Primate_Predict_orosco

February 3, 2023

[1]:
```
# Primate Prediction - Original Case Study Christine Orosco
# Study social hierarchies within a group of 20 Baboons at the Primate Center␣
↪in France.
# Data set is a result of the Case Study conducted and published in the paper:
# Gelardi, V., Godard, J., Paleressompoulle, D., Claidiere, N., & Barrat, A.␣
↪(2020).
# Measuring social networks in primates: wearable sensors versus direct␣
↪observations. Proceedings of the Royal Society A: Mathematical, Physical and␣
↪Engineering Sciences,
# 476(2236), 20190737. https://doi.org/10.1098/rspa.2019.0737
# Retrieved from https://royalsocietypublishing.org/doi/10.1098/rspa.2019.0737␣
↪Jan 15th 2021
# Dataset OBS_data.txt
# Data release date Dec4, 2020. Availale at http://www.sociopatterns.org/
↪datasets/baboons-interactions/
# The entire group consisted of 19 individuals (7 males and 12 females) aged␣
↪from 1 to 23 years old.
```

[2]:
```
# Case Study to predict Sex, Dominant Male, and Family groups

# 1 - Based upon the behavior can we predict the Sex. Sex is the target variable

# 2 - Based upon the behavior can we predict the dominant male
# Identify dominant male by behavior - based upon the type of behavior and␣
↪occurences of each type

# 3 - Based upon the behavior can we identify sub-groups
# look at the clustering of subgroups and the behaviors associated with each␣
↪group.
# Would expect a family group to exhibit carrying, grooming, and touching more␣
↪so than non family groups. i.e mother-child
```

[3]:
```
import pandas as pd
import numpy as np
import datetime as dt

import matplotlib
```

```
import matplotlib.pyplot as plt
pd.set_option("max_columns", 50)
import networkx as nx
from networkx import connected_components
import networkx.algorithms.community as nxcom
import seaborn as sns
import graphviz
import pygraphviz
from networkx.algorithms import approximation as approx
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
import sklearn
from pprint import pprint
import warnings
warnings.filterwarnings('ignore')
```

[4]:
```
# load the data from your dataset using the pandas library
df = pd.read_excel('~/OBS_data2.xls',  header=0)

df1 = df[['Actor', 'Recipient', 'Behavior']].copy()
```

[5]:
```
# If Recipient == Nan replace with UNKNOWN
# If Actor == NaN replace with UNK_Actor
df1.loc[df['Recipient'].isnull(), 'Recipient' ] = 'UNKNOWN'
df1.loc[df['Actor'].isnull(), 'Actor' ] = 'VIVIEN'
```

[6]:
```
# Change SELF with name of Actor
df1.loc[df['Recipient'] == 'SELF', 'Recipient' ] = df['Actor']
```

[7]:
```
# Add Sex column for females

names = ['VIOLETTE','ANGELE','ARIELLE','FEYA','FANA', 'ATMOSPHERE',␣
 ↪'PETOULETTE' , 'KALI', 'LIPS', 'NEKKE', 'VIVIEN', 'LOME', 'MALI']

for x in names:
    df1.loc[df['Actor'] == x, 'Sex'] = 2
```

[8]:
```
# Add the Sex column for males

names = ['EWINE','PIPO','FELIPE', 'BOBO', 'MAKO' , 'HARLEM', 'MUSE']

for x in names:
    df1.loc[df['Actor'] == x, 'Sex'] = 1
```

[9]:
```
# for any NaN make them a male
df1.loc[df1['Sex'].isnull(), 'Sex' ] = 1
```

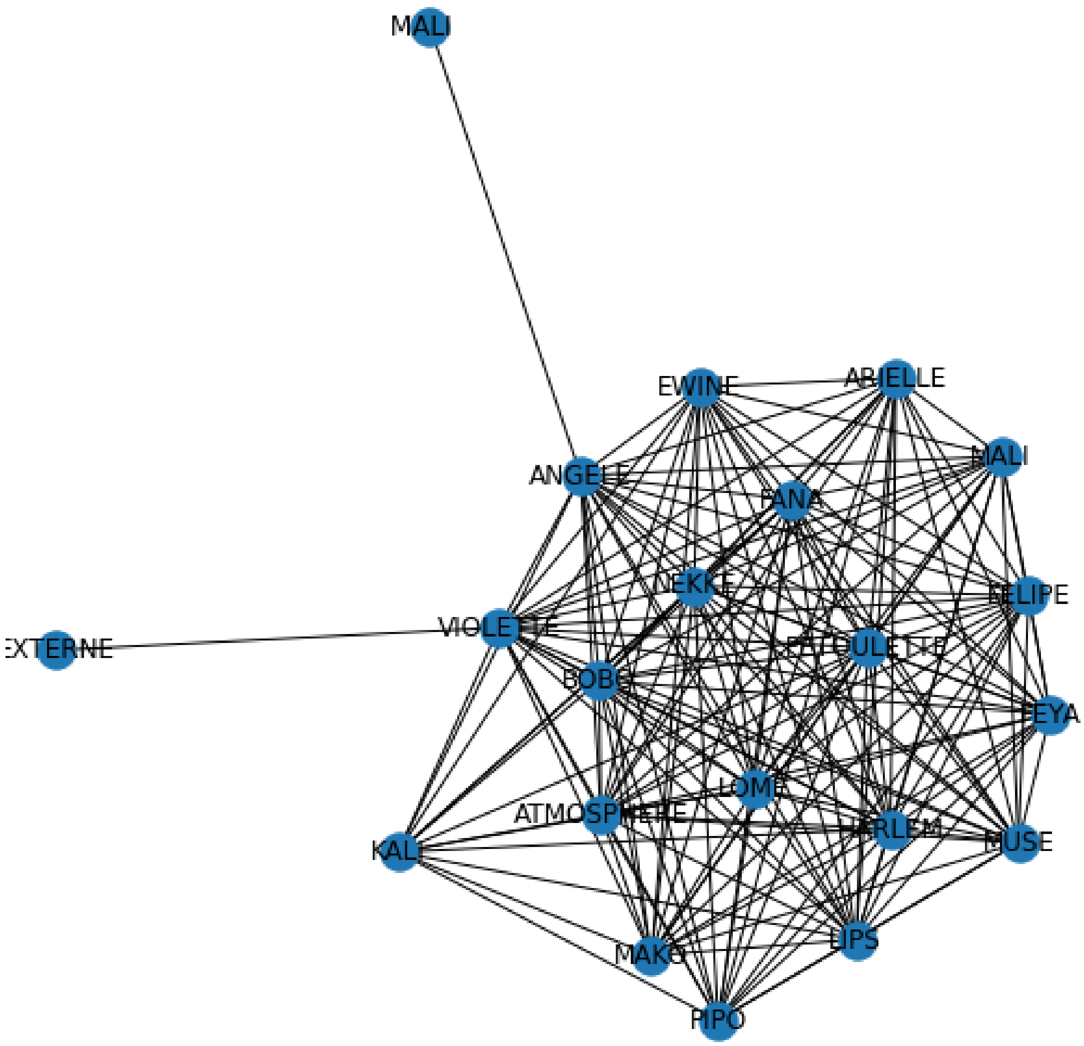
[10]:
```python
# Convert Sex to int
df1['Sex'] = df1['Sex'].astype(int)
df1.query('Sex == 0')
```

[10]:
```
Empty DataFrame
Columns: [Actor, Recipient, Behavior, Sex]
Index: []
```

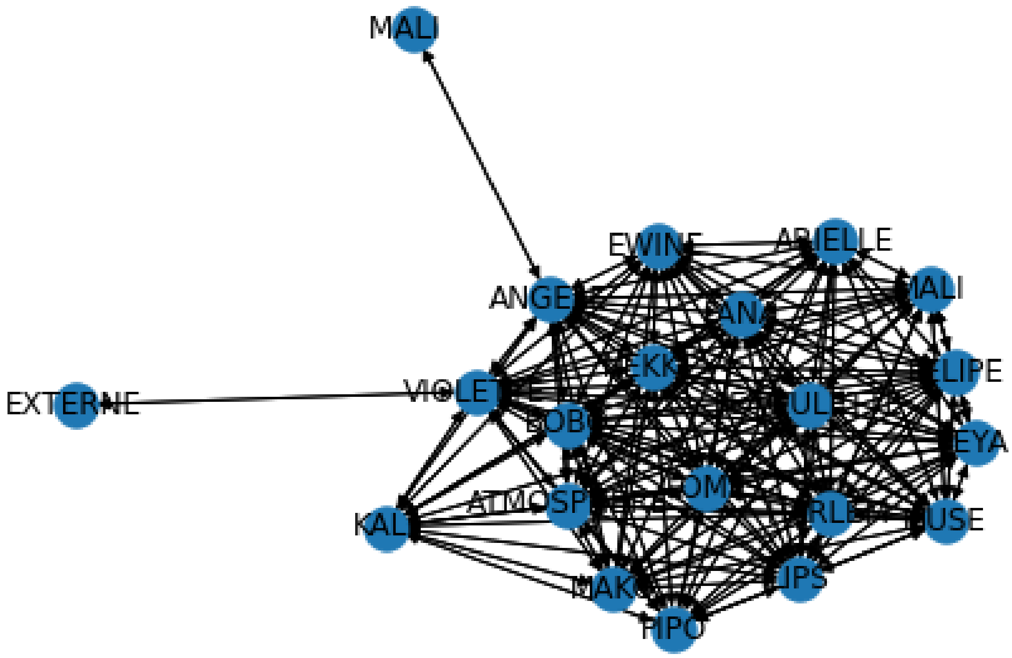
[11]:
```python
# Replace NaN in behavior with Playing with
df1.loc[df['Behavior'].isnull(), 'Behavior'] = 'Playing with'
```

[12]:
```python
# Create subsets to plot links and nodes
df2 = df1[['Actor','Recipient']].copy()

# Remove UNKNOWN and where Actor = Recipient

df2 = df2[(df2['Recipient'] != 'UNKNOWN')].copy()

# Remove SELF links
df2 = df2[(df2['Recipient'] != df2['Actor'])].copy()
```

[13]:
```python
# Plot the network using networkx. Use graphviz to render the networkx graph

g = nx.Graph()
g = nx.from_pandas_edgelist(df2, source='Actor', target='Recipient')

plt.figure(figsize =(7, 7))
pos = nx.nx_agraph.graphviz_layout(g)
nx.draw(g,  pos=pos, with_labels=True)
```



[14]:
```
DG = nx.DiGraph(g)
nx.draw(DG,  pos=pos, with_labels=True)
```



[15]:
```python
# Print the number of connections per node
# Find the highly connected nodes that may suggest family groups because of the number of links and dominant male with the number of links

# create connection dict
conn = {}

# for each node in graph g get the number of connections to the that node
for x in g.nodes:
    conn[x] = len(g[x])
    s = pd.Series(conn, name='connections')
    conn_df = s.to_frame().sort_values('connections', ascending=False)
conn_df
```

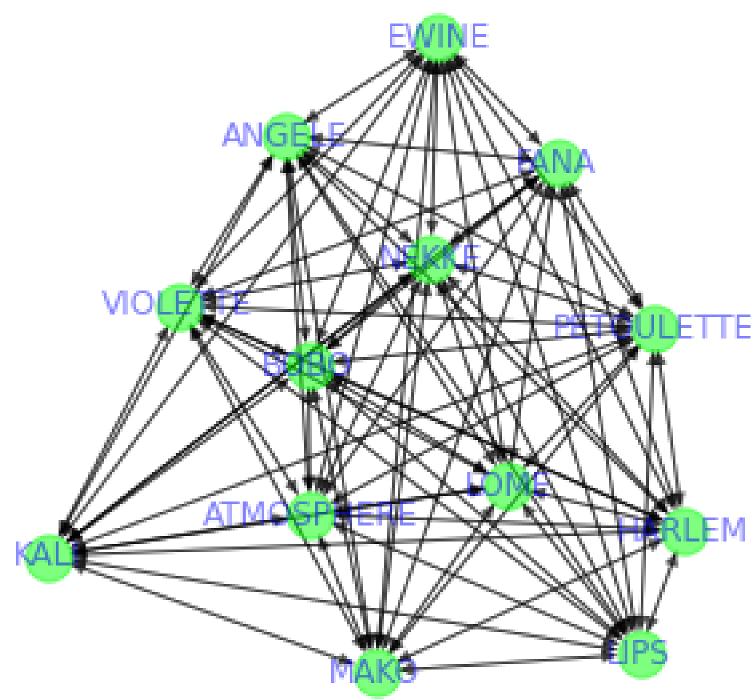
[15]:

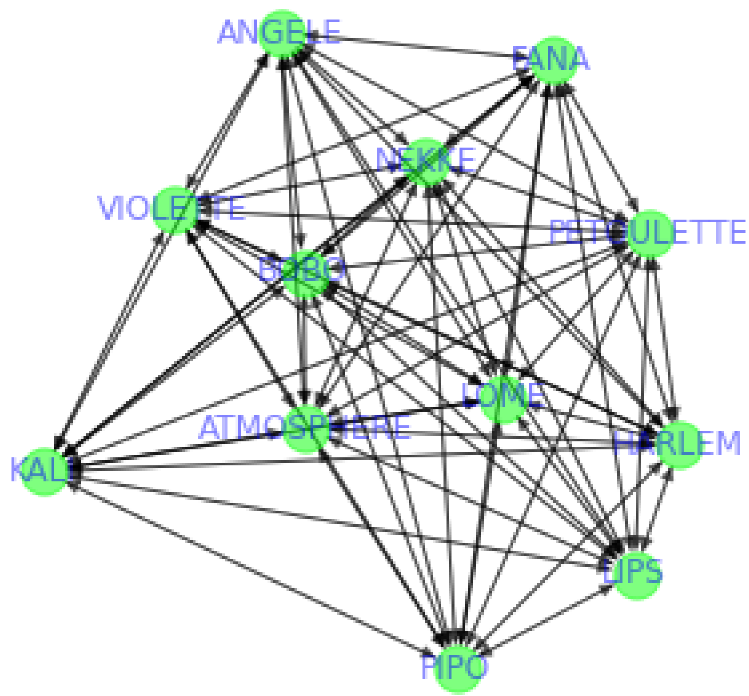
	connections
ANGELE	19
VIOLETTE	19
PETOULETTE	18
LIPS	18
NEKKE	18
LOME	18
BOBO	18
ATMOSPHERE	18

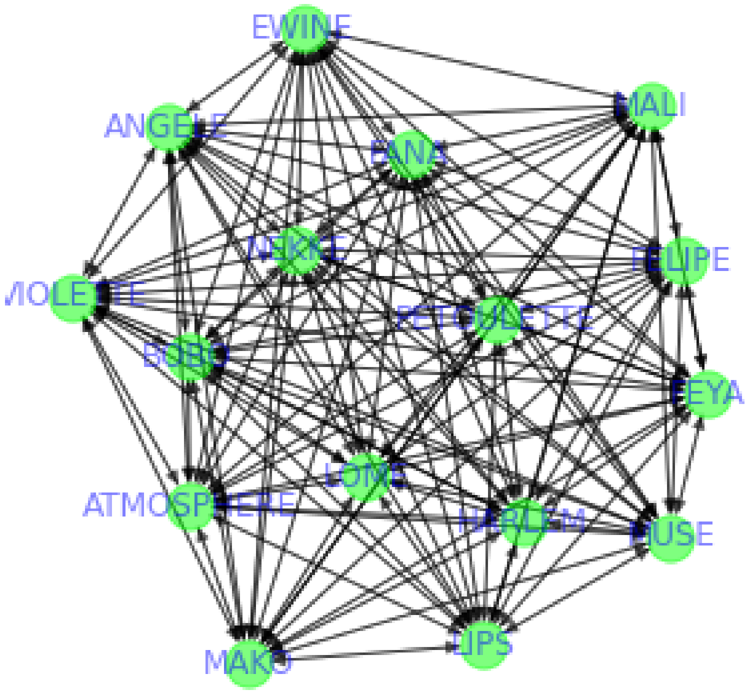
```
FANA                  18
HARLEM                18
EWINE                 17
MUSE                  17
FELIPE                17
FEYA                  17
MALI                  16
MAKO                  16
ARIELLE               16
PIPO                  15
KALI                  13
EXTERNE                1
MALI                   1
```

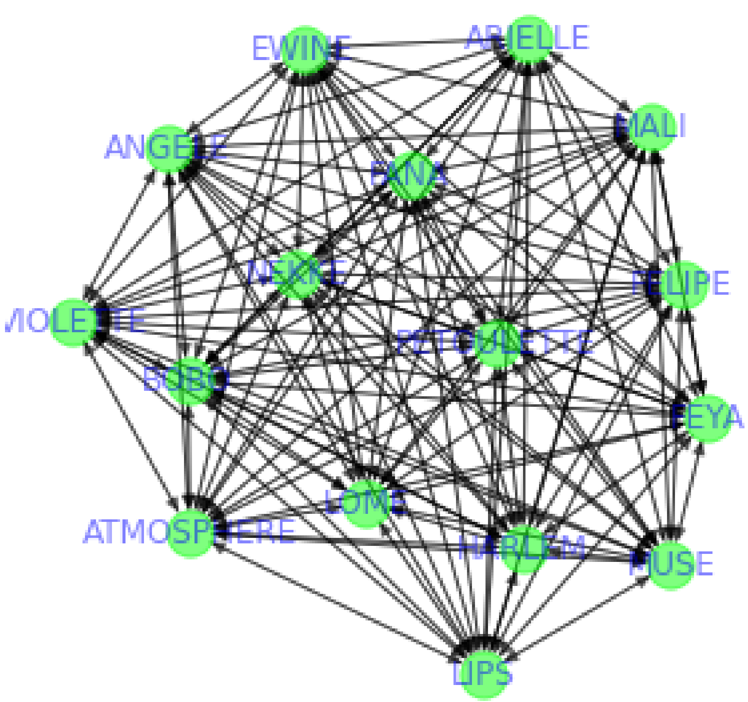
[16]:

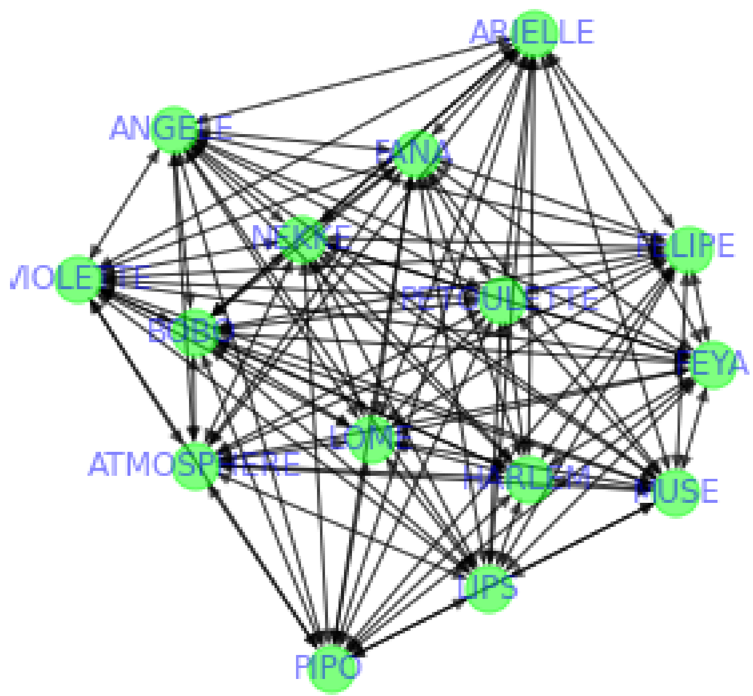
```python
# Find cliques to further refine network subsets

cliques = list(nx.find_cliques(g))

triangles = [clique for clique in cliques if len(clique) > 3]
x_tri = len(triangles)
for n in range(x_tri):
    plt.figure(figsize =(4, 4))
    nx.draw(DG.subgraph(triangles[n]), pos=pos, with_labels=True,␣
 ↪node_color="lime", font_color="blue", alpha=.5)
```




ANGELE
FANA
NEKKE
VIOLETTE
PETOULETTE
BOBO
LOME
ATMOSPHERE
HARLEM
KALI
LIPS
PIPO


EWINE
MALI
ANGELE
FANA
NEKKE
FELIPE
VIOLETTE
PETOULETTE
BOBO
FEYA
LOME
ATMOSPHERE
HARLEM
MUSE
LIPS
MAKO


EWINE
ARIELLE
MALI
ANGELE
FANA
NEKKE
FELIPE
VIOLETTE
PETOULETTE
BOBO
FEYA
LOME
ATMOSPHERE
HARLEM
MUSE
LIPS



[17]:
```
# https://graphsandnetworks.com/community-detection-using-networkx/
# Find the communities

communities = sorted(nxcom.greedy_modularity_communities(g), key=len,␣
↪reverse=True)

# Count the communities

print(f"The Baboon group has {len(communities)} communities.")
```

```
The Baboon group has 3 communities.
```

[18]:
```
# show the clustering
nx.clustering(g)
```

[18]:
```
{'ANGELE': 0.8421052631578947,
 'FELIPE': 0.9705882352941176,
 'LIPS': 0.9411764705882353,
 'NEKKE': 0.9411764705882353,
```

```
 'LOME': 0.9411764705882353,
 'BOBO': 0.9411764705882353,
 'ATMOSPHERE': 0.9411764705882353,
 'FEYA': 0.9705882352941176,
 'PIPO': 0.9619047619047619,
 'KALI': 0.9743589743589743,
 'MUSE': 0.9705882352941176,
 'MAKO': 0.9666666666666667,
 'MALI': 0.9916666666666667,
 'PETOULETTE': 0.9411764705882353,
 'ARIELLE': 0.9833333333333333,
 'VIOLETTE': 0.8421052631578947,
 'HARLEM': 0.9411764705882353,
 'FANA': 0.9411764705882353,
 'EWINE': 0.9558823529411765,
 'EXTERNE': 0,
 'MALI  ': 0}
```

[19]:
```
node_cc = nx.algorithms.approximation.all_pairs_node_connectivity(g)
```

[20]:
```
# Compute node independent paths between two nodes using the shortest path.
approx.local_node_connectivity(g,'VIOLETTE', 'NEKKE' )
```

[20]:
```
18
```

[21]:
```
approx.local_node_connectivity(g,'VIOLETTE', 'PIPO' )
```

[21]:
```
15
```

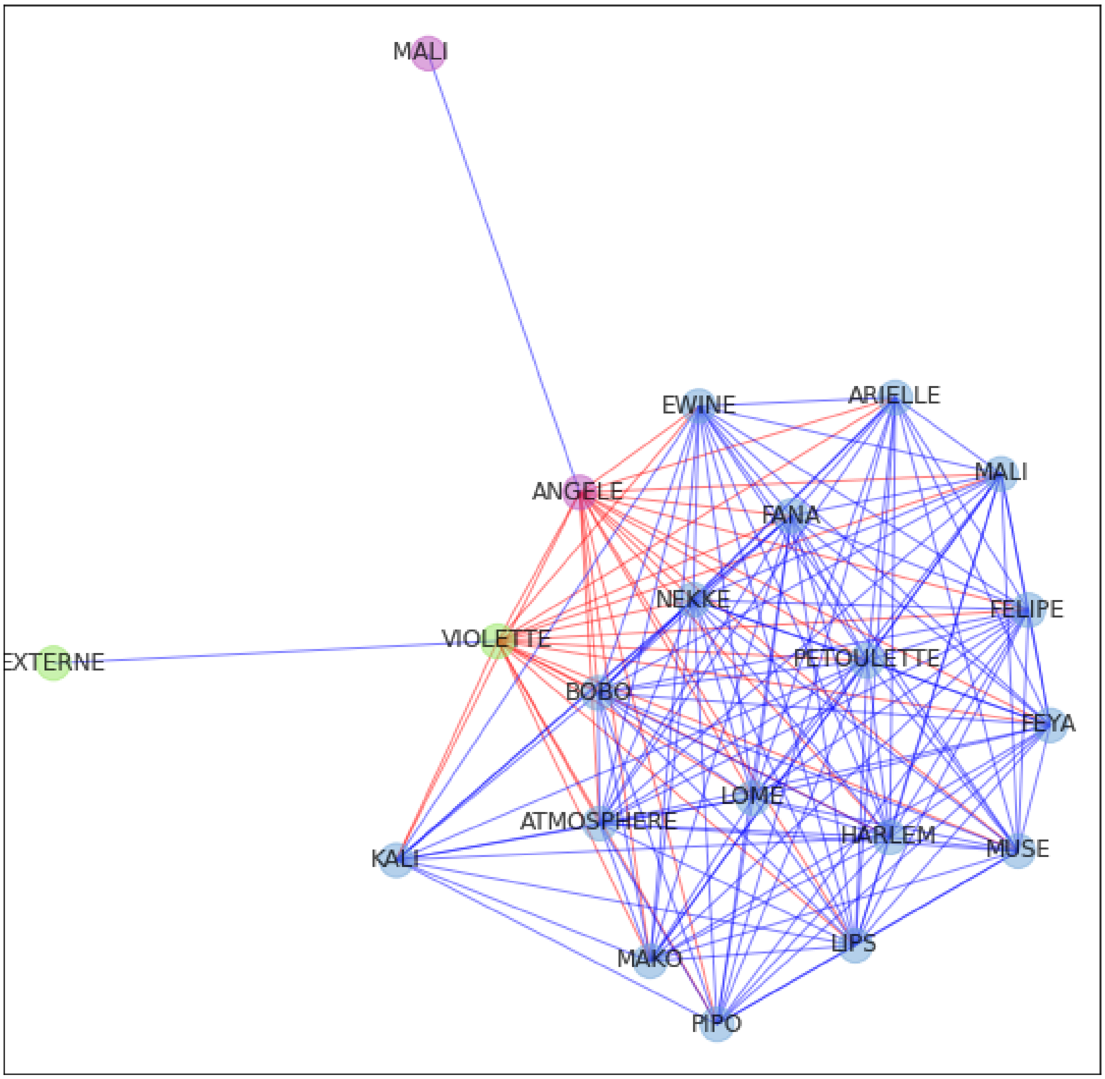
[22]:
```
# define community attribute functions to plot the communities

def set_node_community(g, communities):
    '''Add community to node attributes'''
    for c, v_c in enumerate(communities):
        for v in v_c:
            # Add 1 to save 0 for external edges
            g.nodes[v]['community'] = c + 1

def set_edge_community(g):
    '''Find internal edges and add their community to their attributes'''
    for v, w, in g.edges:
        if g.nodes[v]['community'] == g.nodes[w]['community']:
            # Internal edge, mark with community
            g.edges[v, w]['community'] = g.nodes[v]['community']
        else:
            # External edge, mark as 0
            g.edges[v, w]['community'] = 0
```

```
def get_color(i, r_off=1, g_off=1, b_off=1):
    '''Assign a color to a vertex.'''
    r0, g0, b0 = 0, 0, 0
    n = 16
    low, high = 0.1, 0.9
    span = high - low
    r = low + span * (((i + r_off) * 3) % n) / (n - 1)
    gn = low + span * (((i + g_off) * 5) % n) / (n - 1)
    b = low + span * (((i + b_off) * 7) % n) / (n - 1)
    return (r, gn, b)
```

[23]:
```
# Set node and edge communities

set_node_community(g, communities)
set_edge_community(g)

node_color = [get_color(g.nodes[v]['community']) for v in g.nodes]

# Set community color for edges between members of the same community␣
 ↪(internal) and intra-community edges (external)

external = [(v, w) for v, w in g.edges if g.edges[v, w]['community'] == 0]
internal = [(v, w) for v, w in g.edges if g.edges[v, w]['community'] > 0]
internal_color = ['blue' for e in internal]
external_color = ['red' for e in external]
```

[24]:
```
# Plot each community with different colors for the nodes

g_pos = nx.spring_layout(g)

plt.rcParams.update({'figure.figsize': (10, 10)})

# Draw external edges

nx.draw_networkx(
        g,
        pos=pos,
        node_size=0,
        edgelist=external,
        edge_color=external_color,
        alpha=0.5)

# Draw nodes and internal edges

nx.draw_networkx(
        g,
```

```
        pos=pos,
        node_color=node_color,
        edgelist=internal,
        edge_color=internal_color,
        alpha=0.5)
```

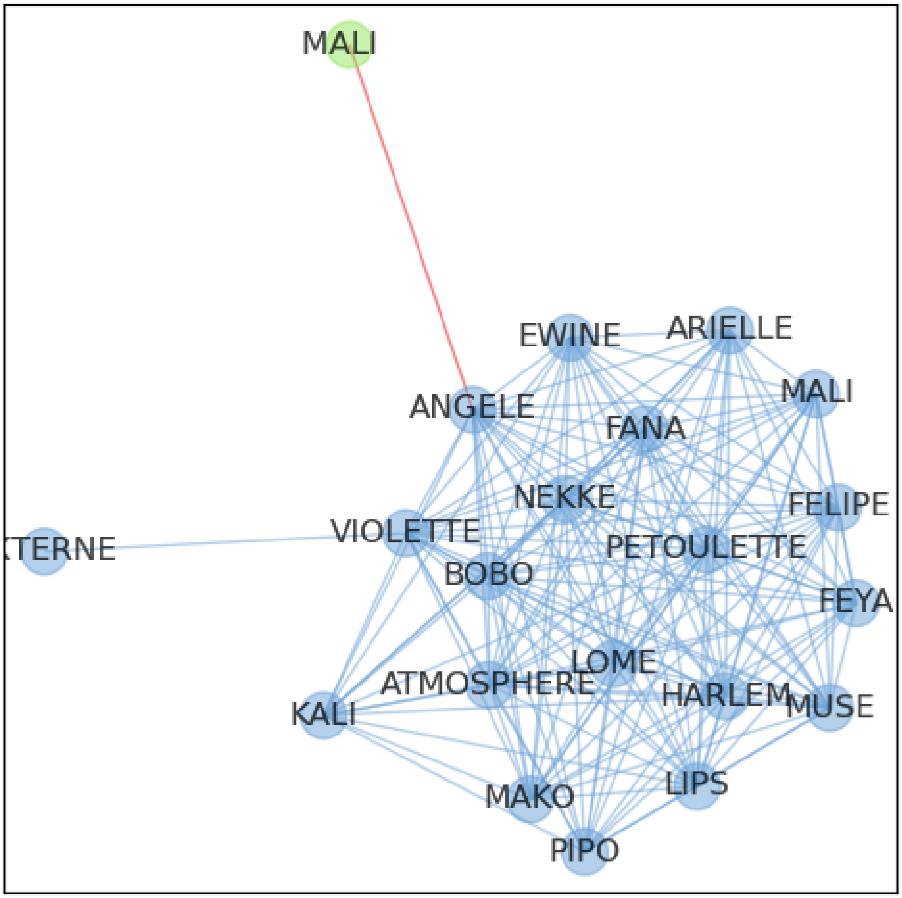


[25]:
```
# Communities using Girvan Newman algorithm

result = nxcom.girvan_newman(g)
communities = next(result)
len(communities)
```

[25]: 2

[26]:

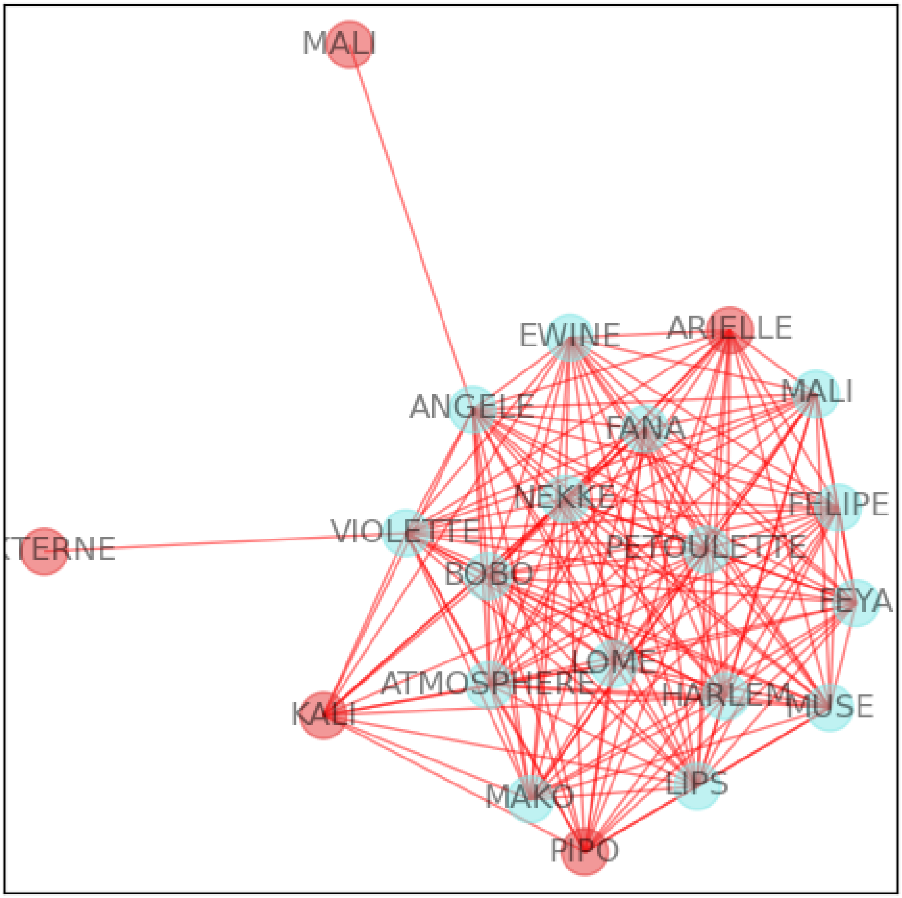
```python
# Draw the communities from the Girvan-Newman algorithm

plt.rcParams.update(plt.rcParamsDefault)
plt.rcParams.update({'figure.figsize': (10, 10)})

# Set node and edge communities

set_node_community(g, communities)
set_edge_community(g)

# Set community color for nodes
node_color = [get_color(g.nodes[v]['community']) for v in g.nodes]

# Set community color for internal edges

external = [(v, w) for v, w in g.edges if g.edges[v, w]['community'] == 0]
internal = [(v, w) for v, w in g.edges if g.edges[v, w]['community'] > 0]
internal_color = [get_color(g.edges[e]['community']) for e in internal]

g_pos = nx.spring_layout(g)

plt.rcParams.update({'figure.figsize': (6, 6)})

# Draw external edges

nx.draw_networkx(
        g,
        pos=pos,
        node_size=0,
        edgelist=external,
        edge_color=external_color,
        alpha=0.5)

# Draw nodes and internal edges

nx.draw_networkx(
        g,
        pos=pos,
        node_color=node_color,
        edgelist=internal,
        edge_color=internal_color,
        alpha=0.5)
```



[27]:

```
# Plot number of cliques

plt.rcParams.update(plt.rcParamsDefault)
plt.rcParams.update({'figure.figsize': (6, 6)})

cliques = list(nx.find_cliques(g))

max_clique = max(cliques, key=len)
node_color = [(0.5, 0.9, 0.3) for v in g.nodes()]

for i, v in enumerate(g.nodes()):
    if v in max_clique:
        node_color[i] = (.5, 0.9, 0.9)
        edge_color='blue'
    else:
        node_color[i] = (.9, 0.2, 0.2)
        edge_color='red'
```

```
nx.draw_networkx(g, node_color=node_color, edge_color=edge_color, pos=pos,␣
↪alpha=.5)
```



[28]:
```
# Degree Centrality

sorted(nx.degree_centrality(g).items(), key=lambda x : x[1], reverse=True)
```

[28]:
```
[('ANGELE', 0.9500000000000001),
 ('VIOLETTE', 0.9500000000000001),
 ('LIPS', 0.9),
 ('NEKKE', 0.9),
 ('LOME', 0.9),
 ('BOBO', 0.9),
 ('ATMOSPHERE', 0.9),
 ('PETOULETTE', 0.9),
 ('HARLEM', 0.9),
 ('FANA', 0.9),
 ('FELIPE', 0.8500000000000001),
```

```
 ('FEYA', 0.8500000000000001),
 ('MUSE', 0.8500000000000001),
 ('EWINE', 0.8500000000000001),
 ('MAKO', 0.8),
 ('MALI', 0.8),
 ('ARIELLE', 0.8),
 ('PIPO', 0.75),
 ('KALI', 0.65),
 ('EXTERNE', 0.05),
 ('MALI  ', 0.05)]
```

[29]:
```
# betweenness centrality refers to a number of shortest paths that pass through␣
↪that node.

sorted(nx.betweenness_centrality(g, normalized=False).items(), key=lambda x :␣
↪x[1], reverse=True)
```

[29]:
```
[('ANGELE', 19.673626373626373),
 ('VIOLETTE', 19.673626373626373),
 ('LIPS', 0.6736263736263736),
 ('NEKKE', 0.6736263736263736),
 ('LOME', 0.6736263736263736),
 ('BOBO', 0.6736263736263736),
 ('ATMOSPHERE', 0.6736263736263736),
 ('PETOULETTE', 0.6736263736263736),
 ('HARLEM', 0.6736263736263736),
 ('FANA', 0.6736263736263736),
 ('EWINE', 0.4641025641025641),
 ('PIPO', 0.31410256410256415),
 ('MAKO', 0.31410256410256415),
 ('FELIPE', 0.27619047619047615),
 ('FEYA', 0.27619047619047615),
 ('MUSE', 0.27619047619047615),
 ('KALI', 0.1380952380952381),
 ('ARIELLE', 0.1380952380952381),
 ('MALI', 0.06666666666666667),
 ('EXTERNE', 0.0),
 ('MALI  ', 0.0)]
```

[30]:
```
# Normalize Values

sorted(nx.betweenness_centrality(g).items(), key=lambda x : x[1], reverse=True)
```

[30]:
```
[('ANGELE', 0.10354540196645459),
 ('VIOLETTE', 0.10354540196645459),
 ('LIPS', 0.0035454019664545974),
 ('NEKKE', 0.0035454019664545974),
```

```
 ('LOME', 0.0035454019664545974),
 ('BOBO', 0.0035454019664545974),
 ('ATMOSPHERE', 0.0035454019664545974),
 ('PETOULETTE', 0.0035454019664545974),
 ('HARLEM', 0.0035454019664545974),
 ('FANA', 0.0035454019664545974),
 ('EWINE', 0.0024426450742240217),
 ('PIPO', 0.0016531713900134954),
 ('MAKO', 0.0016531713900134954),
 ('FELIPE', 0.0014536340852130322),
 ('FEYA', 0.0014536340852130322),
 ('MUSE', 0.0014536340852130322),
 ('KALI', 0.0007268170426065163),
 ('ARIELLE', 0.0007268170426065163),
 ('MALI', 0.0003508771929824561),
 ('EXTERNE', 0.0),
 ('MALI  ', 0.0)]
```

[31]:
```
# Create subset df with the Actor/Recipient/Behavior triplet
# From this df should be able to get counts for each occurrence of behavior

df3 = df1[['Actor', 'Recipient', 'Behavior','Sex']].copy()

# Delete Resting and Other from Behavior.  These are quantities that exceed␣
↪other values and cause an imbalance.

df3.drop(df3.loc[df3['Behavior']=='Resting'].index, inplace=True)
df3.drop(df3.loc[df3['Behavior']=='Other'].index, inplace=True)
```

[32]:
```
# Create pivot table to count the number of occurences of the Actor and the␣
↪recipent behaviors
pivot1 = pd.pivot_table(df3, index=['Actor','Recipient', 'Sex'],␣
↪columns='Behavior', fill_value=0, aggfunc='size')

pd.reset_option('display.max_rows')
```

[33]:
```
# Create copy for feature selection tests
pivot2 = pivot1.copy()
pivot1
```

[33]:
```
Behavior                  Attacking  Avoiding  Carrying  Chasing  Copulating  \
Actor    Recipient Sex
ANGELE   BOBO      2              0         0         0        0           0
         EWINE     2              0         0         0        0           0
         FANA      2              0         0         0        0           0
         FELIPE    2              0         0         0        0           0
         FEYA      2              0         0         0        0           0
```

…			…	…	…	…	…
VIOLETTE	MAKO	2	0	0	0	0	0
	MALI	2	0	0	0	0	0
	MUSE	2	0	0	0	0	0
	NEKKE	2	0	0	0	0	0
	UNKNOWN	2	0	0	0	0	0

Behavior			Embracing	Grooming	Grunting-Lipsmacking	Invisible \
Actor	Recipient	Sex				
ANGELE	BOBO	2	0	0	0	0
	EWINE	2	0	1	0	0
	FANA	2	0	0	1	0
	FELIPE	2	0	18	3	0
	FEYA	2	0	0	4	0
…			…	…	…	…
VIOLETTE	MAKO	2	0	0	0	0
	MALI	2	0	0	0	0
	MUSE	2	0	0	0	0
	NEKKE	2	0	1	1	0
	UNKNOWN	2	0	0	0	26

Behavior			Mounting	Playing with	Presenting	Submission \
Actor	Recipient	Sex				
ANGELE	BOBO	2	0	0	3	0
	EWINE	2	0	0	0	0
	FANA	2	0	0	0	0
	FELIPE	2	0	0	9	1
	FEYA	2	0	0	0	0
…			…	…	…	…
VIOLETTE	MAKO	2	0	0	3	0
	MALI	2	0	5	0	1
	MUSE	2	0	2	4	0
	NEKKE	2	0	0	0	0
	UNKNOWN	2	0	0	0	0

Behavior			Supplanting	Threatening	Touching
Actor	Recipient	Sex			
ANGELE	BOBO	2	0	0	0
	EWINE	2	1	0	0
	FANA	2	0	0	0
	FELIPE	2	0	0	0
	FEYA	2	0	0	1
…			…	…	…
VIOLETTE	MAKO	2	0	0	0
	MALI	2	0	0	1
	MUSE	2	0	0	0
	NEKKE	2	0	0	0

```
          UNKNOWN    2              0            0          0

[270 rows x 16 columns]
```

[34]:

```
# Sum each behavior occurrence by Actor
test = pivot1.sum(level=['Actor', 'Sex'])
test
```

[34]:

```
Behavior          Attacking  Avoiding  Carrying  Chasing  Copulating  Embracing  \
Actor       Sex
ANGELE      2             1         0         0        1           0          0
ARIELLE     2             1         0         0        0           0          2
ATMOSPHERE  2             0         0         0        0           0          0
BOBO        1             0        33         0        0           0          0
EWINE       1             1        22         0        0           0          1
FANA        2             0         0         0        0           0          0
FELIPE      1             6        19         4        5           5          3
FEYA        2             1         0        15        0           0         24
HARLEM      1            21         0         0        3          28          0
KALI        2             0         0         0        0           0          0
LIPS        2             0         0        40        0           0         34
LOME        2             3         0         1        3           0          0
MAKO        1             1         0         2        2           0         12
MALI        2             0         0         1        2           0          2
MUSE        1             2         0         0        0           0          3
NEKKE       2             0         0         0        0           0         30
PETOULETTE  2             0         0         0        0           0          0
PIPO        1            13        21         0        2           6          0
VIOLETTE    2             0         1         0        1           0          0

Behavior          Grooming  Grunting-Lipsmacking  Invisible  Mounting  \
Actor       Sex
ANGELE      2           24                    11         10         0
ARIELLE     2           13                     3         25         0
ATMOSPHERE  2           20                     2         10         0
BOBO        1            2                    15          5         0
EWINE       1           39                     5         31         0
FANA        2           29                     6         16         0
FELIPE      1            5                    16         19        15
FEYA        2           28                    10         25         0
HARLEM      1            5                     9         27        40
KALI        2            8                     3          7         0
LIPS        2           41                     1         41         0
LOME        2            5                     0         31         2
MAKO        1           17                     4         35         0
MALI        2           53                     3         37         0
MUSE        1           46                     3         31         0
```

NEKKE	2	18	3	29	0
PETOULETTE	2	32	23	14	0
PIPO	1	23	22	18	13
VIOLETTE	2	30	6	26	0

Behavior		Playing with	Presenting	Submission	Supplanting \
Actor	Sex				
ANGELE	2	2	21	4	3
ARIELLE	2	2	24	4	0
ATMOSPHERE	2	2	43	0	0
BOBO	1	2	0	12	13
EWINE	1	3	0	1	0
FANA	2	6	25	1	0
FELIPE	1	13	2	16	3
FEYA	2	6	24	0	0
HARLEM	1	16	0	0	1
KALI	2	0	0	2	0
LIPS	2	75	0	2	1
LOME	2	129	0	21	2
MAKO	1	172	0	3	0
MALI	2	70	0	5	0
MUSE	1	88	0	2	0
NEKKE	2	176	0	1	0
PETOULETTE	2	0	43	0	1
PIPO	1	0	0	24	0
VIOLETTE	2	10	34	3	2

Behavior		Threatening	Touching
Actor	Sex		
ANGELE	2	0	4
ARIELLE	2	0	4
ATMOSPHERE	2	0	3
BOBO	1	9	8
EWINE	1	0	6
FANA	2	0	8
FELIPE	1	0	22
FEYA	2	1	7
HARLEM	1	50	16
KALI	2	0	0
LIPS	2	0	13
LOME	2	0	11
MAKO	1	0	15
MALI	2	0	7
MUSE	1	0	11
NEKKE	2	0	10
PETOULETTE	2	1	4
PIPO	1	0	7

```
VIOLETTE   2              3         2
```

[35]:
```
# Reset the index to create Behavior as the index column
# Convert table to long format for plotting behavior counts

pivot1.reset_index(inplace=True)
pivot1.index.names = ['Behavior']
pivot1
```

[35]:
```
Behavior     Actor Recipient  Sex  Attacking  Avoiding  Carrying  Chasing  \
Behavior
0           ANGELE      BOBO    2          0         0         0        0
1           ANGELE     EWINE    2          0         0         0        0
2           ANGELE      FANA    2          0         0         0        0
3           ANGELE    FELIPE    2          0         0         0        0
4           ANGELE      FEYA    2          0         0         0        0
…             …        …   …       …        …        …       …
265       VIOLETTE      MAKO    2          0         0         0        0
266       VIOLETTE      MALI    2          0         0         0        0
267       VIOLETTE      MUSE    2          0         0         0        0
268       VIOLETTE     NEKKE    2          0         0         0        0
269       VIOLETTE   UNKNOWN    2          0         0         0        0

Behavior  Copulating  Embracing  Grooming  Grunting-Lipsmacking  Invisible  \
Behavior
0                  0          0         0                     0          0
1                  0          0         1                     0          0
2                  0          0         0                     1          0
3                  0          0        18                     3          0
4                  0          0         0                     4          0
…             …        …        …                    …         …
265                0          0         0                     0          0
266                0          0         0                     0          0
267                0          0         0                     0          0
268                0          0         1                     1          0
269                0          0         0                     0         26

Behavior  Mounting  Playing with  Presenting  Submission  Supplanting  \
Behavior
0                0             0           3           0            0
1                0             0           0           0            1
2                0             0           0           0            0
3                0             0           9           1            0
4                0             0           0           0            0
…             …            …          …          …           …
265              0             0           3           0            0
266              0             5           0           1            0
```

```
267                0              2           4           0            0
268                0              0           0           0            0
269                0              0           0           0            0

Behavior  Threatening  Touching
Behavior
0                   0         0
1                   0         0
2                   0         0
3                   0         0
4                   0         1
…                 …        …
265                 0         0
266                 0         1
267                 0         0
268                 0         0
269                 0         0

[270 rows x 19 columns]
```

[36]:
```
# Convert pivot table to long format
long_pivot = pivot1.melt(id_vars=['Actor', 'Recipient', 'Sex'],
 ↪var_name=['behavior'], value_name='occ')
long_pivot
```

[36]:
```
         Actor Recipient  Sex   behavior  occ
0       ANGELE      BOBO    2  Attacking    0
1       ANGELE     EWINE    2  Attacking    0
2       ANGELE      FANA    2  Attacking    0
3       ANGELE    FELIPE    2  Attacking    0
4       ANGELE      FEYA    2  Attacking    0
…          …       …  …        …  …
4315  VIOLETTE      MAKO    2   Touching    0
4316  VIOLETTE      MALI    2   Touching    1
4317  VIOLETTE      MUSE    2   Touching    0
4318  VIOLETTE     NEKKE    2   Touching    0
4319  VIOLETTE   UNKNOWN    2   Touching    0

[4320 rows x 5 columns]
```

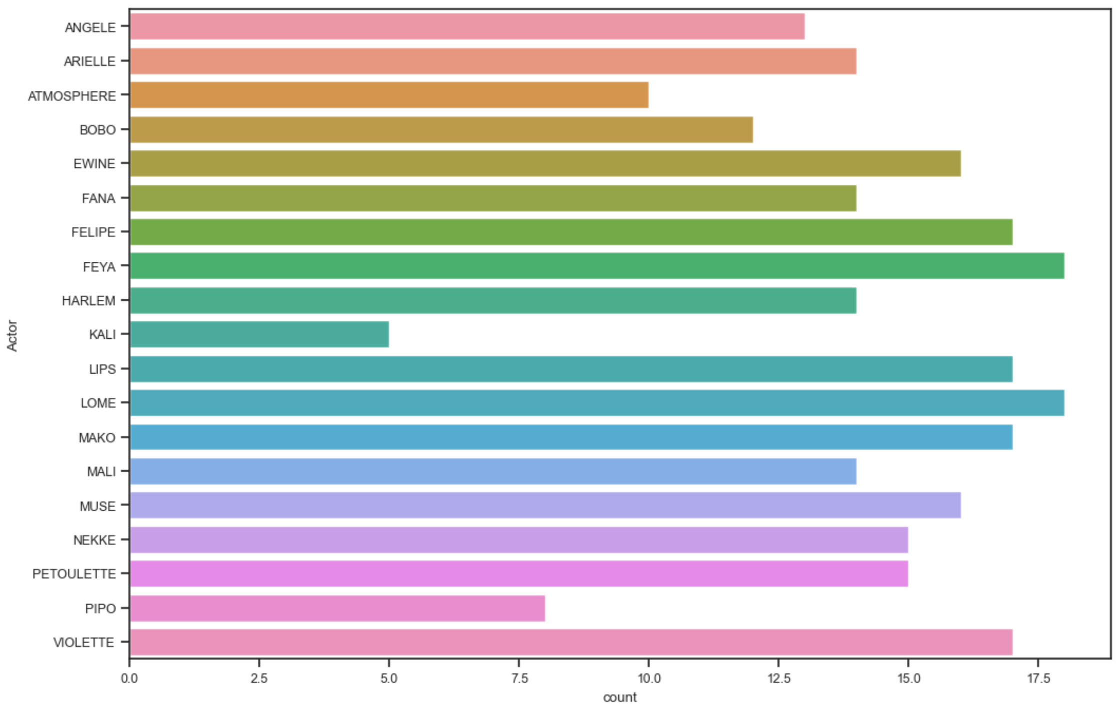
[37]:
```
test.reset_index(inplace=True)
test.index.names = ['Behavior']
```

[38]:
```
test = test.melt(id_vars=['Actor','Sex'], var_name=['behavior'],
 ↪value_name='occ').copy()
test
```

[38]:
```
          Actor  Sex   behavior  occ
0        ANGELE    2  Attacking    1
1       ARIELLE    2  Attacking    1
2    ATMOSPHERE    2  Attacking    0
3          BOBO    1  Attacking    0
4         EWINE    1  Attacking    1
..          ...  ...        ...  ...
299        MUSE    1   Touching   11
300       NEKKE    2   Touching   10
301  PETOULETTE    2   Touching    4
302        PIPO    1   Touching    7
303    VIOLETTE    2   Touching    2

[304 rows x 4 columns]
```

[39]:
```
# Display the total number of behavior observations by actor
sns.set_theme(context="notebook", style="ticks", font_scale=.8, rc={'figure.
 ↪figsize':(12,8)}, color_codes=True)

# Display the count of all behaviors for each Actor
sns.countplot(data=pivot1, y='Actor')
```

[39]: <AxesSubplot:xlabel='count', ylabel='Actor'>

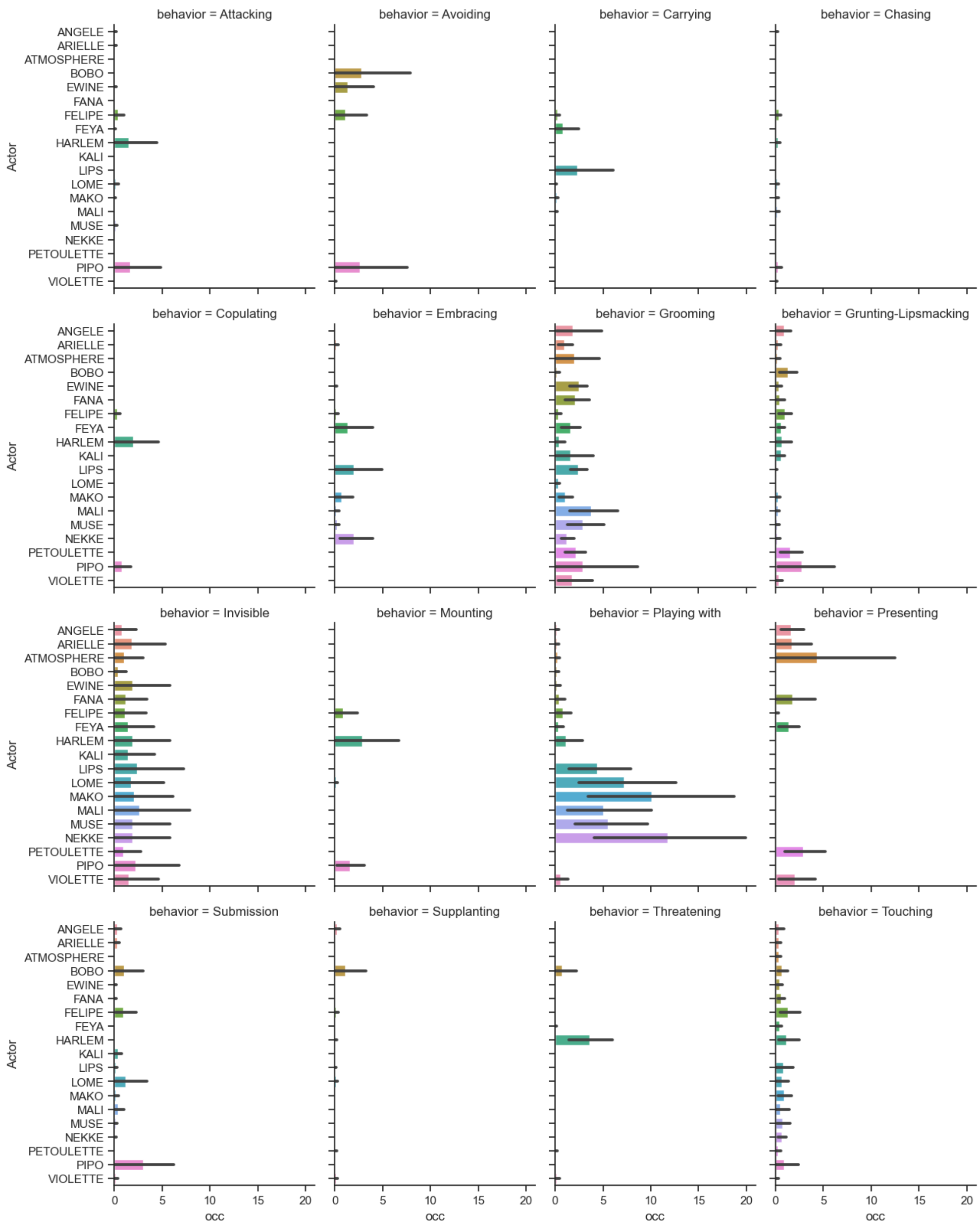


[40]:

```
# Display the number of onservations by behavior category for each actor
sns.set_theme(style="ticks")
plot = sns.catplot(x='occ', y='Actor', col='behavior', kind="bar", data=test, ␣
↪height=4,\
                   col_wrap=4, aspect=.8)
```

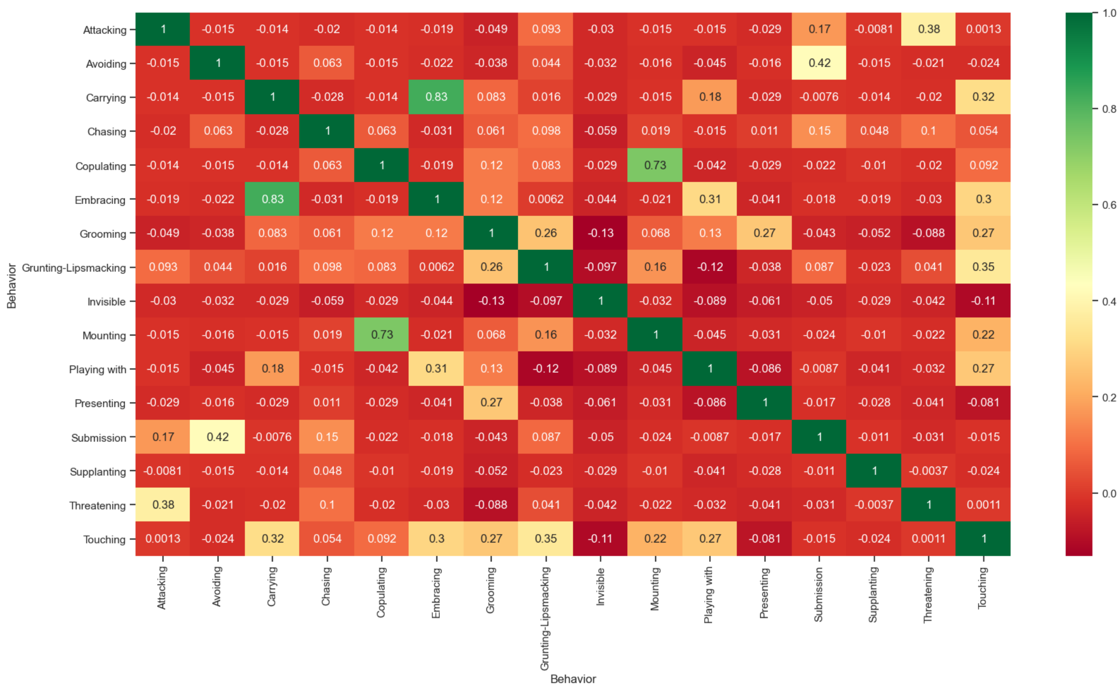
[41]:

```
# Display the number of onservations by behavior category for each actor
sns.set_theme(style="ticks")
plot = sns.catplot(x='occ', y='Actor', col='behavior', kind="bar",␣
↪data=long_pivot,  height=4,\
                   col_wrap=4, aspect=.8)
```



[42]:
```
### Part 2 -
################## Feature Selection Tests #####################
# Use pivot2 for input for feature selection tests
```

[43]:
```
# get correlations of each features in dataset

corrmat = pivot2.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(20,10))

# Plot heatmap using seaborn
g=sns.heatmap(pivot2[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```



[44]:
```
# Identify and drop highly correlated column based upon the correlation matrix and a value >.95

corr_matrix = pivot2.corr().abs()
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape),
                          k=1).astype(np.bool))
to_drop = [column for column in upper.columns if any(upper[column] > 0.95)]
to_drop
```

[44]: []

[45]:
```
############# Feature selection using Chi Square #################

from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

X = pivot2.iloc[:,0:]
y = pivot2['Invisible']

#apply SelectKBest class to extract top 10 best features

bestfeatures = SelectKBest(score_func=chi2)
fit = bestfeatures.fit(X,y)
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(X.columns)

#concat two dataframes for better visualization

featureScores = pd.concat([dfcolumns,dfscores],axis=1)
featureScores.columns = ['Behavior','Score']

print(featureScores.nlargest(18, 'Score'))
```

```
                Behavior        Score
8              Invisible  7017.347826
10          Playing with    58.438247
6               Grooming    33.155378
11            Presenting    16.350598
15              Touching    11.960159
7    Grunting-Lipsmacking    10.976096
5              Embracing     8.402390
12            Submission     7.645418
1               Avoiding     7.266932
9               Mounting     5.298805
14           Threatening     4.844622
2               Carrying     4.768924
0              Attacking     3.784861
4             Copulating     2.952191
13           Supplanting     1.968127
3                Chasing     1.438247
```

[46]:
```
################### Use RFE for Feature Selection #####################
```

[47]:
```
# Feature Extraction Using RFE

# Convert Dataframe into Numpy Array
arr = pivot2.values
arr.shape
```

```
# Create subsets for the LogisticsRegression Model
X = arr[:,0:15]
Y = arr[:,15]

model = LogisticRegression()
rfe = RFE(model, n_features_to_select=16, verbose=1)
fit = rfe.fit(X, Y)

print(f'Num Features: {fit.n_features_}')
print(f'Selected Features: {fit.support_}')
print(f'Feature Ranking: {fit.ranking_}')
```

```
Num Features: 15
Selected Features: [ True  True  True  True  True  True  True  True  True  True
True  True
  True  True  True]
Feature Ranking: [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

[48]:

```
#### Part 3
############################ Model Selection and Evaluation For 1st Prediction␣
 ↪#############################
```

[49]:

```
# Predict Sex based upon behavior and number of occurrences

# Need to convert categorical to numbers
# Had the Actor in the dataframe but results for the Sex prediction came out to␣
 ↪1 for all models so I removed the Actor column

cat_features = ['behavior']
labels = long_pivot['Actor']
data_cat = long_pivot[cat_features]

# One Hot Encoding for the Behavior features
data_cat_dummies = pd.get_dummies(data_cat)
```

[50]:

```
#Train and Split the Dataset into Training and Testing
# Don't include 'occ' as this is a summation and not a behavior category
data_model_X = pd.concat([labels, data_cat_dummies], axis=1)
```

[51]:

```
#Train and Split the Dataset into Training and Testing
# Don't include 'occ' as this is a summation and not a behavior category
data_model_X = pd.concat([labels, data_cat_dummies], axis=1)
```

[52]:

```
# create a whole target dataset that can be used for train and validation data␣
 ↪splitting
# replace the numerical values with strings
```

```
#data_model_y = long_pivot['Sex']

data_model_y = long_pivot['Sex']
```

[53]:
```
# separate data into training and validation and check the details of the␣
↪datasets
# import packages

from sklearn.model_selection import train_test_split
```

[54]:
```
# split the data

X_train, X_test, y_train, y_test = train_test_split(data_model_X, data_model_y,␣
↪test_size =0.3, random_state=8)
```

[55]:
```
# Split the name column from the numerical data in train set
# Want to use the labels in the predictions for comparision


X_labels = X_train['Actor'].copy()
X_train = X_train.iloc[:,1:].copy()
X_train
```

[55]:
```
      behavior_Attacking  behavior_Avoiding  behavior_Carrying  \
2039                   0                  0                  0
842                    0                  0                  0
2163                   0                  0                  0
928                    0                  0                  0
4213                   0                  0                  0
…                    …                  …                  …
2184                   0                  0                  0
2181                   0                  0                  0
2409                   0                  0                  0
2033                   0                  0                  0
1364                   0                  0                  0

      behavior_Chasing  behavior_Copulating  behavior_Embracing  \
2039                 0                    0                   0
842                  1                    0                   0
2163                 0                    0                   0
928                  1                    0                   0
4213                 0                    0                   0
…                  …                    …                   …
2184                 0                    0                   0
2181                 0                    0                   0
2409                 0                    0                   0
2033                 0                    0                   0
```

```
1364                 0                       0                    1

      behavior_Grooming  behavior_Grunting-Lipsmacking  behavior_Invisible  \
2039                  0                              1                   0
842                   0                              0                   0
2163                  0                              0                   1
928                   0                              0                   0
4213                  0                              0                   0
…                   …                              …                   …
2184                  0                              0                   1
2181                  0                              0                   1
2409                  0                              0                   1
2033                  0                              1                   0
1364                  0                              0                   0

      behavior_Mounting  behavior_Playing with  behavior_Presenting  \
2039                  0                      0                    0
842                   0                      0                    0
2163                  0                      0                    0
928                   0                      0                    0
4213                  0                      0                    0
…                   …                      …                    …
2184                  0                      0                    0
2181                  0                      0                    0
2409                  0                      0                    0
2033                  0                      0                    0
1364                  0                      0                    0

      behavior_Submission  behavior_Supplanting  behavior_Threatening  \
2039                    0                     0                     0
842                     0                     0                     0
2163                    0                     0                     0
928                     0                     0                     0
4213                    0                     0                     0
…                     …                     …                     …
2184                    0                     0                     0
2181                    0                     0                     0
2409                    0                     0                     0
2033                    0                     0                     0
1364                    0                     0                     0

      behavior_Touching
2039                  0
842                   0
2163                  0
928                   0
4213                  1
```

```
…                   …
2184                    0
2181                    0
2409                    0
2033                    0
1364                    0

[3024 rows x 16 columns]
```

[56]:
```
y_test
```

[56]:
```
3428    2
2919    2
1316    2
547     2
1824    1
       ..
1852    2
3786    2
2438    2
4238    2
3049    1
Name: Sex, Length: 1296, dtype: int64
```

[57]:
```
# Split the name column from the numerical data in validation set

X_vlabels = X_test['Actor'].copy()
X_test = X_test.iloc[:,1:].copy()
X_test
```

[57]:
```
      behavior_Attacking  behavior_Avoiding  behavior_Carrying  \
3428                   0                  0                  0
2919                   0                  0                  0
1316                   0                  0                  0
547                    0                  0                  1
1824                   0                  0                  0
…                     …                  …                  …
1852                   0                  0                  0
3786                   0                  0                  0
2438                   0                  0                  0
4238                   0                  0                  0
3049                   0                  0                  0

      behavior_Chasing  behavior_Copulating  behavior_Embracing  \
3428                 0                    0                   0
2919                 0                    0                   0
1316                 0                    1                   0
```

```
547                     0                     0                    0
1824                    0                     0                    0
…                  …                    …                    …
1852                    0                     0                    0
3786                    0                     0                    0
2438                    0                     0                    0
4238                    0                     0                    0
3049                    0                     0                    0

      behavior_Grooming  behavior_Grunting-Lipsmacking  behavior_Invisible  \
3428                  0                              0                   0
2919                  0                              0                   0
1316                  0                              0                   0
547                   0                              0                   0
1824                  1                              0                   0
…                   …                            …                 …
1852                  1                              0                   0
3786                  0                              0                   0
2438                  0                              0                   0
4238                  0                              0                   0
3049                  0                              0                   0

      behavior_Mounting  behavior_Playing with  behavior_Presenting  \
3428                  0                      0                    0
2919                  0                      1                    0
1316                  0                      0                    0
547                   0                      0                    0
1824                  0                      0                    0
…                   …                    …                  …
1852                  0                      0                    0
3786                  0                      0                    0
2438                  1                      0                    0
4238                  0                      0                    0
3049                  0                      0                    1

      behavior_Submission  behavior_Supplanting  behavior_Threatening  \
3428                    1                     0                     0
2919                    0                     0                     0
1316                    0                     0                     0
547                     0                     0                     0
1824                    0                     0                     0
…                     …                   …                   …
1852                    0                     0                     0
3786                    0                     0                     1
2438                    0                     0                     0
4238                    0                     0                     0
3049                    0                     0                     0
```

```
      behavior_Touching
3428                  0
2919                  0
1316                  0
547                   0
1824                  0
…                   …
1852                  0
3786                  0
2438                  0
4238                  1
3049                  0

[1296 rows x 16 columns]
```

[58]:
```
# Print number of samples in each set
print("No. of samples in training set: ", X_train.shape[0])
print("No. of samples in validation set:", X_test.shape[0])
```

```
No. of samples in training set:  3024
No. of samples in validation set: 1296
```

[59]:
```
# Sex Male or Female or Unknown
print('\n')
print('The SEX in training set:')
print(y_train.value_counts())
```

```


The SEX in training set:
2    1922
1    1102
Name: Sex, dtype: int64
```

[60]:
```
# Sex in validation set
print('\n')
print('Sex in the validation set:')
print(y_test.value_counts())
```

```


Sex in the validation set:
2    798
1    498
Name: Sex, dtype: int64
```

[63]:
```
#  Import packages

from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import OrdinalEncoder, LabelEncoder
```

[64]:
```
# Create ConfusionMatrix visualizer for LogReg model

model = LogisticRegression(multi_class="auto", solver="liblinear")
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
print(f'Accuracy of logistic regression classifier on test set: {model.
 ↪score(X_test, y_test)}')
```

```
Accuracy of logistic regression classifier on test set: 0.6157407407407407
```

[66]:
```
from sklearn.kernel_ridge import KernelRidge
kr_model  = KernelRidge(alpha=1.0, kernel='rbf', gamma=10000)
kr_model.fit(X_train, y_train)

print(f'Accuracy of logistic regression classifier on test set: {kr_model.
 ↪score(X_test, y_test)}')
```

```
Accuracy of logistic regression classifier on test set: -0.003796656394586151
```

[67]:
```
from sklearn.svm import SVC
SVC_model = SVC(kernel = 'rbf', gamma = .01, C = 100000)
SVC_model.fit(X_train, y_train)
SVC_pred = SVC_model.predict(X_test)
print(f'Accuracy of logistic regression classifier on test set: {SVC_model.
 ↪score(X_test, y_test)}')
```

```
Accuracy of logistic regression classifier on test set: 0.6157407407407407
```

[68]:
```
from sklearn.model_selection import GridSearchCV

svc = SVC(kernel = 'rbf')
params = {"C":[1, 5, 30], "gamma": [1000,2000,4000]}
grid_search = GridSearchCV(svc, params)
grid_search.fit(X_train, y_train)
print(f'Accuracy of logistic regression classifier on test set: {grid_search.
 ↪score(X_test, y_test)}')
```

```
Accuracy of logistic regression classifier on test set: 0.6157407407407407
```

[69]:
```
rf_model = RandomForestClassifier(n_estimators=300, bootstrap = True,␣
 ↪max_features = 'sqrt')
rf_model.fit(X_train, y_train)
rf_pred = rf_model.predict(X_test)
print(f'Accuracy of logistic regression classifier on test set: {rf_model.
 ↪score(X_test, y_test)}')
```

```
Accuracy of logistic regression classifier on test set: 0.6157407407407407
```

[ ]:
```
# Use long_pivot df and delete rows with females
# Only need the males for this prediction
new_pivot = long_pivot[long_pivot['Sex'] == 1]
```

[ ]:
```
# Need to convert categorical to numbers

cat_features = ['behavior']
labels = new_pivot['Actor']
data_cat = new_pivot[cat_features]

# One Hot Encoding
data_cat_dummies = pd.get_dummies(data_cat)
```

[ ]:
```
# Create target variables column
# Assign rank to each male

ranks = [
    (new_pivot['Actor'] == 'HARLEM'),
    (new_pivot['Actor'] == 'PIPO'),
    (new_pivot['Actor'] == 'FELIPE'),
    (new_pivot['Actor'] == 'BOBO'),
    (new_pivot['Actor'] == 'EWINE'),
    (new_pivot['Actor'] == 'MAKO'),
    (new_pivot['Actor'] == 'MUSE')]

values =  [0,1,2,3,4,5,6]

new_pivot['Rank'] = np.select(ranks, values)
data_model_y = new_pivot['Rank']
```

[ ]:
```
# Create full data set for Ordinal Regression
data_model_X = pd.concat([labels, data_cat_dummies], axis=1)

# Create dataframe to store target data_model_y
# Make a copy of the target set

k_df = data_model_X.iloc[:,1:].copy()
k_df['Rank'] = data_model_y
```

```
[ ]: # Split and train the models
X_train, X_val, y_train, y_val = train_test_split(data_model_X, data_model_y,␣
 ↪test_size =0.3, random_state=11)
```

```
[ ]: # Remove Actor from X_val set
X_val = X_val.iloc[:,1:].copy()
```

```
[ ]: # Split the name column from the numerical data in train set
# Want to use the labels in the predictions for comparision

X_labels = X_train['Actor'].copy()
X_train = X_train.iloc[:,1:].copy()
```

```
[ ]: # Print number of samples in each set
print("No. of samples in X training set: ", X_train.shape[0])
print("No. of samples in X validation set:", X_val.shape[0])
```

```
[ ]: # Print number of samples in each set
print("No. of samples in y training set: ", y_train.shape[0])
print("No. of samples in y validation set:", y_val.shape[0])
```

```
[ ]: # Use the MORD module.  Performs several types of Ordinal Regression
# https://pypi.org/project/mord/
import mord
from sklearn import linear_model, metrics, preprocessing
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
labels = ['HARLEM', 'PIPO', 'FELIPE', 'BOBO', 'EWINE', 'MAKO', 'MUSE']
```

```
[ ]: # Instantiate the three types of Ordinal Regression for comparison
# Threshold based
model1 = mord.LogisticAT(alpha=1.)
model1.fit(X_train, y_train)

y_pred = model1.predict(X_train)

print(f'Mean Absolute Error of LogisticAT is: \
      {metrics.mean_absolute_error(y_pred, y_train)}')

print(f'LogAT score: {model1.score(X_val, y_val)}')
print(f'LogAT accuracy score: {accuracy_score(y_train, y_pred,␣
 ↪normalize=False)}\n')
print(f'LogAT Classification Report')
print(f'{metrics.classification_report(y_train, y_pred)}')
```

```
[ ]: # Display Confusion Matrix for LogAT
cm = confusion_matrix(y_train, y_pred)
```

```
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=labels)
disp.plot(cmap='YlOrRd_r')
```

[ ]:
```
# Compute Multi-class cm

cm = metrics.multilabel_confusion_matrix(y_train, y_pred)
cm
```

[ ]:
```
# Instantiate the three types of Ordinal Regression for comparison
# Threshold based
model2 = mord.LogisticIT(alpha=1.)
model2.fit(X_train, y_train)

y_pred = model2.predict(X_train)

print(f'Mean Absolute Error of LogisticIT is: \
      {metrics.mean_absolute_error(y_pred, y_train)}')
print(f'LogIT score: {model2.score(X_val, y_val)}')
print(f'LogIT accuracy score: {accuracy_score(y_train, y_pred,␣
 ↪normalize=False)}\n')
print(f'LogIT Classification Report')
print(f'{metrics.classification_report(y_train, y_pred)}')
```

[ ]:
```
# Display Confusion Matrix for LogIT
cm = confusion_matrix(y_train, y_pred)

disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=labels)
disp.plot(cmap='YlOrRd_r')
```

[ ]:
```
# Compute Multi-class cm

cm = metrics.multilabel_confusion_matrix(y_train, y_pred)
cm
```

[ ]:
```
# Ordinal Ridge
model3 = mord.OrdinalRidge(alpha=1.0, fit_intercept=True, normalize=False,␣
 ↪copy_X=True, max_iter=None, tol=0.001, solver='auto')
model3.fit(X_train, y_train)

y_pred = model3.predict(X_train)

print(f'Mean Absolute Error of ordinalridge is: \
      {metrics.mean_absolute_error(y_pred, y_train)}')
print(f'OrdinalRidge score: {model3.score(X_val, y_val)}')
```

```
print(f'OrdinalRidge accuracy score: {accuracy_score(y_train, y_pred,␣
 ↪normalize=False)}\n')
print(f'OrdinalRidge Classification Report')
print(f'{metrics.classification_report(y_train, y_pred)}')
```

[ ]:
```
metrics.confusion_matrix(y_train, y_pred)
```

[ ]:
```
# Display Confusion Matrix for Ordinal Ridge

cm = confusion_matrix(y_train, y_pred)

disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=labels)
disp.plot(cmap='YlOrRd_r')
```

[ ]:
```
# Compute Multi-class cm

cm = metrics.multilabel_confusion_matrix(y_train, y_pred)
cm
```

[ ]:
```
################ 3. Identify Sub Groups using Clustering algorithms␣
 ↪############################
# Use the long pviot as this has the behavior and actor and number of occurences
```

[ ]:
```
# Kmodes
from kmodes.kmodes import KModes
```

[ ]:
```
# create a subset from long_pivot
x_data = long_pivot[['Actor', 'behavior']].copy()
```

[ ]:
```
# One Hot Encoding

X_beh = pd.get_dummies(x_data['behavior'], )
X_Act = pd.get_dummies(x_data['Actor'])
data_model_X = pd.concat([X_beh, X_Act], axis=1)

# Convert dataframe to array

data_model_X = np.array(data_model_X)

# Run Kmodes clustering

km = KModes(n_clusters=3, init='Cao', n_init=2, verbose=2)
model = km.fit_predict(data_model_X)

# append clusters to dataset
```

```
x_data['clusters'] = km.labels_
x_data['clusters'].unique()
```

[ ]:
```
sns.set_theme(context="notebook", style="ticks", font_scale=.8, rc={'figure.
 ↪figsize':(12,8)}, color_codes=True)

g = sns.FacetGrid(col='Actor',data=x_data,legend_out=False, height=4,\
                  col_wrap=4, aspect=.8)
g.map(sns.scatterplot,'clusters','behavior')
```

[ ]:
```
# Display Clusters with Actors and behaviors

sns.set_theme(context="notebook", style="ticks", font_scale=.8, rc={'figure.
 ↪figsize':(12,8)}, color_codes=True)
plot = sns.catplot(x='clusters', y='Actor', col='behavior', kind="bar",␣
 ↪data=x_data,  height=4,\
                  col_wrap=4, aspect=.8)
```

[ ]:
```
#https://machinelearningmastery.com/clustering-algorithms-with-python/
from sklearn.cluster import AffinityPropagation
from numpy import unique
from numpy import where
from matplotlib import pyplot

plt.rcParams['figure.figsize'] = (5, 5)
plt.rcParams['font.size'] = 10

# define the model
model2 = AffinityPropagation(damping=0.9)

# fit the model
model2.fit(data_model_X)

# assign a cluster to each example
clus = model2.predict(data_model_X)

# retrieve unique clusters
# Assign clusters to data model

x_data['A_cluster'] = clus
```

[ ]:
```
sns.set_theme(context="notebook", style="ticks", font_scale=.8, rc={'figure.
 ↪figsize':(12,8)}, color_codes=True)
plot = sns.catplot(x='A_cluster', y='Actor', col='behavior', kind="bar",␣
 ↪data=x_data,  height=4,\
                 col_wrap=4, aspect=.8)
```

```
[ ]:
```