From social theories to models

Tutors: Fariba Karimi and Lisette Espín-Noboa

Overview

Time: 10:30 - 12:30

10:30 - 11:00	Social theories ● Popularity ● Similarity ● Friend-of-friend ● Activity Network properties & structure
11:00 - 11:30	Network models: Undirected ● Barabasi-Albert Preferential Attachment (PA) ● PA with homophily (PAH) ● PA with triadic closure (PATC) ● PAH with triadic closure (PATCH)
11:30 - 12:00	Network models: Directed ● Directed Homophily (DH) ● Directed Preferential Attachment (DPA) ● DPA with homophily (DPAH)
12:00 - 12:30	Exercise #1

Social theories

Literature

Non-exhaustive list of material covered in this section.

1. Jackson, M. O. (2008). Social and economic networks (Vol. 3). Princeton: Princeton university press.
2. Albert-László Barabás (2016). Network Science. (available online as an interactive book)
3. Jackson, M. O. (2019). The human network: How your social position determines your power, beliefs, and behaviors. Vintage.
4. Stadfeld, C., & Amati, V. (2021). Network mechanisms and network models. In Research Handbook on Analytical Sociology (pp. 432-452). Edward Elgar Publishing.
5. Gamper, M. (2022). Social Network Theories: An Overview. Social Networks and Health Inequalities, 35.
6. Karimi, F., & Oliveira, M. (2022). On the inadequacy of nominal assortativity for assessing homophily in networks. arXiv preprint arXiv:2211.10245.

What are social networks?

Social networks consists of **actors** (nodes/agents) and **relations** (edges/links)

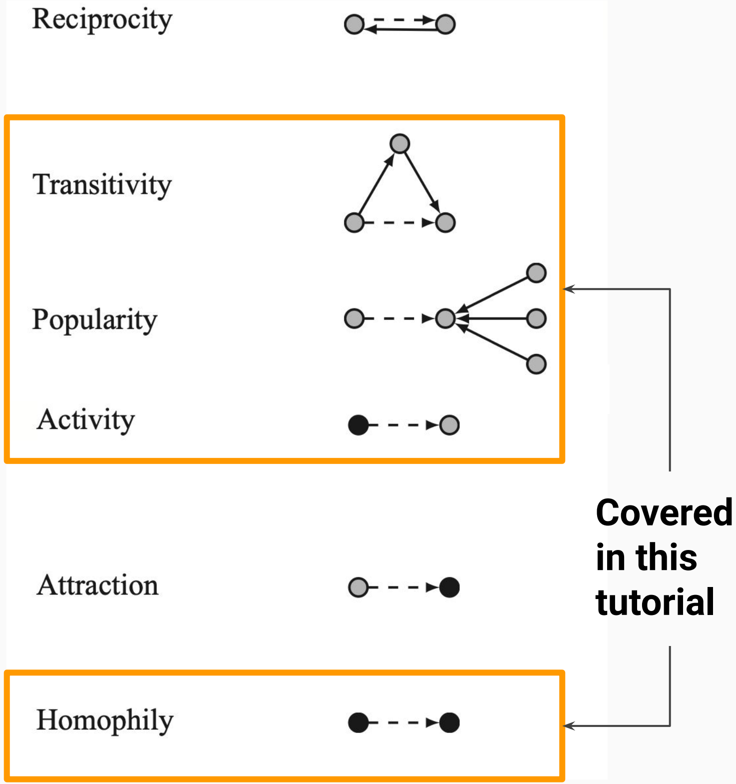
- Actor → person, company, county
  - It may also include entities produced or generated by individuals, e.g., email, retweet.
- Relation → friendship, collaboration, partnership, trade, war, hierarchy
  - When the actor is a resource, the relation may represent a spreading dynamic, access to opportunities, etc.

How do networks form?

Social mechanisms in micro-level govern how we organize our social lifes and interact with others. Some of those social theories include: group identity theory, cultural evolutions, and broadly social psychology theories.

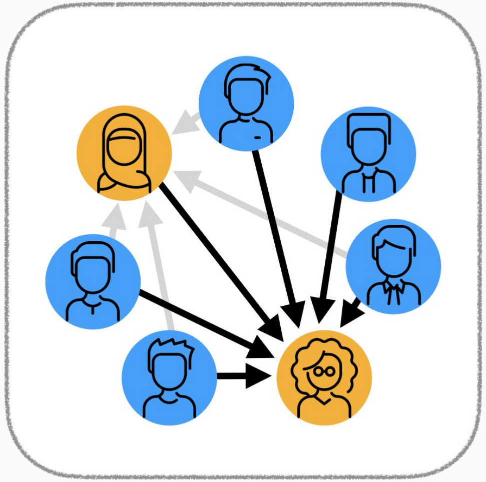
Prevalent **mechanisms** identified in social science literatures:

- Preferential attachment a.k.a. rich-get-richer or Matthew effect
- Homophily and assortative mixing
- Social balance and triadic closure



Stadfeld, Christoph, and Viviana Amati. "Network mechanisms and network models." Research Handbook on Analytical Sociology. Edward Elgar Publishing, 2021

Popularity (preferential attachment)

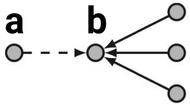


Popularity

The tendency of actors to connect to those who receive ties from many others. The structural position is defined by the **in-degree of the receiver** (target node) of an explained tie.

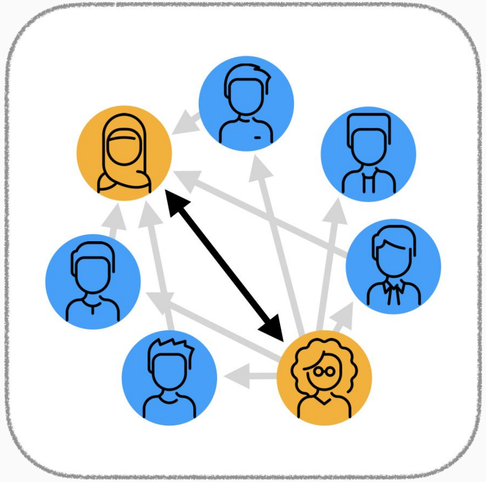
- **Matthew effect or rich-gets-richer effect** mechanism in science discussed by Merton (1968), Price (1976) and others. Increasing recognition of an actor's scientific work (e.g. number of ties in a citation network).
- **Preferential attachment** in the work of Barabási and Albert (1999) operationalised this mechanism in networks.

The presence of a popularity mechanism is not sufficient evidence that a Matthew effect exists in a network, e.g.,, other actor **attributes**, such as the career stage or gender, might send similar signals that affect the beliefs of others.



$$P(a \to b) = P(b|a) = p_{ab} = \frac{k_b}{\sum_c k_c}$$

Homophily (similarity)



Homophily

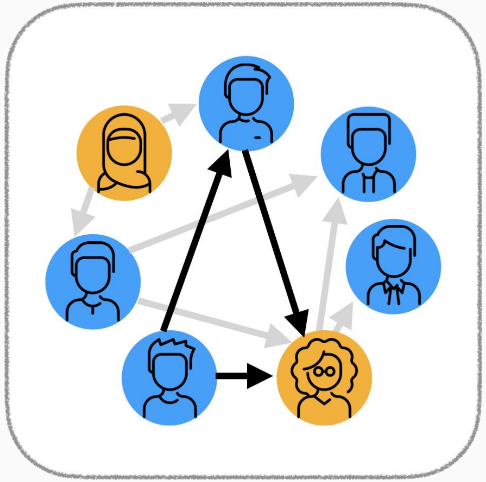
The tendency that similar actors are more likely to connect (Lazarsfeld, et al. 1954; McPherson et al. 2001). Its structural position is defined by **the attribute similarity of the sender and receiver** of the explained tie.

Causal explanations:

- These may be cognitive processes about similarity attraction (Huston and Levinger 1978)
- Structural processes that are affected by existing baseline segregation and social distances in the social setting under study.

$$P(a \to b) = P(b|a) = p_{ab} = similarity(a, b)$$

Transitivity (triadic closure, friends-of-friends)

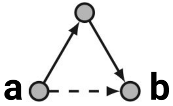


Transitivity

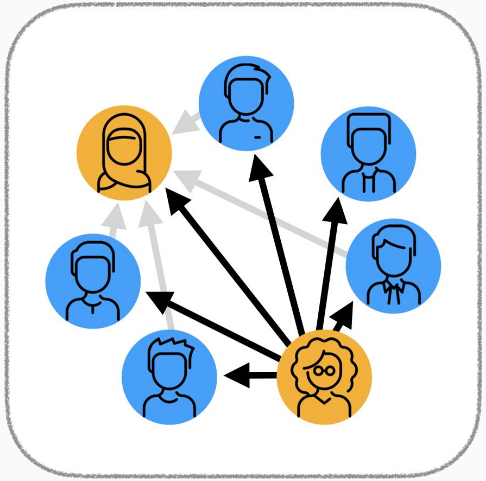
One of the central mechanisms that goes *beyond the dyad* and thus *involves more than two actors*: it expresses the tendency of actors to connect to others to whom they are indirectly tied to through a third actor. The structural position is defined by the presence of a **“two-path” between the sender and the receiver** of the explained tie.

Causal explanations:

- Differences in spatial or social distances and similarity attraction based on an actor attribute (Granovetter 1973).
- Actors may perceive cognitive dissonance and stress if they are not in a positive relationship with those they are indirectly positively tied to (Heider 1958).



$$P(a \rightarrow b) = P(b|a) = p_{ab} = p_{TC} \propto clustering(g)$$



Node Activity

The tendency that actors with specific attributes will be more likely to send ties. The structural positions are defined by **attributes of the sender** of the explained tie. Whether these differences relate to differences in networking resources is not further specified by the mechanism.

a ●- - -▸○ b

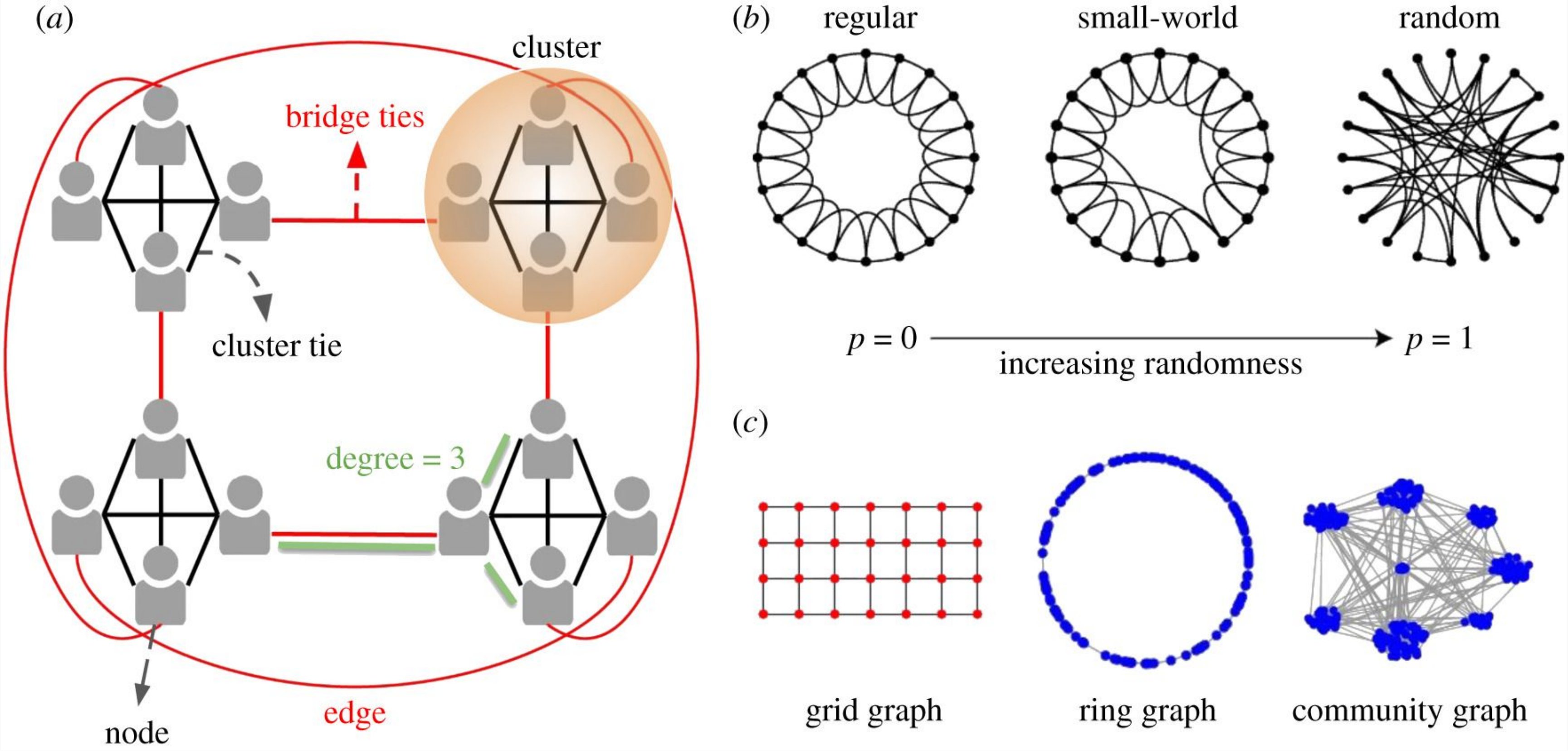
$$P(a \to b) = P(b|a) = p_{ab} \propto activity(a)$$

Network properties and structure

Important properties of social networks

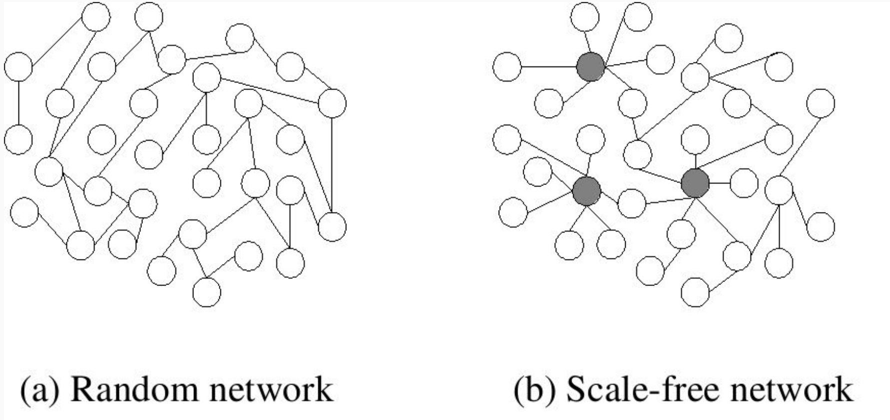
#	Graph	Node	Edge
1	Average and minimum degree (note: average degree does not make sense if you have power-law degree distribution)	Degree (in/out)	Weights
2	Degree distribution (the probability that a randomly selected node in the network has degree k)	Centrality (e.g,. PageRank)	Shortest path
3	Adjacency matrix / Mixing matrix	Clustering coefficient	Homophilous type (MM, Mm, mm, mM)
4	Sparsity (out of the total possible number of edges, how many actually exist)	Activity (high activity = high outdegree)	
5	Diameter		
6	Average Path Length		
7	Connected components		

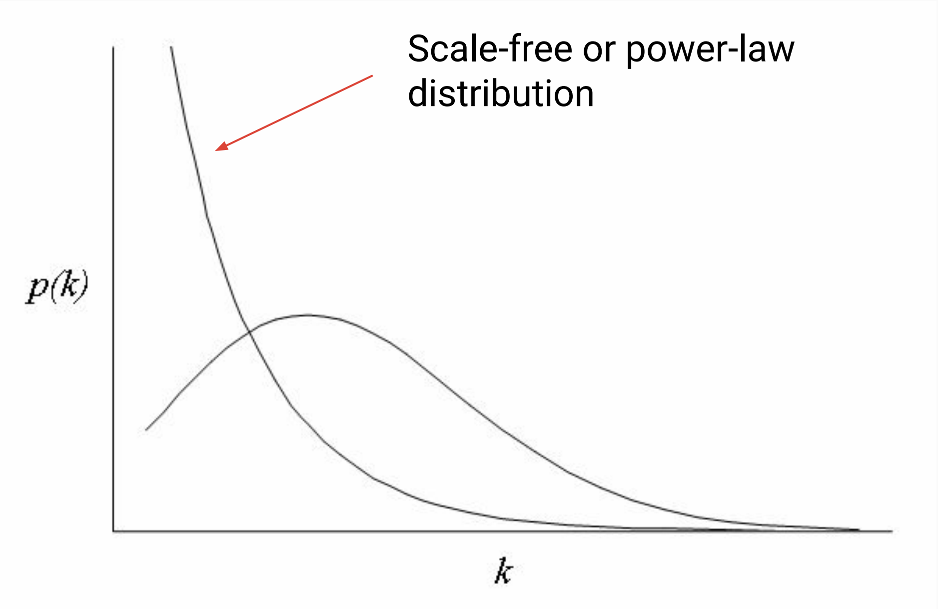
Common structure (topology) of social networks



https://royalsocietypublishing.org/doi/10.1098/rstb.2020.0315

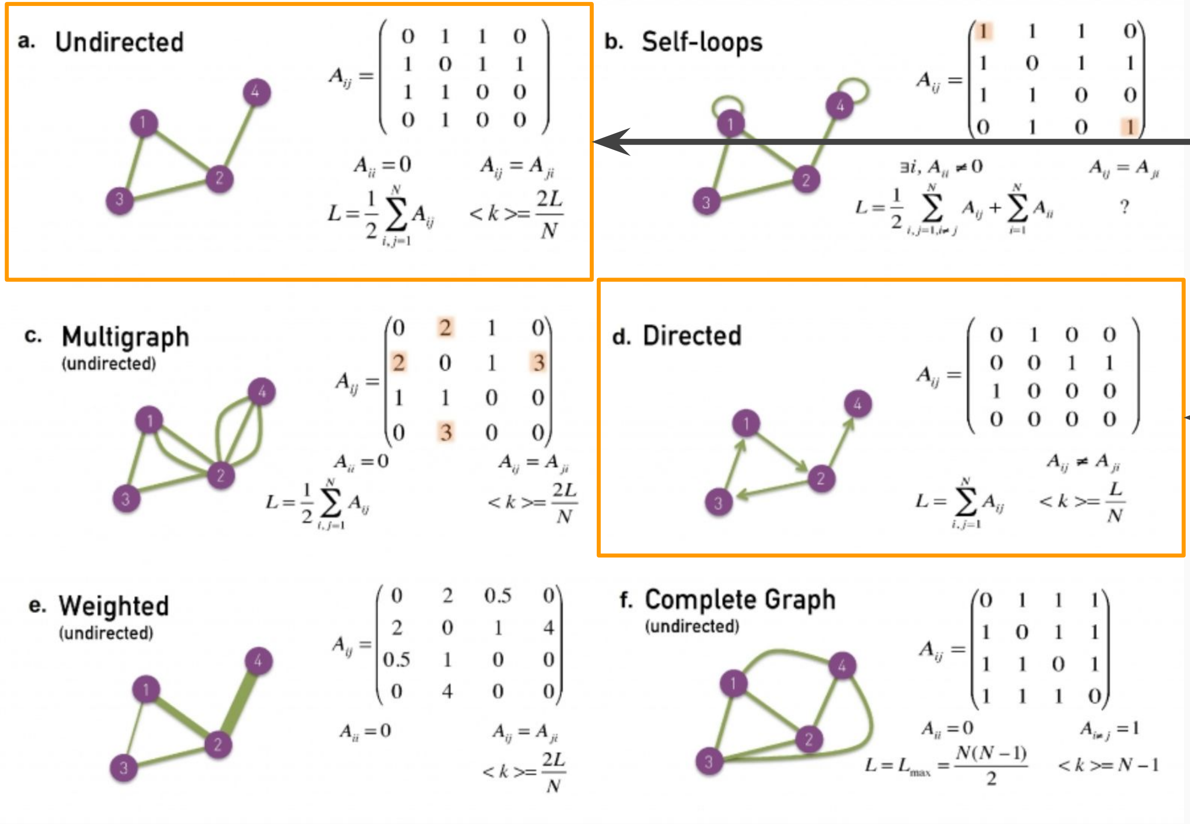
Common structure (topology) of social networks





Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *science*, *286*(5439), 509-512.
Holme, P. (2019). Rare and everywhere: Perspectives on scale-free networks. *Nature communications*, *10*(1), 1016.
Voitalov, I., van der Hoorn, P., van der Hofstad, R., & Krioukov, D. (2019). Scale-free networks well done. *Physical Review Research*, *1*(3), 033034.
Broido, A. D., & Clauset, A. (2019). Scale-free networks are rare. *Nature communications*, *10*(1), 1017.

Graphology (elementary property of the underlying graph)



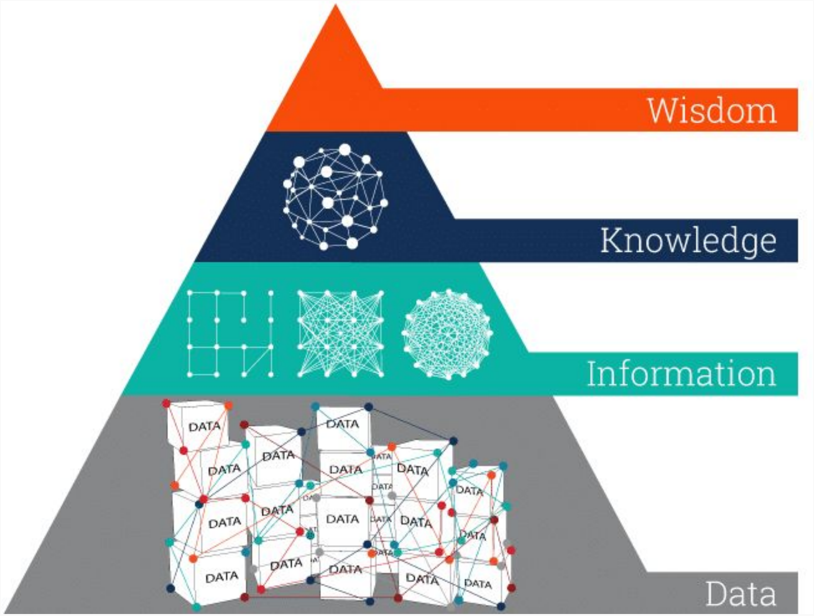
Covered in this tutorial

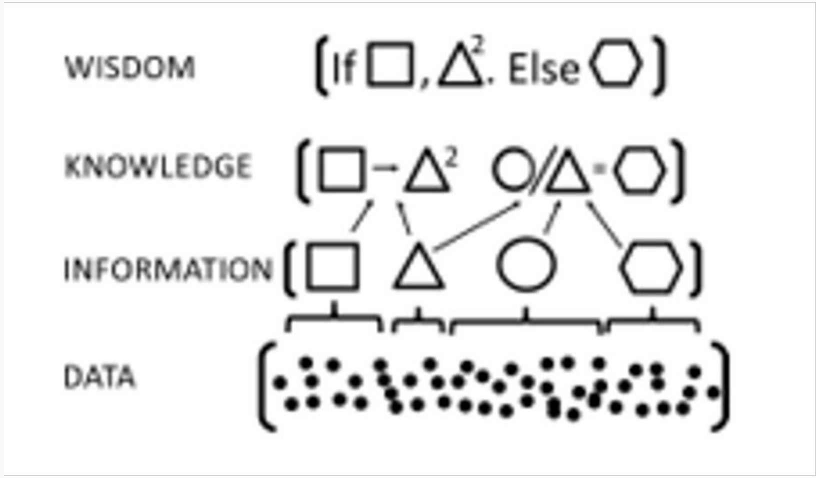
http://networksciencebook.com/chapter/2#summary2

Network models

Why modeling social networks?

The wisdom hierarchy





Page, S. E. (2018). *The model thinker: What you need to know to make data work for you*. Basic Books.
https://www.ontotext.com/knowledgehub/fundamentals/dikw-pyramid/

The seven uses of Models (REDCAPE)

1. **Reason**: to identify conditions and deduce logical implications
2. **Explain**: To provide explanations for empirical phenomena
3. **Design**: to choose features of policies, institutions and rules
4. **Communicate**: to relate knowledge and understandings
5. **Act**: to guide policy choices and strategic actions
6. **Predict**: to make numerical and categorical predictions of future and unknown phenomena
7. **Explore**: to investigate possibilities and hypotheticals scenarios

Page, S. E. (2018). *The model thinker: What you need to know to make data work for you*. Basic Books.

Why modeling social networks?

Mechanistic models refers to the use of social mechanisms to design and develop network models with the goal of understanding their effects on our social world and algorithms.

Holme, P., & Liljeros, F. (2015). Mechanistic models in computational social science. *Frontiers in Physics*, 78.

Why network models in AI and ML?

Data can be only one realization of the social structure. Generating realistic synthetic social networks can help us scrutinize the robustness and fairness of ML algorithms when data is biased or not representative of the reality.

Steinbacher, M., Raddant, M., Karimi, F., Camacho Cuena, E., Alfarano, S., Iori, G., & Lux, T. (2021). Advances in the agent-based modeling of economic and social behavior. *SN Business & Economics*, *1*(7), 99.

Network models

… and where to find them

Class of models in Network Science

Covered in this tutorial

Model Class	Examples	Characteristics
Static Models	Erdos–Rényi Watts-Strogatz	• N fixed • pk exponentially bounded • Static, time independent topologies
Generative Models	Configuration Model Hidden Parameter Model Stochastic Block Model	• Arbitrary pre-defined p_k • Static, time independent topologies
Evolving Network Models	Barabási–Albert Model Bianconi-Barabási Model Initial Attractiveness Model Internal Links Model Node Deletion Model Accelerated Growth Model Aging Model	• p_k is determined by the processes that contribute to the network's evolution. • Time-varying network topologies

Table 6.1

Classes of Models in Network Science

The table summarizes the three main modeling frameworks used in network science, together with their distinguishing features.

http://networksciencebook.com

Pre-requisites

Follow these instructions in case you are using your own environment to run the exercises.

Alternatively, you can run all the exercises in the cloud. We have prepared notebooks to run in Google Colab (more details later).

1. Download and install conda
   conda.io/projects/conda/en/stable/user-guide/install/download.html

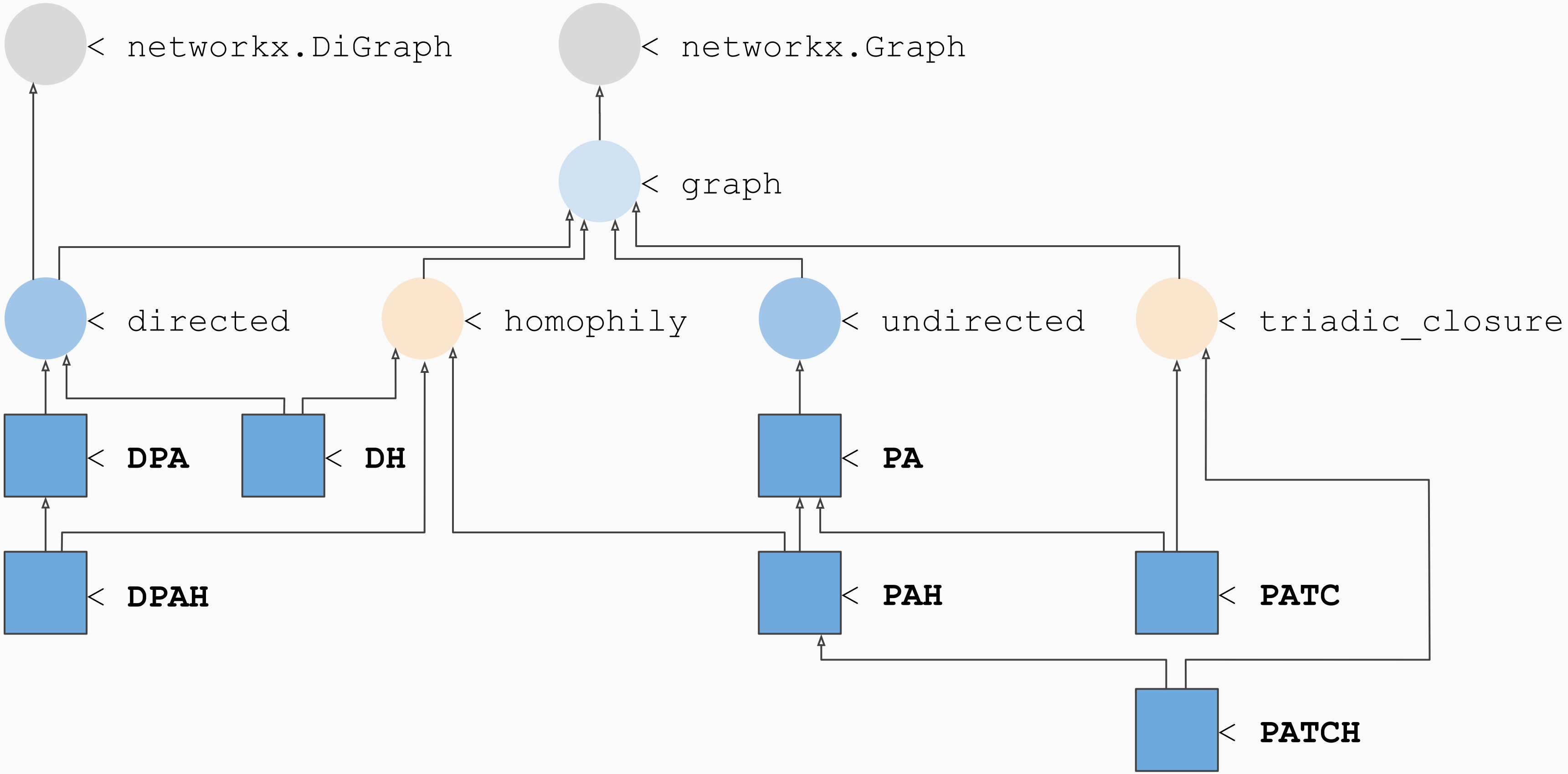
2. Create an environment with python 3.9 or later
   ```
   conda create -n "snma" python=3.9 jupyterlab
   ```

3. Activate your newly created conda environment
   ```
   conda activate snma
   ```

4. Clone the tutorial in your computer
   ```
   git clone
   https://github.com/snma-tutorial/www2023.git
   ```

5. Install the dependencies
   ```
   conda install pip
   pip install -r requirements.txt
   ```

The **`netin`** python package (alpha)



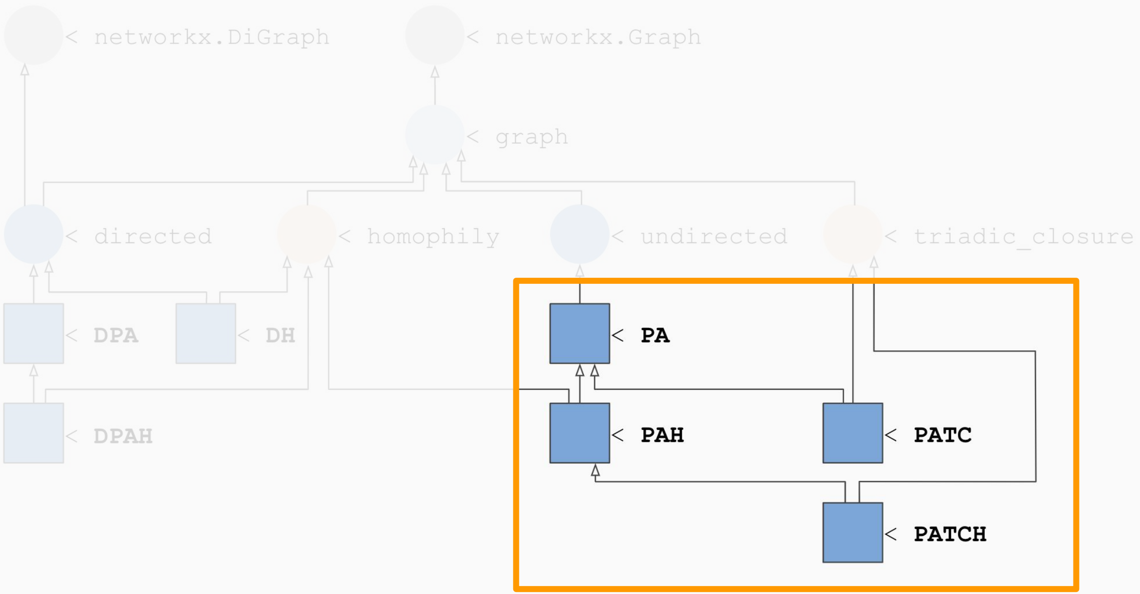
Undirected networks

PA
preferential attachment

PATC
PA + triadic closure

PAH
PA + homophily

PATCH
PAH + triadic closure



`class netin.PA(...)`

Creates a new PA instance. An undirected graph with preferential attachment.

Parameters

n: int

number of nodes (minimum=2)

k: int

minimum degree of nodes (minimum=1)

f_m: float

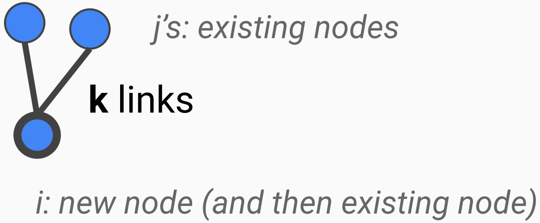
fraction of minorities (minimum=1/n, maximum=(n-1)/n)

seed: object

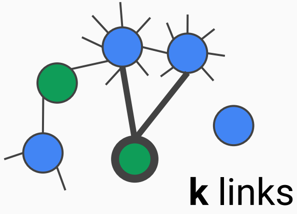
seed for random number generator

STEP 1:
k = 2

STEP 2:



STEP 3 ≤ s ≤ n:

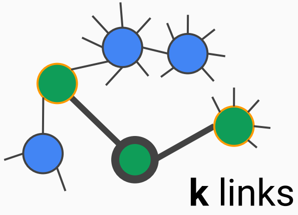


$$p_{ab} = \frac{k_b}{\sum_c k_c}$$

A. L. Barabási & R. Albert "Emergence of scaling in random networks" Science 1999.

```
class netin.PAH(...)
```

STEP 3 ≤ s ≤ n:



$$p_{ab} = \frac{h_{ab}k_b}{\sum_c h_{ac}k_c}$$

Creates a new PAH instance. An undirected graph with preferential attachment and homophily.

Parameters

n: int

number of nodes (minimum=2)

k: int

minimum degree of nodes (minimum=1)

f_m: float

fraction of minorities (minimum=1/n, maximum=(n-1)/n)

h_MM: float

homophily (similarity) between majority nodes (minimum=0, maximum=1.)

h_mm: float

homophily (similarity) between minority nodes (minimum=0, maximum=1.)

seed: object

seed for random number generator

F. Karimi, M. Génois, C. Wagner, P. Singer, & M. Strohmaier “Homophily influences ranking of minorities in social networks” Scientific reports 2018.

`class netin.PATC(...)`

Creates a new PATC instance. An undirected graph with preferential attachment and triadic closure.

Parameters

n: int

number of nodes (minimum=2)

k: int

minimum degree of nodes (minimum=1)

f_m: float

fraction of minorities (minimum=1/n, maximum=(n-1)/n)

tc: float

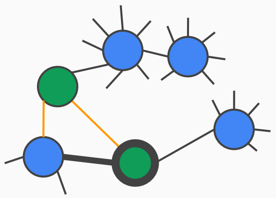
probability of a new edge to close a triad (minimum=0, maximum=1.)

seed: object

seed for random number generator

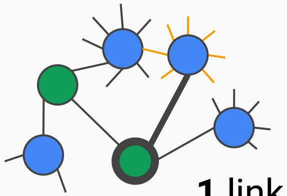
STEP 3 ≤ s ≤ n:
k times

Case 1: p_{TC}



1 link (closes a triangle)
Target 'b' with more nodes in common with 'a'

Case 2: $(1 - p_{TC})$



$$p_{ab} = \frac{k_b}{\sum_c k_c}$$

1 link (via preferential attachment)

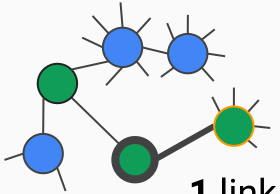
P. Holme and B. J. Kim "Growing scale-free networks with tunable clustering" Phys. Rev. E 2002.

class **netin.PATCH(...)**

STEP 3 ≤ s ≤ n:
k times

Case 1: p_{TC}

Case 2: $(1 - p_{TC})$



$$p_{ab} = \frac{h_{ab} k_b}{\sum_c h_{ac} k_c}$$

1 link
(via preferential attachment and homophily)

Creates a new PATCH instance. An undirected graph with preferential attachment, homophily, and triadic closure.

Parameters

n: int
  number of nodes (minimum=2)

k: int
  minimum degree of nodes (minimum=1)

f_m: float
  fraction of minorities (minimum=1/n, maximum=(n-1)/n)

h_MM: float
  homophily (similarity) between majority nodes (minimum=0, maximum=1.)

h_mm: float
  homophily (similarity) between minority nodes (minimum=0, maximum=1.)

tc: float
  probability of a new edge to close a triad (minimum=0, maximum=1.)

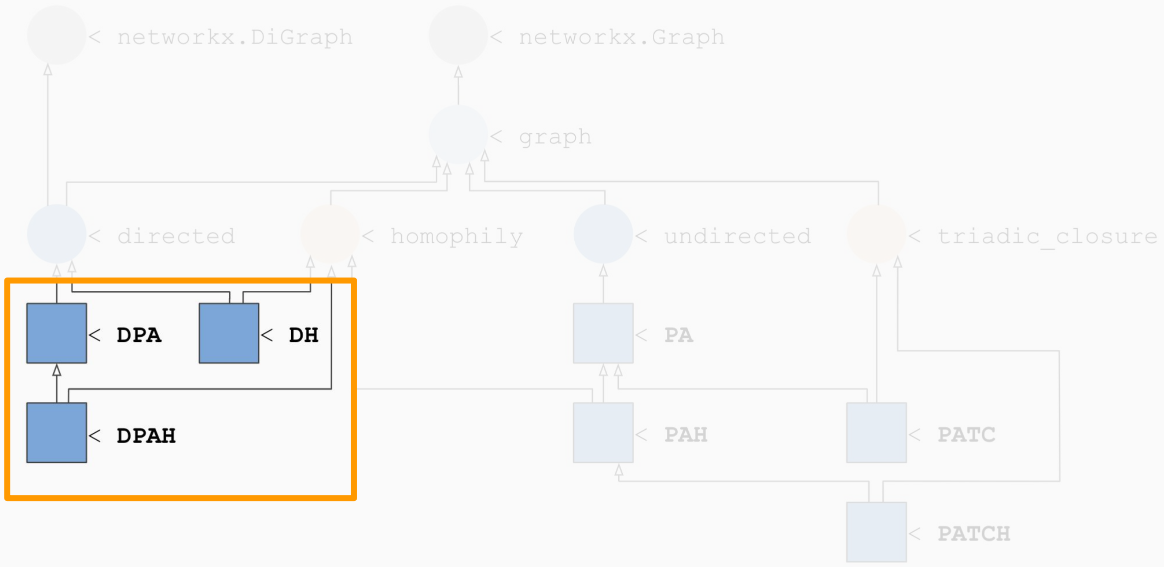
- F. Karimi, M. Génois, C. Wagner, P. Singer, & M. Strohmaier “Homophily influences ranking of minorities in social networks” Scientific reports 2018
- P. Holme and B. J. Kim, “Growing scale-free networks with tunable clustering” Phys. Rev. E 2002.
- PATCH: Forthcoming...

Directed networks

DPA
preferential attachment

DH
homophily

DPAH
DPA + homophily



DPA - Directed preferential attachment

```
class netin.DPA(...)
```

Do while density < d:

Step 1: choose a **source** node
(using the activity of all nodes)

Step 2: choose a **target** node *
(using preferential attachment → in_degree)

* target nodes must have out_degree > 0
(should have been picked as source at least once)

Creates a new DPA instance. A directed graph with preferential attachment.

Parameters

n: int
: number of nodes (minimum=2)

d: float
: edge density (minimum=0, maximum=1)

f_m: float
: fraction of minorities (minimum=1/n, maximum=(n-1)/n)

plo_M: float
: activity (out-degree power law exponent) majority group (minimum=1)

plo_m: float
: activity (out-degree power law exponent) minority group (minimum=1)

seed: object
: seed for random number generator

L. Espín-Noboa, C. Wagner, M. Strohmaier, & F. Karimi "Inequality and inequity in network-based ranking and recommendation algorithms"
Scientific reports 2022

```
class netin.DH(...)
```

Do while density < d:

Step 1: choose a **source** node
(using the activity of all nodes)

Step 2: choose a **target** node *
(using mixing matrix → homophily within/across groups)

* target nodes must have out_degree > 0
(should have been picked as source at least once)

Creates a new DH instance. A directed graph with homophily.

Parameters

n: int
number of nodes (minimum=2)

d: float
edge density (minimum=0, maximum=1)

f_m: float
fraction of minorities (minimum=1/n, maximum=(n-1)/n)

plo_M: float
activity (out-degree power law exponent) majority group (minimum=1)

plo_m: float
activity (out-degree power law exponent) minority group (minimum=1)

h_MM: float
homophily within majority group (minimum=0, maximum=1)

h_mm: float
homophily within minority group (minimum=0, maximum=1)

seed: object
seed for random number generator

L. Espín-Noboa, C. Wagner, M. Strohmaier, & F. Karimi “Inequality and inequity in network-based ranking and recommendation algorithms”
Scientific reports 2022

```
class netin.DPAH(...)
```

Do while density < d:

Step 1: choose a **source** node
(using the activity of all nodes)

Step 2: choose a **target** node *
(using mixing matrix and preferential attachment)

* target nodes must have out_degree > 0
(should have been picked as source at least once)

Creates a new DPAH instance. A directed graph with preferential attachment and homophily.

Parameters

n: int
    number of nodes (minimum=2)

d: float
    edge density (minimum=0, maximum=1)

f_m: float
    fraction of minorities (minimum=1/n, maximum=(n-1)/n)

plo_M: float
    activity (out-degree power law exponent) majority group (minimum=1)

plo_m: float
    activity (out-degree power law exponent) minority group (minimum=1)

h_MM: float
    homophily within majority group (minimum=0, maximum=1)

h_mm: float
    homophily within minority group (minimum=0, maximum=1)

seed: object
    seed for random number generator

L. Espín-Noboa, C. Wagner, M. Strohmaier, & F. Karimi "Inequality and inequity in network-based ranking and recommendation algorithms" Scientific reports 2022

Exercise

Task:

1. Generate 3 undirected graphs.
2. Get to know them (attributes, visualize them, etc.)
3. Plot and compare their type of edges (MM, Mm, mm, mM).
4. Plot and compare the pdf of their degree distributions.

Repeat for other graphs and check the effects of other mechanisms.

(30 min)

Open **`1_exercise.ipynb`**

1. Alternatively, you can open the notebook from Google Colab (you need a Google account):
   [`bit.ly/snma2023-notebooks`](bit.ly/snma2023-notebooks)

Lunch break

see you back at **13:30**