Network Analysis:

The Hidden Structures behind the Webs We Weave

17-338 / 17-668

Triads and Structural Balance

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2-min Quiz, on Canvas

Quick Recap – Last Tuesday’s Lecture

Social ties reflect graph structure

Graph structure reflects nature of the social tie and its context

Reciprocity and index of mutuality

Social ties and information diffusion

Tie persistence and decay

Larger Building Blocks: The Triad

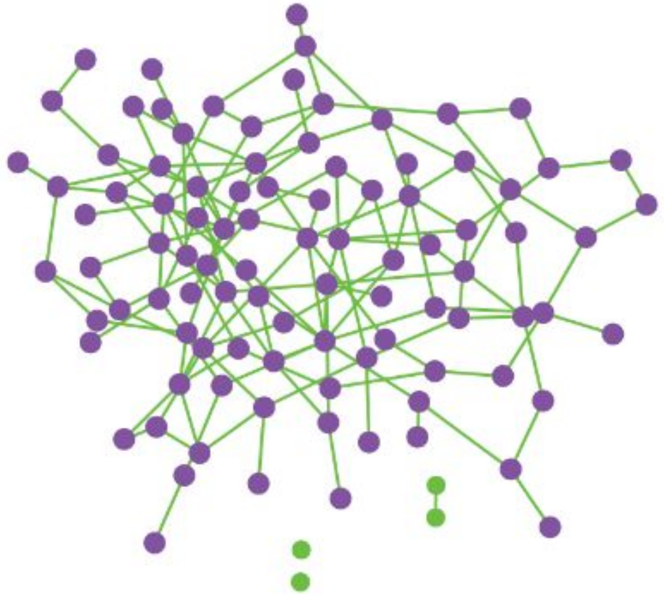
The Triad

Random graphs are useful as a baseline model.

But real-world social networks differ from random graphs in an important way.

They contain more triangles.

These triangles, or connected triads, are the telltale sign of social groups.



Probability of a triangle is close to 0 in random graphs.

The Triad

How is a trio different from a duo?

Dyad is not a group:

- Not perceived as a social group
- Variable and capricious
- Individuality and emotion of the two dictate the relationship

Triad is a group:

- The smallest objectified social group (“me” and “them”)
- The other two can pressure an individual to comply
- Can reduce caprice and uncertainty
- Individual complies out of fear of exclusion
- Individuality is suppressed and the group is cohesive

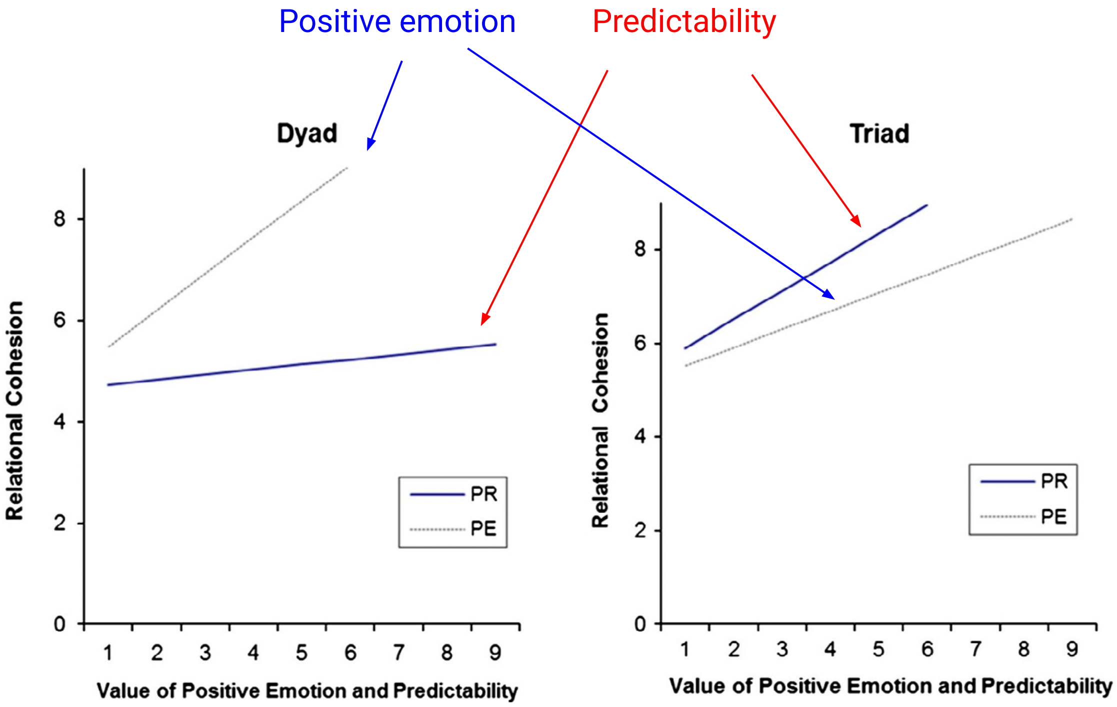
“each of the two [in a dyad] feels himself confronted only by the other, not by a collectivity above him” -Georg Simmel

The Triad

Experimental subjects were divided into either a 2-person exchange or a 3-person exchange condition

Positive emotion was more important for group cohesion in dyads

Predictability of exchange partners was more important for group cohesion in triads

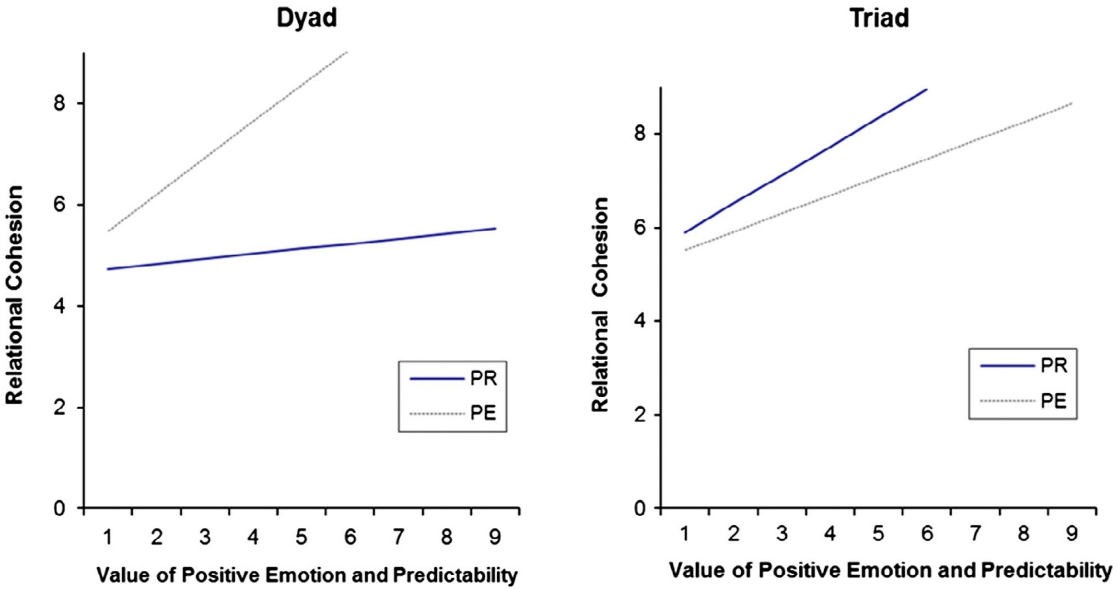


c(Yoon et al, 2013)

The Triad

In short, triads are the smallest social group.

Our aim is to understand the properties of a triad as a starting point for understanding the network properties of larger social groups.



(Yoon et al, 2013)

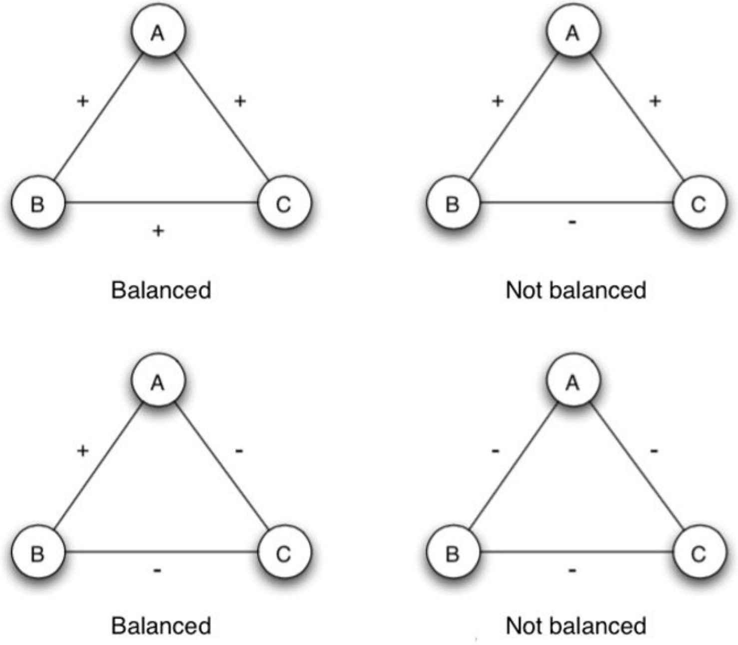
Structural Balance: Triads of Friends and Enemies

One of the earliest models of triads took inspiration from psychology

BALANCE THEORY

FRITZ HEIDER

- People try to avoid cognitive inconsistencies in their relationships
- This idea was applied to triads and developed to structural balance theory



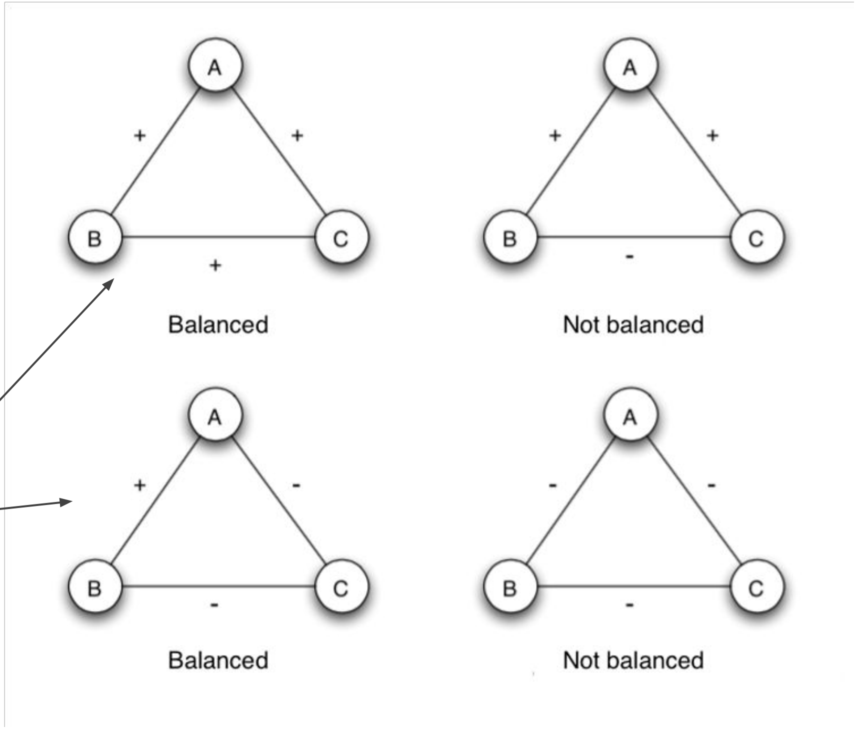
Structural Balance: Triads of Friends and Enemies

Friends: “+”

Enemies: “-”

Structural balance is achieved when

- A friend of my friend is also my friend
- An enemy of my friend is my enemy

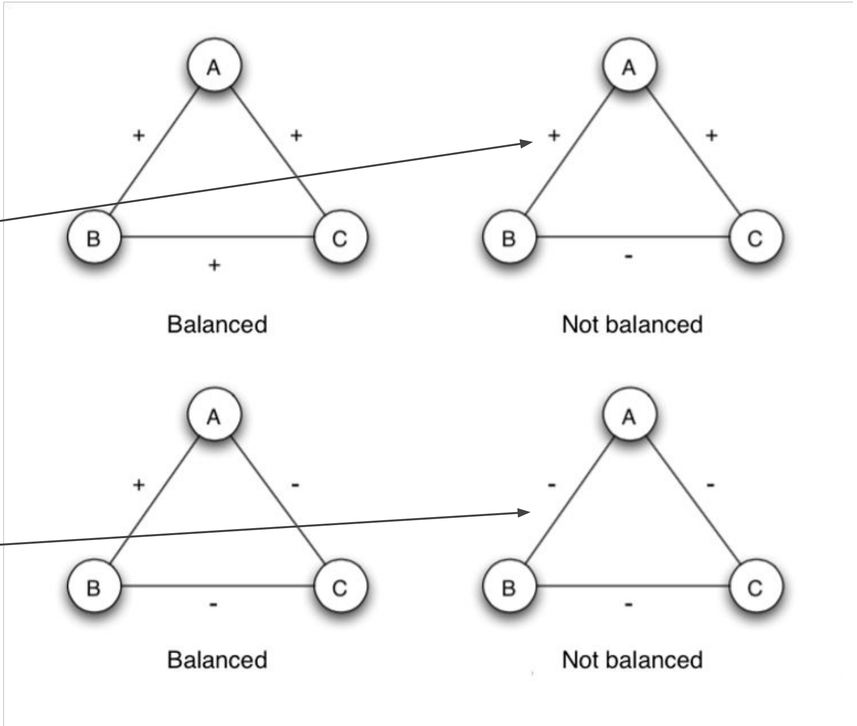


Structural Balance: Triads of Friends and Enemies

Triad is unbalanced when it consists of an **odd number of negative edges**

One negative edge: My two friends are enemies

Three negative edges: The enemy of my enemy is also my enemy



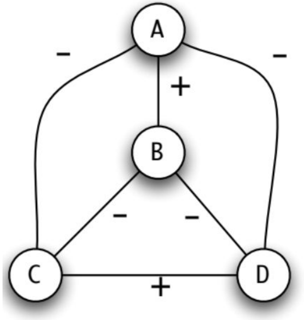
Structural Balance: Triads of Friends and Enemies

We can extend this logic of balance in triads to an entire graph

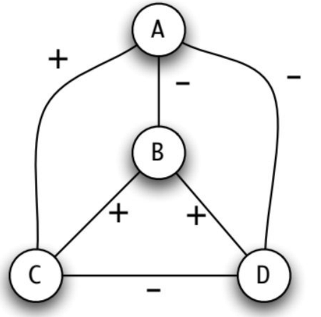
→Are all triads in a graph structurally balanced?

→ Does every triad have an even number of negative ties?

A graph with even a single unbalanced triad is “unbalanced”



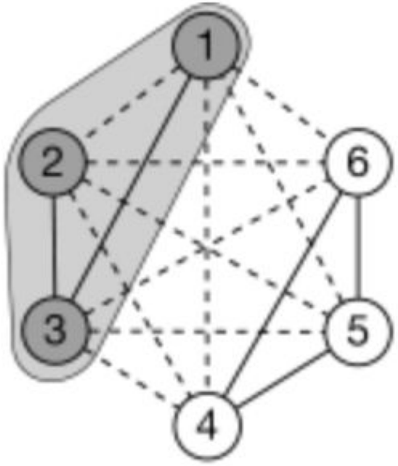
balanced

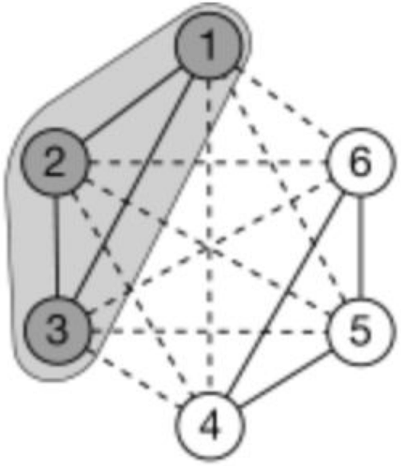


not balanced

Structural Balance: Triads of Friends and Enemies

For these completely connected graphs with positive (solid) and negative (dashed) edges, which one is balanced?





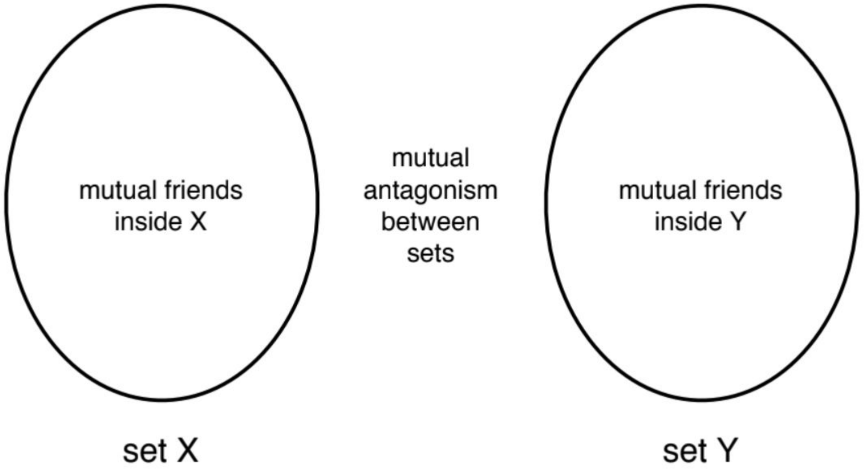
Structural Balance: Triads of Friends and Enemies

A completely connected graph is balanced iff:

(a) all pairs of nodes are friends

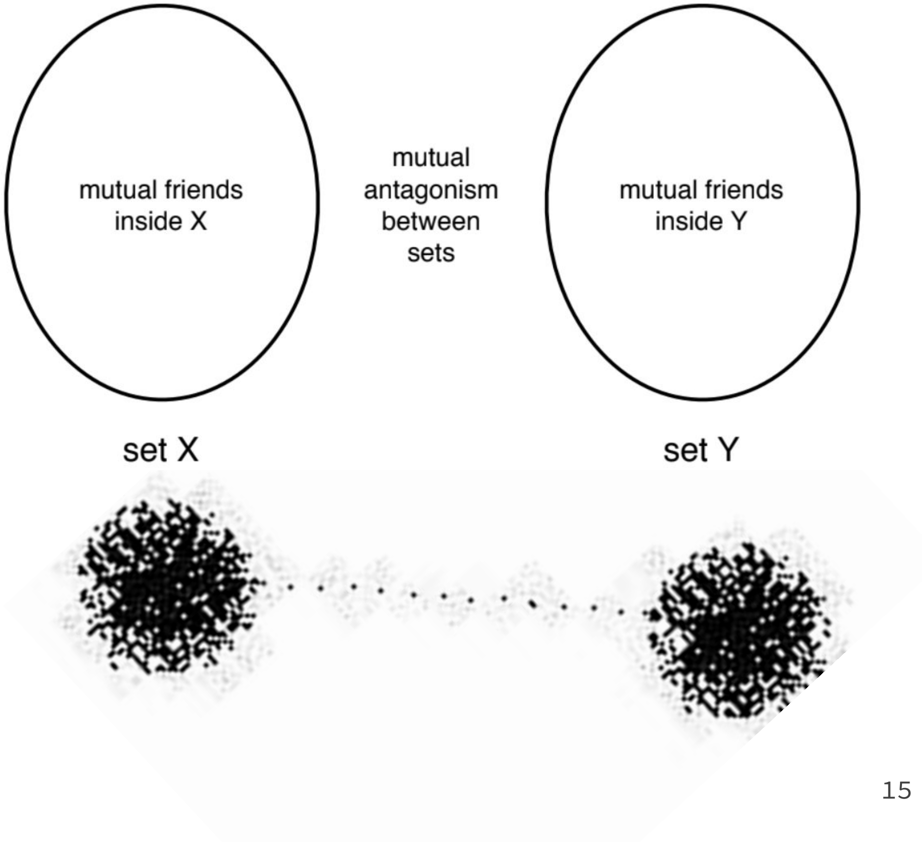
or

(b) all nodes can be divided into two groups X and Y where everyone in the same group are friends and all the pairs between groups are enemies



Structural Balance: Triads of Friends and Enemies

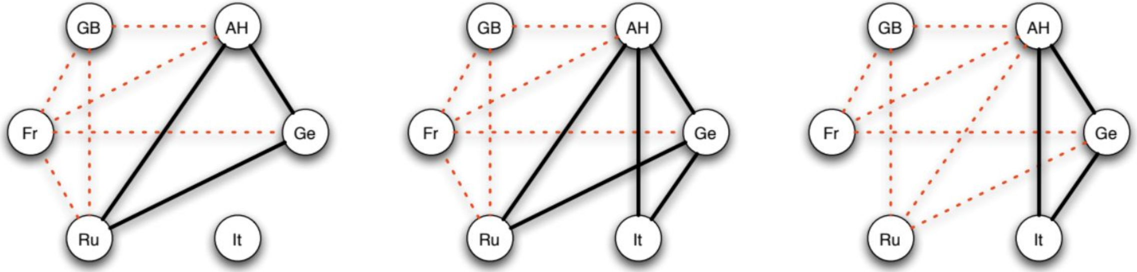
A completely connected, structurally balanced graph implies perfect polarization



Structural Balance: Triads of Friends and Enemies

Toward structural balance in the real world:

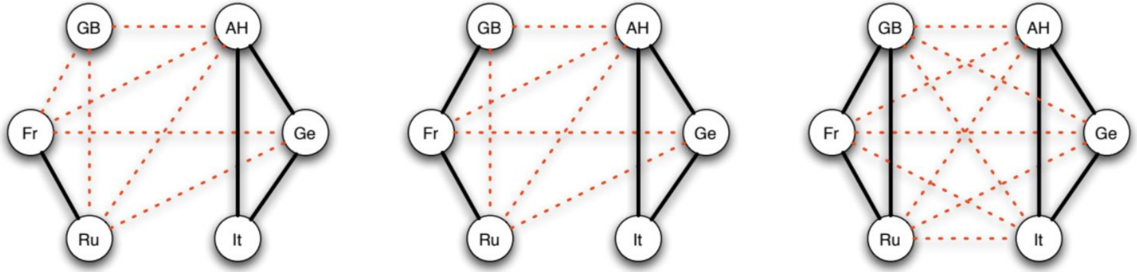
The evolution of alliances among nations in 19th century Europe



(a) *Three Emperors' League 1872–81*

(b) *Triple Alliance 1882*

(c) *German-Russian Lapse 1890*



(d) *French-Russian Alliance 1891–94*

(e) *Entente Cordiale 1904*

(f) *British Russian Alliance 1907*

Solid lines: Allies, Dashed lines: Enemies

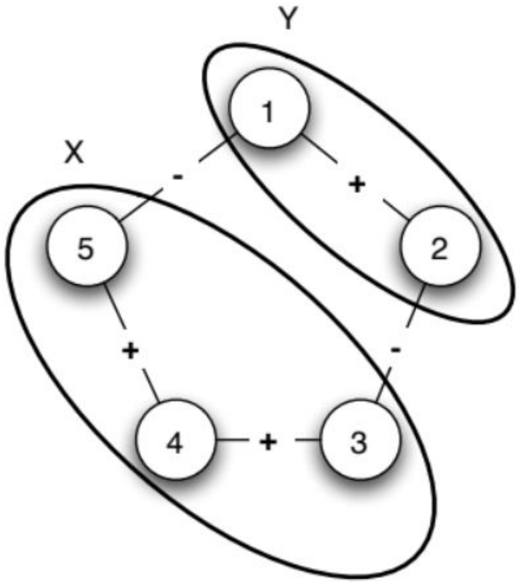
Structural Balance: Triads of Friends and Enemies

What about graphs that are not completely connected?

Balance can be defined for signed graphs in general as the following:

Nodes can be divided into two groups X and Y where all the edges in X are positive, all edges in Y are positive, and all edges between X and Y are negative

(Not all dyads need to be connected)

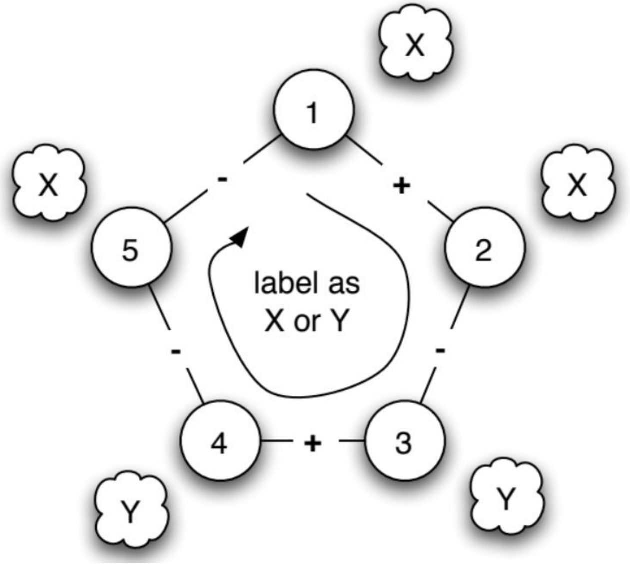


Structural Balance: Triads of Friends and Enemies

How to check for balance:

Search for a cycle of any length that has an odd number of negative edges → Unbalanced

Start from a starting node and label the adjacent node according to the sign of the edge



Structural Balance: Triads of Friends and Enemies

Structural balance is an “ideal type,” a model against which empirical social networks can be evaluated

Measures of structural balance

- **Line index of balance**: How far away is a given graph from perfect balance?
- The minimum number of edges whose signs need to be changed to obtain perfect balance

- **Cycle index for balance**: Proportion of positive cycles in a signed graph

Structural Balance: Triads of Friends and Enemies

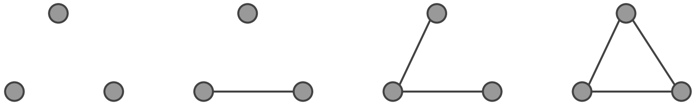
Balance theory is a useful starting point for understanding factions in small groups, group structure, and polarization

As we will see in later lectures, many models of political polarization are based, at their core, on the logic of structural balance

Triads in Directed Graphs

Directed Edges Create More Complexity

Four triadic isomorphism classes exist in an undirected triad



Many different triadic relationships exist in directed networks

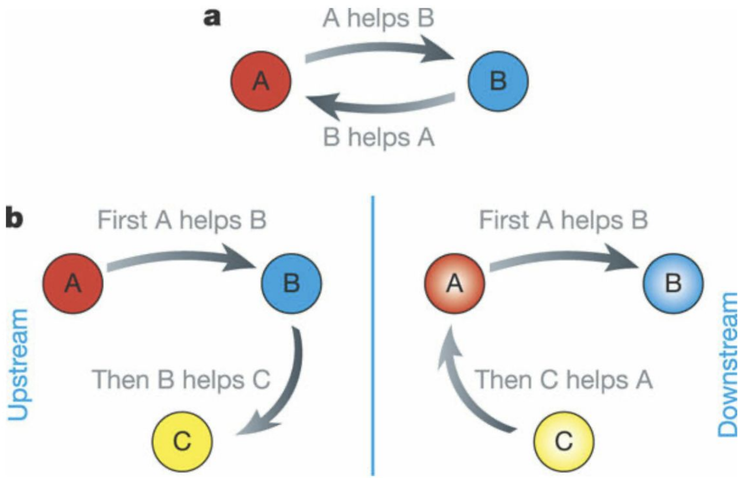
Example: structure of paying respect

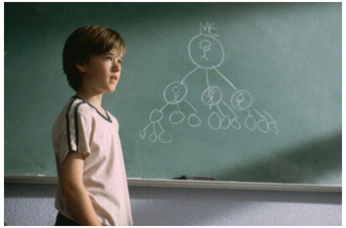
- A→B→C: Hierarchical
- A→B→C→A: Cyclical
- A→B←C: Competitive

An Example of Three-Way Relations: Reciprocity

Example: direct reciprocity (a) vs. generalized reciprocity (b)

- Generalized reciprocity is reciprocity in one direction
- The receiver does not give back to the giver, but **pays it forward**
- Represented as **cycles** (what goes around comes around)
- Such a configuration can require high levels of trust among group members



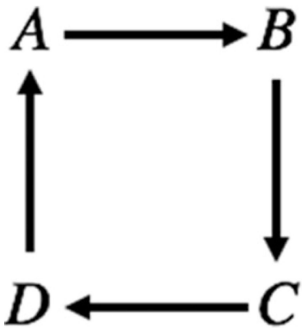


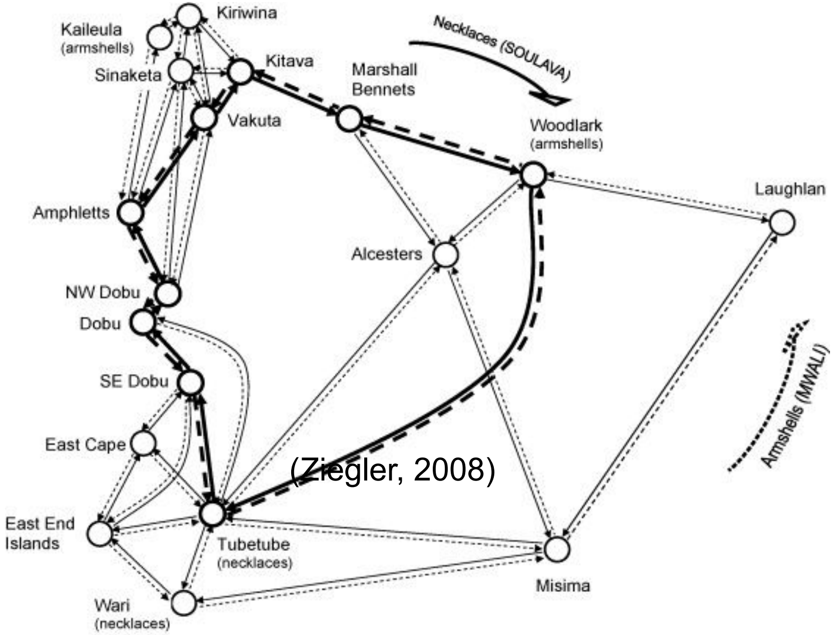
Generalized Reciprocity

A more flexible triad representation is needed to study diverse network phenomena

Example:

Systems of generalized reciprocity: Kula ring



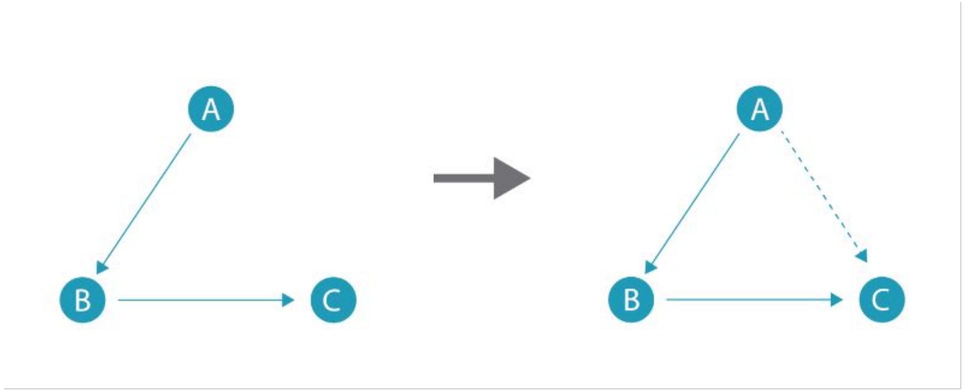


(Ziegler, 2008)

Transitivity

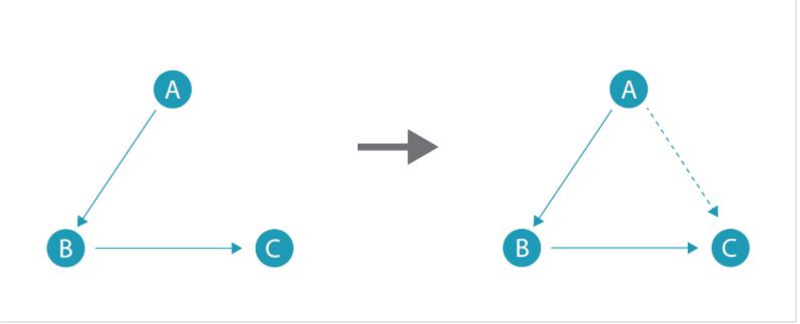
A prevalent triadic pattern in most social networks is transitivity

Triad of A, B, and C is transitive if whenever **A→B** *and* **B→C**, then **A→C**



Transitivity

Transitivity is the most basic structural representation of hierarchy and dominance orders (military, pecking order, monkey grooming)



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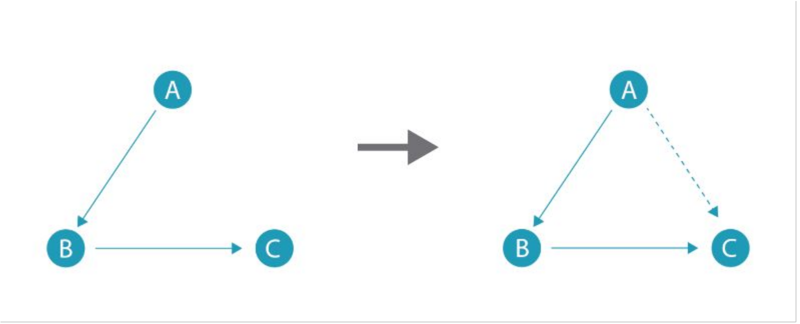
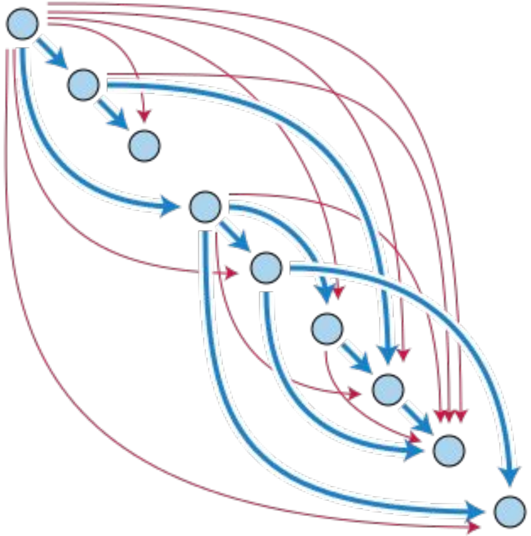


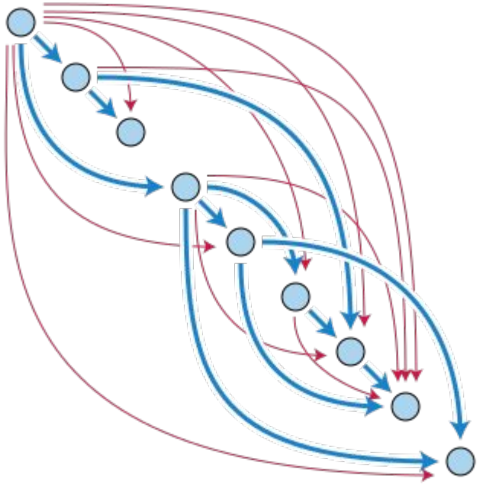


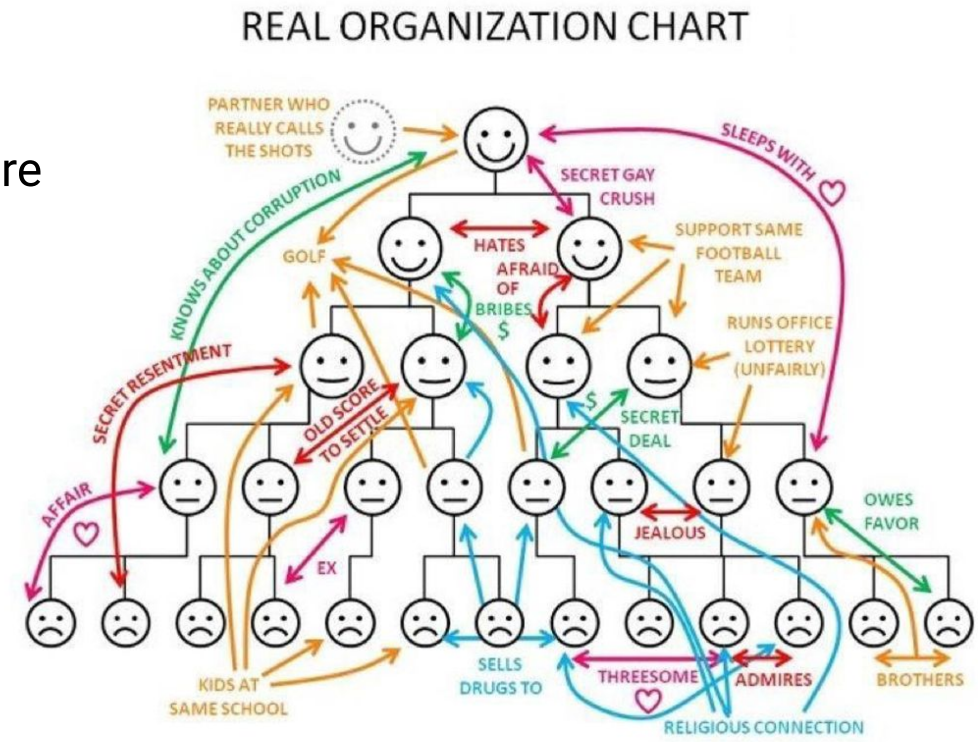
It is the building block of larger structures of hierarchy in networks

Transitivity

Transitivity is also an ideal type

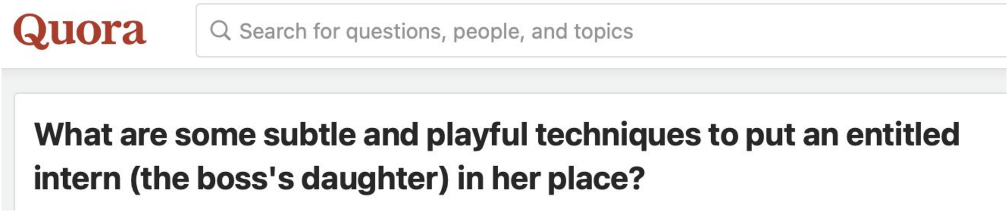
Perfectly transitive networks are rare

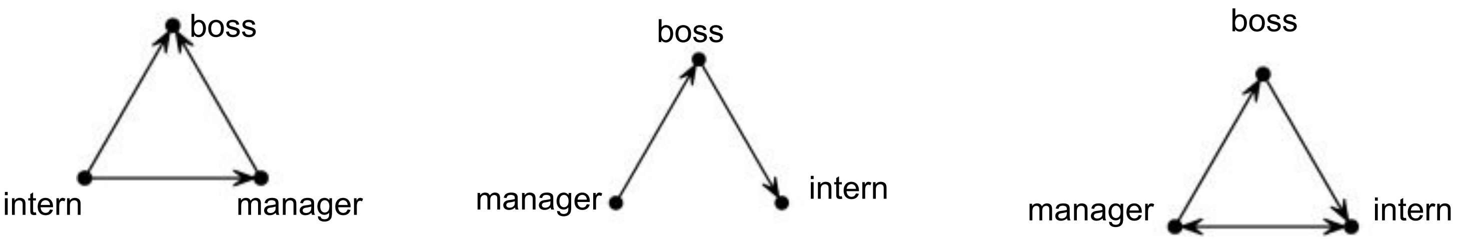




Transitivity

We know when a situation deviates from perfect transitivity





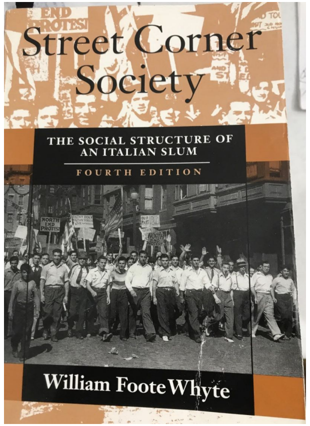
Ideal Transitivity

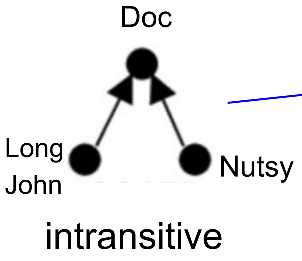
Intransitive Reality → Compromise

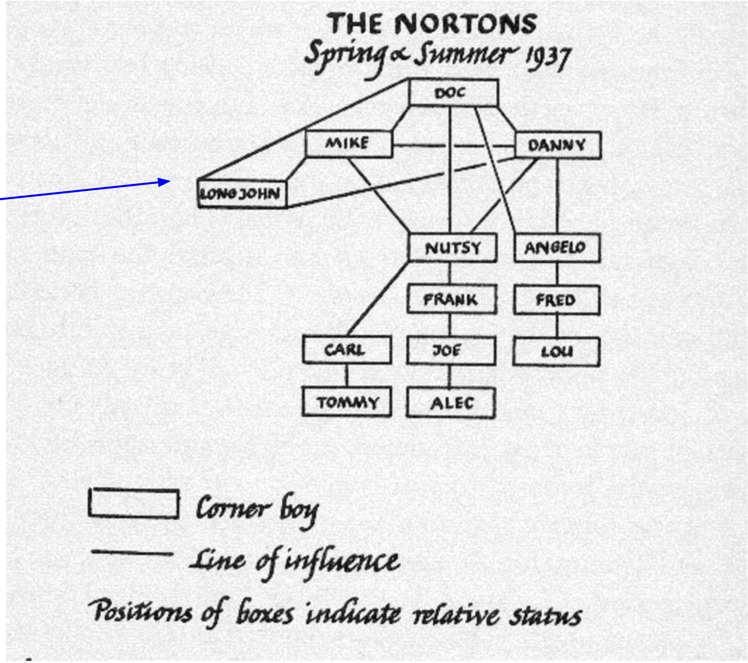
Transitivity

An individual's status tends to be fragile without transitivity

Long John is high in status because of his connections to other high status members, but without the connections to the lower ranks







Triad Census

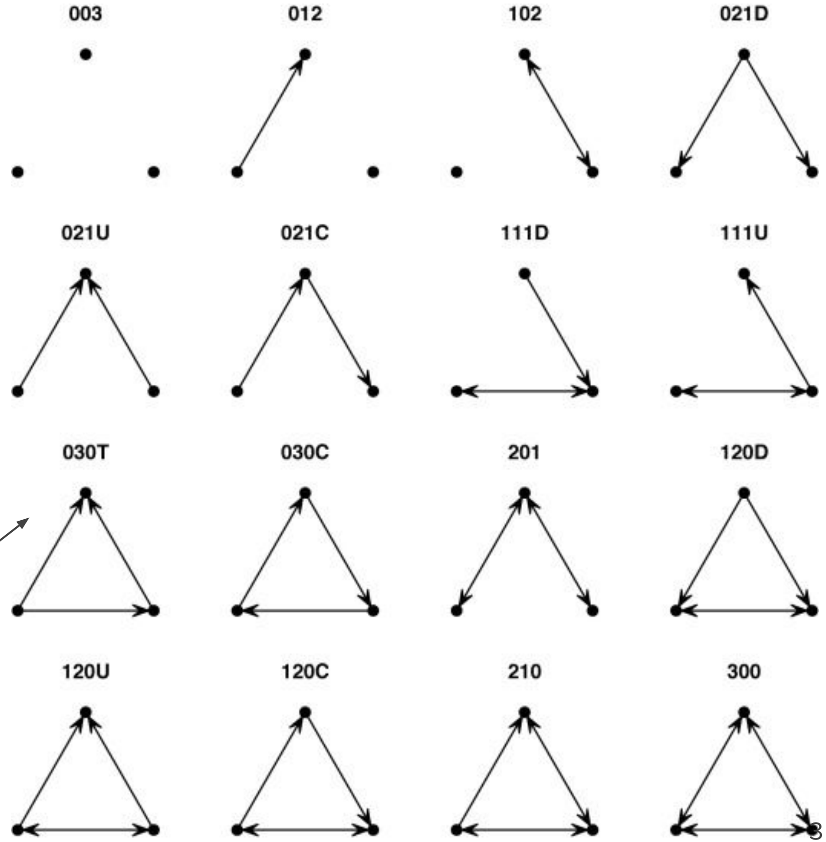
Cycles and transitive triads are part of 16 triad **isomorphism classes**

Built on combinations of dyad isomorphism classes (M, A, N)

Class names are based on the number of M, A, N dyads

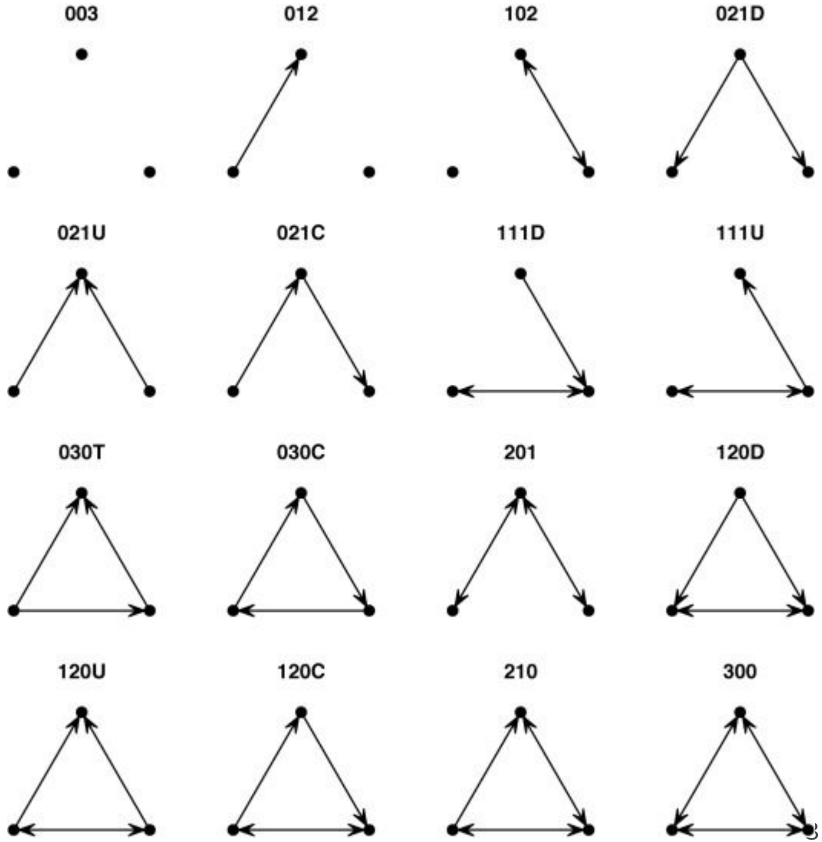
Triad census counts the frequency of these 16 isomorphism classes in a network

Mutual: 0, Asymmetric: 3, Null: 0



Triad Census

Just like the dyad census (M, A, N dyads), the triad census can give clues to the **social forces / mechanisms** that may be prevalent in a given social network

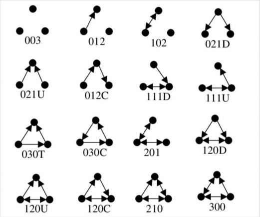


Triad Census

Just like the dyad census (M, A, N dyads), the triad census can give clues to the **social forces / mechanisms** that may be prevalent in a given social network

Example:

Networks where the 030T triads are prevalent are probably hierarchical in nature



Triad type	Triad census	Expected value	Standard deviation
003	376	320.06	9.39
012	366	416.82	14.56
102	143	171.19	9.43
021*D*	114	44.09	6.22
021*U*	34	44.09	6.22
021*C*	35	88.17	8.17
111*D*	39	73.74	7.78
111*U*	101	73.74	7.78
030*T*	23	18.17	3.86
030*C*	0	6.06	2.39
201	20	28.97	4.52
120*D*	16	7.74	2.71
120*U*	25	7.74	2.71
120*C*	9	15.48	3.74
210	23	12.38	3.25

Triad Census

We can also study what structural tendencies characterize a network by looking at the covariance / correlation between different isomorphism classes

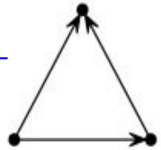
Which classes show high correlation and why?

Covariance matrix of a friendship network

	003	012	102	021D	021U	021C	111D	111U	030T	030C	201	120D	120U	120C	210	300
003	88.2															
012	-107.0	212.0														
102	-44.0	-3.24	88.9													
021D	4.71	-21.4	4.55	38.7												
021U	4.71	-21.4	4.55	-5.35	38.7											
021C	9.42	-42.9	9.11	-10.7	-10.7	66.8										
111D	7.87	-8.65	-19.6	-2.09	-2.09	-4.18	60.5									
111U	7.87	-8.65	-19.6	-2.09	-2.09	-4.18	-13.3	60.5								
030T	6.65	-5.68	3.56	-3.57	-3.57	$\boxed{-7.14}$	-1.01	-1.01	14.9							
030C	2.22	-1.89	1.19	-1.19	-1.19	-2.38	-0.34	-0.34	-1.09	-5.69						
201	3.09	7.29	-18.4	1.12	1.12	2.23	-6.02	-6.02	0.60	0.20	20.5					
120D	2.83	-0.38	-0.52	-0.68	-0.68	-1.35	-1.77	-1.77	-0.63	-0.21	-0.43	7.36				
120U	2.83	-0.38	-0.52	-0.68	-0.68	-1.35	-1.77	-1.77	-0.63	-0.21	-0.43	-0.38	7.36			
120C	5.66	-0.77	-1.04	-1.35	-1.35	-2.71	-3.54	-3.54	-1.25	-0.42	-0.86	-0.76	-0.76	14.0		
210	4.53	2.64	-4.09	-0.06	-0.06	-0.13	-3.66	-3.66	-0.17	-0.06	-3.11	-0.58	-0.58	-1.17	10.5	
300	0.57	0.74	-0.92	0.08	0.08	0.16	-0.40	-0.40	-0.03	-0.01	-0.86	-0.04	-0.04	-0.08	-0.37	1.44

021C

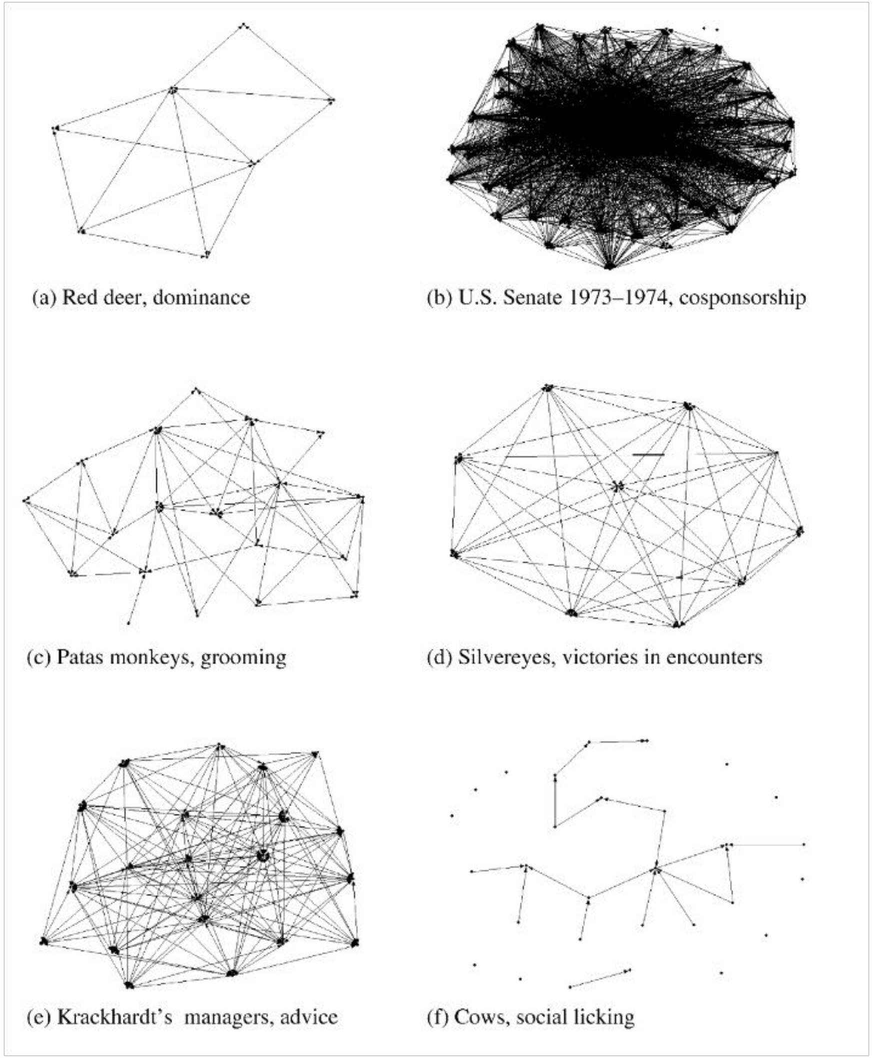
030T



Triad Census

One can gain insight about a community or social group by **comparing the distributions** of the 16 isomorphism classes across different networks

But, direct comparison of the observed isomorphism classes is problematic because networks have different size, density, and dyad distributions (M, A, N)



Triad Census

An apples-to-apples comparison involves comparing the empirical network to a random graph of the same size and same number of dyad isomorphism classes (M, A, N)

By quantifying the deviation from random, we can compare different networks through this deviation

- Interpretation: Relative to a random network, observed network deviates by X amount

random observed

Triad Type	Formula	34 Group		35 Group		44 Group		45 Group	
		Theor. (%)	Real (%)	Theor. (%)	Real (%)	Theor. (%)	Real (%)	Theor. (%)	Real (%)
003	$(1-\Delta)^6$	0.15	1.05	0.00	0.00	17.80	29.26	26.02	38.00
012	$6\Delta(1-\Delta)^5$	1.80	2.10	0.12	0.29	35.60	23.97	39.27	25.94
102	$3\Delta^2(1-\Delta)^4$	1.75	2.45	0.26	1.62	5.93	12.79	4.94	11.95
021D	$3\Delta^2(1-\Delta)^4$	1.75	9.09	0.26	0.74	5.93	6.47	4.94	5.94
021U	$3\Delta^2(1-\Delta)^4$	1.75	1.40	0.26	0.59	5.93	3.24	4.94	2.44
021C	$6\Delta^2(1-\Delta)^4$	3.49	0.00	0.52	0.15	11.87	1.91	9.88	1.06
111D	$6\Delta^3(1-\Delta)^3$	6.78	0.35	2.21	2.21	3.96	0.59	2.49	0.96
111U	$6\Delta^3(1-\Delta)^3$	6.78	12.59	2.21	4.26	3.96	11.91	2.49	7.04
030T	$6\Delta^3(1-\Delta)^3$	6.78	6.99	2.21	1.32	3.96	1.03	2.49	1.01
030C	$2\Delta^3(1-\Delta)^3$	2.26	0.00	0.74	0.15	1.32	0.00	0.83	0.00
201	$3\Delta^4(1-\Delta)^2$	6.58	2.80	4.69	5.88	0.66	4.26	0.31	2.44
120D	$3\Delta^4(1-\Delta)^2$	6.58	2.80	4.69	4.85	0.66	0.00	0.31	0.07
120U	$3\Delta^4(1-\Delta)^2$	6.58	23.08	4.69	8.09	0.66	2.06	0.31	1.50
120C	$6\Delta^4(1-\Delta)^2$	13.16	0.35	9.38	2.94	1.32	0.15	0.63	0.07
210	$6\Delta^5(1-\Delta)$	25.55	17.48	39.71	33.53	0.44	1.18	0.16	0.86
300	Δ^6	8.27	17.48	28.03	33.38	0.02	1.18	0.01	0.71

Triad Census

Limitations of triad census:

Triads are **not independent** of one another

- A change in a single arc affects the isomorphism classes of N-2 triplets

Quantification of the observed isomorphism classes is **deterministic**

- What if the observed triad distribution is one instantiation of a probabilistic tie generating mechanism?

More sophisticated **parametric statistical models** (e.g., Exponential Random Graph Models) are available

- Controls for size, density, dyad types, and other higher order subgraphs
- These models enable asking questions such as, “controlling for the number of cycles in this network, how much effect does transitivity have on tie formation?

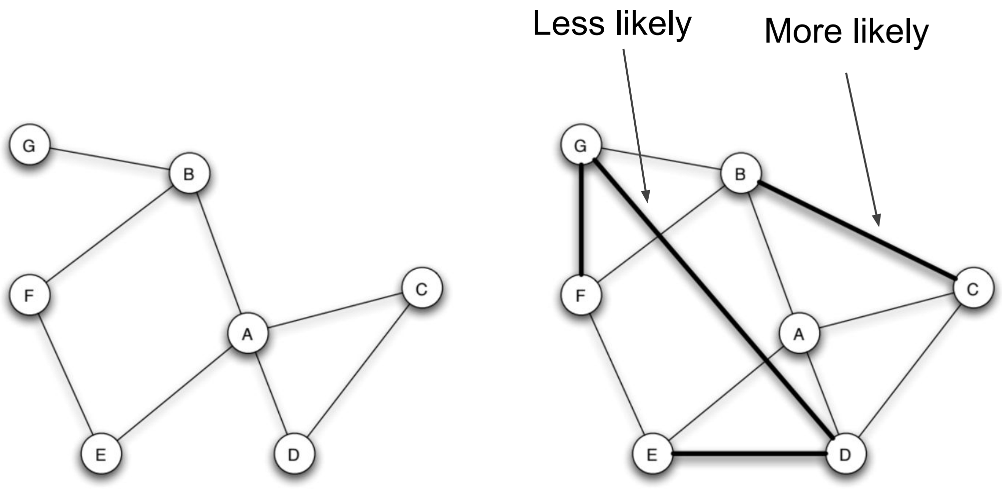
Triadic Closure and Clustering

Triadic Closure

A social network is constantly evolving

- New ties form
- Existing ties decay

In this process, **two nodes that are connected to the same set of other nodes have a higher probability of forming an edge**



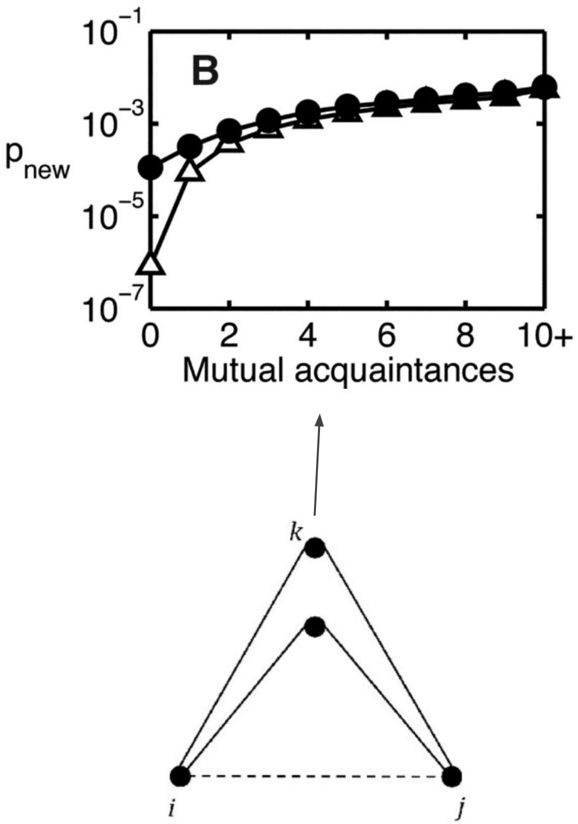
(a) *Before new edges form.* (b) *After new edges form.*

This results in a high frequency of fully connected triads in a network.

Triadic Closure

The more friends in common, the more likely a new tie forms

Email network of students, faculty, and staff at a university



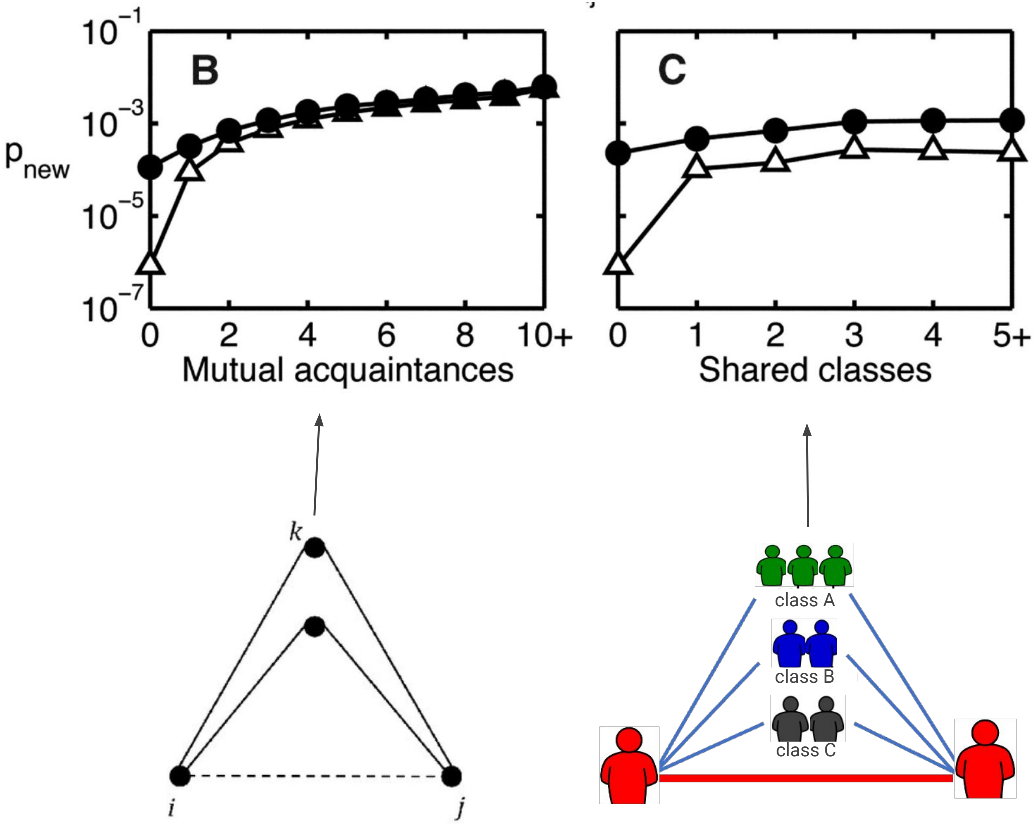
Kossinets and Watts 2006

Triadic Closure

The more friends in common, the more likely a new tie forms

This effect is stronger when the dyad also shares similar social contexts (e.g., two students overlap in multiple classes)

Email network of students, faculty, and staff at a university



Kossinets and Watts 2006

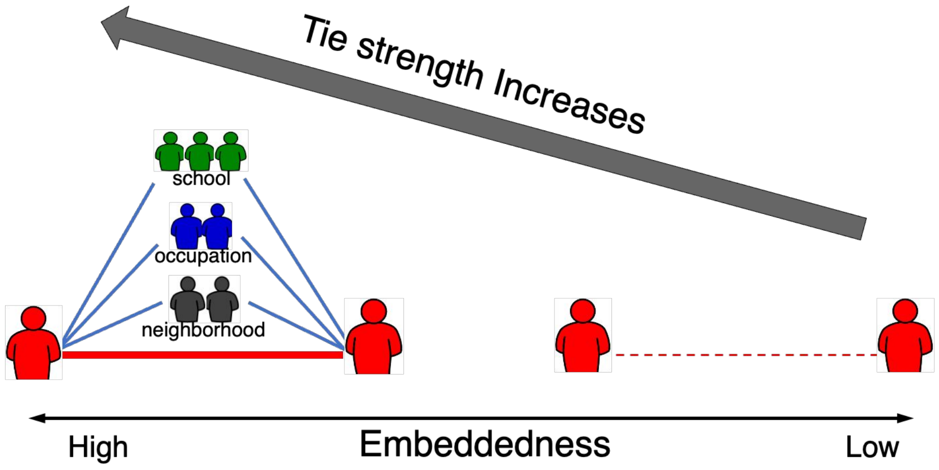
Triadic Closure

Furthermore, an *i-j* tie that closes many triads:

- is less likely to dissolve
- tends to be **stronger** (higher interaction frequency, positive emotions, reciprocity)

The *i-j* tie is highly **embedded** in common network neighbors

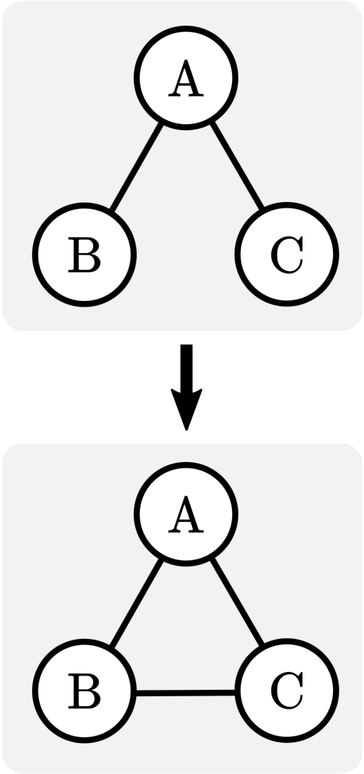
→ Recall the stabilizing force of triads that Simmel argued



Triadic Closure

Why do social networks exhibit strong triadic closure?

- **Opportunity**: If B and C each often spend time with A, they are likely to meet each other
- **Trust**: B and C can trust each other because they trust A
- **Incentives**: A introduces B to C because A believes more can be achieved if the three collaborate
- **Cognitive dissonance**: If A is good buddies with B and C, A may be distressed by the cognitive dissonance → Establish structural balance by introducing the two
- **Homophily**: All three share a common interest, so A is friends with B and C. There is a good chance B and C meet each other even without A's introduction (What a small world!)

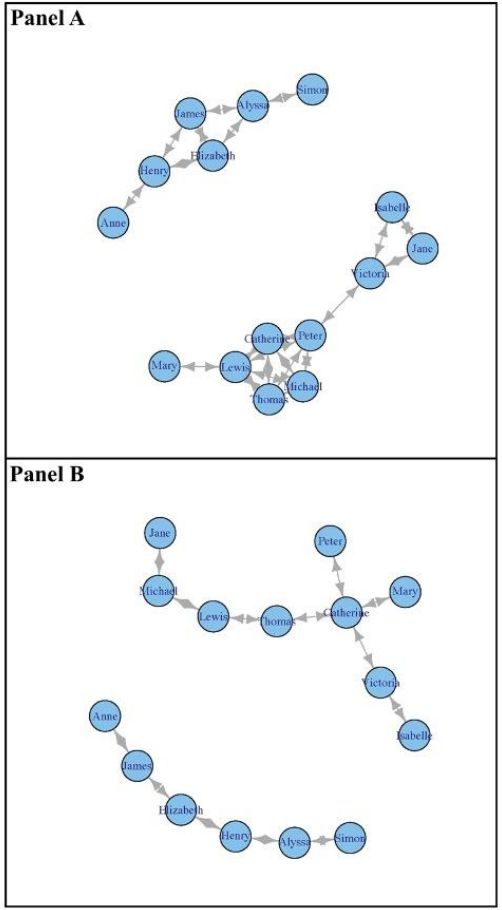


Triadic Closure

Our brain may have evolved to perceive triadic closure

People more accurately remember who is connected to whom in a network with more triadic closure

→ Triadic closure is a sort of information compression heuristic, which may have given an evolutionary advantage



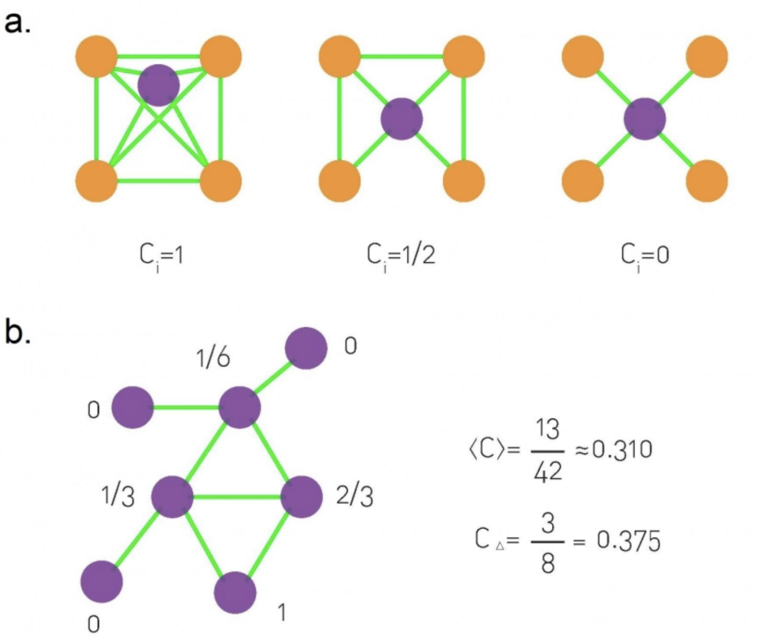
Brashears and Quintain 2015

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 (excluding ties involving *i*)

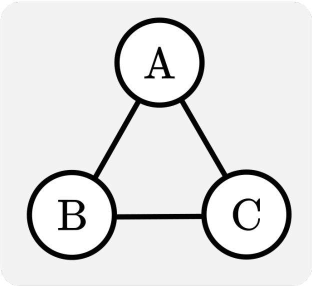
$$C_i = \frac{2L_i}{k_i(k_i - 1)}$$

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

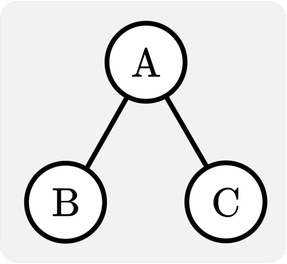
Measurement of Triadic Closure

The extent of triadic closure in a network:

- Global clustering coefficient (i.e., transitivity)



$$C_{\Delta} = \frac{3 \times Number\ Of\ Triangles}{Number\ Of\ Connected\ Triples}$$



This is the ratio of the number of closed triads to the number of open triads in a network

What do you see?

Network	Nodes (N)	Links (L)	Average path length ($\langle \ell \rangle$)	Clustering coefficient (C)
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
C. elegans brain	297	2,345	4.0	0.29
Everglades ecological food web	69	916	2.2	0.55

(Menczer et al, 2020)

High clustering in many human social networks

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(Menczer et al, 2020)

Bipartite network: links only between movies and stars

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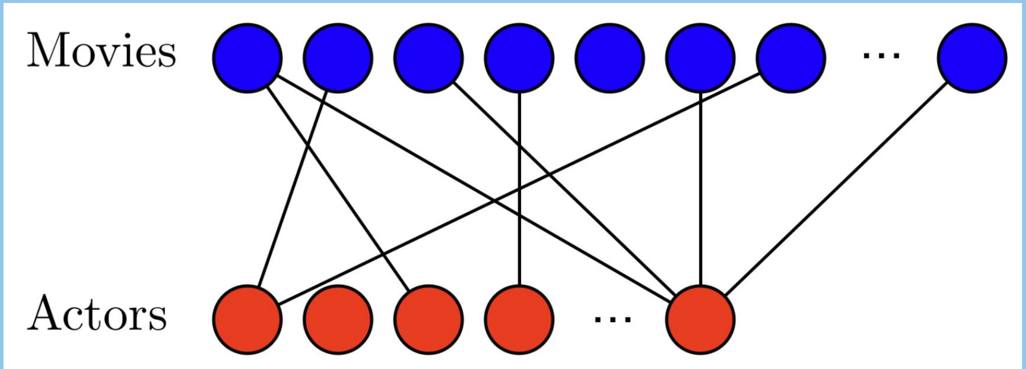

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(Menczer et al, 2020)

Retweet cascade trees look like stars (B rt A, C rt B → C rt A)

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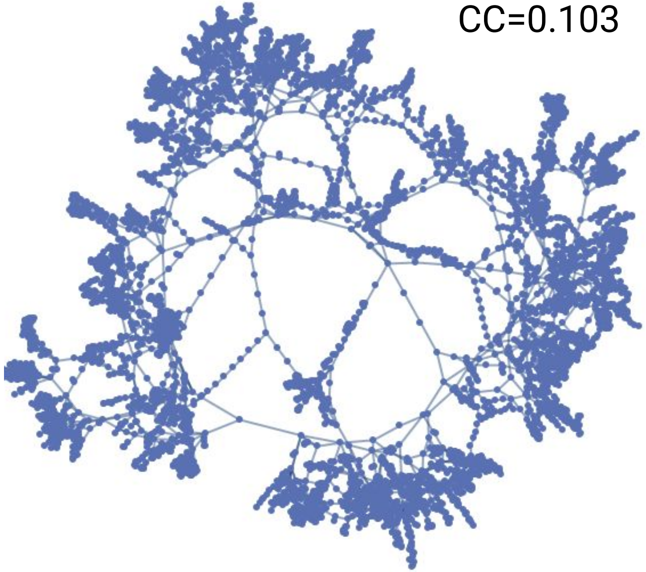
(Menczer et al, 2020)

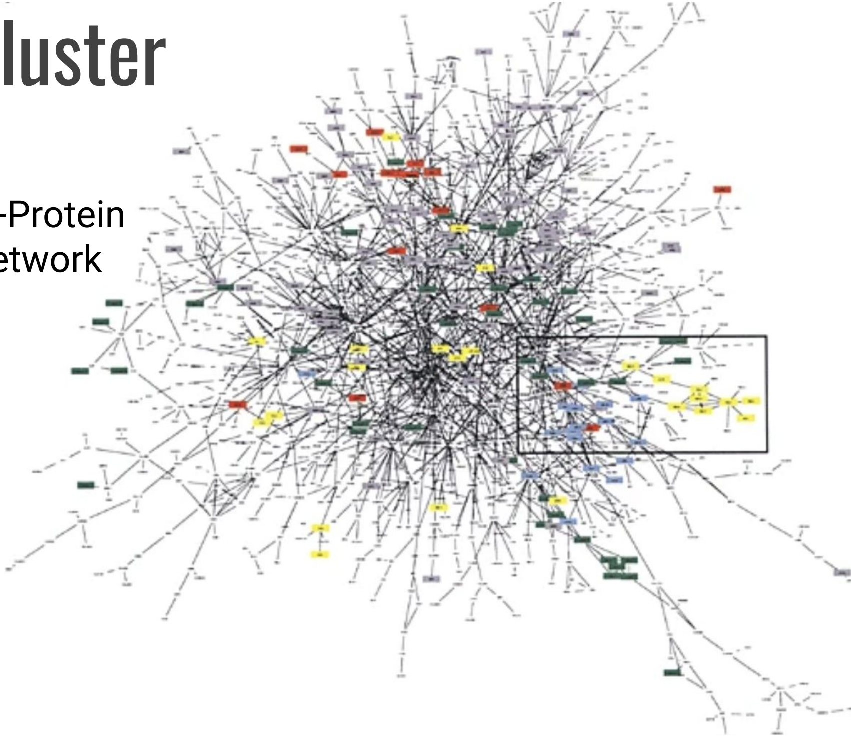
Many non-human networks don't cluster

U.S. Powergrid network

CC=0.103



Yeast Protein-Protein Interaction Network



Measure	TAP		HMS-PCI		Other data sets		
	"Small"	"Medium"	"Small"	"Medium"	Y2H	DIP	TP
Nodes n	193(15)	1,365(1,250)	99(7)	1,544(1,501)	1,870	1,788	434
Interactions I	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

Case Study: Signed Networks in Social Media

(Leskovec, Huttenlocher, & Kleinberg, CHI 2010)

Reminder: We saw signed undirected networks

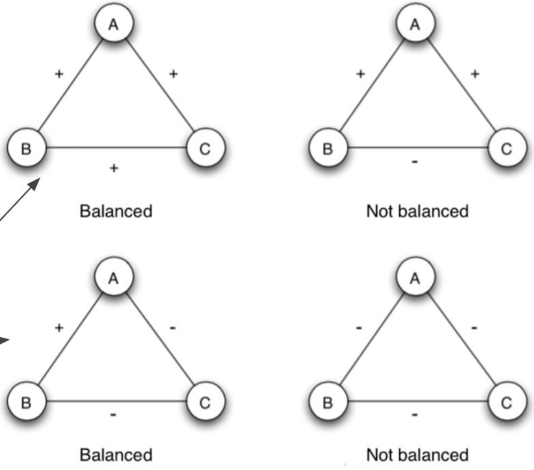
Structural Balance: Triads of Friends and Enemies

Friendships: “+”

Enemy relations: “-”

Structural balance is achieved when

- A friend of my friend is also my friend
- An enemy of my friend is my enemy



10

Reminder: And we saw unsigned directed networks

Transitivity

A prevalent triadic pattern in most social networks is transitivity

Triad of A, B, and C is transitive if whenever **A→B** *and* **B→C**, then **A→C**

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Competing theories

Structural balance theory:

- Triangles with three positive signs (three mutual friends) and those with one positive sign (two friends with a common enemy) are more plausible — and hence should be more prevalent in real networks — than triangles with two positive signs (two enemies with a common friend) or none (three mutual enemies).

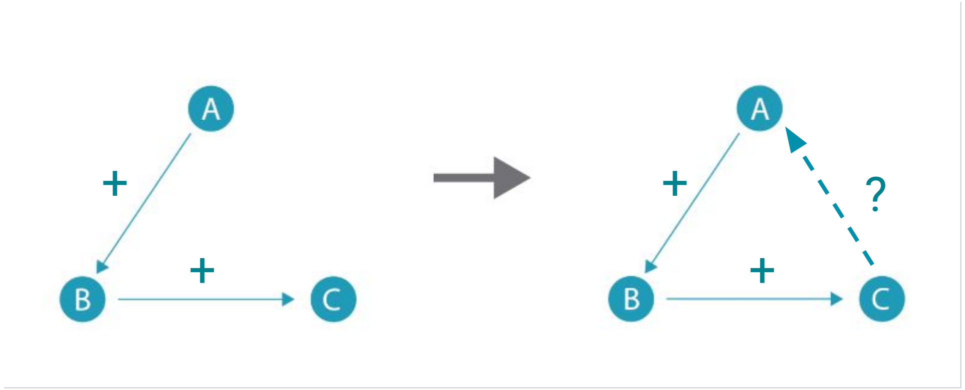
Status theory:

- A positive directed link indicates that the creator of the link views the recipient as having higher status; and a negative directed link indicates that the recipient is viewed as having lower status.

Comparing the two theories

C→A sign?

- Balance theory:
- Status theory:



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C→A sign?

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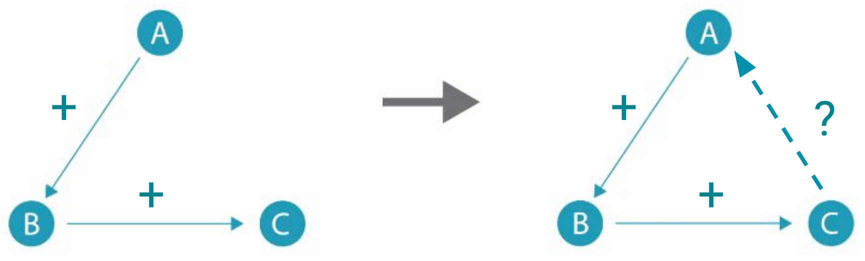
Empirical approach?



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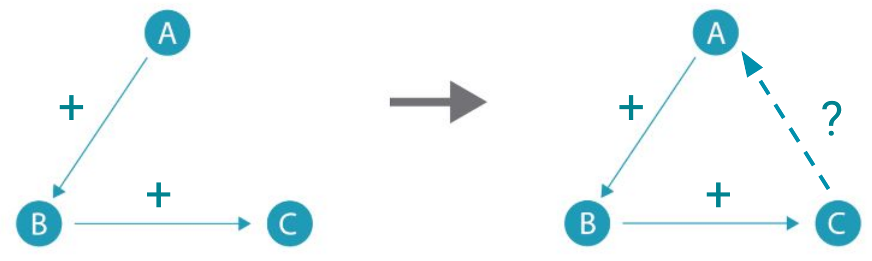


C→A sign?

- Balance theory: +
- Status theory: -

Empirical approach:

- Compute whether the observed number of triads of each type is overrepresented or underrepresented compared to chance.
- Contrast that with the predictions made by the balance and status theories.

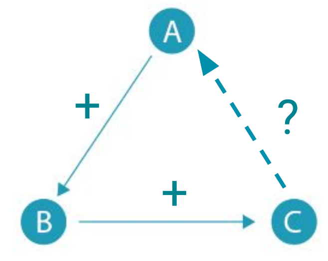
(Leskovec, Huttenlocher, & Kleinberg, CHI 2010)

Highlights

Three networks: online ratings site (trust / distrust), Slashdot discussions ("friends" and "foes"), and Wikipedia admin candidates (votes for / against).

Significant alignment between the observed network data and (weak) structural balance theory:

- triangles with exactly two + edges (two enemies with a common friend) are massively underrepresented in the data relative to chance.
- triangles with three + edges (three mutual friends) are massively overrepresented.



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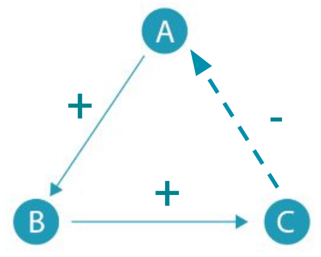

But, status theory is more effective at explaining local patterns of signed links:

- negative links C → A are massively overrepresented relative to chance, with positive links correspondingly underrepresented

Summary

A unique feature of social networks is the dynamics of triads

- Triad is the most elementary group
- Structural balance
- Transitive and cyclical triads
- Triad census
- Triadic closure
- Measures of clustering