## Homophily and assortativity

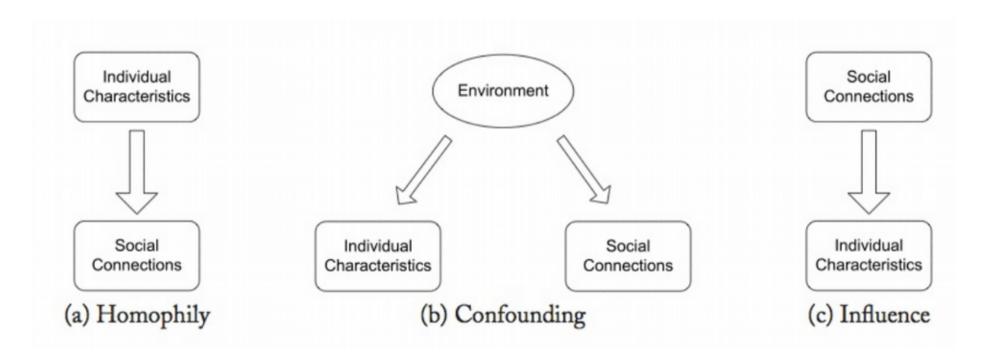
Introduction to Network Science Carlos Castillo Topic 08



#### Sources

- Albert László Barabási: Network Science.
  Cambridge University Press, 2016. Ch 07
- Networks, Crowds, and Markets Ch 03 and 04
- Nicola Barbieri's tutorial on homophily and influence in social networks, 2016
- C. Castillo: Link prediction slides 2016

#### Three models of social correlation



## Three models (cont.)

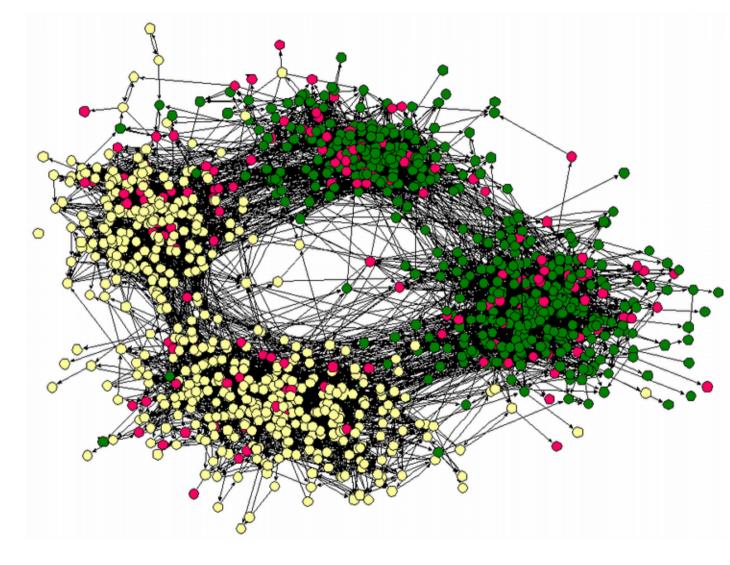
- Homophily: tendency of agents to be connected to similar agents
- **Confounding**: correlation between agent actions can be explained by external factors
- Influence: agent actions influence the actions of their connections

## Think of your own friends

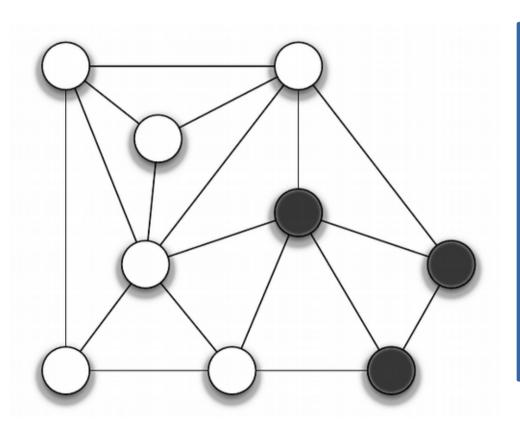
- Your friends are not a random sample
  - Similar age, affluence, interests, beliefs, ... to you (most of them)
- Long-standing observation
  - Plato ("similarity begets friendship")
  - Aristotle (people "love those who are like themselves")

# Friendships by race

(Middle school in the US, ca 2001)



## How to measure homophily?



- Count homogeneous edges (white-white or black-black)
- Count heterogeneous edges (white-black)

## Homophily test

- ullet Suppose the probability of being white is  ${\cal P}$
- The probability of being black is q=1-p
- What is the probability of:
  - A white-white edge
  - A black-black edge
  - A white-black edge

## Homophily test (cont.)

- How many homogeneous edges do we expect?
- Hence, does this graph exhibit homophily?

## Homophily measurement: one-tailed binomial test

 Given G=(V,E) with colors assigned at random (p|V| white nodes and (1-p)|V| black nodes)

$$\forall (i,j) \in E : X_{ij} = Pr[(i,j) \text{ is an heterogeneous edge}]$$

$$X_{ij} \sim \text{Bernoulli}(2p(1-p))$$

The number of heterogeneous edges follows

$$\sum_{(i,j)\in E} X_{ij} \sim \text{Binomial}(L, 2p(1-p))$$

### In our example

We compute

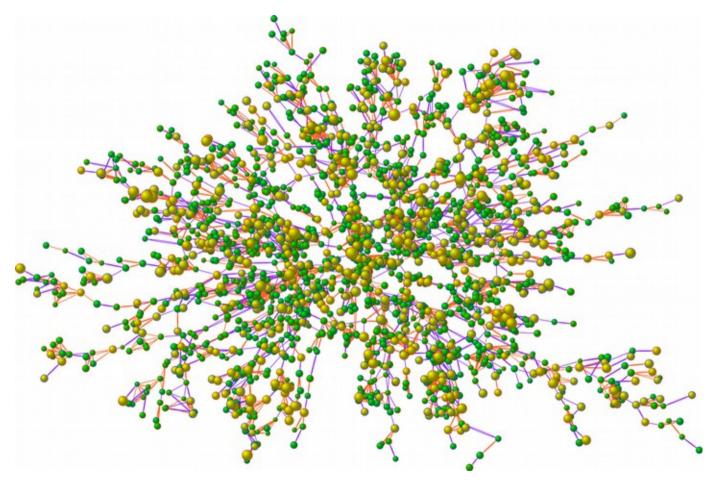
$$Pr[Binomial(L, 2pq) \le 5] = Pr[Binomial(18, 4/9) \le 5]$$
  
= 0.1174

- Hence observing this number of heterogenous edges or less has a probability of more than 10%
- Hence homophily in this case is not significant at 0.05

#### Shuffle tests

- Many network characterization questions can be addressed through shuffle tests
- For homophily, one can compare a characteristic (e.g., probability of having an heterogeneous edge) with the observation in a network in which node labels are shuffled
- This is a general, very powerful technique

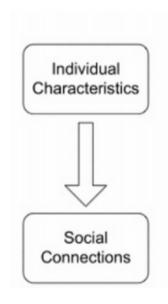
## Is obesity contagious?



Size: BMI

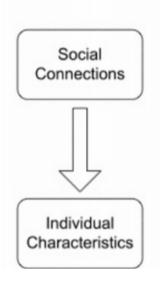
Yellow: obese

#### Selection and social influence



**Selection** is the process by which we chose to connect to people based on our characteristics

**Social influence** is the process by which we transform and are transformed by our connections



What do we see in the obesity study?

## Christakis and Fowler show evidence that in their sample:

- 1)People indeed connect to other similarly obese or not obese (homophily)
- 2)People are affected by external influence to be more or less obese (confounding)
- 3)People change the behavior of others (social influence)

## Thought experiment

Suppose you are asked to design a program to prevent drug addiction by focusing resources in ensuring well-connected people do not become addicted to drugs

Under which circumstances this program would be more successful? Less successful?

## Assortativity

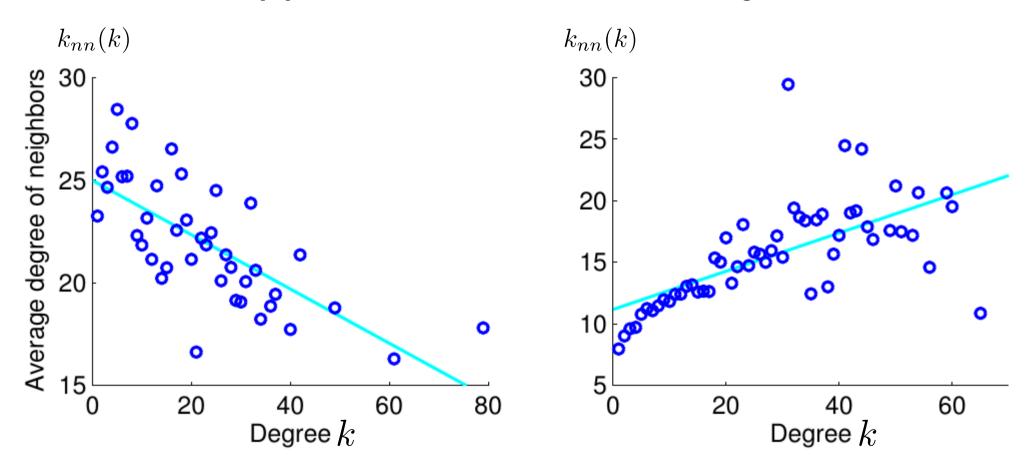
(~Homophily by degree)

#### Evidence of assortative behaviors

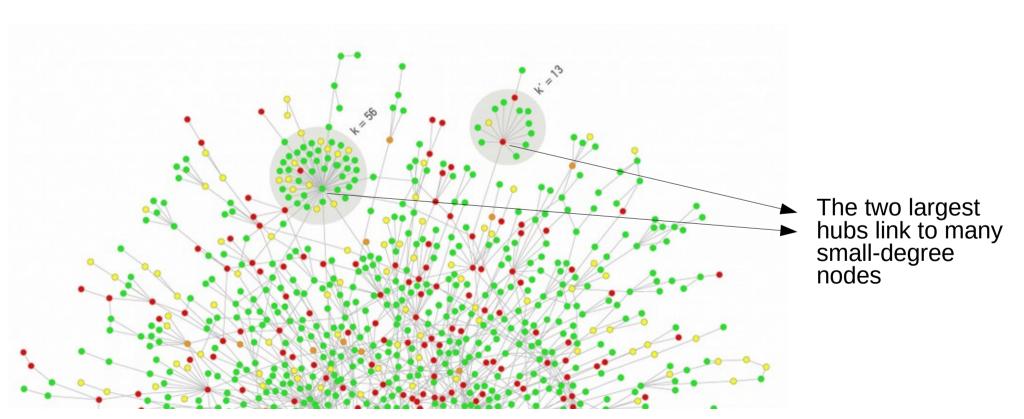
- Celebrities marrying celebrities
- Big companies having people in their boards who are in many boards of big companies
- Famous physicists work with each other
- However, famous rappers don't ...

#### Rappers

#### **Physicists**



# A disassortative network: protein interactions



### Describing degree correlations

- Degree correlation matrix  $e_{ij}$ 
  - Probability that in a randomly selected node, one end has degree i and the other end has degree j

## Degree correlations

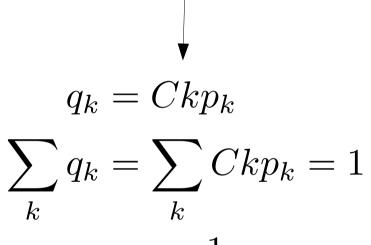
 Probability that a node at the end of a randomly chosen link has degree k

$$q_k = \frac{kp_k}{\langle k \rangle}$$

Degree correlation matrix:

$$e_{ij} = q_i q_j$$

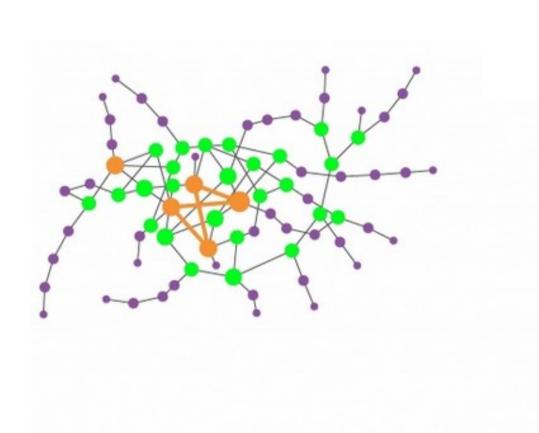
High-degree and highprobability nodes are more likely to be found

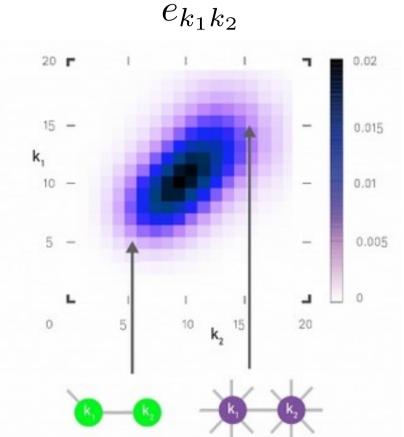


$$C = \frac{1}{\sum_{k} k p_k}$$

$$C = \frac{1}{\langle k}$$

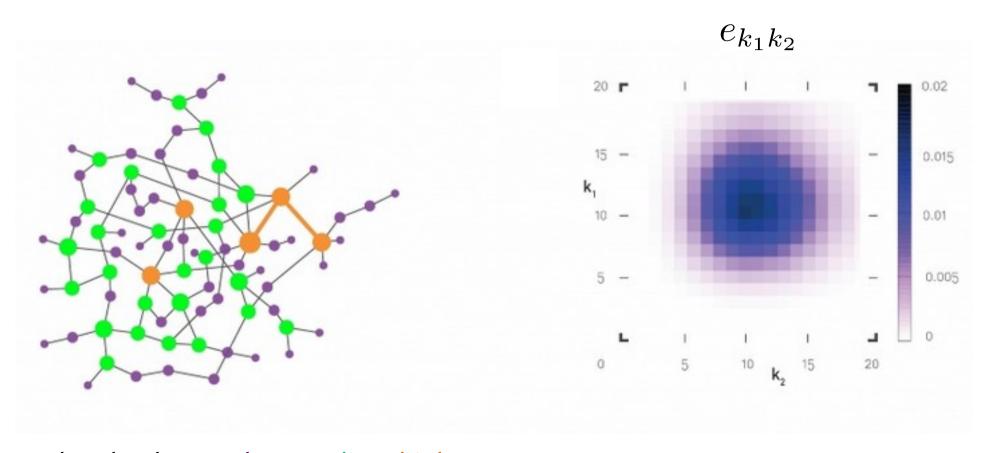
### Assortative behavior





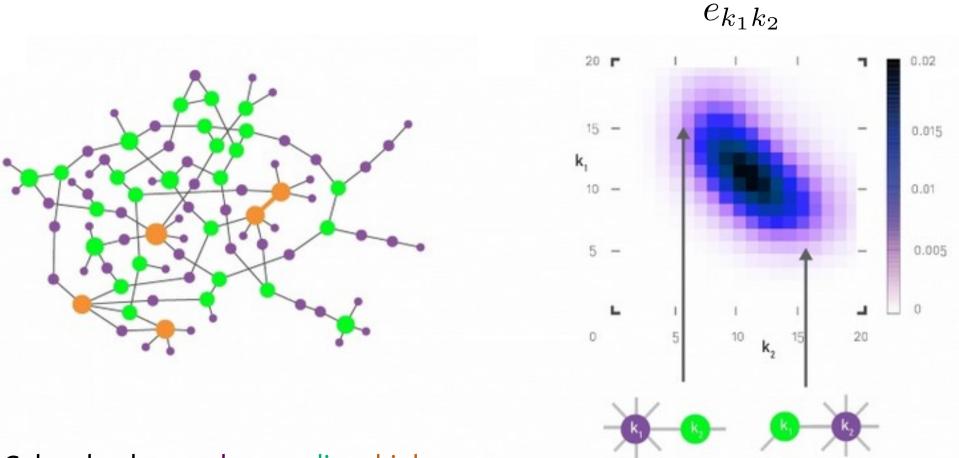
Colors by degree: low medium high

### Neutral behavior



Colors by degree: low medium high

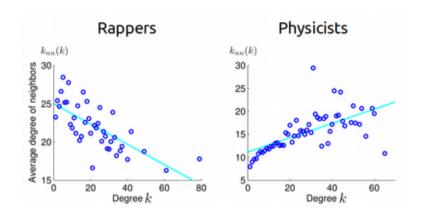
#### Disassortative behavior



Colors by degree: low medium high

## Degree correlation function

$$k_{nn}(k) = \sum_{k'} k' P(k \to k')$$



 $P(k \to k')$  is the probability that by following a link of a node with degree k, we reach a node with degree k'

## Compute the degree correlation function for a neutral network, in which $e_{ij}=q_iq_j$

$$k_{nn}(k) = \sum_{k'} k' P(k \to k')$$
  $q_k = \frac{\kappa p_k}{\langle k \rangle}$ 

#### Note that in a neutral network:

$$P(k \to k') = \frac{e_{kk'}}{\sum_{k'} e_{kk'}}$$

#### Neutral network

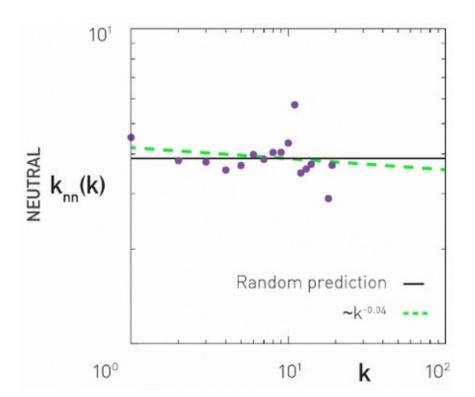
$$k_{nn}(k) = \sum_{k'} k' P(k \to k')$$

In a neutral network

 $k_{nn}(k)$  is independent of k

Assortative: increases

Disassortative: decreases



## Model for degree correlations

$$k_{nn}(k) = ak^{\mu}$$

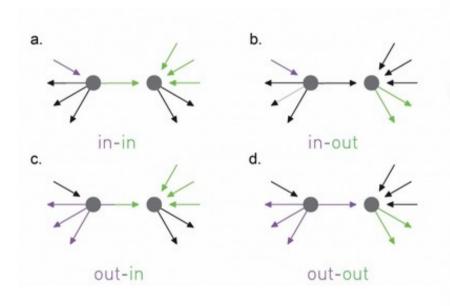
- If  $\mu > 0$  the network is assortative
- If  $\mu = 0$  the network is neutral
- If  $\mu$  < 0 the network is disassortative

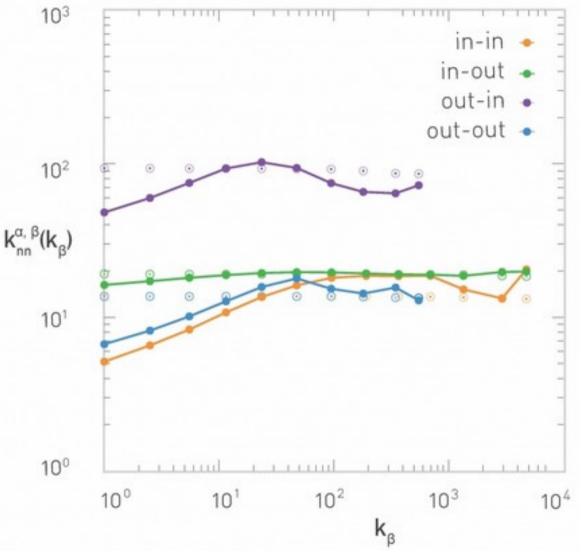
#### Alternative model

$$k_{nn}(k) = ak + b$$

- If a > 0 the network is assortative
- If a = 0 the network is neutral
- If a < 0 the network is disassortative

## Degree correlations in directed networks





#### Note

- Assortative/disassortative observations can be explained in part simply by degree sequences in the network
- This can be addressed with a shuffle test