Anexo IV. Analisis anat?mico-funcional

August 27, 2018

Anexo IV. Analisis anatómico-funcional
José Pedro Manzano
Lenguaje: Python

En este anexo se sigue el procedimiento necesario para, a partir de las matrices de conectividad obtenidas de cada dataset, construir una red binaria de la que extraer las principales propiedades, tanto globales como locales.

Para no hacer el anexo demasiado extenso, las principales conclusiones extraídas de los resultados pueden encontrarse en la memoria del trabajo.

```
In [88]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         import networkx as nx
         import community as cm #python-louvain
         import statistics as st
         import operator as op
         import itertools
         import os
         import sys
         from sklearn import preprocessing
```

Importación de los datos

En esta primera parte, se cargarán las matrices de conectividad individuales de cada sujeto con el objetivo de obtener un promedio de 10 sujetos de cada modalidad. También mantendremos la matriz de un sujeto de cada modalidad para realizar algunas comparaciones:

- **Redes Anatómicos (DTI)** de *sujetos sanos (healthy patients), con Alzheimer* y *Autismo*.
- **Redes Funcionales (fMRI)** de *sujetos sanos (healthy patients), con ADHD' y* Autismo*.

```
In [89]: # Define the pathfiles
         userpath = "/Users/hose/Desktop/TFM_TECI/"    ##### Define your work directory here and

         healthy_dti_path = userpath + "/Datos/Seleccionados/dti_sano/datos/"
         apoe4_dti_path = userpath + "/Datos/Seleccionados/dti_alzheimer/datos/"
         autism_dti_path = userpath + "/Datos/Seleccionados/dti_autism/datos/"
         autism_fmri_path = userpath + "/Datos/Seleccionados/fmri_autismo/datos/"
         adhd_fmri_path = userpath + "/Datos/Seleccionados/fmri_adhd/datos/"
```

```
healthy_fmri_path = userpath + "/Datos/Seleccionados/fmri_sanos/datos/"

pathfiles = [healthy_dti_path, apoe4_dti_path, autism_dti_path, autism_fmri_path, adhd_

# NAME OF NODES
hd_healthy_dti = pd.read_csv(userpath + "/Datos/Seleccionados/dti_sano/nodos/1013090_DT
hd_apoe4_dti = pd.read_csv(userpath + "/Datos/Seleccionados/dti_alzheimer/nodos/APOE-4_
hd_apoe4_dti = hd_apoe4_dti[0:110]
hd_autism_dti = pd.read_csv(userpath + "/Datos/Seleccionados/dti_autism/nodos/ASD47B_DT
hd_autism_fmri = pd.read_csv(userpath + "/Datos/Seleccionados/fmri_autismo/nodos/ASD83B
hd_adhd_fmri = pd.read_csv(userpath + "/Datos/Seleccionados/fmri_adhd/nodos/KKI_1018959
hd_healthy_fmri = pd.read_csv(userpath + "/Datos/Seleccionados/fmri_sanos/nodos/Baltimo

node_names = [hd_healthy_dti, hd_apoe4_dti, hd_autism_dti, hd_autism_fmri, hd_adhd_fmri

## FOR THE SINGLE-SUBJECT LEVEL
individuals = {}
ind_names = ["healthy_dti_ind", "apoe4_dti_ind", "autism_dti_ind", "autism_fmri_ind", "

## FOR THE GROUP-LEVEL
group_avg = {}
groupnames = ["healthy_dti_group", "apoe4_dti_group", "autism_dti_group", "autism_fmri_
```

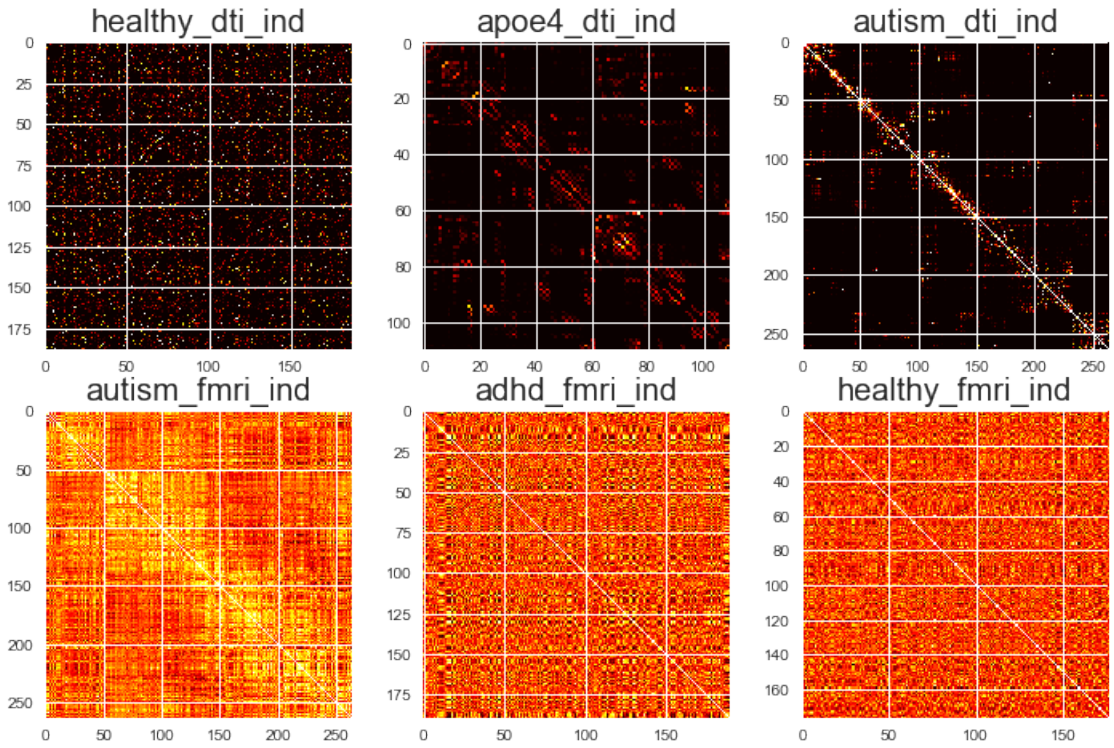
In [90]:
```
# Load connectivity matrixes
n = 0
for i in pathfiles:
    files = os.listdir(i)
    aux = pd.read_csv(i+files[0], header=None, delim_whitespace=True)
    k = 0
    for j in files:
        if k<1:
            print("Individual subject of", ind_names[n], "is", j)
            df = pd.read_csv(i+j, header=None, delim_whitespace=True)
            np.fill_diagonal(df.values,1)    # make sure diagonal = 0
            normalized_df = preprocessing.normalize(df, norm='max')  # normalize
            #normalized_df.columns = node_names[n]
            newname = ind_names[n]
            individuals[newname] = normalized_df
        df = pd.read_csv(i+j, header=None, delim_whitespace=True)
        np.fill_diagonal(df.values,1)
        aux = aux + df
        np.fill_diagonal(aux.values,1)    # make sure diagonal = 0
        k = k + 1

    avg_df = aux/len(files)    # average matrix of groups subjects
    np.fill_diagonal(normalized_df,1)
    normalized_df = preprocessing.normalize(avg_df, norm='max')  # normalize
    #normalized_df.columns = node_names[n]
```

```
            newname = groupnames[n]
            group_avg[newname] = normalized_df
            n = n + 1  #update individual counter
```

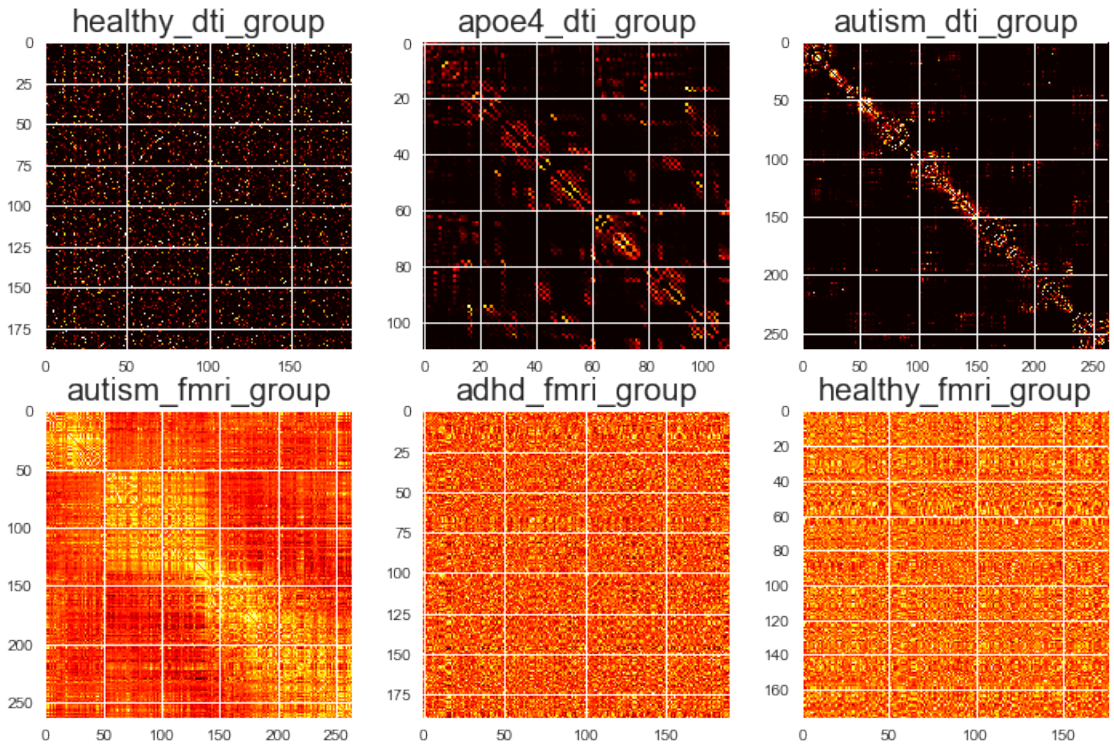
```
Individual subject of healthy_dti_ind is 1013090_DTI_connectivity_matrix_file.txt
Individual subject of apoe4_dti_ind is APOE-4_10_connectivity_matrix_file.txt
Individual subject of autism_dti_ind is ASD38D_DTI_connectivity_matrix_file.txt
Individual subject of autism_fmri_ind is ASD102_rsfMRI_connectivity_matrix_file.txt
Individual subject of adhd_fmri_ind is KKI_1018959_connectivity_matrix_file.txt
Individual subject of healthy_fmri_ind is Baltimore_5560_connectivity_matrix_file.txt
```

Puede ser interesante representar las matrices de conectividad (normalizadas) para tener una primera idea del aspecto de nuestros datos.

```
In [91]: #BY SUBJECTS
         %matplotlib inline
         fig = plt.figure(figsize=(12, 12))
         plt.subplot(331)
         np.fill_diagonal(individuals[ind_names[0]],0)
         plt.imshow(individuals[ind_names[0]], cmap='hot', interpolation='nearest')
         plt.title(ind_names[0], fontsize=20)
         plt.subplot(332)
         np.fill_diagonal(individuals[ind_names[1]],0)
         plt.imshow(individuals[ind_names[1]], cmap='hot', interpolation='nearest')
         plt.title(ind_names[1], fontsize=20)
         plt.subplot(333)
         plt.imshow(individuals[ind_names[2]], cmap='hot', interpolation='nearest')
         plt.title(ind_names[2], fontsize=20)
         plt.subplot(334)
         plt.imshow(individuals[ind_names[3]], cmap='hot', interpolation='nearest')
         plt.title(ind_names[3], fontsize=20)
         plt.subplot(335)
         plt.imshow(individuals[ind_names[4]], cmap='hot', interpolation='nearest')
         plt.title(ind_names[4], fontsize=20)
         plt.subplot(336)
         plt.imshow(individuals[ind_names[5]], cmap='hot', interpolation='nearest')
         plt.title(ind_names[5], fontsize=20)
         plt.savefig('/Users/hose/Desktop/TFM_TECI/simulated_data/healthy_ill_ind')
```



In [92]:
```
#BY AVERAGED GROUPS
fig2 = plt.figure(figsize=(12, 12))
plt.subplot(331)
plt.imshow(group_avg[groupnames[0]], cmap='hot', interpolation='nearest')
plt.title(groupnames[0], fontsize=20)
plt.subplot(332)
np.fill_diagonal(group_avg[groupnames[1]],0)
plt.imshow(group_avg[groupnames[1]], cmap='hot', interpolation='nearest')
plt.title(groupnames[1], fontsize=20)
plt.subplot(333)
plt.imshow(group_avg[groupnames[2]], cmap='hot', interpolation='nearest')
plt.title(groupnames[2], fontsize=20)
plt.subplot(334)
plt.imshow(group_avg[groupnames[3]], cmap='hot', interpolation='nearest')
plt.title(groupnames[3], fontsize=20)
plt.subplot(335)
plt.imshow(group_avg[groupnames[4]], cmap='hot', interpolation='nearest')
plt.title(groupnames[4], fontsize=20)
plt.subplot(336)
plt.imshow(group_avg[groupnames[5]], cmap='hot', interpolation='nearest')
plt.title(groupnames[5], fontsize=20)
plt.savefig('/Users/hose/Desktop/TFM_TECI/simulated_data/healthy_ill_group')
```



Parece evidente que las matrices de conectividad promedio son capaces de filtrar gran parte de la variabilidad individual en las matrices funcionales, lo que revela de forma más evidente la estructura subyacente de la red.

En cuanto a las redes anatómicas parece no existir la misma variabilidad que en las funcionales, ya que el promedio grupal y las individuales se mantienen bastante similares.

CONSTRUCCIÓN DEL GRAFO

El objetivo final es comparar las propiedades de las diferentes redes y discutir si la teoría de grafos puede ser una herramienta útil o complementaria para detectar singularidades entre patologías.

Recuerda que las redes pueden contener valores negativos de correlación. Dado que no existe consenso sobre lo que implica una correlación negativa en DTI o en fMRI, se trabajará con los valores positivos en este caso.

```
In [93]: np.any(individuals[ind_names[4]]<0)  # Any value below of 0?

Out[93]: True

In [94]: individuals[ind_names[4]][individuals[ind_names[4]] < 0] = 0
         np.any(individuals[ind_names[4]]<0)

Out[94]: False

In [96]: for i in range(0,6):
             individuals[ind_names[i]][individuals[ind_names[i]] < 0] = 0
             group_avg[groupnames[i]][group_avg[groupnames[i]]< 0] = 0
```

DEFINE THE NULL-MODELS

A continuación se definen como modelos nulos el modelo de Erdos-Renyi, una red en estrella y una red regular con propiedades similares a las de las redes construidas.

```
In [97]: n=110    # Erdos-Rengi nodes
         m=1200   # Erdos-Rengi links
         Grafos_ind = []
         Grafos_group = []

         # Creation of random graphs to compare with the brain graphs
         Grandom=nx.gnm_random_graph(n,m,seed=123456789) #generador de grafo er, semilla fija
         Gregular=nx.grid_2d_graph(10,11) #generador de grafo regular
         Gstar=nx.star_graph(n-1) #generador de grafo en estrella

         Grafos_ind.append(Grandom)
         Grafos_ind.append(Gregular)
         Grafos_ind.append(Gstar)

         Grafos_group.append(Grandom)
         Grafos_group.append(Gregular)
         Grafos_group.append(Gstar)
```

Como se indicaba en la memoria, como cada matriz proviene de un dataset diferente, tienen un número de nodos y enlaces diferente. Se intentará solventar este problema lo máximo posible para cada modalidad, ajustando el umbral de modo que las redes de DTI tengan un número de enlaces y nodos lo más similar posible. Ídem para las de fMRI.

```
In [98]: #which = lambda lst:list(np.where(lst)[0])  # like which of R language
         def num_of_zeros(xx,thr):
             np.fill_diagonal(x,0)
             xx[xx > thr] = 1
             xx[xx < thr] = 0
             current_links = np.sum(xx)#.values.sum()
             return(current_links)   #links different of 0
```

```
In [99]: # To relabel the nodes of the graph
         def dict_names(x):
             dic={}
             lista_nombres = x[0].tolist()
             lista_nodos = range(len(lista_nombres))
             dic[lista_nodos]=lista_nombres
             return(dic)
```

Y obtenemos las matrices de conectividad binarias tanto paras el promedio grupal como para el individual en cada modalidad:

```
In [101]: ## FOR THE SINGLE-SUBJECT LEVEL
          thr_ind = []
          mat_ind = []
```

```
            n = 0

            for subject_i in individuals:
                x = individuals[subject_i]
                thr = 0.1
                print("Next subject!!!",subject_i)
                flag_error = 0
                flag_if = 0
                flag_else = 0
                while (abs(m - num_of_zeros(x,thr))>150 and (flag_error<2) and (thr<0.7)):       #
                    flag_error = flag_if + flag_else  # to avoid starting to jump into the if and
                    if (m < num_of_zeros(x,thr)):
                        thr = thr + 0.03
                        flag_if = 1
                    else:
                        thr = thr - 0.03
                        flag_else = 1
                x[x > thr] = 1
                x[x < thr] = 0
                matrizAdy = np.matrix(x)
                mat_ind.append(matrizAdy)
                thr_ind.append(thr)
                G_ind = nx.from_numpy_matrix(matrizAdy)
                G_ind.name = "Graph_" + subject_i
                nx.relabel_nodes(G_ind, dict_names(node_names[n]))
                Grafos_ind.append(G_ind)
                n = n + 1
```

```
Next subject!!! healthy_dti_ind
Next subject!!! apoe4_dti_ind
Next subject!!! autism_dti_ind
Next subject!!! autism_fmri_ind
Next subject!!! adhd_fmri_ind
Next subject!!! healthy_fmri_ind
```

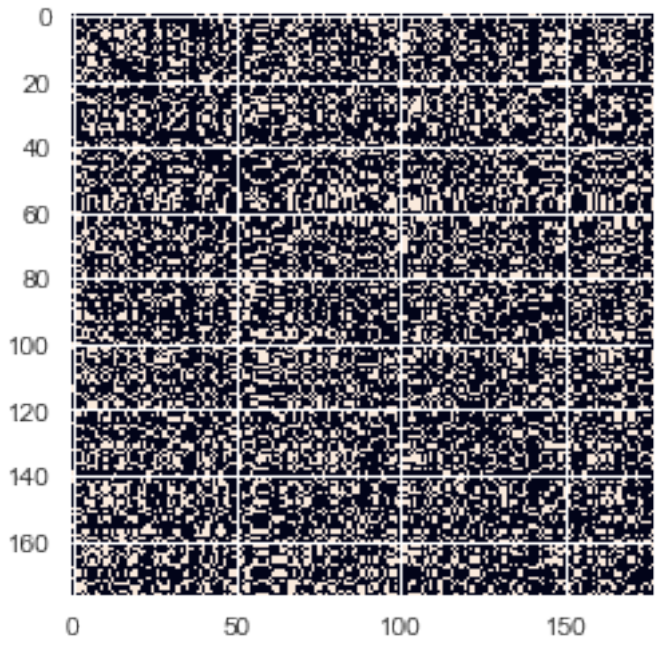
```
In [102]: ## FOR THE GROUP LEVEL
          thr_group = []
          mat_group = []
          n = 0

          for group_i in group_avg:
              x = group_avg[group_i]
              thr = 0.1
              print("Next group average!!!", group_i)
              flag_error = 0
              flag_if = 0
              flag_else = 0
```

```
                while (abs(m - num_of_zeros(x,thr))>150 and (flag_error<2) and (thr<0.7)):       #
                    flag_error = flag_if + flag_else  # to avoid starting to jump into the if and
                    if (m < num_of_zeros(x,thr)):
                        thr = thr + 0.03
                        flag_if = 1
                    else:
                        thr = thr - 0.03
                        flag_else = 1
                x[x > thr] = 1
                x[x < thr] = 0

                matrizAdy = np.matrix(x)
                mat_group.append(matrizAdy)

                thr_group.append(thr)
                G_group = nx.from_numpy_matrix(matrizAdy)
                G_group.name = "Graph_" + group_i
                nx.relabel_nodes(G_group, dict_names(node_names[n]))
                Grafos_group.append(G_group)
                n = n + 1
```

```
Next group average!!! healthy_dti_group
Next group average!!! apoe4_dti_group
Next group average!!! autism_dti_group
Next group average!!! autism_fmri_group
Next group average!!! adhd_fmri_group
Next group average!!! healthy_fmri_group
```

```
In [103]: plt.imshow(group_avg[group_i])
```

```
Out[103]: <matplotlib.image.AxesImage at 0x1a21856668>
```




```
In [104]: group_avg[group_i]
```

```
Out[104]: array([[0., 0., 0., ..., 0., 0., 0.],
                 [0., 0., 1., ..., 0., 0., 0.],
                 [0., 1., 0., ..., 0., 0., 0.],
                 ...,
                 [0., 1., 1., ..., 0., 1., 0.],
                 [0., 0., 1., ..., 0., 0., 0.],
                 [0., 0., 0., ..., 0., 0., 0.]])
```

ANÁLSIS I I - CARACTERÍSTICAS GLOBALES DE LA RED

```
In [105]: ## INDIVIDUAL SUBJECTS TABLE
          tabla1 = []
          tabla2 = []
          tabla3 = []
          for i in range(3,len(Grafos_ind)):
              tabla1.append(len(nx.nodes(Grafos_ind[i])))
              tabla2.append(len(nx.edges(Grafos_ind[i])))
              tabla3.append(thr_ind[i-3])

          columnas=['Healthy_DTI','Alzheimer_DTI','Autism_DTI','Autism_fMRI','ADHD_fMRI','Health
          ind = {0:'Nodes',1:'Edges',2:'Threshold'}
          tabla= pd.DataFrame([tabla1,tabla2,tabla3],columns=columnas)
          tabla.rename(index=ind)
```

Out[105]:

	Healthy_DTI	Alzheimer_DTI	Autism_DTI	Autism_fMRI	ADHD_fMRI	\
Nodes	188.0	110.00	264.0	264.0	190.0	
Edges	2069.0	5995.00	1646.0	12820.0	6459.0	
Threshold	0.7	0.04	0.7	0.7	0.7	

	Healthy_fMRI
Nodes	177.0
Edges	5313.0
Threshold	0.7

In [106]:
```
## GROUP TABLE
tabla1 = []
tabla2 = []
tabla3 = []
for i in range(3,len(Grafos_group)):
    tabla1.append(len(nx.nodes(Grafos_group[i])))
    tabla2.append(len(nx.edges(Grafos_group[i])))
    tabla3.append(thr_group[i-3])

columnas=['Healthy_DTI','Alzheimer_DTI','Autism_DTI','Autism_fMRI','ADHD_fMRI','Health
ind = {0:'Nodes',1:'Edges',2:'Threshold'}
tabla= pd.DataFrame([tabla1,tabla2,tabla3],columns=columnas)
tabla.rename(index=ind)
```

Out[106]:

	Healthy_DTI	Alzheimer_DTI	Autism_DTI	Autism_fMRI	ADHD_fMRI	\
Nodes	188.0	110.00	264.0	264.0	190.0	
Edges	2224.0	5995.00	1873.0	10649.0	5880.0	
Threshold	0.7	0.04	0.7	0.7	0.7	

	Healthy_fMRI
Nodes	177.0
Edges	5440.0
Threshold	0.7

In [107]:
```
# CARACHTERISTICS OF INDIVIDUAL-SUBJECTS GRAPH
Gcluster_ind=[]
Gdegree_ind=[]
Gbet_ind=[]
Gclo_ind=[]
Geff_ind=[]
Gasor_ind=[]
Gseg_ind=[]
Gint_ind=[]
Gpath_ind=[]

for i in range(len(Grafos_ind)):
    aux_degree = 0
    for v in Grafos_ind[i].nodes():
```

```
            aux_degree= aux_degree + Grafos_ind[i].degree(v)
        Gcluster_ind.append(nx.average_clustering(Grafos_ind[i]))
        Gdegree_ind.append((aux_degree)/(len(Grafos_ind[i].nodes())))
        Gbet_ind.append(st.mean(list(nx.betweenness_centrality(Grafos_ind[i]).values())))
        Gclo_ind.append(st.mean(list(nx.closeness_centrality(Grafos_ind[i]).values())))
        Geff_ind.append(nx.global_efficiency(Grafos_ind[i]))
        Gpath_ind.append(nx.average_shortest_path_length(Grafos_ind[i]))
        Gasor_ind.append(nx.degree_assortativity_coefficient(Grafos_ind[i]))
        Gseg_ind.append(Gcluster_ind[i]/Gcluster_ind[0]) #se considera el grafo e-r
        Gint_ind.append(Gpath_ind[i]/Gpath_ind[0])#integración con la eficiencia(en lugar
```

```
/Applications/anaconda3/lib/python3.6/site-packages/networkx/algorithms/assortativity/correlatio
  return (xy * (M - ab)).sum() / numpy.sqrt(vara * varb)
```

```
In [108]: # CARACHTERISTICS OF AVERAGE GROUPS GRAPH

          Gcluster_group=[]
          Gdegree_group=[]
          Gbet_group=[]
          Gclo_group=[]
          Geff_group=[]
          Gasor_group=[]
          Gseg_group=[]
          Gint_group=[]
          Gpath_group=[]

          for i in range(len(Grafos_group)):
              aux_degree = 0
              for v in Grafos_group[i].nodes():
                  aux_degree= aux_degree + Grafos_group[i].degree(v)
              Gcluster_group.append(nx.average_clustering(Grafos_group[i]))
              Gdegree_group.append((aux_degree)/(len(Grafos_group[i].nodes())))
              Gbet_group.append(st.mean(list(nx.betweenness_centrality(Grafos_group[i]).values()
              Gclo_group.append(st.mean(list(nx.closeness_centrality(Grafos_group[i]).values())))
              Geff_group.append(nx.global_efficiency(Grafos_group[i]))
              Gpath_group.append(nx.average_shortest_path_length(Grafos_group[i]))
              Gasor_group.append(nx.degree_assortativity_coefficient(Grafos_group[i]))
              Gseg_group.append(Gcluster_group[i]/Gcluster_group[0]) #se considera el grafo e-r
              Gint_group.append(Gpath_group[i]/Gpath_group[0])#integración con la eficiencia(en
```

```
/Applications/anaconda3/lib/python3.6/site-packages/networkx/algorithms/assortativity/correlatio
  return (xy * (M - ab)).sum() / numpy.sqrt(vara * varb)
```

Podemos mostrar las propiedades extraídas en una tabla para las redes individuales:

```
In [109]: # SUMMARY TABLE OF INDIVIDUAL GRAPHS
          columnas=['Erdos-Renyi','Regular-Graph','Star-Graph','Sano_DTI','Alzheimer_DTI','Autis
```

```
In [109]: ind = {0:'Clustering',1:'Grado Medio',2:'Betweenness Centrality',3:'Closeness Centrali
          tabla= pd.DataFrame([Gcluster_ind,Gdegree_ind,Gbet_ind,Gclo_ind,Geff_ind,Gpath_ind,Gas
          tabla.rename(index=ind)
```

Out[109]:

	Erdos-Renyi	Regular-Graph	Star-Graph	Sano_DTI	\
Clustering	0.196564	0.000000	0.000000	0.551587	
Grado Medio	21.818182	3.618182	1.981818	22.010638	
Betweenness Centrality	0.007486	0.055556	0.009091	0.007207	
Closeness Centrality	0.553271	0.146311	0.506829	0.432862	
Global Efficiency	0.598638	0.208476	0.509091	0.486311	
Average Shortest Path	1.808507	7.000000	1.981818	2.340539	
Asortatividad	-0.001453	0.575822	-1.000000	0.097217	
Segregación(SW)	1.000000	0.000000	0.000000	2.806150	
Integración(SW)	1.000000	3.870596	1.095831	1.294183	

	Alzheimer_DTI	Autismo_DTI	Autismo_fMRI	ADHD_fMRI	\
Clustering	1.000000	0.427841	0.597563	0.605709	
Grado Medio	109.000000	12.469697	97.121212	67.989474	
Betweenness Centrality	0.000000	0.008094	0.002417	0.003441	
Closeness Centrality	1.000000	0.324983	0.612688	0.607637	
Global Efficiency	1.000000	0.366363	0.684209	0.678752	
Average Shortest Path	1.000000	3.120607	1.633310	1.646951	
Asortatividad	NaN	0.281060	0.138660	0.042546	
Segregación(SW)	5.087409	2.176601	3.040048	3.081489	
Integración(SW)	0.552942	1.725516	0.903126	0.910669	

	Sano_fMRI
Clustering	0.530262
Grado Medio	60.033898
Betweenness Centrality	0.003789
Closeness Centrality	0.602223
Global Efficiency	0.669845
Average Shortest Path	1.663136
Asortatividad	0.221284
Segregación(SW)	2.697657
Integración(SW)	0.919618

Y para las redes grupales:

```
In [110]: # SUMMARY TABLE OF GROUP GRAPHS
          columnas=['Erdos-Renyi','Regular-Graph','Star-Graph','Sano_DTI','Alzheimer_DTI','Autis
          ind = {0:'Clustering',1:'Grado Medio',2:'Betweenness Centrality',3:'Closeness Centrali
          tabla= pd.DataFrame([Gcluster_group,Gdegree_group,Gbet_group,Gclo_group,Geff_group,Gpa
          tabla.rename(index=ind)
```

Out[110]:

	Erdos-Renyi	Regular-Graph	Star-Graph	Sano_DTI	\
Clustering	0.196564	0.000000	0.000000	0.576154	
Grado Medio	21.818182	3.618182	1.981818	23.659574	
Betweenness Centrality	0.007486	0.055556	0.009091	0.006938	

```
Closeness Centrality       0.553271       0.146311    0.506829   0.442138
Global Efficiency          0.598638       0.208476    0.509091   0.497207
Average Shortest Path      1.808507       7.000000    1.981818   2.290534
Asortatividad             -0.001453       0.575822   -1.000000   0.040178
Segregación(SW)            1.000000       0.000000    0.000000   2.931133
Integración(SW)            1.000000       3.870596    1.095831   1.266533

                        Alzheimer_DTI  Autismo_DTI  Autismo_fMRI  ADHD_fMRI  \
Clustering                   1.000000     0.475642      0.568661   0.522363
Grado Medio                109.000000    14.189394     80.674242  61.894737
Betweenness Centrality       0.000000     0.007950      0.002684   0.003592
Closeness Centrality         1.000000     0.328346      0.587804   0.597662
Global Efficiency            1.000000     0.373133      0.651731   0.663279
Average Shortest Path        1.000000     3.082959      1.703105   1.675299
Asortatividad                     NaN     0.269762      0.202035   0.162572
Segregación(SW)              5.087409     2.419786      2.893010   2.657476
Integración(SW)              0.552942     1.704698      0.941719   0.926344

                        Sano_fMRI
Clustering               0.568543
Grado Medio             61.468927
Betweenness Centrality   0.003765
Closeness Centrality     0.604267
Global Efficiency        0.673269
Average Shortest Path    1.658898
Asortatividad            0.395006
Segregación(SW)          2.892411
Integración(SW)          0.917275
```

ANÁLISIS II - PROPIEDADES LOCALES DE LA RED

De manera similar, podemos extraer las mismas propiedades para cada nodo en lugar de para toda la red.

```
In [111]: ## FOR INDIVIDUAL SUBJECTS
          Local_prox_ind = []
          Local_bet_ind = []
          Local_clo_ind = []
          Local_cluster_ind = []
          Grado_node_ind = []
          for i in range(0,len(Grafos_ind)):
              Local_prox_ind.append(nx.average_neighbor_degree(Grafos_ind[i]))
              Local_bet_ind.append(nx.betweenness_centrality(Grafos_ind[i]))
              Local_clo_ind.append(nx.closeness_centrality(Grafos_ind[i]))
              Local_cluster_ind.append(nx.clustering(Grafos_ind[i]))
              grado_ind={}
              for v in Grafos_ind[i].nodes():
                      grado_ind[v]=Grafos_ind[i].degree(v)
              Grado_node_ind.append(grado_ind)
```

```
        for i in range(0,len(Grafos_ind)):
            Local_prox_ind[i] = sorted(Local_prox_ind[i].items(),reverse=True,key=op.itemgette
            Local_bet_ind[i] = sorted(Local_bet_ind[i].items(),reverse=True,key=op.itemgetter(
            Local_clo_ind[i] = sorted(Local_clo_ind[i].items(),reverse=True,key=op.itemgetter(
            Local_cluster_ind[i] = sorted(Local_cluster_ind[i].items(),reverse=True,key=op.ite
            Grado_node_ind[i] = sorted(Grado_node_ind[i].items(),reverse=True,key=op.itemgette
```

```
In [112]: ## FOR GROUP AVERAGE SUBJECTS
          Local_prox_group = []
          Local_bet_group = []
          Local_clo_group = []
          Local_cluster_group = []
          Grado_node_group = []
          for i in range(0,len(Grafos_group)):
              Local_prox_group.append(nx.average_neighbor_degree(Grafos_group[i]))
              Local_bet_group.append(nx.betweenness_centrality(Grafos_group[i]))
              Local_clo_group.append(nx.closeness_centrality(Grafos_group[i]))
              Local_cluster_group.append(nx.clustering(Grafos_group[i]))
              grado_group={}
              for v in Grafos_group[i].nodes():
                      grado_group[v]=Grafos_group[i].degree(v)
              Grado_node_group.append(grado_group)

          for i in range(0,len(Grafos_group)):
              Local_prox_group[i] = sorted(Local_prox_group[i].items(),reverse=True,key=op.itemg
              Local_bet_group[i] = sorted(Local_bet_group[i].items(),reverse=True,key=op.itemget
              Local_clo_group[i] = sorted(Local_clo_group[i].items(),reverse=True,key=op.itemget
              Local_cluster_group[i] = sorted(Local_cluster_group[i].items(),reverse=True,key=op
              Grado_node_group[i] = sorted(Grado_node_group[i].items(),reverse=True,key=op.itemg
```

```
In [113]: ## SUMMARY TABLE
          def local_properties(graph_x, propertie_x):
              indc={0:'Erdos-Renyi',1:'Regular-Graph',2:'Star-Graph',3:'Healthy_DTI',4:'Alzheime
              lista=[]
              for i in range(0,len(graph_x)):
                  lista.append(itertools.islice(propertie_x[i],0,4))
              tabla_x= pd.DataFrame(lista)
              tabla_x.rename(index=indc)
              return(tabla_x)
```

En este caso, resumir y mostrar la información es algo más complejo (como se vio antes, son cientos de nodos). Por ello, mostraremos el valor de los 4 nodos más extremos para cada propiedad, en forma de pares de valor (nodo, valor) para tener una idea:

SHORT PATH LENGHTS

INDIVIDUAL SUBJECTS

```
In [61]: indc={0:'Erdos-Renyi',1:'Regular-Graph',2:'Star-Graph',3:'Healthy_DTI',4:'Alzheimer_DTI
         columns = {}
```

```
In [62]: local_properties(Grafos_ind, Local_prox_ind).rename(index=indc)
```

Out[62]:

	0	1
Erdos-Renyi	(47, 24.3)	(67, 24.11764705882353)
Regular-Graph	((2, 2), 4.0)	((2, 3), 4.0)
Star-Graph	(1, 109.0)	(2, 109.0)
Healthy_DTI	(3, 36.26315789473684)	(43, 35.666666666666664)
Alzheimer_DTI	(12, 15.76923076923077)	(8, 15.666666666666666)
Autism_DTI	(55, 20.4)	(51, 19.727272727272727)
Autism_fMRI	(136, 105.63106796116504)	(87, 105.1304347826087)
ADHD_fMRI	(163, 78.33333333333333)	(118, 78.02409638554217)
Healthy_fMRI	(68, 80.0657894736842)	(58, 79.62790697674419)

	2	3
Erdos-Renyi	(92, 24.076923076923077)	(69, 23.666666666666668)
Regular-Graph	((2, 4), 4.0)	((2, 5), 4.0)
Star-Graph	(3, 109.0)	(4, 109.0)
Healthy_DTI	(186, 33.357142857142854)	(4, 33.35)
Alzheimer_DTI	(7, 15.25)	(73, 14.9375)
Autism_DTI	(97, 19.45)	(109, 19.357142857142858)
Autism_fMRI	(68, 105.03658536585365)	(232, 104.76576576576576)
ADHD_fMRI	(96, 78.0)	(159, 78.0)
Healthy_fMRI	(85, 79.6067415730337)	(107, 79.4054054054054)

GROUP AVERAGE

```
In [ ]: local_properties(Grafos_group, Local_prox_group).rename(index=indc)
```

BETWENNESS

INDIVIDUAL SUBJECTS

```
In [64]: local_properties(Grafos_ind, Local_bet_ind).rename(index=indc)
```

Out[64]:

	0	1
Erdos-Renyi	(99, 0.014691107624638211)	(59, 0.01445917683048305)
Regular-Graph	((4, 5), 0.12317750678824708)	((5, 5), 0.12317750678824702)
Star-Graph	(0, 1.0)	(1, 0.0)
Healthy_DTI	(18, 0.060822427403918015)	(124, 0.052536864647576446)
Alzheimer_DTI	(26, 0.09448485800450983)	(29, 0.08366961197166296)
Autism_DTI	(61, 0.0738479674453349)	(94, 0.07131238961409556)
Autism_fMRI	(230, 0.005618113772020311)	(257, 0.005394094206358545)
ADHD_fMRI	(182, 0.009965574773996266)	(85, 0.009915206785946235)
Healthy_fMRI	(50, 0.010623342630312749)	(40, 0.007367022246358978)

	2	3
Erdos-Renyi	(19, 0.014047183900834929)	(42, 0.013750404203352)
Regular-Graph	((5, 4), 0.11884780954126385)	((5, 6), 0.11884780954126385)
Star-Graph	(2, 0.0)	(3, 0.0)
Healthy_DTI	(28, 0.05178185478985241)	(32, 0.04439177829633221)

```
Alzheimer_DTI      (56, 0.06044706928717459)      (85, 0.05998581673615049)
Autism_DTI        (195, 0.058677587257606724)      (63, 0.05333199200741908)
Autism_fMRI        (91, 0.00536511674554631)     (62, 0.005095467814654273)
ADHD_fMRI         (132, 0.007605799398216297)     (34, 0.007545934090884662)
Healthy_fMRI     (117, 0.0068622504758469715)     (93, 0.006639537731329414)
```

GROUP AVERAGE

```
In [65]: local_properties(Grafos_group, Local_bet_group).rename(index=indc)
```

```
Out[65]:                                          0                                1  \
Erdos-Renyi       (99, 0.014691107624638211)      (59, 0.01445917683048305)
Regular-Graph  ((4, 5), 0.12317750678824708)  ((5, 5), 0.12317750678824702)
Star-Graph                         (0, 1.0)                         (1, 0.0)
Healthy_DTI       (137, 0.06044882035598517)     (18, 0.053623443064305935)
Alzheimer_DTI                      (0, 0.0)                         (1, 0.0)
Autism_DTI         (114, 0.07322392222561284)     (195, 0.06536875695098289)
Autism_fMRI       (188, 0.007878824490298208)     (51, 0.007673799008738922)
ADHD_fMRI         (128, 0.008170652790822923)     (74, 0.008076242711278757)
Healthy_fMRI       (54, 0.015531810072773832)    (157, 0.010124987246980726)

                                           2                                3
Erdos-Renyi       (19, 0.014047183900834929)       (42, 0.013750404203352)
Regular-Graph  ((5, 4), 0.11884780954126385)  ((5, 6), 0.11884780954126385)
Star-Graph                         (2, 0.0)                         (3, 0.0)
Healthy_DTI       (19, 0.053025679068215474)     (32, 0.04528613953571924)
Alzheimer_DTI                      (2, 0.0)                         (3, 0.0)
Autism_DTI         (61, 0.058390637299586746)     (94, 0.05198298973216866)
Autism_fMRI       (220, 0.007533870737179082)    (100, 0.007234018919107022)
ADHD_fMRI          (79, 0.007670258763697202)    (122, 0.007482543374321487)
Healthy_fMRI      (125, 0.009140547317157622)    (132, 0.008544249704405708)
```

CLOSENESS

INDIVIDUAL SUBJECTS

```
In [66]: local_properties(Grafos_ind, Local_clo_ind).rename(index=indc)
```

```
Out[66]:                                          0                                1  \
Erdos-Renyi         (42, 0.5828877005347594)       (19, 0.5797872340425532)
Regular-Graph  ((4, 5), 0.18956521739130436)  ((5, 5), 0.18956521739130436)
Star-Graph                         (0, 1.0)        (1, 0.5023041474654378)
Healthy_DTI        (124, 0.5632530120481928)       (76, 0.5483870967741935)
Alzheimer_DTI       (74, 0.4678111587982833)       (10, 0.4560669456066946)
Autism_DTI         (94, 0.43543046357615894)       (61, 0.4332784184514003)
Autism_fMRI        (135, 0.6658227848101266)      (138, 0.6641414141414141)
ADHD_fMRI          (146, 0.6702127659574468)       (81, 0.6608391608391608)
Healthy_fMRI        (50, 0.6984126984126984)      (125, 0.6956521739130435)

                                           2                                3
```

```
Erdos-Renyi          (99, 0.5767195767195767)       (59, 0.5736842105263158)
Regular-Graph  ((4, 4), 0.18632478632478633)  ((4, 6), 0.18632478632478633)
Star-Graph            (2, 0.5023041474654378)        (3, 0.5023041474654378)
Healthy_DTI          (32, 0.5451895043731778)       (19, 0.5373563218390804)
Alzheimer_DTI       (73, 0.45416666666666666)      (57, 0.45228215767634855)
Autism_DTI          (114, 0.4228295819935691)       (63, 0.4161392405063291)
Autism_fMRI         (147, 0.6624685138539043)       (84, 0.6493827160493827)
ADHD_fMRI                     (135, 0.65625)        (1, 0.6539792387543253)
Healthy_fMRI         (26, 0.6929133858267716)      (117, 0.6848249027237354)
```

GROUP AVERAGE

```
In [67]: local_properties(Grafos_group, Local_clo_group).rename(index=indc)
```

```
Out[67]:                                          0                                1  \
Erdos-Renyi          (42, 0.5828877005347594)       (19, 0.5797872340425532)
Regular-Graph  ((4, 5), 0.18956521739130436)  ((5, 5), 0.18956521739130436)
Star-Graph                          (0, 1.0)        (1, 0.5023041474654378)
Healthy_DTI          (19, 0.5683890577507599)       (32, 0.5683890577507599)
Alzheimer_DTI                       (0, 1.0)                        (1, 1.0)
Autism_DTI          (114, 0.4503424657534247)      (94, 0.43833333333333335)
Autism_fMRI         (133, 0.6322115384615384)      (127, 0.6306954436450839)
ADHD_fMRI           (122, 0.6472602739726028)      (146, 0.6472602739726028)
Healthy_fMRI         (50, 0.6616541353383458)       (68, 0.6567164179104478)

                                          2                                3
Erdos-Renyi          (99, 0.5767195767195767)       (59, 0.5736842105263158)
Regular-Graph  ((4, 4), 0.18632478632478633)  ((4, 6), 0.18632478632478633)
Star-Graph            (2, 0.5023041474654378)        (3, 0.5023041474654378)
Healthy_DTI                    (123, 0.55)                    (124, 0.55)
Alzheimer_DTI                    (2, 1.0)                       (3, 1.0)
Autism_DTI          (195, 0.4228295819935691)      (61, 0.41878980891719747)
Autism_fMRI         (130, 0.6306954436450839)      (113, 0.6291866028708134)
ADHD_fMRI            (70, 0.6385135135135135)      (114, 0.6385135135135135)
Healthy_fMRI         (98, 0.6567164179104478)      (163, 0.6567164179104478)
```

CLUSTERING COEFFICIENT

INDIVIDUAL SUBJECTS

```
In [68]: local_properties(Grafos_ind, Local_cluster_ind).rename(index=indc)
```

```
Out[68]:                                       0                          1  \
Erdos-Renyi     (47, 0.3333333333333333)  (73, 0.26143790849673204)
Regular-Graph                ((0, 0), 0)                ((0, 1), 0)
Star-Graph                      (0, 0)                     (1, 0)
Healthy_DTI     (43, 0.8761904761904762)  (173, 0.8717948717948718)
Alzheimer_DTI                 (35, 1.0)   (51, 0.8666666666666667)
Autism_DTI                    (23, 1.0)                (213, 1.0)
Autism_fMRI    (234, 0.7482900136798906)  (199, 0.7448453608247423)
```

```
ADHD_fMRI       (12, 0.7534246575342466)   (41, 0.7406103286384976)
Healthy_fMRI   (156, 0.6938775510204082)   (71, 0.6848370927318296)

                                        2                          3
Erdos-Renyi                  (35, 0.25)  (55, 0.24333333333333335)
Regular-Graph               ((0, 2), 0)                ((0, 3), 0)
Star-Graph                     (2, 0)                     (3, 0)
Healthy_DTI    (165, 0.8666666666666667)                (135, 0.8)
Alzheimer_DTI   (87, 0.8666666666666667)   (95, 0.8666666666666667)
Autism_DTI     (261, 0.8095238095238095)  (169, 0.7619047619047619)
Autism_fMRI    (217, 0.7329292929292929)  (235, 0.7328178694158075)
ADHD_fMRI       (30, 0.7405405405405405)  (183, 0.7330827067669173)
Healthy_fMRI   (111, 0.6754300551768906)  (120, 0.6689291101055806)
```

GROUP AVERAGE

```
In [69]: local_properties(Grafos_group, Local_cluster_group).rename(index=indc)
```

```
Out[69]:                                    0                          1  \
Erdos-Renyi     (47, 0.3333333333333333)  (73, 0.26143790849673204)
Regular-Graph               ((0, 0), 0)                ((0, 1), 0)
Star-Graph                     (0, 0)                     (1, 0)
Healthy_DTI     (38, 0.8333333333333334)  (135, 0.8333333333333334)
Alzheimer_DTI                (0, 1.0)                   (1, 1.0)
Autism_DTI     (261, 0.8666666666666667)   (34, 0.8214285714285714)
Autism_fMRI     (65, 0.8069053708439897)   (60, 0.7718947718947718)
ADHD_fMRI       (77, 0.6453900709219859)  (177, 0.6338797814207651)
Healthy_fMRI    (37, 0.8369230769230769)  (124, 0.8022988505747126)

                                        2                          3
Erdos-Renyi                  (35, 0.25)  (55, 0.24333333333333335)
Regular-Graph               ((0, 2), 0)                ((0, 3), 0)
Star-Graph                     (2, 0)                     (3, 0)
Healthy_DTI    (169, 0.8205128205128205)   (94, 0.8187134502923976)
Alzheimer_DTI                (2, 1.0)                   (3, 1.0)
Autism_DTI      (51, 0.7636363636363637)  (124, 0.7454545454545455)
Autism_fMRI     (61, 0.7616330114135206)   (71, 0.753746694093447)
ADHD_fMRI      (101, 0.6308831306187203)  (123, 0.6265664160401002)
Healthy_fMRI   (140, 0.7425287356321839)   (89, 0.7318548387096774)
```

DEGREE NODE

INDIVIDUAL SUBJECTS

```
In [70]: local_properties(Grafos_ind, Grado_node_ind).rename(index=indc)
```

```
Out[70]:                        0           1           2           3
Erdos-Renyi       (42, 31)    (19, 30)    (99, 29)    (59, 28)
Regular-Graph  ((1, 1), 4) ((1, 2), 4) ((1, 3), 4) ((1, 4), 4)
Star-Graph        (0, 109)      (1, 1)      (2, 1)      (3, 1)
```

Healthy_DTI	(45, 53)	(18, 52)	(32, 51)	(92, 51)
Alzheimer_DTI	(29, 22)	(9, 20)	(74, 20)	(15, 19)
Autism_DTI	(94, 34)	(59, 28)	(61, 27)	(114, 27)
Autism_fMRI	(135, 132)	(138, 130)	(147, 129)	(220, 123)
ADHD_fMRI	(146, 96)	(81, 92)	(135, 90)	(1, 89)
Healthy_fMRI	(50, 100)	(125, 99)	(26, 98)	(117, 95)

GROUP AVERAGE

In [71]:
```
local_properties(Grafos_group, Grado_node_group).rename(index=indc)
```

Out[71]:

	0	1	2	3
Erdos-Renyi	(42, 31)	(19, 30)	(99, 29)	(59, 28)
Regular-Graph	((1, 1), 4)	((1, 2), 4)	((1, 3), 4)	((1, 4), 4)
Star-Graph	(0, 109)	(1, 1)	(2, 1)	(3, 1)
Healthy_DTI	(19, 61)	(18, 58)	(32, 58)	(153, 57)
Alzheimer_DTI	(0, 109)	(1, 109)	(2, 109)	(3, 109)
Autism_DTI	(190, 33)	(61, 32)	(114, 32)	(59, 31)
Autism_fMRI	(96, 112)	(133, 111)	(135, 110)	(113, 109)
ADHD_fMRI	(146, 87)	(122, 86)	(70, 82)	(114, 82)
Healthy_fMRI	(50, 86)	(98, 86)	(104, 85)	(29, 84)