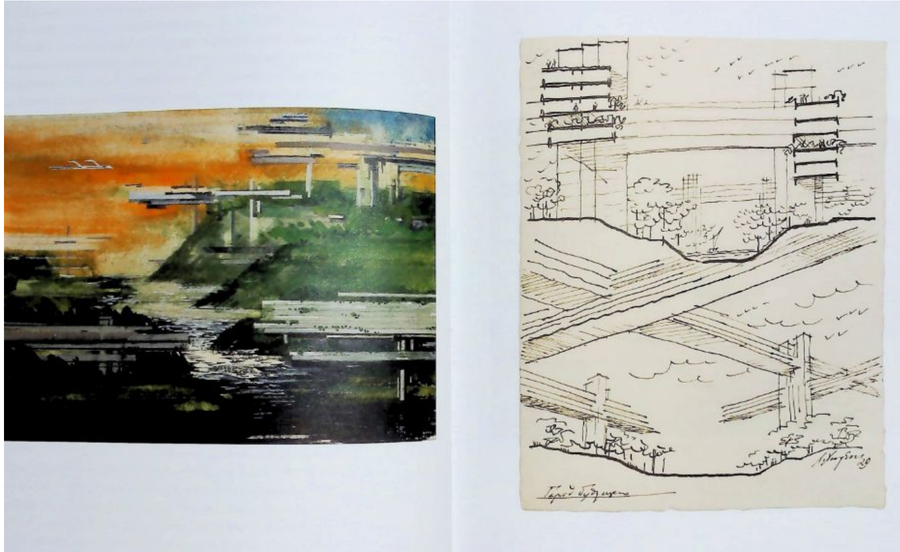


Networks in urbanism and architecture: lecture 2

L.Bauer lecture
LPI, Paris, France
SEA Mumbai, India

Course overview

1. Introduction to networks, urbanism and architecture
   Quantitative and qualitative measures for networks
2. Analysis of city systems
3. Projects discussions

Structure of each lecture **theory** **practice**

Course topics

1. Networks theory and data science
   How to quantitatively characterise networks?
2. Examples: smart and non smart cities data
3. City indices: how to quantify cities?

theory

4. Discussions about projects
   Colab for loading street networks of Mumbai

practice

Part 1
Networks and data science

What we will look at in network science?

1. **Network definition and measures**
2. Networks in time and space
3. Networks from data

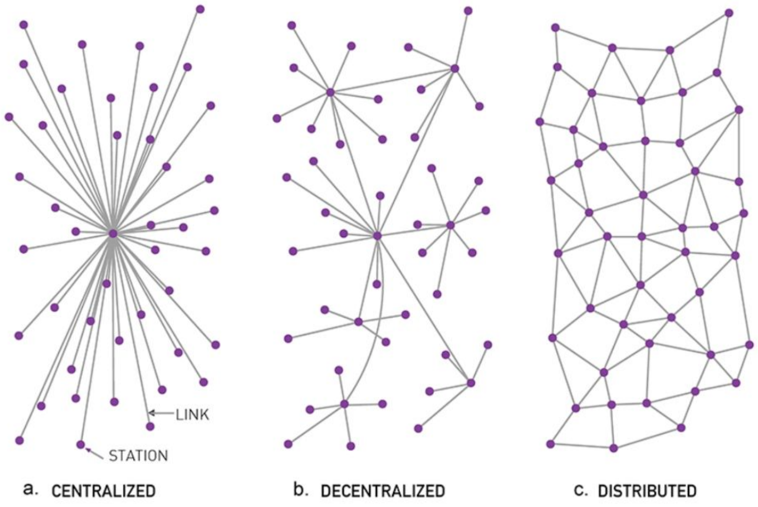
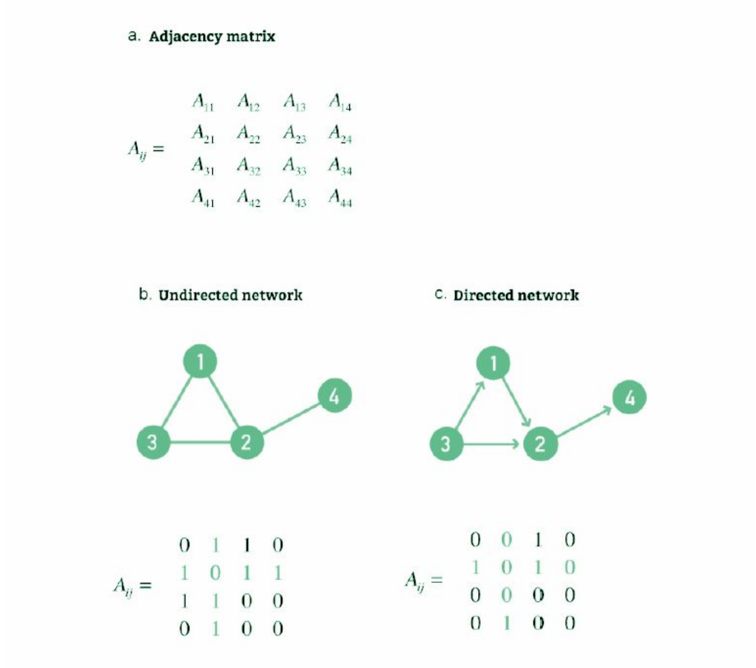
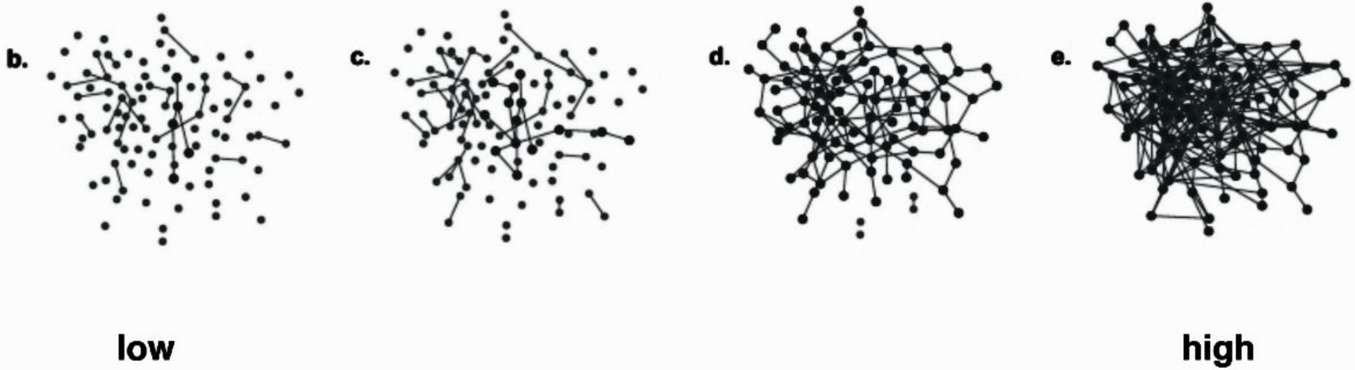


Fig. credits P. Barran.

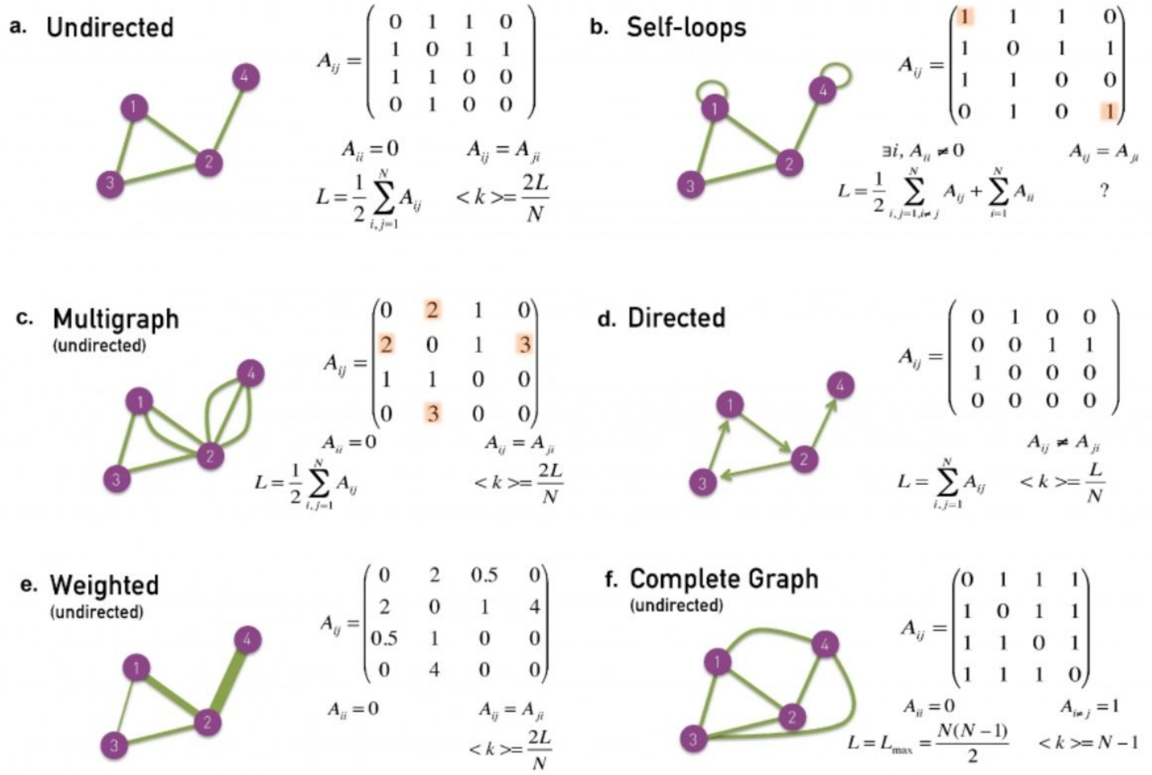
1. Network definitions
How to define a network? From real system to data

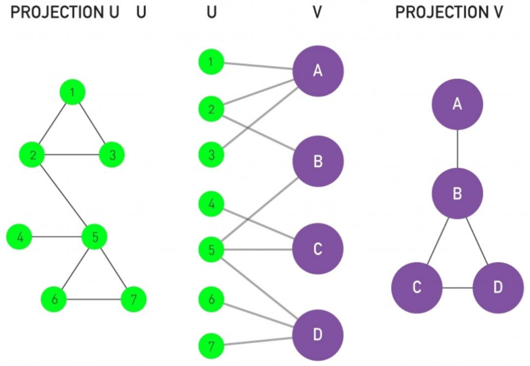


1. Network measures and definitions: density

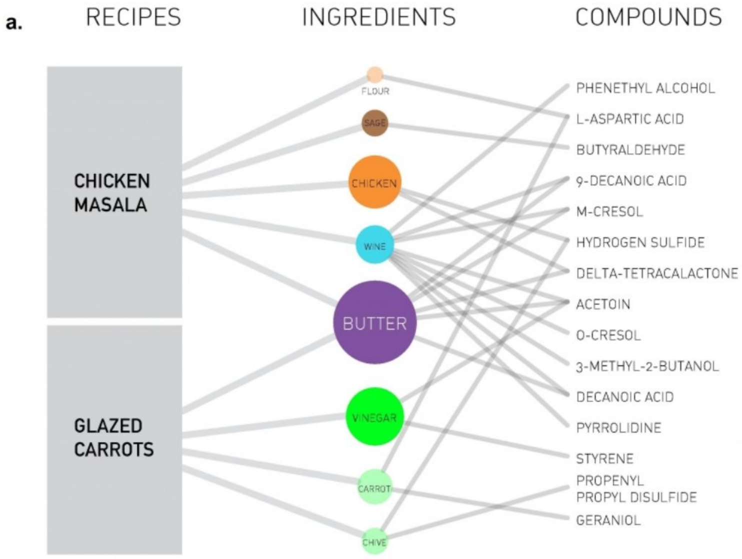


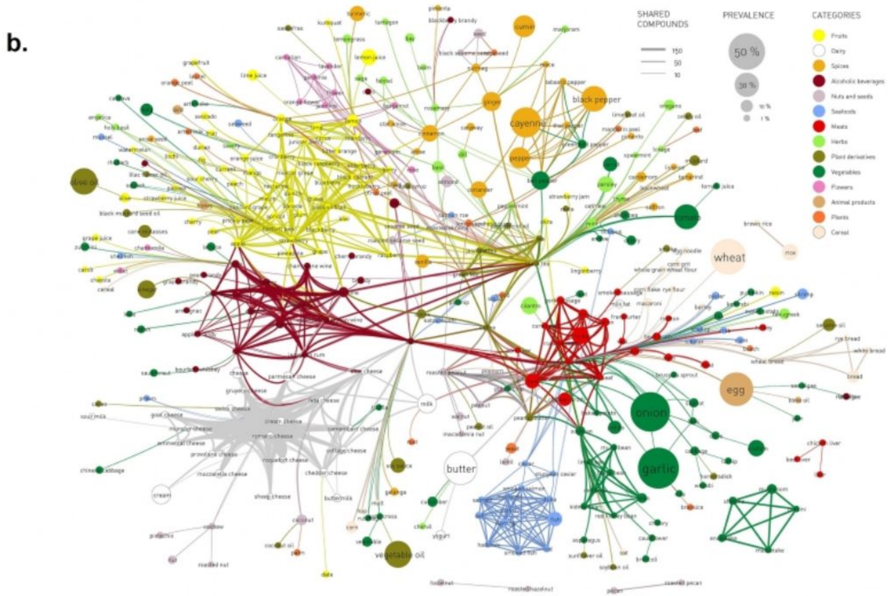
1. Network types





Network types: bipartite networks

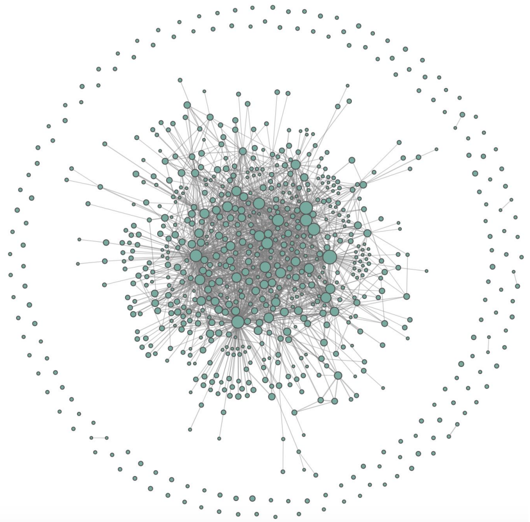




1. Network measures:

Local measures for each node

Global measures for the whole network



Network measures:
Check calculation
on networkx python library

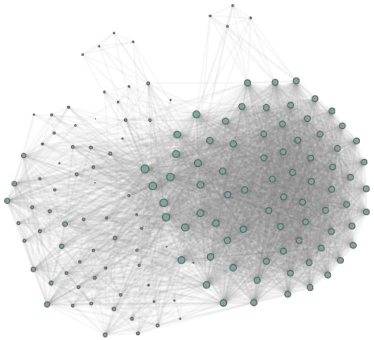
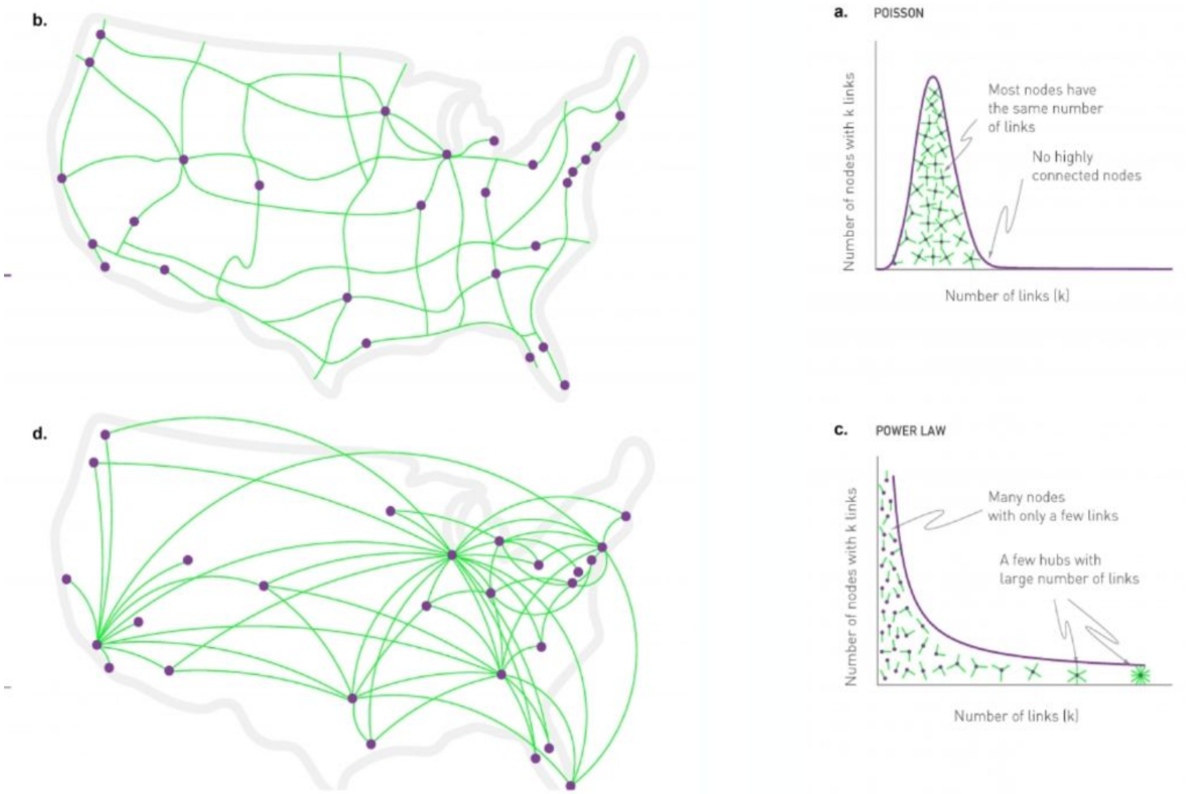


Table 2: Definitions of network science terms and variables.

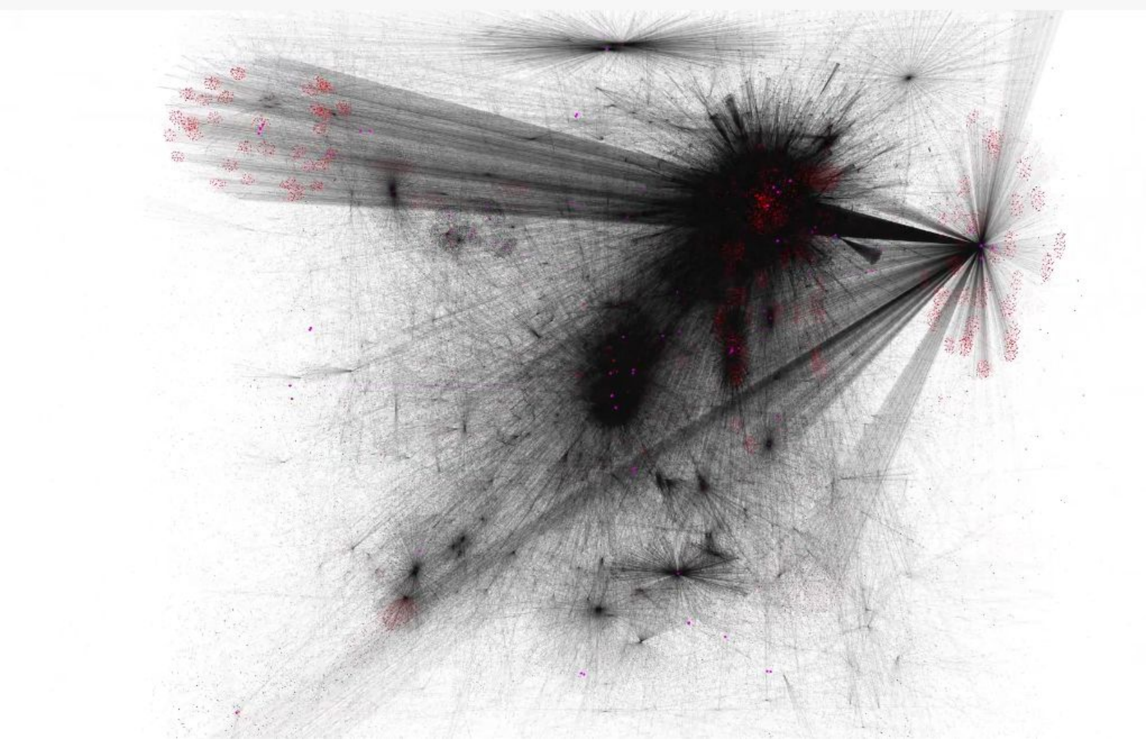
Term/variable	Definition
N	number of nodes, N, in graph
E	number of edges, E, in graph
network density	ratio of the number of edges to the maximum number of possible edges $\frac{2E}{N(N-1)}$
distance, $d(n_i, n_j)$	shortest path between node i and node j $d(n_i, n_j)$ where $n_i, n_j \in N$
average shortest path length, L	average length of shortest path between pairs of nodes $L = \frac{1}{N(N-1)} \cdot \sum_{i \neq j} d(n_i, n_j)$
diameter, D	largest shortest path between nodes $D = \max_{n_i \in N, n_j \in N} d(n_i, n_j)$
closeness centrality	inverse of the sum of the length of the shortest paths between node i and all other nodes in the graph $C_i = \frac{1}{\sum_j d(n_i, n_j)}$
degree, k_i	number of edges attached to node i
average degree, $\langle k \rangle$	average number of edges per node in network $\langle k \rangle = \frac{1}{N} \sum_{n=1}^{N} k_i$
local clustering coefficient, c_i	number of edges between the neighbors of node i divided by the maximum number of edges between those neighbors $c_i = \frac{2\lvert e_{jk} \rvert}{k_i(k_i - 1)}$ where $n_j, n_k \in N_i$, $e_{jk} \in E$
average clustering coefficient, $\langle C \rangle$	average clustering coefficient of nodes in the network $\langle C \rangle = \frac{1}{N} \sum_{n=1}^{N} c_i$
modularity, Q	proportion of edges that fall within subgroups of nodes minus the expected proportion if edges were randomly distributed, range $[-1, 1]$
average efficiency, E_G	measure of how efficiently information is exchanged in the network $E_G = \frac{1}{n(n-1)} \sum_{i \neq j \in N} \frac{1}{d(n_i, n_j)}$
largest connected component	largest group of nodes in the network that are connected to each other in a single component
degree distribution, $P(k)$	probability distribution of node degrees in the network
γ	power-law exponent for the degree distribution
Small world structure	network with short average path lengths and relatively high clustering coefficient (relative to a random graph with similar density)
scale-free network	network with a degree distribution that is power-law distributed

1. Network measures:
Degree measure look more into http://networksciencebook.com/chapter/2

1. Network measures:
Degree or why do we care? How to look into degree distributions?



Visualisation resource



https://gephi.org/users/download/

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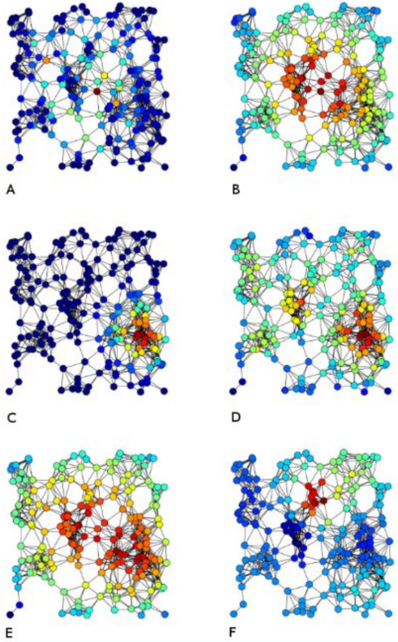
Betweenness centrality **Closeness centrality**

Eigenvector centrality **Degree centrality**

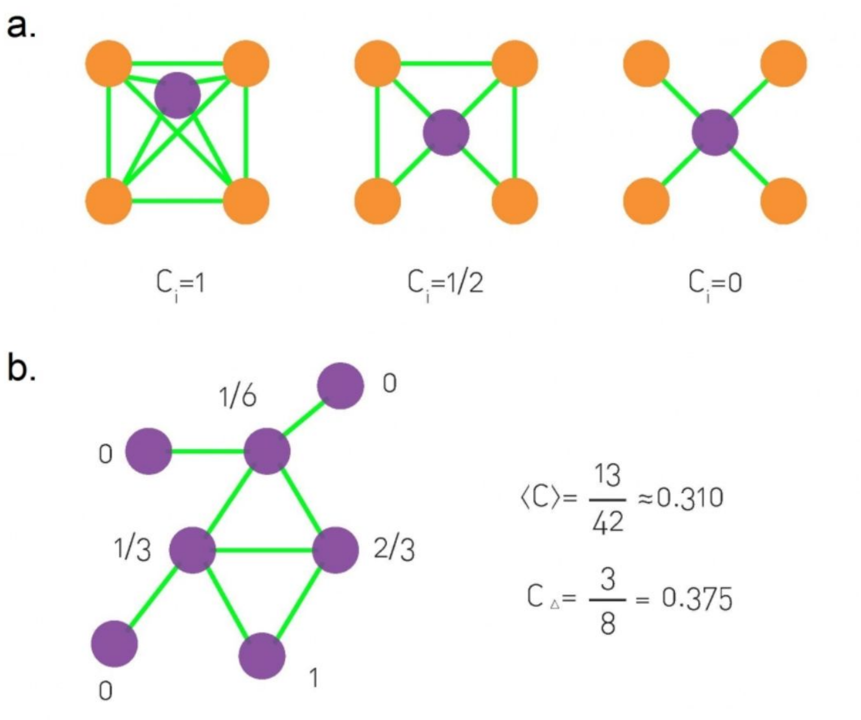
Harmonic centrality **Katz centrality**



1. Network measures

Example of clustering

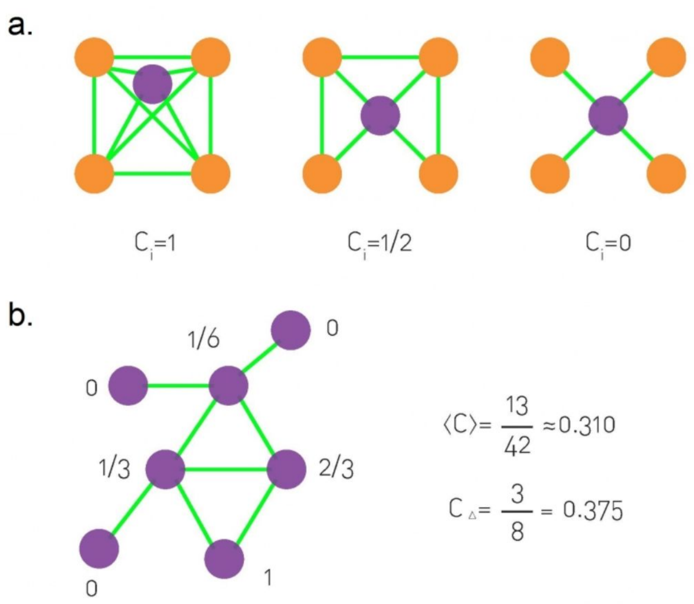
Notebooks at https://github.com/Big-data-course-CRI/materials_big_data_cri_2019



1. Network measures

Example of clustering, paths, betweenness

Notebooks at https://github.com/Big-data-course-CRI/materials_big_data_cri_2019



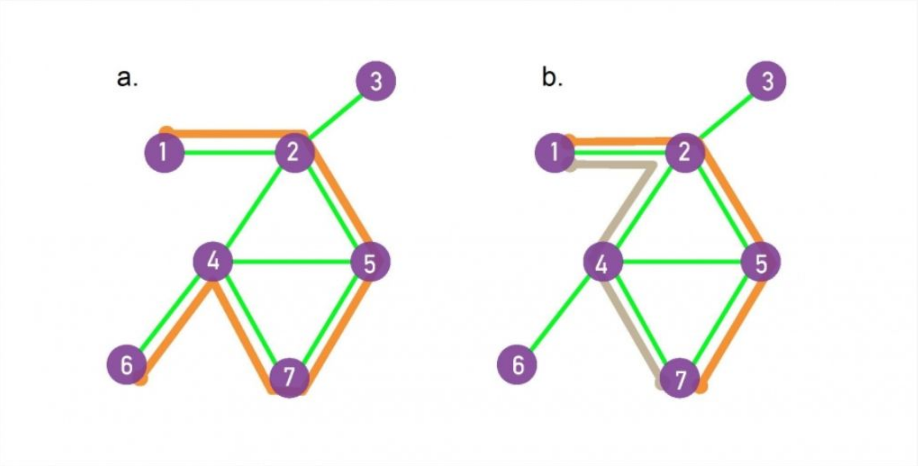


Image 2.12

Paths

- A path between nodes i_0 and i_n is an ordered list of n links P = {(i_0, i_1), (i_1, i_2), (i_2, i_3), ... ,(i_{n-1}, i_n)}. The length of this path is n. The path shown in orange in (a) follows the route 1→2→5→7→4→6, hence its length is n = 5.

What we will look at in network science?

1. Network measures
2. **Networks in time and space**
3. Networks from data

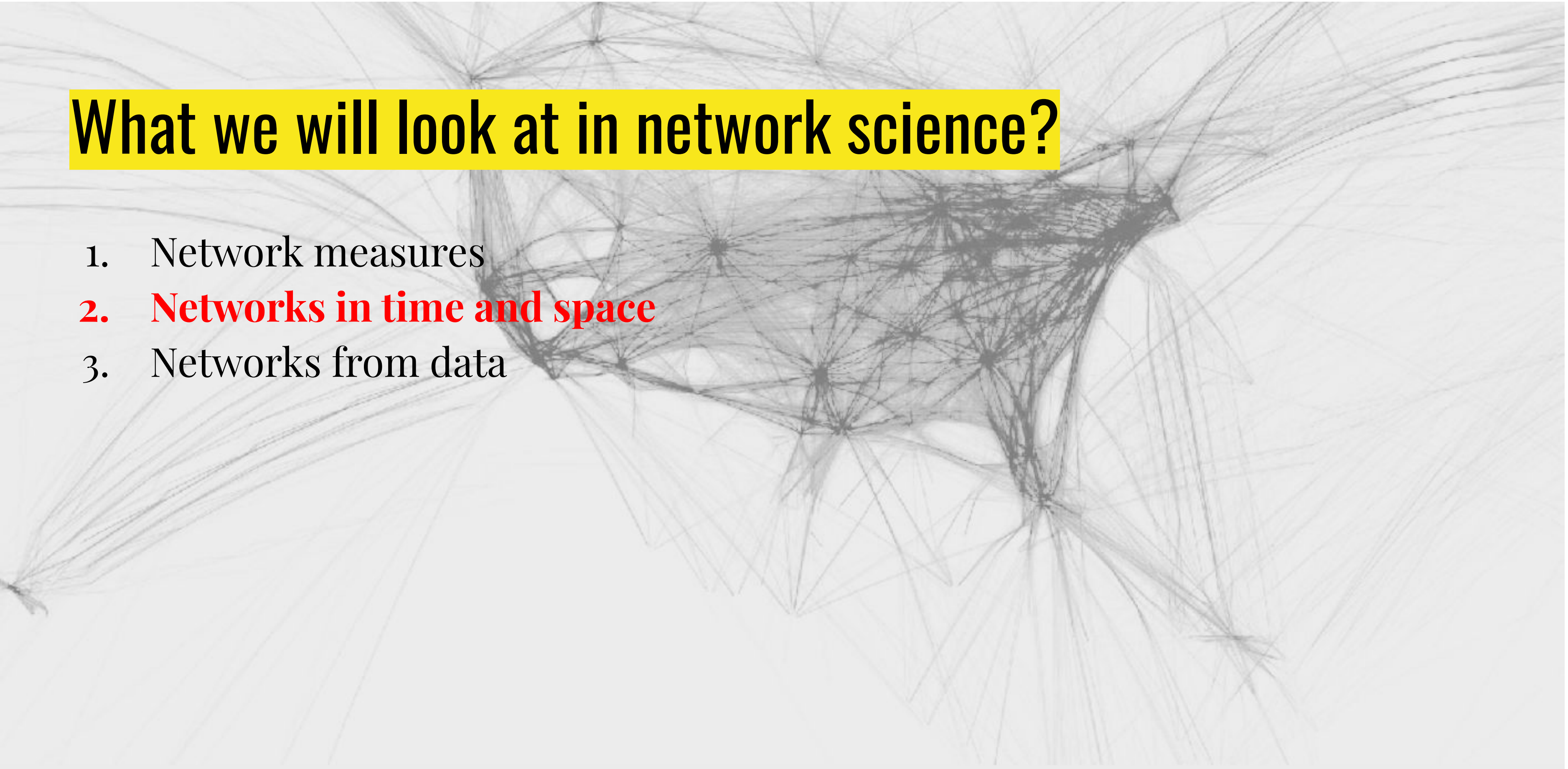
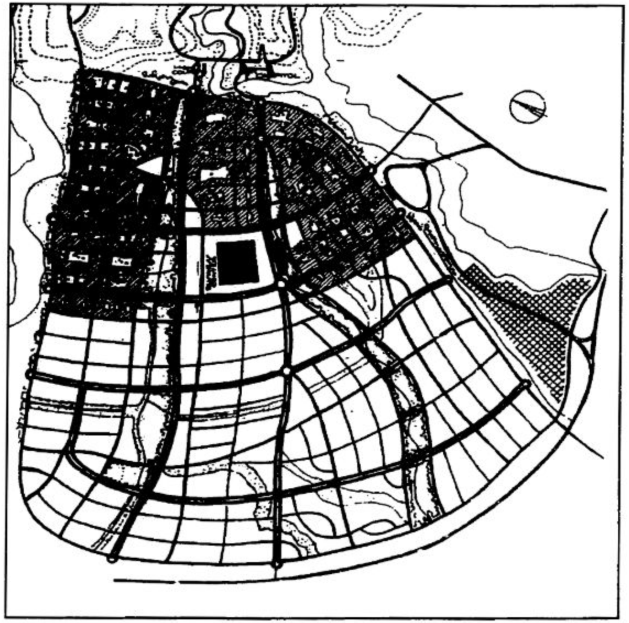


Figure 7.11

Aaron Koblin's *Flight Patterns* (2005): visualization of the flight paths of aircraft crossing North America

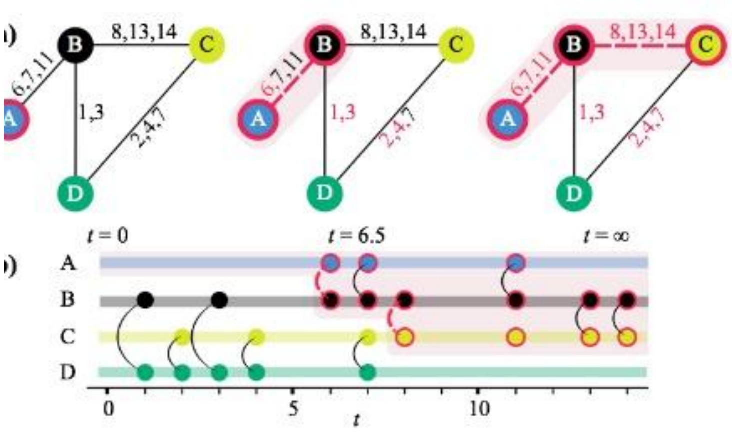
2. Networks in time and space

Master Plan for Chandigarh by Albert Mayer RAIC Journal, 1955 (Evenson Norma, Chandigarh, 1966)



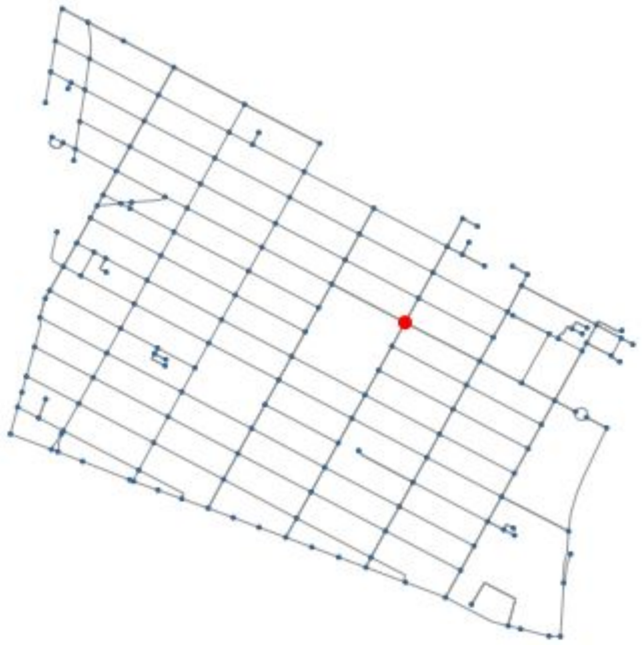
https://arxiv.org/pdf/1108.1780.pdf

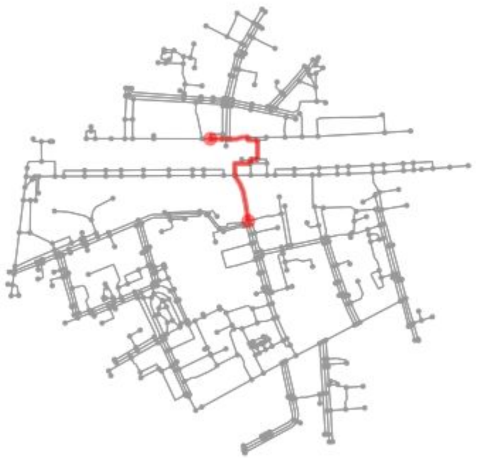
Temporality matters: reachability issue



Review Holme-Saramaki, Phys. Rep. (2012), arXiv:1108.1780

2. Networks in time and space

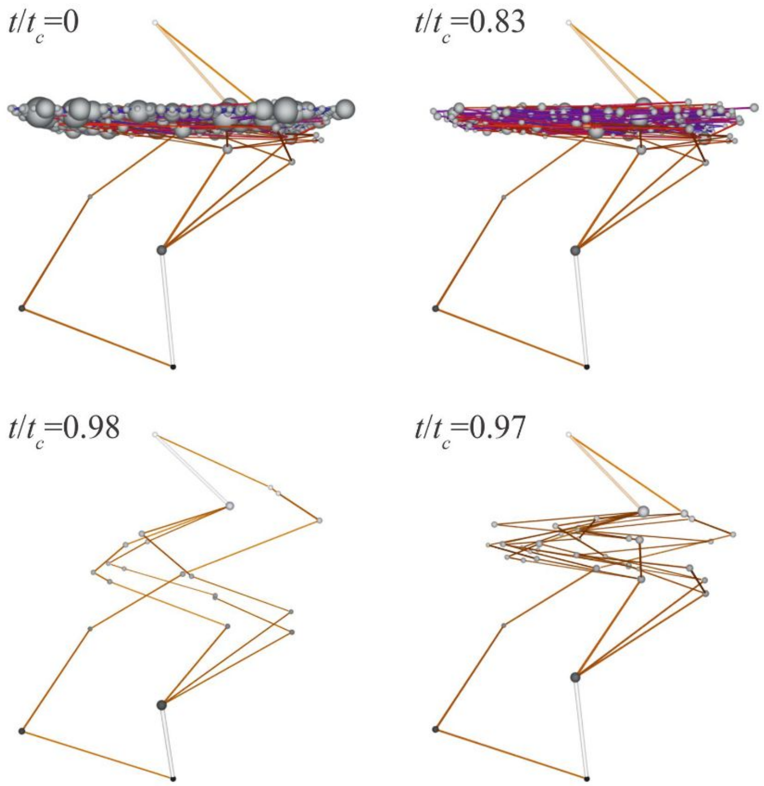




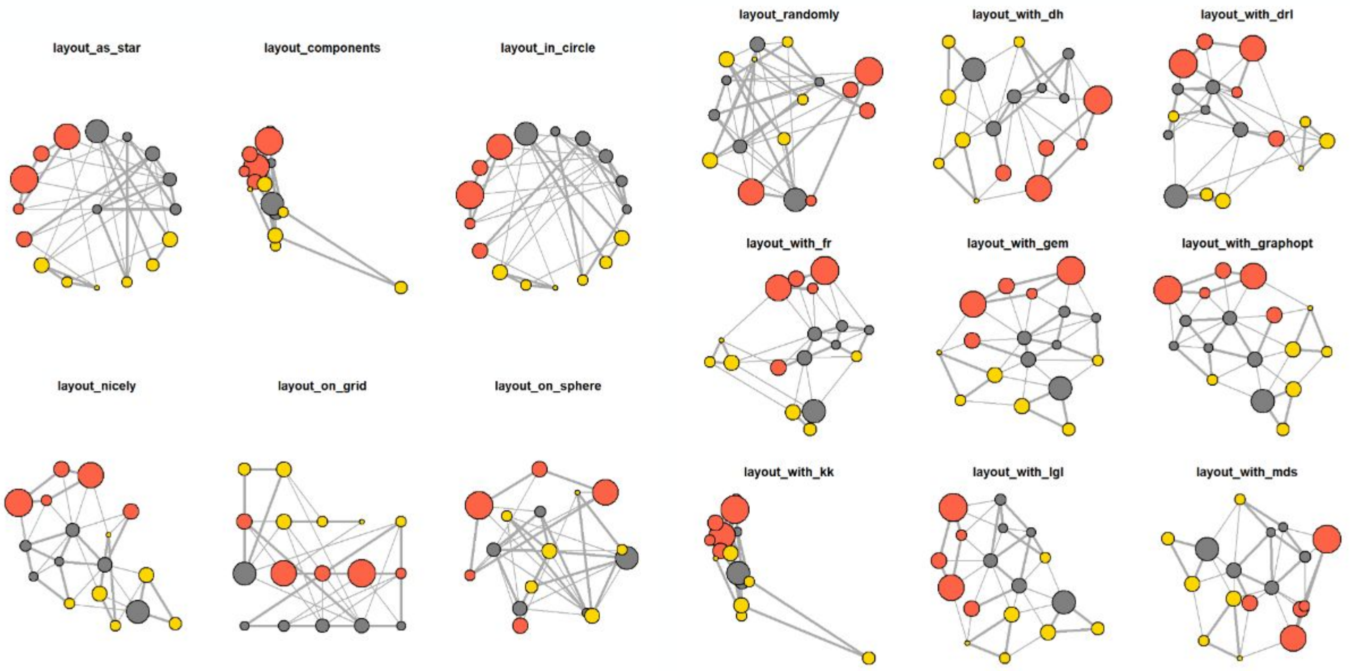
Osmnx for spatial networks analysis
https://arxiv.org/abs/1010.0302

Networks in time and space

https://www.nature.com/articles/s41598-019-44701-6

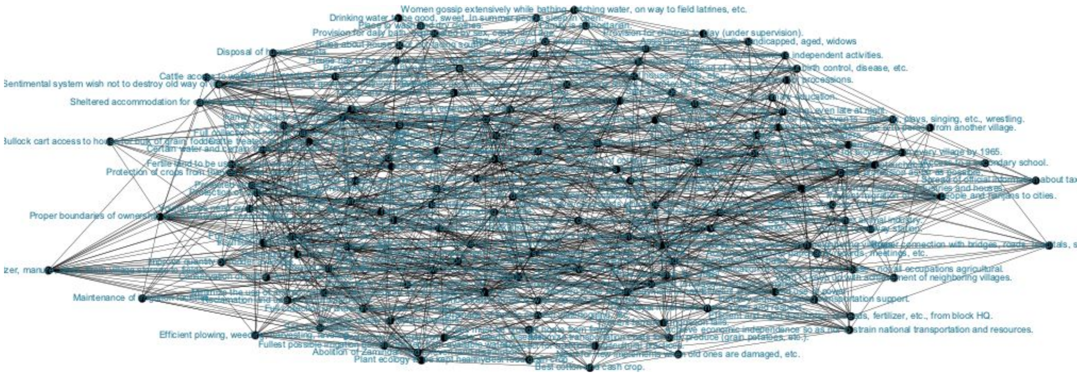


Networks layout (also for Day 3)



Networks in time and space

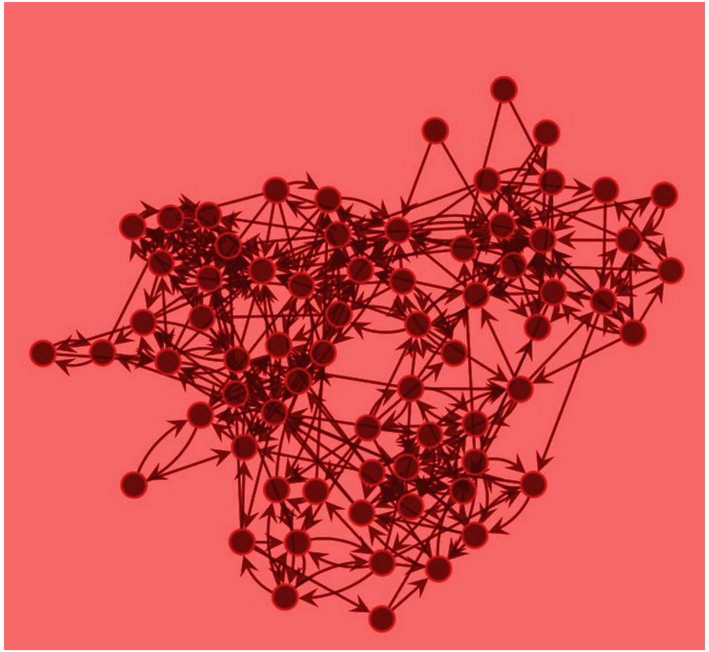
Good resource on spatial networks
M.Barthelemy “Spatial networks”



Good resource on temporal networks
P.Holme, J.Saramaki “Temporal networks”
Holme blog https://petterhol.me/

Where can I get network data?

Example:
Highschool: Illinois high school students (1958). A network of friendships among male students in a small high school in Illinois from 1958. 70 nodes, 366 edges.
https://networks.skewed.de/net/highschool



Example:
Facebook or wikipedia data
https://snap.stanford.edu/data/wiki-meta.html

What we will look at in network science?

1. Network measures
2. Networks in time and space
3. **Networks from data**

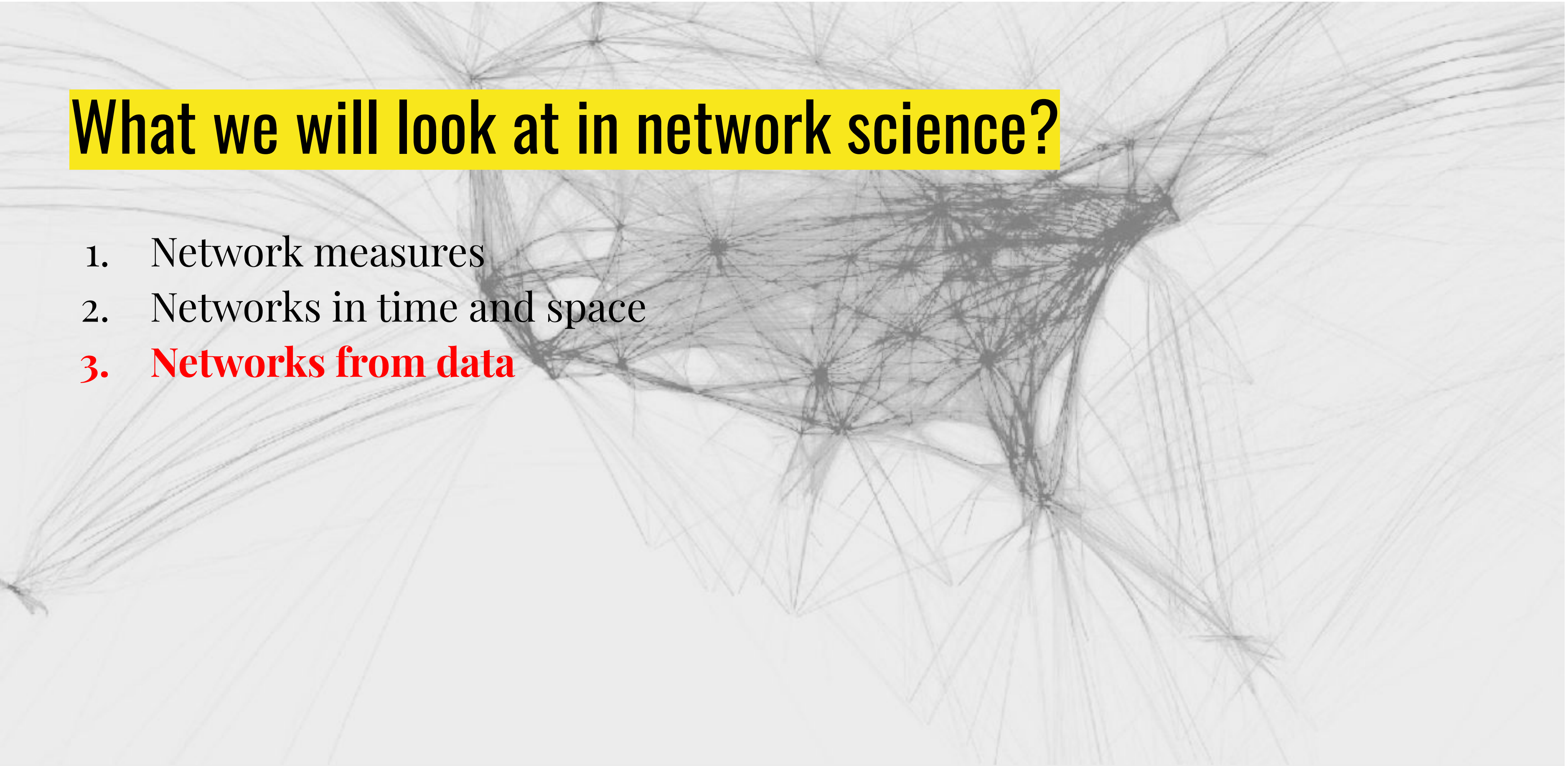


Figure 7.11

Aaron Koblin's *Flight Patterns* (2005): visualization of the flight paths of aircraft crossing North America

How to construct networks from data?

1. Directly build correspondence between links and edges with data (social networks, flights data)
2. Preprocess data (first build correlation from data)

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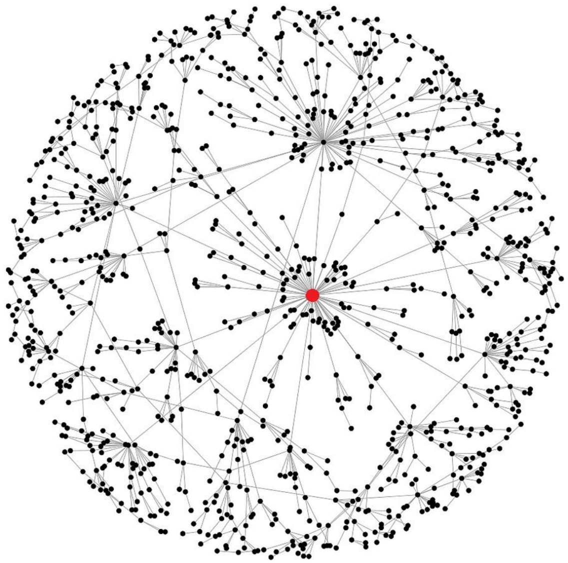

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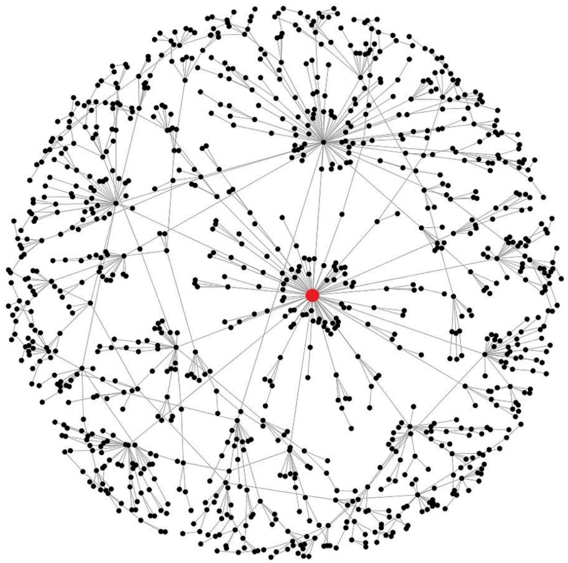


Remember that networks do not give one-to-one Correspondence of your data.
Hence do not generalize

Social networks analysis

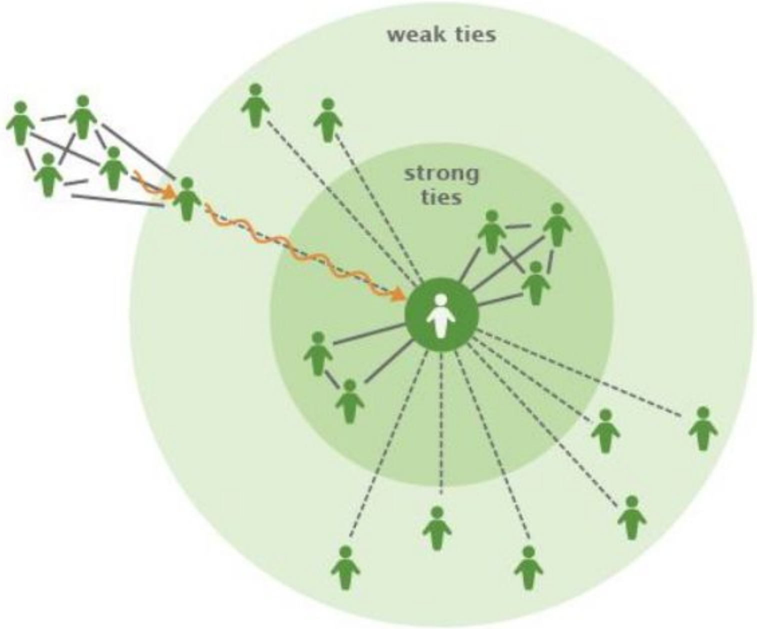
The Strength of Weak Ties[1]

Mark S. Granovetter
Johns Hopkins University

Analysis of social networks is suggested as a tool for linking micro and macro levels of sociological theory. The procedure is illustrated by elaboration of the macro implications of one aspect of small-scale interaction: the strength of dyadic ties. It is argued that the degree of overlap of two individuals' friendship networks varies directly with the strength of their tie to one another. The impact of this principle on diffusion of influence and information, mobility opportunity, and community organization is explored. Stress is laid on the cohesive power of weak ties. Most network models deal, implicitly, with strong ties, thus confining their applicability to small, well-defined groups. Emphasis on weak ties lends itself to discussion of relations *between* groups and to analysis of segments of social structure not easily defined in terms of primary groups.

A fundamental weakness of current sociological theory is that it does not relate micro-level interactions to macro-level patterns in any convincing way. Large-scale statistical, as well as qualitative, studies offer a good deal of insight into such macro phenomena as social mobility, community organization, and political structure. At the micro level, a large and increasing body of data and theory offers useful and illuminating ideas about what transpires within the confines of the small group. But how interaction in small groups aggregates to form large-scale patterns eludes us in most cases.

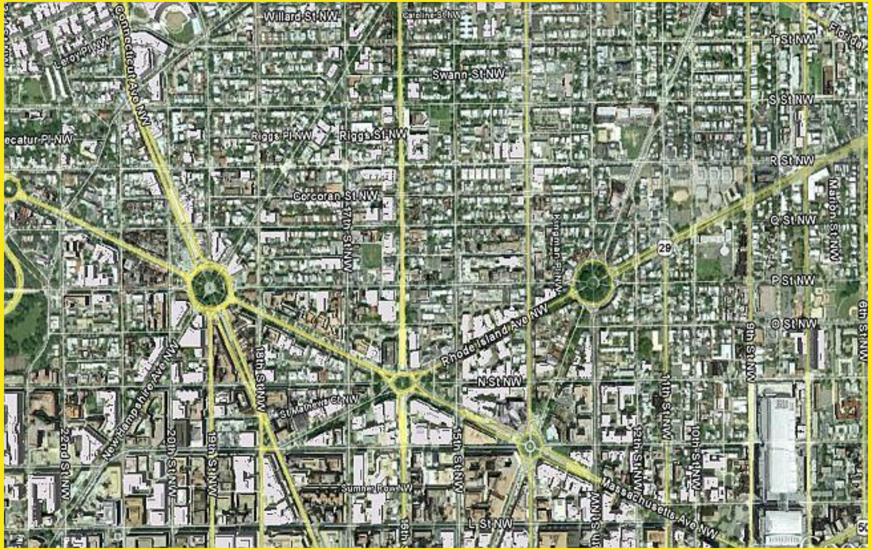
I will argue, in this paper, that the analysis of processes in interpersonal networks provides the most fruitful micro-macro bridge. In one way or another, it is through these networks that small-scale interaction becomes



Part 2

City indices

https://unhabitat.org/wcr/



What are good city indices?

(paste here examples)

Some past examples

https://strelkamag.com/en/article/russian-cities-index

Coding colab session

First rule: if you get errors and correct them, you are learning

Python typical errors:
ValueError: Nominatim could not geocode query to polygonal boundaries

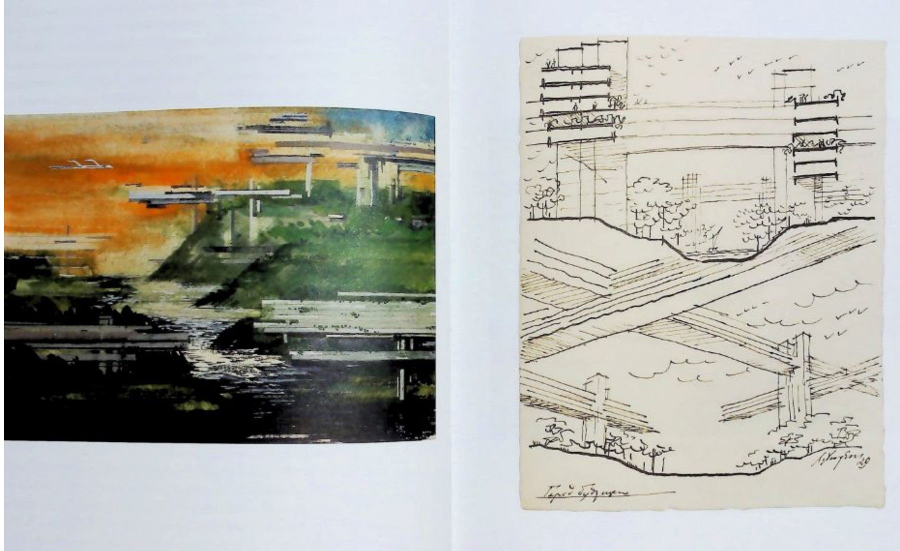
Coding colab session

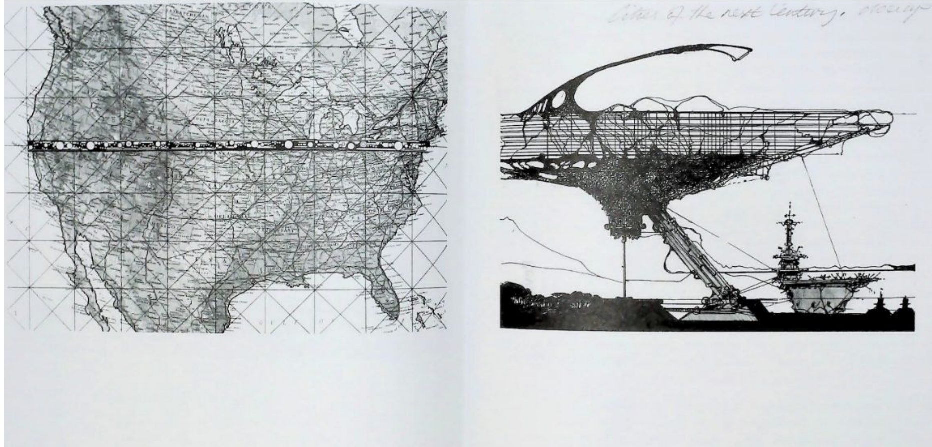
(looking into streets of Mumbai with python notebook)
https://colab.research.google.com/drive/1Ey5Py9RiqNdJHjz6430QEiYhz5vPbyO4?usp=sharing

```
[ ] # first let us convert MultiDigraph into DiGraph
    # Specify the name that is used to seach for the data
    import osmnx as ox
    import networkx as nx

    place_name = 'Mumbai, India'  # Fetch OSM street network from the location
    graphcity = ox.graph_from_place(place_name)# Get place boundary related to the place name as a geodataframe
    area = ox.geocode_to_gdf(place_name)# Plot the streets
    fig, ax = ox.plot_graph(graphcity)
    # compose graph from several graphs in the area


    #save G graph into file
    print(type(graphcity))

    nx.write_edgelist(graphcity, "edgescity.csv", delimiter=" ") # edges with attributes!!!

    edgestrastevere = graphcity.edges.data()  # default data is {} (empty dict)

    #print((edgestrastevere))
    print(type(edgestrastevere))
    #print(edgestrastevere[0])
```

Some books

“The World as an Architectural Project”





Network resources

http://networkrepository.com/networks.php
http://networksciencebook.com/chapter/3#advanced-b

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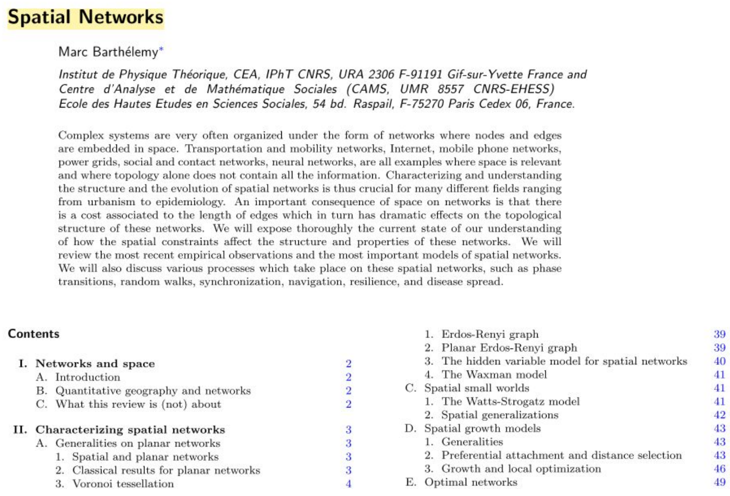

Spatial Networks

Marc Barthélemy*

Institut de Physique Théorique, CEA, IPhT CNRS, URA 2306 F-91191 Gif-sur-Yvette France and Centre d'Analyse et de Mathématique Sociales (CAMS, UMR 8557 CNRS-EHESS) Ecole des Hautes Etudes en Sciences Sociales, 54 bd. Raspail, F-75270 Paris Cedex 06, France.

Complex systems are very often organized under the form of networks where nodes and edges are embedded in space. Transportation and mobility networks, Internet, mobile phone networks, power grids, social and contact networks, neural networks, are all examples where space is relevant and where topology alone does not contain all the information. Characterizing and understanding the structure and the evolution of spatial networks is thus crucial for many different fields ranging from urbanism to epidemiology. An important consequence of space on networks is that there is a cost associated to the length of edges which in turn has dramatic effects on the topological structure of these networks. We will expose thoroughly the current state of our understanding of how the spatial constraints affect the structure and properties of these networks. We will review the most recent empirical observations and the most important models of spatial networks. We will also discuss various processes which take place on these spatial networks, such as phase transitions, random walks, synchronization, navigation, resilience, and disease spread.

Contents