Lund University
Department of Political Science

VT22
Tutor: Tony Ingesson

Soviet intelligence in Stockholm during World War II

A social network analysis

9855 words

Björn Lundberg

Abstract

In this thesis social network analysis is applied on the Venona project KGB cables between Stockholm and Moscow during the World War two. The method is quantitative where words are extracted according to two different coding sheets and structured in tables. Software is then used for calculations and visualization. Theoretical roles for the actors are created and literature is studied to deepen the analysis and help interpret the results.

Key finding is that extracting explicit relations mentioned in the cables corresponded well to both theoretical roles and the literature.

Keywords: Social network theory, social network analysis, Venona, KGB, NetDraw, Usinet, World War two, Intelligence, dark networks, criminal networks, Mercyhurst College, National security agency, NSA, cables

Content

1 Introduction

In this study, the soviet network of spies in Stockholm during the second world war will be examined. There has been a lot of research regarding the individuals of this time but there's also mapping of the spy networks. Since the release of the decrypted cables from the Venona project in the late 90's, many researchers use it as a foundation or a resort for their studies of this topic.

Moving away from the conventional qualitative approach, this study will attempt to analyze these cables quantitatively. The theoretical framework will be social network theory through the perspective of dark networks.

This will contribute to two sections of the literature. One is adding another aspect to the research of the era, all the historical figures and questions unanswered. The second, which is the main focus of this study, is attempting social network analysis on a very complex, fractured and flawed material in an attempt to broaden the fields of where SNA is applicable.

The research questions that this study asks are:

What properties do the network and actors have?
How do the actors compare to an assumed dark network?
How do the actors reflect the literature?

In addition, there will be a critical evaluation of two approaches to collect data from the material.

Disclaimer: Due to a translation error of the author, the legation is in this thesis referred to as the embassy. It was noticed near completion and the timeframe did not allow for recreating the affected graphs. For consistency, embassy is used even where easily changed.

2 Background

2.1 Previous empirical research

Stockholm was a unique location during the second world war (Agrell, 2006, p. 637). Sweden, a neutral country, permitted the warring nations to freely have diplomatic personnel coexist with each other. This allowed for both a marketplace of information as well as illicit intelligence collection. Sweden wasn't the target for this collection with one exception – the Soviet Union.

This historic period of intelligence activity is still a target for research today. Some of it focuses on organization and the intelligence trade. For instance, Inaba (2008, p. 132) has investigated the intelligence cooperation between Japan and Finland in Stockholm which resulted in decrypted soviet messages in the early part of the war. Molander (2007) focuses on the British Special Operations Executive's (SOE) activity in Sweden. Being a two-part study, it shows the British intelligence need and collection methods while also exposing neutral Sweden in fact cooperating with the British during the late part of the war. Agrell (2006) conveys similar research but focuses more on the crucial role individuals have in intelligence cooperation. This directs us to another area of research of this time, individuals.

Olsson (2011, 338-351), who's research starts before the war, maps the German intelligence service network in Sweden. However, the primary object of study is Harald von Koenigsegg. It's common when studying an individual to also include a broader set of events. Lundberg (2016) follows a British diplomat. Here the British activity, including sabotage and counterespionage, is also surveyed.

For Swedish researchers, Raoul Wallenberg is a popular target of study. Matz (2016) investigates disinformation used to discredit Wallenberg. This study expands beyond the second world war but gives an insight in soviet intelligence activities. Another study of Wallenberg by Matz (2013) attempts to conclude the faith of this Swedish diplomat. This research is unique as Matz got access to the soviet cables between Stockholm and Moscow at the time. While likely a one-time opportunity, these cables are available in partly decrypted form under the name Venona. They were collected through SIGINT during the war and after many years, they were released to the public by NSA in the late 90's. These cables have been subject to much research and here Agrell (2003) again needs to be mentioned. With great detail, he tells the story of the characters in the cables while also reviewing the cables and the implications they had in later spy trials.

In this thesis, the Venona project cables will be the object of study.

2.2 Previous theoretical research

As mentioned in the introduction, this thesis will attempt a quantitative method to analyze the Venona cables through a theoretical framework of social network analysis (SNA). While this theory is most often used on legal networks, it has shown to be useful on illicit ones as well. In Milward and Raab (2006) terminology, these are the dark networks. Their research concludes that actors (i.e., a person) and networks in the dark will have certain properties in their attempt to balance staying hidden and being effective in achieving their goals.

In this area of research Leuprecht et al. (2015, p. 904) not only map two networks, but connecting them, revealing more properties. Prominent in the paper, is the use of combinations of SNA measurements values to predict roles in a network. Their data was based on mapping actors together from different sources. Going further, Koschade (2006, p. 562), in analyzing a terrorism network, weigh the values of the relations between actors. This is another approach in understanding the roles and importance of actors in a network.

Bichler's (2019) guide on how SNA research can be conducted on dark networks provides a tool kit including everything from theory and collection to measurement analysis and presentation.

As it seems, no research has yet combined the Venona cables with social network theory, and thus there is a gap, which this thesis will help to fill.

The thesis will be founded on the assumptions of dark networks and then have Bichler's theoretical framework built upon. It will expand the idea of SNA measurement values to assume roles within a network.

In doing so, it will add to the rich research of the Venona project and soviet spy network of World War two. Not only for the visual overview but for the possibility of finding information that otherwise would be hard to find. In addition, it will expand the field of SNA in applying it on very incomplete and flawed material. While not attempting to create a theory due to hardship in providing means of falsifying, the two different coding sheets will help interpreting the data.

3 Theoretical framework

The foundation of the theoretical framework for this study is Milward and Raab's (2006, p. 334) theory of dark networks. Upon this social network theory supplied by Bichler (2019) will be built. In addition, the idea of roles related to SNA measurements expressed by Leuprecht et al. (2015, p. 906) will be used to create theoretical roles in the material.

3.1 Dark networks

Beginning with Milward and Raab (2006, p. 334), this study conforms to the assumption that the Soviet personnel and agents acted in a gray network. Derived from a country's legislation, a bright network is one complying with the law. This is the theme for most SNA research. Contrasting this are dark networks. For their survival they must stay hidden. The illicit means for their aspiration means that detection is detrimental for the network's existence. A gray network is the middle ground. One part legal and one part illegal. Milward and Raab illustrates this with Irish Republican Army comprising of a legal political party connected to an illegal militant branch. This reflects the target of this study. In this sense the legation is legal and thus bright, the envoys are gray with both legal and illegal duties and the agents are dark. Unaware sources would have no purpose to stay hidden and are thus assumed bright.

While the theory of Milward and Raab (2006, p. 353) extends beyond this, such analysis would require a more qualitative approach. The focus here will be the contrasting qualities; need for covertness and the need to act. To collect more human intelligence, an agent would have to be more visible. However, this would increase the risk of attracting attention from the law enforcement. Concluded from this is that notable figures in the SNA graphs are likely to be portrayed in the literature.

3.2 From values to roles

Research of Leuprecht et al. (2015, p. 906) show that actors with certain roles in an illicit network will share some properties. This idea gives confidence to evaluate the coding sheets against theoretical dark network actors in the context of a spy network. See the method chapter for how this is conducted.

3.3 Social network theory

Social network theory is a theory of relations and how these affect actors in a network (Bichler, 2019, pp. 27-34). The relationship between actors and their positioning affects their behavior more than the properties of the actors themselves. Together, the actors and their relations form the structure of the network. The positioning determines an actor's access or exposure to information and determines who they can pass it on to. When an actor *bridges* two subnetworks it acquires control over the information flow (Bichler, 2019, p. 37). The control means power and gives the actor opportunity to act on the information.

Social network theory provides many different measurements for these relations. For this reason, Bichler (2019, p. 173) suggests that the researcher should select those that corresponds to the research question. Considering the dark network this study encompasses, we must choose those that can describe the networks' structure along with the actor's visibility and ability to transmit information. The material also suggest that additional measurements may be needed to trace *artifacts*. This is when a relation is suggested that doesn't exist.

While software can both calculate the measurements as well as visualize them in a graph, it's important to understand what they are based on and what they mean.

3.3.1 Basic definitions

Actors and the ties that link them are the foundational words to describe social network theory (Bichler, 2019, pp. 16-17). Sometimes actors are called nodes or entities depending on what's being described. For this study, *actor* will be used as it reflects a person. Two linked actors are called a *dyad* while three linked actors, like a triangle, a *triad*.

Like actors, the links can be called many things, for instance connection or relation. While those terms will be used interchangeable in this thesis for pedagogic reasons, the more abstract *ties* will be the most common one. These ties can possess many properties. A message from one actor to another would indicate a *directed tie*, called an *arc*. In contrast, *edges* are ties lacking a direction.

The *ties strength* can also be quantified by valuing them (Bichler, 2019, pp. 35-39). Information flowing repeatedly between two nodes would indicate a high value or put differently, a *strong tie.* This would also be true for the number of times an alias is mentioned in the telegrams. Another way of weighing ties is similarity in properties of the actors, *homophily* or simply, sameness. Belonging to the same faction is an example of this.

Two networks may not be connected because they have few common properties. When two actors from two such networks form a relation, creating a *bridge*, it's usually a *weak tie*. However, weak ties do have some benefits. Considering the exclusivity a bridge infers, they can control the flow of information between them. This gives them a high social, financial, or human capital and thus a form of power.

An agent with many exclusive sources would constitute such a bridge and be highly valued. This exclusivity is labeled a *nonredundant tie* (Bichler, 2019, pp. 36-37). With additional ties, the information will have an alternative paths and the bridge is no longer indispensable. Looking at a graph, the absence of ties between two networks is called a *structural hole*. A *transitive* area is the opposite. Here many actors are connected in triads, no one is indispensable (Bichler, 2019, pp. 36-37).

An *egonet* is the local neighborhood of an actor (Bichler, 2019, p. 188). Included are the actor's closest neighbors and in turn, the relations of all actors the two neighbors have in common. Apart from visually isolating an area it can also show who might influence the chosen actor.

There are reasons why one would want to simplify a network (Bichler, 2019, pp. 159-160). One is that some calculations require it. Another is the inherently low quality and fractured data intelligence often provides. It may be more beneficial to conclude that a tie exists rather than how many out of an unknown amount.

By *symmetrizing* a *directed network*, the arcs are converted into edges. Similarly, valued networks can be *dichotomized*, converting links into binary values. A binary value 1 indicates relationship and a 0 does not.

3.3.2 Network properties

A graph may sometimes be *disconnected*, meaning parts of the network, *components*, are not connected to each other (Bichler, 2019, p. 204). When a network consists of several components it can indicate that actors or links are missing (Bichler, 2019, p. 158). By calculating the percentage of actors in the largest component and comparing this to the number of components it can give an appreciation off missing data that otherwise would connect them all into one.

Density measures how connected the actors are to each other (Bichler, 2019, pp. 161-162. The calculation must be done on a dichotomized network and if disconnected, on the main component. The number of ties is compared to the theoretically maximum number of ties. A low density would indicate a chain-like structure. Areas with a comparably high density are called *clusters*. Related to density is *average degree centrality* (Bichler, 2019, p. 163). This refers to the average amount of contacts an actor has (see degree centrality below).

Another value is *degree centralization* which calculates the number of actors connected to the actor with highest individual degree centrality score Bichler, 2019, p. 165) A high value would indicate that one actor has a very central position.

Identifying a network can be done by measuring *average path length* (Bichler, 2019, p. 166). This is the average shortest path (*geodesic distance*), counted in ties, from one actor to all other actors. According to small world theory, in a normal network the average is six. This refers to how many people one person usually can send a message through. A high value would indicate long chains while a low value means a message can spread fast within the network.

By grouping actors with the same degree centrality, it’s possible to identify *subgroups* (Bichler, 2019, p. 210). These *K-Core* values exposes clusters of different sizes. This is not expected in a dark network as high degree would expose its members and can thus help identifying artifacts.

3.4 Actor properties

3.4.1.1. Degree centrality

The measurement of degree centrality counts an actor's direct ties to other actors (Bichler, 2019, p. 163). An actor with a high value relative to the others is defined a hub (Bichler, 2019, p. 174). From a dark network perspective, a *hub* is a very visible actor, and the position is not optimal for someone who wants to stay hidden. As a raw value it's very sensitive to network size and must also be given in *normalized* value when two networks are compared. A directed network will give different values (Bichler, 2019, p. 176). These are *in-degree* and *out*-degree. They count ties only of the corresponding direction.

By comparing in- and out-degree, four different role can be uncovered (Bichler, 2019, 179-180). A *transmitter*, someone considered to be the source of something, will have a high out-degree and a low in-degree. It's important to know that in a dichotomized network, this only means to how many actors one transmits too. Only in a valued network the magnitude of what's being transmitted from the source can be calculated. With that said, an actor with the opposite values, high in-degree, and low out-degree, can be considered a *receiver*. In a dichotomized network it will receive from many and transmit to few. A *carrier* is someone with equal and fairly high levels. Someone with low levels would tend to not be too involved in the network and is assumed to be in the *periphery* of things. It should be noted, and more so with fractured data, that the latter one can be a prominent figure but not yet discovered. A leader could use middlemen to receive and transmit messages.

3.4.1.2. Betweenness centrality

This measure will show the dependency other actors will have on an actor to access information (Bichler, 2019, pp. 182-185). It's calculated on the actor's tendency to be positioned on a geodesic path between other actors. A sole actor between two clusters, a bridge, would have a very high value. The actors in the clusters are thus dependent on the bridge for information.

4 Metod

4.1 Design

A study's methodology is the way knowledge is acquired for the analysis (Lamont, 2015, p. 24). In this empirical study this will be accomplished by extracting quantifiable information from text. The information is divided into categories. While certain categories are assumed, they will have to be adapted to match the material. This means the study is partly inductive (Boréus & Kohl, 2018, p. 58). The coding scheme for this process implies a positivistic perspective as no interpretation is conducted (Lamont, 2015, p. 39).

Quantitative methods have the benefit of managing large amounts of aggregated data (Lamont, 2015, p. 98-99). Precision is also gained in transparency when explicit rules and definitions are used in the coding sheet. Transparency along with validity and reliability are key to a scientific study, especially when text is analyzed (Bergström & Boréus, 2018, p. 42). This is also true for the intra- and intersubjectivity. The first one meaning the researcher ability to repeat coding with identical results and the second other researchers' ability to replicate the study – also with the same results. The greatest pitfall in replicability is the coding.

This study consists of three principal parts. The first one is extracting and converting the material into two structured sets of data using code sheets. Second is creating tables and graphs based on social network theory measurements. The third part consists of the analysis of network and actors. This will be done both for structure and actors. Tables and graphs will be analyzed individually – Bichler (2019, p. 176) asserts that only looking at the graphs, especially for complex networks, can be very misleading. To improve the analysis and help interpreting the values, the data will be evaluated against both theoretical dark network roles and actor descriptions in the literature.

The appendix will include the extraction process, software use and additional tables not included in the Result chapter. In addition, larger versions of the graphs are added. Lastly, I have added tables with additional data collected through the research. This helps transparency but also allows other researchers to use the data.

While great attention has been given to design this research, it should be noted that for this material, there is likely no perfect solution.

4.2 Material

4.2.1 Venona

The material of this study originates from the soviet embassy cable transmissions during the second world war (NSA, p. 1). These were heavily encrypted secret communications concerning their spy network. In 1943 the USA began decrypting these. This was a very meticulous work. In the late 90's the material was released by the National Security Agency (NSA, pp. 3-4). It consisted of about 3000 partly decrypted cables (Agrell, 2003, p. 12).

This study focuses on the KGB traffic between Stockholm and Moscow collection ranging from 1941 to 1946. However, the transcribed versions by Mercyhurst College (Haynes, 2013) will be used instead. While not always accurate, it's considered far better than anything this author can provide. In addition, it will allow for copy/paste when extracting the material, reducing the risk for errors.

4.2.2 Structure of the cables

A typical cable consists of four parts, see picture 4.2.3a and b.

In the header there's information from NSA containing reference number, date issued and a copy number. The reference number is present on each page for that cable. At the end there’s comments and footnotes. These may contain translation clarifications or alternatives and information about alias or persons mentioned. The latter could be identity of an alias, speculated identity or that it’s unknown. It could also give information about a person, often full name, occupation, and location of that occupation. An alias that first was considered unknown can at a later decryption date have a confirmed identity. NSA also gave each cable a short summary as a headline. On a few occasions it could indicate an amendment, a reissue, or correction. For those there’s also a finalized version.

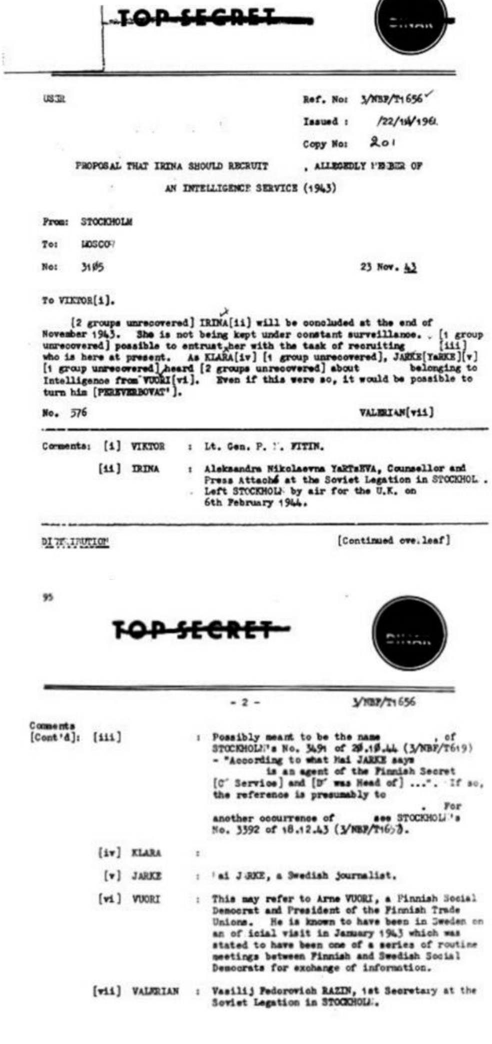
The cable itself has a header with information of sender and receiver location (i.e., STOCKHOLM or MOSCOW), external reference number and date. On a few occasions external number is missing. The message consists of recipient, the text and then be finished by internal serial number and sender. There’s often edits done by pencil and these also persist on the transcribed versions.

4.2.3 Encryption

Very simplified, the enciphering process and consequential decryption can roughly be described as the following (Benson, n.d., p. 26-27). The soviets used a codebook where a number would correspond to a word or a phrase. In addition, a second one-time use codebook would translate those into random numbers. Transmitter and receiver would need to use the same random number codebook. Sometimes the latter codebooks would be reused. This was exploitable and meant that, along with a captured codebook with words, more words could be decrypted. One decrypted word could help decrypting other cables.

In the messages, phrases like [2 groups unrecovered] and [3 groups unrecoverable] are a repeated phenomenon. These groups represent a word in the codebook and cannot be decrypted any further (Benson, n.d., p. 15).

Picture 4.2.3a



95

TOP SECRET

USSR

Ref. No: 3/NBF/T1656

Issued : /22/10/196

Copy No: 201

PROPOSAL THAT IRINA SHOULD RECRUIT , ALLEGEDLY MEMBER OF AN INTELLIGENCE SERVICE (1943)

From: STOCKHOLM

To: MOSCOW

No: 3105 23 Nov. 43

To VIKTOR[i].

[2 groups unrecovered] IRINA[ii] will be concluded at the end of November 1943. She is not being kept under constant surveillance. [1 group unrecovered] possible to entrust her with the task of recruiting [iii] who is here at present. As KLARA[iv] [1 group unrecovered], JARKE[YaRKE][v] [1 group unrecovered] heard [2 groups unrecovered] about belonging to Intelligence from VUORI[vi]. Even if this were so, it would be possible to turn him [PEREVERBOVAT'].

No. 576 VALERIAN[vii]

Comments: [i] VIKTOR : Lt. Gen. P. M. FITIN.

[ii] IRINA : Aleksandra Nikolaevna YaRTsEVA, Counsellor and Press Attaché at the Soviet Legation in STOCKHOLM. Left STOCKHOLM by air for the U.K. on 6th February 1944.

DISTRIBUTION [Continued overleaf]

95

TOP SECRET

- 2 - 3/NBF/T1656

Comments [Cont'd]: [iii] : Possibly meant to be the name , of STOCKHOLM's No. 3491 of 20.10.44 (3/NBF/T1619) - "According to what Mai JARKE says is an agent of the Finnish Secret [C? Service] and [D% was Head of] ...". If so, the reference is presumably to . For another occurrence of see STOCKHOLM's No. 3392 of 18.12.43 (3/NBF/T1657).

[iv] KLARA :

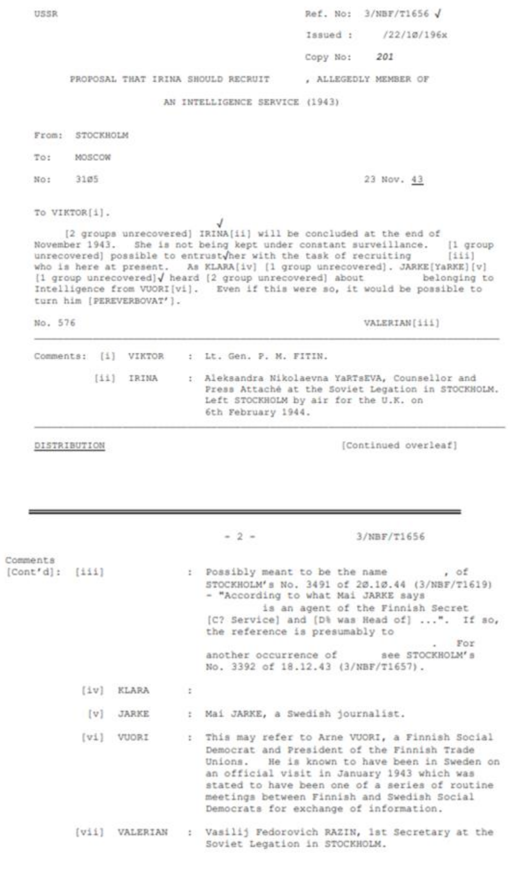
[v] JARKE : Mai JARKE, a Swedish journalist.

[vi] VUORI : This may refer to Arne VUORI, a Finnish Social Democrat and President of the Finnish Trade Unions. He is known to have been in Sweden on an official visit in January 1943 which was stated to have been one of a series of routine meetings between Finnish and Swedish Social Democrats for exchange of information.

[vii] VALERIAN : Vasilij Fedorovich RAZIN, 1st Secretary at the Soviet Legation in STOCKHOLM.

Cable photocopy (National Security Agency, 2021)

Picture 4.2.3b



USSR

Ref. No: 3/NBF/T1656 ✓

Issued : /22/10/196x

Copy No: 201

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From: STOCKHOLM

To: MOSCOW

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To VIKTOR[i].

[2 groups unrecovered] IRINA[ii] will be concluded at the end of November 1943. She is not being kept under constant surveillance. [1 group unrecovered] possible to entrust her with the task of recruiting [iii] who is here at present. As KLARA[iv] [1 group unrecovered]. JARKE[YaRKE][v] [1 group unrecovered] heard [2 group unrecovered] about belonging to Intelligence from VUORI[vi]. Even if this were so, it would be possible to turn him [PEREVERBOVAT'].

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Comments [Cont'd]: [iii] : Possibly meant to be the name , of STOCKHOLM's No. 3491 of 20.10.44 (3/NBF/T1619) - "According to what Mai JARKE says is an agent of the Finnish Secret [C? Service] and [D% was Head of] ...". If so, the reference is presumably to . For another occurrence of see STOCKHOLM's No. 3392 of 18.12.43 (3/NBF/T1657).

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[vii] VALERIAN : Vasilij Fedorovich RAZIN, 1st Secretary at the Soviet Legation in STOCKHOLM.

Transcribed version on cable to the left (Haynes, J., 2011).

4.2.4 Source critique

4.2.4.1. External

This critique refers to the materials sincerity (Bergström & Boréus, 2018, p. 42). Agrell (2003, p. 139) mentions that parts can be missing for political reasons. Sometimes referred to cables are explicitly stated not published (Haynes, 2011, p. 192). This would suggest that efforts are made to not allow a full picture which would indicate a skewed image painted by the cables. Unable to verify this or potential disinformation included, the material is accepted in its current shape.

4.2.4.2. Internal

It’s very important to consider the material’s factual quality (Bergström & Boréus, 2018, p. 42). For this material the critique gravitates towards it’s representability as a whole and the incompleteness of the cables themselves.

Agrell (2003, p. 119-120) estimates that of the Stockholm-Moscow cables, less than five percent were decrypted.

Adding to this, only parts of most cables are fully decrypted. Additionally, there could be translation errors and edits without a clear intent. The comments are not consequential. Unidentified aliases can in later decryptions be identified. However, is it the same person behind the alias still?

There is no consequent way to identify agents in the text. Uppercase is used for both aliases, well-known people, locations, and some objects like specific ships. One could assume that these have their own encipher number in the non-random book. The missing groups remove context making it uncertain whether an agent is a double-agent or not. It’s also hard to prove any relation between actors in the text.

4.3 Coding sheet

Two sets of data will be created. This intends to counter the materials defects and will offer two perspectives. One will focus on the networks structure and one on the flow of information. Comparison will be helpful in the analysis.

4.3.1 Extraction and the remedy of flaws

It's essential to increase actor resolution after extraction of aliases and names (Bichler, 2019, p. 138-139). An error here can radically skew the result. Careful analysis of the comments is crucial for this step. Each actor must have a unique identifier. Obvious spelling variations must be corrected, and an actor's aliases and names must be consolidated into one. For this study the alias has precedence over a name and the English translation over the Russian. Both message and NSAs text will be included in the extraction process.

4.3.2 Categories of actors

The material inconsistency makes patterns hard to find. In the end, four categories were chosen. An alias is a word written in uppercase in the material while a name is in lowercase.

4.3.3 Dataset1

To obtain high reliability, all uppercase words were extracted and then excluded when not falling into these categories (see appendix 9.7). Notable is that the embassy/transmitter is NOT included in this set. Since they are included in each cable, every actor would be linked to them, effectively only showing that the actors were linked to the cable. In the result section I will explain what implication including the embassy would have had on this dataset.

Envoy	(Soviet) envoys are explicitly identified as a person officially employed by the soviets.
Agent	An alias not applicable for Envoy category having both an alias and a name or is identified with such in the reference material.
Unidentified	An alias without name
Civilian	Only a name

This dataset focuses on structure. For each cable all these categories were extracted. Apart from previously mentioned categorization, no interpretation of the text was needed. Reliability is weighted against the loss of context. For this reason, this dataset will both show the network as well as artifacts. The set will be dichotomized. What's important is the fact that actors are mentioned in the same cable and thus suggesting a relation. Even if mentioned multiple times, an actor will only be extracted once per cable.

4.3.4 Dataset2

To examine the information flow of the network some interpretation is needed. This dataset will provide a directed network. However, still dichotomized for the reasons given in dataset1. All actors from dataset1 are included but expanded with the both the exclusion list and all things corresponding the matrix below. While the cables most often contain a sender and a receiver, these are simply condensed into the "embassy".

These are the conditions for something to be identified as a directional flow:

	Text	Datasheet and direction
1	"from X to Y"	X→Y
2	"X attended a meeting with A, B & C"	A→X, B→X, C→X
3	"information confirmed with X"	Embassy→X, X→Embassy
4	"X had a meeting with Y"	X→Y, Y→X

Relations found in this dataset are assumed to be reflecting reality. Impossible to verify, but it helps simplifying the discussion.

4.3.5 Software

- Microsoft Word is used to read the material and copy data into Excel.
- Microsoft Excel is used to compile above material and to format it in a way that NetDraw and Ucinet could read. The process is described in the appendix.
- Ucinet (Borgatti, Everett and Freeman, 2021) was used to create the datasets from the compiled data in Excel which includes doing all the calculations.
- NetDraw (Borgatti, 2002) was used to create the graphs.

4.4 Evaluation of the coding sheets

Since there is no real way to verify the findings, below are two ways enhance the analysis. While it's unlikely the results will fully coincide, large deviations could indicate improper method.

4.4.1 Theoretical dark network

To help interpreting the results, these are the characteristics I would expect dark espionage network actors to possess. This is based on the research of Leuprecht et al. (2015, p. 906) and Milward and Raab (2006, p. 334) mentioned in the theory chapter.

Starting from sources (civilian), only connected to their agents, they would have low out-degree, 0 in-degree and 0 betweenness centrality (undirected: low degree and low betweenness). Agents with many sources and one handler (envoy) can be expected to have high in-degree but low out-degree centrality (undirected: average degree). Betweenness is likely to be high for both directed and undirected. The Envoys, probably handling a manageable number of agents ought to have moderate in- from sources and moderate out-degree centrality for the communication to the agent. Being important for information to reach embassy, their betweenness should be high for both directed and undirected networks.

Unidentified agents and envoys likely have lower centrality values than identified ones. Unidentified sources are presumed to have a low-profile agent either with low centrality or likewise unidentified. No expectation regarding betweenness. However, a large value would suggest a need for more investigation in future research as it could be someone of importance yet uncovered.

4.4.2 Characters of Venona research

For the third research question, Agrell's (2003) "Venona: Spåren från ett underrättelsekrig" will be used as reference material. This is to verify the actor's positioning in the results against in-depth qualitative research. The expectation is that prominent figures in the literature should be prominent in the graphs as well.

5 Results

The tables for dataset1 and dataset2 are the resulting calculation performed by Ucinet (Borgatti, Everett and Freeman, 2021).

Please note that when comparing these datasets, one must remember that they are collected very differently. Apart from how actors were picked, in dataset2 the embassy is present while in dataset1, it's not. While the logic was that it would only add one relation between each actor and the embassy for each cable the actor is present, the implication must be discussed. Remember that these sets are dichotomized. This means that the above hypothesized added relation between actors and embassy, would only count as one for each actor. For example, an actor present in four cables would have resulted in four relations with the embassy, but when dichotomized, only counting as a binary 1. Had this been better? Perhaps more consistent but the added data would add little information of value. This will be explained more in the analysis.

5.1 Acronyms

In the tables, "0.22 (5)" means "normalized (raw)" value. N is the slot number, sorted from high to low after focused measure of a table.

It is important to note that the slot number can be misleading. Actors often share the same value which means that the order is randomized for those. This is amplified a lot with the lower values as they, the non-prominent, were much more common. For instance, all actors only connected to one another actor will have betweenness centrality 0, meaning they will all be randomized. This is a much less of an issue for the top 20 which is why only those are shown in the tables.

Considering dataset1 and dataset2 containing 207 and 116 actors respectively, only the top 20 highest is shown here. The remaining values drops off quickly. The sets in their entirety are easier to visualize in the graphs. Due to space limitations, apart from degree centrality and degree centrality in, the other graphs can be found in the appendix. The ones showed in this chapter will also be present in the appendix for easier comparison.

5.2 Dataset1, degree centrality

Table 5.2.
Source: Dataset1
Top 20 actors of 207 sorted after degree centrality raw values.

N	Actor	Category	Degree Normalized (Raw)	Betweenness Normalized (Raw)
1	KLARA	AGENT	0,26 (53)	0,21 (4494)
2	KHOCHEV	UNIDENTIFIED	0,22 (45)	0,14 (2920)
3	ABRAM	ENVOY	0,15 (31)	0,09 (1955)
4	TERENTIJ	AGENT	0,15 (30)	0,10 (2117)
5	TANNER	CIVILIAN	0,13 (27)	0,01 (123)
6	GRISHA	AGENT	0,13 (27)	0,04 (915)
7	KIN	ENVOY	0,13 (26)	0,04 (920)
8	KOLLONTAJ	ENVOY	0,13 (26)	0,05 (1149)
9	MOUNTAINEER	AGENT	0,12 (25)	0,07 (1506)
10	JACQUES	UNIDENTIFIED	0,12 (24)	0,01 (224)
11	DORA	AGENT	0,11 (23)	0 (110)
12	AALTONEN	CIVILIAN	0,11 (22)	0 (72)
13	PAASIKIVI	CIVILIAN	0,10 (21)	0 (60)
14	KETO	CIVILIAN	0,10 (21)	0 (60)
15	IRINA	ENVOY	0,10 (21)	0,03 (638)
16	NIK	UNIDENTIFIED	0,10 (20)	0 (0)
17	PATRIOT	UNIDENTIFIED	0,10 (20)	0 (0)
18	LAND	UNIDENTIFIED	0,10 (20)	0 (0)
19	MISHA	UNIDENTIFIED	0,10 (20)	0 (0)
20	ULRIK	UNIDENTIFIED	0,10 (20)	0 (0)

5.3 Dataset2, undirected, degree centrality

Table 5.3.
Source: Dataset2
Top 20 actors of 116 sorted after degree centrality, raw values.

N	Actor	Category	Degree Normalized (Raw)	Betweenness Normalized (Raw)
1	EMBASSY	ENOVY	0,504 (58)	0,841 (5513)
2	KLARA	AGENT	0,113 (13)	0,132 (863)
3	MOUNTAINEER	AGENT	0,087 (10)	0,093 (611)
4	KOLLONTAJ	ENOVY	0,078 (9)	0,107 (700)
5	SENATOR	AGENT	0,07 (8)	0,082 (540)
6	VALERIAN	ENOVY	0,052 (6)	0,033 (218)
7	ABRAM	ENOVY	0,052 (6)	0,050 (331)
8	PAUL	UNIDENTIFIED	0,043 (5)	0,058 (380)
9	IRINA	ENOVY	0,043 (5)	0,05 (326)
10	ORESTES	AGENT	0,035 (4)	0,016 (102)
11	GRISHA	AGENT	0,035 (4)	0,05 (327)
12	SEMENOV	ENOVY	0,035 (4)	0,045 (297)
13	TERENTIJ	AGENT	0,026 (3)	0,001 (6)
14	FRIEND	UNIDENTIFIED	0,026 (3)	0,037 (244)
15	VIKTORIA	UNIDENTIFIED	0,026 (3)	0,033 (218)
16	KHOCHEV	UNIDENTIFIED	0,026 (3)	0,033 (219)
17	MAK	UNIDENTIFIED	0,017 (2)	0 ,000 (0)
18	DMITRIEVSKIJ	ENOVY	0,017 (2)	0,017 (110)
19	KRITIK	UNIDENTIFIED	0,017 (2)	0,017 (110)
20	PHILIP	UNIDENTIFIED	0,017 (2)	0,017 (110)

5.4 Dataset2, directed, In-degree centrality

Table 5.4.
Source: Dataset2
Top 20 actors of 116 sorted after in-centrality, raw values

N	Actor	Category	Directed In-Degree Normalized (Raw)	Directed Out-Degree Normalized (Raw)	Directed Betweenness Normalized (Raw)
1	EMBASSY	ENOVY	0,296 (34)	0,287 (33)	0,302 (3964)
2	KLARA	AGENT	0,113 (13)	0,035 (4)	0,050 (652)
3	MOUNTAINEER	AGENT	0,078 (9)	0,052 (6)	0,046 (598)
4	KOLLONTAJ	ENOVY	0,061 (7)	0,026 (3)	0,029 (383)
5	SENATOR	AGENT	0,052 (6)	0,026 (3)	0,021 (270)
6	ABRAM	ENOVY	0,052 (6)	0,043 (5)	0,045 (596)
7	IRINA	ENOVY	0,035 (4)	0,026 (3)	0,026 (345)
8	PAUL	UNIDENTIFIED	0,035 (4)	0,009 (1)	0,004 (48)
9	VALERIAN	ENOVY	0,026 (3)	0,043 (5)	0,013 (173)
10	GRISHA	AGENT	0,026 (3)	0,009 (1)	0,013 (165)
11	KHOCHEV	UNIDENTIFIED	0,026 (3)	0,017 (2)	0,014 (187)
12	ORESTES	AGENT	0,026 (3)	0,035 (4)	0,033 (439)
13	CROAT	UNIDENTIFIED	0,017 (2)	0 (0)	0 (0)
14	VIKTORIA	UNIDENTIFIED	0,017 (2)	0,009 (1)	0,014 (187)
15	OSWALD	AGENT	0,017 (2)	0,009 (1)	0,003 (42)
16	VALENTIN	UNIDENTIFIED	0,017 (2)	0,009 (1)	0 (4)
17	NIKITIN	ENOVY	0,017 (2)	0,009 (1)	0,004 (54)
18	CYRUS	UNIDENTIFIED	0,017 (2)	0,017 (2)	0 (0)
19	SEMENOV	ENOVY	0,017 (2)	0,017 (2)	0,041 (532)
20	FRIEND	UNIDENTIFIED	0,017 (2)	0,017 (2)	0,013 (176)

6 Analysis

6.1 Networks

Bichler (2019, p. 156) suggests the following values should be given when describing a whole network. The values for both sets are undirected.

Table 6.1.
Dataset1 and Dataset2 statistics

	Dataset1	**Dataset2**
Actors	207	116
Ties (total/unique)	1670/1670	262/262
Components	15	3
Density	3,9%	2,0%
Avg degree	8,068	2,259
Degree centralization	22%	49%
Average path length	3,003	2,962

With more than half of the actors in dataset1 being present in dataset2, the first conclusion to draw is that many of them had an explicit relation in the cables. Since the categories chosen for dataset1 would assume a relation to the embassy, the many components suggest many missing relations.

Comparing the relative number of ties by looking at density and knowing that dataset2 contains confirmed relations, it can be assumed that many of the ties in dataset1 are artifacts. The graph for dataset1 will have many fraudulent ties. Since 262 relations in dataset2 are confirmed in text, the difference with dataset1, 1408, are not confirmed in the text. If the number of relations per actor in dataset2 is representing a baseline, with roughly double the actors in dataset 1 would have equally roughly twice the ties, about 500. This way, more than a thousand of the ties are false. This affects density since it’s calculated on theoretical maximal relations. In the visualization, the difference in density suggests that dataset2 will be more of a chainlike structure than dataset1.

Going on to average degree, the normal number of relations in dataset2 are just above two. Again, if this is the baseline, it would be an indication that three quarters of the ties for the actors in dataset1 are artifacts – 1253. Otherwise, if they're all real, and to reach the average of 8 for dataset1, there would have to be a lot of relations hidden in the missing groups of the cables. One could also make the argument, that there would be a lot of missing actors as well.

From degree centralization we can see that it's twice as common to be connected to the largest hub in dataset2. Had the relation discussed in the introduction of this chapter been included, where all actors in dataset would be connected to the embassy, this number would have been 100% for dataset1! Instead, the value now shows that there is a central character in this dataset of which about a fifth are connected to. In a dark network, this is a very visible person. In dataset2, half off the actors are directly connected to one actor.

Finally, looking at average path length, the similarity is intriguing. Here one must remember the difference in data collection. For this value, they are not showing the same thing. For dataset2 it tells us that it's a tighter network than what would normally be expected, insinuating a network. What it means for dataset1 is hard to interpret.

6.2 Actors

Here I will interpret the information we can obtain from the actor tables.

6.2.1 Dataset1

The actor of which 22% were connected to was KLARA. After a very close second, KHOCHEV, the values drop off in a steady rate. High degree centrality values relate to hubs. To get an impression of their sizes, The total amount of ties was 1670, and the first 20 makes up for 522 of those. By dividing the ties by their actors, we get an average of 26,1. For the first ten the values are 314 ties and an average of 34,1. This should be compared of the total average degree of 8. The presence of hubs is thus confirmed.

There's one civilian with high visibility, TANNER. This could suggest that the actor is known for other reasons for than this dark network, alternatively that an illicit actor has managed to stay hidden. Given the risk related to visibility and law enforcement attention, it can be assumed that the connections are to characters on the legal side. One must remember the extraction method though; it is just the occurrence in cables that results in a relation.

Apart from TANNER the top ten is mainly populated by agents and envoys. If this suggests that they are occurring in many cables containing few other actors, few cables and many other actors or anything between is impossible to tell from this. However, while extending the top 20 range of table 5.2, from slot 16 to 33, all actors have 20 connections each. They all also have 0 betweenness and are, apart from WIRTANEN, unidentified. While this could be random, it could mean they are all occurring in the same cable.

Continuing with betweenness, KLARA and KHOCHEV still have the first and second slot. Betweenness drops off much quicker than degree centrality. This could indicate that the mentioned hubs are close the center of the cluster. Regardless, high values mean they are important for information flow. This value is 0 from slot 36 up to 207 meaning that the majority are in the periphery, combined with average degree can reveal more about the network. A betweenness value of 0 indicates they have no influence on the flow. This means that they can only be mentioned once as twice would imply that they would sit on a path between two cables. For this reason, any actor with betweenness of 0 and a degree centrality value higher than 1 must be present in more than one cable.

6.2.2 Dataset2 undirected

Considering the embassy being such a central part of the network, it’s not surprising seeing it having the highest number of relations. As expected in dataset2, the embassy has the most direct connections. Ignoring the embassy for the moment, KLARA is the most prominent one. The degree centrality drops quickly after the first few actors. While the top 20 represents 152 of the 262 ties, the top ten represents 124 – almost 50% of total ties. This tells us that there are a few large hubs of which one, the embassy, is salient. The remaining 252 actors are likely peripheral or share few ties with others. Looking at betweenness centrality, this can be confirmed. 70 actors have 0 betweenness.

The most salient actors are agents and envoys. PAUL, unidentified, with fairly high degree centrality may have undergone detection and could be more prominent than suggested. This possibility is strengthened with sixth highest betweenness centrality. Sorted after that measurement, just like in degree centrality, the top slots are populated by agents and envoys. No civilians are present in the top 20.

6.2.3 Dataset2 directed

From this table one can tell that KLARA likely has many sources, 13, compared to nine and seven for second and third when sorted after in-degree centrality. Remember that the undirected table for dataset2 was dichotomized, meaning that while the sum of KLARA’s in-degree (13) and out-degree (4) still results in a dichotomized 13. Comparing those numbers, it’s clear that KLARA has many sources but few receiving actors. This is true for most agents in the top 20 while envoys have similar in-degree and out-degree, meaning they’re carriers. As assumed, the main receiver is the embassy.

A thing to note about CROAT is the 2 in-degree and 0 out-degree. This means that CROAT receives from two but transmits to none. Being unidentified, this could be an actor of greater importance than revealed in the cables using the coding sheet of dataset2.

6.3 Graphs

Here I will interpret the information we can obtain from the graphs.

6.3.1 Dataset1

There are two noticeable large and a few smaller dense clusters with high transitivity seen in graph 5.4.1 (larger version in appendix). What exactly are they? It in most cases it only means they were mentioned in the same cable. Unless the pattern is replicated in dataset2, it's likely part of the artifacts.

This can be seen analyzing the values as well. K-core means that all actors within that k-core group are connected to everyone else. This is what happens when actors are mentioned in the same cable. To be identifiable like in the graph, their k-core value must be distinguishable high. In the single cable, no information would need to go through them, since everyone is directly connected to everyone. That means they will all have betweenness 0 unless they're also connected to other actors outside of the cable. In other words, looking for high k-core combined with 0 betweenness should identify these possible artifacts. If expanding this method on a much larger portion of the Venona project, this could be used to quickly filter them out.

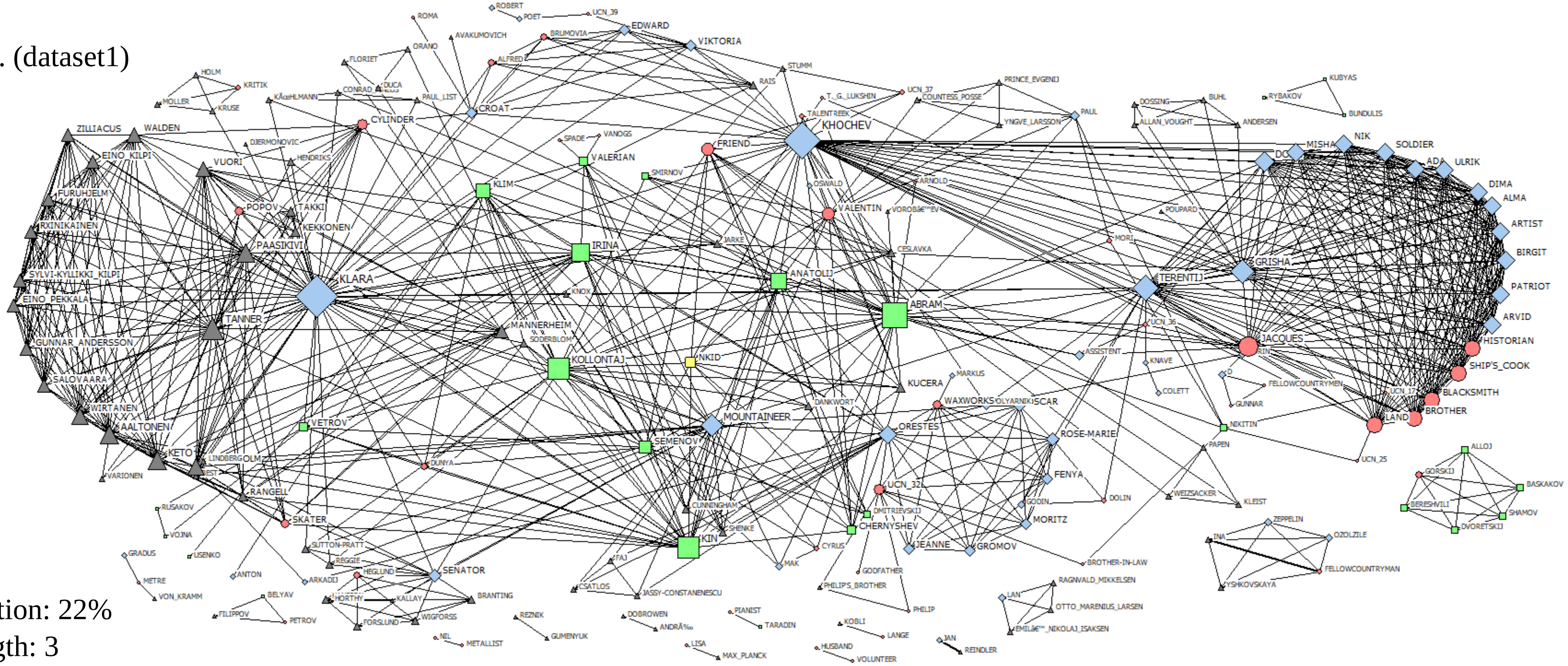
Next are the components of which 14 are very small compared to the main one. These are cables where the actors were never mentioned with anyone in the large component. Even though the dataset is dichotomized, for pedagogic reasons, I let the lines for these components visually reflect the actor's coexistence in the cable (their weighted value before dichotomization). As can be seen, it's not only individual cables, sometimes these components are made from two.

Looking at the first graph where actor size reflects degree centralization, a couple of hubs are noticeable. As we learned by study the numbers, 22% are connected to the biggest one, KLARA. Unfortunately, the shape of the actors makes visual comparison difficult, however, KHOCHEV can be seen as a close second followed by a couple of similar sized ones.

With betweenness centrality KLARA is still the prominent figure. However, the order for the other actors have changed. KLARA, KHOCHEV, MOUNTAINEER and ORESTES stay the same while KOLLONTAJ all but disappears. The same is true for the high degree centrality civilians, especially TANNER.

Finally, the graph shows no chains which is in line with the density value.

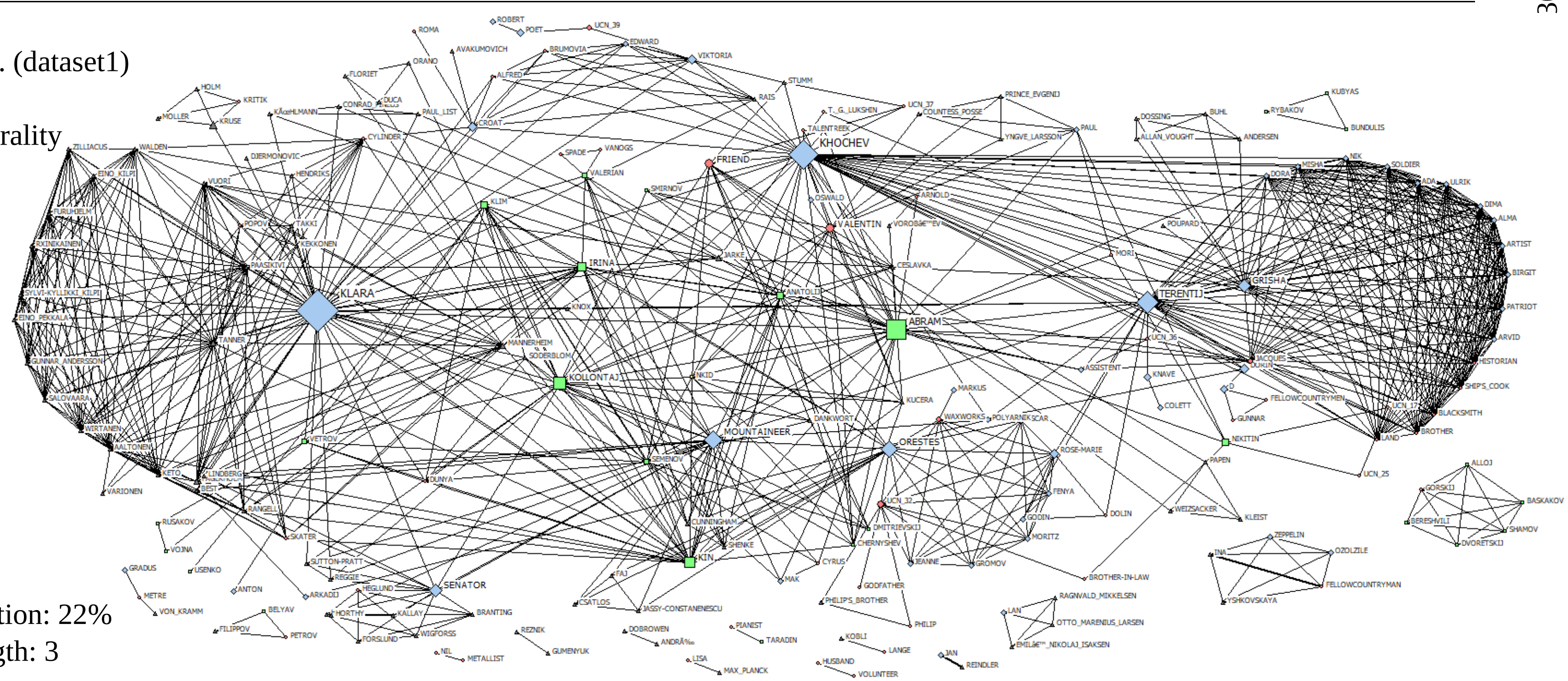
Graph 6.3.1
Source: Table 5.2. (dataset1)
Actor size:
Degree centrality



Envoy
Agent
Civilian
Unidentified

Actors: 207
Total ties: 1670
Unique ties: 1670
Components: 15
Density: 3,9%
Avg degree: 8
Degree centralization: 22%
Average path length: 3

Graph 6.3.2
Source: Table 5.2. (dataset1)
Actor size:
Betweenness centrality



Envoy
Agent
Civilian
Unidentified

Actors: 207
Total ties: 1670
Unique ties: 1670
Components: 15
Density: 3,9%
Avg degree: 8
Degree centralization: 22%
Average path length: 3

6.3.2 Dataset2

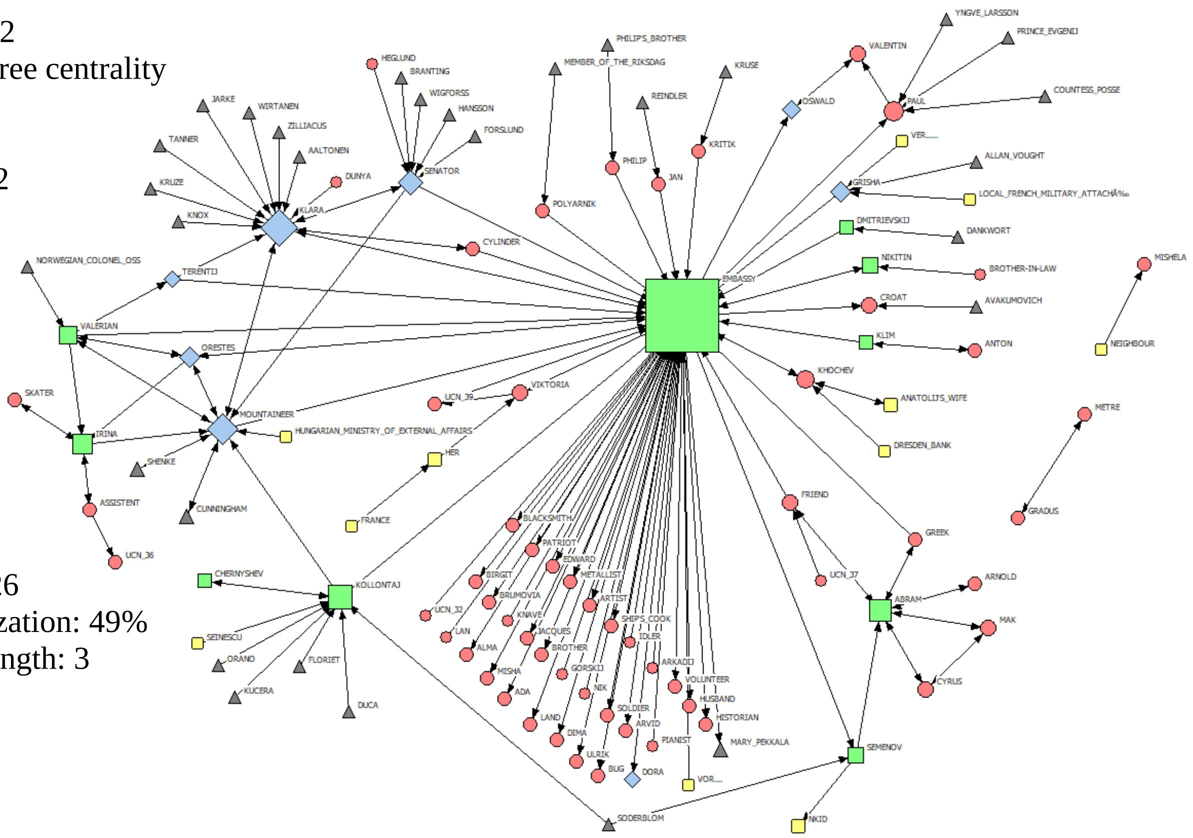
For this dataset there are four different graphs. Beginning by only looking the structure in graph 6.3.2a, the dense clusters of dataset1 are no longer present. This have largely contributed to more chainlike structures, adhering to the lower density. Probably most eye catching are the many actors in the lower part, only connected to the main hub – the embassy. This would typically mean communication between embassy and an actor. Most of these are unidentified. This would suggest either a direct source or that it's an agent with a very low profile.

A few actors are connected to many actors in the periphery. As can be seen, the direction is going inwards. A few complex relations can be seen, tying together the prominent figures in dataset1. Exception are KHOCHEV who no longer is prominent at all, and VALERIAN who now seem to have notable role.

There's little different between this graph and graph 5.4.2b showing betweenness centrality. The reason is hard to circumvent. In the cables, the embassy is the central figure and for this reason it's reasonable that the embassy will have a very central role in the dataset. In fact, when the software let a value, like degree, influence the graphs, there's a minimum and a maximum size for the actors. Normally a value of 0 would not be an issue but here, the difference between 0 and 1 is hardly noticeable in the graph. This is what I referred to in the first part of this chapter. Imagine what this would have done to dataset1 if all actors would have been connected to the embassy. Nonetheless, the smallest actors in the betweenness graph have a value of 0. For the in-degree centrality graphs (6.3.2.c) this is somewhat less of an issue. Agents with many sources will, relative to the others, have a much higher value.

There's always an alternative path from the clusters to the embassy. For that reason, with no structural holes, one could assume the hubs are the most important one to permit information flow from sources to the embassy.

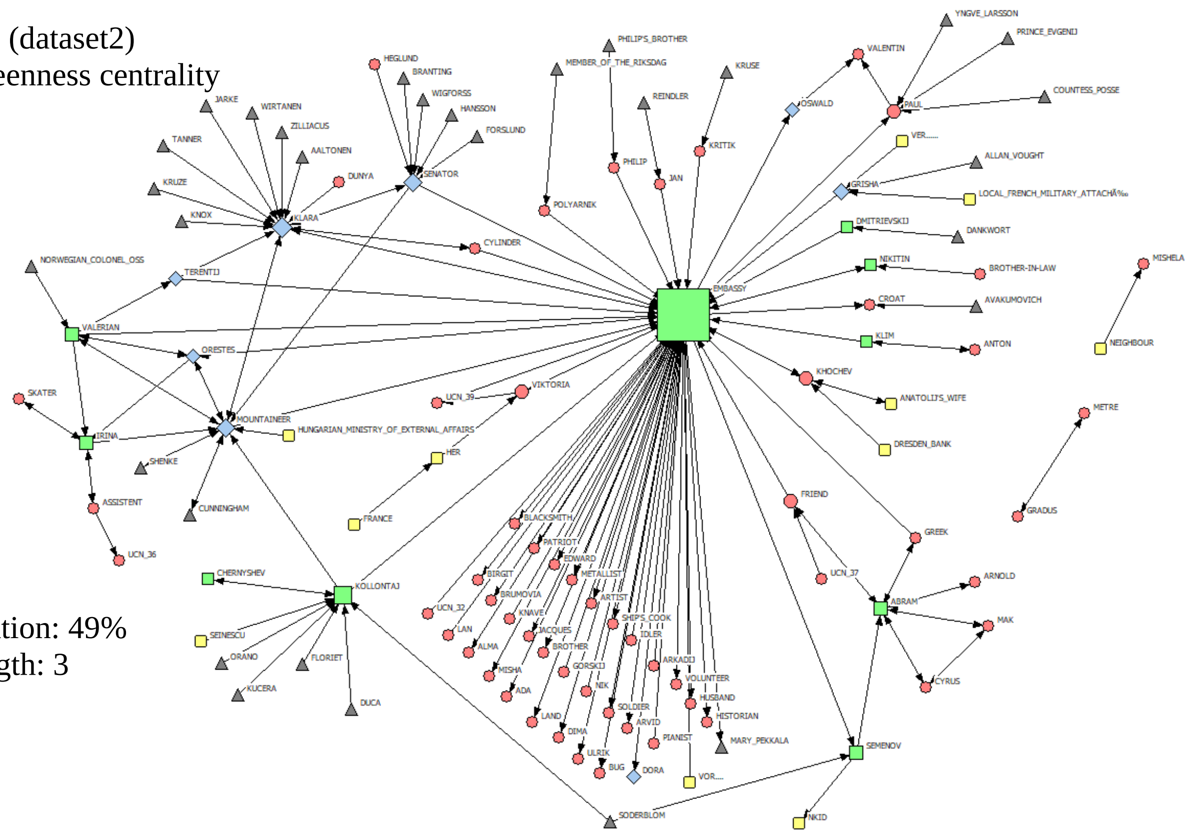
Graph 6.3.2a
Source: Dataset2
Actor size: Degree centrality
Actors: 116
Total ties: 262
Unique ties: 262



Envoy
Agent
Civilian
Unidentified

Components: 3
Density: 2,0%
Avg degree: 2,26
Degree centralization: 49%
Average path length: 3

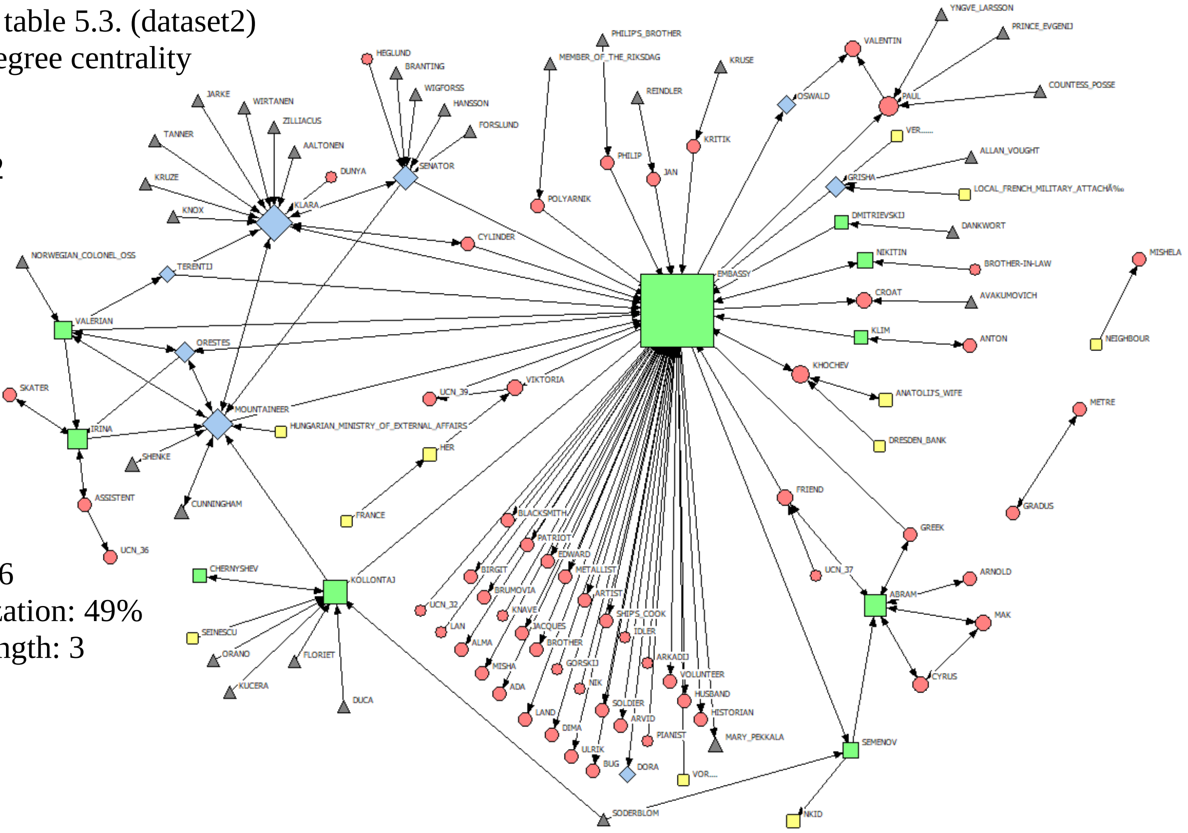
Graph 6.3.2b
Source: table 5.3. (dataset2)
Actor size: Betweenness centrality
Actors: 116
Total ties: 262
Unique ties: 262



Envoy
Agent
Civilian
Unidentified

Components: 3
Density: 2,0%
Avg degree: 2,26
Degree centralization: 49%
Average path length: 3

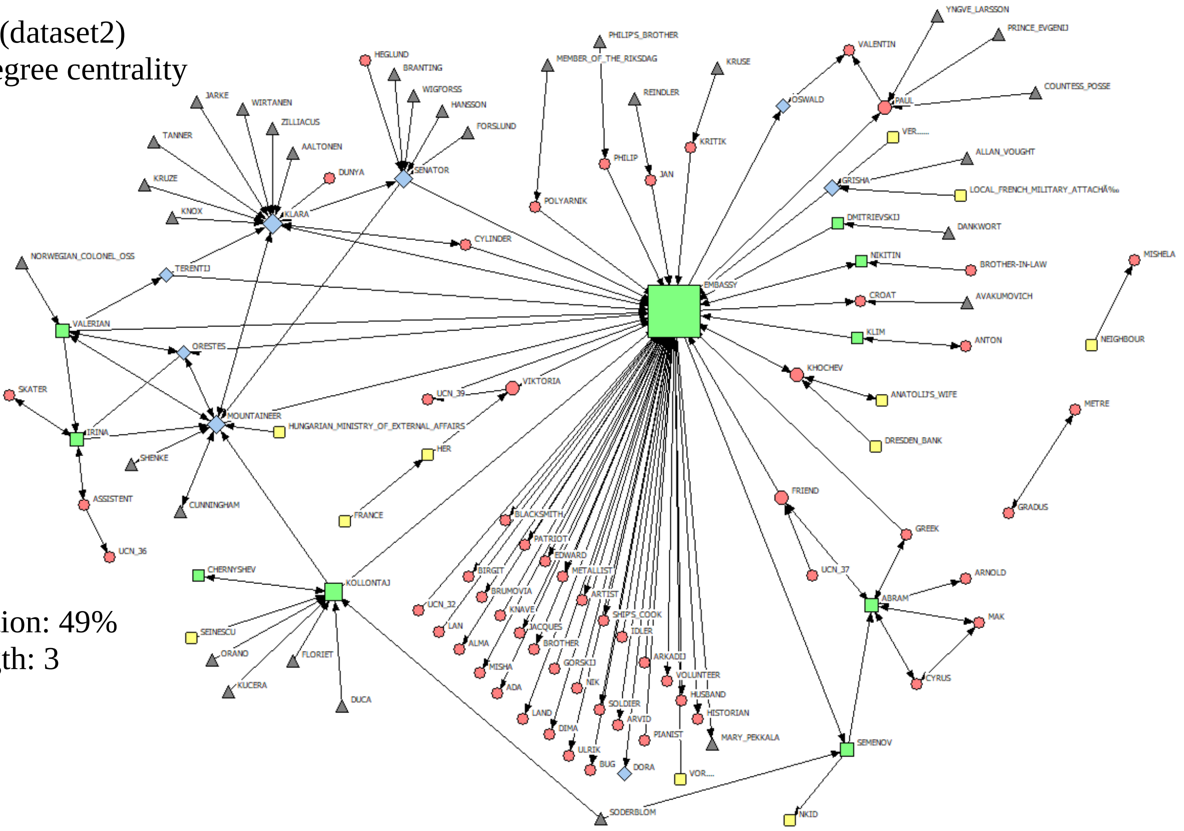
Graph 6.3.2a
Source: Source: table 5.3. (dataset2)
Actor size: In-degree centrality
Actors: 116
Total ties: 262
Unique ties: 262



Envoy
Agent
Civilian
Unidentified

Components: 3
Density: 2,0%
Avg degree: 2,26
Degree centralization: 49%
Average path length: 3

Graph 6.3.2a
Source: table 5.3. (dataset2)
Actor size: Out-degree centrality
Actors: 116
Total ties: 262
Unique ties: 262



Envoy
Agent
Civilian
Unidentified

Components: 3
Density: 2,0%
Avg degree: 2,26
Degree centralization: 49%
Average path length: 3

6.4 Evaluation

6.4.1 Theoretical dark network

6.4.1.1. Dataset1

It is not easy to compare the values for degree and betweenness centrality and then relate this to the order of the actors. How to tell what is a low or high value? One way is to compare slot order for degree and betweenness centrality. As mentioned in the introduction to this chapter, this can be deceiving. Always compare the raw values as well! As it turns out, KLARA and KHOCHEV remains at the top and the top ten are somewhat shuffled. They are all important for maintaining flow.

The most noticeable however, is that the civilians and unidentified in degree centrality top 20, all but one had 0 betweenness centrality. This indicates they were all mentioned once in a cable and together with many others on that occasion.

From this we can conclude, in accordance to to dataset1, that civilians and unidentified indeed often are sources. The dataset agents and envoys could be either/or theoretical dark network agents or envoys ones.

Since this dataset is not directed, it can't evaluate this to the theoretical dark network roles more than this.

6.4.2 Dataset2

For these datasets I have subtracted the in- from the out-degree centrality. This makes the difference easier to identify. A small value would indicate someone transmitting information. A positive value means transmitting more than receiving and conversely, a negative would mean receiving more than transmitting.

6.4.2.1. Civilian

Civilian category would have 0 betweenness, 0 in-degree and low out-degree.

Table 6.4.2.1
Source: Dataset2
Top 20 civilians, sorted after difference out-degree and in-degree centrality

Actor	Directed Degree Out-In	Directed In-Degree Raw	Directed Out-Degree Raw	Directed Betweenness
MARY_PEKKALA	-1	1	0	0
CUNNINGHAM	0	1	1	0
SHENKE	0	1	1	0
KNOX	1	0	1	0
COUNTESS_POSSE	1	0	1	0
AVAKUMOVICH	1	0	1	0
FORSLUND	1	0	1	0
HANSSON	1	0	1	0
JARKE	1	0	1	0
FLORIET	1	0	1	0
SODERBLOM	2	0	2	0
KRUSE	1	0	1	0
DUCA	1	0	1	0
MEMBER_OF_THE_RIKSDAG	1	0	1	0
NORWEGIAN_COLONEL_OSS	1	0	1	0
ORANO	1	0	1	0
ZILLIACUS	1	0	1	0
YNGVE_LARSSON	1	0	1	0
WIRTANEN	1	0	1	0
WIGFORSS	1	0	1	0

In this table 17 out of 20 of the actors corresponds to the theoretical values.

6.4.2.2. Agents

Expected values are high in-, low out-degree and high betweenness centrality.

Table 6.4.2.2
Source: Dataset2
Top 20 agents, sorted after difference out-degree and in-degree centrality

Actor	Directed Degree Out-In	Directed In-Degree Raw	Directed Out-Degree Raw	Directed Betweenness
KLARA	-9	13	4	652
MOUNTAINEER	-3	9	6	598
SENATOR	-3	6	3	270
GRISHA	-2	3	1	165
ORESTES	1	3	4	439
OSWALD	-1	2	1	42
DORA	-1	1	0	0
TERENTIJ	1	1	2	2

Out of eight, six actors have expected difference in degree centrality with KLARA as a notable example. Four of them had the expected betweenness value.

6.4.2.3. Envoy

Moderate in- and out-degree accompanied with a fairly high betweenness centrality is expected. The embassy is not included in this category.

Table 6.4.2.3
Source: Dataset2
Top 20 envoys, sorted after difference out-degree and in-degree centrality

Actor	Directed Degree Out-In	Directed In-Degree Raw	Directed Out-Degree Raw	Directed Betweenness
EMBASSY	-1	34	33	3964
KOLLONTAJ	-4	7	3	383
ABRAM	-1	6	5	596
IRINA	-1	4	3	345
VALERIAN	2	3	5	173
SEMENOV	0	2	2	532
NIKITIN	-1	2	1	54
DMITRIEVSKIJ	0	1	1	55
CHERNYSHEV	0	1	1	0
KLIM	1	1	2	55

Apart from KOLLONTAJ, most have a similar in- and out-degree which was expected. For half of them, betweenness is high adhering to the theoretical dark network.

6.4.2.4. Unidentified

For the unidentified the expectation was low centrality degree based on the idea that they were less visible and thus never detected.

Table 6.4.2.4
Source: Dataset2
Top 20 unidentified, sorted after difference out-degree and in-degree centrality

Actor	Directed Degree Out-In	Directed In-Degree Raw	Directed Out-Degree Raw	Directed Betweenness
PAUL	-3	4	1	48
KHOCHEV	-1	3	2	187
MAK	0	2	2	0
CROAT	-2	2	0	0
VALENTIN	-1	2	1	4
FRIEND	0	2	2	176
VIKTORIA	-1	2	1	187
CYRUS	0	2	2	0
EDWARD	0	1	1	0
POLYARNIK	0	1	1	55
CYLINDER	1	1	2	0
PHILIP	0	1	1	55
ARNOLD	0	1	1	0
METRE	0	1	1	0
BROTHER	0	1	1	0
METALLIST	0	1	1	0
UCN_36	-1	1	0	0
SOLDIER	-1	1	0	0
SHIP'S_COOK	-1	1	0	0
PATRIOT	-1	1	0	0

As it turns out, the unidentified had both lower in- and out-degree centrality. The difference suggests half of them received more than transmitted. Betweenness varied but no large values were observed.

6.5 Literature comparison

In order to see how the datasets reflect the literature, the characters will be introduced. As mentioned, the reference material for this will be Agrell (2003). Information regarding degree and betweenness centrality will be summarized from characters in chapter 8 present in the study's material. Admitting this part of the study is a bit weak due to little scares information, it is assumed that those mentioned at least once are prominent.

While the tables will only include the characters with their own chapter, the graphs will include egonet for all.

6.5.1 Characters

6.5.1.1. SENATOR

SENATOR (Georg Branting) is described to be a centrally positioned person within the Swedish political society (Agrell, 2003, pp. 272-278). He's connected to KLARA, MOUNTAINEER and VALERIAN. Attended a meeting with HEGLUND. It's said that he did not hide his Soviet sympathies.

6.5.1.2. ORESTES

ORESTES (Vilmos Böhm) had a triad relation to VALERIAN and MOUNTAINEER (Agrell, 2003, pp. 295-301). He sends information from MOUNTAINEER to the embassy and has a relation with GRISHA. It's said that he had many valuable contacts. In addition, he was employed by the British and had contact with western allied.

6.5.1.3. KLARA

KLARA (Gusti Stridsberg) was not an intelligence source but had many contacts of which she obtained information (Agrell, 2003, pp. 302-328). Together with CROAT she helped recruiting Cylinder. She had relations with Sutton-pratt, MOUNTAINEER, VALERIAN, Dermanovich and was possibly lover with GRISHA. Information confirmed once with SENATOR and MOUNTAINEER. Her sources were Lindberg, Best, Zilliacus, Jarke, Virtanen, Wuori, Tanner, Kruze and Allan Vought. She infiltrated the embassy personnel. In addition, text says JARKE had a relationship with VALERIAN.

6.5.1.4. GRISHA

GRISHA (Jules M. Guesde) had a conversation with Allan Vought and knew KLARA (Agrell, 2003, pp. 329-339). Information came from the French military attaché. His alias starts with VER…

6.5.2 Tables

6.5.2.1. Dataset1

By simply looking the actor's number slot we can see how well they correspond to the literature. Please not that when the value is the same, the slot number is random.

Table 6.5.2.1
Source: Dataset1
Included actors: See 6.5

	Decree centrality		**Betweenness centrality**	
Actor	Slot	Value	Slot	Value
SENATOR	51	0,06 (12)	10	0,04 (813)
ORESTES	6	0,09 (19)	6	0,06 (1282)
KLARA	1	0,26 (53)	1	0,21 (4494)
GRISHA	33	0,13 (27)	9	0,04 (915)

Senator's visibility is not reflected in dataset1. Being mentioned in both KLARA's and ORESTE's chapters, GRISHA would have been assumed to be more visible. However, KLARA's multitude of contacts is reflected in degree centrality.

6.5.2.2. Dataset2

Table 6.5.2.2
Source: Dataset2
Included actors: See 6.5

Dataset2	**Degree centrality**		**Directed out-degree centrality**		**Directed betweenness centralitty**	
Actor	Slot	Value	Slot	Value	Slot	Value
SENATOR	5	0,052 (6)	7	0,026 (3)	9	0,021 (270)
ORESTES	12	0,026 (3)	5	0,035 (4)	9	0,033 (439)
KLARA	2	0,113 (13)	6	0,035 (4)	2	0,050 (652)
GRISHA	10	0,026 (3)	94	0,009 (1)	14	0,013 (165)

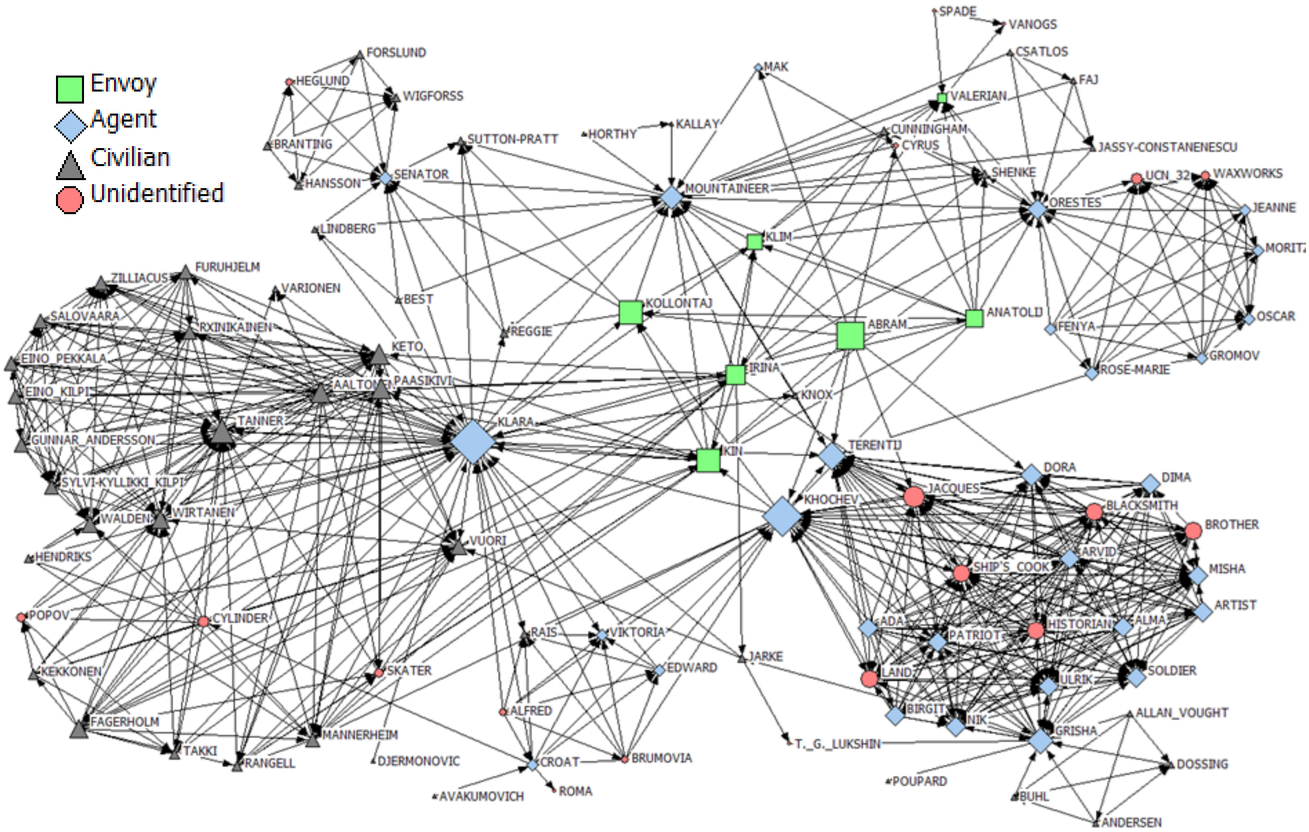
Values are much as what could have been expected. For GRISHA's out-degree centralization slot number, the warning of randomness is repeated. From 21 to 94, all actors have 1 outgoing contact, and then 0 for the rest.

6.5.3 Graphs

6.5.3.1. Dataset1

These egonet graphs of all the actors mentioned in the characters chapters helps visualize what was written. However, as concluded during the structure analysis in 6.1, many of these dense clusters are artifacts. The patterns are easily identifiable, especially when considering the actor size. If one in the cluster is larger than the rest, it indicates that it's present in another cable. Their color and shape – representing category – also reveals that KLARA is more connected to civilians. This is also revealed in the literature, she's not an intelligence source. SENATOR's connection is also reflected being connected to the Swedish parliament and KOLLONTAJ at the soviet embassy.

Graph 6.3.3.1



Source: Dataset1

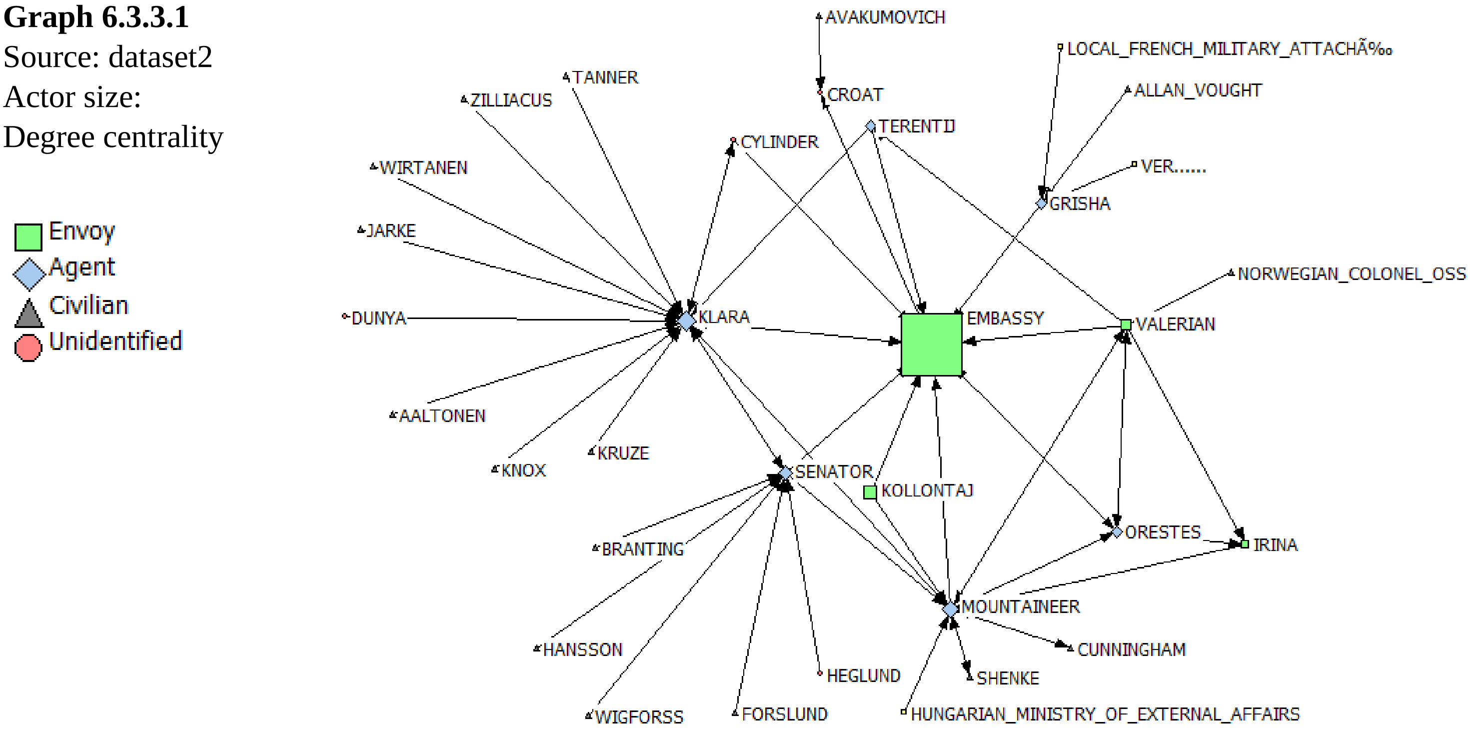
Actor size: Degree centralization

No specific values for this egonet. Please see table 6.1 for full network values.

Egonet: ALLAN_VOUGHT, BRANTING, CROAT, CYLINDER, GRISHA, JARKE, KLARA, KRUZE, MOUNTAINEER, ORESTES, SENATOR, TANNER, VALERIAN, WIRTANEN, ZILLIACUS

6.5.3.2. Dataset2

Graph 6.3.3.1
Source: dataset2
Actor size:
Degree centrality



No specific values for this egonet. Please see table 6.1 for full network values.

Egonet: ALLAN_VOUGHT, BRANTING, CROAT, CYLINDER, GRISHA, JARKE, KLARA, KRUZE, MOUNTAINEER, ORESTES, SENATOR, TANNER, VALERIAN, WIRTANEN, ZILLIACUS

The egonet graph for dataset2 is less cluttered than the dataset1 in graph 6.3.1. It might be visually more useful to notice actors who otherwise would have gone unnoticed. From the egonet, TERENTIJ, IRINA and KOLLONTAJ have been added. Interestingly, they are all highly visible on the previous dataset1 graph. KOLLONTAJ was mentioned indirectly in the chapter of KLARA but had no explicit relation to KLARA and was thus excluded. GRISHA being the same as VER… was mentioned in the literature referenced to a cable. However, SENATOR and BRANTING were not. This suggests that these graphs can be used connect one known and one unknown character, increasing actor resolution.

7 Conclusions

7.1 Discussion

In the introduction, I asked the following questions:

What properties do the network and actors have?
How do the actors compare to an assumed dark network?
How do the actors reflect the literature?

First of all, the difference in results between dataset1 and dataset2 must be discussed. While I showed that k-core can be used to remove artifacts, dataset1 is still too unreliable. However, as a graph it paints a picture in what relational context actors are mentioned, like a visual index. I would argue it does so exemplary and that this adds to the historical research. An interactive software with filter for actor, cable and date would help navigate through the material.

As the evaluation part of the study showed, dataset2 is more trustworthy. This is especially true if one would accept my theoretical roles in dark networks. This dataset shows that the network has a minor chainlike structure and that there's a fair number of relations between the agents and envoys.

As expected, civilians were in large only connected to their handler. The unidentified had values showing less visibility which makes sense. They are usually at the end of each chain.

For those with knowledge of the actors none of this may be news, but one must imagine how clearly this visualizes for instance KLARA's and SENATOR's roles for the uninitiated. Text analysis software should be able to extract information according to datasheet2 for the whole Venona project which would give anyone a very good overview.

The theoretical dark network may be the most prominent indirect result. It was not the purpose of the study, however, they corresponded to the values obtained by the material with a surprisingly high accuracy. This is certainly something for future research to take hold on.

It was not possible within the realms of this study, but a broader scope of literature had probably produced more prominent results. While the values in dataset2 largely matched the expected ones, it was not enough information to draw any conclusions on. However, the egonets provided some interesting insights. In the literature we could see that GRISHA and VER… where the same individual (Agrell, 2003, 329). This was also easily seen in the graphs and suggests that an identified actor can be linked to an unidentified one and that they are the one same character – even if not explicit mentioned. SENATOR and BRANTING are a good example of one such circumstance.

7.2 Future research

With the material's inconsistency and flaws in mind, the theoretical dark network roles were surprisingly accurate. This is definitely something to test on more transparent data of other spy networks. If, with a fairly good understanding of measurements used in social network theory combined with imagining the properties of a role is sufficient for prediction, it opens up for a broader field of research, expanding beyond intelligence networks. One should remember the initiating contribution of Leuprecht et al. (2017) to this area.

As for the Venona project, the obvious suggestion would be to apply this research method to more material and combining it. Another Verona project research would be to apply the second coding sheet to Matz (2013) paper as many characters and relations are mentioned there. This could even qualify for a weighted network. In fact, all the research on individuals at this time could be combined for a data source with much higher validity than used in this study.

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9 Appendix

9.1 Tables

9.1.1 Dataset1, degree centrality

Table 9.1.1 (identical to 5.2
Source: Dataset1
Top 20 actors of 207 sorted after degree centrality raw values.

N	Actor	Category	DC	BC
1	KLARA	AGENT	0,26 (53)	0,21 (4494)
2	KHOCHEV	UNIDENTIFIED	0,22 (45)	0,14 (2920)
3	ABRAM	ENVOY	0,15 (31)	0,09 (1955)
4	TERENTIJ	AGENT	0,15 (30)	0,10 (2117)
5	TANNER	CIVILIAN	0,13 (27)	0,01 (123)
6	GRISHA	AGENT	0,13 (27)	0,04 (915)
7	KIN	ENVOY	0,13 (26)	0,04 (920)
8	KOLLONTAJ	ENVOY	0,13 (26)	0,05 (1149)
9	MOUNTAINEER	AGENT	0,12 (25)	0,07 (1506)
10	JACQUES	UNIDENTIFIED	0,12 (24)	0,01 (224)
11	DORA	AGENT	0,11 (23)	0 (110)
12	AALTONEN	CIVILIAN	0,11 (22)	0 (72)
13	PAASIKIVI	CIVILIAN	0,10 (21)	0 (60)
14	KETO	CIVILIAN	0,10 (21)	0 (60)
15	IRINA	ENVOY	0,10 (21)	0,03 (638)
16	NIK	UNIDENTIFIED	0,10 (20)	0 (0)
17	PATRIOT	UNIDENTIFIED	0,10 (20)	0 (0)
18	LAND	UNIDENTIFIED	0,10 (20)	0 (0)
19	MISHA	UNIDENTIFIED	0,10 (20)	0 (0)
20	ULRIK	UNIDENTIFIED	0,10 (20)	0 (0)

9.1.2 Dataset1, betweenness centrality

Table 9.1.2
Source: Dataset1
Top 20 actors of 207 sorted after betweenness centrality raw values.

N	Actor	Category	DC	BC
1	KLARA	AGENT	0,26 (53)	0,21 (4494)
2	KHOCHEV	UNIDENTIFIED	0,22 (45)	0,14 (2920)
3	TERENTIJ	AGENT	0,15 (30)	0,10 (2117)
4	ABRAM	ENVOY	0,15 (31)	0,09 (1955)
5	MOUNTAINEER	AGENT	0,12 (25)	0,07 (1506)
6	ORESTES	AGENT	0,09 (19)	0,06 (1282)
7	KOLLONTAJ	ENVOY	0,13 (26)	0,05 (1149)
8	KIN	ENVOY	0,13 (26)	0,04 (920)
9	GRISHA	AGENT	0,13 (27)	0,04 (915)
10	SENATOR	AGENT	0,06 (12)	0,04 (813)
11	IRINA	ENVOY	0,10 (21)	0,03 (638)
12	VALENTIN	UNIDENTIFIED	0,07 (15)	0,03 (621)
13	FRIEND	UNIDENTIFIED	0,06 (13)	0,03 (585)
14	UCN_32	UNIDENTIFIED	0,06 (12)	0,03 (560)
15	KLIM	ENVOY	0,08 (16)	0,02 (535)
16	ROSE-MARIE	UNIDENTIFIED	0,05 (11)	0,02 (508)
17	ANATOLIJ	ENVOY	0,09 (18)	0,02 (505)
18	DORIN	UNIDENTIFIED	0,02 (4)	0,02 (489)
19	KRUSE	CIVILIAN	0,02 (4)	0,02 (489)
20	VIKTORIA	UNIDENTIFIED	0,04 (8)	0,02 (489)

9.1.3 Dataset2, undirected, degree centrality

Table 9.1.3 (identical to 5.3)
Source: Dataset2
Top 20 actors of 207 sorted after degree centrality raw values.

N	Actor	Category	Degree Normalized (Raw)	Betweenness Normalized (Raw)
1	EMBASSY	ENOVY	0,504 (58)	0,841 (5513)
2	KLARA	AGENT	0,113 (13)	0,132 (863)
3	MOUNTAINEER	AGENT	0,087 (10)	0,093 (611)
4	KOLLONTAJ	ENOVY	0,078 (9)	0,107 (700)
5	SENATOR	AGENT	0,07 (8)	0,082 (540)
6	VALERIAN	ENOVY	0,052 (6)	0,033 (218)
7	ABRAM	ENOVY	0,052 (6)	0,050 (331)
8	PAUL	UNIDENTIFIED	0,043 (5)	0,058 (380)
9	IRINA	ENOVY	0,043 (5)	0,05 (326)
10	ORESTES	AGENT	0,035 (4)	0,016 (102)
11	GRISHA	AGENT	0,035 (4)	0,05 (327)
12	SEMENOV	ENOVY	0,035 (4)	0,045 (297)
13	TERENTIJ	AGENT	0,026 (3)	0,001 (6)
14	FRIEND	UNIDENTIFIED	0,026 (3)	0,037 (244)
15	VIKTORIA	UNIDENTIFIED	0,026 (3)	0,033 (218)
16	KHOCHEV	UNIDENTIFIED	0,026 (3)	0,033 (219)
17	MAK	UNIDENTIFIED	0,017 (2)	0 ,000 (0)
18	DMITRIEVSKIJ	ENOVY	0,017 (2)	0,017 (110)
19	KRITIK	UNIDENTIFIED	0,017 (2)	0,017 (110)
20	PHILIP	UNIDENTIFIED	0,017 (2)	0,017 (110)

9.1.4 Dataset2, undirected, betweenness centrality

Table 9.1.5
Source: Dataset2
Top 20 actors of 207 sorted after betweenness centrality raw values.

N	Actor	Category	Degree Normalized (Raw)	Betweenness Normalized (Raw)
1	EMBASSY	ENOVY	0,504 (58)	0,841 (5513)
2	KLARA	AGENT	0,113 (13)	0,132 (863)
3	KOLLONTAJ	ENOVY	0,078 (9)	0,107 (700)
4	MOUNTAINEER	AGENT	0,087 (10)	0,093 (611)
5	SENATOR	AGENT	0,070 (8)	0,082 (540)
6	PAUL	UNIDENTIFIED	0,043 (5)	0,058 (380)
7	ABRAM	ENOVY	0,052 (6)	0,050 (331)
8	GRISHA	AGENT	0,035 (4)	0,050 (327)
9	IRINA	ENOVY	0,043 (5)	0,05 (326)
10	SEMENOV	ENOVY	0,035 (4)	0,045 (297)
11	FRIEND	UNIDENTIFIED	0,026 (3)	0,037 (244)
12	KHOCHEV	UNIDENTIFIED	0,026 (3)	0,033 (219)
13	VALERIAN	ENOVY	0,052 (6)	0,033 (218)
14	VIKTORIA	UNIDENTIFIED	0,026 (3)	0,033 (218)
15	GREEK	UNIDENTIFIED	0,017 (2)	0,02 (134)
16	KRITIK	UNIDENTIFIED	0,017 (2)	0,017 (110)
17	NIKITIN	ENOVY	0,017 (2)	0,017 (110)
18	CROAT	UNIDENTIFIED	0,017 (2)	0,017 (110)
19	KLIM	ENOVY	0,017 (2)	0,017 (110)
20	DMITRIEVSKIJ	ENOVY	0,017 (2)	0,017 (110)

9.1.5 Dataset2, directed, In-degree centrality

Table 9.1.4 (identical to 5.4)
Source: Dataset2
Top 20 actors of 207 sorted after in-degree centrality raw values.

N	Actor	Category	Directed In-Degree Normalized (Raw)	Directed Out-Degree Normalized (Raw)	Directed Betweenness Normalized (Raw)
1	EMBASSY	ENOVY	0,296 (34)	0,287 (33)	0,302 (3964)
2	KLARA	AGENT	0,113 (13)	0,035 (4)	0,050 (652)
3	MOUNTAINEER	AGENT	0,078 (9)	0,052 (6)	0,046 (598)
4	KOLLONTAJ	ENOVY	0,061 (7)	0,026 (3)	0,029 (383)
5	SENATOR	AGENT	0,052 (6)	0,026 (3)	0,021 (270)
6	ABRAM	ENOVY	0,052 (6)	0,043 (5)	0,045 (596)
7	IRINA	ENOVY	0,035 (4)	0,026 (3)	0,026 (345)
8	PAUL	UNIDENTIFIED	0,035 (4)	0,009 (1)	0,004 (48)
9	VALERIAN	ENOVY	0,026 (3)	0,043 (5)	0,013 (173)
10	GRISHA	AGENT	0,026 (3)	0,009 (1)	0,013 (165)
11	KHOCHEV	UNIDENTIFIED	0,026 (3)	0,017 (2)	0,014 (187)
12	ORESTES	AGENT	0,026 (3)	0,035 (4)	0,033 (439)
13	CROAT	UNIDENTIFIED	0,017 (2)	0 (0)	0 (0)
14	VIKTORIA	UNIDENTIFIED	0,017 (2)	0,009 (1)	0,014 (187)
15	OSWALD	AGENT	0,017 (2)	0,009 (1)	0,003 (42)
16	VALENTIN	UNIDENTIFIED	0,017 (2)	0,009 (1)	0 (4)
17	NIKITIN	ENOVY	0,017 (2)	0,009 (1)	0,004 (54)
18	CYRUS	UNIDENTIFIED	0,017 (2)	0,017 (2)	0 (0)
19	SEMENOV	ENOVY	0,017 (2)	0,017 (2)	0,041 (532)
20	FRIEND	UNIDENTIFIED	0,017 (2)	0,017 (2)	0,013 (176)

9.1.6 Dataset2, directed, out-degree centrality

Table 9.1.4 (identical to 5.4)
Source: Dataset2
Top 20 actors of 207 sorted after out-degree centrality raw values.

N	Actor	Category	Directed In-Degree Normalized (Raw)	Directed Out-Degree Normalized (Raw)	Directed Betweenness Normalized (Raw)
1	EMBASSY	ENOVY	0,296 (34)	0,287 (33)	0,302 (3964)
2	MOUNTAINEER	AGENT	0,078 (9)	0,052 (6)	0,046 (598)
3	VALERIAN	ENOVY	0,026 (3)	0,043 (5)	0,013 (173)
4	ABRAM	ENOVY	0,052 (6)	0,043 (5)	0,045 (596)
5	ORESTES	AGENT	0,026 (3)	0,035 (4)	0,033 (439)
6	KLARA	AGENT	0,113 (13)	0,035 (4)	0,05 (652)
7	SENATOR	AGENT	0,052 (6)	0,026 (3)	0,021 (270)
8	IRINA	ENOVY	0,035 (4)	0,026 (3)	0,026 (345)
9	KOLLONTAJ	ENOVY	0,061 (7)	0,026 (3)	0,029 (383)
10	FRIEND	UNIDENTIFIED	0,017 (2)	0,017 (2)	0,013 (176)
11	SODERBLOM	CIVILIAN	0 (0)	0,017 (2)	0 (0)
12	GREEK	UNIDENTIFIED	0,009 (1)	0,017 (2)	0,009 (122)
13	SEMENOV	ENOVY	0,017 (2)	0,017 (2)	0,041 (532)
14	CYRUS	UNIDENTIFIED	0,017 (2)	0,017 (2)	0 (0)
15	KLIM	ENOVY	0,009 (1)	0,017 (2)	0,004 (55)
16	CYLINDER	UNIDENTIFIED	0,009 (1)	0,017 (2)	0 (0)
17	TERENTIJ	AGENT	0,009 (1)	0,017 (2)	0 (2)
18	KHOCHEV	UNIDENTIFIED	0,026 (3)	0,017 (2)	0,014 (187)
19	ASSISTENT	UNIDENTIFIED	0,009 (1)	0,017 (2)	0,006 (82)
20	MAK	UNIDENTIFIED	0,017 (2)	0,017 (2)	0 (0)

9.2 Dataset1

For this procedure, Excel (Version 2204) was used with a Visual Basic script (VBA). Each row represents a cable. To format the data for Usinet (Borgatti, Everett and Freeman, 2002) and NetDraw (Borgatti, 2002) each dyad relation needs its own row. The script created all possible combinations since the dataset requires all actors within a cable to be connected to each other. The 77 cables resulted in 922 dyads.

Cable 1	"ABRAM"	"MORI"	"NIKITIN"	"PAUL"
Cable 2	"ABRAM"	"NIKITIN"		

ENTITY 1	**ENTITY 2**	
"ABRAM"	"MORI"	
"ABRAM"	"NIKITIN"	←
"ABRAM"	"PAUL"	
"MORI"	"NIKITIN"	
"MORI"	"PAUL"	
"NIKITIN"	"PAUL"	
"ABRAM"	"NIKITIN"	←

Rows with two identical dyads was consolidated into 1

making a dichotomized network.

ENTITY 1	**ENTITY 2**	**WEIGHT**
"ABRAM"	"MORI"	1
"ABRAM"	"NIKITIN"	← **2**
"ABRAM"	"PAUL"	1
"MORI"	"NIKITIN"	1
"MORI"	"PAUL"	1
"NIKITIN"	"PAUL"	1

9.2.1 Dataset1 VBA script (see 9.2)

```
Sub VBA_Venona_Dataset1()
Dim wb As Workbook: Set wb = ActiveWorkbook

Dim wsDSET2x As Worksheet
Set wsDSET2x = wb.Sheets("DATASET1x")
Dim tblDSET2t As ListObject
Set tblDSET2t = wsDSET2x.ListObjects("DATASET1t")

Dim wsDSET1 As Worksheet
Set wsDSET1 = wb.Sheets("DSET1")
Dim tblDSET1 As ListObject
Set tblDSET1 = wsDSET1.ListObjects("DSET1")

Dim MaxRow_S2 As Integer
Dim MaxCol_S2 As Integer
Dim Arow As Integer
Dim Acol As Integer
Dim iRow_S2 As Integer
Dim iColF_S2 As Integer
Dim iColT_S2 As Integer
Dim C As Integer
Dim iFROM As Integer
Dim iTO As Integer
Dim valueFROM As String
Dim valueTO As String
Dim iRow_D2 As Integer
Dim colFROM As Integer
Dim colTO As Integer

iRow_D2 = 2
iCol_S2 = 1
MaxRow_S2 = tblDSET1.ListRows.Count
For iRow_S2 = 1 To MaxRow_S2
MaxCol_S2 = tblDSET1.DataBodyRange(iRow_S2, iCol_S2).End(xlToRight).Column
       For colFROM = 1 To MaxCol_S2 - 1
        valueFROM = tblDSET1.DataBodyRange(iRow_S2, colFROM).Value
             For colTO = colFROM + 1 To MaxCol_S2
            valueTO = tblDSET1.DataBodyRange(iRow_S2, colTO).Value
            wsDSET2x.Cells(iRow_D2, 1) = valueFROM
            wsDSET2x.Cells(iRow_D2, 2) = valueTO
            iRow_D2 = iRow_D2 + 1
            Next
        Next
Next
End Sub
```

9.3 Dataset2

Each relation was added to its own row according to code sheet2.

FROM	TO
"MORI"	"NIKITIN"
"MORI"	"PAUL"
"NIKITIN"	"PAUL"
"ABRAM"	"NIKITIN"

9.4 UCINET

To create statistics for a whole network, the corresponding VNA-file was used with the UCINET menu command: Network/Multiple measures/Network level command.

To create statistics for each actor, the corresponding VNA-file was used with the UCINET menu command: Network/Multiple measures/Node level

During this creation you can dichotomize and symmetrize when needed.

9.5 NETDRAW

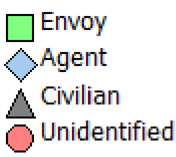
The VNA-files for NetDraw were created in Excel. The data is saved into a text-file with suffix VNA. Creating these sections can be automated but requires some knowledge of Excel. Here are the first four actors for each section.

--- This part defines the ID for the actors

```
*Node data
ID
"AALTONEN"
"ABRAM"
"ADA"
"ALFRED"
```

--- This part adds the label, shape, color

```
*Node properties
ID labeltext shape and color
"AALTONEN" "AALTONEN" 3 8421504
"ABRAM" "ABRAM" 2 8454016
"ACQUAINTANCE" "ACQUAINTANCE" 1 8421631
"ADA" "ADA" 7 15780518
```



--- This part connects the actors with ties.

```
*Tie data
FROM TO
"D" "DORIN"
"D" "FELLOWCOUNTRYMEN"
"D" "GUNNAR"
"FELLOWCOUNTRYMEN" "GUNNAR"
```

--- This part adds properties to the ties, in this case size.

```
*Tie properties
FROM TO size
"D" "DORIN" 1
"D" "FELLOWCOUNTRYMEN" 1
```

"D" "GUNNAR" 1
"FELLOWCOUNTRYMEN" "GUNNAR" 1

9.6 Node resolution

These are some of the alternative actor names identified through comments.

ACTOR	ALTERNATES	ACTOR	ALTERNATES
ASSISTENT	ASSISTANT	JARKE	YaRKE/MAY/MAJ
BELYaEV	PETROV	KIN	KEEN
BOER	BUR	KLARA	CLARA
BROTHER	BRAT	KNAVE	VALET
BRUMOV	BRUMOVIYa	KNOX	NOKS
Conrad PINEUS	KONRAD PINEUS	KOLLONTAJ	MISTRESS[KhOZYaJKA
CROAT	KhORVAT	KUCERA	KUChERA
CYLINDER	TsILINDR	KÜHLMANN	KYuL'MAN
CYRUS	KIR	LÖFGREN	LEFGREN
DEGREE	GRADUS	METRE	METR
DIETL	DITL	MOUNTAINEER	GORETs
EDWARD	EDUARD	NIK	NICK
FLORIET	FLOR'E	ORESTES	OREST
FORSLUND	FURSLUND	POUPARD	PUPPARD
FRIEND	DRUG	SEINESCU	ShEJNESKU
Godfather	KUM	SHIP's COOK	KOK
GREEK	GREK	SKATER	KON'KOBEZhET
GRISHA	GRIShA	TALENT	TALANT
GÖRING	GERING	VANOGS	VANGOS
HEGLUND	KhEGLUND	VIKTORIA	VIKTORIYa/VICTORIA
HUSBAND	MUZh	VOLUNTEER	DOBROVOLETs
JAN	YaN	WIGFORSS	VIGFORS

9.7 Exclusion list

Excluded cables

- Duplicated
- Amendments
- Error

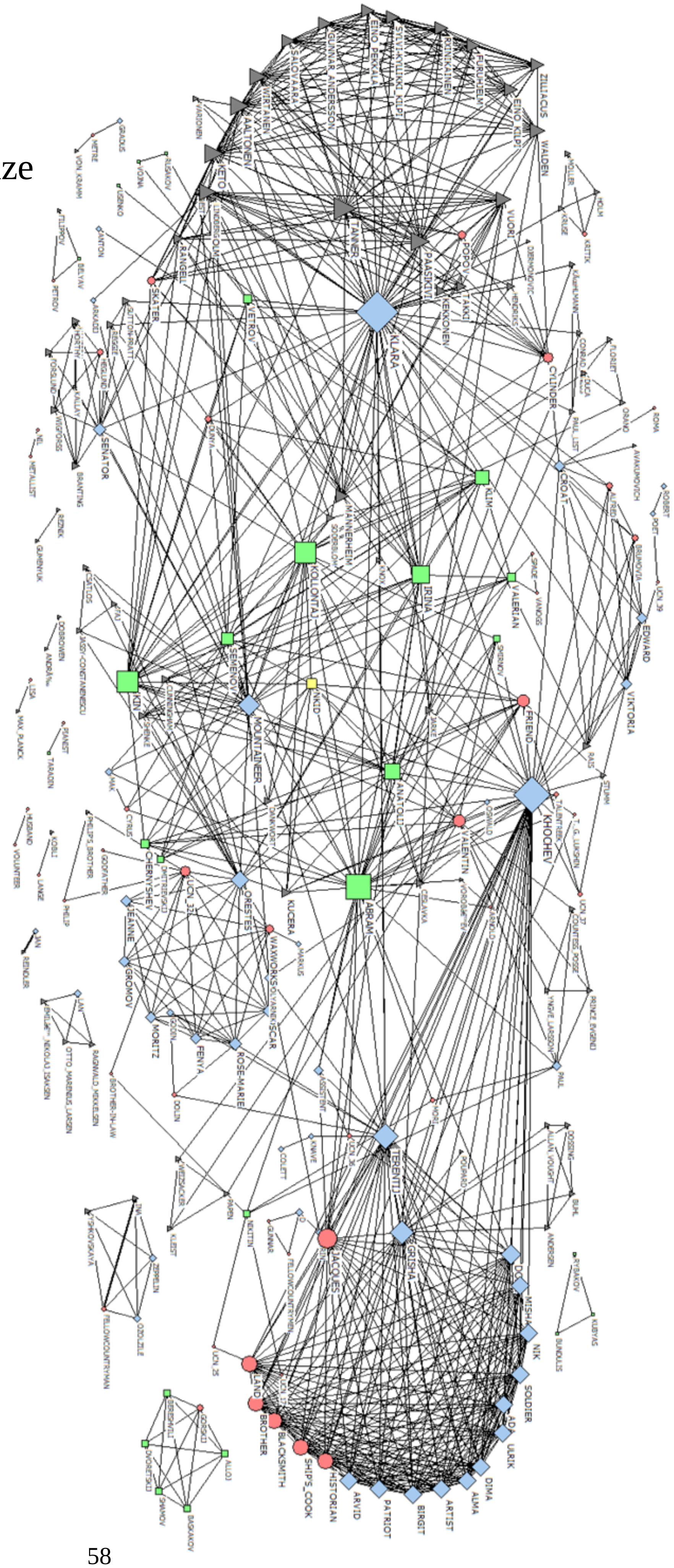
Excluded words after data collection for dataset1

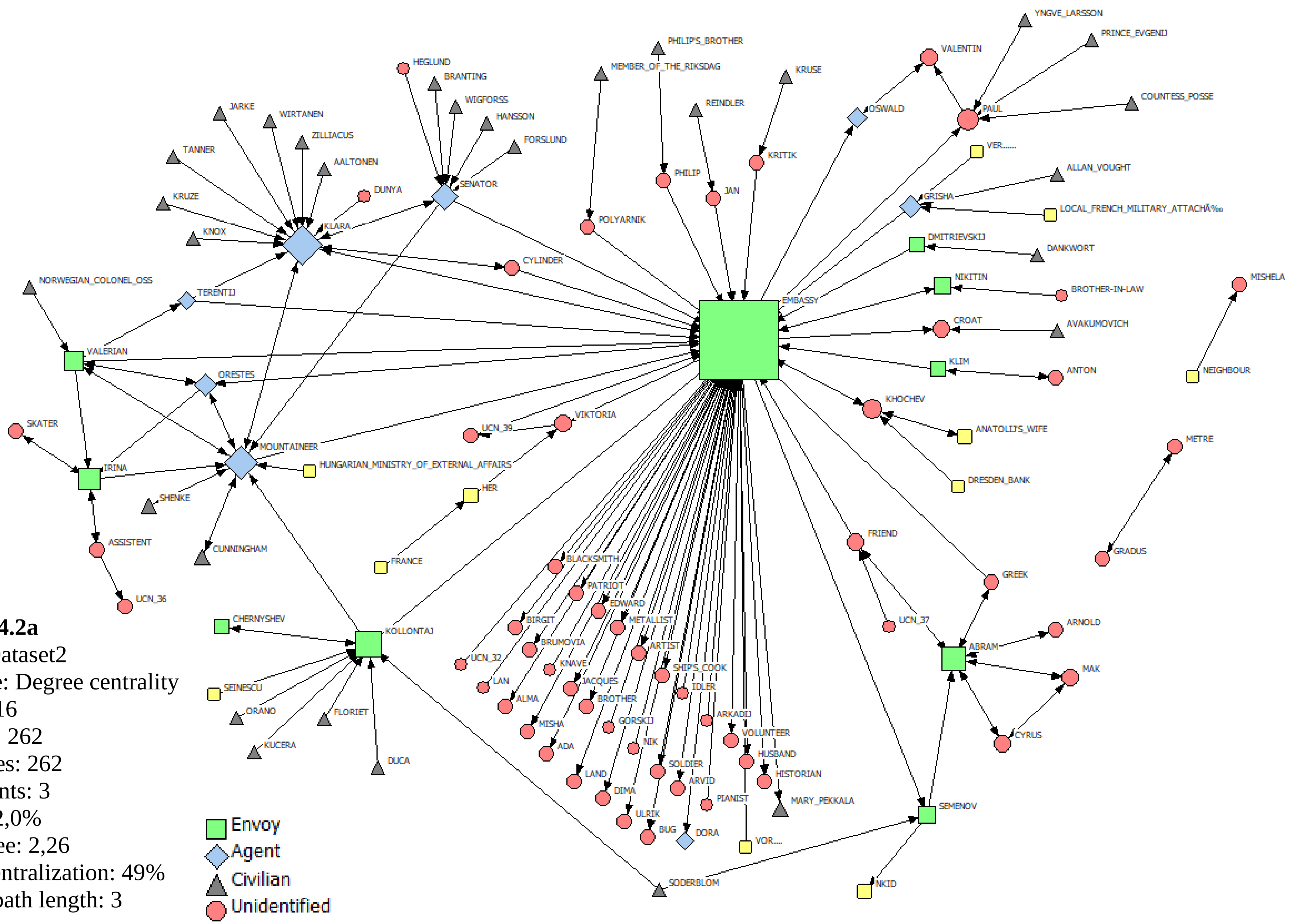
- Cables regarding events in Moscov
- Lakes, countries (LOCATION)
- Ships, companies, legations (OBJECT)
- No information in comment (NOCOMMENT)
- Hitler, Himler, Tito etc (IGNORED
- Incomplete word (…)

All excluded words can be seen in 9.9 in the appendix.

9.8 Graphs, large size

Graph 6.3.1
Source: Dataset1
Actor size:
Degree centrality
Actors: 207
Total ties: 1670
Unique ties: 1670
Components: 15
Density: 3,9%
Avg degree: 8
Degree centralization: 22%
Average path length: 3





Graph 5.4.2a
Source: Dataset2
Actor size: Degree centrality
Actors: 116
Total ties: 262
Unique ties: 262
Components: 3
Density: 2,0%
Avg degree: 2,26
Degree centralization: 49%
Average path length: 3

9.9 Actor/category/year

Stockholm – Moscow KGB cables (Haynes, 2011).

Actor	Category	Sum	41	42	43	44	45	46
ADA	AGENT	1			1			
ALMA	AGENT	1			1			
ANTON	AGENT	1				1		
ARKADIJ	AGENT	1		1				
ARTIST	AGENT	1			1			
ARVID	AGENT	1			1			
ASSISTENT	AGENT	2		1	1			
BIRGIT	AGENT	1			1			
COLETT	AGENT	1		1				
CROAT	AGENT	4			2	2		
D	AGENT	4	4					
DIMA	AGENT	1			1			
DORA	AGENT	2			2			
DORIN	AGENT	2	2					
EDWARD	AGENT	2			2			
FENYA	AGENT	2		2				
FROST	AGENT	1			1			
GODIN	AGENT	1		1				
GRADUS	AGENT	1				1		
GREEK	AGENT	3				3		
GRISHA	AGENT	8		4	1		3	
GROMOV	AGENT	2		2				
IDLER	AGENT	2					2	
JAN	AGENT	3				3		
JEANNE	AGENT	1		1				
KHOCHEV	AGENT	8	1		3	2	2	
KLARA	AGENT	18			4	12	2	
KNAVE	AGENT	3	1	2				
LAN	AGENT	1			1			
MAK	AGENT	3			3			
MARKUS	AGENT	1		1				
MISHA	AGENT	1			1			
MORITZ	AGENT	1		1				
MOUNTAINEER	AGENT	10			2	8		
NIK	AGENT	2		1	1			
ORESTES	AGENT	7		2	1	4		
OSCAR	AGENT	3		2		1		
OSWALD	AGENT	4					4	
OZOLZILE	AGENT	1					1	
PATRIOT	AGENT	1			1			
PAUL	AGENT	2		1		1		
POET	AGENT	2		2				
POLYARNIK	AGENT	2	1	1				
REZNIK	AGENT	1					1	
ROBERT	AGENT	1		1				
ROMAN	AGENT	1				1		
ROSE-MARIE	AGENT	3		3				
SENATOR	AGENT	3			1	2		
SOLDIER	AGENT	1			1			
TERENTIJ	AGENT	8	1	2	3	2		
ULRIK	AGENT	2			2			
VIKTORIA	AGENT	2			2			
ZEPPELIN	AGENT	1					1	
AALTONEN	CIVILIAN	3			1	2		
ALLAN_VOUGHT	CIVILIAN	1					1	
ANDERSEN	CIVILIAN	1					1	
ANDRÉ	CIVILIAN	1					1	
AVAKUMOVICH	CIVILIAN	1			1			
BEST	CIVILIAN	1				1		
BRANTING	CIVILIAN	1			1			
BROWDER	CIVILIAN	1						1
BUHL	CIVILIAN	1					1	
CESLAVKA	CIVILIAN	1					1	
CONRAD_PINEUS	CIVILIAN	1			1			
COUNTESS_POSSE	CIVILIAN	1				1		
CSATLOS	CIVILIAN	1				1		
CUNNINGHAM	CIVILIAN	1				1		
DANKWORT	CIVILIAN	1			1			
DJERMONOVIC	CIVILIAN	1					1	
DOBROWEN	CIVILIAN	1					1	
DOSSING	CIVILIAN	1					1	
DUCA	CIVILIAN	1				1		
EINO_KILPI	CIVILIAN	1				1		
EINO_PEKKALA	CIVILIAN	1				1		
EMIL'_NIKOLAJ_ISAKSEN	CIVILIAN	1			1			

Actor	Category	Sum	41	42	43	44	45	46
FAGERHOLM	CIVILIAN	3		1	1	1		
FAJ	CIVILIAN	1				1		
FILIPPOV	CIVILIAN	1					1	
FLORIET	CIVILIAN	1				1		
FORSLUND	CIVILIAN	1			1			
FURUHJELM	CIVILIAN	1				1		
GUMENYUK	CIVILIAN	1					1	
GUNNAR_ANDERSSON	CIVILIAN	1				1		
HANSSON	CIVILIAN	2			1		1	
HELYAEV	CIVILIAN	1					1	
HENDRIKS	CIVILIAN	1				1		
HOLM	CIVILIAN	1					1	
HORTHY	CIVILIAN	1				1		
INA	CIVILIAN	1					1	
JARKE	CIVILIAN	3		1	1	1		
JASSY-CONSTANENESCU	CIVILIAN	2				2		
KALLAY	CIVILIAN	1				1		
KEKKONEN	CIVILIAN	1				1		
KETO	CIVILIAN	2			1	1		
KLEIST	CIVILIAN	1			1			
KNOX	CIVILIAN	1				1		
KOBLI	CIVILIAN	1				1		
KRUSE	CIVILIAN	2				1	1	
KUCERA	CIVILIAN	1					1	
KÜHLMANN	CIVILIAN	1			1			
LINDBERG	CIVILIAN	1				1		
MANNERHEIM	CIVILIAN	3			1	2		
MARY_PEKKALA	CIVILIAN	1		1				
MAX_PLANCK	CIVILIAN	1				1		
MOLLER	CIVILIAN	1					1	
NORWEGIAN_COLONEL_OSS	CIVILIAN	1				1		
ORANO	CIVILIAN	1				1		
OTTO_MARENIUS_LARSEN	CIVILIAN	1			1			
PAASIKIVI	CIVILIAN	2			1	1		
PAPEN	CIVILIAN	1			1			
PAUL_LIST	CIVILIAN	1			1			
PHILIP'S_BROTHER	CIVILIAN	1		1				
POUPARD	CIVILIAN	1		1				
PRINCE_EVGENIJ	CIVILIAN	1				1		
RAGNVALD_MIKKELSEN	CIVILIAN	1			1			
RAIS	CIVILIAN	2			2			
RANGELL	CIVILIAN	1			1			
REGGIE	CIVILIAN	1				1		
REINDLER	CIVILIAN	1				1		
RXINIKAINEN	CIVILIAN	1				1		
SALOVAARA	CIVILIAN	1				1		
SHENKE	CIVILIAN	1				1		
SODERBLOM	CIVILIAN	1			1			
STUMM	CIVILIAN	2			2			
SUTTON-PRATT	CIVILIAN	1				1		
SYLVI-KYLLIKKI_KILPI	CIVILIAN	1				1		
TAKKI	CIVILIAN	1				1		
TANNER	CIVILIAN	6			1	5		
VARIONEN	CIVILIAN	1				1		
VON_KRAMM	CIVILIAN	1				1		
VOROB'EV	CIVILIAN	1				1		
VUORI	CIVILIAN	3			2	1		
WALDEN	CIVILIAN	2				2		
WEIZSACKER	CIVILIAN	1			1			
WIGFORSS	CIVILIAN	1			1			
WIRTANEN	CIVILIAN	2				2		
YNGVE_LARSSON	CIVILIAN	1				1		
YSHKOVSKAYA	CIVILIAN	1					1	
ZILLIACUS	CIVILIAN	1				1		
BORMANN	IGNORED	1					1	
CHEKIST	IGNORED	1			1			
DIETL	IGNORED	1		1				
FRANCO	IGNORED	1				1		
GESTAPO	IGNORED	3		1	2			
GOEBBELS	IGNORED	1			1			
GÖRING	IGNORED	3			3			
HIMMLER	IGNORED	5	1		1	2	1	
HITLER	IGNORED	9			2	6	1	
KEITEL	IGNORED	1			1			
MANSTEIN	IGNORED	1			1			
MILCH	IGNORED	1			1			
QUISLING	IGNORED	1				1		
RIBBENTROP	IGNORED	5			1	3	1	
TITO	IGNORED	2			1	1		
WOLFF	IGNORED	1			1			
ZEITZLER	IGNORED	1			1			
ABO	LOCATION	3				3		
ALAND_ISLANDS	LOCATION	1			1			
AMERICA	LOCATION	6			2	3	1	
AREA_OF_THE_BUG	LOCATION	1				1		
ASTRAKHAN	LOCATION	1				1		
AUSTRIA	LOCATION	1		1				
BALTIC	LOCATION	1					1	
BELGRADE	LOCATION	4			1		3	
BERLIN	LOCATION	8			2	6		

Actor	Category	Sum	41	42	43	44	45	46
BERNE	LOCATION	1				1		
BORNHOLM	LOCATION	1					1	
BREMEN	LOCATION	1			1			
BRITAIN	LOCATION	2			2			
BUCHAREST	LOCATION	1				1		
BUDAPEST	LOCATION	2				2		
BULGARIA	LOCATION	1			1			
COLONY	LOCATION	1			1			
COPENHAGEN	LOCATION	1					1	
CRIMEA	LOCATION	1			1			
DAGO	LOCATION	1						1
DANUBE	LOCATION	1				1		
DARELIA	LOCATION	1			1			
DENMARK	LOCATION	3				1	2	
DILLINGEN	LOCATION	1			1			
EMDEN	LOCATION	1			1			
ENGLAND	LOCATION	1				1		
EUROPE	LOCATION	1	1					
FINLAND	LOCATION	20		4	6	7	3	
FOREST_BRETHREN	LOCATION	1						1
FRANCE	LOCATION	3			1	1	1	
FURT-ON-ODER	LOCATION	1		1				
FŰHRERHAUPTQUARTIER	LOCATION	1			1			
GDYNIA	LOCATION	2			2			
GERMANY	LOCATION	7		2	3	1	1	
GOTTRÖRA	LOCATION	1				1		
HAMBURG	LOCATION	2			1	1		
HANGO	LOCATION	1			1			
HELSINKI	LOCATION	8			1	5	2	
HOLTENAU	LOCATION	1			1			
HOMBURG	LOCATION	1			1			
HUNGARY	LOCATION	2			1	1		
IRAN	LOCATION	2			2			
ISLAND_OF_OSEL	LOCATION	1				1		
JAPAN	LOCATION	1			1			
KASSEL	LOCATION	1			1			
KATYN	LOCATION	1				1		
KHAR'KOV	LOCATION	1				1		
LAHN	LOCATION	1			1			
LATVIA	LOCATION	1					1	
LEIPZIG	LOCATION	1			1			
LENINGRAD	LOCATION	4				4		
LONDON	LOCATION	1			1			
LORRAINE	LOCATION	1			1			
MACEDONIA	LOCATION	1			1			
MALMO	LOCATION	1		1				
MARIEFRED	LOCATION	1				1		
MEZŐLABOR-EPERJES-SVIDNIK	LOCATION	1				1		
MOSCOW	LOCATION	8			2	4	1	1
MÄLSÅKER	LOCATION	1				1		
NARVIK	LOCATION	1				1		
NEUNKIRCHEN	LOCATION	2			2			
NORWAY	LOCATION	10		1	3	2	4	
ODESSA	LOCATION	1		1				
OESEL	LOCATION	1						1
OSLO	LOCATION	1			1			
PARIS	LOCATION	2			1		1	
POLAND	LOCATION	1					1	
RAUMA	LOCATION	1					1	
RESIDENCY	LOCATION	2			2			
RIGA	LOCATION	1				1		
ROME	LOCATION	1				1		
RUMANIA	LOCATION	1			1			
RUSSIA	LOCATION	3			1	2		
SALTSJÖBADEN	LOCATION	1			1			
SLOVAKIA	LOCATION	1				1		
SPAIN	LOCATION	1					1	
STALINGRAD	LOCATION	1				1		
STETTIN	LOCATION	1			1			
STOCKHOLM	LOCATION	32		4	4	13	9	2
STRALSUND	LOCATION	1				1		
SVIR	LOCATION	1			1			
SWEDEN	LOCATION	20	1	2	6	6	4	1
SWINEMÜNDE	LOCATION	1			1			
SWITZERLAND	LOCATION	3		2	1			
USA	LOCATION	1			1			
USSR	LOCATION	22		1	7	9	4	1
WARTENBURG	LOCATION	1			1			
WEINMAR	LOCATION	1			1			
WESER	LOCATION	1			1			
ANATOLIJ'S_WIFE	NOCOMMENT	1					1	
BEMA	NOCOMMENT	1		1				
DFP	NOCOMMENT	1	1					
DINULESCU	NOCOMMENT	1				1		
GHYCZY	NOCOMMENT	1				1		
GITSI	NOCOMMENT	1				1		
GRASSMAN	NOCOMMENT	1				1		
GUSTAV	NOCOMMENT	1				1		
K.'S_WIFE	NOCOMMENT	1		1				
KANITZ	NOCOMMENT	1		1				
KN	NOCOMMENT	1				1		
KORKHIN	NOCOMMENT	2					2	
NURCK	NOCOMMENT	1						1
P.K	NOCOMMENT	1					1	

Actor	Category	Sum	41	42	43	44	45	46
POL'SKIJ	NOCOMMENT	1					1	
PUTTGEN	NOCOMMENT	1				1		
SEINESCU	NOCOMMENT	1				1		
ADMIRAL_SCHEER	OBJECT	1			1			
DAGENS_NYHETER	OBJECT	1			1			
DRESDEN_BANK	OBJECT	2				2		
FINNS	OBJECT	1				1		
FREE_GERMANY"_COMMITTEE	OBJECT	1			1			
GHT	OBJECT	1					1	
GNEISENAU	OBJECT	1			1			
GRAF_ZEPPELIN	OBJECT	1			1			
LEICA	OBJECT	1					1	
LEITZ	OBJECT	1					1	
LOKAL-ANZEIGER	OBJECT	1			1			
LUBLIN_GOVERNMENT	OBJECT	1					1	
LÜTZOW	OBJECT	1			1			
MT	OBJECT	1					1	
NAVAL_NEIGHBOUR	OBJECT	1				1		
NAVAL_NEIGHBOURS	OBJECT	2		1		1		
NAZI	OBJECT	1					1	
NKD	OBJECT	1				1		
NKID	OBJECT	3			1	1	1	
NOBEL_PRIZE	OBJECT	1				1		
NÚRNBERG	OBJECT	1			1			
OKW	OBJECT	1				1		
OTDEL	OBJECT	1					1	
SOCIAL-DEMOKRATEN	OBJECT	1			1			
SOVIET_SHIP_"MAJ"	OBJECT	1				1		
SS	OBJECT	1				1		
STUMM√BROTHERS	OBJECT	1			1			
TEATAJA	OBJECT	1					1	
THE_NEUNKIRCHEN_IRON_WORKS_LTD	OBJECT	1			1			
ABRAM	SOVIET	15		1	8	4	2	
ALLOJ	SOVIET	1				1		
ANATOLIJ	SOVIET	5			2	1	2	
BASKAKOV	SOVIET	1				1		
BELYAV	SOVIET	1					1	
BERESHVILI	SOVIET	1				1		
BOER	SOVIET	1				1		
BUNDULIS	SOVIET	1					1	
CHERNYSHEV	SOVIET	1					1	
DMITRIEVSKIJ	SOVIET	1			1			
DVORETSKIJ	SOVIET	1				1		
IRINA	SOVIET	7		1	4	2		
KIN	SOVIET	4			3		1	
KLIM	SOVIET	4			1	3		
KOLLONTAJ	SOVIET	11			4	3	4	
KUBYAS	SOVIET	1					1	
NIKITIN	SOVIET	4		1	1	1	1	
RUSAKOV	SOVIET	1				1		
RYBAKOV	SOVIET	1					1	
SEMENOV	SOVIET	4			4			
SHAMOV	SOVIET	1				1		
SMIRNOV	SOVIET	1					1	
TARADIN	SOVIET	1					1	
USENKO	SOVIET	1				1		
VALERIAN	SOVIET	2				1	1	
VETROV	SOVIET	3			1	1	1	
VOJNA	SOVIET	1				1		
ACQUAINTANCE	UNIDENTIFIED	1					1	
ALFRED	UNIDENTIFIED	1			1			
ARNOLD	UNIDENTIFIED	1				1		
BLACKSMITH	UNIDENTIFIED	1			1			
BROTHER	UNIDENTIFIED	2		1	1			
BROTHER-IN-LAW	UNIDENTIFIED	2		1		1		
BRUMOVIA	UNIDENTIFIED	1			1			
BUG	UNIDENTIFIED	1				1		
CHANCE	UNIDENTIFIED	3					3	
CYLINDER	UNIDENTIFIED	4				4		
CYRUS	UNIDENTIFIED	3			3			
DOLIN	UNIDENTIFIED	1		1				
DUNYA	UNIDENTIFIED	2			1		1	
FELLOWCOUNTRYMAN	UNIDENTIFIED	1					1	
FELLOWCOUNTRYMEN	UNIDENTIFIED	1	1					
FRIEND	UNIDENTIFIED	4			4			
GODFATHER	UNIDENTIFIED	1		1				
GORSKIJ	UNIDENTIFIED	1				1		
GUNNAR	UNIDENTIFIED	1	1					
HEGLUND	UNIDENTIFIED	1			1			
HISTORIAN	UNIDENTIFIED	1			1			
HUSBAND	UNIDENTIFIED	2					1	1
JACQUES	UNIDENTIFIED	4		1	2		1	
KRITIK	UNIDENTIFIED	1					1	
LAND	UNIDENTIFIED	1			1			
LANGE	UNIDENTIFIED	1				1		
LISA	UNIDENTIFIED	1				1		
LÖFGREN	UNIDENTIFIED	1				1		
METALLIST	UNIDENTIFIED	1				1		
METRE	UNIDENTIFIED	2				2		
MISHELA	UNIDENTIFIED	1				1		
MORI	UNIDENTIFIED	1		1				
NIL	UNIDENTIFIED	1				1		
PETROV	UNIDENTIFIED	1					1	
PHILIP	UNIDENTIFIED	1		1				

Actor	Category	Sum	41	42	43	44	45	46
PIANIST	UNIDENTIFIED	1					1	
POPOV	UNIDENTIFIED	1				1		
RAMSAY	UNIDENTIFIED	1		1				
ROMA	UNIDENTIFIED	1				1		
SECRETARIAT	UNIDENTIFIED	2		2				
SERGEANT	UNIDENTIFIED	3		3				
SHIP'S_COOK	UNIDENTIFIED	1			1			
SKATER	UNIDENTIFIED	1			1			
SPADE	UNIDENTIFIED	1					1	
SUSANNA	UNIDENTIFIED	1				1		
T._G._LUKSHIN	UNIDENTIFIED	1		1				
TALENT	UNIDENTIFIED	2				2		
TRIO	UNIDENTIFIED	1		1				
UCN_17	UNIDENTIFIED	1			1			
UCN_25	UNIDENTIFIED	1			1			
UCN_32	UNIDENTIFIED	4		4				
UCN_33	UNIDENTIFIED	1		1				
UCN_36	UNIDENTIFIED	1			1			
UCN_37	UNIDENTIFIED	1			1			
UCN_39	UNIDENTIFIED	2		1	1			
VALENTIN	UNIDENTIFIED	4				1	3	
VANOGS	UNIDENTIFIED	1					1	
VOLUNTEER	UNIDENTIFIED	2					1	1
VRONSKIJ	UNIDENTIFIED	1				1		
WAXWORKS	UNIDENTIFIED	2		2				
......IN	…	1		1				
.....ONEN	…	1	1					
....KUS	…	1		1				
BAR.NOV	…	1					1	
BIS…	…	1			1			
BOR...	…	1			1			
DANK....	…	1			1			
DER....	…	1					1	
EL...	…	1			1			
ER.…	…	1		1				
GREGOR_KRO.LLOV..	…	1					1	
K..ICH	…	1					1	
KONDA.....	…	1				1		
L.	…	1		1				
VER......	…	1		1				
VOR....	…	1				1		