Final Course Project

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Overview This is Final Course Project

Import libraries

R library

```r
library(reticulate)
#use_condaenv("smm638", required = TRUE)
library(car)
library(sna)
library(ergm)
library(dplyr)
library(tidyr)
```

Python library

```python
import pandas as pd
import networkx as nx
from networkx.algorithms import bipartite as bp
import matplotlib.pyplot as plt
import numpy as np
import itertools
from IPython.display import Image
import matplotlib
from graph_tool.all import *
import random
```

Load data

HR_edges.csv

```
# load data
fr = pd.read_csv('/Users/adam/Desktop/Bayes/Class/Network_Analytics/SMM638/FCP/
deezer_clean_data/HR_edges.csv')
# data preview
fr.head()
```

```
   node_1  node_2
0       0    4076
1       0   29861
2       0   53717
3       0   23820
4       0   39945
```

HR_genres.json

```
import json
with       open('/Users/adam/Desktop/Bayes/Class/Network_Analytics/SMM638/FCP/
deezer_clean_data/HR_genres.json', 'r') as f:
    pr_json = json.load(f)
pr_json["11542"]
```

```
['Indie Rock', 'Indie Pop/Folk', 'International Pop', 'Rap/Hip Hop', 'Pop',
'Rock', 'Indie Pop', 'Alternative']
```

Convert the dictionary into a Pandas

```
pr = pd.json_normalize(pr_json).T
pr.rename({0: 'genres'}, axis=1, inplace=True)
pr.head()
```

```
                                                   genres
13357                                               [Pop]
11542  [Indie Rock, Indie Pop/Folk, International Pop...
11543                                  [Dance, Pop, Rock]
11540                       [International Pop, Jazz, Pop]
11541                                       [Rap/Hip Hop]
```

```
pr_original = pr
```

Separate rows

```
pr = pr.explode('genres')
pr.reset_index(inplace=True)
```

```
pr.rename({'index': 'user_id'}, axis=1, inplace=True)
pr.head()
```

```
  user_id             genres
0   13357                Pop
1   11542         Indie Rock
2   11542     Indie Pop/Folk
3   11542  International Pop
4   11542        Rap/Hip Hop
```

two-mode (Bipartite) networks

data botton_nodes top_nodes edges

```
bottom_nodes                                                                     =
pr["user_id"].drop_duplicates().reset_index(drop=True).to_numpy()
top_nodes = pr["genres"].drop_duplicates().reset_index(drop=True).to_numpy()
edges = pr[['user_id', 'genres']].values.tolist()
```

Graph creation

```
# empty graph
bg = nx.Graph()
# add nodes
bg.add_nodes_from(bottom_nodes, bipartite=0)
bg.add_nodes_from(top_nodes, bipartite=1)
# get nx object
bg.add_edges_from(edges)
# `is bipartite` check
is_bip = nx.is_bipartite(bg)
```

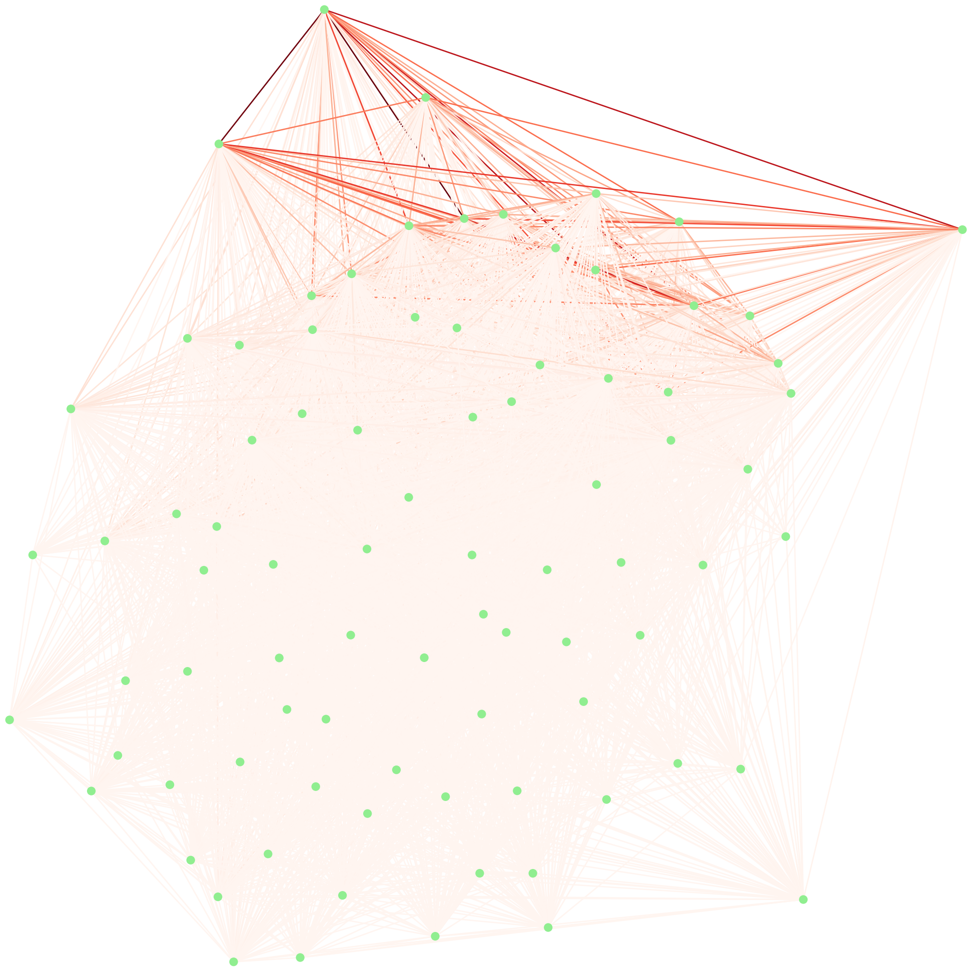
Weighted projections of the two-mode networks

```
#g_b_w = bp.weighted_projected_graph(bg, bottom_nodes, ratio=True)
g_t_w = bp.weighted_projected_graph(bg, top_nodes, ratio=True)
```

plot two-mode networks network

```
# Create the figure and specify the size
plt.figure(figsize=(12, 12))

# Draw the network
edges = g_t_w.edges(data=True)
weights = [w["weight"] for u, v, w in edges]
vmin = min(weights)
```

```python
vmax = max(weights)

pos = nx.kamada_kawai_layout(g_t_w)
nx.draw(
    g_t_w,
    pos,
    with_labels=False,
    node_color="lightgreen",
    node_size=30,
    edge_color=weights,
    edge_cmap=plt.cm.Reds,
    edge_vmin=vmin,
    edge_vmax=vmax,
)

# Add text annotation if needed
plt.text(1, 1, "A", fontsize=12, ha="center")

# Show plot
plt.show()
```



Create Z matrix

create X matrix and Z matrix

```
user_genre_matrix = pr.pivot_table(index='user_id', columns='genres',
aggfunc=lambda x: 1, fill_value=0)

# calculate genre-genre matrix Z
Z = np.dot(user_genre_matrix.T, user_genre_matrix)
# print(Z)

# change ndarray Z to DataFrame
```

```
Z_df         =         pd.DataFrame(Z,         index=user_genre_matrix.columns,
columns=user_genre_matrix.columns)

Z_df
```

```
genres                    Acoustic Blues  African Music  ...  Vocal jazz  West Coast
genres                                                    ...
Acoustic Blues                        14              2  ...           4           0
African Music                          2            107  ...           9           2
Alternative                           12             80  ...         313          72
Alternative Country                    2              1  ...          14           0
Asian Music                            0              3  ...           4           2
...                                  ...            ...  ...         ...         ...
Trance                                 0              8  ...           9           7
Tropical                               0              3  ...           3           0
Urban Cowboy                           0              3  ...           7           1
Vocal jazz                             4              9  ...         374           0
West Coast                             0              2  ...           0         107

[84 rows x 84 columns]
```

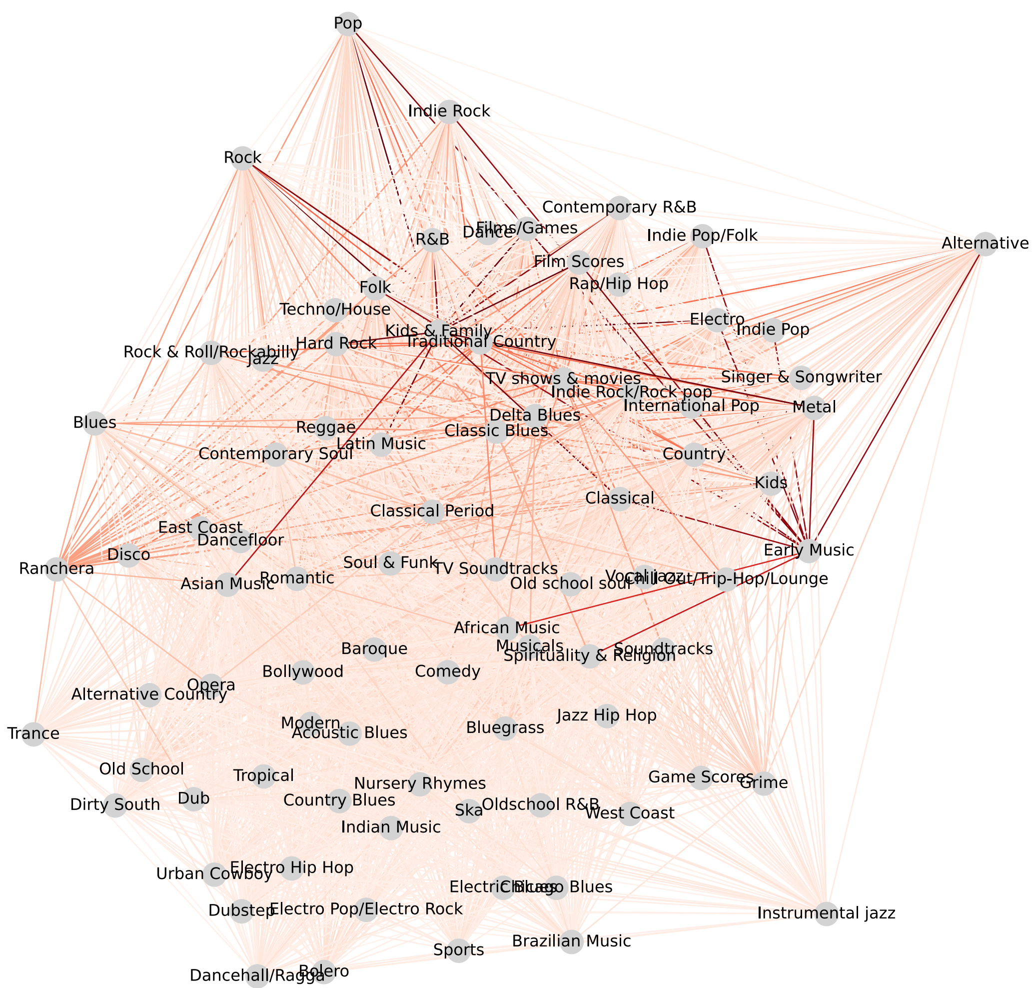
Community Detection

Visualize the network

```
# fix node positions for better visualization
pos = nx.spring_layout(g_t_w, seed=123)
# draw the network
nx.draw(
       g_t_w,  pos,  with_labels=True,  node_color="lightgray",  node_size=300,
edge_color="gray"
)
```

Community detection using Girvan-Newman's algorithm

```python
# edge betweenness centrality
edge_betweenness = nx.edge_betweenness_centrality(g_t_w)
# set the value min and max make color lookable
vmin = min(edge_betweenness.values())
vmax = max(edge_betweenness.values())
# network visualization
pos = nx.kamada_kawai_layout(g_t_w)
plt.figure(figsize=(12, 12))
nx.draw(
    g_t_w,
    pos,
    with_labels=True,
    node_color="lightgray",
    node_size=300,
    edgelist=edge_betweenness.keys(),
    edge_color=list(edge_betweenness.values()),
    edge_cmap=plt.cm.Reds,
    edge_vmin=vmin,
    edge_vmax=vmax,
)
```



Community detection using Louvaine's algorithm (Z matrix)

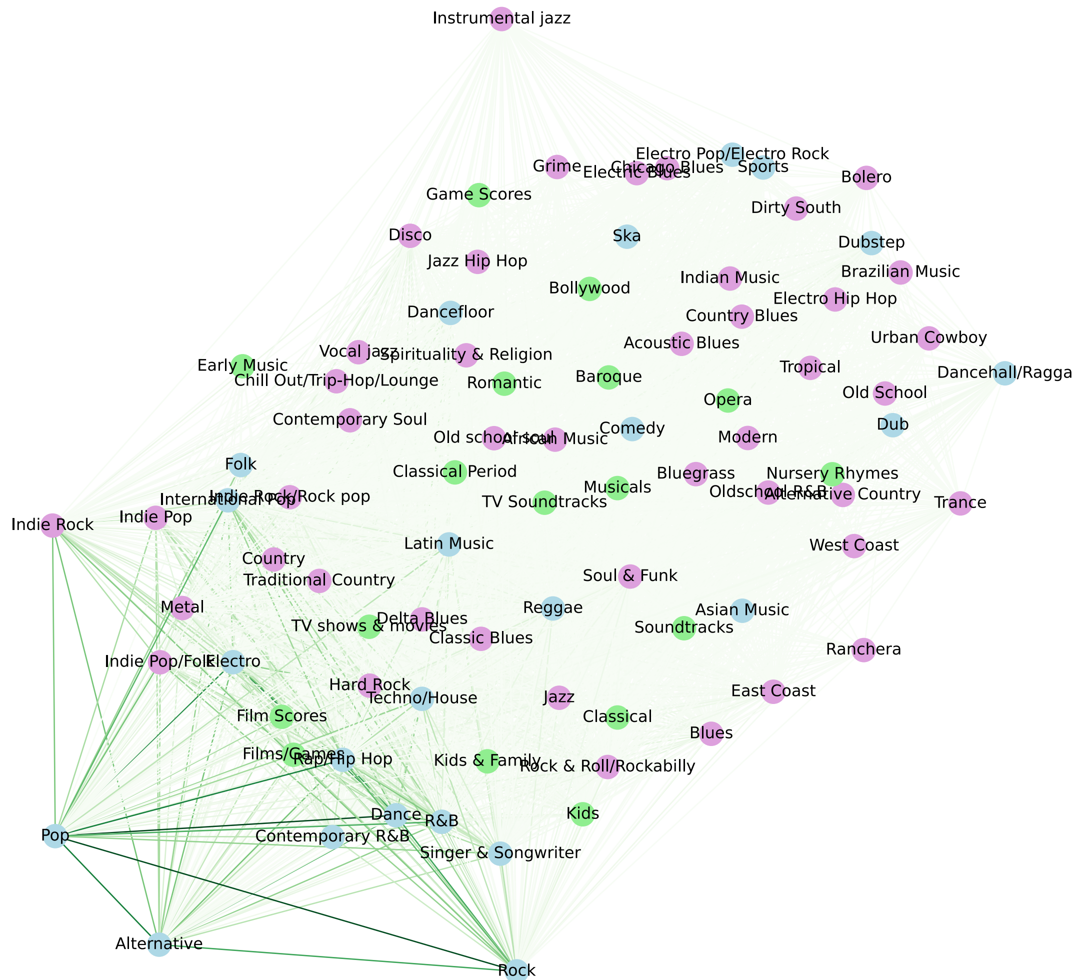
Change Z matrix to Graph

```
g_z_matrix = nx.Graph()

# add node
for node in Z_df.columns:
    g_z_matrix.add_node(node)

# add edges
for i in Z_df.columns:
    for j in Z_df.columns:
```

```
        if i != j and Z_df.loc[i, j] > 0:
            g_z_matrix.add_edge(i, j, weight=Z_df.loc[i, j])
```

Fit the Louvain algorithm to the weighted network

```
# fit the Louvain algorithm to the weighted network
fit = nx.community.louvain_communities(g_z_matrix, weight="weight")
# retrieve the communities
communities = tuple(sorted(c) for c in fit)
# visualize the network with the identified communities
colors = [
    (
        "plum" if node in communities[0]
        else "lightgreen" if node in communities[1]
        else "lightblue"
    )
    for node in g_z_matrix.nodes
]
# visualize the network
pos = nx.kamada_kawai_layout(g_z_matrix)
plt.figure(figsize=(12, 12))
nx.draw(
    g_z_matrix,
    pos,
    with_labels=True,
    node_color=colors,
    node_size=300,
    edge_color=[g_z_matrix[u][v]["weight"] for u, v in g_z_matrix.edges],
    edge_cmap=plt.cm.Greens,
    #alpha=0.5,
)
```



Weighted Stochastic Blockmodeling (WSBM)

Change NetworkX graph into graph-tool graph

```
# create graph-tool's graph
g_z_matrix_WSBM = Graph(directed=False)

# add node
vprops = g_z_matrix_WSBM.new_vertex_property("string")
vertices = {}
for node in g_z_matrix.nodes:
    v = g_z_matrix_WSBM.add_vertex()
```

```
    vertices[node] = v
    vprops[v] = node

g_z_matrix_WSBM.vp["name"] = vprops

# add edge
eweights = g_z_matrix_WSBM.new_edge_property("float")
for u, v, data in g_z_matrix.edges(data=True):
    edge = g_z_matrix_WSBM.add_edge(vertices[u], vertices[v])
    eweights[edge] = data["weight"]

g_z_matrix_WSBM.ep["weight"] = eweights  # add weight to graph
```

Inferring the Modular Structure of Networks with Weighted Stochastic Blockmodeling

```
# set random seed
seed = 41
random.seed(seed)
np.random.seed(seed)
graph_tool.all.seed_rng(seed)

# model fit
state = minimize_nested_blockmodel_dl(
           g_z_matrix_WSBM,   state_args=dict(recs=[g_z_matrix_WSBM.ep.weight],
rec_types=["real-exponential"])
)
# improve solution with merge-split
for i in range(100):
    ret = state.multiflip_mcmc_sweep(niter=10, beta=np.inf)
state.draw(
    edge_color=prop_to_size(g_z_matrix_WSBM.ep.weight, power=1, log=True),
    ecmap=(matplotlib.cm.inferno, 0.6),
    eorder=g_z_matrix_WSBM.ep.weight,
       edge_pen_width=prop_to_size(g_z_matrix_WSBM.ep.weight,  1,  4,  power=1,
log=True),
    edge_gradient=[],
    output_size=(800, 800),
    output="genre-wsbm.png",
)
```

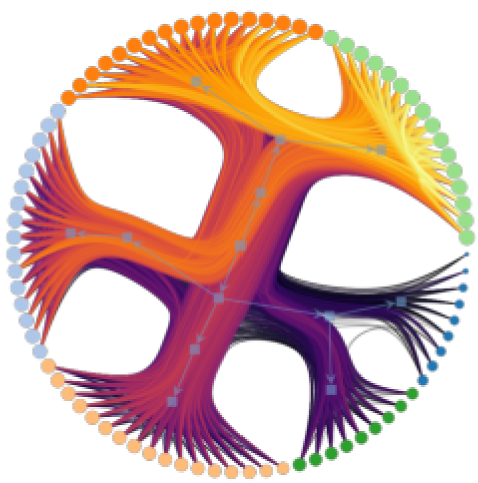
```
(<VertexPropertyMap  object  with  value  type  'vector<double>',  for  Graph
0x308463aa0,  at  0x314746f30>,  <GraphView object,  directed,  with  97  vertices
and  96  edges,  edges  filtered  by  (<EdgePropertyMap  object  with  value  type
'bool',  for Graph  0x30832cd10,  at  0x30832cc20>,  False),  vertices  filtered  by
(<VertexPropertyMap object with value type 'bool', for Graph 0x30832cd10, at
```

```
0x308497200>, False), at 0x30832cd10>, <VertexPropertyMap object with value type
'vector<double>', for Graph 0x30832cd10, at 0x314744830>)
```

```
# show the plot
#Image(filename="genre-wsbm.png")
img = matplotlib.image.imread('genre-wsbm.png')
plt.imshow(img)
plt.axis('off')
```

```
(-0.5, 799.5, 798.5, -0.5)
```

```
plt.show()
```



Getting a Multi-Level Community Classification

```
levels = state.get_bs()

level_communities = []

for level_idx, level in enumerate(levels):
    community_mapping = {}
    for v_idx, community_id in enumerate(level):
        if community_id not in community_mapping:
```

```python
            community_mapping[community_id] = []
        community_mapping[community_id].append(g_z_matrix_WSBM.vp["name"][v_idx])

    level_communities.append(community_mapping)
    print(f"Level {level_idx} Communities:")
    for community_id, nodes in community_mapping.items():
        print(f"  Community {community_id}: {nodes}")
```

```
Level 0 Communities:
  Community 61: ['Acoustic Blues', 'Baroque', 'Bluegrass', 'Bollywood', 'Country
Blues', 'Indian Music', 'Modern', 'Nursery Rhymes', 'Tropical']
  Community 46: ['African Music', 'Alternative Country', 'Bolero', 'Chicago
Blues', 'Dub', 'Electric Blues', 'Electro Hip Hop', 'Game Scores', 'Grime',
'Jazz Hip Hop', 'Old School', 'Oldschool R&B', 'Opera', 'Ska', 'Sports', 'Urban
Cowboy', 'West Coast']
  Community 70: ['Alternative', 'Contemporary R&B', 'Dance', 'Electro',
'Film Scores', 'Films/Games', 'Indie Pop', 'Indie Pop/Folk', 'Indie Rock',
'International Pop', 'Pop', 'R&B', 'Rap/Hip Hop', 'Rock', 'Singer & Songwriter',
'Techno/House']
  Community 21: ['Asian Music', 'Brazilian Music', 'Chill Out/Trip-Hop/Lounge',
'Comedy', 'Dancehall/Ragga', 'Dirty South', 'Dubstep', 'Electro Pop/Electro
Rock', 'Instrumental jazz', 'Musicals', 'Old school soul', 'Soundtracks',
'Spirituality & Religion', 'TV Soundtracks', 'Trance', 'Vocal jazz']
  Community 31: ['Blues', 'Classical', 'Contemporary Soul', 'Country',
'Dancefloor', 'Disco', 'East Coast', 'Folk', 'Hard Rock', 'Indie Rock/Rock pop',
'Jazz', 'Kids', 'Latin Music', 'Metal', 'Reggae', 'Rock & Roll/Rockabilly', 'Soul
& Funk']
  Community 0: ['Classic Blues', 'Classical Period', 'Delta Blues', 'Early Music',
'Kids & Family', 'Ranchera', 'Romantic', 'TV shows & movies', 'Traditional
Country']
Level 1 Communities:
  Community 2: ['Acoustic Blues', 'Baroque', 'Classic Blues', 'Classical',
'Contemporary Soul', 'Hard Rock', 'Indian Music', 'Indie Rock', 'Musicals',
'Nursery Rhymes', 'Opera', 'Pop', 'Rock', 'Singer & Songwriter', 'Soundtracks',
'TV Soundtracks', 'TV shows & movies', 'Tropical']
  Community 0: ['African Music', 'Alternative', 'Alternative Country', 'Asian
Music', 'Bluegrass', 'Bolero', 'Bollywood', 'Brazilian Music', 'Chicago Blues',
'Comedy', 'Contemporary R&B', 'Country Blues', 'Dancefloor', 'Dancehall/Ragga',
'Delta Blues', 'Dirty South', 'Disco', 'Dub', 'East Coast', 'Electric Blues',
'Electro', 'Electro Hip Hop', 'Electro Pop/Electro Rock', 'Film Scores', 'Films/
Games', 'Folk', 'Grime', 'Indie Pop', 'Indie Pop/Folk', 'Indie Rock/Rock pop',
'International Pop', 'Jazz Hip Hop', 'Kids', 'Kids & Family', 'Latin Music',
'Metal', 'Old school soul', 'Oldschool R&B', 'R&B', 'Ranchera', 'Rap/Hip Hop',
'Reggae', 'Rock & Roll/Rockabilly', 'Ska', 'Spirituality & Religion', 'Sports',
'Techno/House', 'Traditional Country', 'Trance', 'West Coast']
  Community 3: ['Blues', 'Chill Out/Trip-Hop/Lounge', 'Country', 'Dance', 'Soul
& Funk', 'Urban Cowboy', 'Vocal jazz']
```

```
  Community 6: ['Classical Period']
   Community 4: ['Dubstep', 'Early Music', 'Game Scores', 'Instrumental jazz',
'Jazz', 'Modern', 'Old School', 'Romantic']
Level 2 Communities:
  Community 2: ['Acoustic Blues', 'Baroque']
  Community 3: ['African Music']
  Community 0: ['Alternative', 'Alternative Country', 'Asian Music']
  Community 1: ['Bluegrass']
Level 3 Communities:
  Community 0: ['Acoustic Blues', 'Alternative', 'Asian Music']
  Community 1: ['African Music', 'Alternative Country']
Level 4 Communities:
  Community 0: ['Acoustic Blues', 'African Music']
  Community 1: ['Alternative']
Level 5 Communities:
  Community 0: ['Acoustic Blues']
  Community 1: ['African Music']
Level 6 Communities:
  Community 0: ['Acoustic Blues', 'African Music']
Level 7 Communities:
  Community 0: ['Acoustic Blues']
  Community 1: ['African Music']
```

Visualisation of WSBM

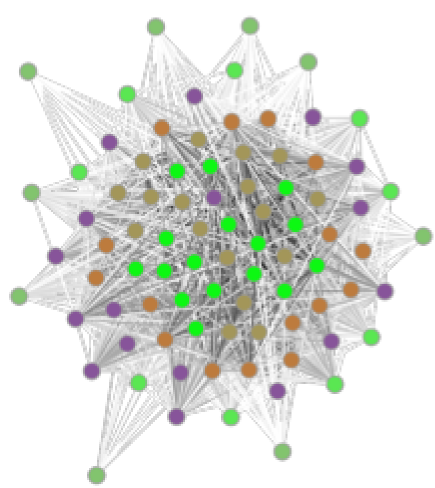
```
# choose level
selected_level = 0

level_blocks = levels[selected_level]

# color
g_z_matrix_WSBM.vp["color"] = g_z_matrix_WSBM.new_vp("vector<double>")
color_map     =     {community_id:     [np.random.rand(),     np.random.rand(),
np.random.rand()] for community_id in set(level_blocks)}
for v in g_z_matrix_WSBM.vertices():
    g_z_matrix_WSBM.vp["color"][v] = color_map[level_blocks[int(v)]]

# draw
graph_draw(
    g_z_matrix_WSBM,
    vertex_fill_color=g_z_matrix_WSBM.vp["color"],
    edge_color=prop_to_size(g_z_matrix_WSBM.ep.weight, power=1, log=True),
    output_size=(800, 800),
    output="level_0_visualization.png",
)
```

```
<VertexPropertyMap object with value type 'vector<double>', for Graph
0x308463aa0, at 0x312212ba0>
```

```
#Image(filename="level_0_visualization.png")
img = matplotlib.image.imread('level_0_visualization.png')
plt.imshow(img)
plt.axis('off')
```

```
(-0.5, 720.5, 799.5, -0.5)
```

```
plt.show()
```



Genres similarity network

Building Genres similarity Networks

calculate node_degree, clustering_coefficent

```
g = nx.from_pandas_edgelist(fr, source="node_1", target="node_2")
nx.is_directed(g)
```

```
False
```

```
nx.is_weighted(g)
```

```
False
```

```
# node degree
g_node_degree = nx.degree(g)
g_degree_dict = dict(g_node_degree)
# clustering coefficent
g_clustering = nx.clustering(g)
```

```
node_metrics = pd.DataFrame({
    'user_id': list(g_degree_dict.keys()),
    'node_degree': list(g_degree_dict.values()),
          'clustering_coefficient':  [g_clustering[user_id]  for  user_id  in
g_degree_dict.keys()]
})
pr_new = pr
pr_new['user_id'] = pd.to_numeric(pr_new['user_id'], errors='coerce')

combined_data = pr_new.merge(node_metrics, on='user_id', how='left')

genres_attribute_data = combined_data.groupby('genres', as_index=False).agg(
    avg_node_degree=('node_degree', 'mean'),
    avg_clustering_coefficient=('clustering_coefficient', 'mean')
)
```

load data from python

```
fr_r <- py$fr
pr_r <- py$pr
# Z matrix
Z_df <- py$Z_df
genres_attribute_data_r <- py$genres_attribute_data
```

create network from Z matrix

```
Z_matrix <- as.matrix(Z_df)
```

```
attribute_list <- do.call(list, genres_attribute_data_r)
```

```
genres_net <- network(
        x = Z_matrix, directed = FALSE,
```

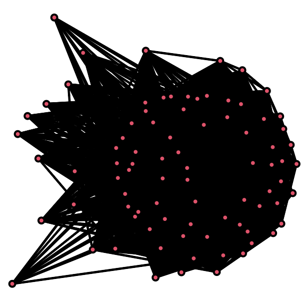
```
        vertex.attr = attribute_list
)
```

```
genres_net
```

```
 Network attributes:
  vertices = 84
  directed = FALSE
  hyper = FALSE
  loops = FALSE
  multiple = FALSE
  bipartite = FALSE
  total edges= 2779
    missing edges= 0
    non-missing edges= 2779

 Vertex attribute names:
    avg_clustering_coefficient avg_node_degree genres vertex.names

 Edge attribute names not shown
```

Network visualization

```
plot(genres_net)
```



Descriptive statistics

density

```r
gden(genres_net)
```

```
[1] 0.7971888
```

cug test

```r
cug.test(
        dat = genres_net, FUN = "gden", cmode = "size"
)
```

```

Univariate Conditional Uniform Graph Test

Conditioning Method: size
Graph Type: digraph
Diagonal Used: FALSE
Replications: 1000

Observed Value: 0.7971888
Pr(X>=Obs): 0
Pr(X<=Obs): 1
```

reciprocity

```r
grecip(genres_net, measure = "dyadic.nonnull")
```

```
Mut
  1
```

```r
cug.test(
        dat = genres_net, FUN = "grecip",
        FUN.args = list(measure = "dyadic.nonnull"), cmode = "edges"
)
```

```

Univariate Conditional Uniform Graph Test

Conditioning Method: edges
Graph Type: digraph
Diagonal Used: FALSE
```

```
Replications: 1000

Observed Value: 1
Pr(X>=Obs): 0
Pr(X<=Obs): 1
```

ERGM estimation

Simple 'edge' model

```
mod_rand <- ergm(formula = genres_net ~ edges)
summary(mod_rand)
```

```
Call:
ergm(formula = genres_net ~ edges)

Maximum Likelihood Results:

      Estimate Std. Error MCMC % z value Pr(>|z|)
edges  1.36882    0.04212      0    32.5   <1e-04 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

     Null Deviance: 4833  on 3486  degrees of freedom
 Residual Deviance: 3516  on 3485  degrees of freedom

AIC: 3518  BIC: 3524  (Smaller is better. MC Std. Err. = 0)
```

Edges & node attributes

```
mod_homoph1 <- ergm(genres_net ~ edges +
        absdiff("avg_node_degree") +
        absdiff("avg_clustering_coefficient")
)
summary(mod_homoph1)
```

```
Call:
ergm(formula = genres_net ~ edges + absdiff("avg_node_degree") +
    absdiff("avg_clustering_coefficient"))

Maximum Likelihood Results:

                                    Estimate Std. Error MCMC % z value Pr(>|z|)
edges                                2.79217    0.08566      0   32.60   <1e-04
absdiff.avg_node_degree             -0.15128    0.01458      0  -10.38   <1e-04
absdiff.avg_clustering_coefficient -16.00433    1.43762      0  -11.13   <1e-04
```

```
edges                                ***
absdiff.avg_node_degree              ***
absdiff.avg_clustering_coefficient ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

     Null Deviance: 4833  on 3486  degrees of freedom
 Residual Deviance: 2926  on 3483  degrees of freedom

AIC: 2932  BIC: 2950  (Smaller is better. MC Std. Err. = 0)
```

```
mod_homoph2 <- ergm(genres_net ~ edges +
        absdiff("avg_node_degree") +
        absdiff("avg_clustering_coefficient") +
        nodecov("avg_node_degree") +
        nodecov("avg_clustering_coefficient"))
summary(mod_homoph2)
```

```
Call:
ergm(formula = genres_net ~ edges + absdiff("avg_node_degree") +
    absdiff("avg_clustering_coefficient") + nodecov("avg_node_degree") +
    nodecov("avg_clustering_coefficient"))

Maximum Likelihood Results:

                                     Estimate Std. Error MCMC % z value
edges                                0.587854   0.347280      0   1.693
absdiff.avg_node_degree             -0.091987   0.016128      0  -5.704
absdiff.avg_clustering_coefficient -14.339354   1.523784      0  -9.410
nodecov.avg_node_degree             -0.019085   0.008942      0  -2.134
nodecov.avg_clustering_coefficient  11.528102   1.068248      0  10.792
                                   Pr(>|z|)
edges                                0.0905 .
absdiff.avg_node_degree              <1e-04 ***
absdiff.avg_clustering_coefficient   <1e-04 ***
nodecov.avg_node_degree              0.0328 *
nodecov.avg_clustering_coefficient   <1e-04 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

     Null Deviance: 4833  on 3486  degrees of freedom
 Residual Deviance: 2794  on 3481  degrees of freedom

AIC: 2804  BIC: 2835  (Smaller is better. MC Std. Err. = 0)
```