Diffusion of Microfinance Final Project

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1 Final Project

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1.1 Network Data Description

The network we chose for our project comprises socio-centric data collected from a village in rural Karnataka, India. Sociocentric studies focus on a small population and attempt to ascertain all of the social relationships within a set of interconnected individuals (Marin and Wellman, 2011). For large-scale socio-centric data collection efforts, the most practical means of eliciting the names of social contacts is administering surveys distributed uniformly to the entire population (Burt, 1984; Marin, 2004).

In the Karnataka data, information was collected via a survey as part of a study to understand the network diffusion of microfinance. The microfinance institution Bharatha Swamukti Samsthe (BSS) relies on word-of-mouth communication to reach potential borrowers. The researchers collected the network data 6 months before the BSS's entry into the village. The individual survey collected social network data, asking participants (egos) the name of those people with whom they have social connections (alters) along 12 dimensions. This kind of question is called a "name generator," and they represent the nodes in our network. There are 110 nodes in our network.

The purpose of our project is to analyze the characteristics of the networks elicited by 12 different name generators. Name generator questions included interactive (people with whom an ego interacts during the day); role relation (specific relationships such as spouse or mother), and exchange ties (people with whom an ego engages in reciprocal service provisions such as borrowing and lending money). The following questions were used to form the edges in our directed graph, and there are 736 edges in our network:

(1) Talk to: Name the 4 non-relatives whom you speak to the most.
(2) Visit their home: In your free time, whose house do you visit?
(3) Invite home: Who visits your house in his or her free time?
(4) Borrow rice from: If you needed to borrow kerosene or rice, to whom would you go?
(5) Lend rice to: Who would come to you if he/she needed to borrow kerosene or rice?
(6) Borrow money from: If you suddenly needed to borrow 50 Rupees for a day, whom would you ask? (This represents roughly one days wages in these villages).
(7) Lend money to: Who do you trust enough that if he/she needed to borrow 50 Rupees for a day you would lend it the him/her?
(8) Give advice to: Who comes to you for advice?
(9) Take advice from: If you had to make a difficult personal decision, whom would you ask for advice?

(10) Help during emergency: If you had a medical emergency and were alone at home whom would you ask for help in getting to a hospital?
(11) Related to: Name any close relatives, aside those in this household, who also live in this village?
(12) Go to temple with: Do you visit temple/mosque/church? Do you go with anyone else? What are the names of these people?

Because an edge is formed if either of those relations exixt between the nodes in our sociocentric data, our network is an "or type" network.

1.1.1 Importing packages

[2]:
```
import numpy as np
import networkx as nx
import pandas as pd
import matplotlib.pyplot as plt
```

1.1.2 Import network data

[3]:
```
MF_0 = np.load("MF_0.npy")
MF_1 = np.load("MF_1.npy")
MF_2 = np.load("MF_2.npy")
MF_3 = np.load("MF_3.npy")
MF_4 = np.load("MF_4.npy")
MF_5 = np.load("MF_5.npy")
MF_6 = np.load("MF_6.npy")
MF_7 = np.load("MF_7.npy")
MF_8 = np.load("MF_8.npy")
MF_9 = np.load("MF_9.npy")
MF_10 = np.load("MF_10.npy")
MF_11 = np.load("MF_11.npy")
Gender = pd.read_csv("MF_gender.csv")
Caste = pd.read_csv("MF_caste.csv")
Age = pd.read_csv("MF_age.csv")
# The Or network that I will most likely be using:
MF_OR = np.load("MF_OR.npy")
```

1.1.3 1. Exploring the data

Number of edges, nodes, whether graph is connected, inspecting components

[4]:
```
#Number of edges:
num_edges = np.sum(np.sum(MF_OR, axis = 0))
print("There are", num_edges,"edges in the OR network")
#Numebr of nodes:
num_nodes = len(MF_OR)
print("There are", num_nodes, "nodes in the OR network")
```

```
There are 736.0 edges in the OR network
There are 110 nodes in the OR network
```

[5]:
```
Or_G_undir = nx.to_networkx_graph(MF_OR)
print("Is the OR network connected?", nx.is_connected(Or_G_undir))
```

```
Is the OR network connected? False
```

[6]:
```
components = list(nx.connected_components(Or_G_undir))
print("Here are the different components:", components)
```

```
Here are the different components: [{0, 1, 2, 3, 4, 5, 6, 7, 12, 13, 14, 15, 16,
17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36,
37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56,
57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76,
77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96,
97, 98, 99, 100, 101, 102, 103, 104, 105, 106, 107, 108, 109}, {8, 9, 10, 11}]
```

It appears that all the nodes except for 8, 9, 10, and 11 are one component, and the rest of the nodes are another component; hence, the network is disconnected.

It's interesting that in a village, four people who form their own component are completly disconnected from any other person in the small village.

Exploring the anomalous nodes' metadata (nodes 8, 9, 10, 11):

[7]:
```
print("8 has gender value", Gender.iloc[8][0])
print("9 has gender value", Gender.iloc[9][0])
print("10 has gender value", Gender.iloc[10][0])
print("11 has gender value", Gender.iloc[11][0])
# two men, two women

print("8 is age", Age.iloc[8][0])
print("9 is age", Age.iloc[9][0])
print("10 is age", Age.iloc[10][0])
print("11 is age", Age.iloc[11][0])
#ages 40, 30, 56 and 40

print("8 has caste value", Caste.iloc[8][0])
print("9 has caste value", Caste.iloc[9][0])
print("10 has caste value", Caste.iloc[10][0])
print("11 has caste value", Caste.iloc[11][0])
#8,9 are Scheduled Class, 10,11 are OBC
```

```
8 has gender value 1
9 has gender value 2
10 has gender value 1
11 has gender value 2
8 is age 40
9 is age 30
10 is age 56
11 is age 40
8 has caste value 1
```

```
9 has caste value 1
10 has caste value 0
11 has caste value 0
```

The potential explanation for why nodes 8, 9, 10, and 11 are isolated may lie behind the caste system in India. Those respondents identify themselves as members of lower castes, including Scheduled Castes (SCs) and Other Backward Classes (OBCs). Nodes 8 and 9 belong to the Scheduled Castes (often known as Dalits, or historically by the pejorative term "untouchables"), while nodes 10 and 11 are members of Other Backward Classes.

Caste segregation remains prevalent in India. For example, a substantial share of Brahmins says they would not be willing to accept a person who belongs to a Scheduled Caste as a neighbor. Indians conduct their social lives primarily within caste hierarchies, with a majority of Indians say that their close friends are mostly members of their caste. This explains why nodes 8,9,10,11 form their connected component.

Our prediction at this time is that 8,9 and 10,11 are couples that live isolated from the rest of their tribe.

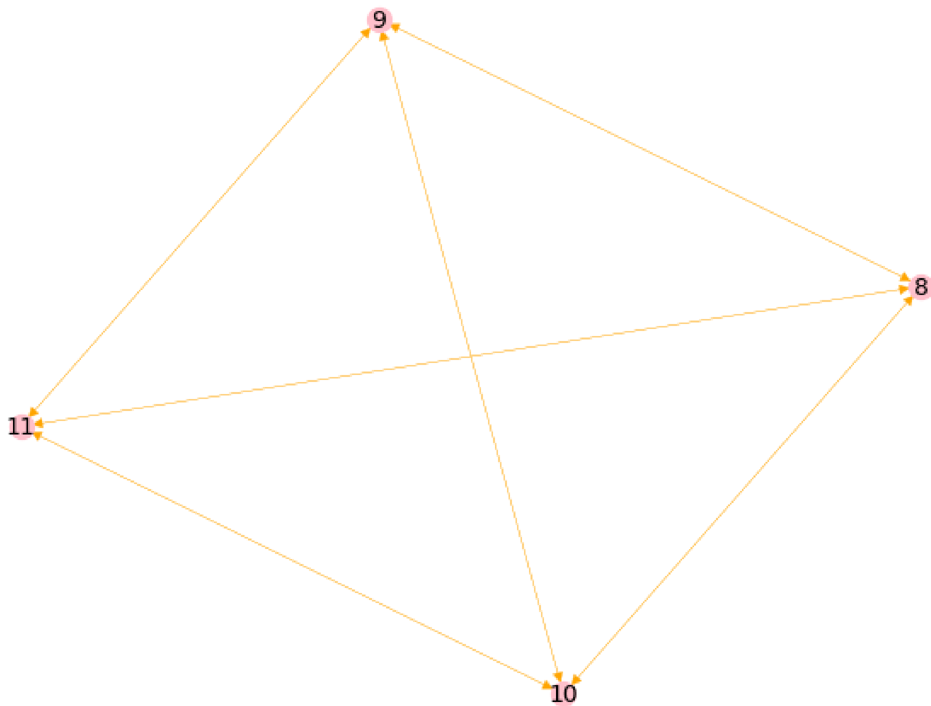
Within the smaller relation data, are these four ever split into a smaller subgroup?

[8]:
```
#Borrow money?
MF_0_G = nx.to_networkx_graph(MF_0)
components_0 = list(nx.connected_components(MF_0_G))
# In this smaller network, {8, 9, 10, 11} are their own component
#Get advice?
MF_1_G = nx.to_networkx_graph(MF_1)
components_1 = list(nx.connected_components(MF_1_G))
#Yes
#Borrow material goods?
MF_3_G = nx.to_networkx_graph(MF_3)
components_3 = list(nx.connected_components(MF_3_G))
#Yes
#Kin?
MF_8_G = nx.to_networkx_graph(MF_8)
components_8 = list(nx.connected_components(MF_8_G))
#Yes, they are related to just each other and nobody else
#non-relative socializing:
MF_7_G = nx.to_networkx_graph(MF_7)
components_7 = list(nx.connected_components(MF_7_G))
#Yes...???
```

Suprisingly enough, all four nodes continue to be their own subgroup rather than splitting when name non-relative community members with whom they socialize. Since they all named each other as kin this seems untrue. This leads us to believe that the cast devide is behind the division or this is an error in the data collection. It's possible that this family didn't want to take the time in filling out the survey, maybe the head of the house filled it out for all members and did it incorrectly.

[10]:
```
Or_G = nx.to_networkx_graph(MF_x_G, create_using = nx.DiGraph) #x is the␣
↪relation being viewed (0,1,2.. etc.)
```

```
Family = nx.subgraph(Or_G, [8,9,10,11])
nx.draw(Family, node_color='pink', node_size=100, edge_color='orange', width =␣
↪0.2, with_labels=True, font_size = 10)
#all the nodes are mutual
```



Additionally, as seen in the network graph above, these four mutually relate to one other for every sub-relation no matter what, further proving that this is a data collection issue.

1.1.4 2. Creating an adjacency matrix

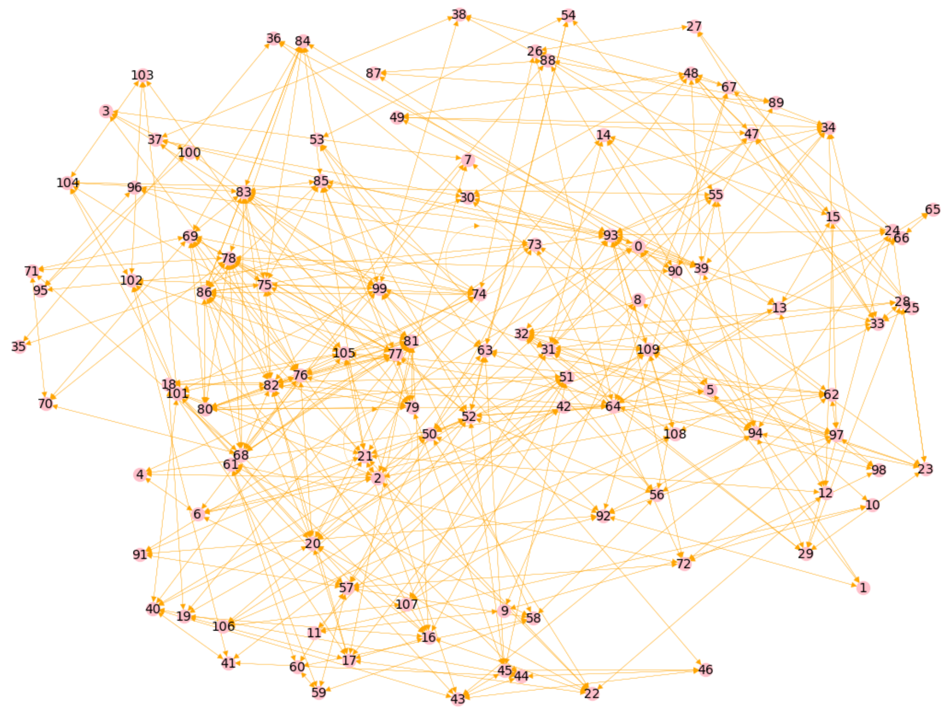
[11]:
```
#print(MF_OR): Only gives truncated version of adjacency matrix
#np.shape(MF_OR): The array is 110x110 so maybe we prefer the truncated version
#list(MF_OR): Returns full matrix, but it's quite large and not visually helpful
```

1.1.5 3. Plotting the network

***Directed network**

[12]:
```
Or_G = nx.to_networkx_graph(MF_OR, create_using = nx.DiGraph)
pos = nx.spring_layout(Or_G, k=1)
plt.figure(figsize = (12,9) )
```

```python
nx.draw(Or_G, pos, node_color='pink', node_size=100, edge_color='orange', width
↪= 0.2, with_labels=True, font_size = 10)
```



1.1.6 4. Finding the central most nodes

[13]:
```python
deg_cen = nx.degree_centrality(Or_G)
close_cen = nx.closeness_centrality(Or_G)
eig_cen = nx.eigenvector_centrality(Or_G)
betw_cen = nx.betweenness_centrality(Or_G)

print('The person with highest degree centrality is', max(deg_cen, key=lambda
↪key: deg_cen[key]))
print('The person with highest closeness centrality is', max(close_cen,
↪key=lambda key: close_cen[key]))
print('The person with highest eigenvector centrality is', max(eig_cen,
↪key=lambda key: eig_cen[key]))
print('The person with highest betweenness centrality is', max(betw_cen,
↪key=lambda key: betw_cen[key]))
```

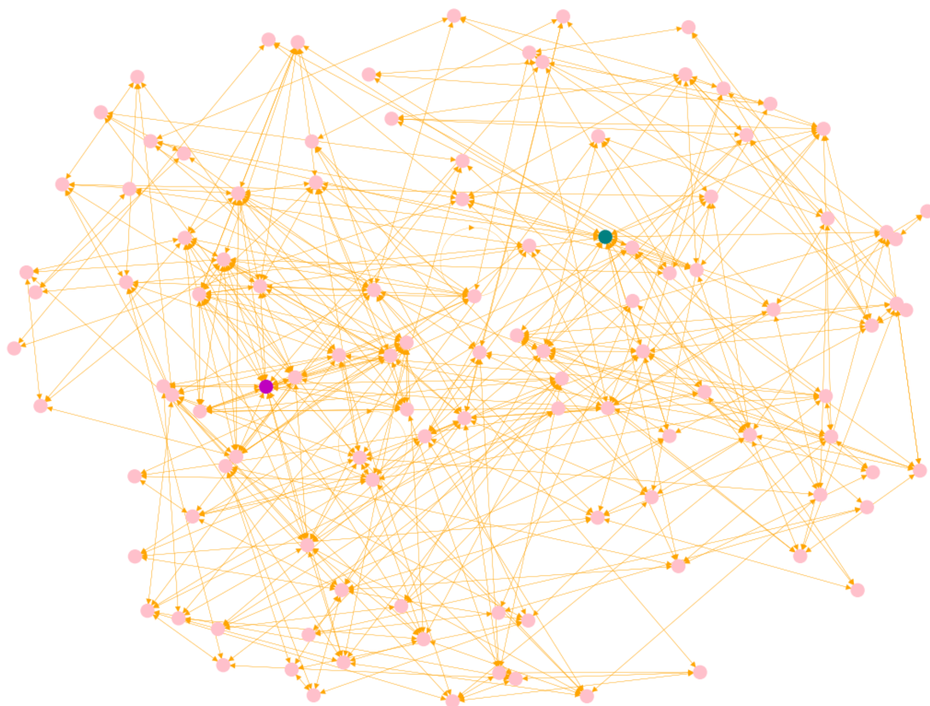
```
The person with highest degree centrality is 82
The person with highest closeness centrality is 93
```

```
The person with highest eigenvector centrality is 82
The person with highest betweenness centrality is 93
```

Changing the color of each most central node

[14]:
```
colors = ['pink'] * len(MF_OR)
colors[82] = 'm' # node 82 had the highest degree and eigenvector centrality
colors[93] = 'teal' # node 93 had the highest closeness and betweenness␣
↪centrality
```

[15]:
```
plt.figure(figsize = (12,9) )
nx.draw(Or_G, pos, node_color=colors, node_size=100, edge_color='orange', width␣
↪= 0.2, with_labels=False)
```



In this dataset, two nodes: 82 and 93 are considered the most central, each with two measures of centrality considering it as the node of highest centrality.

1.1.7 5. Finding and plotting communities in the network

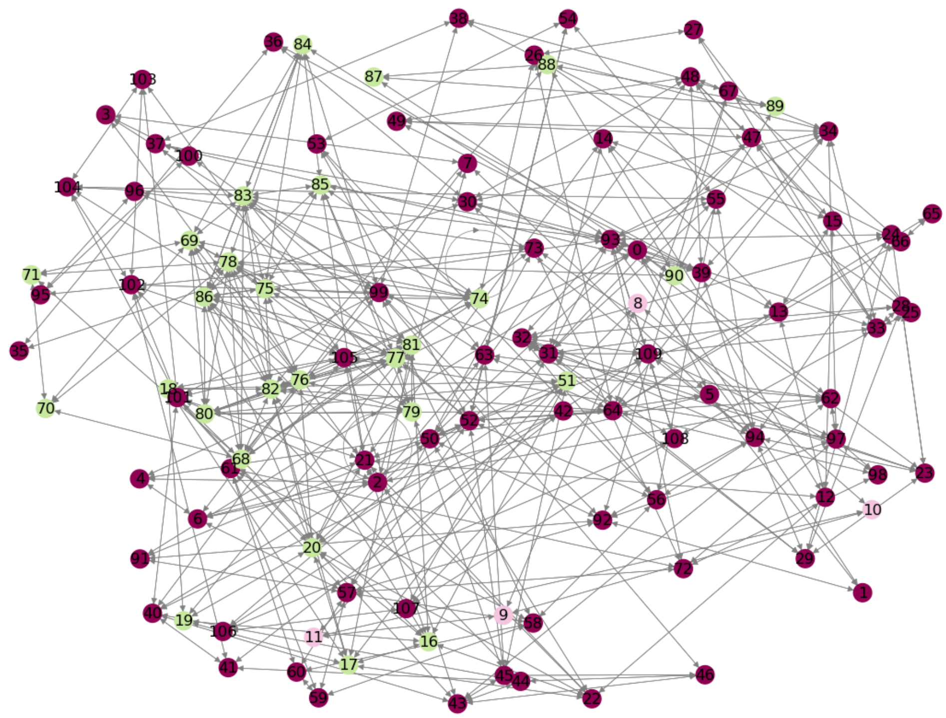
Using the Girvan Newman algorithm

[16]:
```
comm = nx.algorithms.community.girvan_newman(Or_G)
gn_communities = tuple(sorted(c) for c in next(comm))
```

```python
# plotting communities function:
import matplotlib.cm as cmx
def Plot_Comm(Network, C, position = None):
    cmap = cmx.get_cmap(name='PiYG')
    N = len(Network.nodes())
    K = len(C)
    color_map = ['k']*N
    for i in range(K):
        for j in range(len(C[i])):
            color_map[ C[i][j] ] = cmap(i/K)
    if position is None:
        pos = nx.spring_layout(Network, k=0.25,iterations=20)
    else:
        pos = position
    fig = plt.figure()
    plt.figure(figsize = (12,9) )
    nx.draw(Network, pos, node_color=color_map, node_size=200,␣
 ↪edge_color='grey', width = 0.5, with_labels=True)
    plt.show()
    return

Plot_Comm(Or_G, gn_communities, pos)
```

```
<Figure size 640x480 with 0 Axes>
```



[17]:

```
print("Caste value of the nodes highlighted in green")
print("78 has caste value", Caste.iloc[78][0])
print("88 has caste value", Caste.iloc[88][0])
print("18 has caste value", Caste.iloc[18][0])
print("17 has caste value", Caste.iloc[17][0])
print("16 has caste value", Caste.iloc[16][0])
print("20 has caste value", Caste.iloc[20][0])
print("19 has caste value", Caste.iloc[19][0])
print("81 has caste value", Caste.iloc[81][0])
print("82 has caste value", Caste.iloc[82][0])
print("70 has caste value", Caste.iloc[70][0])
print("71 has caste value", Caste.iloc[71][0])
print("68 has caste value", Caste.iloc[68][0])
print("Caste value of the nodes highlighted in red")
print("2 has caste value", Caste.iloc[2][0])
print("4 has caste value", Caste.iloc[4][0])
print("14 has caste value", Caste.iloc[14][0])
print("23 has caste value", Caste.iloc[23][0])
print("30 has caste value", Caste.iloc[30][0])
print("40 has caste value", Caste.iloc[40][0])
```

```
print("67 has caste value", Caste.iloc[67][0])
print("96 has caste value", Caste.iloc[96][0])
print("92 has caste value", Caste.iloc[92][0])
print("66 has caste value", Caste.iloc[66][0])
print("13 has caste value", Caste.iloc[13][0])
print("47 has caste value", Caste.iloc[47][0])
print("42 has caste value", Caste.iloc[42][0])
```

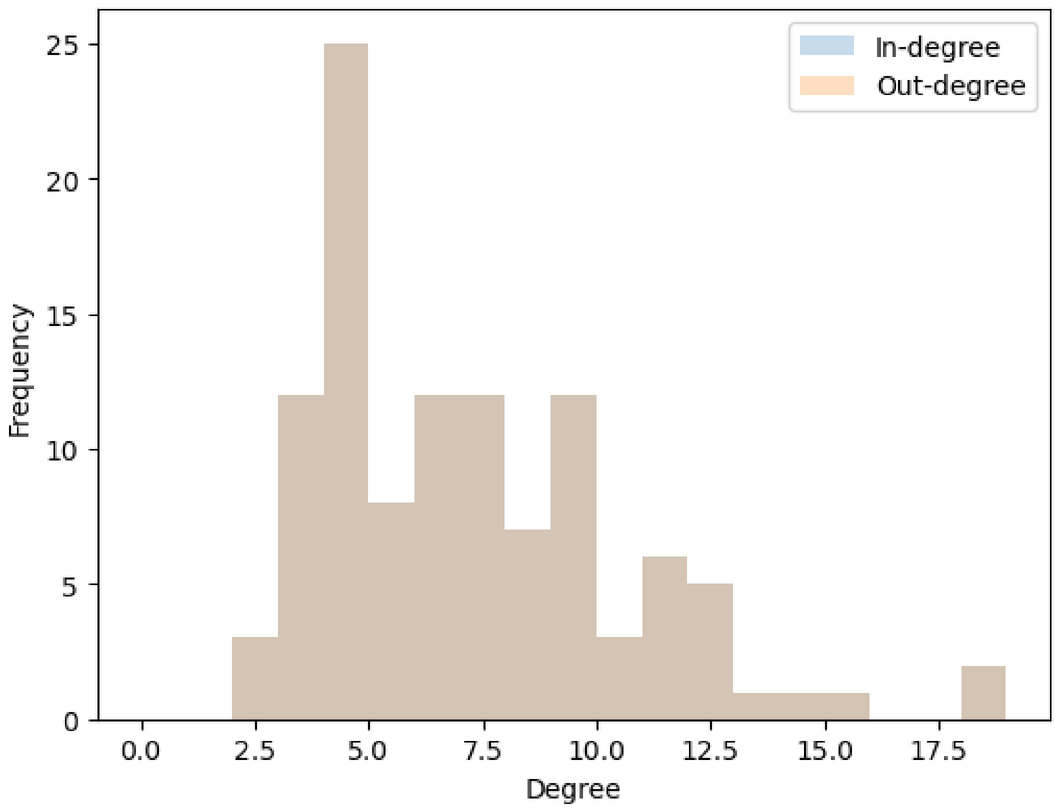
```
Caste value of the nodes highlighted in green
78 has caste value 1
88 has caste value 1
18 has caste value 0
17 has caste value 0
16 has caste value 0
20 has caste value 1
19 has caste value 1
81 has caste value 0
82 has caste value 1
70 has caste value 0
71 has caste value 0
68 has caste value 0
Caste value of the nodes highlighted in red
2 has caste value 0
4 has caste value 1
14 has caste value 0
23 has caste value 2
30 has caste value 2
40 has caste value 2
67 has caste value 0
96 has caste value 1
92 has caste value 1
66 has caste value 0
13 has caste value 0
47 has caste value 2
42 has caste value 2
```

Do the identified communities make sense given the context of your data? Using the Girvan Newman algorithm, we identified three communities. The first one is the connected component 8,9,10, and 11, we identified previously. The second community is highlighted in green, and it still belongs to a larger community. The caste system might be behind the community divide. The large connected cmponent belongs to General and Scheduled Tribe castes, while members of the green community belong to the Scheduled Castes and Other Backward Classes. These findings also support the idea that there might have been some error during data collection. It's possible that 8-9-10-11 community didn't want to take the time to fill out the survey; maybe the head of the house filled it out for all members and did it incorrectly.

1.1.8 6. Degree distribution

[18]:
```
# Calculate in-degree and out-degree of each node
in_degree = [d[1] for d in Or_G.in_degree()]
out_degree = [d[1] for d in Or_G.out_degree()]

# Plot the histograms
plt.hist(in_degree, bins=range(max(in_degree) + 2), alpha=0.25,␣
 ↪label='In-degree')
plt.hist(out_degree, bins=range(max(out_degree) + 2), alpha=0.25,␣
 ↪label='Out-degree')
plt.legend()
plt.xlabel('Degree')
plt.ylabel('Frequency')
plt.show()
```



Since it is a directed network and we are looking closely at the diffusion of information, meaning how the information is spreaded out, we only consider out-degree of each ego. From looking at the histogram, the most frequent degree is around 3.5-4 that about 25 egos have that degree.

In context, about 25 out of 110 villagers have spreaded information to an average of 2.5-4 others within the village about the microfinance, regardless of whether they are participants or not.

Significantly, there are a few individuals who have greatly high degree that is above 12.5.

Our assumption is that these individuals might be node 82 and 93 (and other siginificantly central nodes) which are the most central in the network as we explored before. Nevertheless, it is important to note that the spread of information is more greatly impacted by the major group of individuals that have moderate degrees than the minor group of individuals that have extremely high degrees. Yet, it is also essential to acknowledge that the network is explanded more widely thanks to the formation of 4 main communities and 2 central nodes, since they initate and/or radiate the connection circles, which assumably help other individuals to have a certain number of degree different than 0.

1.2 Conclusion

1. Do you think about this dataset differently than you did before? When we just started working with the dataset, we have not learned about information cascade yet. The dataset gave us insight into a real-life application of information cascade as the particiaption of some nodes in the microfinance program stimulated the behavior change of other nodes as they switched from being non-participants to participating. The analysis of the network shows that some disconnected communities will be very hard to reach, and hence an extra resources should be spent to ensure the equitable spread of information about opportunities such as microfinance. The analysis also allows us to predict how information about microfinance loans was diffused among the residents of village five.

2. Did you learn anything about the discipline/domain the network lies in? Through this paper, we learned about the most common types to collect socio-centric data and different kinds of relations that form edges amongst the nodes in socio-centric networks. We also learned how the information about new policies spreads locally as the microfinance institution Bharatha Swamukti Samsthe (BSS) relied on word-of-mouth communication to reach potential borrowers.

3. What's something you wish you could learn about the network that you might not have a tool for? Regarding evaluating nodes' effectiveness as injection points, we would like to know whether it is network distance to these leaders that stimulated the spread of information about microfinance or whether it is the participation of those nodes that stimulated the spread of the information about microfinance.

We could also learn the code or tool to have an analysis that tells us each bar of the histogram associated with which nodes in the network so that we have information on who has what degree. From that, we could draw connections between the number of people each individual decides to introduce to and their kinds of relation/tie/interaction with each other. As a result, we could gain more knowledge about how the characteristics of a network and the formation of each community affect the spreading/diffusion of information at an individual level.

4. Is there any metadata about the nodes/edges that you wish you could have to interpret your findings better? From reading the paper The Diffusion of Microfinance by Banerjee, Chandrasekhar, Duflo, and Jackson, we learned that our data has the data only of the survey respondents, but it does have the data on those who were nominated by the respondents so-called nonparticipants. The paper points out that nonparticipants were much more numerous. Participants are 7 times more likely to pass the information, but nonparticipants accounted for one-third of the eventual informedness. If we had the data on nonparticipants as well, maybe the 8-9-10-11 component would not be disconnected from the larger connected component.

It would also be nice to know how long nodes 8-9-10-11 have been a part of the village and their occupation as well. This information could also give more insight into why nodes 82 and 93 are considered the most central.

1.3 Works Cited

Burt, R.S., 1984. Network items and the general social survey. Soc. Netw. 6, 293–339.

Marin, A., 2004. Are respondents more likely to list alters with certain characteristics? Implications for name generator data. Soc. Netw. 26, 289–307.

Marin, A., Wellman, B., 2011. Social network analysis: an introduction. In: Scott, J., Carrington, P. (Eds.), The SAGE Handbook of Social Network Analysis. Sage, Thousand Oaks, CA, p. 11.