Web 信息处理与应用 Lab2-1:
网络中节点影响力及社区发现: Erdös 共同作者网络的挖掘

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1 数据集描述

文件 **Erdos.html** 给出了 **Paul Erdos** 的 **511** 名共同作者名单，与他们下面列出的共同作者一起。给出了与鄂尔多斯的第一份联合文件的日期，其次是联合出版物的数量（如果它不止一个）。名称后面有一个星号表明这个 **Erdos** 合作者是众所周知的死者。

2 数据预处理与 Erdös 共同作者网络的建立

数据预处理策略：

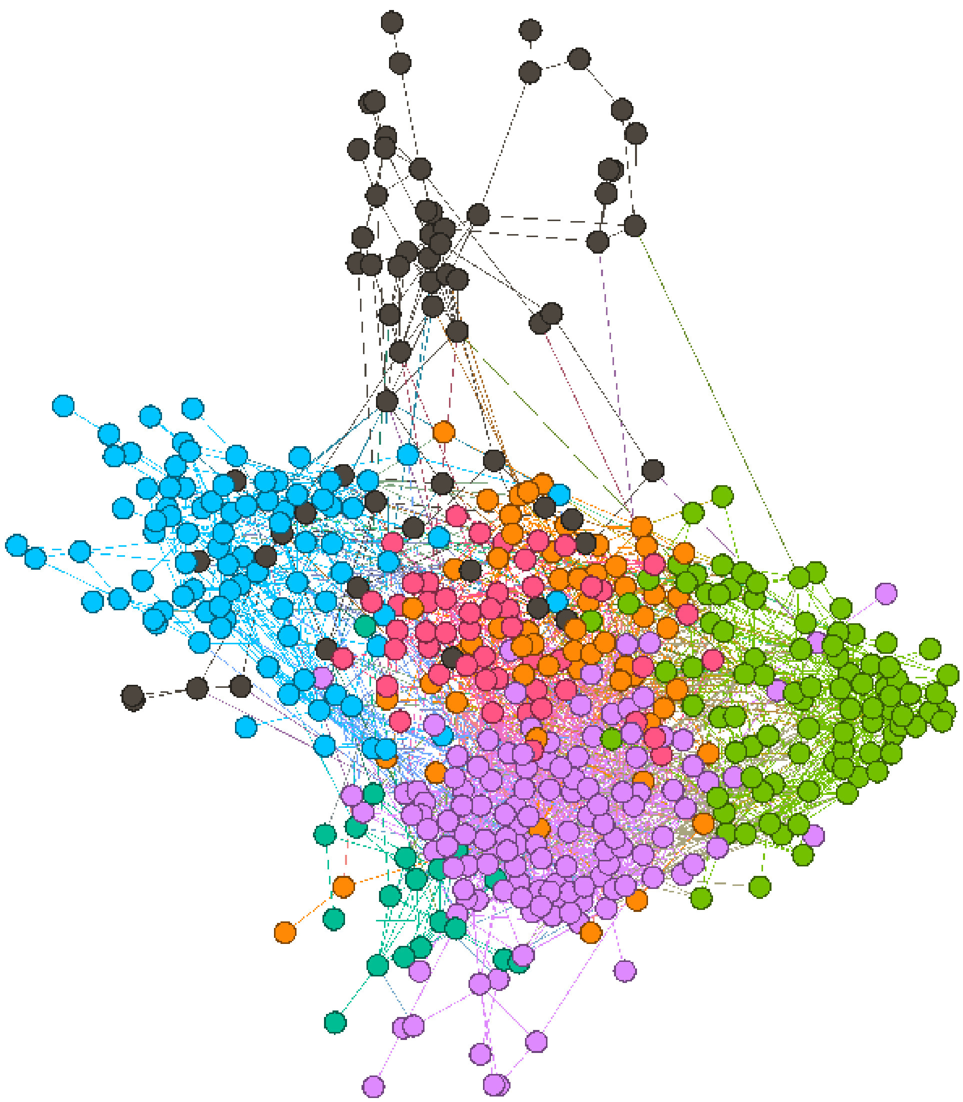
1. 由于这个图非常的大，所以可以忽略重名，死亡，合作数量等稀疏的信息以降低分析的复杂度。

2. 利用 **networkx** 包建立网络结构。

3. 删除一些度数很少的节点降低分析时的干扰。

4. 手动删除 **html** 标签和其他信息方便处理。

共同作者网络初步建立如下图所示：(可以粗略地看到 **8** 个左右的社区)



3 影响力分析

3.1 Degree Centrality

Degree Centrality 认为，度数越大的节点，越具有影响力，选取度数最大的 50 个节点，代码如下：

```
# Degree Centrality Influence Analyse
CoAuthGraphDict = nx.convert.to_dict_of_lists(CoAuthGraph)
DegreeDict = {}
for node in CoAuthGraph.nodes:
    DegreeDict[node] = len(CoAuthGraphDict[node])

SortedDegree = sorted(DegreeDict.items(),key = lambda x:x[1],reverse = True)
InfluentialAnalyseData = open("../data2/InfluentialAnalyseData.txt",'w')
print("Top 50 of the most influential node under Degree Centrality: \n",end = '')
InfluentialAnalyseData.write("Top 50 of the most influential node under Degree Centrality: \n")
for i in range(50):
    print( str(i + 1) + ' : ' + str(SortedDegree[i]) + '\n',end = '')
InfluentialAnalyseData.write( str(i + 1) + ' : ' + str(SortedDegree[i]) + '\n')
```

3.2 Closeness Centrality

Closeness Centrality 认为，到图上其他点平均距离越小的点，越具有影响力，选取到图上其他点平均距离最小的 50 个节点，代码如下：

```
# Closeness Centrality Influence Analyse
NumberOfNodes = len((list)(CoAuthGraph.nodes))
ClosenessDict = {}
for node_form in CoAuthGraph.nodes:
    SumDistanse = 0
    for node_to in CoAuthGraph.nodes:
        try:
            SumDistanse += nx.shortest_path_length(CoAuthGraph,node_form,node_to)
        except nx.exception.NetworkXNoPath:
            SumDistanse += NumberOfNodes * 10
    #print(node_form + str(( NumberOfNodes - 1 ) / SumDistanse))
    ClosenessDict[node_form] = ( NumberOfNodes - 1 ) / SumDistanse
SortedCloseness = sorted(ClosenessDict.items(),key = lambda x:x[1],reverse = True)

print("Top 50 of the most influential node under Closeness Centrality: \n",end = '')
InfluentialAnalyseData.write("Top 50 of the most influential node under Closeness Centrality: \n")
for i in range(50):
    print( str(i + 1) + ' : ' + str(SortedCloseness[i]) + '\n',end = '')
    InfluentialAnalyseData.write( str(i + 1) + ' : ' + str(SortedCloseness[i]) + '\n')
```

3.3 两种方法的结果对比

Closeness Centrality 和 Degree Centrality 的运行结果对比如下：仔细观察会发现左右两行有很多相同的名字，所以两种方法都有一定的效果但并不完全相同

Node	Degree Centrality	Node	Closeness Centrality
ALON,NOGAM.	435	ALON,NOGAM.	0.0022076341214382735
HARARY,FRANK'	315	GRAHAM,RONALDLEWIS	0.0022072631603754877
COLBOURN,CHARLESJOSEPH	244	FUREDI,ZOLTAN	0.0022069908350490835
SHELAH,SAHARON	223	BOLLOBAS,BELA	0.002206952782513424
TUZA,ZSOLT	223	RODL,VOJTECH	0.0022068420148237716
SALAMON,PETER	220	SPENCER,JOELHAROLD	0.002206832714226083
WEST,DOUGLASBRENT	201	HARARY,FRANK	0.0022066940600661356
GRAHAM,RONALDLEWIS	196	TUZA,ZSOLT	0.0022066712345272027
LUCA,FLORIAN	193	CHUNG,FANRONGKING(GRAHAM)	0.002206440046886851
HSU,DERBIAUFRANK	170	LOVASZ,LASZLO	0.002206410887718393
BOLLOBAS,BELA	166	NESETRIL,JAROSLAV	0.002206401590754258
PACH,JANOS	154	KLEITMAN,DANIELJ.	0.0022063944067901788
KLEITMAN,DANIELJ.	152	WORMALD,NICHOLASCHARLES	0.0022063145411641413
ODLYZKO,ANDREWMICHAEL	151	ODLYZKO,ANDREWMICHAEL	0.0022063090479738155
JANSON,SVANTE	149	SOS,VERATURAN	0.002206283272599896
RODL,VOJTECH	145	SZEMEREDI,ENDRE	0.002206276089406274
LOVASZ,LASZLO	145	FRANKL,PETER	0.0022062482021566843
CAMERON,PETERJ.	145	PACH,JANOS	0.002206232146181265
CHUNG,FANRONGKING(GRAHAM)	142	BABAI,LASZLO	0.0022060213275537617
SAKS,MICHAELEZRA	140	GYARFAS,ANDRAS	0.00220593853205897
FABER,VANCE	138	RUZSA,IMREZ.	0.0022058768619027257
LINIAL,NATHAN	137	TROTTER,WILLIAMTHOMAS	0.0022058688365880113
HELL,PAVOL	136	SAKS,MICHAELEZRA	0.0022058675694383943
DIACONIS,PERSIW.	133	FAUDREE,RALPHJASPER,JR.	0.0022058667246727917
KOREN,ISRAEL	132	LUCZAK,TOMASZ	0.0022058460281176437
HEDETNIEMI,STEPHENTRAVIS	126	STRAUS,ERNSTGABOR	0.002205816884647457
SHALLIT,JEFFREYOUTLAW	126	CHVATAL,VACLAV(VASEK)	0.002205783518431504
FUREDI,ZOLTAN	123	SIMONOVITS,MIKLOS	0.0022057645128103795
WORMALD,NICHOLASCHARLES	123	WEST,DOUGLASBRENT	0.0022057442405088376
NESETRIL,JAROSLAV	122	POMERANCE,CARLBERNARD	0.0022056897605448053
KOSTOCHKA,ALEXANDRV.	121	WINKLER,PETERMANN	0.002205646685269152
ARONOV,BORIS	119	KOSTOCHKA,ALEXANDRV.	0.0022056357055660137
WINKLER,PETERMANN	118	HAJNAL,ANDRAS	0.002205633594097173
HENNING,MICHAELANTHONY	115	COLBOURN,CHARLESJOSEPH	0.0022055111358210045
SPENCER,JOELHAROLD	114	HELL,PAVOL	0.002205485379086944
GODDARD,WAYNEDEAN	114	THOMASSEN,CARSTEN	0.002205430489693633
CHARTRAND,GARYTHEODORE	112	KOMLOS,JANOS	0.002205408534701299
POMERANCE,CARLBERNARD	112	JANSON,SVANTE	0.0022053937575487355
MCKAY,BRENDANDAMIEN	111	BURR,STEFANANDRUS	0.0022052814576604147
STINSON,DOUGLASROBERT	111	CHARTRAND,GARYTHEODORE	0.002205266260057938
BABAI,LASZLO	107	FRAENKEL,AVIEZRISIEGMUND	0.002205216447162765
HOFFMAN,ALANJEROME	105	LEHEL,JENO	0.0022051839433512746
LUCZAK,TOMASZ	105	MCKAY,BRENDANDAMIEN	0.002205110074615795
MCELIECE,ROBERTJAMES	102	ROTHSCHILD,BRUCELEE	0.0022051024769694084
TETALI,PRASADVENKATASITARAMAVARA	97	CAMERON,PETERJ.	0.0022050910805979933
CHUI,CHARLESKAM-TAI	95	LINIAL,NATHAN	0.0022050505611202883
KLAWE,MARIAMARGARET	93	Seymour,PaulD.	0.0022050497169803377
AVIS,DAVIDMICHAEL	91	SCHELP,RICHARDHERBERT	0.0022049817658343815
FRAENKEL,AVIEZRISIEGMUND	91	TETALI,PRASADVENKATASITARAMAVARA	0.0022049724809098574
TOVEY,CRAIGAARON	91	GRANVILLE,ANDREWJAMES	0.0022049281675745407

4 社区发现

4.1 GirvanNewman 算法的步骤

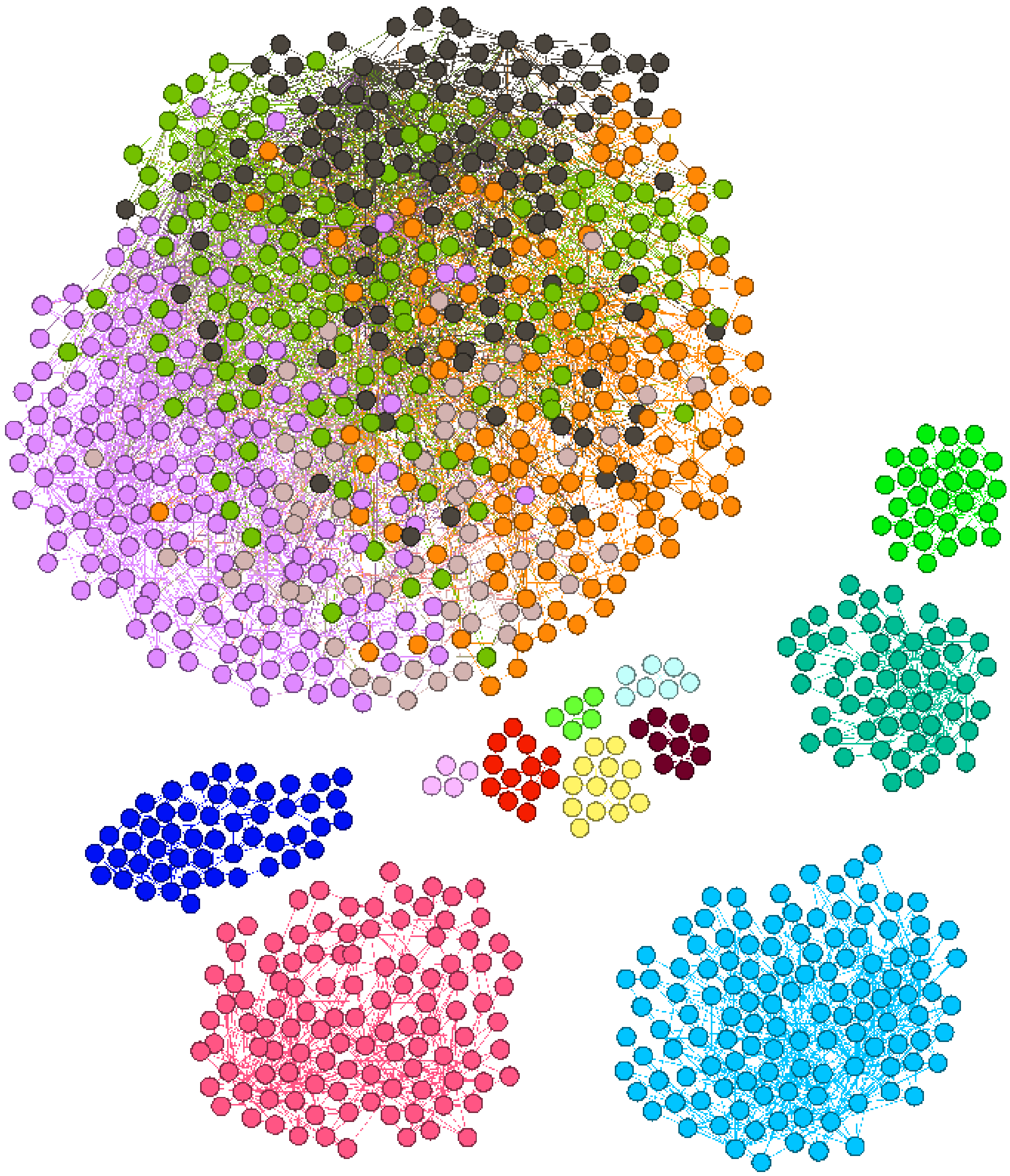
GirvanNewman 算法的基本思想：在模块性没有达到要求之前，不断切除边界数最大的边。

```
def run(self):
while True:
    ModulQ = self.get_modularity()
    print("Get Modularity:" + str(ModulQ))
    if (ModulQ > self.Q) or (self.Graph.number_of_edges() == 0):
        break
    self.cut_bridge()
    ###############################################################
    DegreeDict = (dict)(nx.degree(self.Graph))
    NodeList = list( self.Graph.nodes() )
    for node in NodeList:
        if DegreeDict[node] <= 1:
            self.Graph.remove_node(node)
    ###############################################################
```

```
def get_modularity(self):
print("Computing Modularity...")
Communities = nx.connected_components(self.Graph)
DegreeDict = (dict)(nx.degree(self.Graph))
Modularity = 0.0
Nodes = list(self.Graph.nodes())
AdjMatrix = nx.adj_matrix(self.Graph)
NumberOfEdges = nx.number_of_edges(self.Graph)

for Com in Communities:
    for node_from in Com:
        for node_to in Com:
            Modularity += (
        float(AdjMatrix[Nodes.index(node_from),Nodes.index(node_to)]) -
        float(DegreeDict[node_from] * DegreeDict[node_to]) /
        float(2 * NumberOfEdges) )

Modularity = Modularity / ( 2 * NumberOfEdges )
return Modularity
```

```
def cut_bridge(self):
OriginCommunityNum = nx.number_connected_components(self.Graph)
NewCommunityNum = OriginCommunityNum
print("Begin Cut ...",end ='\t')
CutTimes = 0
while NewCommunityNum <= OriginCommunityNum:

    # print("Computing Betweenness...",end='\t')
    EdgeBetweenness = nx.edge_betweenness_centrality(self.Graph)
    # print("Betweenness get.")
    CutTimes = CutTimes + 1
    ###########################################################################
    # 这里每次只删除一条界边数最高的边
    # EBSortedOrder = sorted(EdgeBetweenness.items(),key=lambda x:x[1],reverse=True)
    # self.Graph.remove_edge(EBSortedOrder[0][0][0],EBSortedOrder[0][0][1])
    ###########################################################################

    # 一次性删除所有界边数最高的边加快收敛速度:
    MaxEB = max(EdgeBetweenness.values())
    for edge, bet in EdgeBetweenness.items():
        if float(bet) == MaxEB:
            self.Graph.remove_edge(edge[0],edge[1])

    NewCommunityNum = nx.number_connected_components(self.Graph)

print("Cut: " + str(CutTimes) + " Edges.")
```

GirvanNewman 算法的运行结果，可以看到一共有 12 个明显的社区，其中 8 个已经被划分出来了，此时的模块性已经大于 0.5



4.2 NormalizedCut 谱聚类算法的步骤

NormalizedCut 谱聚类算法的核心思想是通过在图的 Laplacian 矩阵的特征向量组成的点的特征向量上运行聚类算法发现社区，代码如下：

```
    def run(self):
    EigenVectorForCut = self.spectral_cut()
    Clusters = self.k_means(EigenVectorForCut.T)
    Communities = self.get_community(Clusters)
    print(len(Communities))
    return Communitiesfootnotesize
```

```
    def spectral_cut(self):
    '''
        Compute eigenvectors for Laplacian matrix of the graph
    '''
    DegreeDict = (dict)(nx.degree(self.Graph))
    self.D = np.diag(list(DegreeDict.values())).astype(float)
    self.D_05 = np.diag(list(DegreeDict.values())).astype(float)

    for i in range(self.D_05.shape[0]):
        if self.D_05[i][i] != 0:
            self.D_05[i][i] = self.D_05[i][i] ** (-0.5)
    self.M = nx.adjacency_matrix(self.Graph).todense()
    self.M.astype(float)
    LaplacianMatrix =
    np.dot( np.dot( self.D_05, ( self.D - self.M ) ), self.D_05 )
    print("Getting eigenvectors...")
    EigenValues, EigenVectors = np.linalg.eig(LaplacianMatrix)
    print("Eigenvectors get.")
    return np.array( EigenVectors[:self.expected_community_number] )
```

NormalizedCut 谱聚类算法的运行结果，这里在聚类时选择 GirvanNewman 算法的先验结果，即聚为 12 个类，删除掉一些边缘节点之后，可以看到 NormalizedCut 谱聚类算法同样可以找到相似的 12 个社区的核心结构，但是在一些边缘节点上划分错误较大，所以社区不是很”丰满“，在这一点上比 GirvanNewman 算法略差，但在运行速度上快于 GirvanNewman 算法。