

# **National Research University Higher School of Economics**

Faculty of Social Sciences

**Introduction to Network Analytics**

**Homework 2**

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# 1 Task 1

In this task, we were to transform the Network 8 (“Positive and negative choices in a football team”) to Pajek [1]. The given network is **unimodal** (vertices represent only football players), **signed** (positive and negative relationships are observed between players), and both **arcs** and **edges** are present in the network. The original network is displayed in the figure below.

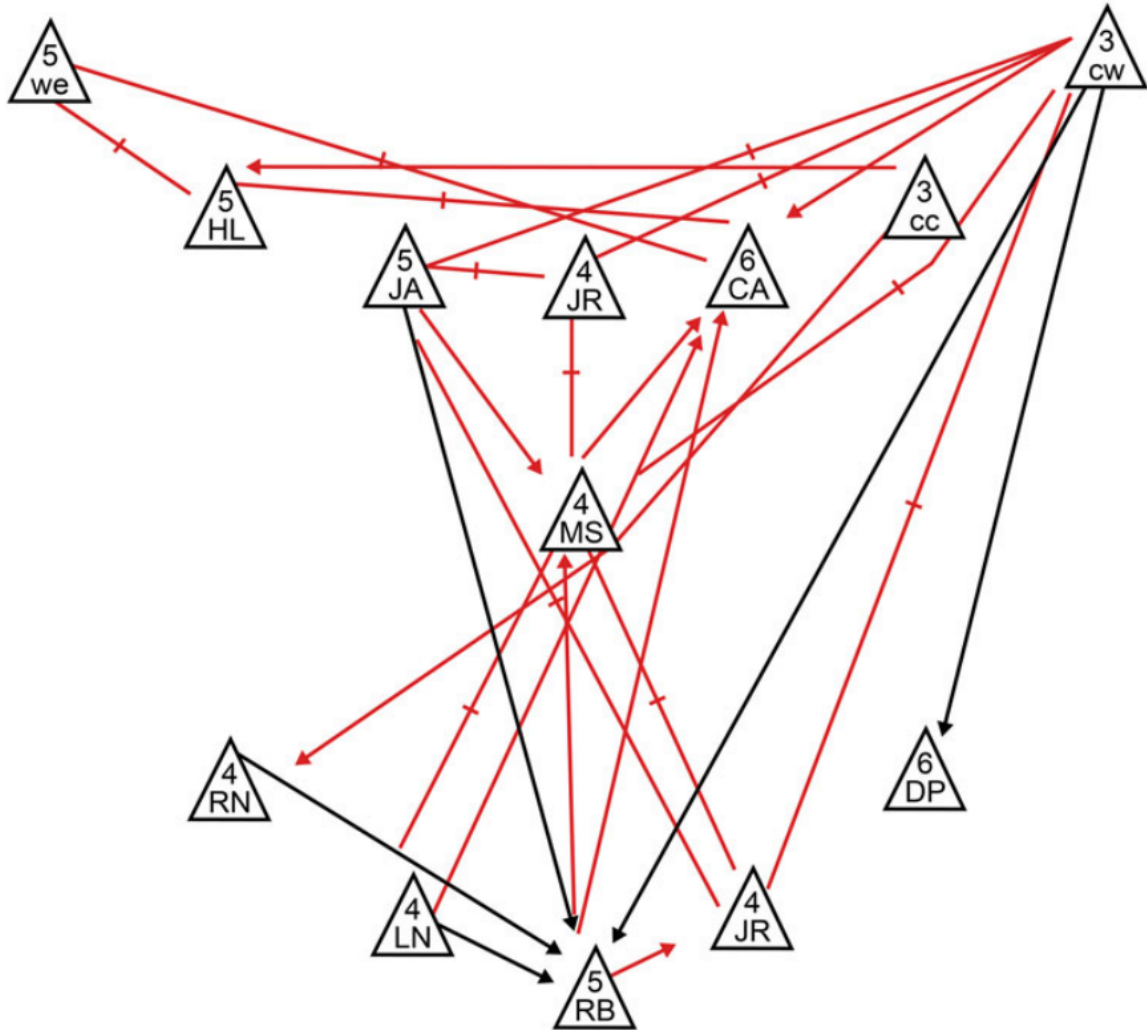


Figure 1 – Original network

At first, we created a Pajek’s network data format (**.net**) file with all vertices, arcs and edges of the network [2]. In addition, the colours of lines were specified [3]. The structure of the file is listed below.

```
1 *Vertices 13
2   1 "5 WE"
3   2 "5 HL"
4   3 "5 JA"
```

```

5      4 "4 JR"
6      5 "6 CA"
7      6 "3 CC"
8      7 "3 CW"
9      8 "4 MS"
10     9 "4 RN"
11    10 "4 LN"
12    11 "5 RB"
13    12 "4 JR"
14    13 "6 DP"
15 *Arcs
16     3 8 1 c Dandelion
17     3 11 -1 c RedOrange
18     6 2 1 c Dandelion
19     6 9 1 c Dandelion
20     7 11 -1 c RedOrange
21     7 13 -1 c RedOrange
22     8 5 1 c Dandelion
23     9 11 -1 c RedOrange
24    10 5 1 c Dandelion
25    10 11 -1 c RedOrange
26    11 5 1 c Dandelion
27    11 12 1 c Dandelion
28 *Edges
29     1 2 1 c RedViolet
30     1 5 1 c RedViolet
31     2 5 1 c RedViolet
32     3 7 1 c RedViolet
33     3 4 1 c RedViolet
34     3 12 1 c RedViolet
35     4 7 1 c RedViolet
36     4 8 1 c RedViolet
37     7 8 1 c RedViolet
38     7 12 1 c RedViolet
39     8 10 1 c RedViolet
40     8 12 1 c RedViolet

```

Listing 1 – Pajek net file

Next, we proceeded with visualisation of the network [4]. After selecting **Draw** command, the default circular layout of the network appeared (Figure 2).

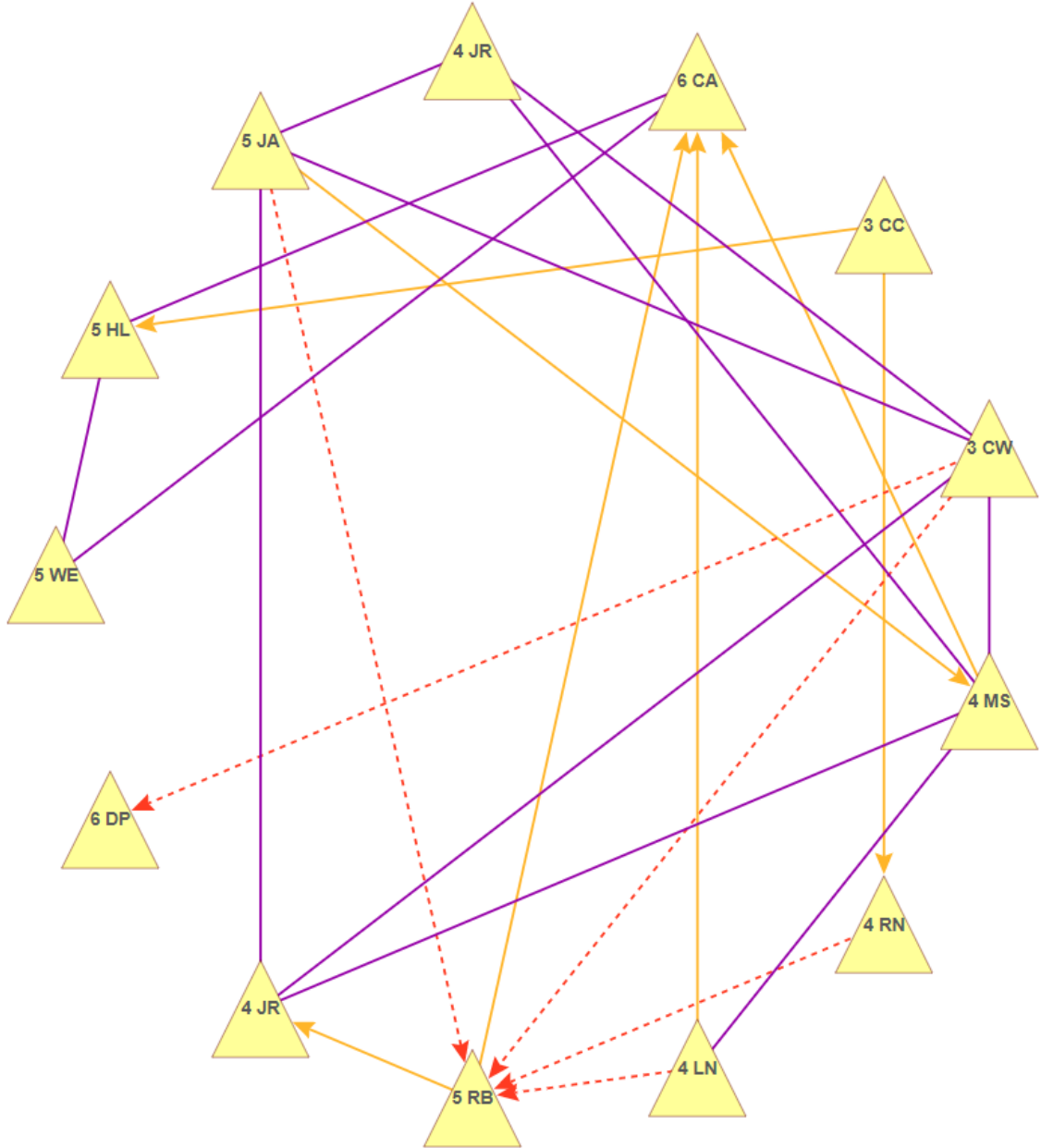


Figure 2 – Default layout

To restore the resemblance, we need to manually move vertices, as on the original network. The layout might be not very neat, however, it represents the **actual positions** of a football team in a stadium. This way we understand how the observed network describes the actual situation in a football game.

The result is in the Figure 3.

As it is common in network analysis, negative links are drawn with **dotted lines**, and here we additionally marked them with red colour. Arcs have arrows on the ends and they are orange or red, and edges are violet (all edges are positive).

We may try another layout — **Kamada-Kawai**. This layout puts important ver-

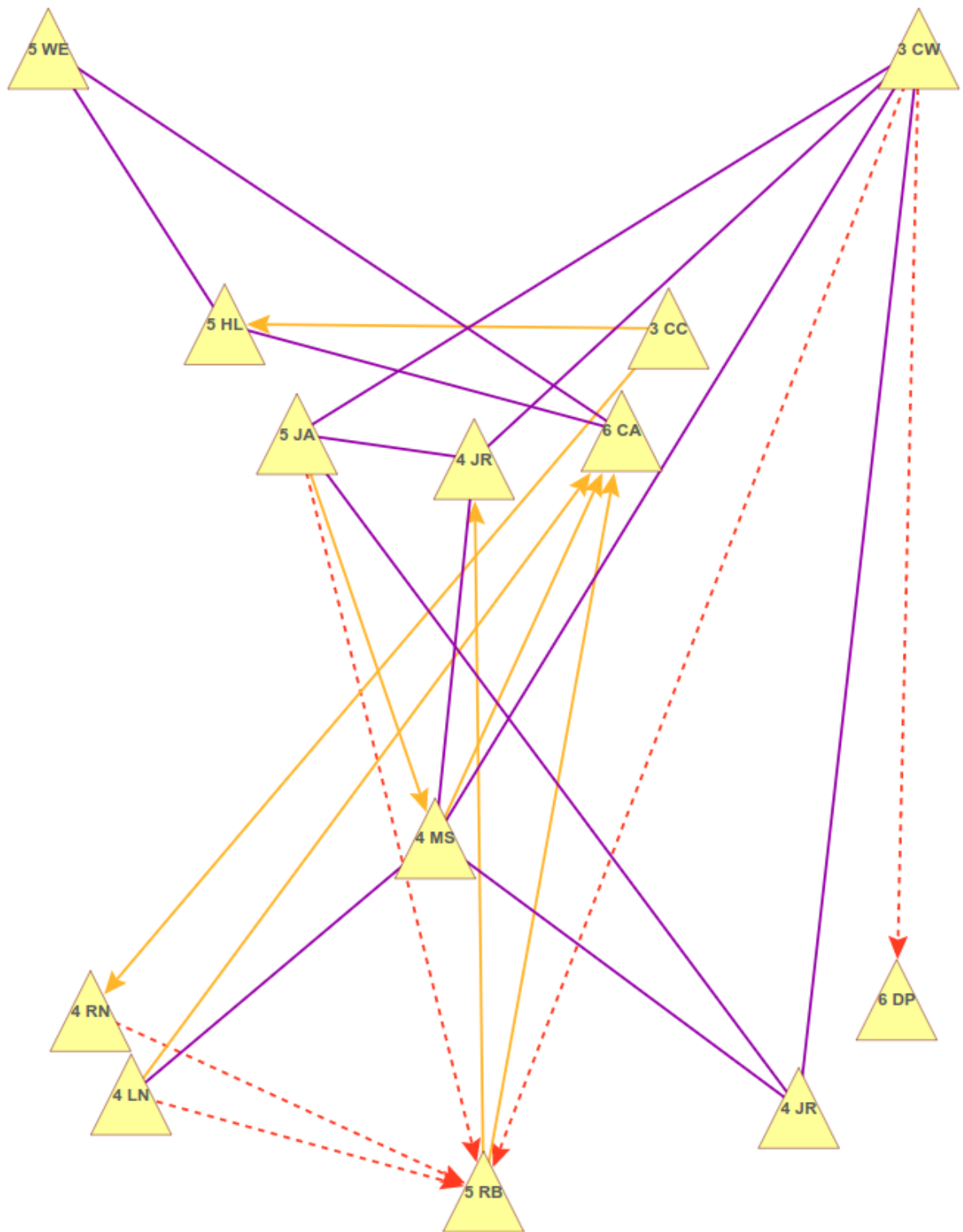


Figure 3 – The layout similar to the given network

tices closer to the centre of the diagram. The result looks satisfying (Figure 4)



## 2 Task 2

In this task, we are to analyse the Mexican polite elite network, which is displayed in the picture below. At first glance, one can notice that the given network is undirected and unweighted. Let us examine the network more closely.

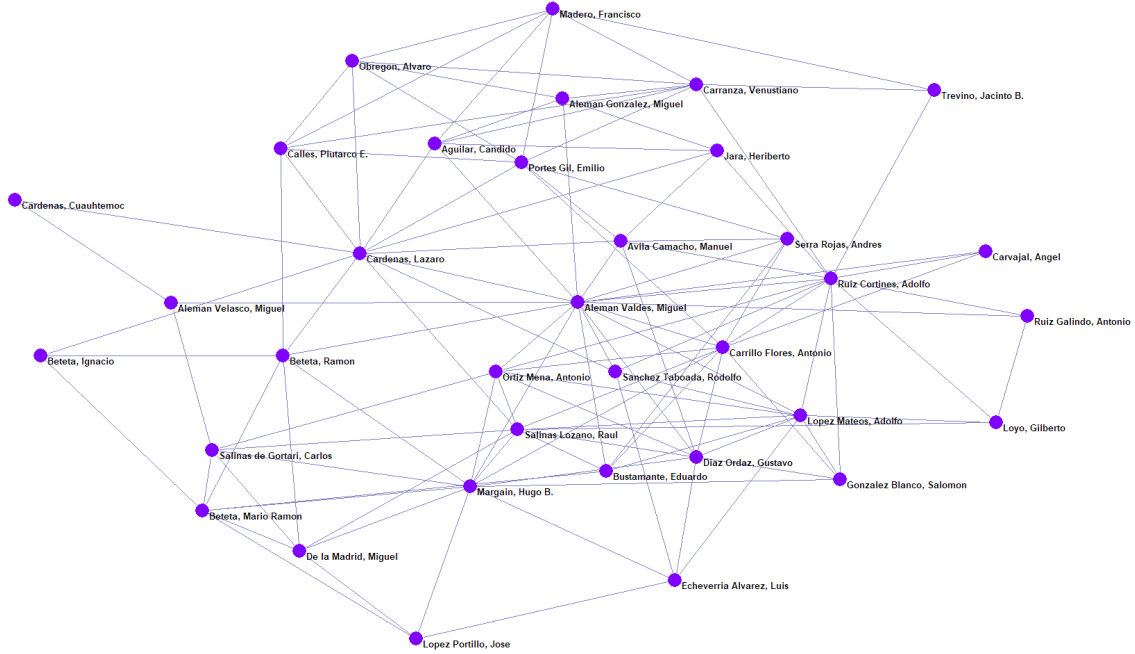


Figure 5 – Mexican polite elite network

### 2.1 Subtask 1

Overall, the network has **35 vertices**, which represent Mexican presidents and close collaborators, and **117 edges** that indicate the presence of political, kinship, friendship, or business ties between the actors (Figure 6). Also, our network has zero arcs (due to its **undirected nature**), no loops. Given that all of the network's lines are equal to 1, we can confirm that the network is **unweighted**. Since the observed network does not differentiate between the types of actor interaction, it is **unimodal** and **does not contain multiple lines**. The density of our network, which is basically the ratio of links to nodes, is quite low, reaching 0.196, which means that only 19.6 percent of all possible edges are present. This implies that the network is not as connected as it could be. The network's **average degree** equals **6.69**, which suggests that on average, each node in the network has 6.69 links.



```

kilobytes of free virtual address space:  137 434 464 676 kB

=====
1. mexican_power.net (35)
=====
Number of vertices (n): 35
-----

```

	Arcs	Edges
Total number of lines	0	117
Number of loops	0	0
Number of multiple lines	0	0

```

-----
Density1 [loops allowed]    = 0.19102041
Density2 [no loops allowed] = 0.19663866
Average Degree = 6.68571429

```

Figure 6 – General network information

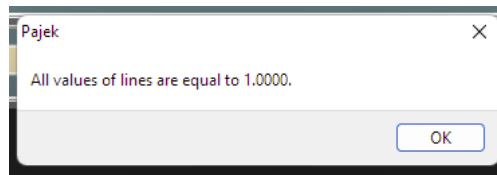


Figure 7 – the network is unweighted

As can be noticed from Figure 8, the network's **lowest degree** equals 2 (Cuauhtémoc Cárdenas), whereas the largest amounts — to 17 (Miguel Alemán Valdés). Thus, we can conclude that having direct contact with many other actors, Miguel Alemán Valdés is the **most influential node** in our network. The network's plot with the vertex sizes and colours adjusted by their degree values can be viewed in the ...

```

=====
5. All Degree of N1 (35)
=====
Dimension: 35
The lowest value:          2.0000
The highest value:         17.0000
-----
Sum (all values):          234.0000

Arithmetic mean:           6.6857
Median:                     6.0000
Standard deviation:         3.2669
 2.5% Quantile:             2.8500
 5.0% Quantile:             3.0000
95.0% Quantile:            12.3000
97.5% Quantile:            13.6000

```

Figure 8 – Degree

The network's **diameter** amounts to 4, which refers to the length of the longest shortest path — in our case, it is the path from Madero Francisco to José López Portillo (Figure 9).

```

=====
Searching the longest shortest path in 1. mexican_power.net (35)
=====
Working...

Result:
The longest shortest path from Madero, Francisco (1) to Lopez Portillo, Jose (29). Diameter is 4.

```

Figure 9 – Degree

Our network has only **one component**, consisting of the whole graph (Figure 10). As is known, an undirected graph is called connected if there is a path between every pair of distinct vertices of the graph. Since a component of a graph is defined as a maximal subgraph in which a path exists from every node to every other, we can conclude that the given network is **connected**.

```

=====
Strong Components
=====
Working...
Number of components: 1
Size of the largest component: 35 vertices (100.000%).

```

Figure 10 – Number of components

Looking at the **triad census** of our network, one can not help but notice that only 4 types of triads are present (a characteristic of undirected graphs): an **empty triad** (003), a triad with a **reciprocated connection** between two vertices (102), a triad with **two mutual relations and one null relation** (201), a **complete triad** (300). So, it is obvious that there are many cases of empty triads, or triads with one reciprocated connection (Figure 11).

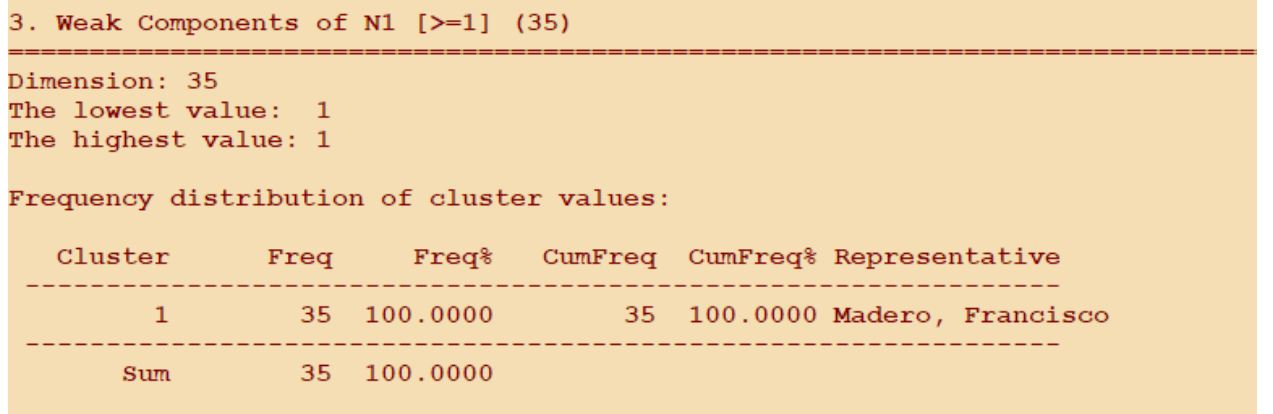
Meanwhile, triads with two relations, or the ones in which all three dyads have a relationship are not as common. Thus, since the majority of triads are concentrated in the left side of the triad distribution, we can assume that the network is **not quite connected**. This corresponds to the fact that only 19.6 percent of all possible edges are present.

Triadic Census 1. mexican_power.net (35)				
Working...				
Type	Number of triads (ni)	Expected (ei)	(ni-ei)/ei	Model
3 - 102	2460	316.24	6.78	Balance
16 - 300	101	0.38	265.93	Balance
1 - 003	3435	1759.44	0.95	Clusterability
4 - 021D	0	316.24	-1.00	Ranked Clusters
5 - 021U	0	316.24	-1.00	Ranked Clusters
9 - 030T	0	154.81	-1.00	Ranked Clusters
12 - 120D	0	18.95	-1.00	Ranked Clusters
13 - 120U	0	18.95	-1.00	Ranked Clusters
2 - 012	0	2583.95	-1.00	Transitivity
14 - 120C	0	37.89	-1.00	Hierarchical Clusters
15 - 210	0	9.28	-1.00	Hierarchical Clusters
6 - 021C	0	632.47	-1.00	Forbidden
7 - 111D	0	154.81	-1.00	Forbidden
8 - 111U	0	154.81	-1.00	Forbidden
10 - 030C	0	51.60	-1.00	Forbidden
11 - 201	549	18.95	27.98	Forbidden
Transitive	101	193.08		
Intransitive	549	1059.81		
Chi-Square: 62165.5364***				
1 cells (6.25%) have expected frequencies less than 5.				
The minimum expected cell frequency is 0.38.				

Figure 11 – Triadic Census

## 2.2 Subtask 2

As expected, the largest (**weak**) **component** is the whole graph. The result corresponds to the one we have established in the Subtask 1 because there is no distinction between weak and strong components in undirected graphs.



```
3. Weak Components of N1 [ >=1 ] (35)
=====
Dimension: 35
The lowest value: 1
The highest value: 1

Frequency distribution of cluster values:

  Cluster      Freq    Freq%    CumFreq  CumFreq% Representative
-----
          1         35  100.0000         35  100.0000 Madero, Francisco
-----
        Sum         35  100.0000
```

Figure 12 – Triadic Census

Now, we are to compute the **standard importance measures** of the largest component — the network itself — and rank nodes in accordance with their centrality values.

High **betweenness** indicates an actor who is on many paths between other actors. The higher the value, the more powerful the actor is. In our case, with the betweenness value amounting to 0.2303, the most powerful actor is Miguel Alemán Valdés. The second best is Lázaro Cárdenas, whose score is lower by 0.0732 points (Figure 13).

The **closeness centrality** of a node measures its average farness (inverse distance) to all other nodes. The highest value equals 0.6667, while the lowest amounts to 0.3864. Thus, as expected, the node with the shortest distances to all other nodes is Miguel Alemán Valdés, whereas Lázaro Cárdenas is a few points behind him (Figure 14).

**Freeman’s degree centrality** shows the number of connections that the political elites have. Having direct contact with 17 actors, Miguel Alemán Valdés is the most central node. Following Miguel Alemán Valdés with 13 ties, Adolfo Ruiz Cortines ranks second.

1. Betweenness centrality in N1 (35)						
Dimension: 35						
The lowest value:		0.0000				
The highest value:		0.2302				
Highest values:						
Rank	Vertex	Value	Id			
1	12	0.2302	Aleman Valdes, Miguel			
2	10	0.1570	Cardenas, Lazaro			
3	18	0.1316	Ruiz Cortines, Adolfo			
4	20	0.0896	Margain, Hugo B.			
5	31	0.0649	Salinas Lozano, Raul			
6	23	0.0598	Carrillo Flores, Antonio			
7	14	0.0582	Beteta, Ramon			
8	7	0.0389	Portes Gil, Emilio			
9	19	0.0353	Lopez Mateos, Adolfo			
10	2	0.0309	Carranza, Venustiano			
Sum (all values):		1.1729				
Arithmetic mean:		0.0335				
Median:		0.0160				
Standard deviation:		0.0487				
2.5% Quantile:		0.0019				
5.0% Quantile:		0.0026				
95.0% Quantile:		0.1392				
97.5% Quantile:		0.1680				
Vector Values		Frequency	Freq%	CumFreq	CumFreq%	
(	...	0.0000]	1	2.8571	1	2.8571
(	0.0000	...	30	85.7143	31	88.5714
(	0.0767	...	2	5.7143	33	94.2857
(	0.1535	...	2	5.7143	35	100.0000
Total			35	100.0000		

Figure 13 – Betweenness Centrality

4. All closeness centrality in N1 (35)

Dimension: 35

The lowest value:0.3864

The highest value:0.6667

Highest values:

Rank	Vertex	Value	Id
1	12	0.6667	Aleman Valdes, Miguel
2	10	0.5862	Cardenas, Lazaro
3	23	0.5763	Carrillo Flores, Antonio
4	18	0.5667	Ruiz Cortines, Adolfo
5	31	0.5484	Salinas Lozano, Raul
6	20	0.5484	Margain, Hugo B.
7	14	0.5397	Beteta, Ramon
8	19	0.5313	Lopez Mateos, Adolfo
9	28	0.5231	Ortiz Mena, Antonio
10	11	0.5231	Avila Camacho, Manuel

Sum (all values):16.8776

Arithmetic mean:0.4822

Median:0.4722

Standard deviation:0.0615

2.5% Quantile:0.3864

5.0% Quantile:0.3959

95.0% Quantile:0.5793

97.5% Quantile:0.5983

Vector Values	Frequency	Freq%	CumFreq	CumFreq%
( ... 0.3864]	0	0.0000	0	0.0000
( 0.3864 ... 0.4798]	20	57.1429	20	57.1429
( 0.4798 ... 0.5732]	12	34.2857	32	91.4286
( 0.5732 ... 0.6667]	3	8.5714	35	100.0000
Total	35	100.0000		

Figure 14 – Closeness Centrality

5. All Degree of N1 (35)					
=====					
Dimension: 35					
The lowest value:		2.0000			
The highest value:		17.0000			
Highest values:					
Rank	Vertex	Value	Id		
-----					
1	12	17.0000	Aleman Valdes, Miguel		
2	18	13.0000	Ruiz Cortines, Adolfo		
3	10	12.0000	Cardenas, Lazaro		
4	20	12.0000	Margain, Hugo B.		
5	23	11.0000	Carrillo Flores, Antonio		
6	31	10.0000	Salinas Lozano, Raul		
7	19	10.0000	Lopez Mateos, Adolfo		
8	7	8.0000	Portes Gil, Emilio		
9	28	8.0000	Ortiz Mena, Antonio		
10	2	8.0000	Carranza, Venustiano		
-----					
Sum (all values):		234.0000			
Arithmetic mean:		6.6857			
Median:		6.0000			
Standard deviation:		3.2669			
2.5% Quantile:		2.8500			
5.0% Quantile:		3.0000			
95.0% Quantile:		12.3000			
97.5% Quantile:		13.6000			
-----					
Vector Values		Frequency	Freq%	CumFreq CumFreq%	
-----					
(	...	2.0000]	1	2.8571	1 2.8571
(	2.0000 ...	3.0000]	5	14.2857	6 17.1429
(	3.0000 ...	4.0000]	2	5.7143	8 22.8571
(	4.0000 ...	5.0000]	6	17.1429	14 40.0000
(	5.0000 ...	6.0000]	7	20.0000	21 60.0000
(	6.0000 ...	7.0000]	4	11.4286	25 71.4286
(	7.0000 ...	8.0000]	3	8.5714	28 80.0000
(	8.0000 ...	9.0000]	0	0.0000	28 80.0000
(	9.0000 ...	10.0000]	2	5.7143	30 85.7143
(	10.0000 ...	11.0000]	1	2.8571	31 88.5714
(	11.0000 ...	12.0000]	2	5.7143	33 94.2857
(	12.0000 ...	13.0000]	1	2.8571	34 97.1429
(	13.0000 ...	14.0000]	0	0.0000	34 97.1429
(	14.0000 ...	15.0000]	0	0.0000	34 97.1429
(	15.0000 ...	16.0000]	0	0.0000	34 97.1429
(	16.0000 ...	17.0000]	1	2.8571	35 100.0000
-----					
Total		35	100.0000		

Figure 15 – All Degree Centrality

Let us plot the network, partitioned by the degree centrality measure (Figure 16).

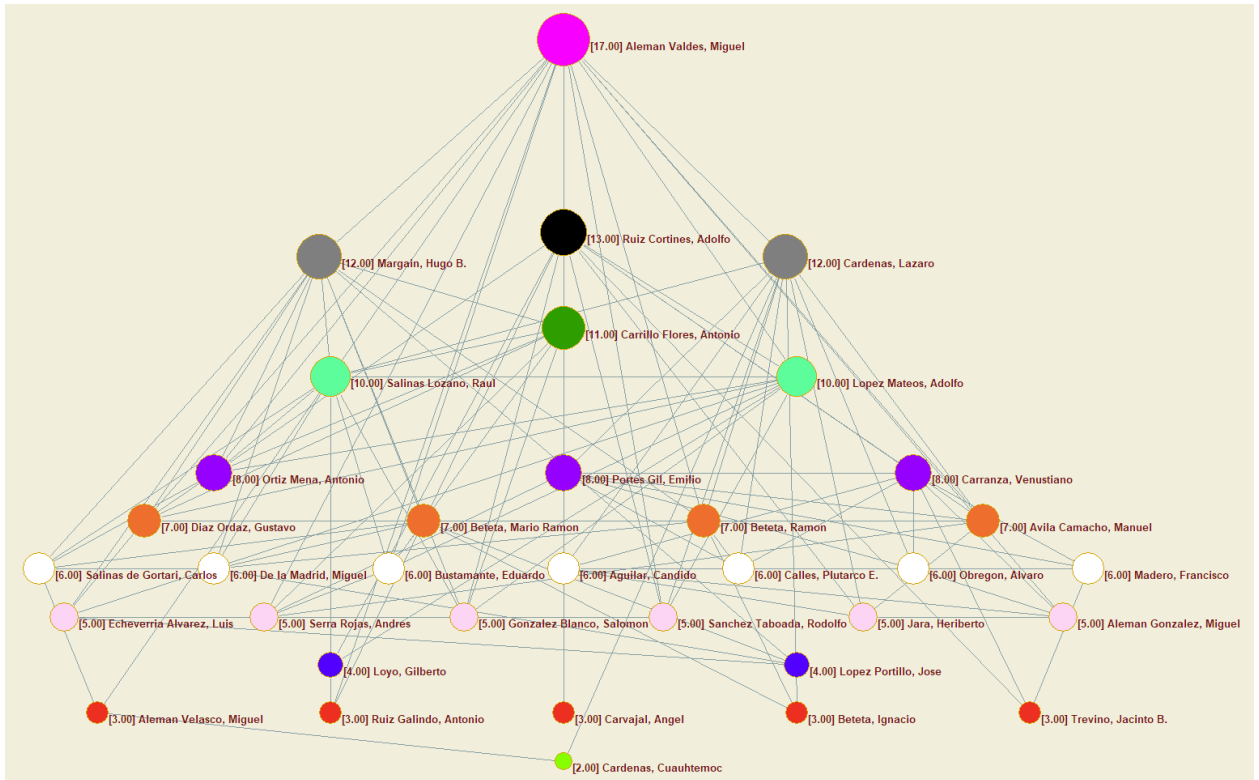


Figure 16 – All Degree Centrality

In this layout, the vertex with the highest degree value is at the top, whereas the least central ones are positioned below. The nodes are coloured according to their degree values as well.

As can be seen, the most common degree value is 6 (7 actors), while the most unique ones are 2, 11, 13, 17. With only two connections present, Cuauhtémoc Cárdenas is the least central node, whereas positioned at the very top, Miguel Alemán Valdés is the most powerful one.



## 2.3 Subtask 3

Now, let us determine the cores in our network (Figure 17).

6. All core partition of N1 (35)					
Dimension: 35					
The lowest value: 2					
The highest value: 5					
Frequency distribution of cluster values:					
Cluster	Freq	Freq%	CumFreq	CumFreq%	Representative
2	2	5.7143	2	5.7143	Aleman Velasco, Miguel
3	5	14.2857	7	20.0000	Trevino, Jacinto B.
4	3	8.5714	10	28.5714	Sanchez Taboada, Rodolfo
5	25	71.4286	35	100.0000	Madero, Francisco
Sum	35	100.0000			

Figure 17 – All core partition

**Coreness** is a measure that can help identify tightly interlinked groups within a network. A **k-core** is a maximal group of entities, all of which are connected to at least  $k$  other entities in the group. In the  $k$ -core, each actor is connected to at least  $k$  other actors. The given network contains a large 5-core (25 vertices). In addition, there is a 2-core (2 vertices), a 3-core (5 vertices), and a 4-core (3 vertices).

Given that the 5-core is the one, we can conclude that the actors in our network entertain close ties with a large group of people: 71.42 per cent of the members of the elites socialise with at least 5 other political actors.

The plot of the largest core is shown below.

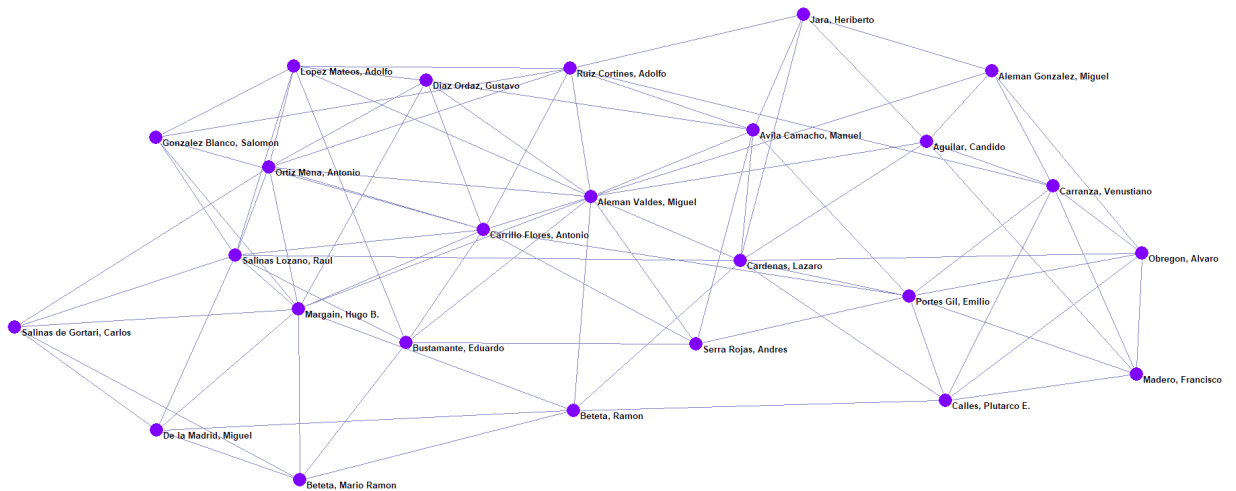


Figure 18 – The plot of the largest core

## 2.4 Subtask 4

Now we have to use an **island approach** to determine some link islands in the network.

By definition, an **island** is a subnetwork of vertices connected directly or indirectly by lines with a value greater than the lines to vertices outside the subnetwork [5]. So, to successfully apply this approach we need to measure the values of links in the network. To do so, we may use the 3-rings method.

**3-rings** method means that the ring counts are stored as line values — how many times each line belongs to 3-rings. In Pajek, we select **Create New Network > with Ring Counts stored as Line Values > 3-Rings > Undirected**. The result is on the figure below.

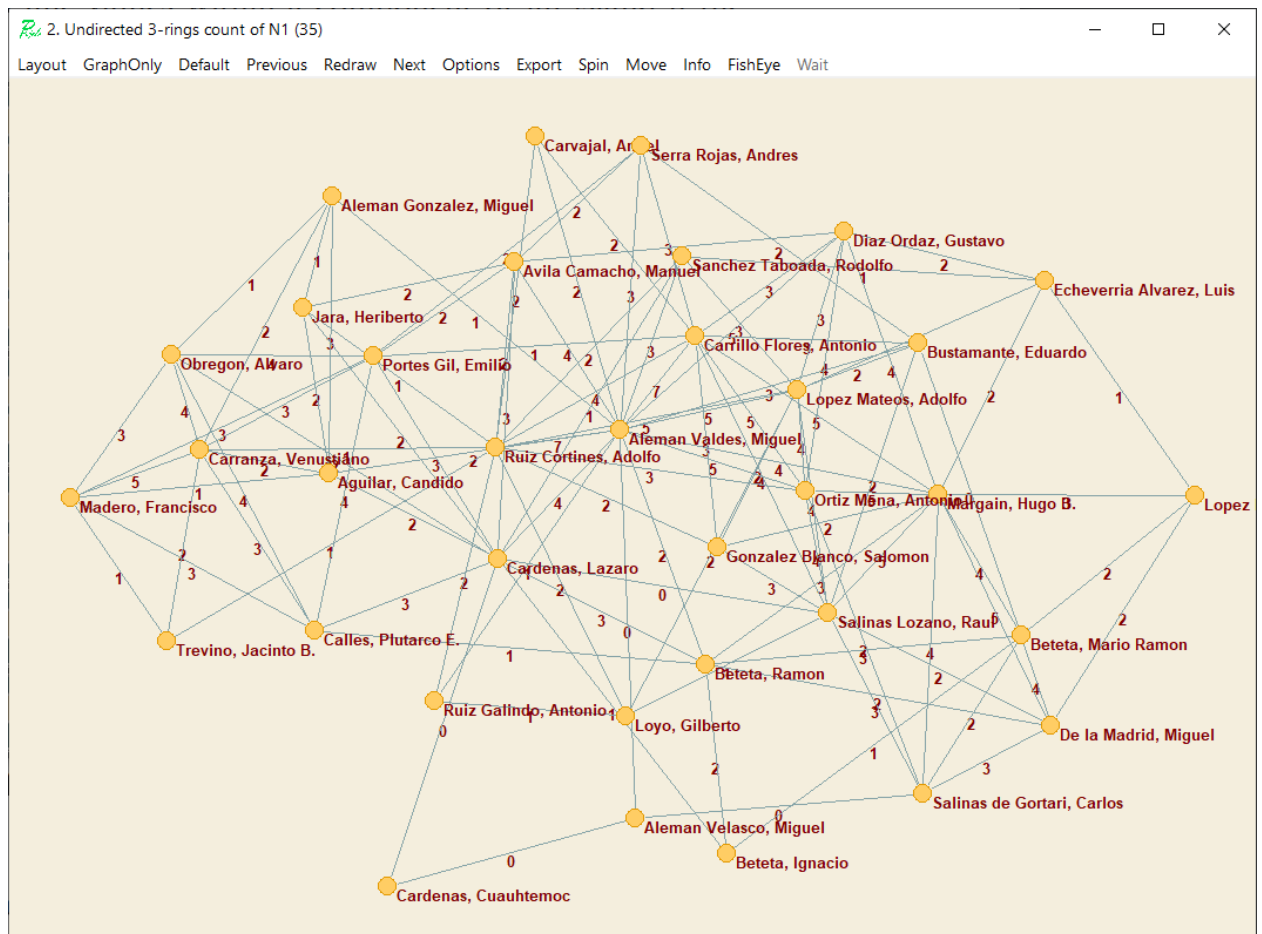


Figure 19 – Weighted network

Next, we should try and determine some link islands in the network. To select islands, we have to specify the **maximum size** of it. Depending on this, the number of islands varies. First, we select 10, and then the number will be increased to 18.

### 2.4.1 Maximum Size 18

Firstly, we create a weighted network (**Create New Network > with Ring Counts stored as Line Values > 3-Rings > Undirected**). Then we enable **Generate Network with Islands** and select **Network > Create Partition > Islands > Line Weights, Maximum Size – 18, Minimum Size – 2** (Figure 20-21). Next, we remove isolated vertices (**Network > Create Partition > Degree > All, Operations > Network + Partition > Extract > SubNetwork Induced by Union of Selected Clusters**).

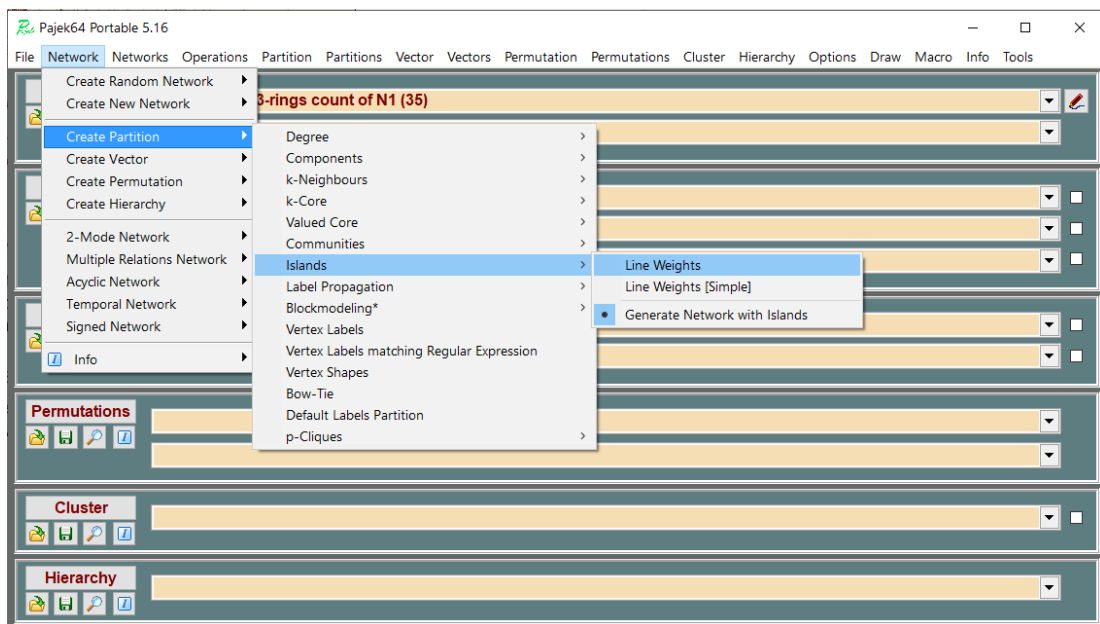


Figure 20 – Generate Islands

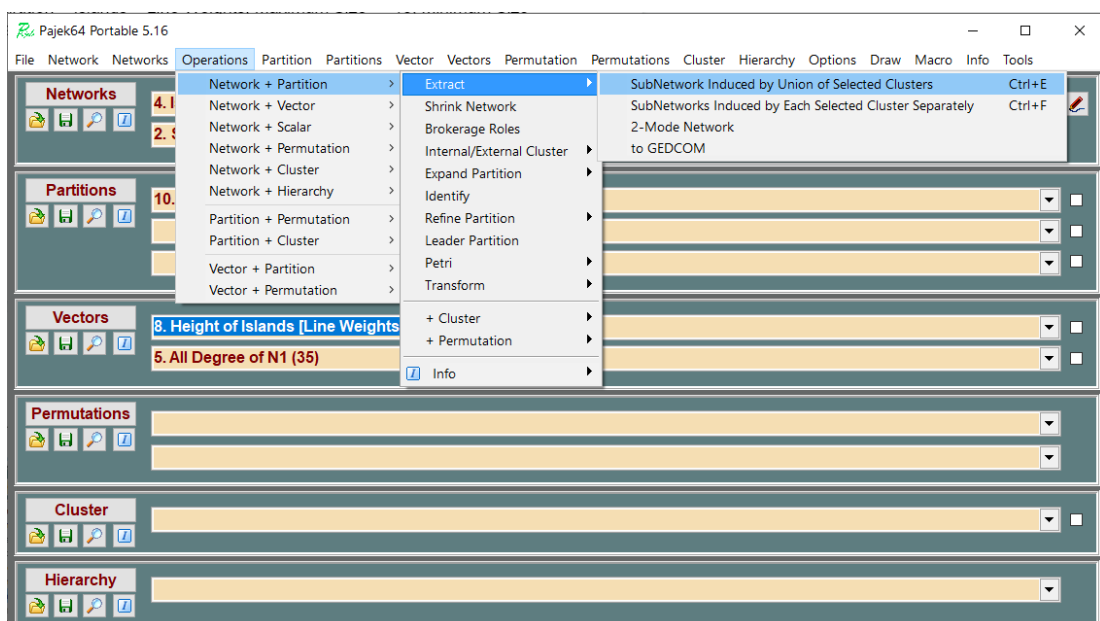


Figure 21 – Remove isolated vertices

After all, we can get a very nice diagram by drawing **Network + First Partition** and selecting **Separate Components**.

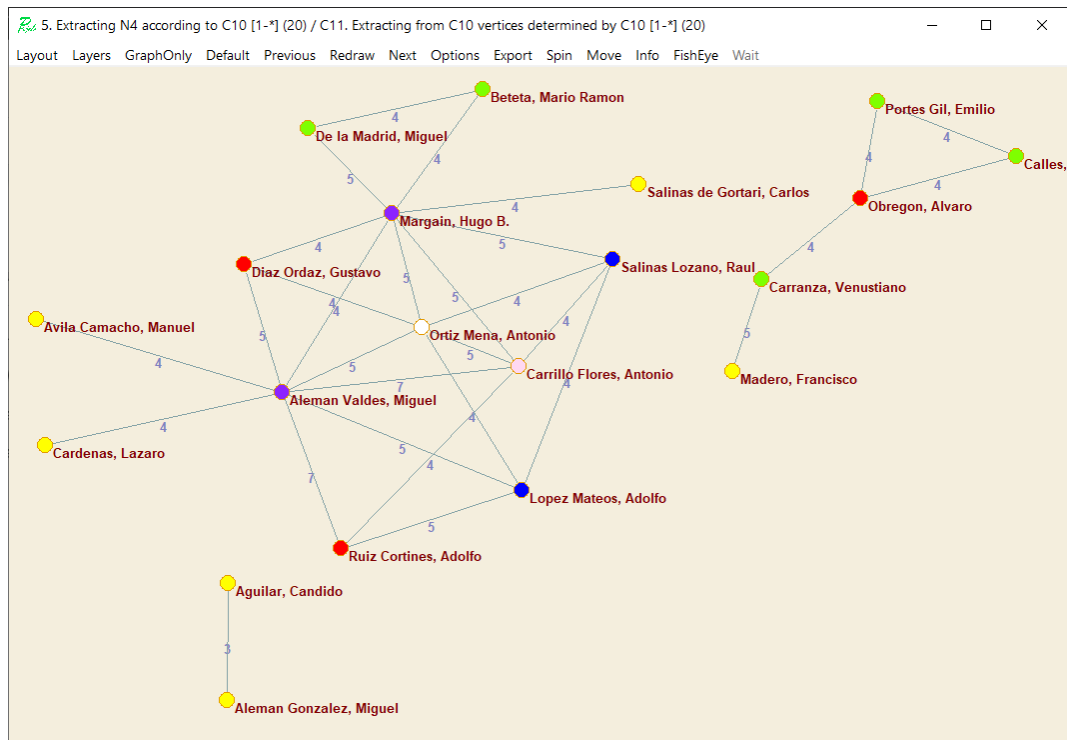


Figure 22 – Generated Islands

What we see is **three islands**, and colours in this case represent the **height of each vertex** (for example, white one is the highest point of the island). The big island contains **13 vertices**, and two others — **2 and 5 vertices** (Figure 23).

```

=====
9. Islands [Line Weights] in N3 [2,18] (35, Islands=3)
=====
Dimension: 35
The lowest value: 0
The highest value: 3

Frequency distribution of cluster values:

```

Cluster	Freq	Freq%	CumFreq	CumFreq%	Representative
0	15	42.8571	15	42.8571	6
1	2	5.7143	17	48.5714	5
2	13	37.1429	30	85.7143	10
3	5	14.2857	35	100.0000	1
Sum	35	100.0000			

Figure 23 – Islands

In order to interpret the picture, we should apply given **attributes** to the network (military/civilians and year). For doing that, we have to **cut unused items** from **mexican\_year.clu** and **mexican\_military.clu** partitions (add islands partition as the second one and select **Partitions > Extract SubPartition (Second from**

**First).** Also we copy the year partition to a vector, thus we can add these values to vertex labels: **Options > Mark Vertices Using > Vector Values**).

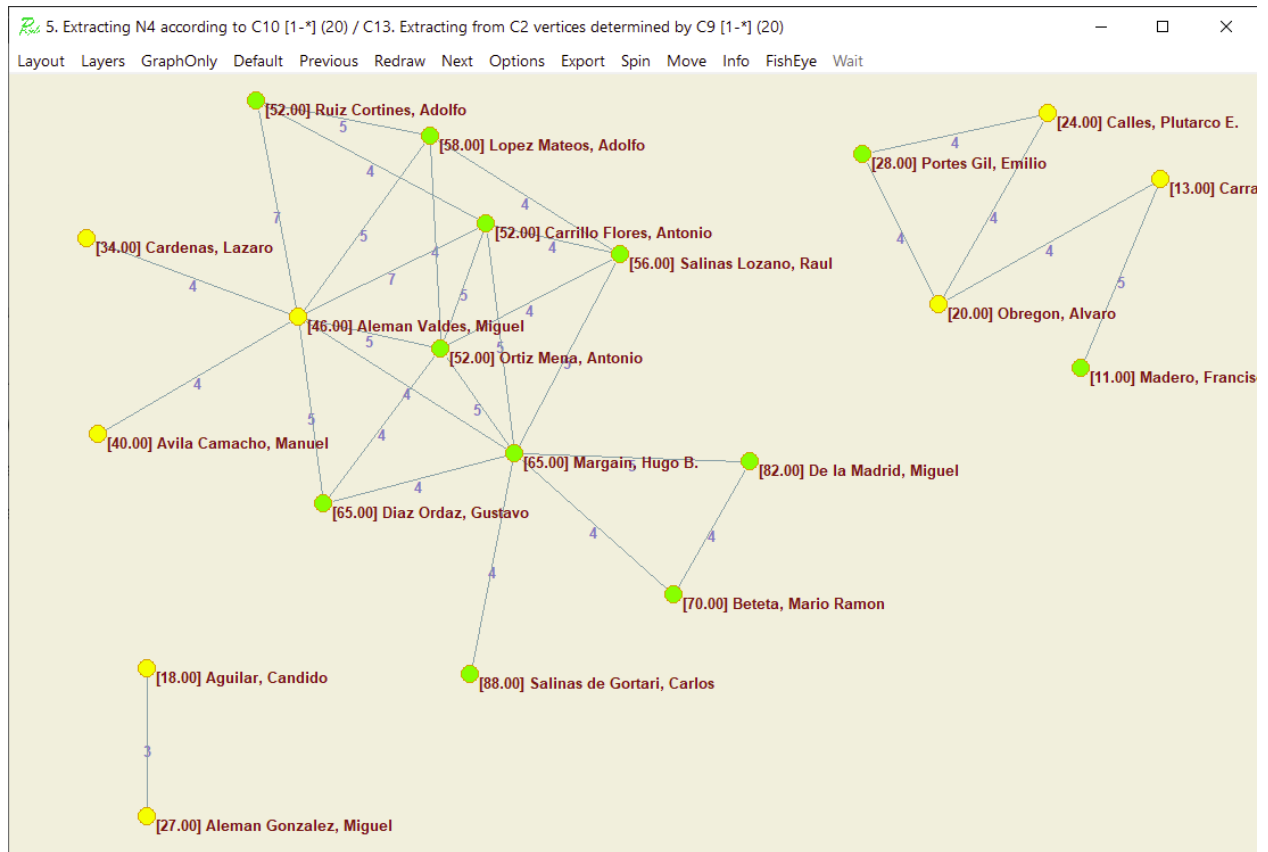


Figure 24 – Islands with attributes

Here we see that the big island consists **mostly of civilians** (green colour), so those civilian actors form a cohesive group with links of significant values. Also this island is mostly constructed of people who were active in the **second half of the century**, as can be observed from the labels.

The island of size 5 consists of three military and two civilian actors, all of whom were active **between 1911 and 1928**. So it may be suggested that during that time such a mixed group was active.

The island of size 2 is not particularly informative.

### 2.4.2 Maximum Size 10

Let's reduce the maximum size of an island to 10. Create new islands with **Network > Create Partition > Islands > Line Weights, Maximum Size – 10, Minimum Size – 2**. Also we remove isolated vertices (**Network > Create Partition > Degree > All, Operations > Network + Partition > Extract > SubNetwork Induced by Union of Selected Clusters**). The result is on the figure below.

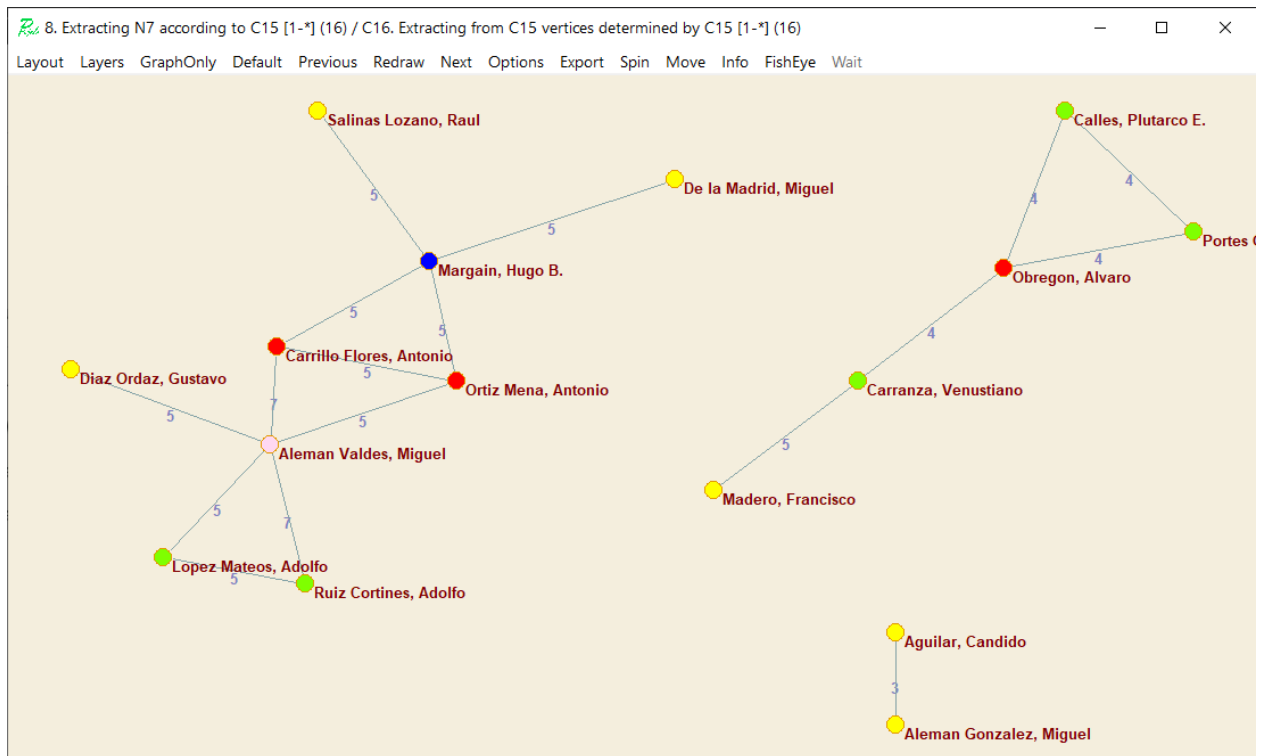


Figure 25 – Generated Islands

Again, we should apply attributes to the islands (Figure 26).

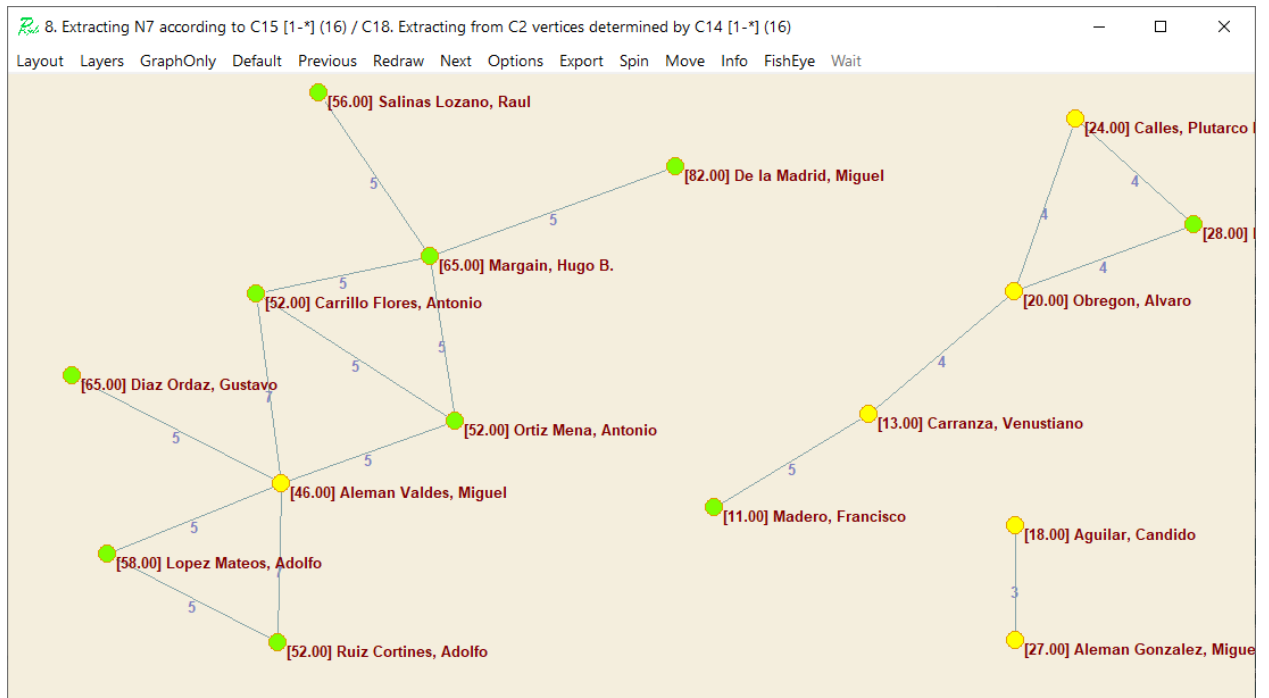


Figure 26 – Islands with attributes

As might be seen, two small islands did not change, and the biggest island now contains only **9 vertices**. They are **mostly civilians**, except one (with the most height).

This version of the island is **more coherent** than in the previous case, and here we may see that all actors have been active **since 1946** (after World War II). Furthermore, this island might have been “started” with the military person *Aleman Valdes* (1946), as he is in the middle of the island, and all other actors who performed later are directly or indirectly connected to him.

## 2.5 Subtask 5

Now we need to make a **line-cut** of the network. Line-cut is another useful technique for **extracting parts of a network** where only lines (and their vertices) above a certain value are retained [6]. In other words, we select only those parts of the network where values of lines are above a certain threshold, and those parts are probably of more importance than others.

To do so in Pajek, we start with the **weighted network** from the previous step and select **Network > Create New Network > Transform > Remove > Lines with Value > lower than**. But before we start, it is useful to analyse what **line values** are present in the network (**Network > Info > Line Values**, Figure 27).

3. Undirected 3-rings count of N1 (35)						
Lowest value of line:		0.00000000				
Highest value of line:		7.00000000				
Line Values			Frequency	Freq%	CumFreq	CumFreq%
(	...	0.0000]	6	5.1282	6	5.1282
(	0.0000 ...	1.0000]	19	16.2393	25	21.3675
(	1.0000 ...	2.0000]	37	31.6239	62	52.9915
(	2.0000 ...	3.0000]	26	22.2222	88	75.2137
(	3.0000 ...	4.0000]	17	14.5299	105	89.7436
(	4.0000 ...	5.0000]	10	8.5470	115	98.2906
(	5.0000 ...	6.0000]	0	0.0000	115	98.2906
(	6.0000 ...	7.0000]	2	1.7094	117	100.0000
Total			117	100.0000		

Figure 27 – Line Values

As we see, lines with values from 0 to 2 form 52% of the network, so to get more important half of it, we may cut starting with value 3.



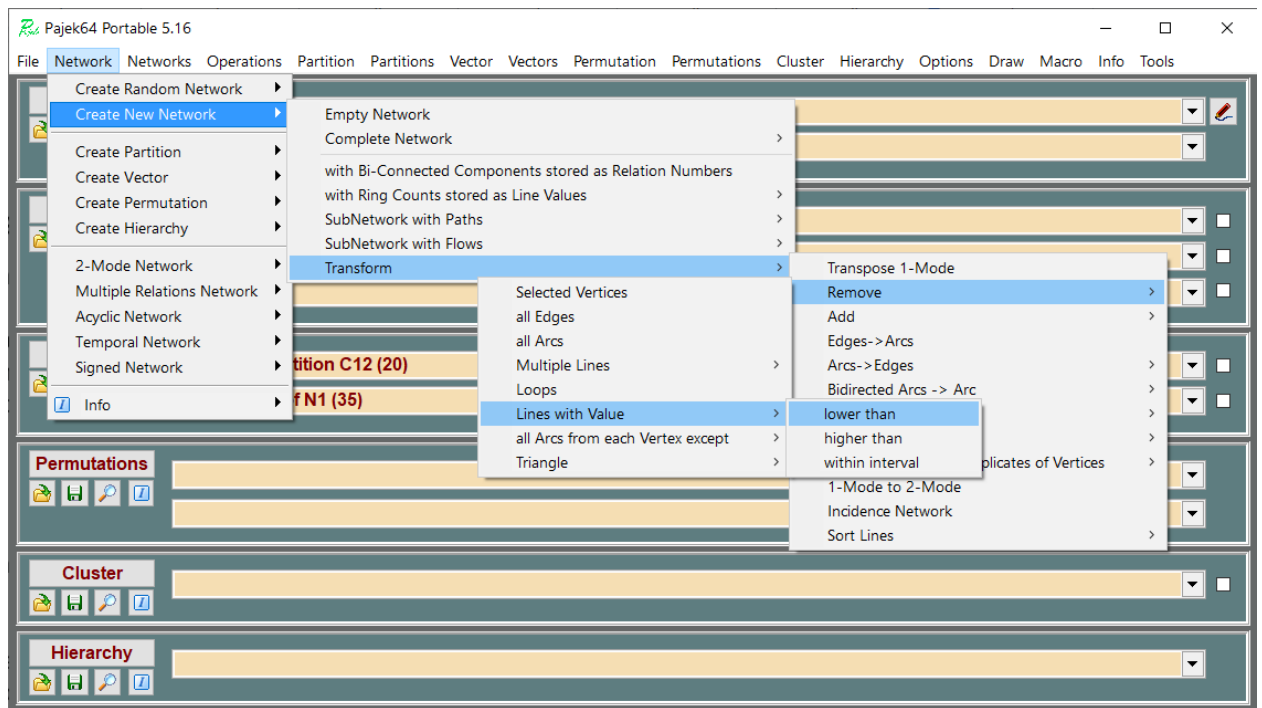


Figure 28 – Line-cut

After applying attributes, we see that the separated part of the network is rather massive. It contains mostly civilians, however, all military actors are connected with each other. It also could be noticed that years are increasing from right to left, specifically on the left there is a well-connected group of vertices (in a star shape) with year varying between 1911 and 1928. In fact, this group has already been observed before, as it is an island.

9. Removed lines with values lower than 3.0000 in N3 (35) / C2. mexican\_military.du (35)

Layout Layers GraphOnly Default Previous Redraw Next Options Export Spin Move Info FishEye Wait

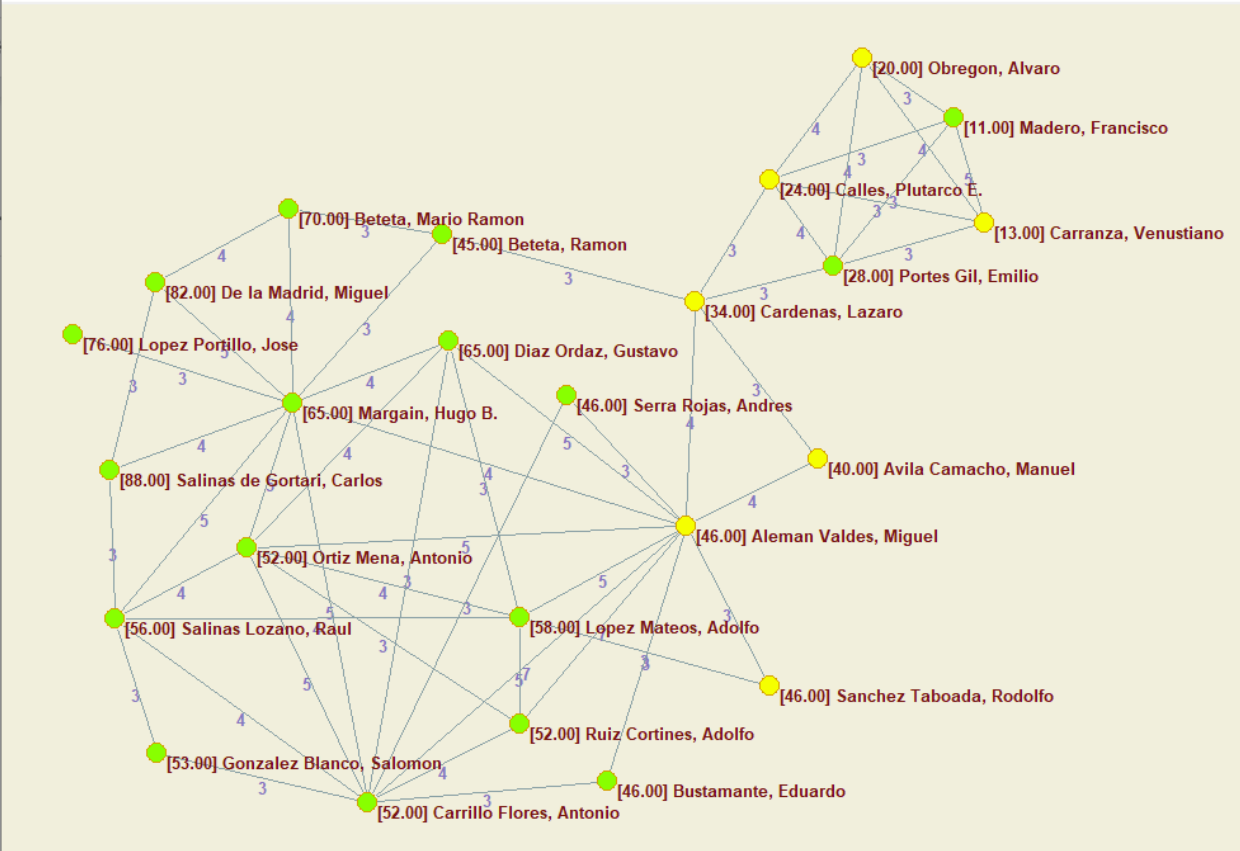


Figure 29 – The result of line-cut of 3

Let's cut further and select the threshold of 4.

10. Removed lines with values lower than 4.0000 in N3 (35) / C2. mexican\_military.du (35)

Layout Layers GraphOnly Default Previous Redraw Next Options Export Spin Move Info FishEye Wait

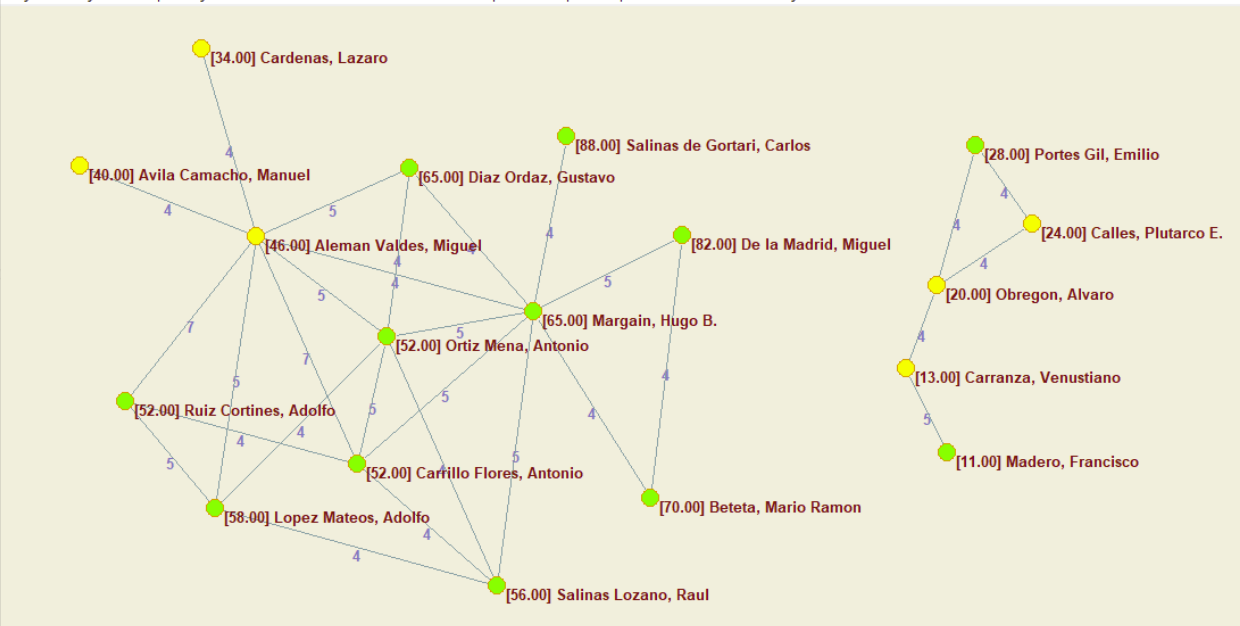


Figure 30 – The result of line-cut of 4

Now the smaller island is separated from the bigger one, and the number of vertices decreased as well. In fact, the big one is similar to the big island we discussed earlier. So we may conclude that in our case **line-cut works similarly to the island approach**.

Additionally, if we remove isolated vertices from the line-cut network, we can limit the property partitions by doing the following. **Select All degree partition, then Partition > Binarize partition**. Then Extract SubPartition and copy the result to vector.

## 2.6 Subtask 6

## References

- [1] Jurgen Pfeffer and Linton C. Freeman. Social Network Visualization, Methods of, pages 1–25. Springer Berlin Heidelberg, Berlin, Heidelberg, 2019.
- [2] Vladimir Batagelj. First steps to network visualization with pajek. <http://vlado.fmf.uni-lj.si/pub/networks/pajek/howto/FirstSteps.PDF>, May 2002.
- [3] Andrej Mrvar and Vladimir Batagelj. Programs for Analysis and Visualization of Very Large Networks. Reference Manual List of commands with short explanation. University of Ljubljana, Slovenia, version 5.16 edition, 2022.
- [4] Vladimir Batagelj. Pajek workshop. <http://pierreferancois.wifeo.com/documents/Tutoriel-Pajek---Slide-1.pdf>, March 2009.
- [5] Wouter De Nooy, Andrej Mrvar, and Vladimir Batagelj. Exploratory Social Network Analysis with Pajek: Revised and Expanded Edition for Updated Software. Structural Analysis in the Social Sciences. Cambridge University Press, 3 edition, 2018.
- [6] Vladimir Batagelj, Patrick Doreian, Anuska Ferligoj, and Natasa Kejzar. Line Cuts, page 139–141. John Wiley & Sons, 2014.