SOCIAL NETWORK ANALYSIS ADV.R PROJECT

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INDEX
1) COVER PAGE
2) INTRODUCTION
3) DATA COLLECTION
4) CODE EXPLANATION
5) DATA VISUALIZATION
6) CONCLUSION
7) BIBLIOGRAPHY

INTRODUCTION

Social Network Analysis (SNA) is the process of exploring or examining the social structure by using graph theory. It is used for measuring and analysing the structural properties of the network. It helps to measure relationships and flows between groups, organizations, and other connected entities. SNA is the process of investigating social structures through the use of networks and graph theory. It characterizes networked structures in terms of nodes (individual actors, people, or things within the network) and the ties, edges, or links (relationships or interactions) that connect them.

Before we start let us see some network analysis terminology:

A network is represented as a graph, which shows links (if any) between each vertex (or node) and its neighbours.

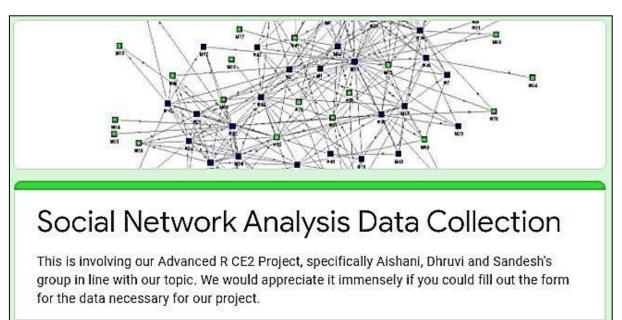
A line indicating a link between vertices is called an edge.

A group of vertices that are mutually reachable by following edges on the graph is called a component.

The edges followed from one vertex to another are called a path.

DATA COLLECTION

Data – we hear so much about it, but do we really understand the importance of data collection? At its most basic, data is simply a collection of different facts, including numbers, measurements, and observations, that have been translated into a form that computers can process. This might sound easy, but data is effectively changing the world we live in and the way that we work. For example, here:



We performed a survey within our class in order to analyse the social interactions among our classmates primarily through means of WhatsApp and Instagram.

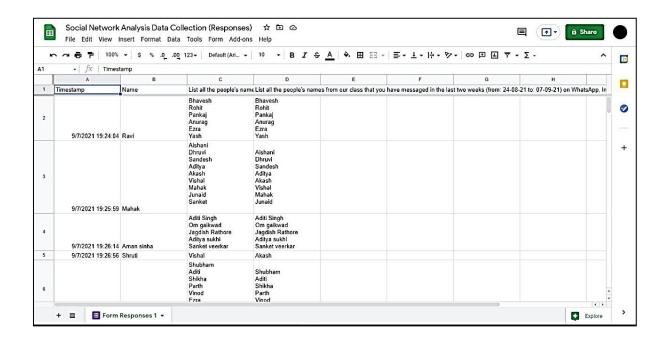
Name
Your answer

The questions included the name of the person who responded in order to track the initial and/or terminal node for a given interaction.

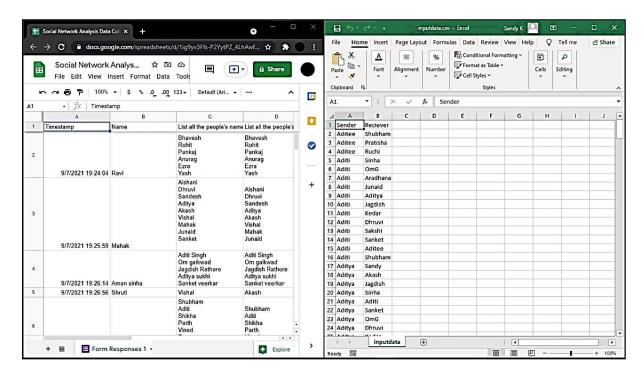
List all the people's names from our class that you have messaged in the last two weeks (from: 24-08-21 to: 07-09-21) on WhatsApp, Instagram or other platforms (Gmail, Linkedin etc.)

List all the people's names from our class that you have messaged in the last two weeks (from: 24-08-21 to: 07-09-21) on WhatsApp, Instagram or other platforms (Gmail, Linkedin etc.)

Responders were asked to filled out both received and sent messages (interactions) in order to minimize human error and/or bias in case of e.g., a responder forgetting about a message they received (would otherwise make a "hole" in the datapoints) would be compensated by the opposite node since they likely report on the same interaction that the first responder forgot.

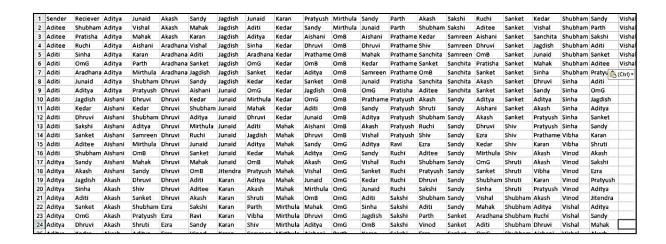


Above displayed image shows raw Data from all the 40 responses.

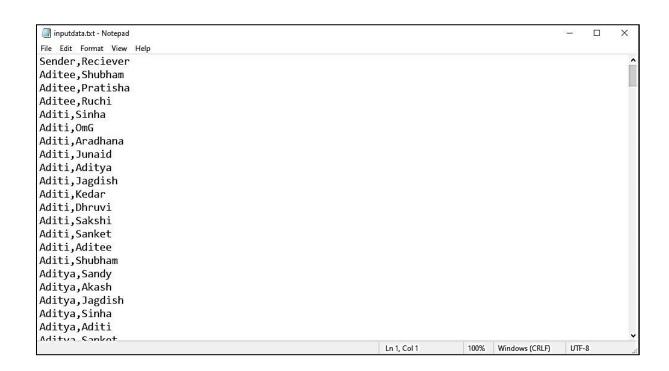


All spam/troll responses were removed manually alongside removing "invalid" response (people that failed to submit a response but were part of the response pool received) followed by transposing data into a usable .csv file.

For example name like Mahak was often observed to be misspelled as Mahek, Mehak, Mehek, Mahek therefore the above changes were made to manually correct/standardize spellings of names preventing "false" nodes of alternate spellings.



After filtering everything out a .csv is created that roughly distinguishes the collected data.



A list of the sender and receiver is now sorted and generated for further use!!

CODE EXPLANATION

The code that one writes must be understood not only by the machine but also by humans. Quality should always be everyone's priority. Throughout the development process, the goal should be the delivery of good quality and working code. Hence the code that we have here not only shows the precise and easy to understand visualizations but is also well-documented and thoroughly analysed.

```
package 'igraph' successfully unpacked and MD5 sums checked
package 'readr' successfully unpacked and MD5 sums checked
package 'tidyr' successfully unpacked and MD5 sums checked
package 'RColorBrewer' successfully unpacked and MD5 sums checked
```

First all the required packages are installed.

Next as you can see the data is stored in the variables of the R global environment.

```
IGRAPH eachb3b UNW- 35 254 --
+ attr: name (v/c), Freq (e/n), weight (e/n)
+ edges from eachb3b (vertex names):

[1] Aditi --Aradinana Aditi --Araditee Dhruvi --Aditee Dhruvi --Aditya Aditi --Sakshi --Aditee Aditi --Sakshi --Aditee Aditi --Sakshi Dhruvi --Aditya --Aksah Dhruvi --Aditya --Sinha Aditya --Sinha Aditya --Sinha Aditya --Vinod Aditya --Vinal Aditya --Aishani Dhruvi --Aishani Aditya --Aishani --Aditya --Aksah Dhruvi --Aishani --Aditya --Aksah --Aditya --Vinod Aditya --Vinal Aditya --Aishani --Aditya --Aishani --Adity
```

A raw network of data and nodelist is created using the igraph library.

Then a slice of the interaction matrix and an edge list is generated to further simply the data.

In the above image it is shown the betweenness of the raw values is shown and it is observed that Aditya has highest betweenness value i.e 7.

Next the degrees data is shown where again the person with maximum degrees of nodes is Aditya.

```
> #2. Eigenvector centrality
> df_eig <- evcent(df) Svector
> V(df) SEigen-df_eig
| 0.82142237 0.43567336 0.55995482 0.60905180 0.22653326 0.62642791 0.43782729 0.57295036 0.80113474 0.12267920 0.51841305 0.16258828
| [25] 0.16631464 0.29498626 0.16302204 0.12923592 0.13986391 0.01071669 0.03594372 0.18681239 0.16033461 0.02048658 0.10924202
> Which.max(df_eig)
Aditya
7
> #3. Betweenness centrality
> V(df) Sbetweenness (df, directed = FALSE)
> V(df) Sbetweenness (df, directed = F
```

Next on further checking the eigenvector centrality and the betweenness centrality the same maximum is observed.

Then a summary of the data frame is printed to give a clearer view.

```
> hist(V(df)$degree,
+ col = 'green',
+ main = 'Histogram of Node Degree',
+ ylab = 'Frequency',
+ xlab = 'Degree of Vertices')
>
```

Next the visualizations are generated starting with the plotting of a histogram.

The measure of the indicators of the network structure density is then graphed. Here the edge density is observed to be 0. 4268908.

```
#2. Plotting a network with the betweenness centrality

par(Ope"white")

set.seed(1001)

plot(df.edge.color = 'lightblue', vertex. label.color= "black", vertex. label.cex =1, vertex.color='orange',

vertex.color=pal[as.numeric(as.factor(vertex.atr(df. "Class"))]],

vertex.size = df.bw/4, edge.width=sqrt(E(df)Sweight/800),

layout = layout.sphere, main = "Network with betweenness centrality")

#3.1. between degree and betweenness centrality

plot(V(df)Sdegree, V(df)Sbetweenness)

#3.2. between degree and eigenvector centrality

plot(V(df)Sdegree, V(df)Sbetweenness)

#3.1. Louvain clustering

cnet <- cluster_edge_betweenness(df) # You can check which vertices belongs to which clusters.

Warning messages:

1: In cluster_edge_betweenness(df):

At community.c:#60 :Membership vector will be selected based on the lowest modularity score.

2: In cluster_edge_betweenness(df):

At community.c:#67 :Modularity calculation with weighted edge betweenness community detection might not make sense -- modularity treats edge weights as similarities while edge betweenness tents them as distances

#2. Plotting the Betweenness Centrality network with the community detection

set.seed(1001) # To duplicate the computer process and create exactly the same network repetitively you should set the seed.

plot(cnet, df, edge.color = 'lightblue', vertex.label.cex =0.9,

vertex.color='yellow', vertex.label.color='black',

vertex.color='yellow', vertex.label.color='black',

layout = layout.fruchterman.reingold, main = "Betweenness centrality network with the community detection")

set.seed(1001) # To duplicate the computer process and create exactly the same network repetitively you should set the seed.
```

The visualizations of the network with the betweenness centrality, between degree and eigenvector centrality, between degree and betweenness centrality, betweenness centrality network with the community detection and other visualization using tkplot are charted.

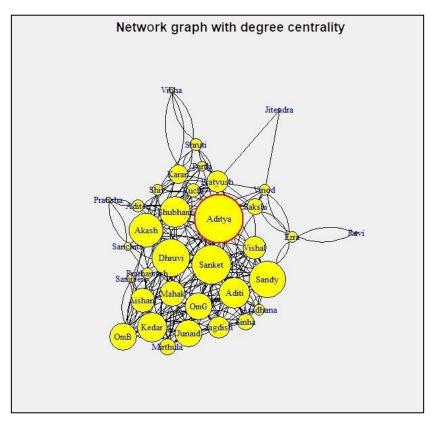
DATA VISUALIZATION

With so much information being collected through data, we must have a way to paint a picture of that data so we can interpret it.

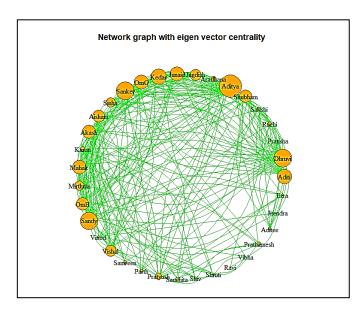
Data visualization gives us a clear idea of what the information means by giving it visual context through maps or graphs.

This makes the data more natural for the human mind to comprehend and therefore makes it easier to identify trends, patterns, and outliers within large data sets.

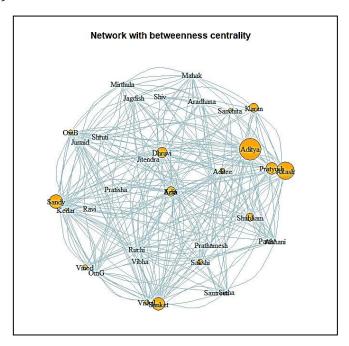
Here we have different types of graphs, plots and visualizations that are used for the project:



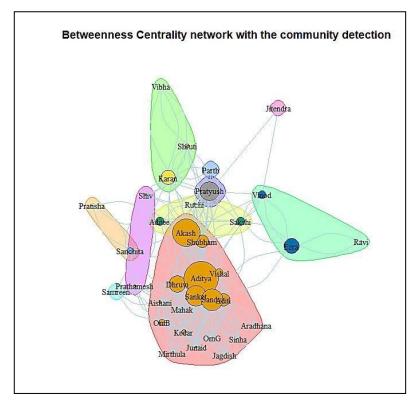
Network graph with degree centrality: In a connected graph, the normalized closeness centrality (or closeness) of a node is the average length of the shortest path between the node and all other nodes in the graph. Thus, the more central a node is, the closer it is to all other nodes. is the number of nodes in the graph. This is a graph which shows the network on the basis of degree centrality. Its vertices depict the betweenness. I.e.: Bigger the vertex, higher the betweenness. The layout used here is the Fruchterman Re.ingold layout.

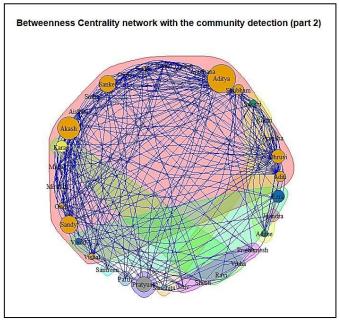


Network graph with eigen vector centrality: Eigenvector centrality is a measure of the influence a node has on a network. If a node is pointed to by many nodes (which also have high eigenvector centrality) then that node will have high eigenvector centrality. Eigenvector centrality differs from in-degree centrality: a node receiving many links does not necessarily have a high eigenvector centrality (it might be that all linkers have low or null eigenvector centrality). Moreover, a node with high eigenvector centrality is not necessarily highly linked (the node might have few but important linkers).

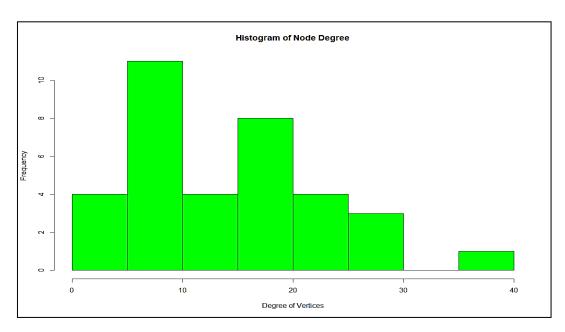


A network with betweenness centrality: Betweenness centrality finds wide application in network theory; it represents the degree to which nodes stand between each other. a node with higher betweenness centrality would have more control over the network, because more information will pass through that node.





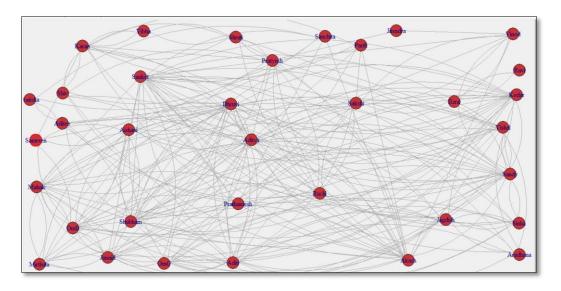
Betweenness clarity network with community detection: Detecting communities in a network is one of the most important tasks in network analysis. In a large-scale network, such as an online social network, we could have millions of nodes and edges. Detecting communities in such networks becomes a herculean task. Therefore, we need community detection algorithms that can partition the network into multiple communities.

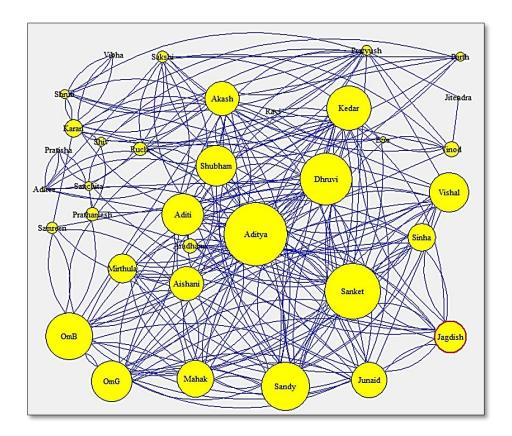


A Histogram is a chart plotting a variable, against the number of occurrences in the variable category. It is a quick way to get information about a sample distribution without detailed statistical graphing or analysis. This plot will show you if your data values are centered (normally distributed), skewed to one side or the other, or have more than one 'mode' - localized distribution concentrations. Here, a histogram of node degree with the frequency on the Y-axis and the degree of vertices on X-axis is plotted.

INTERACTIVE PLOTTING:

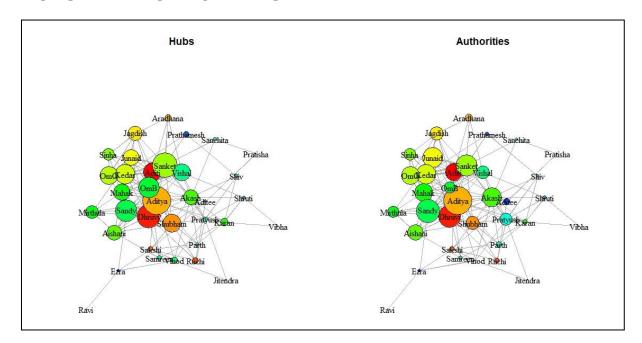
TkPlot





The tkplot command creates a new Tk window with the graphical representation of graph. tkplot and its companion functions serve as an interactive graph drawing facility. Not all parameters of the plot can be changed interactively right now though, eg. the colours of vertices, edges, and also others have to be pre-defined. tkplot is an interactive graph drawing facility. It is not very well developed at this stage, but it should be still useful.

HUBS AND AUTHORITIES:



Authority and hub values are defined in terms of one another in a mutual recursion. An authority value is computed as the sum of the scaled hub values that point to that page. A hub value is the sum of the scaled authority values of the pages it points to.

CONCLUSION

Social Network Analysis in R, Social Network Analysis (SNA) is the process of exploring the social structure by using graph theory. It is mainly used for measuring and analysing the structural properties of the network. It helps to measure social network relationships (Facebook, Twitter likes comments following etc..), Email connectivity, flows between groups, organizations, and other connected entities.

In this project we observe that the interaction between students of SY Data Science is quite frequent and Aditya being the CR of the class has the highest number of interactions with the students.

BIBLIOGRAPHY

Form Link for Data collection:

https://forms.gle/fzr1sSa4H8QMDTfX6

Information regarding SNA:

https://www.geeksforgeeks.org/social-network-analysis-using-r-programming/

 $\frac{https://medium.com/@615162020004/social-network-analysis-with-r-centrality-measure-86d7 fa 273574}{measure-86d7 fa 275574}{measure-86d7 fa 275574}{measure-86d7 fa 275574}{measure-86d7 fa 275574}{measure-86d7 fa 275574}$

 $\frac{https://medium.com/analytics-vidhya/social-network-analysis-in-r-part-1-ego-network-ab6b0d23ebc8}{}$