## **Enron Email Network Analysis**

Analysis is based on Enron Email network data which is derived from <a href="http://www.cis.jhu.edu/~parky/Enron/">http://www.cis.jhu.edu/~parky/Enron/</a>. This contains a small subset of the large network. This data was originally made public, and posted to the web, by the Federal Energy Regulatory Commission during its investigation. Nodes of the network are email addresses and if an address i sent at least one email to address j, the graph contains an undirected edge from i to j.

Notebook Goal- We are trying to parse the data into clusters and find out the central person in the network based on its clusters. Its an easy task but this model can be used for variety of use cases like Citation Network, Twitter network and so on.

Further Analysis can be done based on the notebook result.

## Process-

- 1. Explore data
- 2. Compute the partition of the graph nodes which maximises the modularity by using the Louvain heuristices. (Cluster Partition)
- 3. Connected component to check whether the nodes are connected.
- 4. Betweeness Centrality for a particular cluster
- 5. Bfs tree based on the most central node.

```
In [ ]: !conda install seaborn # This is for seaborn package for scatter plot using se
aborn
```

Import Environment variables needed for the notebook model

```
In [84]: import numpy as np
  import pandas as pd
  import seaborn as sns
  import networkx as nx
  import matplotlib.pyplot as plt
  %matplotlib inline
```

Read the Text file into networkx graph

Print and check the data (no. of nodes and edges)

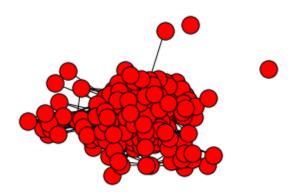
In [5]: print (nx.info(enron))

Name:

Type: Graph

Number of nodes: 184 Number of edges: 2216 Average degree: 24.0870

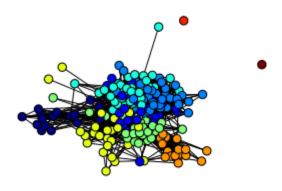
In [6]: sp= nx.spring\_layout(enron) # Using the spring Layout in networkx



## Community Detection (Cluster Partition)

In [9]: import community

In [10]: parts = community.best\_partition(enron)
 values = [parts.get(node) for node in enron.nodes()]



```
In [12]: mod = community.modularity(parts,enron)
print("modularity:", mod)
```

modularity: 0.375837260846616

This means that the network is not a dense network. Higher the modularity denser the network.

```
In [16]: print(parts) # Lets print the result of the partition
{0: 0, 1: 1, 2: 2, 3: 3, 4: 4, 5: 4, 6: 3, 7: 5, 8: 6, 9: 0, 10: 2, 11: 1, 1
```

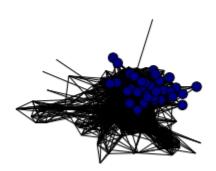
```
2: 4, 13: 0, 14: 2, 15: 1, 16: 3, 17: 2, 18: 5, 19: 3, 20: 0, 21: 5, 22: 1, 2
3: 6, 24: 3, 25: 6, 26: 3, 27: 4, 28: 5, 29: 1, 30: 0, 31: 6, 32: 5, 33: 6, 3
4: 4, 35: 5, 36: 2, 37: 4, 38: 1, 39: 3, 40: 5, 41: 2, 42: 4, 43: 2, 44: 5, 4
5: 2, 46: 2, 47: 3, 48: 0, 49: 2, 50: 1, 51: 4, 52: 5, 53: 4, 54: 2, 55: 0, 5
6: 2, 57: 4, 58: 4, 59: 3, 60: 1, 61: 3, 62: 3, 63: 4, 64: 5, 65: 1, 66: 4, 6
7: 4, 68: 1, 69: 4, 70: 1, 71: 7, 72: 4, 73: 4, 74: 4, 75: 1, 76: 5, 77: 5, 7
8: 2, 79: 0, 80: 2, 81: 2, 82: 2, 83: 4, 84: 2, 85: 5, 86: 5, 87: 5, 88: 2, 8
9: 3, 90: 3, 91: 0, 92: 1, 93: 3, 94: 4, 95: 6, 96: 1, 97: 2, 98: 6, 99: 3, 1
00: 5, 101: 2, 102: 3, 103: 6, 104: 0, 105: 4, 106: 2, 107: 4, 108: 6, 109:
4, 110: 1, 111: 1, 112: 1, 113: 6, 114: 1, 115: 3, 116: 2, 117: 8, 118: 3, 1
19: 0, 120: 3, 121: 5, 122: 6, 123: 4, 124: 6, 125: 5, 126: 3, 127: 2, 128:
4, 129: 0, 130: 2, 131: 0, 132: 3, 133: 5, 134: 3, 135: 3, 136: 3, 137: 2, 1
38: 5, 139: 2, 140: 3, 141: 3, 142: 0, 143: 3, 144: 4, 145: 1, 146: 4, 147:
4, 148: 0, 149: 5, 150: 3, 151: 6, 152: 0, 153: 5, 154: 2, 155: 1, 156: 2, 1
57: 2, 158: 6, 159: 2, 160: 1, 161: 6, 162: 1, 163: 4, 164: 3, 165: 1, 166:
2, 167: 5, 168: 1, 169: 1, 170: 6, 171: 3, 172: 1, 173: 1, 174: 3, 175: 2, 1
76: 3, 177: 6, 178: 4, 179: 2, 180: 2, 181: 4, 182: 2, 183: 5}
```

As we can see, each key value of node is given a partition value. Suppose now we only want the partition value 2:

```
In [27]: bparts = {k:v for (k, v) in parts.items() if v == 2}
    print(bparts)
```

{2: 2, 182: 2, 137: 2, 10: 2, 139: 2, 130: 2, 78: 2, 80: 2, 81: 2, 82: 2, 84: 2, 14: 2, 88: 2, 154: 2, 156: 2, 157: 2, 159: 2, 97: 2, 36: 2, 101: 2, 166: 2, 17: 2, 41: 2, 106: 2, 43: 2, 45: 2, 46: 2, 175: 2, 49: 2, 179: 2, 116: 2, 54: 2, 56: 2, 180: 2, 127: 2}

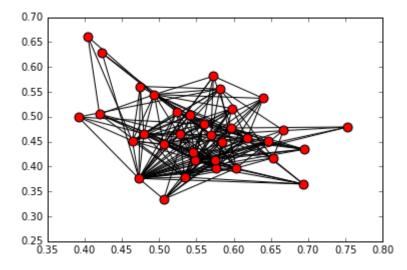
- In [28]: values1 = [bparts.get(node) for node in enron.nodes()]
- In [29]: plt.axis("off")
  x = nx.draw\_networkx(enron, pos = sp, cmap = plt.get\_cmap("jet"), node\_color =
   values1, node\_size = 90, with\_labels = False)



## Shows only the network of patition Value 2

{2, 130, 137, 10, 139, 14, 17, 154, 156, 157, 159, 36, 166, 41, 43, 45, 46, 1 75, 49, 179, 180, 54, 182, 56, 78, 80, 81, 82, 84, 88, 97, 101, 106, 116, 12 7}

In [87]: sub\_enron = enron.subgraph(key) # Making a subgraph out of the keys of the par tition In [32]: subgraph = nx.draw\_networkx(sub\_enron, pos = sp,node\_size = 80, with\_labels =
False)



This is the Sub graph of the cluster 2. We will be focusing on this for finding the most cenral node

```
sorted(nx.connected_components(sub_enron), key = len, reverse=True) # Check an
          d grouping the conncetd component.
Out[34]: [{2,
            14,
            17,
            36,
            41,
            43,
            45,
            46,
            49,
            54,
            56,
            78,
            80,
            81,
            82,
            84,
            88,
            97,
            101,
            106,
            116,
            127,
            130,
            137,
            139,
            154,
            156,
            157,
            159,
            166,
            175,
            179,
            180,
```

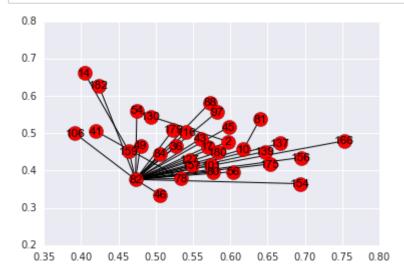
This network sub graph has only 1 connceted component. Now Lets check the betweeness centrality for this sub graph

182}]

```
In [89]: | nx.betweenness centrality(sub enron)
Out[89]: {2: 0.014589723012182905,
          10: 0.026366056463708168,
          14: 0.0009358288770053476,
          17: 0.04551603798957356,
          36: 0.00695494592553416,
          41: 0.012535706228691443,
          43: 0.01604348810231163,
          45: 0.0020209093738505503,
          46: 0.001502419149477973,
          49: 0.026581145258744176,
          54: 0.0,
          56: 0.027853882599871895,
          78: 0.03954197562250409,
          80: 0.03530459006887197,
          81: 0.0033712474888945476,
          82: 0.2136933794551038,
          84: 0.021612357727761808,
          88: 0.0009602787096393234,
          97: 0.014902244449408582,
          101: 0.012037403807614564,
          106: 0.0006111535523300229,
          116: 0.017223449211906064,
          127: 0.004620923738570796,
          130: 0.0631339060360355,
          137: 0.0,
          139: 0.0021475256769374414,
          154: 0.0007299889652830828,
          156: 0.0028987352516764275,
          157: 0.07116726001458692,
          159: 0.036583646373093415,
          166: 0.0,
          175: 0.003932345368331528,
          179: 0.0038982902619266254,
          180: 0.0032221524374512053,
          182: 0.00012732365673542143}
```

As you can see the 82 has the maximum betweeness centrality. That means it acts as the bridge in the network. WE will now try to apply the breadth first serach tree algorithm taking 82 as the starting point

In [92]: nx.draw\_networkx(bfs, pos = sp,node\_size = 200, with\_labels = True) #Plot the
 BFS tree



From the above graph we can makeout that there is some kind of a heirarchy in the network. We can even find out who was used as a cc or bcc in this email network. For Example, in above graph - look at the link 82-78-154.. We can say that 78 sent some data to 154 keeping 82 as cc. Since its an undirected graph its hard to make out but we can surely get some major points from this to understand the network.

Lets try to run hits

In [93]: hits = nx.hits(sub\_enron, max\_iter=100, tol=1e-08, nstart=None, normalized=Tru
e) # cannot make out the output. Please give your inputs.
print(hits)

({2: 0.031817349869161154, 182: 0.00954208834280252, 137: 0.00982322454101678 4, 10: 0.046357776911443216, 139: 0.024999342277107577, 130: 0.03771361440022 4325, 14: 0.006238644266323655, 80: 0.04416051260379766, 17: 0.04160124234044 1054, 82: 0.061999138232737214, 84: 0.04835227853275319, 78: 0.04635723030818 7995, 88: 0.02005738881940745, 154: 0.0230484998760797, 156: 0.02092054283226 148, 157: 0.052792817851167434, 159: 0.033334948246978316, 97: 0.022739768344 48666, 36: 0.022172326273056923, 101: 0.028083744896090976, 166: 0.0127087319 20856248, 81: 0.022764378463125422, 41: 0.015104281490668992, 106: 0.01370670 538815923, 43: 0.034291897959348686, 45: 0.032366122803062336, 46: 0.02238185 3656058555, 175: 0.01611087282942599, 49: 0.03691762394416883, 179: 0.0287894 87056251443, 180: 0.023330097064370867, 54: 0.013013989296203003, 56: 0.03480 449044539484, 116: 0.03773979261242065, 127: 0.02385719530495966}, {2: 0.0318 1734986836458, 182: 0.00954208834402947, 137: 0.009823224542817316, 10: 0.046 35777690908403, 139: 0.024999342274258395, 130: 0.03771361440387287, 14: 0.00 6238644267460254, 80: 0.044160512599597995, 17: 0.04160124234369831, 82: 0.06 19991382330177, 84: 0.04835227853378155, 78: 0.04635723030405851, 88: 0.02005 7388820366482, 154: 0.023048499873518626, 156: 0.020920542830199423, 157: 0.0 52792817849430934, 159: 0.03333494825153892, 97: 0.022739768349418384, 36: 0. 022172326269623233, 101: 0.02808374489138619, 166: 0.012708731921028045, 81: 0.02276437846297017, 41: 0.015104281487725845, 106: 0.013706705391168044, 4 3: 0.03429189796037765, 45: 0.03236612280346297, 46: 0.02238185365416197, 17 5: 0.016110872832268947, 49: 0.03691762394715635, 179: 0.028789487056402108, 180: 0.023330097062721256, 54: 0.013013989298942473, 56: 0.0348044904454208 4, 116: 0.03773979261484644, 127: 0.023857195301823803})

In [ ]: