Social Network Analysis - Final Group Project

Group F

3/13/2019

1.Objective

In any organization, building relationships among members is considered a way to improve interpersonal relations. When taking into account social activities for members, it can be an added competitive advantage to identify people's preferences and seek a common ground for their interactions.

A platform that gathers information about the social activities of individuals, for example, a leisure app, can be used to tailor an organization's team building exercises and events.

For this analysis, a leisure app has been identified as a good platform on which to strengthen social relationships among individuals in an organization. Organization here is taken to mean any organized group of people with a particular purpose.

2.Data Gathering and Processing

Idea: MBD O1-GroupF as a Big Data consulting company was approached by IE to identify the best way to leverage networking among HST students. "Students are always coding and studying so we need to help them strengthen their social bounds for them to have a better professional future."

MBD O1-GroupF came out with and innovative disrupting solution based in Social Network Analysis: *NET-IE*.

Net IE Logo

NET-IE is an interactive social analysis tool that thoroughly analyzes the IE Student Network, identifying key insights for networking optimization. *MBD O1-GroupF* was capable of understanding key network properties such as centrality measures, transitivity, reciprocity, community detection and information diffusion.

The following document explains each step taken for the creation of the tool, as well as the main insights and conclusions.

2.1.Data Gathering

A survey was conducted to understand the leisure activities of master students at IE University. The leisure activities that were considered fall into three categories:

- Music
- Sports
- Movie

The structure of the survey was as follows: Each applicant would select at most 3 genres of movies, music, and sport. Each applicant would provide at most 3 names of their favourite movies, music artists, and sports players.

Other information collected from the survey:

- Email address – used as a unique identifier for each applicant.
- Academic program – name of the program being taken at IE.
- Country of birth – used to categorize individuals based on country & region.
- Movies, music, and sports preferences.
- Names of top 3 favourite movies, top 3 musicians, and top 3 athletes.

Overall, a total of 85 responses were collected and this was used to conduct a social network analysis of IE students.

2.2.Data processing

In the resulting network, the students are represented as nodes and the leisure shared interests are represented as edges. Depending on the type and number of shared interests, the edges will have different weights as stated in the following table.

Common denominator between 2 nodes	Weight assigned
Country of birth	0
Region	0
Academic program	0
Genre (of music, sport, or movie)	5
Top of mind artist, musician, or athlete	10
Similar considerations for artist, musician, or athlete	7

In general terms, a commonality of two students regarding to music genre, sport, or movie genre, adds 5 points to the weight of the connection. If both of the students share Top of Mind (TOM) for a specific Artist, Athlete or Movie, 10 points are added to the weight, and if they just consider a specific Artist, Athlete or Movie (without being TOM), 7 points are added to the connection weight.

3.Data Exploration and Analysis

3.1.OVERALL DISTRIBUTION OF PREFERENCES

The interactive tree map below shows the distribution of IE students preferences concerning music, films and sports. Once a main preference category is selected, the relative amount of students preferring a specific sport or genre is represented by the size of box. Granularity by geographic region and gender can be accessed by clicking on the respective boxes.

3.2.DISTRIBUTION OF PREFERENCES BY GENDER

Following are three charts that compare preferences for music, film and sport between males and , where the blue dot represents the relative number of males, and the pink dot represents the relative number of females.

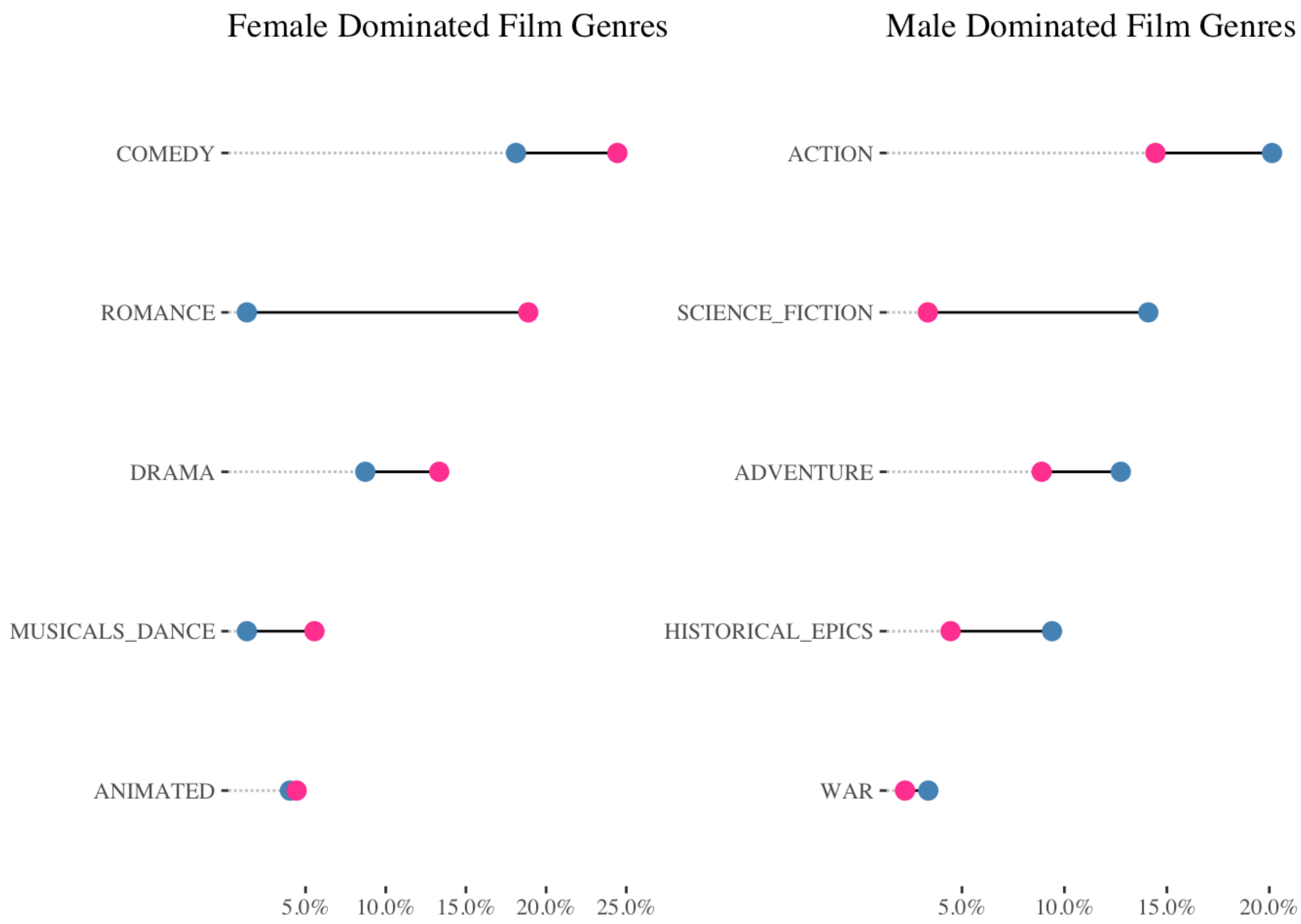
It's interesting to see how Males prefer Genres such as Rock and Electronic, while Females prefer Pop and Reggaeton.

Regarding movies, Males are more interested in Action and SciFi, while Females are more interested in Comedy and Romance.

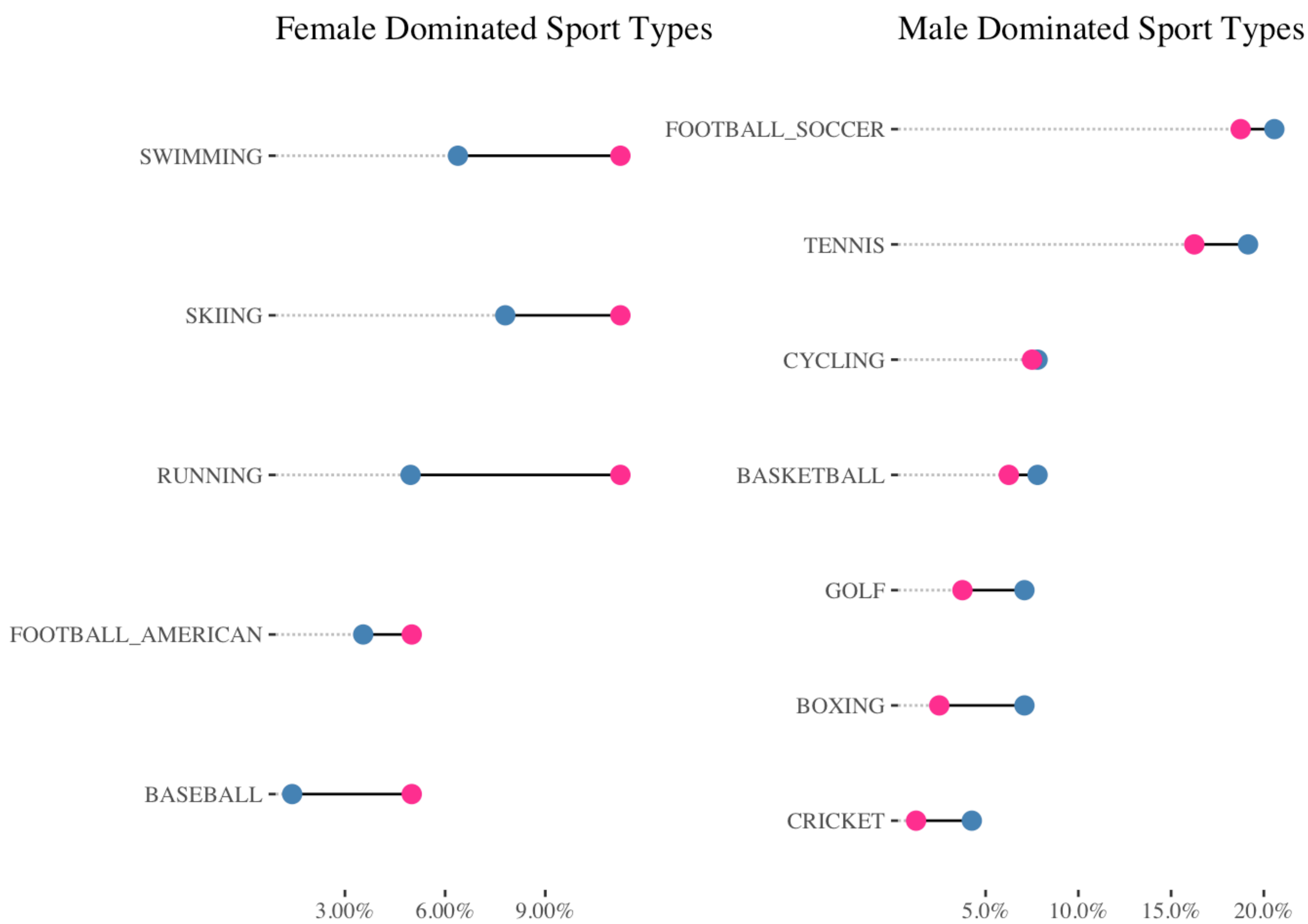
For Sport preferences, Males prefer Football (Soccer) and Tennis while Females prefer Swimming and Skiing.

3.2.1.MUSIC

3.2.2.MOVIES

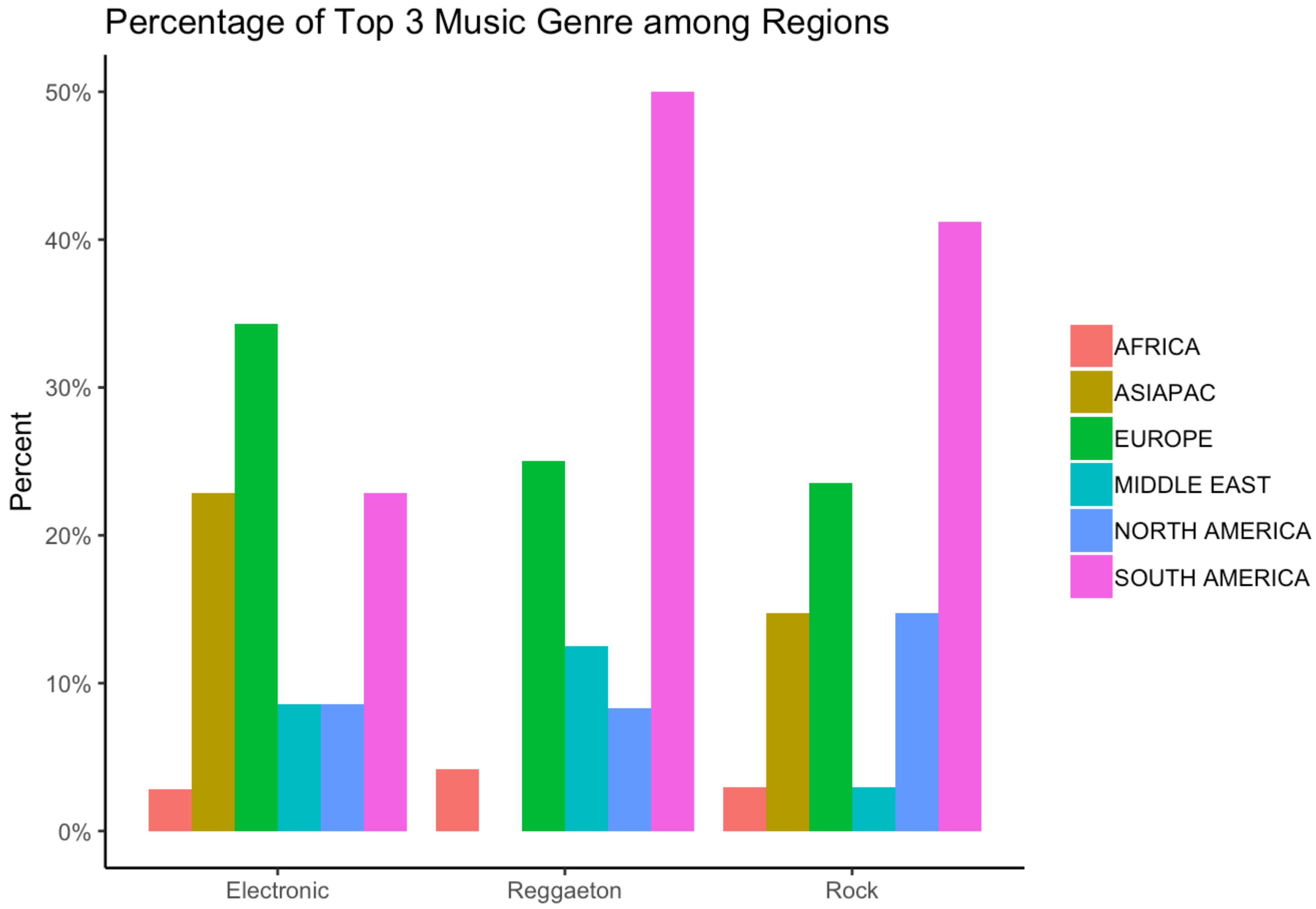


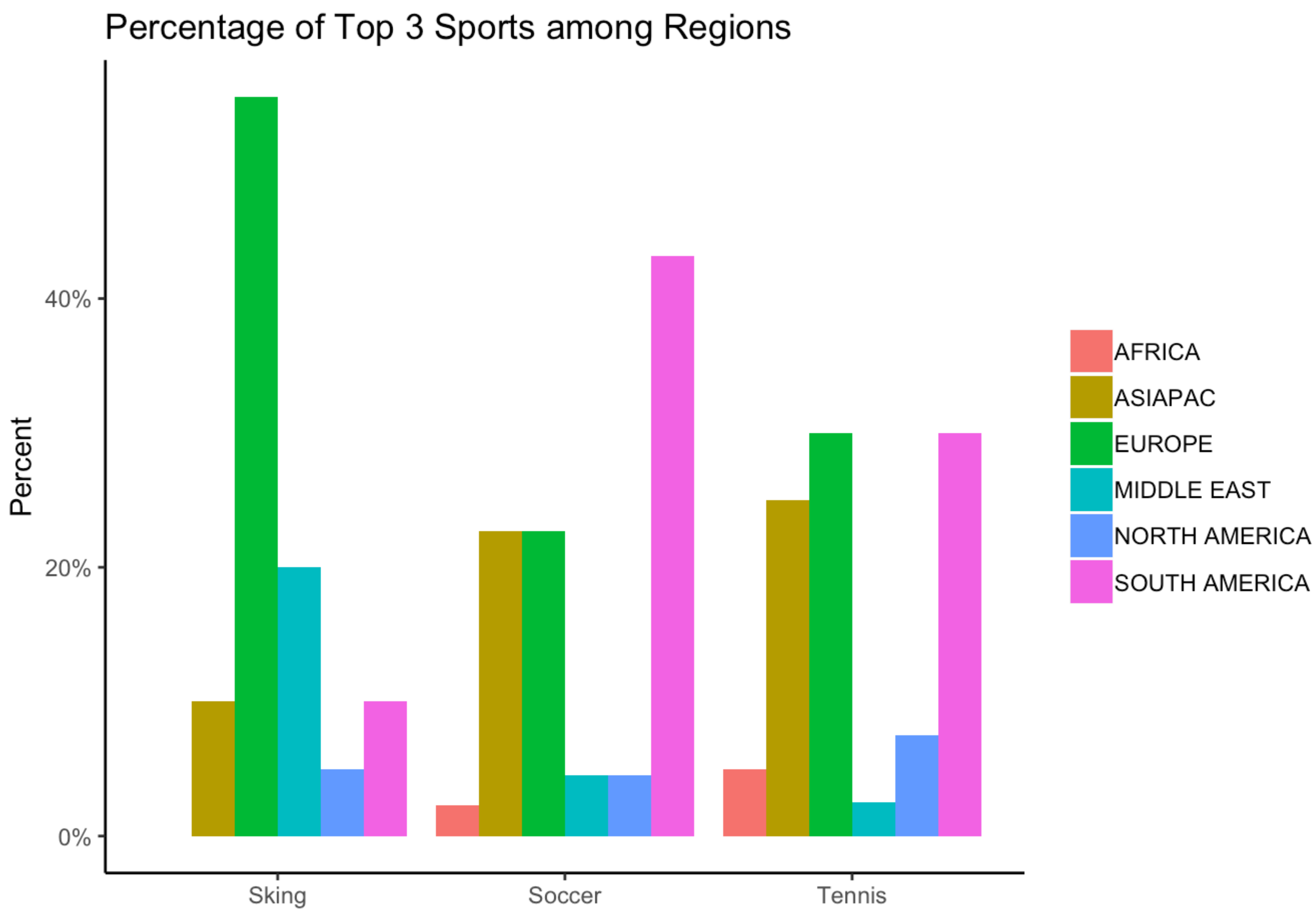
3.2.3.SPORT

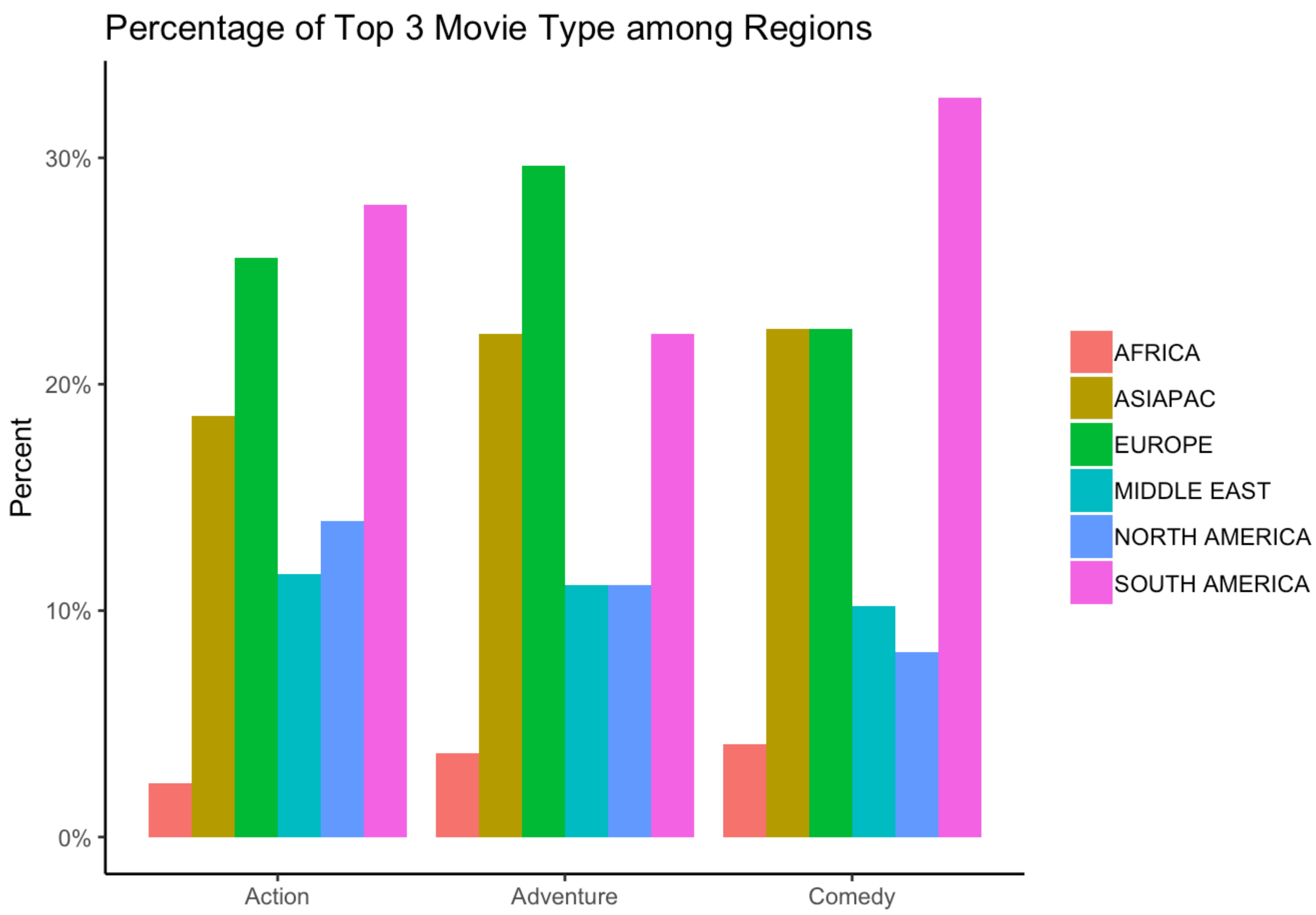


3.3.Distribution by Geographic Region

The barcharts below display the geographic distribution of the three most popular music genres, three most popular movie genres, and three most popular sports.


Percentage of Top 3 Music Genre among Regions
Percent
50%
40%
30%
20%
10%
0%
Electronic
Reggaeton
Rock
AFRICA
ASIAPAC
EUROPE
MIDDLE EAST
NORTH AMERICA
SOUTH AMERICA


Percentage of Top 3 Sports among Regions
Percent
40%
20%
0%
Sking
Soccer
Tennis
AFRICA
ASIAPAC
EUROPE
MIDDLE EAST
NORTH AMERICA
SOUTH AMERICA



4.General Graph Centrality Measures

4.1.Degree Distribution

4.1.1Summary

The average degree centrality of the leisure network is 79.46. This means that on average, each person is directly connected to approximately 80 other people based on their preference for music, movies, and sports. With a maximum of three options for each leisure activity, the likelihood of a connection to another student is high which results in this high degree centrality.

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   51.00   78.00   81.00   79.46   83.00   84.00
```

4.1.2Standard Deviation of Leisure Graph Degree

Several insights can be drawn from the standard deviations of this network. With regards to the student leisure preference network, the standard deviation is fairly smaller way smaller than the average. This implies that while the overall average is quite high at approximately 80, since paticipants can choose up to 3 options to each leaisure activities, all of us are directly connected to a bunch of people.

```
## [1] 5.111968
```

4.2.Network Properties

4.2.1.Average Path Length and Network Diameter

The average path length describes the average distance between any two vertices. The network diameter describes the longest possible distance between two vertices in terms of the most efficient path. The average path length is 1.054 which shows a highly connected graph. Similarly, the diameter of the leisure network graph is 2. This suggests that the distance between two most unrelated students in terms of the leisure activities is still very small, which means that to get to the furthest person in the network, you need to only pass through 2 people.

```
## [1] 1.054062
```

```
## [1] 2
```

4.3.Clustering Coefficient

The clustering coefficient measures the transitivity of a network, that is how connected closed groups of vertices are with each other. The global clustering coefficient gives an indication of the overall clustering in the network, while the local clustering coefficient gives an indication of the embeddedness of single nodes.

4.3.1.Global Transitivity

The global clustering coefficient for our leisure graph is about 0.952, which is extremly.This suggests that our leisure network is very transitively connected.

```
## [1] 0.9527613
```

4.3.2.Local Transitivity

Meanwhile, the local clustering coefficient has similar value as the global clustering coefficient, which is 0.953. Meaning that the groups are tightly knited by sharing the common leisure activities in terms of music, sports and movie.

```
## [1] 0.9533111
```

4.4.Top 20 degree centrality students

Degree centrality measures how many vertices connect to a single one.

	Key	Name	Gender	Program	Degree
2	14	CAMILLE COALLIER	F	MBD	84
3	18	PHILIPPE EL HAGE	M	MBD	84
14	53	TOMAS TELLO	M	MBD	84
16	57	DAVID DALEL	M	MCXI	84
17	60	TIMOTHY ONG	M	IMBA	84
18	78	ALEJANDRO MARQUEZ	M	IMBA	84
19	79	SANTIAGO ZULUAGA	M	IMBA	84
20	81	KEVIN CUNNINGHAM	M	IMBA	84
1	1	ALFONSO BUCAG	M	MBD	83
4	2	YEGNESH SUNDAR	M	MBD	83
5	22	ALBERTO LOMBATTI	M	MBD	83
6	23	ANDREW RIZK	M	MBD	83
7	28	RAFAEL HERNANDEZ	M	MBD	83
8	30	ALEJANDRO KOURY	M	MBD	83
9	31	KARL FERDINAND	M	MBD	83
10	32	FRANZ-ANTON GRAF BASSELET	M	MBD	83
11	34	MARCOS BERGES	M	MBD	83
12	37	ANDREW MARTINEZ	M	MBD	83
13	52	LAURA DOMINGUEZ	F	IMBA	83
15	54	SANTIAGO RODRIGUEZ	M	MRCB	83

4.5.Top 20 Betweeness Students

Betweeness measures the average length of shortest paths that pass through a vertex. High betweeness can be understood as links between different closed clusters of students.

	Key	Name	Gender	Program	Betweeness
1	14	CAMILLE COALLIER	F	MBD	3
2	18	PHILIPPE EL HAGE	M	MBD	3
11	53	TOMAS TELLO	M	MBD	3
12	57	DAVID DALEL	M	MCXI	3
14	60	TIMOTHY ONG	M	IMBA	3
16	78	ALEJANDRO MARQUEZ	M	IMBA	3
17	79	SANTIAGO ZULUAGA	M	IMBA	3
18	81	KEVIN CUNNINGHAM	M	IMBA	3
15	66	ALFREDO POMBO	M	IMBA	3
3	28	RAFAEL HERNANDEZ	M	MBD	3
4	30	ALEJANDRO KOURY	M	MBD	3
10	52	LAURA DOMINGUEZ	F	IMBA	3
19	82	ADELAIDE ISSAACS	F	MIR	3

13	58	JR CORTEZ	M	IMBA	3
9	48	RAHUL VERMA	M	MBD	3
7	42	PILAR LIMON	F	MBD	3
5	33	SEBASTIAN VASQUEZ	M	MBD	3
20	83	IVANNA DACCARET	F	MTDHR	3
6	37	ANDREW MARTINEZ	M	MBD	3
8	43	VIKAS AGARWAL	M	MBD	3

4.6.Top 20 Closeness Students

Closeness centrality measures the average distance from any given vertex to all other vertices.

	Key	Name	Gender	Program	Closeness
2	14	CAMILLE COALLIER	F	MBD	1.00
3	18	PHILIPPE EL HAGE	M	MBD	1.00
14	53	TOMAS TELLO	M	MBD	1.00
16	57	DAVID DALEL	M	MCXI	1.00
17	60	TIMOTHY ONG	M	IMBA	1.00
18	78	ALEJANDRO MARQUEZ	M	IMBA	1.00
19	79	SANTIAGO ZULUAGA	M	IMBA	1.00
20	81	KEVIN CUNNINGHAM	M	IMBA	1.00
1	1	ALFONSO BUCAG	M	MBD	0.99
4	2	YEGNESH SUNDAR	M	MBD	0.99
5	22	ALBERTO LOMBATTI	M	MBD	0.99
6	23	ANDREW RIZK	M	MBD	0.99
7	28	RAFAEL HERNANDEZ	M	MBD	0.99
8	30	ALEJANDRO KOURY	M	MBD	0.99
9	31	KARL FERDINAND	M	MBD	0.99
10	32	FRANZ-ANTON GRAF BASSELET	M	MBD	0.99
11	34	MARCOS BERGES	M	MBD	0.99
12	37	ANDREW MARTINEZ	M	MBD	0.99
13	52	LAURA DOMINGUEZ	F	IMBA	0.99
15	54	SANTIAGO RODRIGUEZ	M	MRCB	0.99

From the analysis above, the top 20 students of degree, betweeness and closeness centrality are pretty similar showing that those top students have chosen the most popular activities in terms of music, sports and movie, which leads them to have high degree, betweeness and closeness centrality at the same time.

5.Music Interest Analysis

5.1.Centrality Analysis for music interests

5.1.1.Summary

The average degree centrality of the music sub-network is 50.73. This means that on average, each student is directly connected to approximately 51 other students based on their specific preference for music. If we compare this indicator with the general graph degree centrality measure of 79.46, we can see that the average level of connection decreases aproximately by 29 students.

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    7.00   44.00   52.00   50.73   60.00   71.00
```

5.1.2.top 10 students of music Centrality

The following table shows the top 10 students ranked by degree centrality for the Music Sub-graph. As we can see, this ranking differs from the initial degree centrality measure ranking of the general graph. Considering this, if IE wants to develop a Networking event narrowed down to a specific topic such as music, or for example leverage the Campus Life Clubs with the selection of influential students, it would be important to understand who are the important nodes for the specific topic.

	Key	Name	Gender	Program	Degree	Genre_1	Genre_2	Genre_3
4	37	ANDREW MARTINEZ	M	MBD	71	ELECTRONIC	ROCK	POP
1	11	JONATHAN SERRANO	M	MBD	70	ELECTRONIC	REGGAETON	ROCK
7	62	CAROLINA ROMERO	F	IMBA	70	ELECTRONIC	REGGAETON	ROCK
8	66	ALFREDO POMBO	M	IMBA	70	ELECTRONIC	REGGAETON	ROCK
2	12	JEAN RENE ESPILLAT	M	MBD	66	HIP-HOP	REGGAETON	ROCK
6	60	TIMOTHY ONG	M	IMBA	65	ELECTRONIC	ROCK	R&B
9	80	LAURA PALACIO CORRA	F	MVDM	65	REGGAETON	ROCK	POP
10	81	KEVIN CUNNINGHAM	M	IMBA	65	ELECTRONIC	JAZZ	ROCK
5	52	LAURA DOMINGUEZ	F	IMBA	64	REGGAETON	ROCK	POP
3	31	KARL FERDINAND	M	MBD	63	CLASSICAL	ELECTRONIC	ROCK

5.1.3.top 10 students of music Betweenness

The following table shows the top 10 students ranked by Betweenness for the Music Sub-graph. Betweenness represents the number of shortest paths that pass through a given node. We can see that the student with the highest shortest number of paths passing through him is Vaibhav Jaitly.

	Key	Name	Gender	Program	Betweeness	Genre_1	Genre_2	Genre_3
7	41	VAIBHAV JAITLY	M	MBD	32	BLUES	ELECTRONIC	POP
1	11	JONATHAN SERRANO	M	MBD	31	ELECTRONIC	REGGAETON	ROCK
9	62	CAROLINA ROMERO	F	IMBA	31	ELECTRONIC	REGGAETON	ROCK
10	66	ALFREDO POMBO	M	IMBA	31	ELECTRONIC	REGGAETON	ROCK
2	12	JEAN RENE ESPILLAT	M	MBD	31	HIP-HOP	REGGAETON	ROCK
8	43	VIKAS AGARWAL	M	MBD	30	CLASSICAL	ELECTRONIC	HIP-HOP
5	30	ALEJANDRO KOURY	M	MBD	29	BLUES	ROCK	POP
3	27	ANTONIA SCHULZE	F	MBD	29	ELECTRONIC	RAP	POP
6	37	ANDREW MARTINEZ	M	MBD	29	ELECTRONIC	ROCK	POP
4	28	RAFAEL HERNANDEZ	M	MBD	29	CLASSICAL	REGGAETON	ROCK

5.1.4.top 10 students of music Closeness

A student is central if he can easily interact with other students. We believe for the purpose of NET-IE, along with Degree Centrality, Closeness Centrality is one of the most important indicators. For a given student of the graph, we want to know how easily he can relate with other students.

	Key	Name	Gender	Program	Closeness	Genre_1	Genre_2	Genre_3
4	37	ANDREW MARTINEZ	M	MBD	0.87	ELECTRONIC	ROCK	POP
1	11	JONATHAN SERRANO	M	MBD	0.86	ELECTRONIC	REGGAETON	ROCK
7	62	CAROLINA ROMERO	F	IMBA	0.86	ELECTRONIC	REGGAETON	ROCK
8	66	ALFREDO POMBO	M	IMBA	0.86	ELECTRONIC	REGGAETON	ROCK
2	12	JEAN RENE ESPILLAT	M	MBD	0.82	HIP-HOP	REGGAETON	ROCK
6	60	TIMOTHY ONG	M	IMBA	0.82	ELECTRONIC	ROCK	R&B
9	80	LAURA PALACIO CORRA	F	MVDM	0.82	REGGAETON	ROCK	POP
10	81	KEVIN CUNNINGHAM	M	IMBA	0.82	ELECTRONIC	JAZZ	ROCK
5	52	LAURA DOMINGUEZ	F	IMBA	0.81	REGGAETON	ROCK	POP
3	31	KARL FERDINAND	M	MBD	0.80	CLASSICAL	ELECTRONIC	ROCK

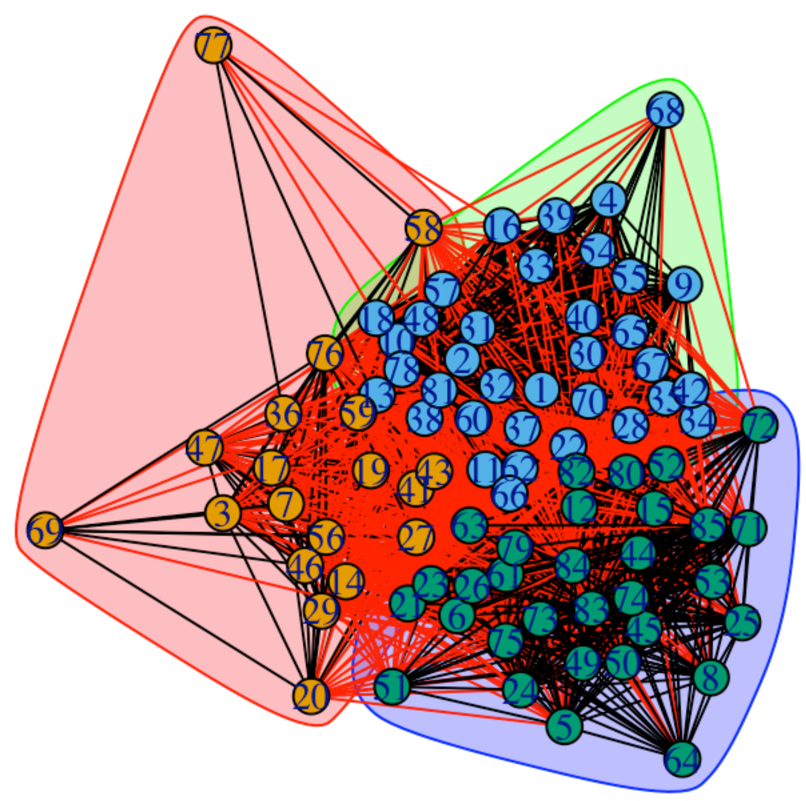
5.2.Community Detection for Music interests

Now that we clearly understand centrality measures for the general network and music sub-network, we can detect communities of students depending on their music tastes. Community detection may Help IE discover and label the different groups of students to have a clear idea of their targets for any music-related activity.

For this purpose, we are using the Louvain Modularity Method (fast greedy optimization) to identify communities. This method seeks to optimize modularity, explained as the density of edges inside communities to edges outside communities. Optimizing this value leads to the best possible grouping of nodes of a given network. According to M.E.J Newman in his paper *Modularity and community structure in networks*, “Networks with high modularity have dense connections between the nodes within modules (communities) but sparse connections between nodes in different modules.”

For this exercise, three communities were detected and can be seen in the following plot.

IE Musical Communities



5.3.Music Community Analysis

The most important characteristic of segmentation algorithms is being able to label the resulting communities. To achieve this, we analyze which music genres over-index and under-index within each group, and analyze complementary labeling variables such as gender or nationality.

Community #1: Rap it up

This community over-indexes in Rap genre and clearly under-indexes in Reggaeton and Rock music. The members of this community even more than liking Rap, are characterized for not having Rock nor Reggaeton inside their music preferences. Most of them are male, from non-Latin-American countries.

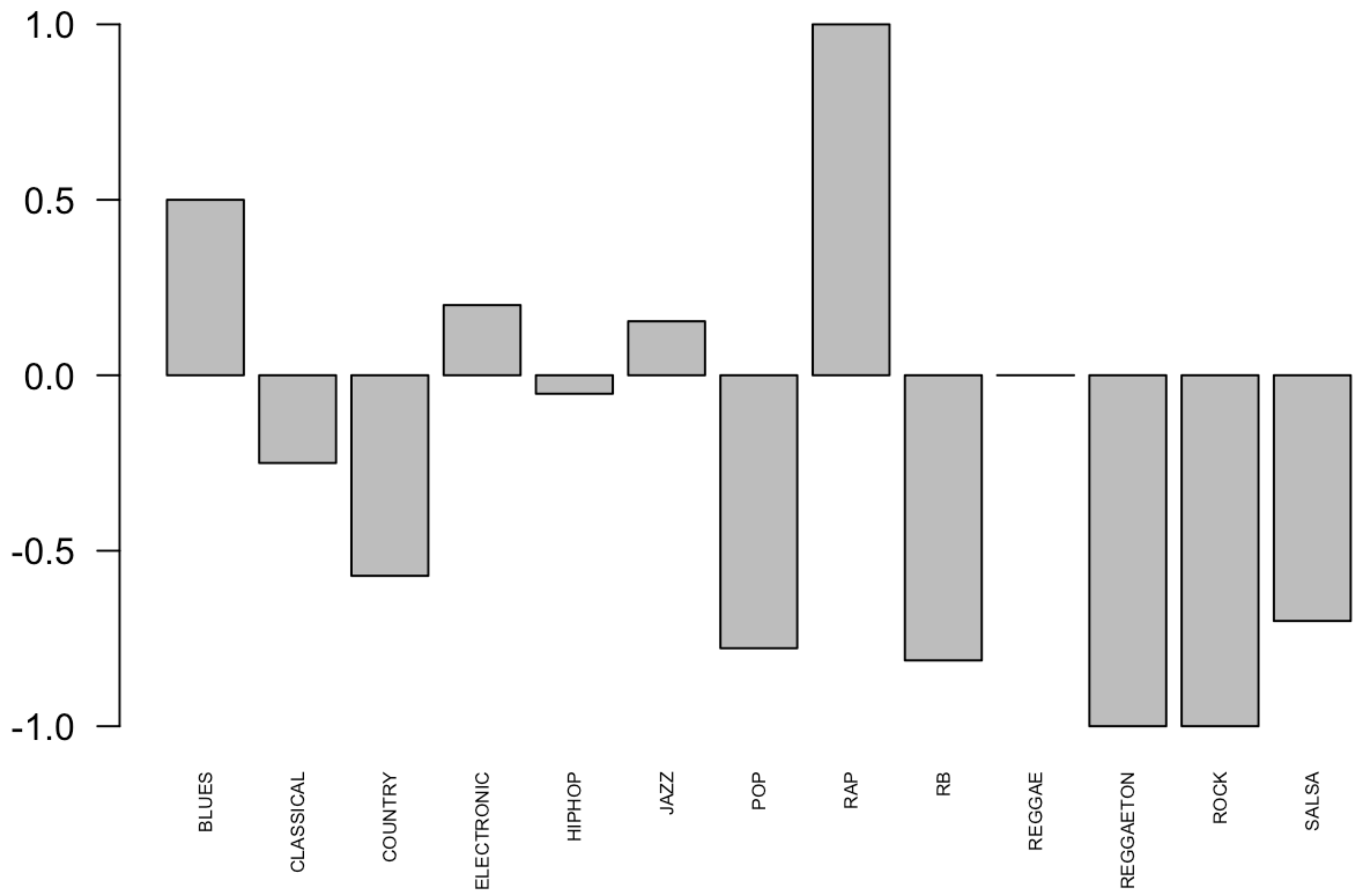
Community #2: Hard and Heavy

This is the biggest community in number of students. It is characterized mainly as a Rock loving community. Reggaeton and Hip Hop may be seen as divergent genres. Male is also the predominant gender.

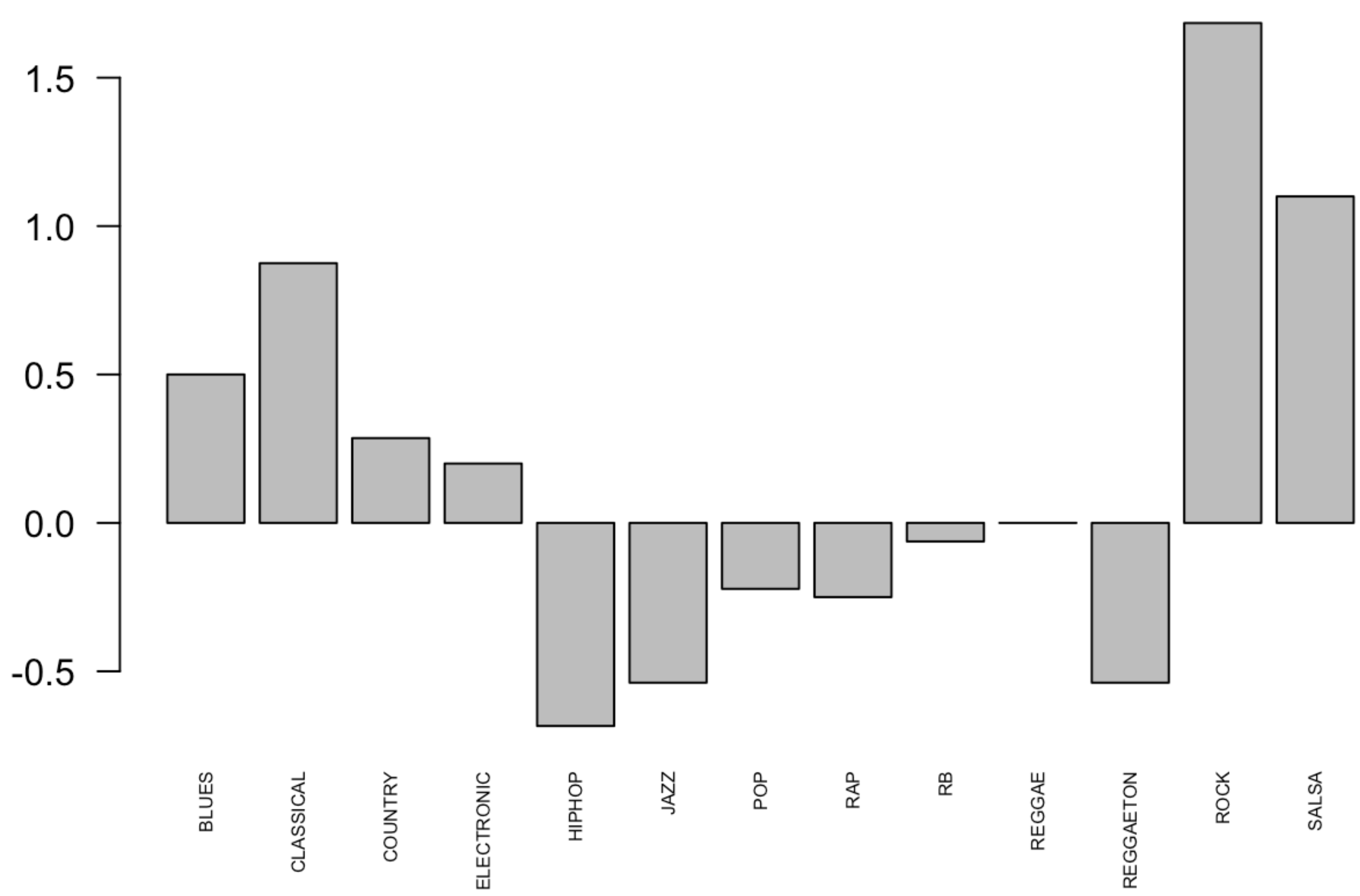
Community #3: Party beasts

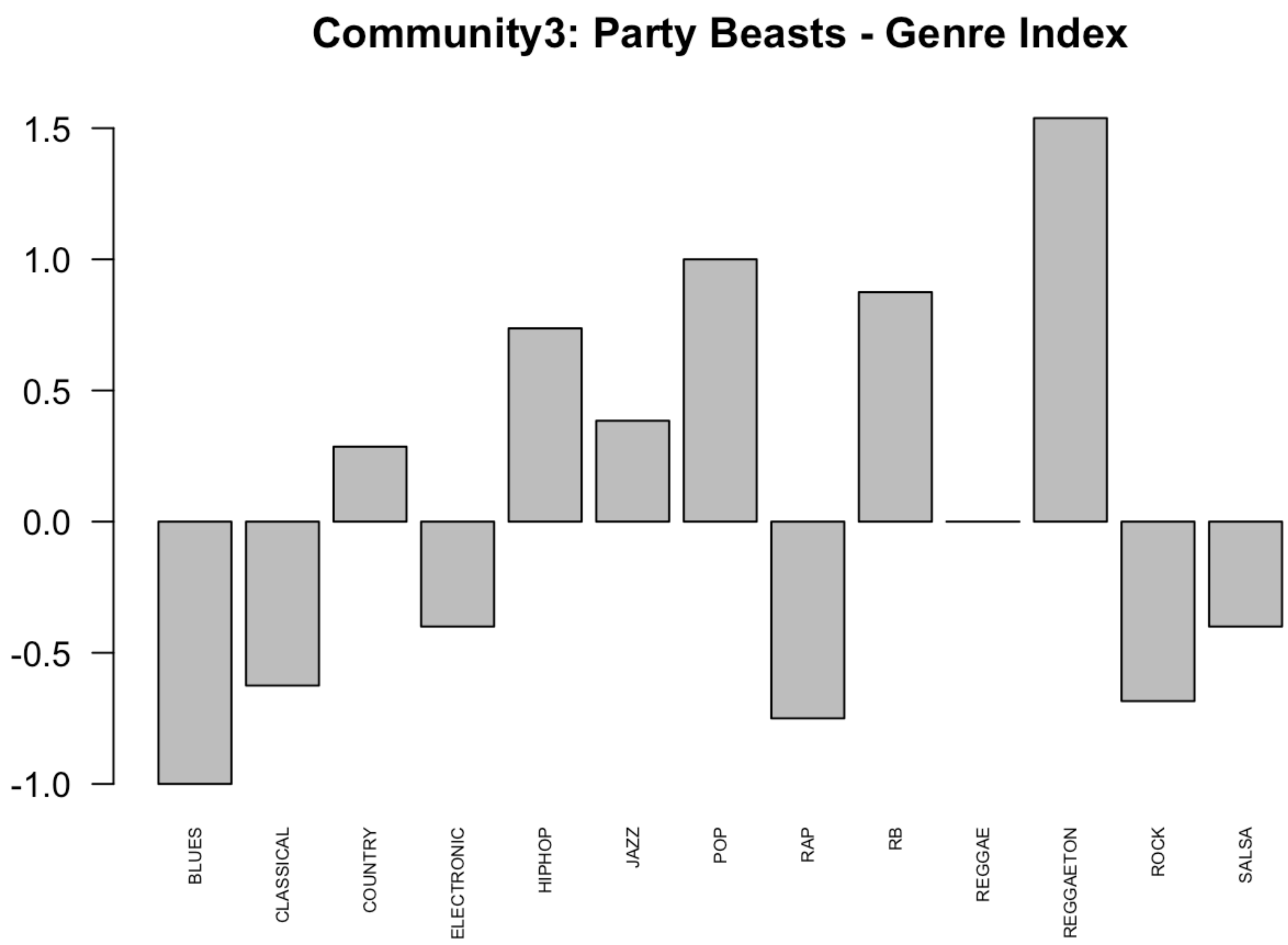
In this community we find the Reggaeton lovers. As opposed from the previous communities, most of the students in this community are Females. They also like Pop music and R&B as side music preferences.

Community1: Rap It Up - Genre Index



Community2: Hard and Heavy - Genre Index





As a final additional analysis, now that we identified communities we can also understand who the most influential people are within each community:

5.3.1.Betweeness of music community 1

	Key	Name	Gender	Region	Betweeness
10	41	VAIBHAV JAITLY	M	ASIAPAC	32
11	43	VIKAS AGARWAL	M	ASIAPAC	30
7	27	ANTONIA SCHULZE	F	EUROPE	29
16	59	YAWEN ZHANG	F	ASIAPAC	20
14	56	JUAN RUIZ	M	LATIN AMERICA	20
12	46	EDUARDO GARGIULO	M	EUROPE	19
9	36	DUARTE DIAS DE COSTA	M	EUROPE	19
18	76	VICTOR VU	M	ASIAPAC	18
2	7	GIULIO DEFELICE	M	EUROPE	17
15	58	JR CORTEZ	M	ASIAPAC	13
5	19	GERALD WALRAVENS	M	EUROPE	13
3	14	CAMILLE COALLIER	F	NORTH AMERICA	11
8	29	MORITZ STEINBRECHER	M	EUROPE	10
1	3	MRAD AZOURY	M	MIDDLE EAST	9
4	17	FEDERICO LOGUERICO	M	EUROPE	7
6	20	LOUIS DUBAERE	M	EUROPE	6
13	47	FURQUAN SHAUKAT	M	MIDDLE EAST	0
17	69	CRISTHIAN GARCIA	M	LATIN AMERICA	0
19	77	SCOTT PAN	M	ASIAPAC	0

5.3.2.Betweeness of music community 2

	Key	Name	Gender	Region	Betweeness
6	11	JONATHAN SERRANO	M	EUROPE	31
28	62	CAROLINA ROMERO	F	LATIN AMERICA	31
30	66	ALFREDO POMBO	M	LATIN AMERICA	31
12	30	ALEJANDRO KOURY	M	LATIN AMERICA	29
18	37	ANDREW MARTINEZ	M	NORTH AMERICA	29

11	28	RAFAEL HERNANDEZ	M	LATIN AMERICA	29
1	1	ALFONSO BUCAG	M	ASIAPAC	29
7	13	ABHYUDAYA CHOUMAL	M	ASIAPAC	28
9	18	PHILIPPE EL HAGE	M	MIDDLE EAST	27
23	48	RAHUL VERMA	M	ASIAPAC	27
14	32	FRANZ-ANTON GRAF BASSELET	M	EUROPE	27
13	31	KARL FERDINAND	M	EUROPE	26
35	81	KEVIN CUNNINGHAM	M	NORTH AMERICA	24
31	67	DEMETRIS PERDIKOS	M	EUROPE	24
33	70	ANDREA KATIPUNAN	M	ASIAPAC	24
10	22	ALBERTO LOMBATTI	M	EUROPE	22
27	60	TIMOTHY ONG	M	ASIAPAC	22
21	40	STEPHANIE NJERENGA	F	AFRICA	18
29	65	LIA FERNANDEZ	F	ASIAPAC	18
26	57	DAVID DALEL	M	LATIN AMERICA	18
2	2	YEGNESH SUNDAR	M	ASIAPAC	17
19	38	ALVARO ROMERO VILLA	M	EUROPE	17
22	42	PILAR LIMON	F	LATIN AMERICA	16
34	78	ALEJANDRO MARQUEZ	M	LATIN AMERICA	15
8	16	JUAN PABLO GARCIA	M	LATIN AMERICA	13
5	10	CHRISTINE UTENDORF	F	EUROPE	13
16	34	MARCOS BERGES	M	LATIN AMERICA	13
17	35	DANIEL RUSSOTTO	M	NORTH AMERICA	13
25	55	BREOGAN PARDO	M	EUROPE	12
24	54	SANTIAGO RODRIGUEZ	M	LATIN AMERICA	10
20	39	FEI DAI	M	ASIAPAC	7
15	33	SEBASTIAN VASQUEZ	M	LATIN AMERICA	5
4	9	SHEENA MILES	F	NORTH AMERICA	3
3	4	ANWITA BHURE	F	ASIAPAC	0
32	68	SOHAMJIT MUKHERJEE	M	ASIAPAC	0

5.3.3.Betweeness of music community 3

	Key	Name	Gender	Region	Betweeness
4	12	JEAN RENE ESPILLAT	M	LATIN AMERICA	31
28	82	ADELAIDE ISSAACS	F	NORTH AMERICA	29
27	80	LAURA PALACIO CORRA	F	LATIN AMERICA	25
25	75	MANUEL DE ASIS	M	EUROPE	24
16	52	LAURA DOMINGUEZ	F	LATIN AMERICA	23
7	23	ANDREW RIZK	M	AFRICA	23
18	61	ESTEFANIA TRUJILLO	F	LATIN AMERICA	22
26	79	SANTIAGO ZULUAGA	M	LATIN AMERICA	22
5	15	CELINE KHOURY	F	MIDDLE EAST	21
2	6	STAVROS TSEMTEMDEIDIS	M	EUROPE	21
10	26	SEBASTIAN MONTERO	M	LATIN AMERICA	21
19	63	NINA CALANO	F	ASIAPAC	18
23	73	ABIGAIL CUENCA	F	ASIAPAC	16

6	21	IRUNE MAURY	F	LATIN AMERICA	15
13	49	NAYLA FAKHOURY	F	MIDDLE EAST	15
14	50	CATERINA SELMAN	F	LATIN AMERICA	15
29	83	IVANNA DACCARET	F	LATIN AMERICA	14
8	24	CAROLIN KROGER	F	EUROPE	14
31	85	CAROLINA AVILA	F	NORTH AMERICA	13
24	74	MAITA LIMCAOCO	F	ASIAPAC	13
11	44	SIYAO LU	F	ASIAPAC	13
12	45	FRANCESCA MANONI	F	EUROPE	11
22	72	ZHENGUAN GU	F	ASIAPAC	11
30	84	ORIANA MADRIGAL	F	LATIN AMERICA	10
17	53	TOMAS TELLO	M	LATIN AMERICA	9
1	5	JESSICA MATTA	F	MIDDLE EAST	9
21	71	ROMANO ALONZO	M	ASIAPAC	8
15	51	ASHLEY OMAHONY	M	EUROPE	6
9	25	ANDREA SALVATI	M	EUROPE	5
3	8	GABRIELLA RIBER	F	EUROPE	3
20	64	TATINA YACAMAN	F	LATIN AMERICA	0

6.Sports Interest Analysis

6.1.Centrality Analysis for Sports interests

6.1.1.Summary

The average degree centrality of the leisure network for only sports is 51.29. This means that on average, each person is directly connected to approximately 52 other people based on their preference for sports. If we compare this indicator with the general graph degree centrality measure of 79.46, we can see that the average level of connection decreases aproximately by 28 students.

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    6.00   43.00   53.00   51.29   63.00   73.00
```

6.1.2.top 10 students of sport Centrality

The following table shows the top 10 students ranked by degree centrality for the Sports Sub-graph. As we can see, this ranking differs from the initial degree centrality measure ranking of the general graph. Considering this, if IE wants to develop a Networking event narrowed down to a specific topic such as sports, or for example leverage the Campus Life Clubs with the selection of influential students, it would be important to understand who are the important nodes for the specific topic.

	Key	Name	Gender	Program	Degree	Activity_1	Activity_2	Activity_3
1	14	CAMILLE COALLIER	F	MBD	73	FOOTBALL_SOCCER	TENNIS	SKIING
7	38	ALVARO ROMERO VILLA	M	MBD	73	FOOTBALL_SOCCER	TENNIS	SKIING
6	36	DUARTE DIAS DE COSTA	M	MBD	72	FOOTBALL_SOCCER	TENNIS	SKIING
4	30	ALEJANDRO KOURY	M	MBD	71	FOOTBALL_SOCCER	TENNIS	CYCLING
5	34	MARCOS BERGES	M	MBD	71	FOOTBALL_SOCCER	TENNIS	GOLF
8	42	PILAR LIMON	F	MBD	71	FOOTBALL_SOCCER	TENNIS	RUNNING
9	48	RAHUL VERMA	M	MBD	71	FOOTBALL_SOCCER	TENNIS	BOXING
10	79	SANTIAGO ZULUAGA	M	IMBA	71	FOOTBALL_SOCCER	TENNIS	CYCLING
2	27	ANTONIA SCHULZE	F	MBD	70	FOOTBALL_SOCCER	TENNIS	RUNNING
3	29	MORITZ STEINBRECHER	M	MBD	70	FOOTBALL_SOCCER	TENNIS	RUNNING

6.1.3.top 10 students of sport Betweeness

The following table shows the top 10 students ranked by Betweenness for the Sports Sub-graph. Betweenness represents the number of shortest paths that pass through a given node. We can see that the student with the highest shortest number of paths passing through him is Camille Coallier.

	Key	Name	Gender	Program	Betweeness	Activity_1	Activity_2	Activity_3
1	14	CAMILLE COALLIER	F	MBD	38	FOOTBALL_SOCCER	TENNIS	SKIING
7	38	ALVARO ROMERO VILLA	M	MBD	38	FOOTBALL_SOCCER	TENNIS	SKIING
2	2	YEGNESH SUNDAR	M	MBD	38	FOOTBALL_SOCCER	TENNIS	CRICKET
8	43	VIKAS AGARWAL	M	MBD	38	FOOTBALL_SOCCER	TENNIS	CRICKET
3	22	ALBERTO LOMBATTI	M	MBD	34	FOOTBALL_SOCCER	SWIMMING	SKIING
10	80	LAURA PALACIO CORRA	F	MVDM	33	FOOTBALL_SOCCER	SWIMMING	CYCLING
9	48	RAHUL VERMA	M	MBD	33	FOOTBALL_SOCCER	TENNIS	BOXING
5	34	MARCOS BERGES	M	MBD	32	FOOTBALL_SOCCER	TENNIS	GOLF
6	36	DUARTE DIAS DE COSTA	M	MBD	31	FOOTBALL_SOCCER	TENNIS	SKIING
4	25	ANDREA SALVATI	M	MBD	31	FOOTBALL_SOCCER	SWIMMING	BOXING

6.1.4.top 10 students of sport Closeness

A student is central if he can easily interact with other students. We believe for the purpose of NET-IE, along with Degree Centrality, Closeness Centrality is one of the most important indicators. For a given student of the graph, we want to know how easily he can relate with other students.

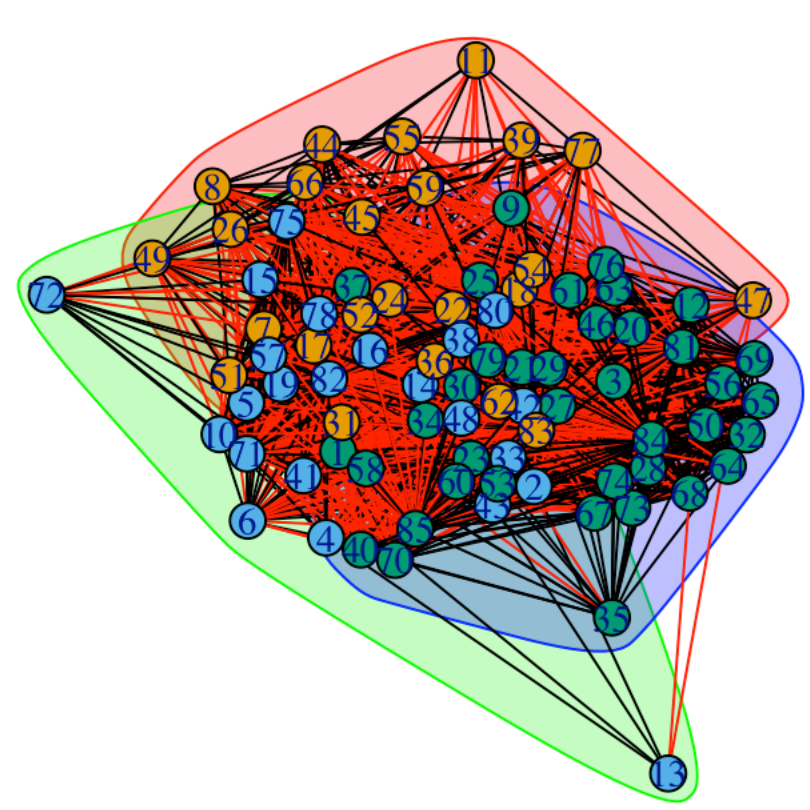
	Key	Name	Gender	Program	Closeness	Activity_1	Activity_2	Activity_3
1	14	CAMILLE COALLIER	F	MBD	0.88	FOOTBALL_SOCCER	TENNIS	SKIING
7	38	ALVARO ROMERO VILLA	M	MBD	0.88	FOOTBALL_SOCCER	TENNIS	SKIING
6	36	DUARTE DIAS DE COSTA	M	MBD	0.88	FOOTBALL_SOCCER	TENNIS	SKIING
4	30	ALEJANDRO KOURY	M	MBD	0.87	FOOTBALL_SOCCER	TENNIS	CYCLING
5	34	MARCOS BERGES	M	MBD	0.87	FOOTBALL_SOCCER	TENNIS	GOLF
8	42	PILAR LIMON	F	MBD	0.87	FOOTBALL_SOCCER	TENNIS	RUNNING
9	48	RAHUL VERMA	M	MBD	0.87	FOOTBALL_SOCCER	TENNIS	BOXING
10	79	SANTIAGO ZULUAGA	M	IMBA	0.87	FOOTBALL_SOCCER	TENNIS	CYCLING
2	27	ANTONIA SCHULZE	F	MBD	0.86	FOOTBALL_SOCCER	TENNIS	RUNNING
3	29	MORITZ STEINBRECHER	M	MBD	0.86	FOOTBALL_SOCCER	TENNIS	RUNNING

6.2.Community Detection for Sports interests

Now that we clearly understand centrality measures for the general network and sports sub-network, we can detect communities of students depending on their sports preferences. Community detection may Help IE discover and label the different groups of students to have a clear idea of their targets for any sports-related activity.

For the sports section, three communities were detected and can be seen in the following plot.

IE Sports Communities



6.3.Sports Community Analysis

The most important characteristic of segmentation algorithms is being able to label the resulting communities. To achieve this, we analyze which sports activity over-index and under-index within each group, and analyze complementary labeling variables such as gender or nationality.

Community #1: The “Blast”

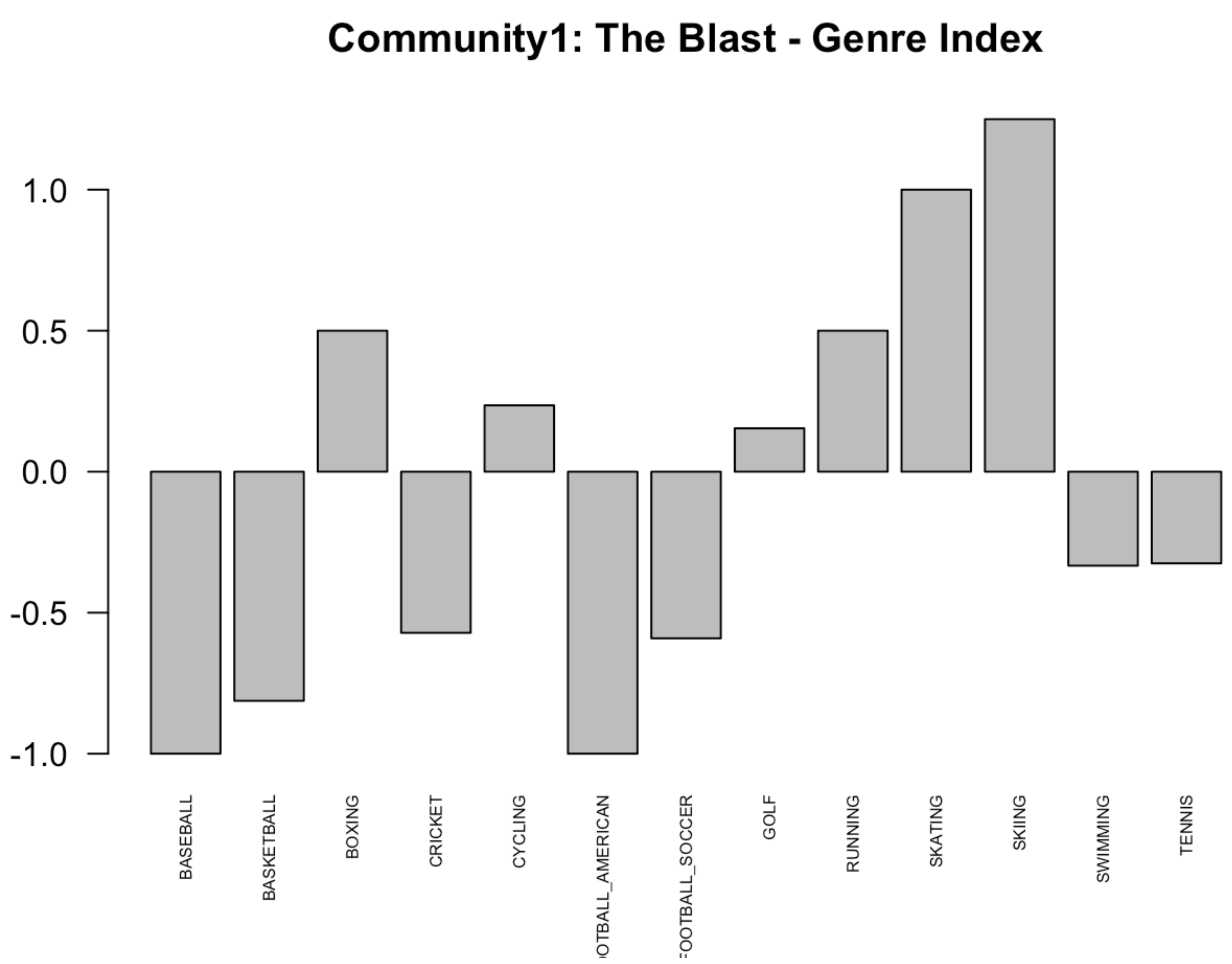
This community over-indexes in activity of skiing, skating, running and boxing, while Baseball, Basketball and American Football are under-indexes. The members of this community even more than liking skiing, are characterized for not having ball game inside their sports preferences. Most of them are from Latin-America and Europe.

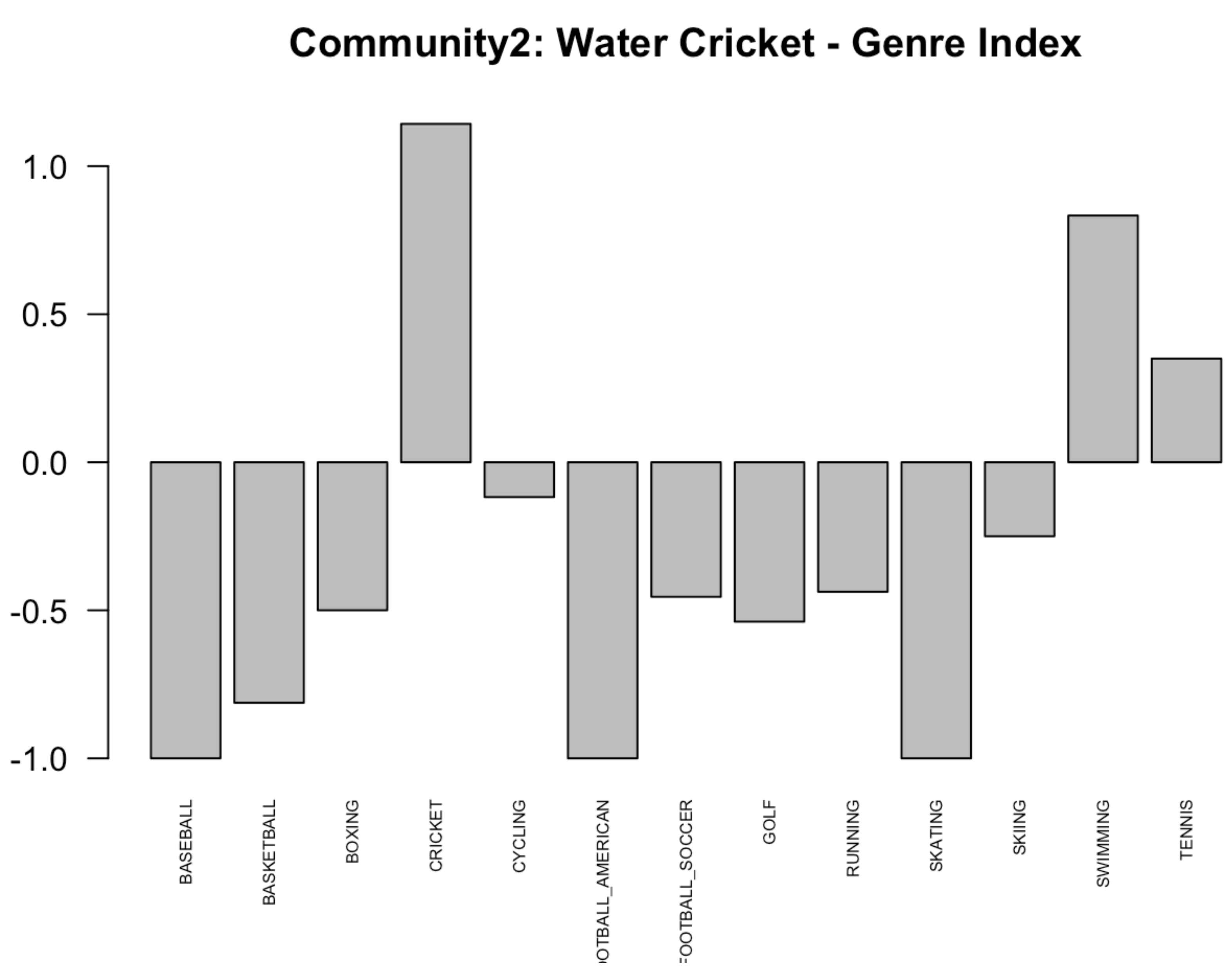
Community #2: Water Cricket

In this community we find the cricket and swimming lovers. As opposed from the previous communities, most of the students in this community are from Asia pacific. They also like tennis as side sports preferences.

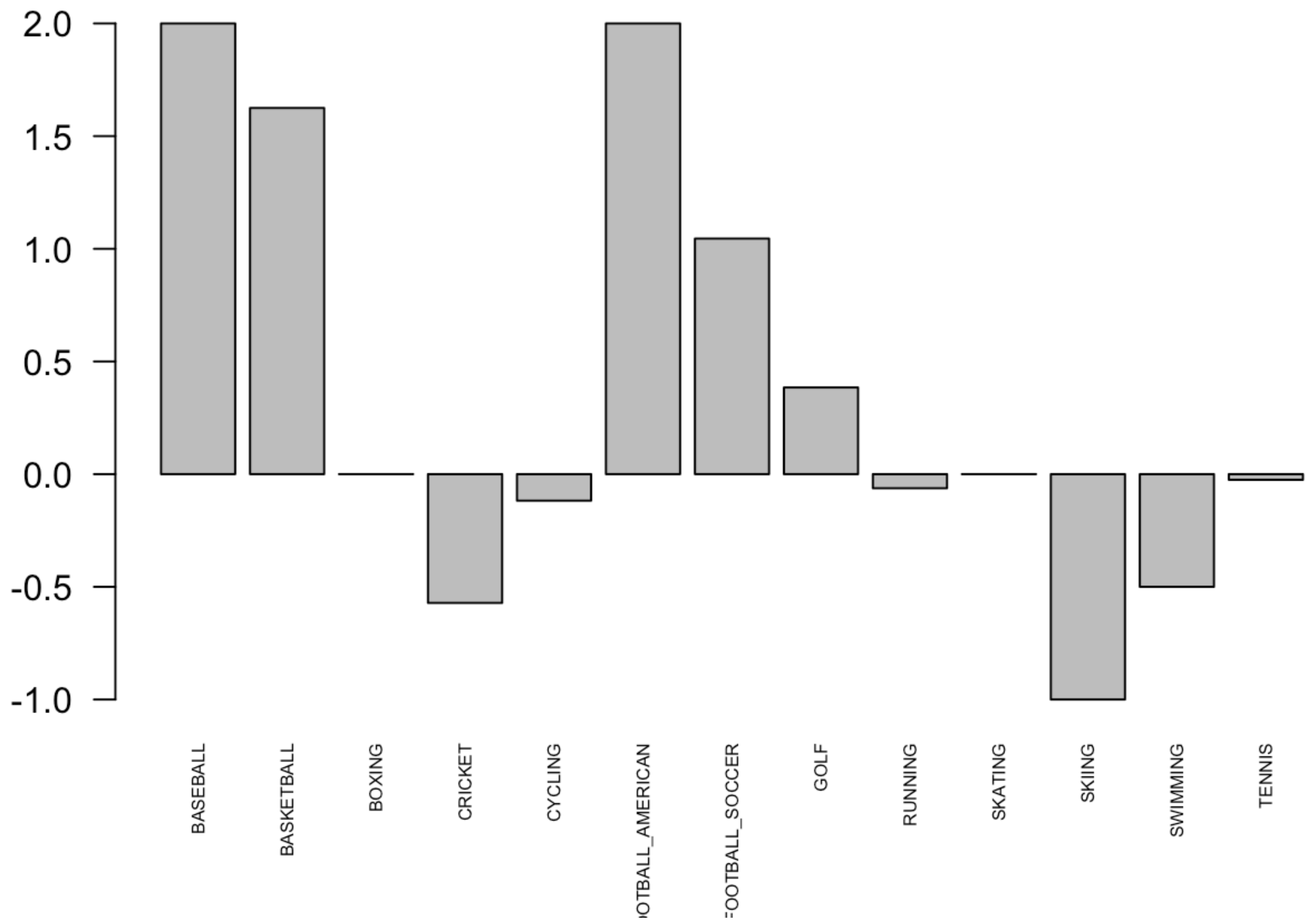
Community #3: Point Guard

This is the biggest community in number of students. It is characterized mainly as a ball game lover community. skiing and swimming may be seen as divergent genres. Male is the predominant gender.





Community3: Point Guard - Genre Index



As a final additional analysis, now that we identified communities we can also understand who the most influential people are within each community:

6.3.1.Betweeness of sports community 1

	Key	Name	Gender	Region	Betweeness
6	22	ALBERTO LOMBATTI	M	EUROPE	34
10	36	DUARTE DIAS DE COSTA	M	EUROPE	31
5	18	PHILIPPE EL HAGE	M	MIDDLE EAST	30
21	62	CAROLINA ROMERO	F	LATIN AMERICA	28
24	83	IVANNA DACCARET	F	LATIN AMERICA	28
18	54	SANTIAGO RODRIGUEZ	M	LATIN AMERICA	25
17	52	LAURA DOMINGUEZ	F	LATIN AMERICA	24
9	31	KARL FERDINAND	M	EUROPE	22
7	24	CAROLIN KROGER	F	EUROPE	17
1	7	GIULIO DEFELICE	M	EUROPE	16
13	45	FRANCESCA MANONI	F	EUROPE	15
4	17	FEDERICO LOGUERICO	M	EUROPE	15
8	26	SEBASTIAN MONTERO	M	LATIN AMERICA	12
22	66	ALFREDO POMBO	M	LATIN AMERICA	12
16	51	ASHLEY OMAHONY	M	EUROPE	11
20	59	YAWEN ZHANG	F	ASIAPAC	10
14	47	FURQUAN SHAUKAT	M	MIDDLE EAST	7
23	77	SCOTT PAN	M	ASIAPAC	7
19	55	BREOGAN PARDO	M	EUROPE	5
15	49	NAYLA FAKHOURY	F	MIDDLE EAST	4
2	8	GABRIELLA RIBER	F	EUROPE	4
12	44	SIYAO LU	F	ASIAPAC	3
11	39	FEI DAI	M	ASIAPAC	3
3	11	JONATHAN SERRANO	M	EUROPE	1

6.3.2.Betweeness of sports community 2

	Key	Name	Gender	Region	Betweeness

7	14	CAMILLE COALLIER	F	NORTH AMERICA	38
12	38	ALVARO ROMERO VILLA	M	EUROPE	38
1	2	YEGNESH SUNDAR	M	ASIAPAC	38
15	43	VIKAS AGARWAL	M	ASIAPAC	38
22	80	LAURA PALACIO CORRA	F	LATIN AMERICA	33
16	48	RAHUL VERMA	M	ASIAPAC	33
13	41	VAIBHAV JAITLY	M	ASIAPAC	30
14	42	PILAR LIMON	F	LATIN AMERICA	30
11	33	SEBASTIAN VASQUEZ	M	LATIN AMERICA	22
23	82	ADELAIDE ISSAACS	F	NORTH AMERICA	21
10	19	GERALD WALRAVENS	M	EUROPE	20
17	57	DAVID DALEL	M	LATIN AMERICA	20
21	78	ALEJANDRO MARQUEZ	M	LATIN AMERICA	17
3	5	JESSICA MATTA	F	MIDDLE EAST	16
8	15	CELINE KHOURY	F	MIDDLE EAST	16
9	16	JUAN PABLO GARCIA	M	LATIN AMERICA	15
20	75	MANUEL DE ASIS	M	EUROPE	14
2	4	ANWITA BHURE	F	ASIAPAC	12
5	10	CHRISTINE UTENDORF	F	EUROPE	9
18	71	ROMANO ALONZO	M	ASIAPAC	9
4	6	STAVROS TSEMTEMDEIDIS	M	EUROPE	0
6	13	ABHYUDAYA CHOUMAL	M	ASIAPAC	0
19	72	ZHENGUAN GU	F	ASIAPAC	0

6.3.3.Betweeness of sports community 3

	Key	Name	Gender	Region	Betweeness
14	34	MARCOS BERGES	M	LATIN AMERICA	32
8	25	ANDREA SALVATI	M	EUROPE	31
12	30	ALEJANDRO KOURY	M	LATIN AMERICA	29
35	79	SANTIAGO ZULUAGA	M	LATIN AMERICA	29
9	27	ANTONIA SCHULZE	F	EUROPE	28
11	29	MORITZ STEINBRECHER	M	EUROPE	28
25	63	NINA CALANO	F	ASIAPAC	26
24	61	ESTEFANIA TRUJILLO	F	LATIN AMERICA	25
6	21	IRUNE MAURY	F	LATIN AMERICA	24
20	53	TOMAS TELLO	M	LATIN AMERICA	22
34	76	VICTOR VU	M	ASIAPAC	21
23	60	TIMOTHY ONG	M	ASIAPAC	21
16	37	ANDREW MARTINEZ	M	NORTH AMERICA	20
2	3	MRAD AZOURY	M	MIDDLE EAST	20
5	20	LOUIS DUBAERE	M	EUROPE	20
1	1	ALFONSO BUCAG	M	ASIAPAC	19
22	58	JR CORTEZ	M	ASIAPAC	19
29	68	SOHAMJIT MUKHERJEE	M	ASIAPAC	16
7	23	ANDREW RIZK	M	AFRICA	16
36	81	KEVIN CUNNINGHAM	M	NORTH AMERICA	15

18	46	EDUARDO GARGIULO	M	EUROPE	15
38	85	CAROLINA AVILA	F	NORTH AMERICA	10
10	28	RAFAEL HERNANDEZ	M	LATIN AMERICA	9
28	67	DEMETRIS PERDIKOS	M	EUROPE	9
37	84	ORIANA MADRIGAL	F	LATIN AMERICA	9
4	12	JEAN RENE ESPILLAT	M	LATIN AMERICA	7
32	73	ABIGAIL CUENCA	F	ASIAPAC	7
33	74	MAITA LIMCAOCO	F	ASIAPAC	7
17	40	STEPHANIE NJERENGA	F	AFRICA	6
31	70	ANDREA KATIPUNAN	M	ASIAPAC	6
3	9	SHEENA MILES	F	NORTH AMERICA	5
19	50	CATERINA SELMAN	F	LATIN AMERICA	5
15	35	DANIEL RUSSOTTO	M	NORTH AMERICA	2
26	64	TATINA YACAMAN	F	LATIN AMERICA	2
13	32	FRANZ-ANTON GRAF BASSELET	M	EUROPE	0
21	56	JUAN RUIZ	M	LATIN AMERICA	0
27	65	LIA FERNANDEZ	F	ASIAPAC	0
30	69	CRISTHIAN GARCIA	M	LATIN AMERICA	0

7.Movies Interest Analysis

7.1.Centrality Analysis for Movie interests

7.1.1.Summary

The average degree centrality of the leisure network for only movie is 60.9. This means that on average, each person is directly connected to approximately 61 other people based on their preference for movie. With a maximum of three options for each leisure activity, the likelihood of a connection to another student even based on a single activity is high, which results in this high degree centrality. Higher degree centrality of movie due to more concentrated choices made by students. If we compare this indicator with the general graph degree centrality measure of 79.46, we can see that the average level of connection decreases aproximately by 19 students.

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    9.00   55.00   65.00   60.09   72.00   75.00
```

7.1.2.top 10 students of movie Centrality

The following table shows the top 10 students ranked by degree centrality for the movie Sub-graph. As we can see, this ranking differs from the initial degree centrality measure ranking of the general graph. Considering this, if IE wants to develop a Networking event narrowed down to a specific topic such as movie, or for example leverage the Campus Life Clubs with the selection of influential students, it would be important to understand who are the important nodes for the specific topic.

	Key	Name	Gender	Program	Degree	Genre_1	Genre_2	Genre_3
9	6	STAVROS TSEMTEMDEIDIS	M	MBD	75	ACTION	COMEDY	HISTORICAL_EPICS
1	18	PHILIPPE EL HAGE	M	MBD	74	ACTION	COMEDY	SCIENCE_FICTION
2	2	YEGNESH SUNDAR	M	MBD	74	ACTION	ADVENTURE	COMEDY
4	3	MRAD AZOURY	M	MBD	74	ACTION	ADVENTURE	COMEDY
5	30	ALEJANDRO KOURY	M	MBD	74	ACTION	COMEDY	HISTORICAL_EPICS
10	64	TATINA YACAMAN	F	MRED	74	ACTION	COMEDY	DRAMA
3	28	RAFAEL HERNANDEZ	M	MBD	73	COMEDY	DRAMA	SCIENCE_FICTION
6	31	KARL FERDINAND	M	MBD	73	ACTION	ADVENTURE	COMEDY
7	52	LAURA DOMINGUEZ	F	IMBA	73	ACTION	COMEDY	SCIENCE_FICTION
8	56	JUAN RUIZ	M	MRED	73	COMEDY	DRAMA	SCIENCE_FICTION

The Top 10 students of degree centrality of movie are from 73 to 75. This means that on average, each person is directly connected to approximately 73 to 75 other people based on their preference for movie. From the table, we can observed that they are the top students due to most of their movie preferences are the 3 most popular movie genres (Action, Adventure and Comedy).

7.1.3top 10 students of movie Betweeness

The following table shows the top 10 students ranked by Betweenness for the Movie Sub-graph. Betweenness represents the number of shortest paths that pass through a given node. We can see that the student with the highest shortest number of paths passing through him is Alfredo Pombo.

	Key	Name	Gender	Program	Betweeness	Genre_1	Genre_2	Genre_3
8	66	ALFREDO POMBO	M	IMBA	26	ACTION	COMEDY	HORROR
9	78	ALEJANDRO MARQUEZ	M	IMBA	26	ACTION	COMEDY	HORROR
4	39	FEI DAI	M	MBD	23	COMEDY	HISTORICAL_EPICS	SCIENCE_FICTION
5	53	TOMAS TELLO	M	MBD	23	COMEDY	HISTORICAL_EPICS	SCIENCE_FICTION
7	6	STAVROS TSEMTEMDEIDIS	M	MBD	22	ACTION	COMEDY	HISTORICAL_EPICS
2	14	CAMILLE COALLIER	F	MBD	22	ACTION	ANIMATED	COMEDY
6	59	YAWEN ZHANG	F	MIF	22	ACTION	ANIMATED	COMEDY
1	1	ALFONSO BUCAG	M	MBD	21	ACTION	COMEDY	WAR
3	30	ALEJANDRO KOURY	M	MBD	20	ACTION	COMEDY	HISTORICAL_EPICS
10	84	ORIANA MADRIGAL	F	MRCB	20	ACTION	ADVENTURE	ROMANCE

High betweeness can be understood as more links between different closed clusters of students. The top students here we have regards to the movie between are slightly different from the ones in degree of centrality. This can be explained by the super different tastes (communities) occurs. For instance, Action, Comedy and Science Fiction can be grouped as mainstream movies while Horror and War can be concluded as unpopular movie types. Thus, the students who have higher betweeness are the ones who have chosen their movie preferences in both tastes (communities).

7.1.4.top 10 students of movie Closeness

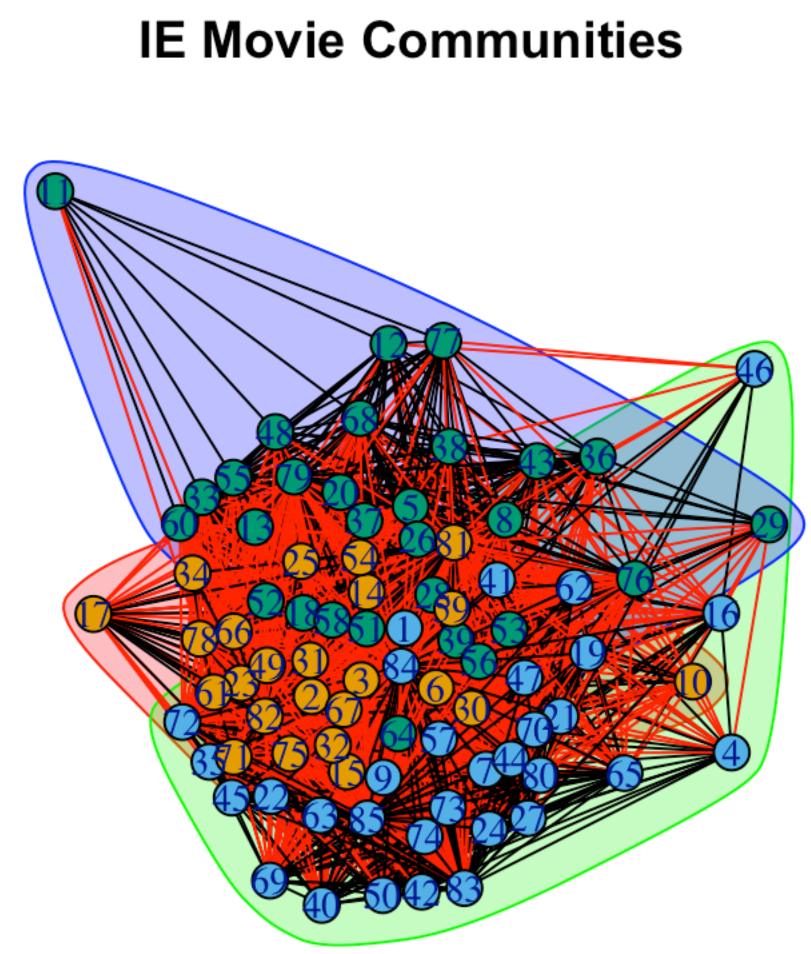
	Key	Name	Gender	Program	Closeness	Genre_1	Genre_2	Genre_3
9	6	STAVROS TSEMTEMDEIDIS	M	MBD	0.90	ACTION	COMEDY	HISTORICAL_EPICS
1	18	PHILIPPE EL HAGE	M	MBD	0.89	ACTION	COMEDY	SCIENCE_FICTION
2	2	YEGNESH SUNDAR	M	MBD	0.89	ACTION	ADVENTURE	COMEDY
4	3	MRAD AZOURY	M	MBD	0.89	ACTION	ADVENTURE	COMEDY
5	30	ALEJANDRO KOURY	M	MBD	0.89	ACTION	COMEDY	HISTORICAL_EPICS
10	64	TATINA YACAMAN	F	MRED	0.89	ACTION	COMEDY	DRAMA
3	28	RAFAEL HERNANDEZ	M	MBD	0.88	COMEDY	DRAMA	SCIENCE_FICTION
6	31	KARL FERDINAND	M	MBD	0.88	ACTION	ADVENTURE	COMEDY
7	52	LAURA DOMINGUEZ	F	IMBA	0.88	ACTION	COMEDY	SCIENCE_FICTION
8	56	JUAN RUIZ	M	MRED	0.88	COMEDY	DRAMA	SCIENCE_FICTION

The higher the closeness (with normalization), the closer the given vertex to every other vertex. The top 10 students of closeness centrality are exactly the same as top 10 students of degree of centrality. This is because the more popular movie type the students have chosen, the more links between them and other students and the closer for them to other students.

7.2.Community Detection for Movie interests

Now that we clearly understand centrality measures for the general network and movie sub-network, we can detect communities of students depending on their movie prefernece s. Community detection may Help IE discover and label the different groups of students to have a clear idea of their targets for any movie-related activity.

For this exercise, three communities were detected and can be seen in the following plot.



7.3.Movie Community Analysis

We analyze which movie genres over-index and under-index within each group, and analyze complementary labeling variables such as gender or nationality.

Community #1: The Warriors

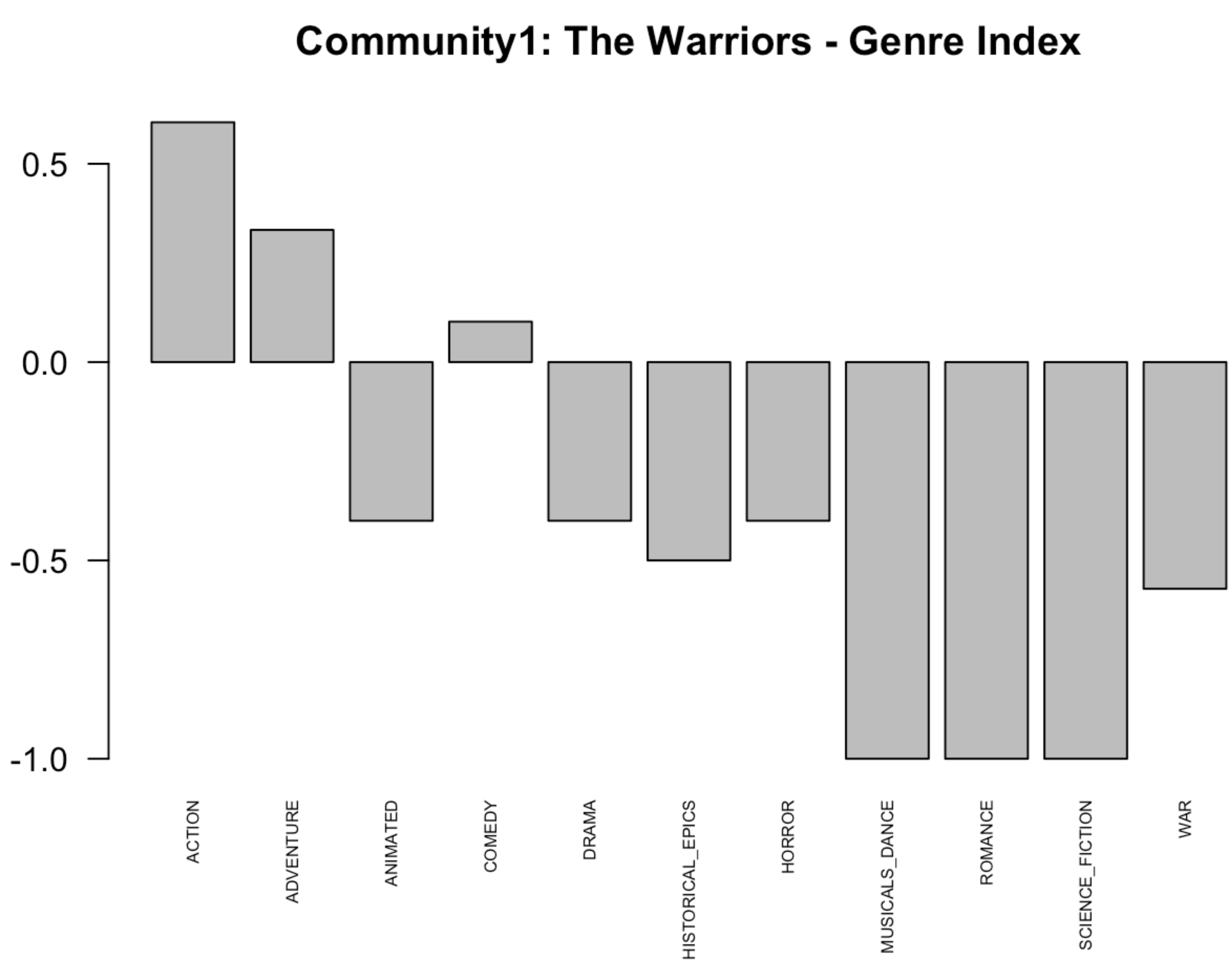
This community over-indexes in Action and Adcenture movie and clearly under-indexes in Musical, Romance and Scienc Fiction movie. Most of them are male.

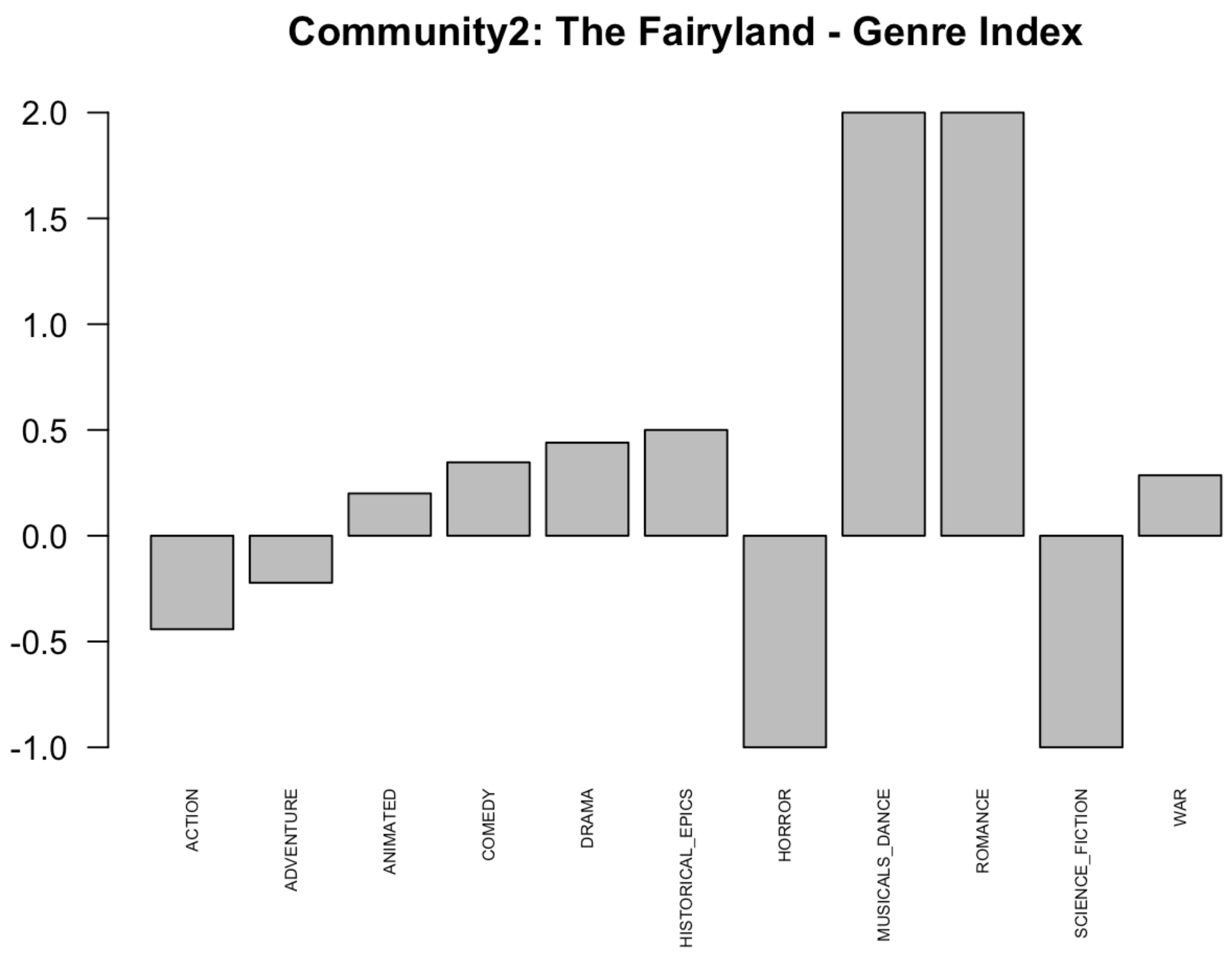
Community #2: The Fairyland

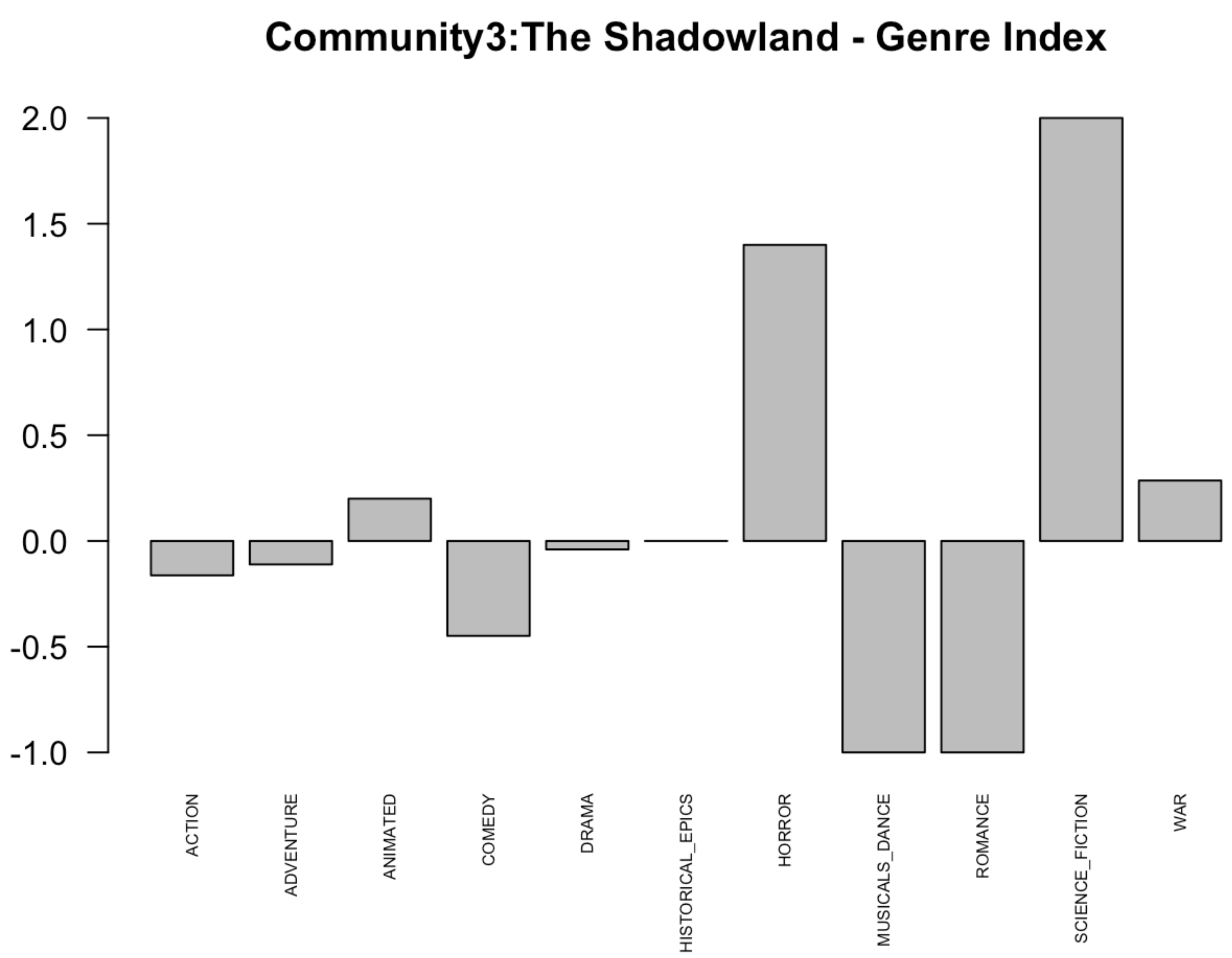
For the students in movie community 2, they prefer more on the Musical, Romance, Drama and Comedy movie insted of Horror, Science Fiction and Action Movie. Most of them are female.

Community #3:The Shadowland

For the students in movie community 3, they prefer more on the unreal movies like Science Fiction and Horror movie. Musical, Romance and Comedy Movie may be seen as divergent genres.







As a final additional analysis, now that we identified communities we can also understand who the most influential people are within each community:

7.3.1.Betweeness of movie community 1

	Key	Name	Gender	Region	Betweeness
18	66	ALFREDO POMBO	M	LATIN AMERICA	26
22	78	ALEJANDRO MARQUEZ	M	LATIN AMERICA	26
3	6	STAVROS TSEMTEMDEIDIS	M	EUROPE	22
5	14	CAMILLE COALLIER	F	NORTH AMERICA	22
16	59	YAWEN ZHANG	F	ASIAPAC	22
10	30	ALEJANDRO KOURY	M	LATIN AMERICA	20
23	81	KEVIN CUNNINGHAM	M	NORTH AMERICA	17
1	2	YEGNESH SUNDAR	M	ASIAPAC	14
2	3	MRAD AZOURY	M	MIDDLE EAST	14
11	31	KARL FERDINAND	M	EUROPE	13
21	75	MANUEL DE ASIS	M	EUROPE	12

6	15	CELINE KHOURY	F	MIDDLE EAST	12
12	32	FRANZ-ANTON GRAF BASSELET	M	EUROPE	12
8	23	ANDREW RIZK	M	AFRICA	11
14	49	NAYLA FAKHOURY	F	MIDDLE EAST	11
17	61	ESTEFANIA TRUJILLO	F	LATIN AMERICA	11
19	67	DEMETRIS PERDIKOS	M	EUROPE	11
24	82	ADELAIDE ISSAACS	F	NORTH AMERICA	11
9	25	ANDREA SALVATI	M	EUROPE	10
15	54	SANTIAGO RODRIGUEZ	M	LATIN AMERICA	10
13	34	MARCOS BERGES	M	LATIN AMERICA	6
20	71	ROMANO ALONZO	M	ASIAPAC	6
4	10	CHRISTINE UTENDORF	F	EUROPE	1
7	17	FEDERICO LOGUERICO	M	EUROPE	0

7.3.2.Betweeness of movie community 2

	Key	Name	Gender	Region	Betweeness
1	1	ALFONSO BUCAG	M	ASIAPAC	21
31	84	ORIANA MADRIGAL	F	LATIN AMERICA	20
18	47	FURQUAN SHAUKAT	M	MIDDLE EAST	18
13	41	VAIBHAV JAITLY	M	ASIAPAC	17
3	7	GIULIO DEFELICE	M	EUROPE	16
25	70	ANDREA KATIPUNAN	M	ASIAPAC	16
29	80	LAURA PALACIO CORRA	F	LATIN AMERICA	15
15	44	SIYAO LU	F	ASIAPAC	15
7	21	IRUNE MAURY	F	LATIN AMERICA	14
21	62	CAROLINA ROMERO	F	LATIN AMERICA	13
10	27	ANTONIA SCHULZE	F	EUROPE	12
20	57	DAVID DALEL	M	LATIN AMERICA	11
23	65	LIA FERNANDEZ	F	ASIAPAC	11
9	24	CAROLIN KROGER	F	EUROPE	10
4	9	SHEENA MILES	F	NORTH AMERICA	10
26	72	ZHENGUAN GU	F	ASIAPAC	10
5	16	JUAN PABLO GARCIA	M	LATIN AMERICA	10
6	19	GERALD WALRAVENS	M	EUROPE	9
27	73	ABIGAIL CUENCA	F	ASIAPAC	8
22	63	NINA CALANO	F	ASIAPAC	7
32	85	CAROLINA AVILA	F	NORTH AMERICA	7
8	22	ALBERTO LOMBATTI	M	EUROPE	7
11	35	DANIEL RUSSOTTO	M	NORTH AMERICA	7
16	45	FRANCESCA MANONI	F	EUROPE	7
28	74	MAITA LIMCAOCO	F	ASIAPAC	7
14	42	PILAR LIMON	F	LATIN AMERICA	5
19	50	CATERINA SELMAN	F	LATIN AMERICA	5
30	83	IVANNA DACCARET	F	LATIN AMERICA	5
2	4	ANWITA BHURE	F	ASIAPAC	3
24	69	CRISTHIAN GARCIA	M	LATIN AMERICA	1

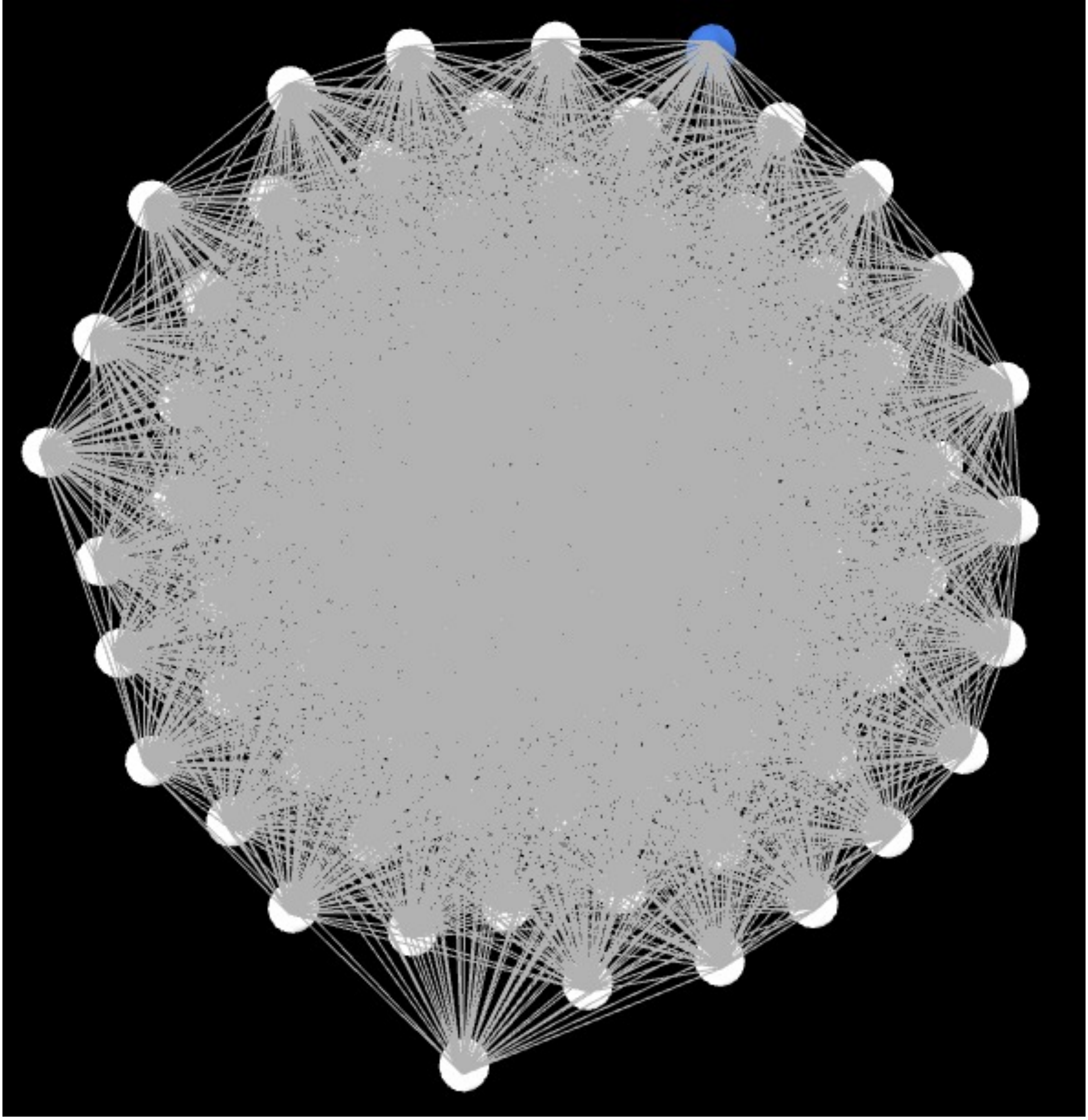
12	40	STEPHANIE NJERENGA	F	AFRICA	1
17	46	EDUARDO GARGIULO	M	EUROPE	0

7.3.3.Betweeness of movie community 3

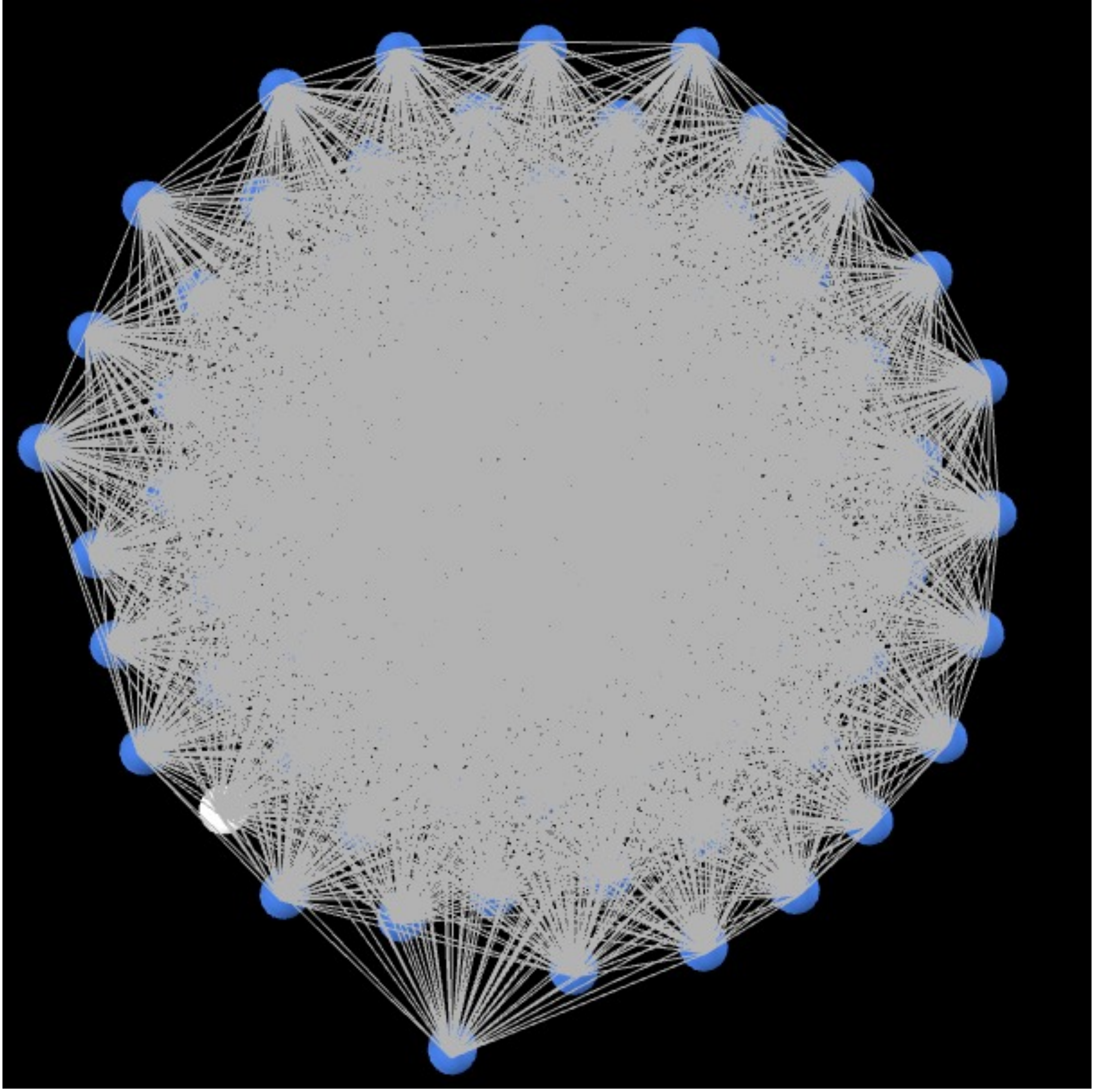
	Key	Name	Gender	Region	Betweeness
15	39	FEI DAI	M	ASIAPAC	23
20	53	TOMAS TELLO	M	LATIN AMERICA	23
9	28	RAFAEL HERNANDEZ	M	LATIN AMERICA	18
22	56	JUAN RUIZ	M	LATIN AMERICA	18
25	64	TATINA YACAMAN	F	LATIN AMERICA	17
6	18	PHILIPPE EL HAGE	M	MIDDLE EAST	17
26	68	SOHAMJIT MUKHERJEE	M	ASIAPAC	16
18	51	ASHLEY OMAHONY	M	EUROPE	15
23	58	JR CORTEZ	M	ASIAPAC	15
19	52	LAURA DOMINGUEZ	F	LATIN AMERICA	15
17	48	RAHUL VERMA	M	ASIAPAC	14
1	5	JESSICA MATTA	F	MIDDLE EAST	14
8	26	SEBASTIAN MONTERO	M	LATIN AMERICA	14
13	37	ANDREW MARTINEZ	M	NORTH AMERICA	14
11	33	SEBASTIAN VASQUEZ	M	LATIN AMERICA	14
21	55	BREOGAN PARDO	M	EUROPE	14
24	60	TIMOTHY ONG	M	ASIAPAC	14
7	20	LOUIS DUBAERE	M	EUROPE	14
12	36	DUARTE DIAS DE COSTA	M	EUROPE	13
14	38	ALVARO ROMERO VILLA	M	EUROPE	12
16	43	VIKAS AGARWAL	M	ASIAPAC	12
2	8	GABRIELLA RIBER	F	EUROPE	11
29	79	SANTIAGO ZULUAGA	M	LATIN AMERICA	10
4	12	JEAN RENE ESPILLAT	M	LATIN AMERICA	10
28	77	SCOTT PAN	M	ASIAPAC	9
5	13	ABHYUDAYA CHOUMAL	M	ASIAPAC	9
27	76	VICTOR VU	M	ASIAPAC	8
10	29	MORITZ STEINBRECHER	M	EUROPE	1
3	11	JONATHAN SERRANO	M	EUROPE	0

8.Information Difussion

Considering the graph shows high level of transitivity, the information difussion is very fast. With the first iteration, almost all of the nodes turn into blue, which means each node can reach to every other node in a very efficienct way.



A caption



A caption

9.Net IE Shiny App

9.1.Ideation

Following the overall distributions explored above, the user is invited to explore conncetions between IE students by their preferences through the following network visualization prototype.

9.2.Prototype

Leisure Network Analysis

Select connections of interest

Overall

Group