Project Title

Name1 Surname1, Degree Programme, ID number (matricola)
Name2 Surname2, Degree Programme, ID number (matricola)

1 Introduction

The context includes: the general field (e.g., literature, history, archaeology, tourism, biology, forensics, religious studies); the specific application (e.g., literary analysis, quantitative history, genetics, virology, forensics intelligence, tourism planning, biblical quantitative studies).

2 Problem and Motivation

What are the problems you want to address? Why are those problems important (impact, theoretical and/or practical needs, etc.)? What are the main contributions of the project?

3 Datasets

How did you gather the data? Did you digitise it? How? Is the material publicly available? What tools did you use 1) to handle (store, manipulate) the data and 2) to compute measures on the data?

3.1 London Gang Network Dataset

The primary dataset used for this analysis is the **London Gang Network**. The data was gathered from a public academic repository widely used for social network analysis, hosted by the UCINET Software project.
The material is publicly available and was accessed from the following URL: [1].

3.1.1 Digitisation and Data Handling

The dataset was already available in a digital format; no manual digitization was required. For the purpose of this study, the data was formatted as a CSV file (`LONDON_GANG.csv`), representing the adjacency matrix of the network (comprising 54 nodes). A corresponding attribute file, `LONDON_GANG_ATTR.csv`, provides node-level data for each member. These attributes include `Age`, `Birthplace`, `Residence`, `Arrests`, `Convictions`, `Prison`, `Music`, and `Ranking`. For the purpose of this study, only the **Birthplace** attribute was utilized. This decision was based on it being the sole common attribute available for both the London network and the Italian network. For **1) handling and manipulating** the data, the **Python** programming language was used, specifically the `pandas` library. The `pandas.read_csv` function was employed to load the adjacency matrix into a DataFrame structure.

3.1.2 Computing Measures

For **2) computing measures** on the data, the Python library `NetworkX` was used.
The `pandas` DataFrame (containing the adjacency matrix) was converted into a `NetworkX` graph object using the `nx.from_pandas_adjacency` function. This graph object then served as the foundation for computing all measures.

[1] `https://sites.google.com/site/ucinetsoftware/datasets/covert-networks/london-gang`

4 Validity and Reliability

How closely does the model of your dataset represent reality (validity)? How does the way you treat the data affect the reproducibility of the study (reliability)?

4.1 London Gang Network Dataset

4.1.1 Validity (Representation of Reality)

The model of the dataset—a graph of 54 nodes and 315 edges—is a structural abstraction of a complex, real-world social system. The validity, or how closely this model represents reality, is subject to several key considerations:

- **Incompleteness of Covert Data:** The dataset maps a "covert network." By definition, such networks are hidden. The data (likely sourced from surveillance or police records) is almost certainly an incomplete snapshot. We must assume that some real-world relationships were unobserved and are missing from the model.
- **Static vs. Dynamic Reality:** The dataset represents the network at a single point in time. Real-world social structures are dynamic, with ties forming, dissolving, and changing in strength. Our model does not capture this temporal evolution.
- **Unweighted Analysis of Weighted Data:** The source data is weighted (with values such as 1, 2, and 3), likely representing the frequency or strength of the relationship. In our analysis, we employed standard, unweighted measures (e.g., `nx.density`, `nx.diameter`, `nx.degree_centrality`). This was an intentional choice to focus purely on the **topological structure**, but it is a significant simplification. The model treats a strong, frequent bond as equivalent to a weak, infrequent one, which impacts the real-world interpretation of influence and cohesion.

In summary, the model is a valid (as it is academically vetted) but simplified, static, and unweighted representation of the network's topology, not a complete or dynamic reflection of its real-world social complexity.

4.1.2 Reliability (Reproducibility)

The reliability of this study—the ability for another researcher to reproduce the exact same results—is **high**. This is ensured by the methodology used to treat the data:

- **Public Data:** The dataset was sourced from a stable, public, and citable URL. Any researcher can access the exact same source file (`LONDON_GANG.csv`), eliminating data collection as a variable.
- **Open-Source, Deterministic Tools:** The entire analysis was conducted using open-source Python libraries (`pandas` and `NetworkX`). The functions used for calculating measures (`nx.density`, `nx.betweenness_centrality`, etc.) are deterministic. Given the same input graph, they will produce the identical output every time.
- **Transparent Workflow:** The data treatment was minimal and explicit: loading the CSV via `pandas`, handling indices, converting it to a `NetworkX` graph, and applying specific functions. This step-by-step process can be scripted and shared, ensuring perfect reproducibility.

5 Measures and Results

What measures did you apply (brief explanation of how they work)? How do they relate to the intent of the study? Why are they relevant? What is the connection among the gathered data, the applied measures, and the properties found?

MAYBE WE SHOULD INCLUDE THE MATHEMATICAL FORMULAS OF THE METRICS

For both the italian and London gang, we study the same metrics and compare them. In fact, we start by studying **general structural metrics**. These include:

- density which is the ratio between existing ties and all possible ties and measures cohesian (high density means that communication is easier and that there is lower vulnerability to central node removal);
- average degree which is defined as the average number of connections per node and indicates member activity and level of engagement;
- network diameter and average path length which are respectively the maximum and average length of paths between nodes and are able to measure the network's efficiency in transmitting information or orders;
- clustering coefficient which corresponds to the probability that a node's neighbors are connected to each other and highlights closed subgroups or internal "cells", it is useful for understanding resilience and community;
- modularity which measures the presence of well-defined internal communities and can reveal internal divisions and possible subgroups or cliques.

Besides, we study **centrality metrics**. In particular, we focus on:

- degree centrality which is based on the number of direct connections a node has and is useful to identify the most active or influential members of the network;
- betweeness centrality which is the number of times a node lies on the shortest paths between other nodes and highlights brokers or gatekeepers (nodes critical for the flow of information);
- closeness centrality which is defined as the reciprocal of the sum of a node's distances to all other nodes. A node close to all others can quickly spread information or orders;
- eigenvector centrality. This metric defines importance by being connected to other important nodes and highlights leaders recognized by the most influential members.

Finally, we study the roles and vulnerability based on the metrics calculated previously we aim to identify key roles like leader, broker and peripheral members. We use a combination of centrality, degree, betweeness and clustering to identify who in the network leads, mediates between subgroups and remains peripheral.

We define leaders as the nodes that have both degree and eigenvector centrality values among the top 5% of all nodes: leaders are both broadly connected (high degree) and well positioned

near other influential nodes (high eigenvector). Brokers are those that fall within the top 5% for betweenness centrality, meaning they often act as bridges between different parts of the network. Peripherals are nodes in the bottom 5% for degree centrality, indicating that they have few connections and limited influence within the network.

We also study the k-core and core-periphery structure to inspect implicit hierarchy and concentration of power. A k-core is the part of the network where every node has at least k connections to other nodes within that part. We computed core numbers for all nodes and identified the main core - the highest k that still has nodes. The main core has k equal to the maximum core number in the network, and we report how many nodes it contains (out of the total) and list which nodes belong to it."

We study the cohesion and network robustness by studying metrics like density, average path length and k-core decompostion in a network where the central nodes have been removed and compare them to the values of the original network to study the impact of removing central nodes.

At last, in order to explore how ethnic background influences the internal structure of both the Italian and London gang networks, we conduct a series of **attribute-based network analyses** focusing on the *Birthplace* variable.

The objective is to determine whether individuals tend to associate mainly with others of the same national origin ethnic homophily or whether the networks exhibit patterns of cross-ethnic integration.
We use the following key-metrics:

- **Assortativity coefficient and mixing matrix**: to quantify the extent of homophily by *Birthplace* and to visualize how frequently connections occur within or between different nationality groups.
- **Centrality measures (degree, betweenness, eigenvector)**: to identify whether specific ethnic groups occupy more central or influential structural positions in the network.
- **Community composition and diversity**: communities were detected using a modularity-based algorithm, and their ethnic heterogeneity was assessed through the **Shannon Diversity Index** (H), which measures the balance and variety of nationalities within each community. To quantify this diversity, the Shannon index was computed as:

  $$H = -\sum_i p_i \log(p_i)$$

  where p_i represents the proportion of members from group i within a community. Higher H values indicate more ethnically diverse communities.
- **Inter-group connectivity**: calculated as the proportion of edges linking individuals of different *Birthplace* categories, indicating the level of cross-ethnic interaction.
- **Subgraph analysis by Birthplace**: used to evaluate the internal cohesion of each nationality group in terms of network density and clustering coefficient.

It is worth noting that the italian network is not connected, and therefore the network diameter and average path length are calculated for the largest connected component of the network. This is also true when we remove the central nodes.

5.1 Italian gang

5.1.1 Structural analysis

Using the Library Networkx [**?**] from Python we studied different aspects of the italian gang network.
In figure 1 a plot of the network is shown where each node is colored according to its country label.

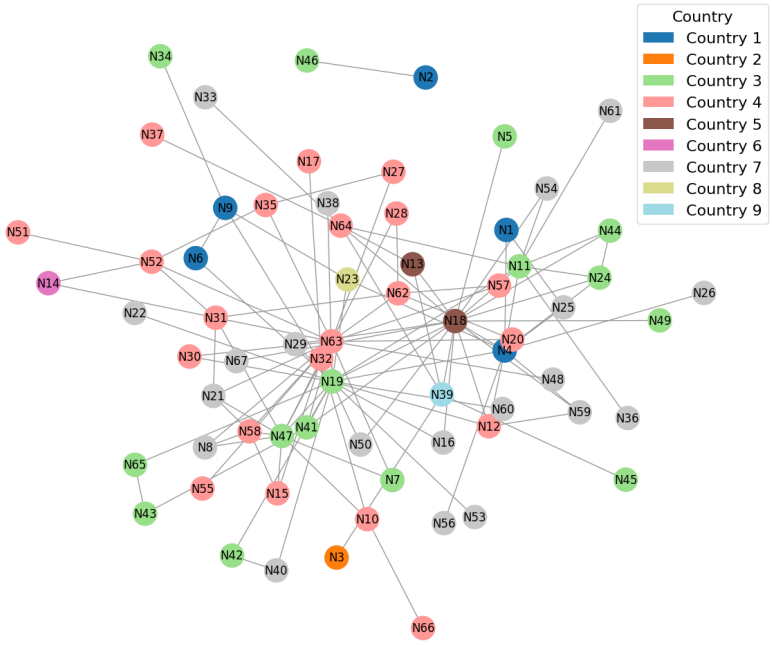


Figure 1: Italian Network graph visualization. Each node is colored according to its country label

5.1.2 Ethnicity analysis

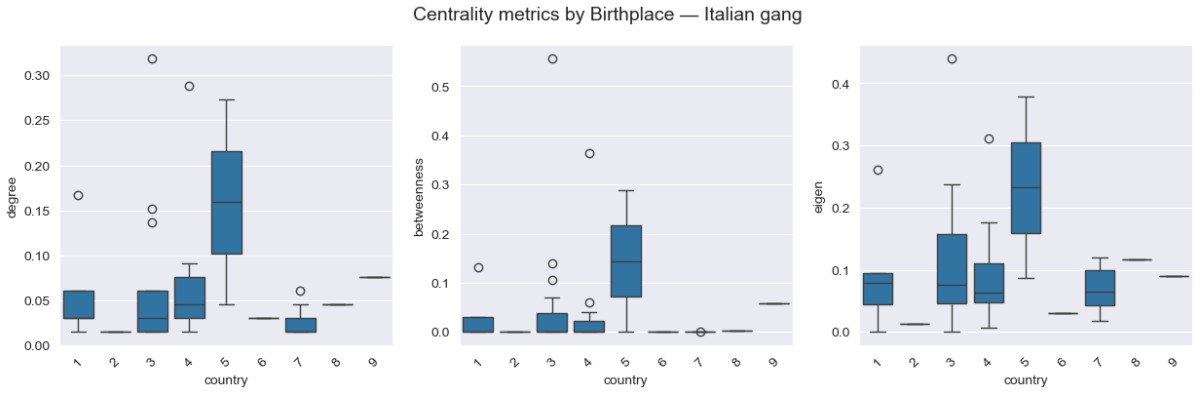
The analysis of the Italian gang network shows a **moderate tendency toward ethnic homophily**, with an assortativity coefficient of 0.150. This value suggests that individuals show a slight preference for connecting with others sharing the same *Birthplace*, though overall the network remains relatively integrated.

The **mixing matrix** confirms this trend: while several diagonal values (e.g., for groups 3, 4, and 5) are higher (indicating intra-group cohesion) many off-diagonal entries are also non-negligible. This demonstrates a considerable number of **cross-national connections**, supporting the idea of partial ethnic mixing.

Table 1: Mean centrality by Birthplace – Italian gang

	1	2	3	4	5	6	7	8	9
1	0.018	0.000	0.031	0.004	0.004	0.000	0.022	0.009	0.000
2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004
3	0.031	0.000	0.096	0.053	0.031	0.000	0.061	0.004	0.004
4	0.004	0.000	0.053	0.228	0.013	0.009	0.035	0.000	0.004
5	0.004	0.000	0.031	0.013	0.009	0.000	0.026	0.000	0.009
6	0.000	0.000	0.000	0.009	0.000	0.000	0.000	0.000	0.000
7	0.022	0.000	0.061	0.035	0.026	0.000	0.000	0.000	0.000
8	0.009	0.000	0.004	0.000	0.000	0.000	0.000	0.000	0.000
9	0.000	0.004	0.004	0.004	0.009	0.000	0.000	0.000	0.000

When analyzing **centrality measures**, group 5 clearly stands out as the most central and structurally influential, with the highest mean degree (0.159), betweenness (0.144), and eigenvector centrality (0.233). Groups 3 and 9 also exhibit moderate centrality levels, suggesting participation in brokerage or connective roles. In contrast, groups such as 2, 6, and 7 show minimal centrality values, occupying peripheral positions within the network. Overall, influence appears somewhat concentrated but not monopolized by a single nationality.



The **community analysis** identified five major communities. Most of these display mixed ethnic compositions, with only one cluster (community 4) being entirely dominated by two groups (1 and 3). The mean Shannon diversity index ($H = 1.174$) indicates high internal heterogeneity, suggesting that communities are composed of members from multiple national origins rather than segregated along ethnic lines.

Furthermore, 64.91% of all connections occur between individuals of different Birthplace categories, a clear indicator of **strong cross-ethnic integration**. This finding supports the interpretation that ethnic background is not a dominant organizing factor in the structure of the Italian gang.

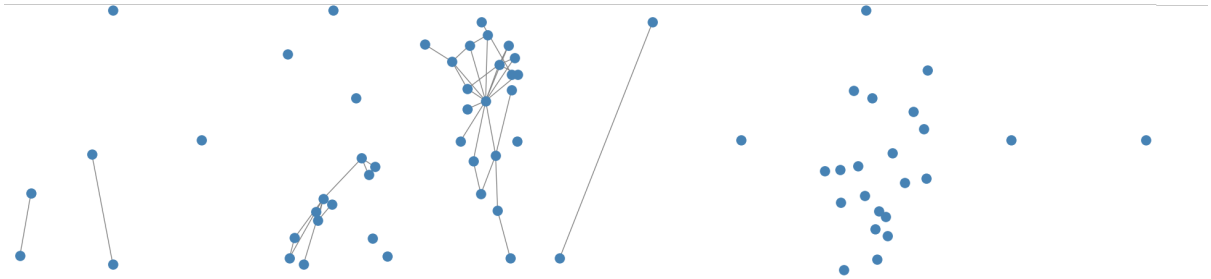
Subgraph analysis by *Birthplace* reveals additional information:

- Group **4** (21 nodes, density = 0.124) forms the largest and most internally cohesive subcommunity.

- Group **5**, although small (2 nodes), is fully interconnected (density = 1.000), representing a tightly bonded dyad.
- Other groups (6, 7, 8, 9) show limited or no internal links, implying **dependence on inter-ethnic ties** for maintaining connectivity.

Table 2: Subgraph-level statistics by Birthplace – Italian gang

Country	Nodes	Edges	Density	Clustering
1	5	2	0.200	0.000
2	1	0	0.000	0.000
3	15	11	0.105	0.156
4	21	26	0.124	0.294
5	2	1	1.000	0.000
6	1	0	0.000	0.000
7	20	0	0.000	0.000
8	1	0	0.000	0.000
9	1	0	0.000	0.000



In summary, the Italian gang exhibits **moderate homophily but high overall integration**, with collaboration patterns largely transcending national divisions. Ethnicity appears to play a **secondary role** in shaping relational dynamics.

5.2 London gang

This section will report the results of the metrics mentioned in 5 regarding the London gang network 54 nodes, 315 edges.
In figure 2 a plot of the network is shown where each node is colored according to its birthplace label.

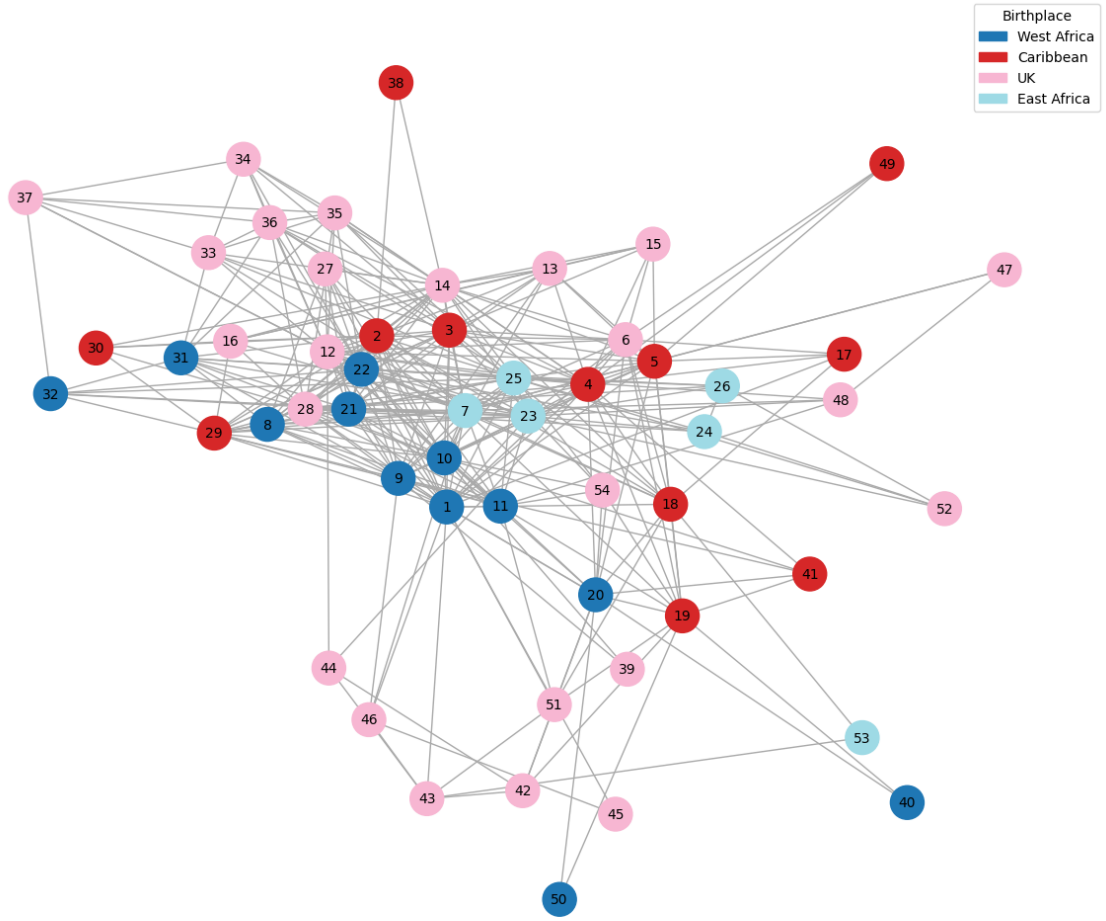


Figure 2: London Network graph visualization. Each node is colored according to its birthplace label

5.2.1 Macro-level Cohesion and Structure

These measures assess the overall "connectedness" and efficiency of the network as a whole.

Metric	Result	Interpretation (What it means)
Density	0.2201	The network is extremely dense and highly interconnected.
Average Degree	11.67	On average, each member is connected to almost 12 others.
Average Path Length	2.05	Any two members can reach each other in just 2 "hops" on average.
Diameter	4	The maximum separation between any two members is 4 "hops".
Avg. Clustering Coeff.	0.6331	The network is rich in tightly-knit local subgroups (cliques).
Modularity	0.2665	The network operates as a single, cohesive bloc; it is not fragmented into separate factions.

5.2.2 Micro-level Centrality and Social Roles

These measures identify the most important nodes, allowing us to define social roles.

Leaders The most influential, connected, and central members.

Node	Degree	Betweenness	Closeness	Eigenvector
1	0.4717	0.1087	0.6543	0.2367
7	0.4717	0.0755	0.6543	0.2433
12	0.4717	0.0596	0.6386	0.2494

Table 3: Leader nodes (Degree ≥ 0.4594 & Eigenvector ≥ 0.2357)

Brokers Members who act as "bridges" connecting different parts of the network.

Node	Degree	Betweenness	Closeness	Eigenvector
1	0.4717	0.1087	0.6543	0.2367
7	0.4717	0.0755	0.6543	0.2433
4	0.3962	0.0725	0.6163	0.1747

Table 4: Broker nodes (Betweenness ≥ 0.0670)

Peripheral Members Marginal members with few connections, existing on the network's edges.

Node	Degree	Betweenness	Closeness	Eigenvector
38	0.0377	0.0000	0.4109	0.0256
39	0.0377	0.0000	0.3926	0.0258
40	0.0377	0.0000	0.3557	0.0107
45	0.0377	0.0000	0.4015	0.0164
50	0.0377	0.0000	0.3557	0.0107
53	0.0377	0.0003	0.3681	0.0088

Table 5: Peripheral nodes (Degree ≤ 0.0377)

5.2.3 Hierarchy and Vulnerability

These measures test the power structure and resilience of the network.

K-Core Decomposition The most densely connected "core" of the network is identified. The analysis reveals a main core with a **k-value of 11**. This core consists of **13 nodes** (out of 54). The nodes in this core are: `[1, 2, 7, 8, 9, 10, 11, 12, 21, 22, 23, 25, 29]`.

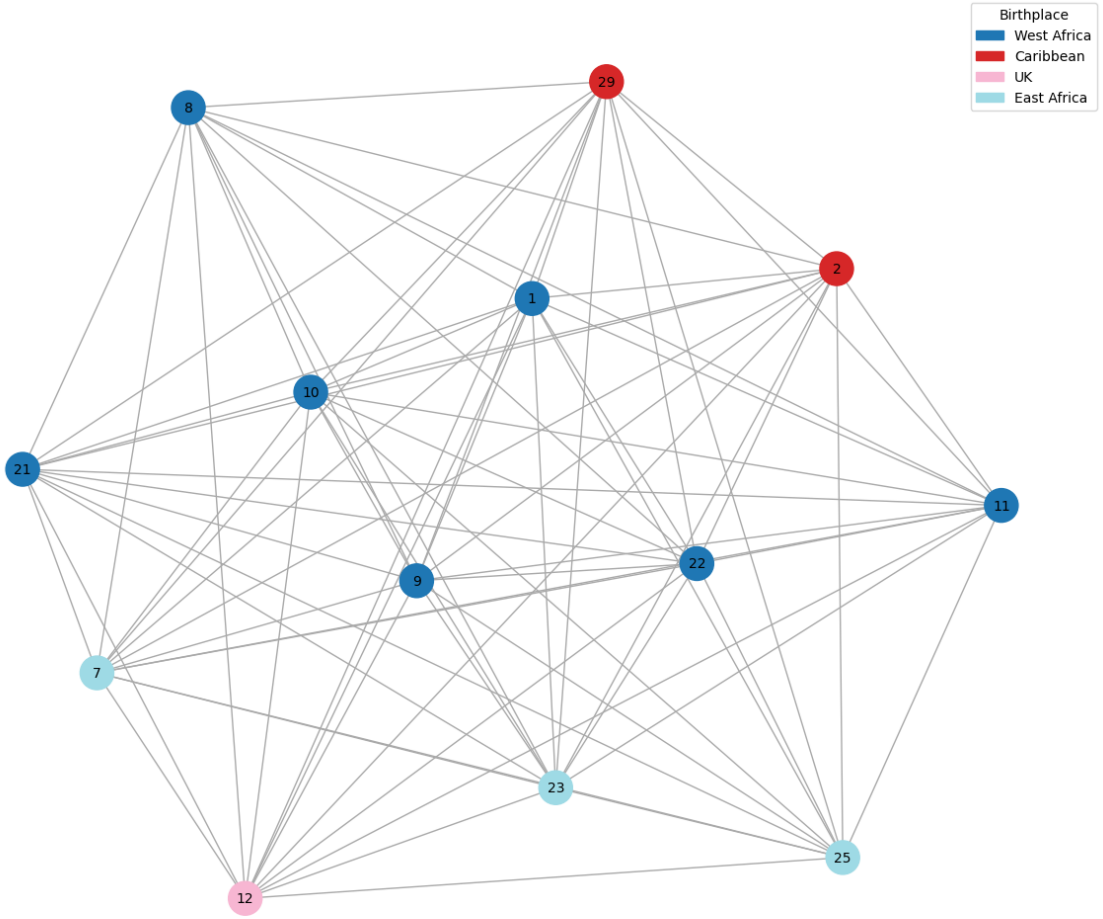


Figure 3: Core of London Network graph visualization.

Vulnerability Simulation We simulated the removal of the identified leaders (Nodes 1, 7, 12), representing a **5.56% reduction in nodes**, and recalculated cohesion metrics. This measure connects roles (leaders) to cohesion (robustness). The results show the network is **extremely robust**: removing the top 3 leaders did not fragment the network (it remained connected). The network density was reduced to **0.1906**, and the average path length increased to **2.2180** (an **8.00%** increase). The high density and clustering create redundancy, making the network resilient to targeted attacks.

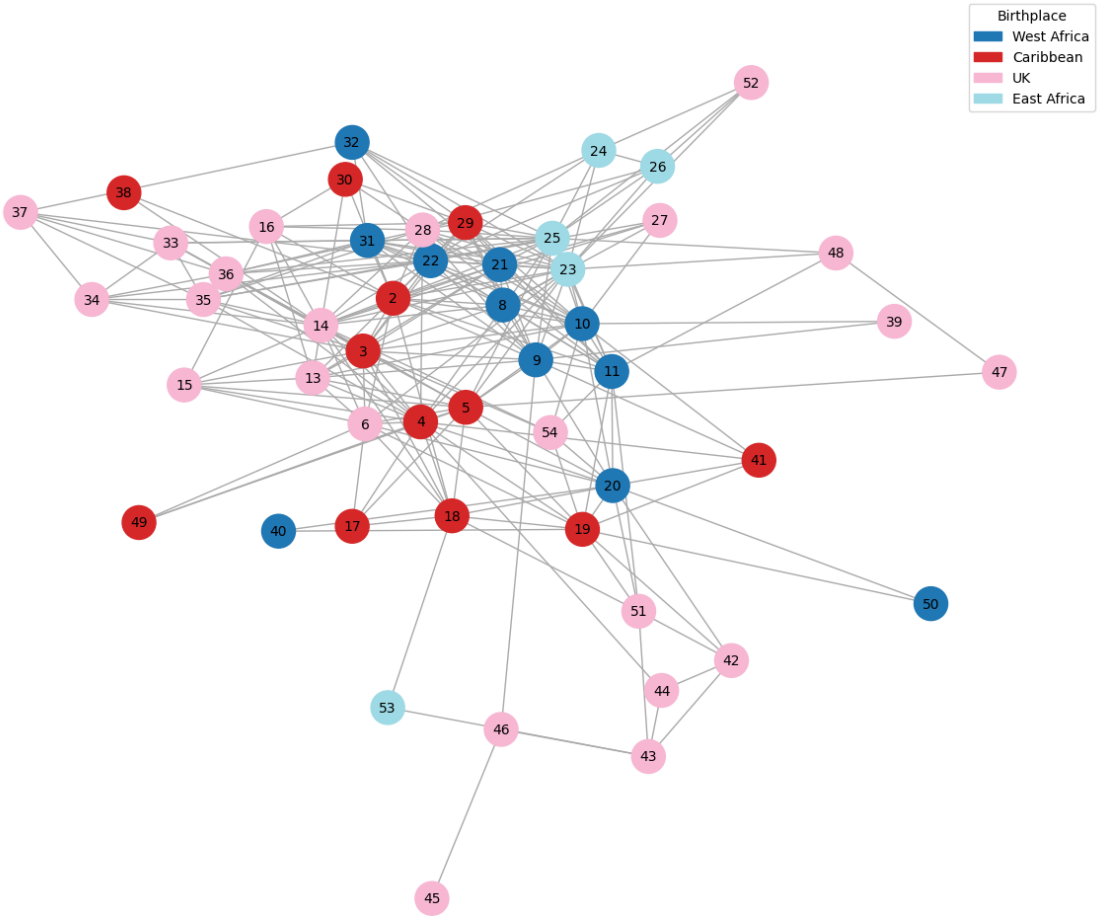


Figure 4: London Network sub-graph visualization without leaders.

5.2.4 Synthesis: Connection Between Data, Measures, and Properties

The **properties** are what we discovered: a "small-world" network (path length 2.05), highly cohesive (density 0.22), locally clustered (clustering 0.63), but undivided (modularity 0.26). It possesses a clear hierarchy (k-core 11) and defined social roles (Leaders 1, 7, 12), all of which combine to make it exceptionally **robust**.

5.2.5 Ethnicity analysis

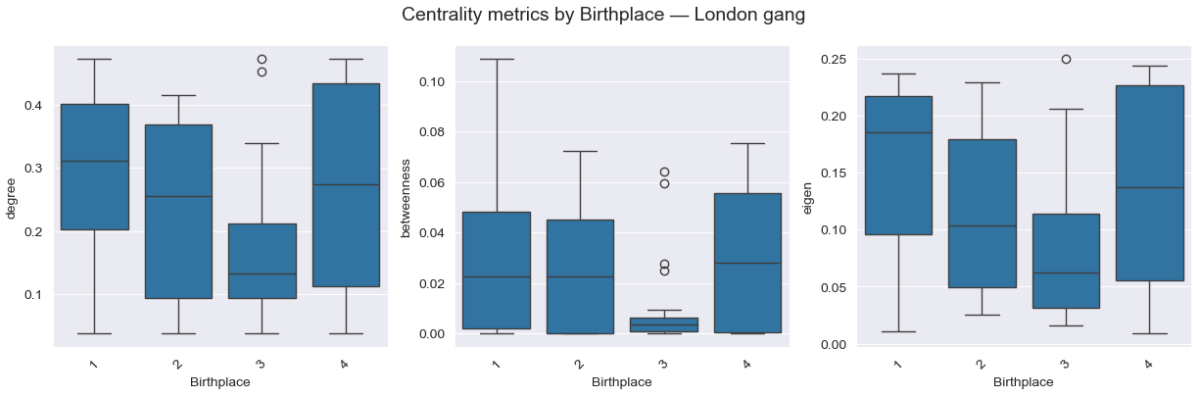
The analysis of the London gang network shows a **weak but positive tendency toward ethnic homophily**, with an assortativity coefficient of 0.113. This indicates that individuals display a mild preference for forming ties with others sharing the same *Birthplace*, although the overall network remains relatively integrated.

The **mixing matrix** confirms this observation: diagonal values (particularly for groups 1 and 3) are slightly higher, indicating intra-group cohesion, while off-diagonal entries remain substantial. This balance highlights the presence of numerous **cross-ethnic connections** within the gang's structure.

Table 6: Mixing matrix (proportion of connections between Birthplace groups) – London gang

	1	2	3	4
1	0.111	0.060	0.076	0.041
2	0.060	0.073	0.076	0.025
3	0.076	0.076	0.146	0.043
4	0.041	0.025	0.043	0.025

When analyzing **centrality measures**, groups 1 and 4 emerge as the most central and structurally influential, with the highest mean degrees (0.286 and 0.267 respectively) and eigenvector centralities (0.152 and 0.135). Group 2 follows closely, while group 3 (despite being the largest) exhibits the lowest centrality values, suggesting a more peripheral or clustered role. This pattern implies that influence and connectivity are distributed across multiple ethnic groups, rather than concentrated in a single one.



The **community analysis** identified four main communities, each with different degrees of ethnic diversity. Community 0 displays a relatively balanced composition (1: 38%, 2: 10%, 3: 29%, 4: 24%), while community 1 is dominated by groups 2 and 3. Communities 2 and 3 are less diverse, with community 2 almost entirely composed of group 3 members. The mean Shannon diversity index ($H = 0.886$) indicates moderate internal diversity, slightly lower than in the Italian network.

Table 7: Community composition by Birthplace – London gang

Community	1	2	3	4
0	0.38	0.10	0.29	0.24
1	0.20	0.35	0.40	0.05
2	0.00	0.14	0.86	0.00
3	0.00	0.33	0.67	0.00

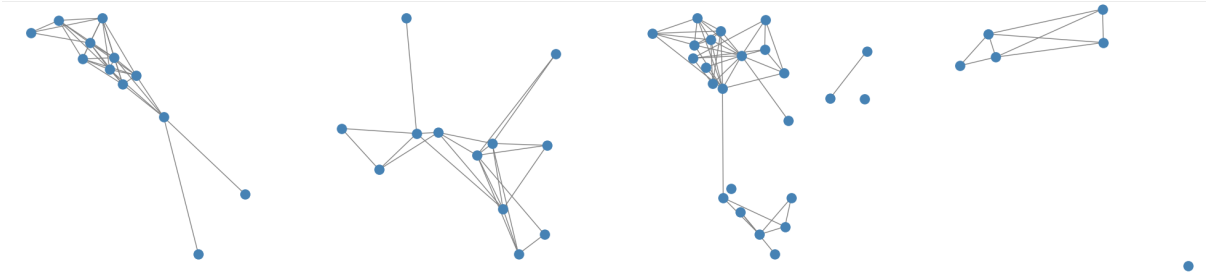
Furthermore, 64.44% of all connections occur between individuals of different *Birthplace* categories, demonstrating a high degree of cross-ethnic integration. As in the Italian case, national origin does not appear to be a key organizing principle in the network's structure.

Subgraph analysis by *Birthplace* provides additional insight:

- Groups **1** and **4** exhibit the highest internal density (0.530 and 0.533 respectively) and clustering, indicating strong intra-group cohesion.
- Group **3**, while the largest (24 nodes), has a lower internal density (0.167), suggesting looser internal connectivity and a more outward orientation.
- Group **2** shows intermediate density (0.348) and clustering, forming connections both internally and across groups.

Table 8: Subgraph-level statistics by Birthplace – London gang

Birthplace	Nodes	Edges	Density	Clustering
1	12	35	0.530	0.658
2	12	23	0.348	0.636
3	24	46	0.167	0.506
4	6	8	0.533	0.722



In summary, the London gang network displays slightly lower diversity but comparable integration when compared to the Italian case. While certain groups form cohesive internal clusters, the overall structure is characterized by extensive cross-ethnic linkage and distributed influence across national backgrounds. Ethnicity, therefore, plays only a minor role in shaping the gang's internal connectivity patterns.

5.3 Comparison

General structural metrics

Centrality Metric	Italian Network	London Network
Density	0.0516	
Average Degree	3.0430	
Diameter	6	
Average Path Length	3.012	
Average Clustering Coefficient	0.4347	
Number of communities	5	
Modularity Score	0.5561	

Centrality Metrics

Centrality Metric	Italian Network		London Network	
	Top 3 nodes	Value	Top 3 nodes	Value
Degree Centrality	N19	0.3182		
	N63	0.2879		
	N18	0.2727		
Betweenness Centrality	N19	0.5558		
	N63	0.3633		
	N18	0.2881		
Closeness Centrality	N19	0.5397		
	N63	0.4597		
	N18	0.4563		
Eigenvector Centrality	N19	0.4394		
	N18	0.3784		
	N63	0.3110		

Roles and Vulnerability

		Italian Network	London Netwo
	Leaders	N19, N63, N18, N4	
	Brokers	N19, N63, N18, N47	
	Peripheral	N2, N3, N5, N17, N22, N26, N33, N34, N36, N37, N38, N45, N46, N48, N49, N51, N53, N55, N56, N60, N61, N66, N67	
Main core	k	3	
	Number of nodes	20 (out of 67)	
	Nodes in the core	'N4', 'N8', 'N11', 'N12', 'N13', 'N15', 'N18', 'N19', 'N21', 'N24', 'N31', 'N32', 'N39', 'N41', 'N44', 'N47', 'N58', 'N59', 'N63', 'N64'	
After Removal	Nodes	24 in the largest component (64 remaining)	
	Number of components	18	
	Average shortest path length	3.1341	
	density	0.1014	
	Node reduction	64.18%	
	Increase in average path	4.05%	

6 Conclusion

Qualitative analysis of the quantitative findings of the study.

7 Critique

Do you think your work solves the problem presented above? To which extent (completely, what parts)? Why? What could you have done differently to answer your research problems (e.g., gather data with additional information, build your model differently, apply alternative measures)?