Homework 10

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4/27/2021

This document contains the survey results from the survey we ran in class. 1. Prepare the data for the network analysis (create a separate edge and node list) 2. Calculate measures of centrality and similarity in networks depending on the type of tie? Which tie type generates the most similar network in terms of introversion? Which tie type is the most dissimilar? 3. Do introverts tend to be at the periphery while extraverts are in the center of the network? Motivate.

The options for each name are the following: 1. I have texted in the last 7 days 2. I have met during my time in MBDS 3. Is my friend 4. I ask for advice/help 5. Asks me for help/advice Options for the introversion question: 1. Introverted 2. Middle ground 3. Extraverted

```r
# Load packages and an xls file
library(readxl)
library(network)
```

```
## Warning: package 'network' was built under R version 4.0.5
```

```
## network: Classes for Relational Data
## Version 1.16.1 created on 2020-10-06.
## copyright (c) 2005, Carter T. Butts, University of California-Irvine
##                     Mark S. Handcock, University of California -- Los Angeles
##                     David R. Hunter, Penn State University
##                     Martina Morris, University of Washington
##                     Skye Bender-deMoll, University of Washington
##  For citation information, type citation("network").
##  Type help("network-package") to get started.
```

```r
library(igraph)
```

```
## Warning: package 'igraph' was built under R version 4.0.5
```

```
##
## Attaching package: 'igraph'
```

```
## The following objects are masked from 'package:network':
##
##     %c%, %s%, add.edges, add.vertices, delete.edges, delete.vertices,
##     get.edge.attribute, get.edges, get.vertex.attribute, is.bipartite,
##     is.directed, list.edge.attributes, list.vertex.attributes,
##     set.edge.attribute, set.vertex.attribute
```

```
## The following objects are masked from 'package:stats':
##
##     decompose, spectrum
```

```
## The following object is masked from 'package:base':
##
##     union
```

```r
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 4.0.5

## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.3     v purrr   0.3.4
## v tibble  3.1.1     v dplyr   1.0.5
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   1.4.0     v forcats 0.5.1

## Warning: package 'ggplot2' was built under R version 4.0.4

## Warning: package 'tibble' was built under R version 4.0.5

## Warning: package 'tidyr' was built under R version 4.0.5

## Warning: package 'readr' was built under R version 4.0.5

## Warning: package 'dplyr' was built under R version 4.0.5

## Warning: package 'forcats' was built under R version 4.0.5

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::as_data_frame() masks tibble::as_data_frame(), igraph::as_data_frame()
## x purrr::compose()       masks igraph::compose()
## x tidyr::crossing()      masks igraph::crossing()
## x dplyr::filter()        masks stats::filter()
## x dplyr::groups()        masks igraph::groups()
## x dplyr::lag()           masks stats::lag()
## x purrr::simplify()      masks igraph::simplify()
```

```r
hw10<- read_excel("hw10.xlsx")

node<- read_excel("hw10.xlsx", skip = 1)
colnames(node) <- c("ID", 1:40, "trait")

# Does node have a correct format. I'm not sure how it suppose to be
```

##1. Prepare the data for the network analysis (create a separate edge and node list)

```r
#create the edge list
edge_prep <- node %>% pivot_longer(col = -c(ID, trait), names_to = "in-tie", values_to = "value") %>%
  rename (`out-tie` = ID)

edgelist <- separate_rows(edge_prep, value, sep =",") %>% select(!trait) %>%
  rename (`tie-type` = value)

as.character(edgelist$`tie-type`)
```

```
##    [1] NA  NA  NA  NA  NA  NA  NA  "4" NA  "4" "1" NA  NA  NA  NA  NA  NA  "1"
##   [19] "2" "3" "4" "5" NA  "1" "3" "4" "5" "4" NA  NA  NA  NA  NA  NA  NA  "4"
##   [37] NA  NA  NA  NA  "1" "2" "3" "4" "5" NA  "1" "3" "4" "5" NA  NA  NA  NA
##   [55] NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA
##   [73] NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  "2"
##   [91] "1" NA  "1" NA  NA  NA  NA  "1" "2" "3" "4" "5" NA  "1" "3" "4" "5" NA
##  [109] NA  "1" "5" NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  "1" "3" "4"
##  [127] "5" NA  "1" "2" "3" "4" "5" NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA
##  [145] NA  NA  NA  NA  "1" "2" "3" "4" "5" NA  "1" "2" "3" "4" NA  NA  NA  "1"
##  [163] "2" "3" "4" "5" NA  NA  NA  NA  NA  "1" "3" "4" NA  NA  NA  NA  NA  "1"
```

```
##  [181] "2" "3" "4" "1" "2" "3" "4" NA  NA  NA  NA  NA  NA  "2" "2" "3" "1" "2"
##  [199] "3" "4" "5" NA  NA  "1" "2" "3" "4" "5" NA  NA  "1" "2" "3" "1" "2" "3"
##  [217] "4" "5" NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA
##  [235] "3" NA  NA  "3" NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  "3" NA
##  [253] NA  NA  "3" NA  NA  NA  NA  NA  NA  NA  NA  "1" "2" "1" NA  NA  "2" NA
##  [271] "4" NA  NA  NA  NA  "1" NA  "1" "1" NA  "1" "2" "1" NA  "4" NA  NA  NA
##  [289] NA  NA  NA  "2" "1" "3" "4" NA  "2" NA  NA  NA  "2" NA  NA  NA  NA  NA
##  [307] "1" "2" "3" "5" "2" "3" "4" NA  NA  "1" "2" "3" "4" "5" "1" "2" "3" "4"
##  [325] "5" "4" "4" NA  "4" NA  "1" "3" "4" NA  NA  "1" "2" "3" "4" "5" "3" NA
##  [343] "1" "2" "3" "4" "5" "1" "2" "3" "4" "5" "3" "4" "1" "3" "4" "5" "2" "3"
##  [361] NA  NA  NA  "1" "2" "3" "4" "1" "2" "3" "4" "5" "1" "3" "4" NA  "1" "2"
##  [379] "3" "4" "5" "1" "3" "4" "5" "1" "3" "4" "5" "2" "2" "3" "4" NA  NA  NA
##  [397] NA  NA  NA  NA  NA  NA  NA  NA  "4" NA  "4" NA  "1" NA  NA  "1" "3" NA
##  [415] NA  NA  NA  NA  "4" NA  NA  NA  NA  NA  NA  "1" "4" "5" "4" NA  NA  NA
##  [433] "1" "4" "5" NA  "5" "4" NA  NA  NA  NA  "5" NA  NA  NA  NA  NA  NA  "4"
##  [451] NA  NA  NA  "1" "3" "4" "5" NA  NA  NA  NA  NA  "1" "2" "3" "4" "5" NA
##  [469] NA  "4" "1" "5" "1" "3" "4" "5" NA  NA  NA  NA  "1" "2" "3" "4" "5" "3"
##  [487] "4" NA  NA  "1" "2" "3" "4" "5" "1" "3" "4" "5" "4" "5" NA  NA  NA  NA
##  [505] NA  NA  NA  NA  NA  NA  "1" "2" "3" "4" "5" "1" "2" "3" "4" "5" NA  "2"
##  [523] "3" "4" NA  NA  NA  NA  NA  NA  NA  NA  NA  "1" "2" "3" "4" "5" "1" "2"
##  [541] "3" NA  "2" "5" NA  NA  NA  NA  "5" "1" "2" "3" "4" "5" "1" "2" "3" "4"
##  [559] "5" "1" "2" "3" "4" "5" NA  "1" "2" "3" "4" "5" NA  NA  "2" "3" NA  "2"
##  [577] "3" "4" "5" NA  NA  NA  NA  "1" "2" "3" "2" NA  NA  NA  "2" NA  "2" "4"
##  [595] "2" "2" "4" NA  NA  "1" "2" "4" NA  "2" "1" "2" "2" NA  "2" "2" "4" "2"
##  [613] "3" "4" "2" NA  NA  "1" "2" "4" NA  NA  "1" "2" "3" "4" "1" "2" "3" "4"
##  [631] NA  "2" "2" "2" "2" "2" "2" "4" "2" NA  NA  NA  NA  "1" "2" "3" "4" NA
##  [649] NA  "1" "2" "3" "4" "5" "1" "2" "3" "4" "5" NA  "4" "1" "4" "5" "4" NA
##  [667] NA  NA  NA  NA  NA  NA  "2" "2" NA  "4" "4" "5" "2" NA  NA  NA  "2" "2"
##  [685] "4" NA  "1" "2" "3" "4" "5" "4" NA  NA  NA  NA  NA  "1" "2" "3" "4" "5"
##  [703] NA  NA  "4" "5" NA  "1" NA  NA  "5" NA  "1" "4" "1" "4" "5" "4" "1" "4"
##  [721] "5" NA  "1" "4" "5" NA  NA  NA  NA  "1" "3" "4" "5" "4" "5" NA  "1" "2"
##  [739] "3" "4" "1" "3" "4" "5" NA  NA  NA  "4" "5" NA  "1" "4" "5" "1" "3" "4"
##  [757] "1" "3" "4" "5" NA  NA  NA  "1" "3" "4" "5" "1" "1" "3" "4" "5" NA  NA
##  [775] NA  NA  NA  "1" "2" "3" "4" "5" NA  NA  "1" "2" "3" "4" "5" "2" "3" NA
##  [793] "4" NA  NA  "1" "1" "3" "4" "5" NA  NA  "3" "4" NA  NA  "1" NA  "1" "2"
##  [811] "3" "4" "5" NA  "1" "3" NA  NA  NA  NA  NA  "1" "2" "3" "4" "5" NA  "1"
##  [829] "2" "3" "4" "5" "2" "3" NA  NA  "1" "2" "3" "4" "5" "2" "1" "2" "3" "4"
##  [847] "5" NA  NA  NA  NA  NA  NA  NA  "1" "2" "3" "4" "5" NA  "1" "2" "3" "4"
##  [865] "5" NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  "2" "4" "5" NA  NA  NA
##  [883] "1" "2" "3" "4" "5" NA  NA  NA  NA  NA  "4" "5" "1" "4" "5" NA  NA  NA
##  [901] NA  NA  NA  NA  NA  NA  NA  "1" "2" "3" "4" "5" NA  "3" "4" NA  NA  NA
##  [919] NA  NA  "4" NA  "4" NA  "1" "3" "1" "3" NA  NA  NA  NA  "1" "3" "4" "5"
##  [937] NA  "1" "3" "4" "5" "4" NA  NA  NA  NA  NA  "1" "3" NA  "4" "1" "3" "4"
##  [955] "5" NA  NA  NA  "1" "3" "4" "5" NA  NA  NA  NA  NA  NA  NA  "2" "4" "2"
##  [973] "4" "5" NA  NA  "4" NA  NA  "1" "2" "4" "5" NA  NA  NA  NA  "1" "2" "3"
##  [991] "4" "5" NA  NA  NA  NA  "1" "2" "4" "5" NA  NA  NA  NA  NA  NA  "1" "2"
## [1009] "4" "5" NA  "4" "5" "2" "4" "5" NA  NA  NA  NA  NA  NA  NA  NA  NA  NA
## [1027] NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA
## [1045] NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA  NA
## [1063] NA  NA  NA  NA  NA  NA  "1" "2" "3" "4" NA  NA  "1" "2" "3" "4" "5" "1"
## [1081] "2" "3" "4" "5" NA  "1" "2" "3" "4" NA  "4" NA  NA  "3" "4" "5" NA  NA
## [1099] NA  NA  "2" "3" "2" NA  "4" "1" "3" "2" "3" NA  NA  NA  "2" "1" "2" "1"
## [1117] "3" "4" NA  "1" "2" "3" "4" NA  NA  NA  "1" "2" "3" "4" "5" NA  NA  "1"
## [1135] "3" "4" "5" NA  NA  NA  "2" "3" "1" NA  "1" "2" "3" "4" "5" "2" NA  "4"
```

```
## [1153] "1" NA  "1" NA  NA  NA  "1" NA  NA  "1" "2" "3" "4" "5" "1" "2" "3" "4"
## [1171] "5" "1" "3" "4" "5" NA  NA  NA  NA  NA  NA  NA  "2" "4" "1" "2" "3" "4"
## [1189] "5" NA  NA  NA  NA  NA  "1" "3" "4" "5" NA  NA  NA  NA  "5" "1" "3" "4"
## [1207] NA  NA  "1" "3" "4" NA  NA  "4" NA  "4" NA  NA  NA  NA  NA  NA  NA  NA
## [1225] NA  "3" "4" "5" "2" "4" NA  NA  NA  NA  NA  NA  "4" "3" "4" NA  "3" "4"
## [1243] "5" "3" "3" NA  "1" "3" "4" "5" NA  NA  NA  NA  NA  NA  "1" "2" "3" "4"
## [1261] "5" NA  NA  "1" "2" "3" "4" "5" NA  NA  "1" "2" "4" NA  NA  NA  NA  NA
## [1279] NA  NA  NA  NA  "2" "2" NA  "4" "1" "3" "4" "5" "2" "1" "5" NA  NA  "2"
## [1297] "1" "2" "4" NA  "1" "2" "3" "4" "5" NA  NA  "2" "1" "2" "3" "4" "5" NA
## [1315] NA  NA  NA  "1" "4" "5"
```

```
edgelist$`tie-type`[is.na(edgelist$`tie-type`)] = 0 #NA values for tie-type to 0

edgelist <- na.omit(edgelist)
edgelist <- edgelist %>%
  arrange(`out-tie`) %>%
  filter(`out-tie` != `in-tie`)
##there are 3 variables in the edge list: out-tie, in-tie, and tie.


#creating nodelist
inclass <- subset(node, select = -c(2:41) )
inclass <- na.omit(inclass)
absent_people <- tibble (ID= c(3,4,8,9,10,11,12,13,14,16,19,21,22,25,26,27,29,37,39), trait = NA) #peop
nodelist <-rbind (inclass, absent_people) %>% arrange(`ID`) #combine  people took the survey and people
```

##2. Calculate measures of centrality and similarity in networks depending on the type of tie? Which tie type generates the most similar network in terms of introversion? Which tie type is the most dissimilar?

Looking at the information centrality, tie type 4 (I ask for advice/help) has the greatest centralization while tie type 5 (Asks me for help/advice). Betweenness is also another measure of centrality which shows us how well-connected the parts are. In terms of betweenness, tie type 3 (Is my friend) ranks the highest and tie type 2 (I have met during my time in MBDS) is the lowest. Likewise, tie type 3 also ranks the highest for reciprocity, though tie type 4 ranks the lowest. As for closeness, tie type 2 ranks the closest and tie type 3 is the least closest.

Tie type 1 (I have texted in the last 7 days) generates the most similar network in terms of introversion, while tie type 3 generates the most dissimilar.

```
classnormsnet <- network(edgelist, vertex.attr = nodelist, matrix.type = "edgelist", ignore.eval = FALSE
summary(classnormsnet)
```

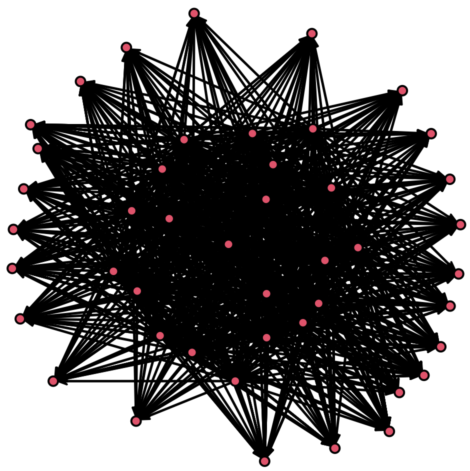
```
## Network attributes:
##   vertices = 45
##   directed = TRUE
##   hyper = FALSE
##   loops = FALSE
##   multiple = FALSE
##   bipartite = FALSE
##  total edges = 1246
##    missing edges = 0
##    non-missing edges = 1246
##  density = 0.6292929
##
## Vertex attributes:
##
```

```
##  ID:
##    numeric valued attribute
##    attribute summary:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    7.00   18.00   18.56   29.00   40.00
##
##  trait:
##    numeric valued attribute
##    attribute summary:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   1.000   2.000   2.000   2.042   2.000   3.000      21
##   vertex.names:
##    character valued attribute
##    45 valid vertex names
##
## Edge attributes:
##
##  tie-type:
##    character valued attribute
##    attribute summary:
##   0   1   2   3   4   5
## 551 143 133 131 176 112
##
## Network adjacency matrix:
##     1  2  5  6  7 1 10 11 12 13 14 15 16 17 18 19 2 20 21 22 23 24 25 26 27 28
##  1  0  0  0  0  0 0  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
##  2  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 0  1  1  1  1  1  1  1  1  1
##  5  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
##  6  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
##  7  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
## 1   0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 10  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 11  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 12  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 13  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 14  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 15  0  0  0  0  0 1  1  1  1  1  1  0  1  1  1  1 1  1  1  1  1  1  1  1  1  1
## 16  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 17  0  0  0  0  0 1  1  1  1  1  1  1  1  0  1  1 1  1  1  1  1  1  1  1  1  1
## 18  0  0  0  0  0 1  1  1  1  1  1  1  1  1  0  1 1  1  1  1  1  1  1  1  1  1
## 19  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 2   0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 20  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  0  1  1  1  1  1  1  1  1
## 21  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 22  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 23  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  0  1  1  1  1  1
## 24  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  0  1  1  1  1
## 25  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 26  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 27  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 28  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  0
## 29  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 3   0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 30  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
```

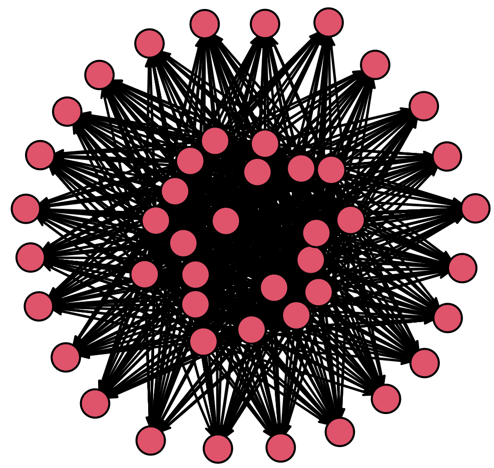
```
## 31  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
## 32  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
## 33  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
## 34  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
## 35  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
## 36  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
## 37  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 38  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
## 39  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 4   0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 40  0  0  0  0  0 1  1  1  1  1  1  1  1  1  1  1 1  1  1  1  1  1  1  1  1  1
## 5   0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 6   0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 7   0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 8   0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
## 9   0  0  0  0  0 0  0  0  0  0  0  0  0  0  0  0 0  0  0  0  0  0  0  0  0  0
##     29 3 30 31 32 33 34 35 36 37 38 39 4 40 5 6 7 8 9
##   1  1 1  1  1  1  1  1  1  1  1  1  1 1  1 1 1 1 1 1
##   2  1 1  1  1  1  1  1  1  1  1  1  1 1  1 1 1 1 1 1
##   5  1 1  1  1  1  1  1  1  1  1  1  1 1  1 0 1 1 1 1
##   6  1 1  1  1  1  1  1  1  1  1  1  1 1  1 1 0 1 1 1
##   7  1 1  1  1  1  1  1  1  1  1  1  1 1  1 1 1 0 1 1
## 1    0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 10   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 11   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 12   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 13   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 14   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 15   1 1  1  1  1  1  1  1  1  1  1  1 1  1 1 1 1 1 1
## 16   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 17   1 1  1  1  1  1  1  1  1  1  1  1 1  1 1 1 1 1 1
## 18   1 1  1  1  1  1  1  1  1  1  1  1 1  1 1 1 1 1 1
## 19   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 2    0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 20   1 1  1  1  1  1  1  1  1  1  1  1 1  1 1 1 1 1 1
## 21   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 22   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 23   1 1  1  1  1  1  1  1  1  1  1  1 1  1 1 1 1 1 1
## 24   1 1  1  1  1  1  1  1  1  1  1  1 1  1 1 1 1 1 1
## 25   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 26   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 27   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 28   1 1  1  1  1  1  1  1  1  1  1  1 1  1 1 1 1 1 1
## 29   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 3    0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 30   1 1  0  1  1  1  1  1  1  1  1  1 1  1 1 1 1 1 1
## 31   1 1  1  0  1  1  1  1  1  1  1  1 1  1 1 1 1 1 1
## 32   1 1  1  1  0  1  1  1  1  1  1  1 1  1 1 1 1 1 1
## 33   1 1  1  1  1  0  1  1  1  1  1  1 1  1 1 1 1 1 1
## 34   1 1  1  1  1  1  0  1  1  1  1  1 1  1 1 1 1 1 1
## 35   1 1  1  1  1  1  1  0  1  1  1  1 1  1 1 1 1 1 1
## 36   1 1  1  1  1  1  1  1  0  1  1  1 1  1 1 1 1 1 1
## 37   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 38   1 1  1  1  1  1  1  1  1  1  0  1 1  1 1 1 1 1 1
```

```
## 39   0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 4    0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 40   1 1  1  1  1  1  1  1  1  1  1  1 1  0 1 1 1 1 1
## 5    0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 6    0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 7    0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 8    0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
## 9    0 0  0  0  0  0  0  0  0  0  0  0 0  0 0 0 0 0 0
```

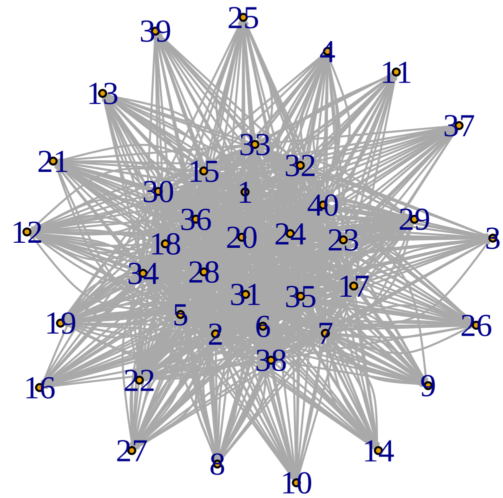
```
plot(classnormsnet, vertex.cex = 1) # very dense
```



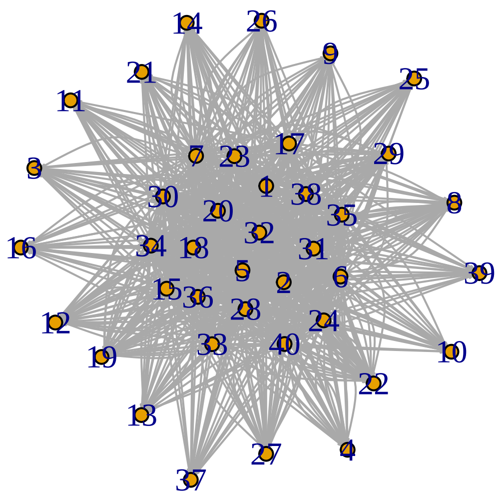
```
plot(classnormsnet, vertex.cex = 3)
```



```r
# graphing the network

network_class <- graph_from_data_frame(d = edgelist, vertices = nodelist, directed = TRUE)
plot(network_class, edge.arrow.size = 0.1, vertex.size = 3)
```




```r
plot(network_class, edge.arrow.size = 0.1, vertex.size = 6)
```



Edgelist based on Tie-Type, Nodelist based on trait

```
# edgelist based on tie-type, nodelist based on trait

edgelist1 <- edgelist %>% filter(`tie-type` == 1)
edgelist2 <- edgelist %>% filter(`tie-type` == 2)
edgelist3 <- edgelist %>% filter(`tie-type` == 3)
edgelist4 <- edgelist %>% filter(`tie-type` == 4)
edgelist5 <- edgelist %>% filter(`tie-type` == 5)

nodelist_introvert <- nodelist %>% filter(trait==1)
nodelist_extrovert <- nodelist %>% filter(trait == 3)

network_class_tietype1 <- graph_from_data_frame(d = edgelist1, vertices = nodelist, directed = TRUE)
network_class_tietype2 <- graph_from_data_frame(d = edgelist2, vertices = nodelist, directed = TRUE)
network_class_tietype3 <- graph_from_data_frame(d = edgelist3, vertices = nodelist, directed = TRUE)
network_class_tietype4 <- graph_from_data_frame(d = edgelist4, vertices = nodelist, directed = TRUE)
network_class_tietype5 <- graph_from_data_frame(d = edgelist5, vertices = nodelist, directed = TRUE)
```

Density Density is the number of ties relative to the number of possible ties

From greatest to least, the rank of tie types in terms of density is as follows:

1. I ask for advice/help (tie type 4)
2. I have texted in the last 7 days (tie type 1)
3. I have met during my time in MBDS (tie type 2)
4. Is my friend (tie type 3)
5. Asks me for help/advice (tie type 5)

```r
# density based on tie type


edge_density(network_class_tietype1, loops = F)
```

```
## [1] 0.09166667
```

```r
edge_density(network_class_tietype2, loops = F)
```

```
## [1] 0.08525641
```

```r
edge_density(network_class_tietype3, loops = F)
```

```
## [1] 0.08397436
```

```r
edge_density(network_class_tietype4, loops = F)
```

```
## [1] 0.1128205
```

```r
edge_density(network_class_tietype5, loops = F)
```

```
## [1] 0.07179487
```

Reciprocity

From greatest to least, the rank of tie types in terms of reciprocity is as follows:

1. Is my friend (tie type 3)
2. I have met during my time in MBDS (tie type 2)
3. I have texted in the last 7 days (tie type 1)
4. Asks me for help/advice (tie type 5)
5. I ask for advice/help (tie type 4)

```r
#reciprocity


reciprocity(network_class_tietype1)
```

```
## [1] 0.4895105
```

```r
reciprocity(network_class_tietype2)
```

```
## [1] 0.5112782
```

```r
reciprocity(network_class_tietype3)
```

```
## [1] 0.5648855
```

```r
reciprocity(network_class_tietype4)
```

```
## [1] 0.3863636
```

```r
reciprocity(network_class_tietype5)
```

```
## [1] 0.4821429
```

Transitivity

From greatest to least, the rank of tie types in terms of transitivty is as follows:

1. I have met during my time in MBDS (tie type 2)
2. Is my friend (tie type 3)
3. I ask for advice/help (tie type 4)

4. I have texted in the last 7 days (tie type 1)
5. Asks me for help/advice (tie type 5)

```r
# transitivity

transitivity(network_class_tietype1, type="global")
```

```
## [1] 0.3579088
```

```r
transitivity(network_class_tietype2, type="global")
```

```
## [1] 0.4365427
```

```r
transitivity(network_class_tietype3, type="global")
```

```
## [1] 0.4279835
```

```r
transitivity(network_class_tietype4, type="global")
```

```
## [1] 0.4114404
```

```r
transitivity(network_class_tietype5, type="global")
```

```
## [1] 0.3059034
```

Diameter

The following tie types have a diameter of 5:
1. I have texted in the last 7 days (tie type 1) 2. I have met during my time in MBDS (tie type 2) 3. Is my friend (tie type 3)

The following tie types have a diameter of 4:
4. I ask for advice/help (tie type 4) 5. Asks me for help/advice (tie type 5)

```r
# Diameter

diameter(network_class_tietype1, directed=F, weights=NA)
```

```
## [1] 5
```

```r
diameter(network_class_tietype2, directed=F, weights=NA)
```

```
## [1] 5
```

```r
diameter(network_class_tietype3, directed=F, weights=NA)
```

```
## [1] 4
```

```r
diameter(network_class_tietype4, directed=F, weights=NA)
```

```
## [1] 4
```

```r
diameter(network_class_tietype5, directed=F, weights=NA)
```

```
## [1] 4
```

Closeness

Closeness measures how close people are to everyone else

From closest to least close, the rank of tie types is as follows:

1. I have met during my time in MBDS (tie type 2)
2. I ask for advice/help (tie type 4)
3. I have texted in the last 7 days (tie type 1)

4. Asks me for help/advice (tie type 5)
5. Is my friend (tie type 3)

```r
#calculating closeness

mean(closeness(network_class_tietype1, mode="all", weights=NA))
```

```
## Warning in closeness(network_class_tietype1, mode = "all", weights = NA): At
## centrality.c:2784 :closeness centrality is not well-defined for disconnected
## graphs
```

```
## [1] 0.003790316
```

```r
mean(closeness(network_class_tietype2, mode="all", weights=NA))
```

```
## Warning in closeness(network_class_tietype2, mode = "all", weights = NA): At
## centrality.c:2784 :closeness centrality is not well-defined for disconnected
## graphs
```

```
## [1] 0.004634212
```

```r
mean(closeness(network_class_tietype3, mode="all", weights=NA))
```

```
## Warning in closeness(network_class_tietype3, mode = "all", weights = NA): At
## centrality.c:2784 :closeness centrality is not well-defined for disconnected
## graphs
```

```
## [1] 0.001634019
```

```r
mean(closeness(network_class_tietype4, mode="all", weights=NA))
```

```
## Warning in closeness(network_class_tietype4, mode = "all", weights = NA): At
## centrality.c:2784 :closeness centrality is not well-defined for disconnected
## graphs
```

```
## [1] 0.003956749
```

```r
mean(closeness(network_class_tietype5, mode="all", weights=NA))
```

```
## Warning in closeness(network_class_tietype5, mode = "all", weights = NA): At
## centrality.c:2784 :closeness centrality is not well-defined for disconnected
## graphs
```

```
## [1] 0.002451302
```

Betweenness

Betweenness is the shortest paths between nodes that go through a given node

From most betweenness to least betweenness, the rank of ties in terms of betweenness is as follows:

1. Is my friend (tie type 3)
2. I ask for advice/help (tie type 4)
3. Asks me for help/advice (tie type 5)
4. I have texted in the last 7 days (tie type 1)
5. I have met during my time in MBDS (tie type 2)

```r
mean(betweenness(network_class_tietype1, directed=F, weights=NA))
```

```
## [1] 21.475
```

```r
mean(betweenness(network_class_tietype2, directed=F, weights=NA))
```

```
## [1] 21.725
```

```r
mean(betweenness(network_class_tietype3, directed=F, weights=NA))
```

```
## [1] 10.825
```

```r
mean(betweenness(network_class_tietype4, directed=F, weights=NA))
```

```
## [1] 16.625
```

```r
mean(betweenness(network_class_tietype5, directed=F, weights=NA))
```

```
## [1] 16.975
```

Degree
Degree looks at the number of ties in a network

From greatest to least, the rank of tie types in terms of degree is as follows:
1. I ask for advice/help (tie type 4) 2. I have texted in the last 7 days (tie type 1) 3. I have met during my time in MBDS (tie type 2) 4. Is my friend (tie type 3) 5. Asks me for help/advice (tie type 5)

```r
mean(degree(network_class_tietype1, mode="all"))
```

```
## [1] 7.15
```

```r
mean(degree(network_class_tietype2, mode="all"))
```

```
## [1] 6.65
```

```r
mean(degree(network_class_tietype3, mode="all"))
```

```
## [1] 6.55
```

```r
mean(degree(network_class_tietype4, mode="all"))
```

```
## [1] 8.8
```

```r
mean(degree(network_class_tietype5, mode="all"))
```

```
## [1] 5.6
```

Centrality Degree

Information Centrality is the number of all paths between nodes that go through a given node

From greatest centralization to least centralization, the rank of tie types is as follows:

1. I ask for advice/help (tie type 4)
2. I have met during my time in MBDS (tie type 2)
3. Is my friend (tie type 3)
4. I have texted in the last 7 days (tie type 1)
5. Asks me for help/advice (tie type 5)

```r
centr_degree(network_class_tietype1, mode="in", normalized=T)
```

```
## $res
##  [1] 2 6 3 2 8 7 0 3 5 0 4 6 4 1 4 2 0 9 6 4 1 8 1 2 1 1 3 9 7 4 5 2 3 5 5 4 1 2
## [39] 1 2
##
## $centralization
## [1] 0.1391026
##
## $theoretical_max
## [1] 1560
```

```r
centr_degree(network_class_tietype2, mode="in", normalized=T)
```

```
## $res
##  [1]  1 10  1  2  7 10  0  4  2  1  0  0  1  1  2  1  1 11  9  2  4  2  4  1  1
## [26]  2  6 10  3  2  8  2  1  7  7  4  1  1  0  1
##
## $centralization
## [1] 0.1967949
##
## $theoretical_max
## [1] 1560
```

```r
centr_degree(network_class_tietype3, mode="in", normalized=T)
```

```
## $res
##  [1] 1 9 0 2 8 8 0 2 0 0 0 6 2 1 4 1 0 9 4 6 2 7 3 1 0 0 4 6 8 4 7 4 3 6 4 6 0 2
## [39] 0 1
##
## $centralization
## [1] 0.1467949
##
## $theoretical_max
## [1] 1560
```

```r
centr_degree(network_class_tietype4, mode="in", normalized=T)
```

```
## $res
##  [1]  1  9  1  2  8  8  1 15  3  9  1  4  3  1  2  0  0  9  5  6 12  6  1  1  1
## [26]  2  2 10 16  4  6  3  3  5  4  8  0  2  0  2
##
## $centralization
## [1] 0.2974359
##
## $theoretical_max
## [1] 1560
```

```r
centr_degree(network_class_tietype5, mode="in", normalized=T)
```

```
## $res
##  [1] 4 2 1 2 7 8 0 0 4 0 1 2 2 1 1 0 0 8 4 5 1 7 1 2 0 3 1 8 3 4 6 2 3 5 5 5 0 2
## [39] 0 2
##
## $centralization
## [1] 0.1333333
##
## $theoretical_max
## [1] 1560
```

Mean Distance

The mean distance between nodes, in order from least to greatest, is as follows:

1. Is my friend (tie type 3)
2. I ask for advice/help (tie type 4)
3. I have met during my time in MBDS (tie type 2)
4. I have texted in the last 7 days (tie type 1)
5. Asks me for help/advice (tie type 5)

```r
mean_distance(network_class_tietype1, directed=T)
```

```
## [1] 2.226804
```

```r
mean_distance(network_class_tietype2, directed=T)
```

```
## [1] 2.207792
```

```r
mean_distance(network_class_tietype3, directed=T)
```

```
## [1] 2.039301
```

```r
mean_distance(network_class_tietype4, directed=T)
```

```
## [1] 2.1406
```

```r
mean_distance(network_class_tietype5, directed=T)
```

```
## [1] 2.231855
```

Which tie type generates the most similar network in terms of introversion? Which tie type is the most dissimilar?

In terms of introversion…
Most similar network: "I have texted in the last 7 days"
Most dissimilar network: "Is my friend"

```r
node <- nodelist
node[is.na(node)] <- -1

net <- graph_from_data_frame(d = edgelist, vertices = node, directed = TRUE)
net1 <- graph_from_data_frame(d = edgelist1, vertices = node, directed = TRUE)
net2 <- graph_from_data_frame(d = edgelist2, vertices = node, directed = TRUE)
net3 <- graph_from_data_frame(d = edgelist3, vertices = node, directed = TRUE)
net4 <- graph_from_data_frame(d = edgelist4, vertices = node, directed = TRUE)
net5 <- graph_from_data_frame(d = edgelist5, vertices = node, directed = TRUE)

#filter edgelist for all 5 tie types...then calculate this measure for 5 networks and see which is most
#Similarity

assortativity(net1, V(net1)$trait, directed=T)
```

```
## [1] 0.1235727
```

```r
assortativity(net2, V(net2)$trait, directed=T)
```

```
## [1] -0.03062123
```

```r
assortativity(net3, V(net3)$trait, directed=T)
```

```
## [1] -0.04311202
```

```r
assortativity(net4, V(net4)$trait, directed=T)
```

```
## [1] 0.003559696
```

```r
assortativity(net5, V(net5)$trait, directed=T)
```

```
## [1] 0.06082053
```

##3 Do introverts tend to be at the periphery while extraverts are in the center of the network? Motivate.

We use both decision tree and regression to examine if introverts tend to be at the periphery while extraverts are in the center of the network. The input is the trait (level of introvert/extravert) and the output is the degree/betweenness.

Both the decision tree models are unable to predict any patterns. The regression model also does not show any significances. The small sample size is our limitation. We come to conclude that trait (introvert/extravert) does not predict where introverts andextraverts are in the network.

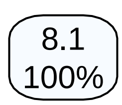
```
library(rpart)
library(rpart.plot)
```

```
## Warning: package 'rpart.plot' was built under R version 4.0.3
```

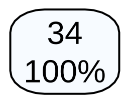
```
library(caret)
```

```
## Warning: package 'caret' was built under R version 4.0.3

## Loading required package: lattice

##
## Attaching package: 'caret'

## The following object is masked from 'package:purrr':
##
##     lift
```

```
#decision tree: betweenness and trait
tree_bt <- nodelist %>% mutate (between = betweenness(network_class, directed=F, weights=NA))
model_tree_bt <- rpart(between ~ as.factor(trait), method = "anova", data = tree_bt, cp = 0.00001)
rpart.plot(model_tree_bt)
```



```r
#decision tree: degree and trait
tree_dg <- nodelist %>% mutate (degree = degree(network_class, mode="in"))
model_tree_dg <- rpart(degree ~ as.factor(trait), method = "anova", data = tree_dg, cp = 0.00001)
rpart.plot(model_tree_dg)
```




```r
#regression: bewteenness and trait
summary(lm(between ~ as.factor(trait), data = tree_bt))
```

```
##
## Call:
## lm(formula = between ~ as.factor(trait), data = tree_bt)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.1672 -2.8235 -0.7542  1.6553  7.4106
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)          9.5566     1.9448   4.914 0.000112 ***
## as.factor(trait)2  -1.8153     2.1304  -0.852 0.405359
## as.factor(trait)3  -0.8197     2.7504  -0.298 0.769085
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.369 on 18 degrees of freedom
##   (19 observations deleted due to missingness)
```

```
## Multiple R-squared:  0.04433,    Adjusted R-squared:  -0.06186
## F-statistic: 0.4175 on 2 and 18 DF,  p-value: 0.6649
```

Contributions: Kim: Q1 Ryan and Ammar: Q2 Elaina and Meghan: Q3