

Plan for today:

- Discuss Homework 1
- Slota presents: Patterns of influence in a recommendation network
- Quick review (triadic closure, homophily, temporal nets)
- Strong and weak links and strong triadic closure
- Diffusive processes
- Growth models
- CODE MODE

Last class



Social network growth's
primary driver

GM: link prediction

- Homophily → selection
influence

"like attracts like"

GM: vertex classification
/labeling

- Temporal networks

→ change over time

GM: useful for evaluating methods
for the above GM problems

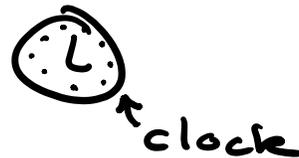
Today: strength of "ties" and diffusive processes

Strong vs. weak ties

↳ strength of links
or edge weights

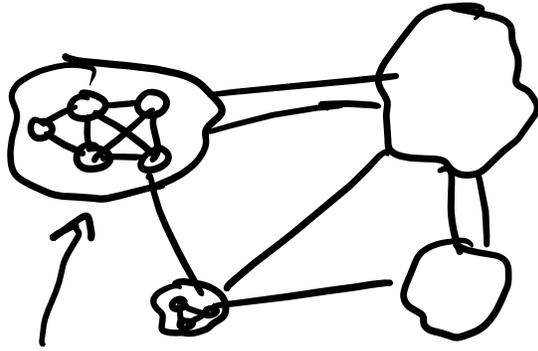
e.g., # of communications
time spent together
etc.

STORY O'CLOCK



Empirically: job seekers found
more positions through
acquaintances than close friends
(sp?)

Why? → Consider the structure
of a social network



dense subgraphs loosely connected
(community)

From this: Consider information flow
↳ diffusion

- Assume it travels via edges
- Information spreads quickly within a community
- It flows more slowly across communities

Relating back to our story:

- within a job seeker's community, they probably already have all available information
- Over time, information from other communities will reach that job seeker

And consider:

strong tie: strong connection, often within a community

weak tie: weaker connection, often between communities

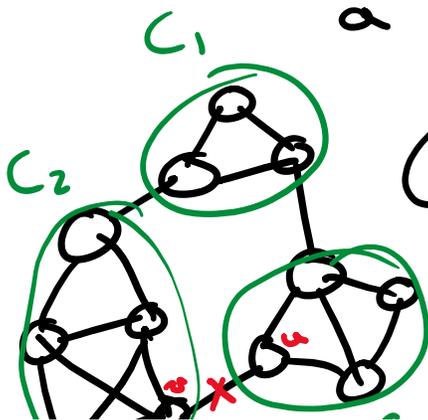
Take together: novel information often must traverse weak ties to reach new vertices

Ties and connectivity
and diffusion

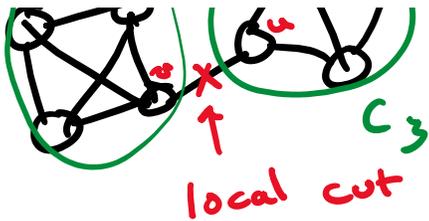
weak ties \approx cut edges
 \uparrow
related

While a weak tie is not a cut

\hookrightarrow we do have a notion of a local cut or local bridge



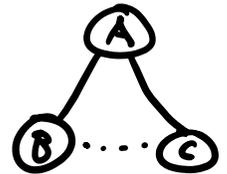
\hookrightarrow removing such an edge will increase shortest path lengths



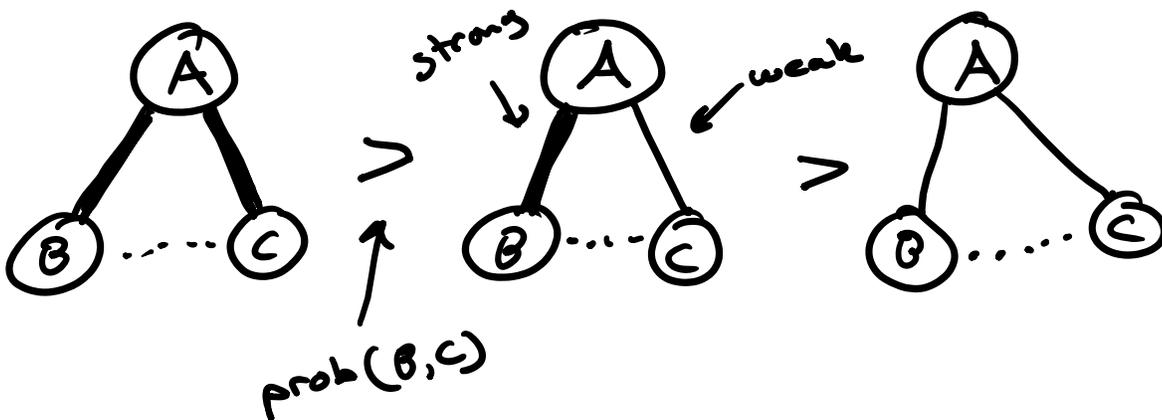
=> weak ties, local cuts, and diffusion are all related

Q: How does the strength of a connection impact triadic closure?

↳ strong triadic closure



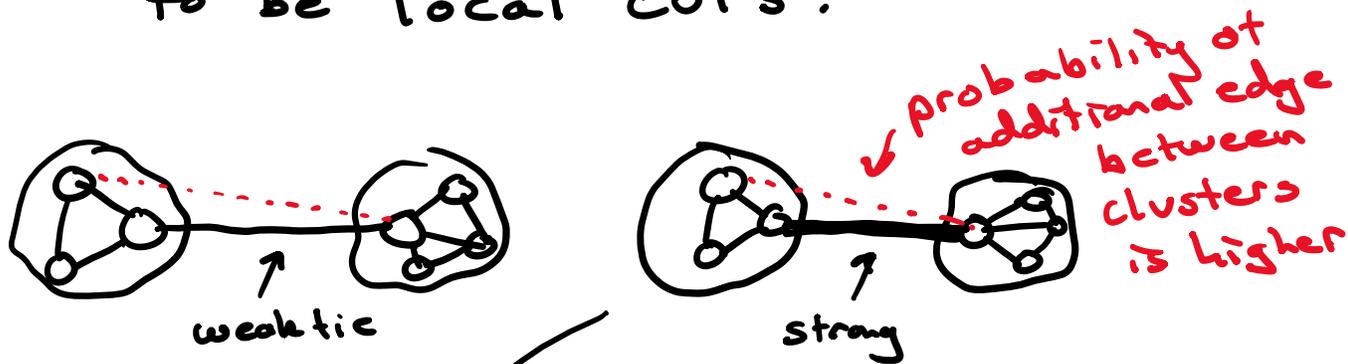
If A is connected to Bⁱ, C with strong ties, edge (B,C) is more likely arise than if A's connections were weak ties



Why are weak ties more likely to be local cuts?

...ability of...

to be local cuts?



Over time, we expect the clusters to merge

Let's experiment and observe

- consider a weighted sheep social networks

First: correlate neighborhood overlaps with tie strengths

Second: remove ties in order

strong \rightarrow weak

weak \rightarrow strong

observe connectivity impacts

Diffusive Processes

Generally: how information, data,

Generally: how information, data, etc. spreads through a network

Basic model: vertex-centric behavior
→ v updates its state based on the state of its neighbors

Complexity of this behavior is driven by how the diffusive process spreads across edges

→ updates could be heuristic, explicitly mathematically defined, some randomness, usually with some reduction over neighbors

→ small local changes can have global results ("butterfly effect")

A simple diffusive algorithm

→ label propagation algorithm

For $v \in V(G)$ ← unique vertex id
→ $id(v)$

For $v \in V(G)$ \swarrow $\dots v$
state[v] = vid(v)

while updates occur:

For $v \in V(G)$: \swarrow hash table
counts = $\{\}$

For $u \in N(v)$:

counts[state[u]] += 1

state[v] = argmax(counts)

(ties broken randomly)

Q: How are diffusion and network ties related:

→ cutting weak ties increases avg. shortest path lengths, decreases spread rate of diffusion

↳ disconnecting a graph can halt diffusion

Think: resilience, epidemiology

Growth Models

Note: our observations depend on some underlying growth

on same underlying growth mechanism

(triadic closure on social nets)

Many networks also grow via preferential attachment

→ high degree vertices are more likely to gain new connections

aka "rich get richer"

Story #2: Slota wins an award

↳ RPI gave me an award for winning an award

↳ RPI gave me tenure in part b/c of awards

↳ RPI gave me another award for getting tenure

→ G-M: high degree vertices are high degree for same basic underlying reason

underlying reason

Barabasi-Albert Model:

Start with some V vertices

add a new vertex v and attach
it to an existing vertex u with

$$\text{probability } p_{v,u} = \frac{d(u)}{\sum_{i \in V(G)} d(i)}$$

explains degree skew and
other "power law-ish" properties