### **Network Analysis:**

# The Hidden Structures behind the Webs We Weave 17-213 / 17-668

#### Homophily and Degree Correlation (Part 1) Thursday, September 14, 2023

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#### 2-min Quiz, on Canvas

#### Quick Recap – Last Tuesday's Lecture

Graph signature of social ties

Social tie dynamics

#### **Case Study: Clustering Coefficient**

#### **Measurement of Triadic Closure**

The extent of triadic closure in a network:

 Local clustering coefficient: The probability that two neighbors of a node are connected
 Number of ties among i's neighbors

 $C_i = \frac{2L_i^{(\text{excluding ties involving }i)}}{k_i(k_i - 1)}$ 

The average across *all* nodes is that network's "local" clustering coefficient

## **b**. 1/6

1/3

C.=1

a.

$$C_{i}=1/2 \qquad C_{i}=0$$

$$C_{i}=0$$

Last Thursday





Magguro	Т	TAP		HMS-PCI		Other data sets		
Weasure	"Small"	"Medium"	"Small"	" "Medium" Y2H D	DIP	TP		
Nodes n	193(15)	1,365(1,250)	99(7)	1,544(1,501)	1,870	1,788	434	
Interactions /	191(38)	3,230(3,150)	67(7)	3,481(3,456)	2,240	3,003	868	
Connectance C	0.01(0.36)	0.003(0.004)	0.01(0.33)	0.003(0.003)	0.001	0.002	0.009	
Clustering cc	0.248(0.66)	0.216(0.233)	0.071(0)	0.048(0.049)	0.068	0.188	0.054	
Diameter D	(1.94)	(4.93)	(1.81)	(4.41)				
Longest path	(4)	(12)	(3)	(11)				
Stretch parameter b	0.78	0.48	0.65	0.34	0.34	0.53	0.55	

#### What do you see?

Network	Nodes	Links	Average path length $(\ell \ell)$	Clustering
Network	(/ / )	(L)		
Facebook Northwestern Univ.	10,567	488,337	2.7	0.24
IMDB movies and stars	563,443	921,160	12.1	0
IMDB co-stars	252,999	1,015,187	6.8	0.67
Twitter US politics	18,470	48,365	5.6	0.03
Enron email	87,273	321,918	3.6	0.12
Wikipedia math	15,220	194,103	3.9	0.31
Internet routers	190,914	607,610	7.0	0.16
US air transportation	546	2,781	3.2	0.49
World air transportation	3,179	18,617	4.0	0.49
Yeast protein interactions	1,870	2,277	6.8	0.07
<i>C. elegans</i> brain	297	2,345	4.0	0.29
Everglades ecological food web	69	916	2.2	0.55

#### High clustering in many human social networks

	Nodes	Links	Average path	Clustering
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#### **Bipartite network: links only between movies and stars**

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IMDB movies and stars	Movies			0
IMDB co-stars				0.67
Twitter US politics		$\chi > \chi$		0.03
Enron email				0.12
Wikipedia math				0.31
Internet routers	Actors			0.16
US air transportation	546	2,781	3.2	0.49
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#### Retweet cascade trees look like stars (B rt A, C rt B $\rightarrow$ C rt A)

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#### Birds of a Feather

### Example: Retweet network on Twitter

#### Example: Social network from a town's middle school and high school



# Homophily: Often, nodes that are connected to each other in a social network tend to have similar characteristics

The majority of links for each node go to nodes of the same color.

The majority of links connect nodes of the same color.

"People love those who are like themselves." - Aristotle

"Similarity begets friendship." -Plato

(homo: same, phil: love  $\rightarrow$  love for something that is the same)



# Homophily: Often, nodes that are connected to each other in a social network tend to have similar characteristics

Salient dimensions:

- Race, ethnicity
- Gender, sex
- Age
- Religion
- Occupation/education



#### Homophily: Gender

Salient dimensions:

- Race, ethnicity
- Gender, sex
- Age
- Religion
- Occupation/education



#### Homophily: Education

Tie probability decreases as the difference in education increases between two people

Tie probability is lower for non-kin

The effect is stronger in more recent years



Smith et al. 2014

#### Homophily: Age

Age homophily slightly increased over time

Higher levels of homophily at 20s and 60s:

Why?

Age Distribution of Alters by Age of Respondent, Proportion Above Chance: 1985



Age Distribution of Alters by Age of Respondent, Proportion Above Chance: 2004



Smith et al. 2014

#### Homophily: Age

OkCupid data: Women are most interested in men their own age.





a woman's age vs. the age of the men who look best to her

#### Homophily: Age

OkCupid data: Men are most interested in women in their early 20s.

Dataclysm Who We Are\* Christian Rudder





#### Aside: The dark side of homophily

Exceedingly easy to connect with people who share our worldviews and unfriend / unfollow people with different opinions.



Information can be shared and consumed in such a selective and efficient way as to influence our opinions very effectively.

Result: segregation and polarization of our online communities.

High risk of manipulation by misinformation and social bots.

#### **Competing mechanisms**

**Selection** ("homophily"): If people are similar in some way, they are more likely to select each other and become connected.

Social influence: People who are friends become more similar over time.

#### Homophily: Intrinsic vs contextual effects



Given a particular characteristic of interest (like race, or age), is there a simple test we can apply to a network to estimate whether it exhibits homophily according to this characteristic?

Imagine this is the friendship network of an elementary-school classroom, with colors representing different genders.



What would it mean for the network <u>not</u> to exhibit homophily by gender?



What would it mean for the network <u>not</u> to exhibit homophily by gender?

The proportion of male and female friends a person has should look like the background male/female distribution in the full population.



What would it mean for the network <u>not</u> to exhibit homophily by gender?

If we were to randomly assign each node a gender according to the gender balance in the real network, then the number of cross-gender edges should not change significantly relative to what we see in the real network.



Suppose a p fraction of all individuals are male, and a q fraction are female.

Consider a given edge in this network:

- both ends of the edge will be male with probability ... ?
- both ends will be female with probability ...?
- if one end is male and the other is female, or vice versa, then we have a cross-gender edge with probability ...?



Suppose a p fraction of all individuals are male, and a q fraction are female.

Consider a given edge in this network:

- both ends of the edge will be male with probability *p*<sup>2</sup>
- both ends will be female with probability q<sup>2</sup>
- if one end is male and the other is female, or vice versa, then we have a cross-gender edge with probability 2pq



Homophily test:

If the fraction of cross-gender edges is significantly less than 2pq, then there is evidence for homophily.

p = 2/3 and q = 1/3 in our example 2pq = 4/9 = 8/18 5 / 18 edges are cross-gender

With no homophily, one should expect to see 8 cross-gender edges rather than than 5, so this example shows some evidence of homophily.



#### Aside: Networks can also exhibit inverse homophily

If the fraction of cross-gender edges is significantly <u>more</u> than 2pq.

Do you remember any example?

#### Aside: Networks can also exhibit heterophily

If the fraction of cross-gender edges is significantly <u>more</u> than 2pq.

Yes! The high school dating network



### Summary

We've seen another fundamental property of networks: similarity between neighbors

(Recall short paths connecting nodes and triangles formed by common neighbors)

One <u>extremely</u> powerful analysis technique: comparison to a random (shuffled) network. We'll see another one (longitudinal analysis) next time.