



INDIAN INSTITUTE OF TECHNOLOGY, DELHI

ELL-880

Social Network Analysis

Submitted To:

Amit Nanavati
Sougata Mukherjea

Submitted By :
Ajinkya Wasnik(2018EET2569)

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1 2 Pivotal Graph: General scheme, Algorithm and example graph.

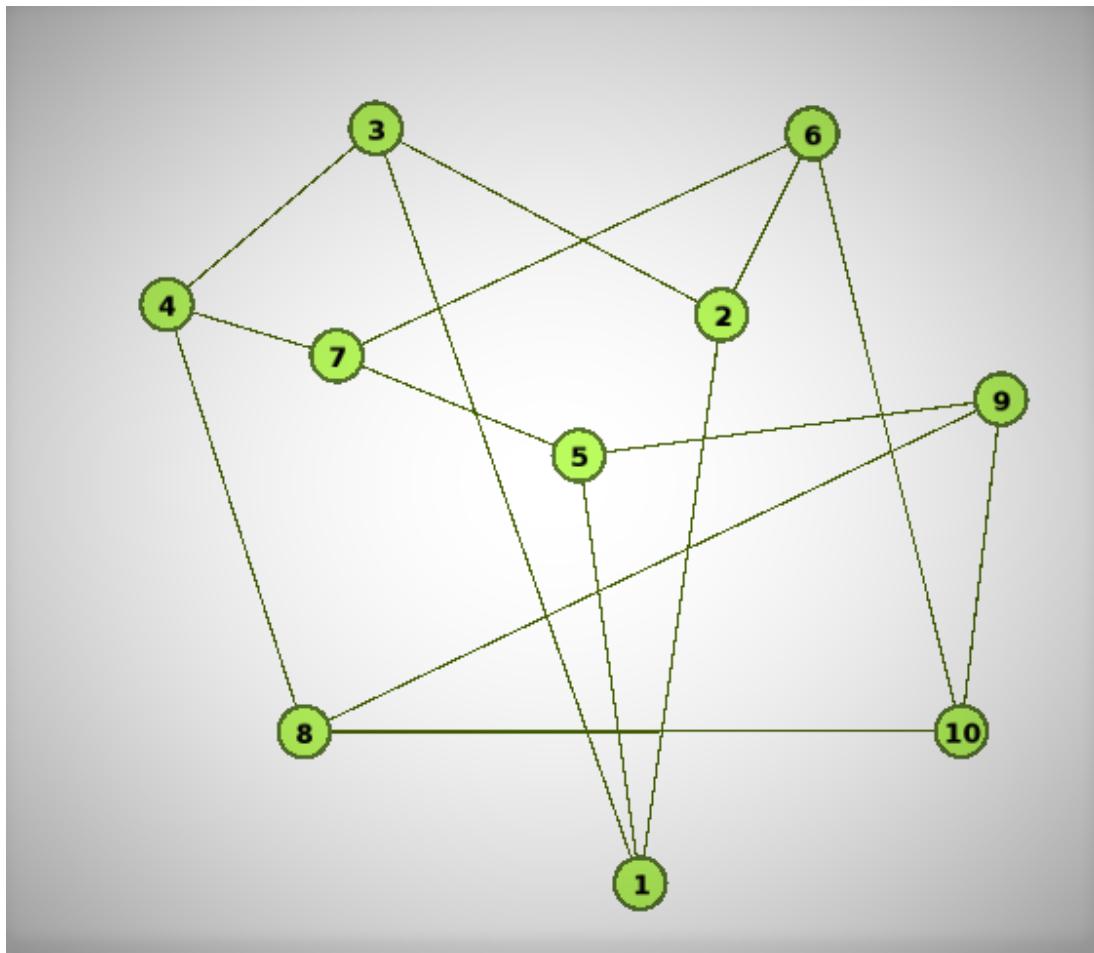


fig: 2-pivotal graph with atleast 2 pairs of neighbours.

	1	2	3	4	5	6	7	8	9	10
Pair 1	(2,5)	(1,6)	(1,4)	(3,7)	(1,7)	(2,7)	(4,5)	(4,9)	(5,8)	(6,8)
Pair 2	(3,5)	(3,6)	(2,4)	(3,8)	(1,9)	(2,10)	(4,6)	(4,10)	(5,10)	(6,9)

fig: Table for pairs for each pivotal node.

ALGORITHM: K-PIVOTAL GRAPH

BEGIN:

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Start with 1 node.
LOOP while next V[ i ] exist:
  IF V[ i ] has k+1 neighbours then
    WHILE k pairs for V[ i ] are NOT formed:
      (pi ,pj):=take sequentially from i=1 a possible pair
      IF (pi ,pj) not in PLIST then
        add (pi ,pj) to PLIST at i row
      ENDIF
    END
  ELSE
    IF (ADDEDGE())!=( pi ,pj) for any i and j) then
      add that edge
    ELSE
      add new vertex to the graph
    END.
  END.
**PLIST is the list for storing k-Pairs of the graph against
the respective pivot node(shown in table for drawn 2-pivotal graph).
**(pi ,pj): here pi is the first element of pair and pj is the
second element of pair

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2 Information Cascade Model: Real life parameter and probabilities.

In real life there are many more parameters which are essential for the information cascade to work well and hold true.

Three ingredients were considered in the model:

- A) STATES OF THE WORLD: Good or Bad(G/B)
- B) PAYOFFs: Each individual receives a payoff based on her decision to accept or reject the option.
- C) SIGNALS(S): Either High or Low(H/L)

Here we came up with some assumptions for the model & they were that:

- i) There is a decision to be made
- ii) People make the decision sequentially , and each person can observe the choices made by those who acted earlier .
- iii) Each person has some private information that helps guide their decision .
- iv) A person cant directly observe the private information that other people know, but he or she can make inferences about this private information from what they do.

But all above need not hold in real life .

> Like the private information which is guiding people need not be unknown, for eg. In the ball experiment if someone cheats and get a peek at other person withdrawn ball or someone knowingly shows colour of his ball to class .

> Also if other person watches specific movie by considering his private information of rating from some website usually IMDb in real life but that makes people private information as common . (unknowingly)

> Choices & Mood are also really underrated parameters which were missed out completely .

> Mood drives people no matter how rational they want to think .

> Consider Restaurant example where some person goes for lunch in

restaurant A while he see that there is a rush in restaurant B where private info is that he read some gmaps reviews. Point to note is if the person wished to have Italian dish and restaurant A doesnt have Italian menu then he anyway wont follow cascade model, no matter what no. of people go to A.

> Also if someone wishes to have some personal time with his dear ones he would definitely prefer the one with less rush.

> Its not also always about choice but its also about coupons. Nowadays no mat

>>>So, the Choice & Mood parameters played a major role in the decision which were firm enough for not letting the person get influenced.

INDIVIDUAL DECISION MULTIPLE SIGNAL

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Signals	states	
	B	G
L	q	1-q
H	1-q	q

So we consider choice/mood any parameter along with the signal.

→ High signal along the choice & mood combination would eventually result in the prob. considered.

So we will make similar changes into the individual decision & multiple signals.

→ Signal will be a private info glued along choice of person which is intrinsic & hard to change.

for ex: If person loves hard music over romantic you'll always prefer your choice

1. Individual decision

lets replace 'H' with $(C \cap H)$

Now changes would be immediately reflected.

lets name $(C \cap H)$ with new variable (mood).

$$\begin{aligned}
 R(G|M) &= \frac{P_G(G \cap M)}{P_G(M)} \\
 &= \frac{P_G(G) P_G(M|G)}{P_G(M)} \\
 &= \frac{R(G) P_G(M|G)}{P_G(G) P_G(M|G) + P_G(B) P_G(M|B)} \\
 &= \frac{P_G(G) P_G(M|G)}{P_G(G) P_G(H \cap C|G) + P_G(B) P_G(H \cap C|B)} \\
 &= \frac{pq}{pq + (1-p)(1-q)} \\
 &> p \quad (\because pq + (1-p)(1-q) < pq + (1-p)q = q)
 \end{aligned}$$

value $R(G) = p$; $P_G(B) = 1-p$
 $P_G(H \cap C|G) = q$; $P_G(H \cap C|B) = 1-q$.

2. Multiple Signals

Important step as we have to understand how people make use of decision sequences of other people, i.e. how an individual should use the evidence of multiple signals.

So

$$\Pr[S] = \Pr[G]\Pr[S|G] + \Pr[B]\cdot\Pr[S|B]$$

$$= pq^a(1-q)^b + (1-p)(1-q)^a q^b$$

where we assume both high signal and choice are satisfied 'a' times and are not followed 'b' times.

$$\Pr[S|G] = q^a(1-q)^b$$

$$\Pr[G|S] = \frac{pq^a(1-q)^b}{pq^a(1-q)^b + (1-p)(1-q)^a q^b}$$

Solving already, we can reduce denominator to $q^a(1-q)^b$

$$\text{So it reduces } \Pr[G|S] = \frac{\cancel{pq^a(1-q)^b}}{\cancel{q^a(1-q)^b}}$$

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