEL

Problem: Does not conserve degrees !

- Central nodes have higher degrees
- Those at the periphery have lower ones.

