Enron Network Analysis Tutorial

r date()

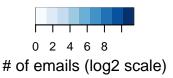
Enron Tutorial

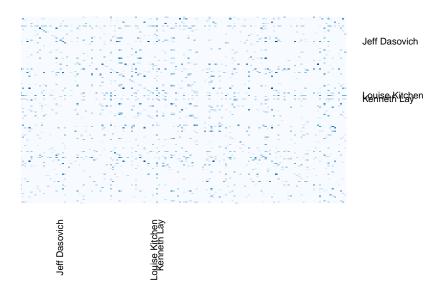
We provide this Enron Tutorial as an appendix to the paper in Journal of Statistical Education, *Network Analysis with the Enron Email Corpus*. The paper describes the centrality measures in detail, and we go through the steps in the R analysis here.

As in the .Rmd file with the R code, be sure to install the pacakges WGCNA and igraph.

The first step of the analysis is to import the data and create the adjacency matrix of our choice. AM represents emails sent from node i to node j with messages sent via CC weighted as described in the paper. The transpose of the matrix AMt represents emails received by node i from node j (again, with CC values weighted differently than messages sent directly to an individual). The sum of the two matrices, AM2, represents the total email correspondence (sent and received) between nodes i and j.

We can represent the adjacency matrix graphically using a heatmap.





Eigenvector Centrality

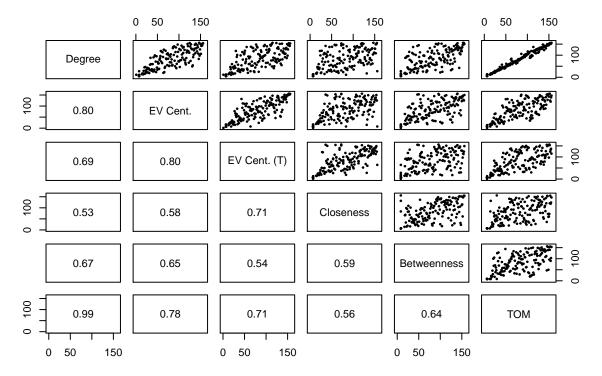
The first measure of centrality that we use is eigenvector centrality; the evcent function is available in the igraph package. Degree, Betweenness, and Closeness centrality measures are also given in the igraph package.

```
# eigenvalue centrality (on both directed graphs),
# degree, betweenness, and closeness
eng <- graph.adjacency(do.call(rbind,AMlist))</pre>
                                                    # creates a network graph using the adjacency matrix
engt <- graph.adjacency(do.call(cbind,AMlist))</pre>
                                                     # creates a network graph using the transpose of the a
eigcent <- igraph::evcent(eng, directed=TRUE)</pre>
                                                     # eigenvalue centrality
eigcentt <- igraph::evcent(engt, directed=TRUE)</pre>
                                                     # eigenvalue centrality on transpose of graph
dcent <- igraph::degree(eng)</pre>
                                                  # degree centrality
bmeas <- igraph::betweenness(eng)</pre>
                                                  # betweenness
cmeas <- igraph::closeness(eng)</pre>
                                                    # closeness
# TOM
AM2 \leftarrow AM2 / max(AM2)
                                                    # set values between 0 and 1
TOM <- TOMsimilarity(AM2)
                                                    # create TOM
## ..connectivity..
## ..matrix multiplication..
## ..normalization..
## ..done.
```

```
TOMrank <- as.matrix(apply(TOM,1,sum)) # grab its row-sums
rownames(TOMrank) <- rownames(AM)
colnames(TOMrank) <- "value"
```

Initially, we plot the ranks of the individuals based on the different measures of centrality. The ranks are clearly correlated, but we can also see that they seem to be measuring different qualities of the email correspondence matrix.

Ranking Metrics Comparison



Next, we lists the top 10 most central individuals for each metric. Note that we use the negative of the centrality measure so that the order function produces the first individual as the most central.

```
EVcentT = rownames(AM)[order(-eigcentt$vector)],
    Close = rownames(AM)[order(-cmeas)],
    Between = rownames(AM)[order(-bmeas)],
    TOM = rownames(AM)[order(-TOMrank)])
rankedEnron[1:10,]
```

```
##
               Degree
                                EVcent
                                                 EVcentT
                                                                     Close
## 1
        Jeff Dasovich
                            Tana Jones
                                        Sara Shackleton
                                                            Robert Benson
## 2
         Mike Grigsby Sara Shackleton
                                            Susan Bailey
                                                             Mike Grigsby
## 3
           Tana Jones Stephanie Panus
                                            Marie Heard
                                                           Louise Kitchen
## 4
      Sara Shackleton
                           Marie Heard
                                              Tana Jones
                                                          Kevin M. Presto
## 5
      Richard Shapiro
                                                              Susan Scott
                          Susan Bailey
                                        Stephanie Panus
## 6
       Steven J. Kean
                              Kay Mann
                                        Elizabeth Sager
                                                               Scott Neal
## 7
       Louise Kitchen Louise Kitchen
                                          Jason Williams
                                                           Barry Tycholiz
## 8
          Susan Scott Elizabeth Sager
                                          Louise Kitchen
                                                             Greg Whalley
## 9
                        Jason Williams Jeffrey T. Hodge Phillip K. Allen
       Michelle Lokay
## 10
        Chris Germany
                         Jeff Dasovich
                                            Gerald Nemec
                                                            Jeff Dasovich
##
             Between
                                  TOM
## 1
      Louise Kitchen
                        Jeff Dasovich
## 2
        Mike Grigsby Richard Shapiro
## 3
         Susan Scott
                      Steven J. Kean
## 4
       Jeff Dasovich
                         Mike Grigsby
## 5
           Mary Hain
                           Tana Jones
## 6
          Sally Beck Sara Shackleton
## 7
         Kenneth Lay
                            Mary Hain
## 8
          Scott Neal
                          Marie Heard
## 9
          Kate Symes Stephanie Panus
## 10 Cara Semperger
                          Susan Scott
```

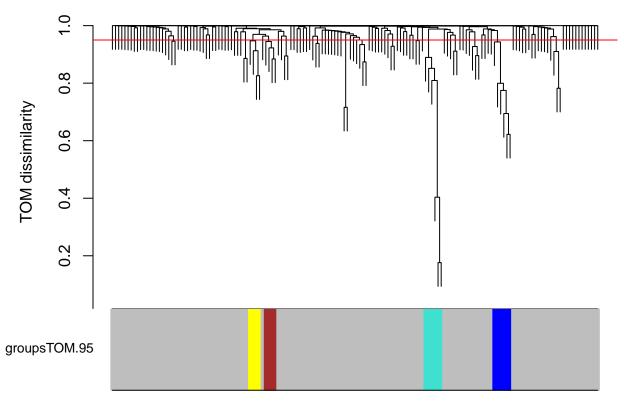
Hierarchical Clustering

Below, we create the heirarchical cluster with both the symmetric (sent and received) adjacency email matrix as well as the TOM adjacency build from the symmetric measures. After building the dendrogram, we find groups of employees who are strongly linked and report the names of the individuals.

min 4 per group, cutoff=0.9

```
0.8
   1 - S&R/max(S&R)
         9.0
         0.4
         0.2
         0.0
       groups.9
table(groups.9)
## groups.9
##
        blue
                   grey turquoise
##
                    147
row.names(AM)[groups.9=="turquoise"]
## [1] "Susan Bailey"
                           "Marie Heard"
                                              "Tana Jones"
                                                                 "Stephanie Panus"
## [5] "Sara Shackleton"
row.names(AM)[groups.9=="blue"]
## [1] "Jeff Dasovich"
                           "Mary Hain"
                                              "Steven J. Kean"
                                                                 "Richard Shapiro"
### Now cluster with TOM
\textit{\# for the next plot, dissimilarity uses TOM metric to encorporate neighbors}
dissTOM=TOMdist(AM2)
## ..connectivity..
## ..matrix multiplication..
## ..normalization..
## ..done.
```

min 4 per group, cutoff=0.95



```
table(groupsTOM.95)
```

```
## groupsTOM.95
## blue brown grey turquoise yellow
## 6 4 136 6 4
```

row.names(AM)[groupsTOM.95=="turquoise"]

```
## [1] "Robert Badeer" "Jeff Dasovich" "Mary Hain"
## [4] "Steven J. Kean" "Richard Shapiro" "James D. Steffes"
```

```
row.names(AM)[groupsTOM.95=="blue"]
```

```
## [1] "Susan Bailey" "Marie Heard" "Tana Jones" "Stephanie Panus"

row.names(AM)[groupsTOM.95=="brown"]

## [1] "Lindy Donoho" "Michelle Lokay" "Mark McConnell" "Kimberly Watson"

row.names(AM)[groupsTOM.95=="yellow"]
```