A Semantic Network Analysis of Laundering Drug Money

Martin Neumann[1] & Nicholas Sartor[2]

Abstract

This article presents a case study of a money-laundering process. A database of police interrogations for a number of interrelated cases shows the enormous complexity of this process, exceeding the capacities of manual reconstruction. For this reason, semantic networks were reconstructed from the textual data, using the natural language processing techniques of artificial intelligence. These enabled the semantic field of this particular case to be dissected. The results reveal highly professional worldwide financial transactions. Criminal activity benefited from the infrastructure of offshore centres of the legal financial economy and permeated legal business, and the borders between legal and illegal activities became blurred. In fact, the money-laundering activity was only uncovered after the network broke down. Before the group had become known following an outbreak of internal conflict, the concealment of illegal sources of money had not been detected by law enforcement agencies. A case study does not allow for generalization. In particular, this case is not representative because the actors had access to significant resources beyond the reach of petty criminals. However, the findings from this case suggest that, in principle, professional money launderers are able to evade money-laundering regulations.

Keywords: Money laundering, layering illegal assets, text-mining, semantic networks

INTRODUCTION

Money laundering is often perceived, by both scientists and the general public, as a threat to legal society (Quirk, 1997; Steinko, 2012). In globalized times, it is assumed that criminals take advantage of the extended global financial economy. The threat scenario assumes that the intrusion of illegal money will undermine the integrity and stability of the financial system. This claim is built on the fact that legal companies are an essential part of the social and economic order, and that the social order of society is called into question by corrupt companies carrying out money-laundering activities. The transnational character of professional money laundering arguably undermines legal society. Since law enforcement is based on the authority of individual states, transnational activities can easily escape the limits of law enforcement agencies; therefore, the state is no longer the frame within which to establish social order (Steinko, 2012).

However, since money laundering is obviously undertaken in the shadows, empirical data remain sparse. Public opinion is based on speculation. Moreover, the international anti-money-laundering regime is only weakly based on scientific and empirical foundations and has to rely to some degree on *ad hoc* assumptions

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[1] Corresponding author, University of Koblenz. Email: maneumann@uni-koblenz.de.
[2] University of Koblenz. Email: nicholassartor@uni-koblenz.de.

(Gilmour, 2014; Levi & Reuter, 2006; Van Duyne & Levi, 2005). A financial action task force (FATF) was established in 1989 to provide policy recommendations to fight money laundering and terrorist financing (Turner, 2015). However, the effectiveness of such measures is rarely evaluated (Levi & Reuter, 2006). In fact, statistical inspection of a Spanish example only weakly supported the threat scenario (Steinko, 2012): while this study found a few instances of transnational activities, the great majority were neither transnational nor highly professional. This result is all the more surprising since Spain is a major transit country for illicit drugs imported from Africa and destined for the European drug market. This calls into question the validity of the threat scenario.

The unclear data motivate a closer inspection of the process of money laundering. Statistical figures do not reveal details of how the process of money laundering impacts on society. For this reason, a case study is examined here, which will contribute to knowledge of the processes and mechanisms involved in money laundering. Since this is a case study, it is not representative and its findings do not allow for generalization. However, it enables in-depth insights into how money laundering is actually undertaken and how it impacts on society. The data are taken from a number of police interrogations in related criminal investigations centred on a group of drug dealers. The investigations were not undertaken to investigate money laundering, but were initiated after an outbreak of violence within the criminal group, which has been investigated using classical qualitative methods, namely a grounded theory approach (Neumann & Lotzmann, forthcoming). However, the interrogations also provide rich insights into "everyday" processes in the criminal group. While the data shed little light on the production and distribution of drugs, they reveal many details about the laundering of drug money. The capital stock was equivalent to several hundred million Euros, yet the money-laundering activities were only uncovered after the network had collapsed into violent internal conflicts. It was only as a result of investigations initiated to address the violence that the police gained access to certain information. For instance, the shock caused by the violence, which included numerous murders, may have motivated witnesses to cooperate with the police and to testify about the illegal background of certain economic activities.

However, the data consist of several hundred pages of documentation from the police interrogations. Pieces of information about the money laundering can be found scattered in various interrogations throughout the documents. It became clear on first inspection of the texts that the money laundering consisted of hundreds of activities and financial transactions in which many people all over the world had been involved to a greater or lesser degree. These data could not be handled manually with an interpretative approach. Thus, the grounded theory that we had successfully applied to a previous analysis of the escalation of violence was inappropriate for this research question. For this reason, we applied the methodology of text-mining and semantic network analysis, which has been facilitated by recent developments in information technology. Text-mining

software scans a document for relevant words and text phrases, and semantic network analysis constructs relationships between these elements (Diesner, Frantz, & Carley, 2005). In contrast to social networks, which are relations between people, semantic networks are relations between any entities that are meaningful with regard to a particular research question. This web of relations can be denoted as the semantic field of the case in question. Thus, we applied a methodology of semi-automatic, computer-guided information extraction to cope with the complexity of the data.

The paper will proceed as follows. First, the approach will be placed in theoretical context. Next, the methodological approach will be explained in some detail to show how textual data in the police interrogations were transformed into semantic networks. There then follows a detailed presentation of the results, ending with some concluding remarks.

Theoretical approach

Semantic networks and actor network theory (ANT): Dissecting the field of money laundering

While semantic networks can be analysed with measures and visualizations taken from social network analysis, there is nevertheless a difference between "semantic networks" and classical "social network analysis" (SNA). In SNA, a network is generated by "physical" (or measurable) contacts between people; for instance, if one person makes a telephone call to another person, this is proof that the two people really are in contact with each other. A semantic network is based on measures of the proximity of terms in a text document. We use the concept of co-occurrence, which assumes that two terms are meaningfully related if they appear close together. For instance, in the sentence "John is tall", the words "John" and "tall" are rather close. In a semantic network, a relationship between the semantic concepts "John" and "tall" would be constructed. However, if two terms appear together in a piece of text, it does not prove that the terms are in "contact" with each other or have something in common. It may be just by chance that in a text document certain terms appear quite near to each other; the relationship is not based on physical activity, such as making a phone call, or on a personal statement that person A says he is a friend of person B. For instance, in the sentence "I think of John and the moon is red", the words "John" and "moon" are close together; nevertheless, they are not related. There is thus a danger of false positives. Later in this paper, we give a more technical explanation of the research process, showing how we attempted to minimize the likelihood of such errors.

On the other hand, the technique has advantages over classical SNA. Classical SNA consists simply of the persons involved in a network. The "ontology", that is, the description of the domain, is restricted to persons, and thus restricts the information that can be extracted from SNA. The situation is different in *semantic* networks. Concepts may be anything for which a word exists. The "network of concepts" is

not restricted to persons. For this reason, much more information can be extracted than in classical SNA. This relates to features of actor network theory (ANT). While differences undoubtedly exist between semantic networks and classical approaches to ANT, there is one important commonality: ANT treats actors and non-actors, and material and non-material concepts, equally. This is also true of semantic network analysis. There are therefore parallels in the objectives and results of ANT and semantic network analysis.

ANT cannot be reduced to a single coherent theory, but is rather a bundle of various studies originating from science and technology research. However, the core objective of ANT has been described as follows:

> You do not go about doing your business in a total vacuum but rather under the influence of a wide range of surrounding factors. The act you are carrying out and all of these influencing factors should be considered together. This is exactly what the term actor network accomplishes. An actor network, then, is the act linked together with all of its influencing factors (which again are linked), producing a network (Hanset & Monteiro, 1998, Ch.6).

In this way, ANT attempts to reconstruct how human and non-human elements interact. This has been called a material semiotic approach (Latour, 2005) which explores the relational ties between concepts that constitute a certain field. These concepts may be a multitude of different entities. For instance, Isaac Newton did not invent the theory of gravitation on his own. He relied on observational data from astronomers (who are human actors), as well as on support from the Royal Society (which is a socially-constructed value; money, for example, can be described as a semiotic entity since its value as an exchange medium depends on social agreement) and his room in Trinity College (which is material). All these together were constitutive of the scientific innovation ascribed to Newton (Bardini, 2000). Thus, all these elements constitute an actor network: "the actor is the network of heterogeneous relations that [are] able to redefine and transform what it is made of" (Callon, 1987, p.93). While it is certainly true that important differences exist, in this regard semantic networks share a central objective with ANT, namely to dissect relationships between concepts from different ontological domains. The concepts in semantic networks are not only actors (as in social network analysis), but also include, for instance, tasks, resources and human actors. Construction of the network enables us to investigate how these heterogeneous elements are related in the constitution of a certain field, in our case the field of money laundering. The basis of the network is the text. Thus, the network describes semiotic relations: constructs related by their meaning.

Social and human capital

Classical SNA has been widely applied in criminological research (Baker & Faulkner, 1993; Duijn, Kashirin, & Slot, 2014; Klerks, 2001; Krebs, 2002; Sparrow, 1991). It is particularly appropriate for analysing the *social* capital of actors (Bourdieu, 1984; Wassermann & Faust, 1994) because analytic concepts such as degree centrality or betweenness centrality enable one to identify actors holding strategic positions in a network (Duijn et al., 2014). Degree centrality reveals central hubs in networks by identifying those actors who have more contacts with more actors. By contrast, betweenness centrality measures broker positions, by identifying actors who hold positions between different cliques. These actors can bridge structural holes or, in other words, enable contacts between otherwise disconnected parts of the overall network (Wassermann & Faust, 1994).

The innovation of semantic networks is to enable the extraction of information about linkages between human actors and non-human, material and non-material aspects related to the field of interest. This has advantages for the purpose of examining criminal activity. For instance, semantic networks provide an opportunity for the analysis of *human* capital. The concept of human capital originates from economic theory and denotes the specific knowledge, skills and competencies of employees involved in a production process. The same concept can be applied to criminal activities (Sparrow, 1991). Depending on the degree of professionalization, money laundering may involve specialized competencies in financial transactions. Knowledge and access to specific resources can be identified by analysing relationships between human actors and non-material elements such as tasks or resources.

The field: Money laundering

In our case, the field of investigation is money laundering. For criminals to enjoy or to re-invest the profits of their business, it is important that illegal money is transformed into legally usable wealth. In recent decades, the global dimension of money laundering has attracted increasing attention. Although the source of illegal wealth may be any illegal activity, the most important is drug trafficking (Harnischmacher, 2009). Money laundering is the process of legalizing illegal assets (Schneider, Dreer, & Riegler, 2006). According to Schneider et al. (2006), four goals can be distinguished. The first goal is to hinder confiscation by the public authorities, while nevertheless retaining control over the money, which is the second goal. For this purpose, the money is imported into the legal financial economy, which is the third goal. The final goal is protection from criminal prosecution. Typically, it is assumed that money laundering consists of three phases: placement, layering and integration. This three-phase model was first developed by the US customs authorities and has since been adopted worldwide by, for example, the United Nations Office on Drugs and Crime (Levi & Reuter, 2006).

Placement is the process through which illegal assets are introduced into the financial system in the first instance. Often it involves breaking down huge amounts of money into small portions. Placement can take various forms, such as investment in amusement halls, insurance companies or real-estate projects. Other options are to bring money physically outside the country of origin to areas with less well-protected financial markets – so-called offshore financial centres. These are often countries such as Netherland Antilles or Bermuda, but Jersey and some Swiss cantons may also be considered. In the course of globalization, these offshore centres gained in importance, not only to the legal financial economy but also to illegal financial activities (Coats & Rafferty, 2007). However, in this phase a direct link between the illegal source and the first placement in the legal market still exists; thus, the origin of the asset can still be retraced. For this reason, the second stage, layering, is essential.

Layering is the process of obscuring the sources of the money, making the investor anonymous in order to foil criminal prosecution. This can be done in various ways, and often involves multiple financial transactions. If these are undertaken across borders, it becomes increasingly unlikely that the source will remain visible (Harnischmacher, 2009).

Integration is the final step that reallocates the money back into the hands of the investor, with the origin of the profit now hidden from public view. This ensures that the goal of retaining control over the asset is achieved. Like layering, this process is also open to the creativity of the actors. As examples, the literature mentions real-estate trade, the acquisition of companies (often companies with huge cash flows, such as restaurants, amusement halls, etc.), and fictitious financial transactions that, again, may result in investment in legal economic activities (Harnischmacher, 2009; Levi & Reuter, 2006).

In achieving these goals, financial intermediaries such as banks, investment funds and insurance companies, and also "underground banks", play a crucial role (Levi & Reuter, 2006). For this reason, the financial economy is assumed to be vulnerable to being undermined in illegal ways. As early as 1989, the FATF was established to protect global financial systems from money laundering, financing terrorism and other financial crimes (Levi & Reuter, 2006; Turner, 2015). Forty recommendations, including reporting suspicious transactions, were originally formulated to increase financial transparency. Since the FATF was first set up, its mandate has been constantly expanded. However, the FATF is an instrument of soft law: it is an agreement between states, but does not have the authority of international treaties that can provide concrete prescriptions (Brumer, 2010). Rather, it is a committee of experts that monitors states and provides recommendations. Thus, the case study presented here can be regarded as a test case for the efficiency of the soft law prevention of financial crime.

DATA AND METHODOLOGY

The database consisted of police interrogations in a number of interrelated cases. Documentation on the interrogations was delivered by the police to the researchers after being anonymised using software tools. However, the data are not publicly available, so the protection of privacy was ensured. Basically, the procedure consists of two parts: text mining and the extraction of semantic networks (Diesner & Carley, 2010; Diesner, Carley, & Tambayong, 2012; Diesner et al., 2005; McCallum, 2005). This procedure reveals relational information from textual data, and is carried out in several consecutive steps. First, data pre-processing is required, followed by node identification and edge identification. The tools used were AutoMap for text mining and ORA for network construction; both were developed at the Center for Computational Analysis of Social and Organizational Systems at Carnegie Mellon University. They were chosen because they are connected by a common interface, which facilitates the integration of text mining and network analysis, and because ORA is a network analysis tool that provides more analytical power than pure text-mining tools.

However, methodologically, police interrogations pose a challenge for analysis because of the demands of extracting a network from a huge corpus of unstructured textual data in natural language. It turned out that a great deal of manual work and control was necessary, since information extraction tools are highly language sensitive. Ready-made dictionaries that facilitate text mining exist in more prominent applications of text-mining technologies, such as sentiment analysis in Twitter feeds (Voinea & Schatten, 2015). However, they do not exist for very specialized domains such as money laundering. From the perspective of natural language processing (NLP), it appears that "the state of the art methods in natural language processing are still not robust enough to work well in unrestricted text domains to generate accurate semantic representations of texts" (Aggarwal & Zhai, 2012, p.3). This statement is corroborated by the fact that, in the analysis that was performed, manual and automatic data analysis were tightly interwoven (Sartor, 2015).

Text Mining

Text mining aims to extract information from texts. Technically, pre-processing of the data was undertaken first, followed by identification of the basic forms of concepts and classification according to a meta-ontology. All these steps involved the mutual interplay of manual and computational analysis.

First, pre-processing consists of error cleaning and the removal of non-content-bearing concepts (words that are only grammatically relevant). Words eliminated by a so-called "stop word filter" included words like "the". Punctuation marks were also eliminated, and words were transformed to lower case. This was undertaken automatically. Metadata were also eliminated, including, for example, pagination and data that had been included by the police, such as the names of police

investigations. Errors in the translation and compilation of the data also had to be resolved. The original document was a scanned PDF file that had to be transformed with OCR tools before it could be imported into the analysis software. Errors occurred during this process. For instance, the number "5" was sometimes identified as the character "S" by the OCR tool. These steps in the pre-processing were undertaken manually.

Next, to identify basic units of information, words that contained essentially the same information were reduced to a common form. In particular, different spellings of the names of persons, locations and organizations were reduced to a single form. For example, the abbreviation "Ltd." had sometimes been used to denote a company, and sometimes not; and in the witness statements, an individual such as "John Smith" (a fictitious example) had sometimes been called "Mr. Smith" or just "John". Moreover, words that together formed a semantic unit (technically n-grams) were combined using an underscore character, for example the transformation of "several thousand dollars" to "several_thousand_dollars". The text-mining software created a concept list of more than 13,000 concepts that had been detected automatically, and included suggestions about the form into which the concepts might be transformed (denoted as "concept from" and "concept to"). Concepts forming the basic unit of information ("concept to") were checked and revised manually to maximize accuracy. Often, this involved going back to the original document to inspect the context.[3]

The next central step was to classify these words according to a meta-ontology taken from the literature (Diesner & Carley, 2005). This meta-ontology defines the classes of objects with which the world can be described. The world consists of the following classes:

Agents: This means simply persons.

Organizations: These are mostly companies.

Resources: In principle, this is something from which somebody can gain something. It turned out to be rather difficult to classify terms consistently as resources. With respect to money laundering, resources are mostly flows of money, but they are also real estate ownership, etc.

Tasks: These are efforts that somebody has to make, that take place over at least a certain length of time. Paying rent for a flat would be a task, whereas buying a company would be classified as an event.

Groups: These are people teaming up together. In our data, this turned out to be unimportant.

Events: An event is everything that is (or can be) associated with a date.

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[3] Whereas in larger bodies of text this problem can partly be resolved by machine learning technologies, in our case the body of text was too small and heterogeneous for such technologies, even though it was too big and complex for qualitative research.

Locations: These are places, but are of different sizes. Locations range from whole countries, such as Switzerland or Curacao, to street numbers.

However, only those words were selected that belonged or might be relevant to money laundering. As the interviews were originally conducted to investigate the outbreak of violence in the criminal group, many words could obviously be found that described acts of violence. Since the focus of this text analysis was money laundering, these words were ignored in the analysis. Thus, words such as cash, company, contract, etc. were included, but *not* words such as murder, intimidation, etc. In fact, the meta-ontology also contains the class "unknown". All words that appeared to be irrelevant to the task of analysing money laundering were assigned to this category and deleted from the analysis. A few concepts in the "unknown" class were retained, as it was unclear to the authors whether or not they were relevant. Deleted words were replaced by "xxx". This had the advantage that the distance between relevant concepts was preserved, a feature that became important in the development of the semantic network. Applying the delete list reduced the number of concepts from 13,511 to a final number of 4,123. Note that the assignment of concepts to the meta-ontology was undertaken by a mutual interplay of automatic and manual work. Initial suggestions were made by the analysis software. However, the error rate was high and the detection rate was small – most concepts were classified as unknown; therefore, the classification was revised manually. This was done by one author and cross-checked by the other author to minimize misleading classifications.

In the network diagrams, the different classes of the ontology appear in different colours (see Figures 3 to 7). Agents are red, resources are turquoise, tasks are blue, locations are dark red, and organizations are green. First, we show the count of concepts preserved for the subsequent network analysis (see Table 1).

Table 1. List of concepts in the data

Classes	Nodes
Agent	357
Event	892
Knowledge	16
Location	353
Organization	472
Resource	1,202
Role	190
Task	380
Unknown	72
Attribute	173
Group	16

Before undertaking a network analysis, the relationships between the words needed to be identified. Since the analysis was based on police interrogations, the network revealed what the police suspected to be involved in money laundering. Network identification is based on the concept of co-occurrence, when two terms appear quite near to each other in the text. What "quite near" means can be manually adjusted, so that, for example, no more than five or no more than ten words must lie between two terms. After initial experiments, a window size of five was applied. At this stage, it became important that deleted terms had been replaced by "xxx" in the text-mining phase of the research, so that the distance between the terms had been preserved. The assumption of a measure of proximity based on co-occurrence is that two words are related in terms of semantic content if they appear close together. However, to reduce the likelihood of false positives, only those relationships that appeared together a number of times were used for the network analysis. The assumption was that it was unlikely that a chance co-occurrence would happen frequently. After initial experiments with different frequencies, the frequency was set to at least 10. Applying this filter also reduced the number of isolated nodes. Co-occurrence is the basis for edge identification from textual data. Once edges are identified, networks of edges can be constructed. These are based on the meta-ontology, insofar as a network can be constructed, for example that relates actors and organizations. These networks can then be analysed by measures of classical network theory such as degree centrality or the construction of ego networks.

RESULTS

In this section, networks of interest with regard to money laundering are documented and briefly explained. It should be noted that the networks cannot be regarded as proof of money-laundering activities, particularly not in juridical terms. However, they reveal patterns that provide hints about how the activity was organized. This limitation is also partly due to the fact that the data were anonymous. Police investigators with access to the non-anonymous version were able to connect the broad patterns with their additional experience based on detailed knowledge of a particular case.

First, as the most basic analysis, the central actors and organizations were identified. These guided the following analysis, insofar as the central actors and organizations appeared frequently in the later networks. In the next steps, the organizational structure was revealed in more detail. This provided the basis for tracing the money flow throughout the organizational structure in a number of further analyses. Details emerged of the roles of specific persons and locations: for example, the network of relations of the concept of money laundering was merged with the network of relations of one of the central actors, and the offshore location Curacao was

examined in close detail. Finally, the semantic field of the associated concepts was investigated by a clique analysis.

Figure 1. Ranking of agents according to degree centrality
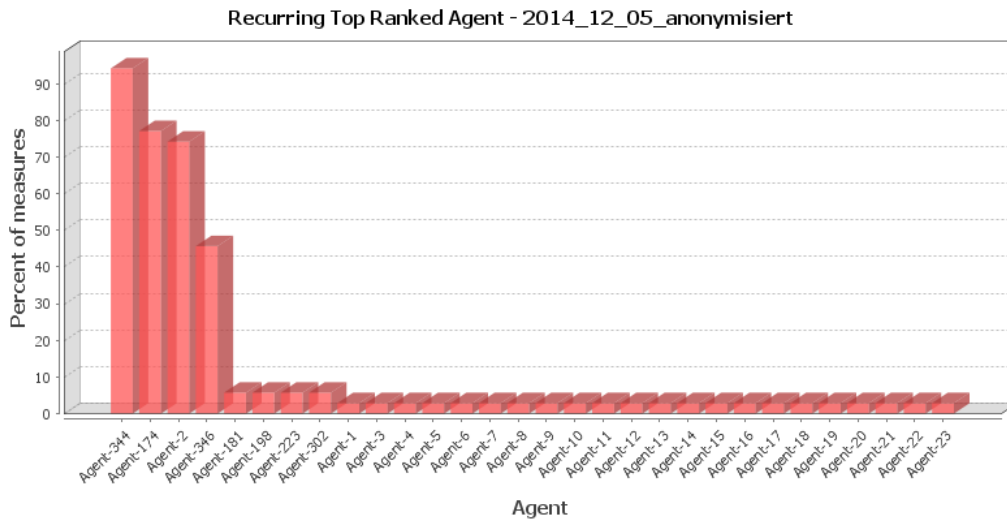
First, the central actors were identified based on their degree centrality, that is, on having the highest number of edges. Figure 1 reveals that a small number of actors were central hubs in the network. The five central actors were agents 344, 174, 2, 346 and 181. However, Figure 1 shows immediately that agent 181 was far less central than the top four. The same was done for the organizations found in the data, as shown in Figure 2. The ranking of the organizations also reveals that certain organizations were the most important. The three most important were organizations 31, 447 and, unsurprisingly, the bank. However, the decline in degree centrality is smoother than in the case of the actors. This is a first indicator that the central actors were involved in multiple organizations.

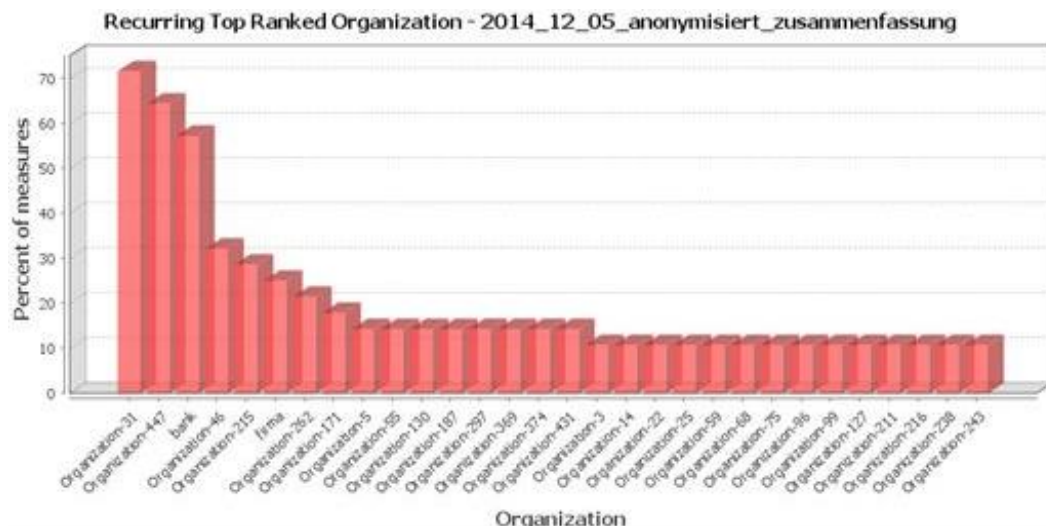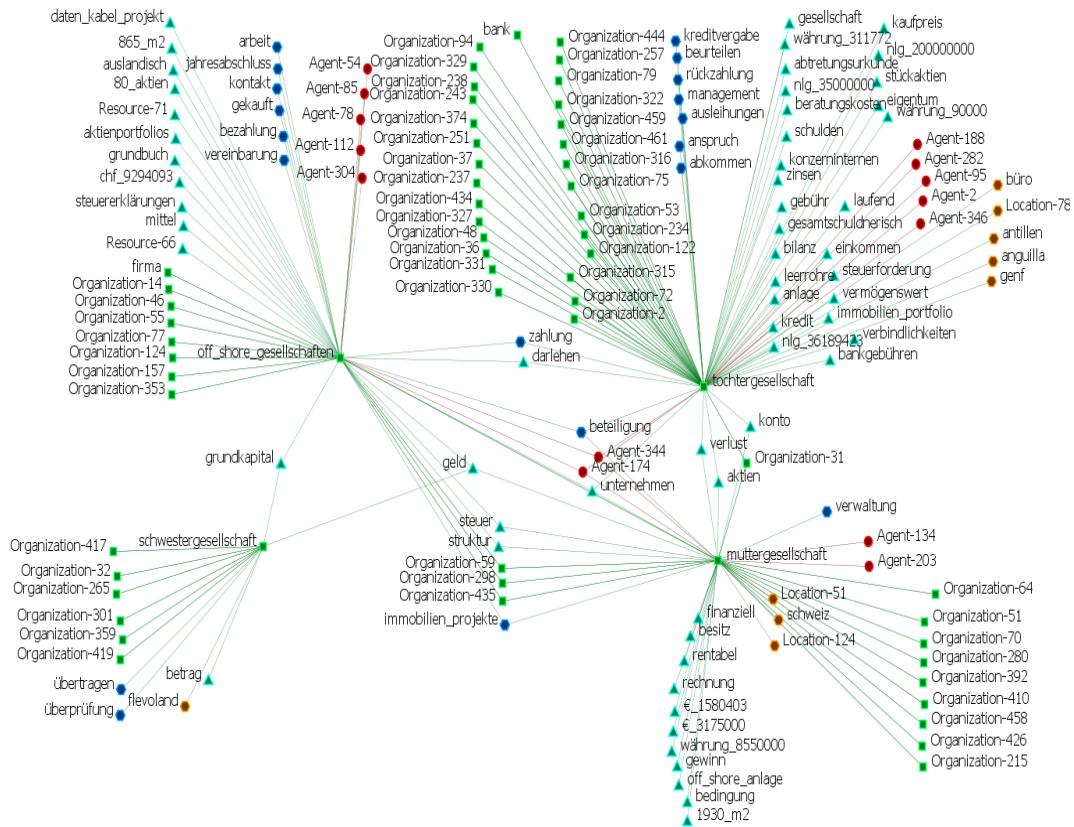**Figure 2. Ranking of organizations according to degree centrality**

Figure 3 provides details of how the "system" of organizations was structured. It shows how the organizations were related to one another, as well as to the actors, resources and (some) tasks.

**Figure 3. Structure of the network of companies**

First of all, it becomes apparent from Figure 3 that the organizational structure consisted of a complex web of interrelated companies. The central concepts of the organizations are parent companies ("muttergesellschaft"), subsidiary companies ("tochtergesellschaft"), affiliate companies ("schwestergesellschaft") and offshore companies. The central parent organization had control of various organizations, such as organizations 64 to 215 which can be seen in the lower right corner of the figure. The parent is directly linked to offshore companies, indicating the importance of offshore centres. In between the concepts of the parent and subsidiary companies, we find organization 31. This organization is identified as the most central according to its degree centrality. We see that it plays a specific role by relating the parent company to its daughter companies. The companies are bound together by means of shares ("aktien") and losses ("verlust"). These concepts can be found in the figure just next to organization 31. Thus, Figure 3 explains how organization 31 gained centrality in its role in the network of companies.

The affiliate companies ("schwestergesellschaft") are connected to the parent companies via the concept of money ("geld"), which can be found in the middle of the figure between these two concepts. The affiliate companies are also related to

the offshore companies by the holding of capital ("grundkapital"). Thus, capital seems to be the central binding force in the company network, with shares and losses as ties between the parent company and the subsidiary companies, and equity holding ("beteiligung") connecting offshore centres, the parent organization and subsidiary companies. Similarly, the subsidiary companies are connected to the offshore companies via payment (the blue node of the task "zahlung") of loans (the resource "darlehen"). Note, furthermore, that the concept of real-estate project ("immobilien_projekte") is connected to the parent company and to the offshore companies, as can be seen by the blue dot at the bottom in the middle, indicating a transfer of tasks of projects within the alliance of firms. Such a transfer of tasks to offshore companies hints at the purpose of concealment. This is typical of tax evasion, and also of money laundering, being the process of layering as described in the money-laundering cycle. Moreover, real-estate business is a well-known method of integration in the process of money laundering.

Figure 4. Money flow
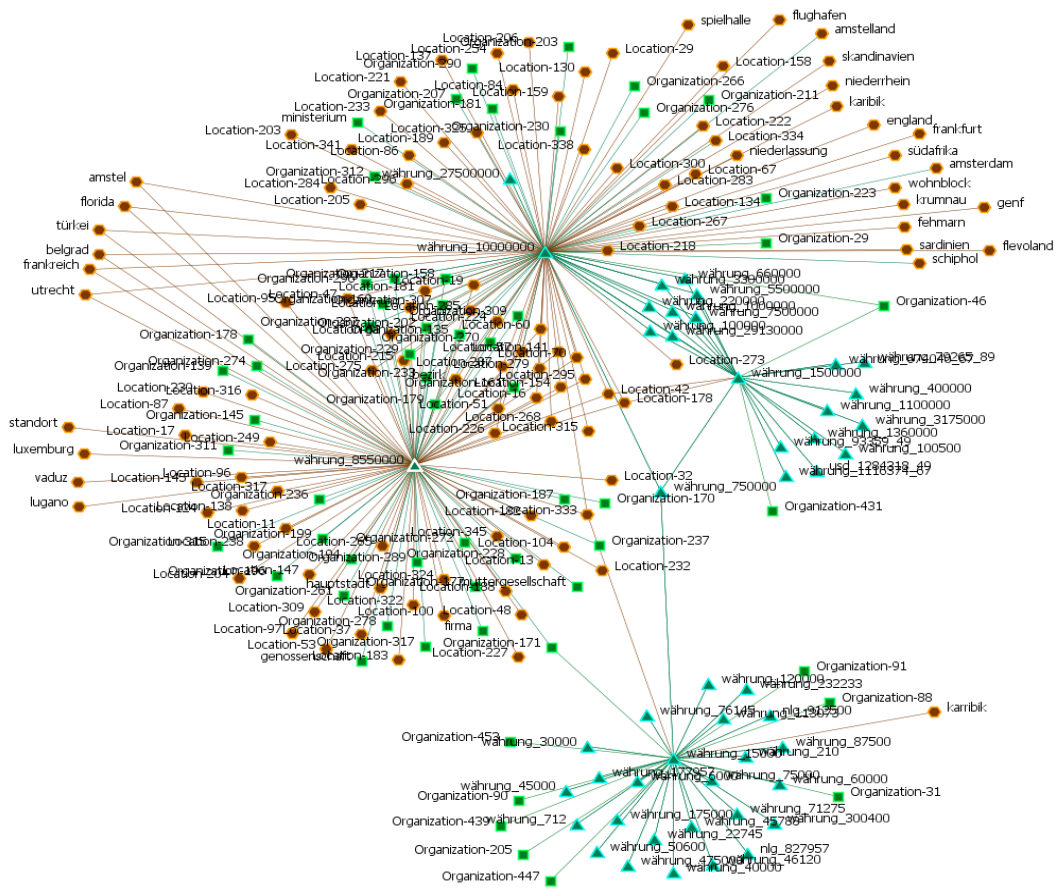
Reconstructing the network of the company structure indicates a high degree of professionalism. In the centre are agents 344 and 174, who are the two most important actors according to their degree centrality. They are directly linked to the concepts of parent company, subsidiary company and offshore company. In this way they have key access to the resources of the company network.

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Figure 5. Management of concealment
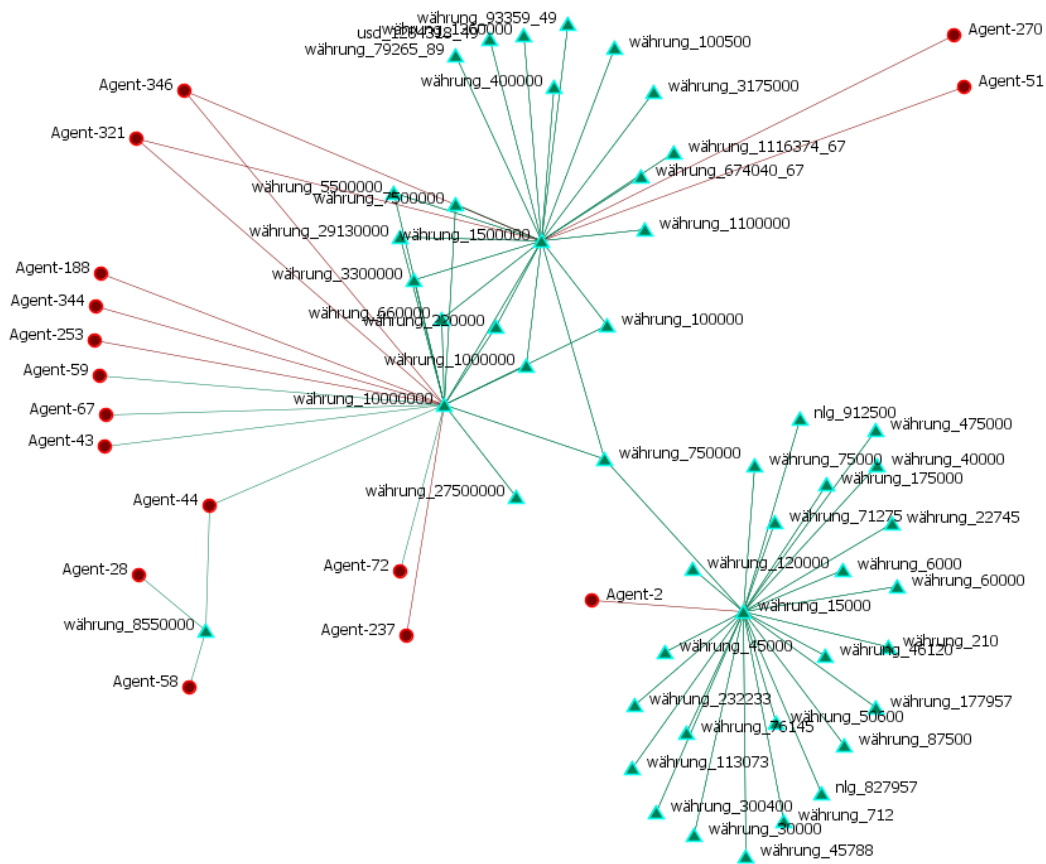
Concealment is investigated in greater detail in Figure 4. This shows a network of resources, locations and organizations. The first thing to note in Figure 4 is a cloud of densely connected organizations and locations on the left in the middle of the figure. The cloud is connected to specific amounts of money ("währung 8,550,000" on the left and "währung 10,000,000" at the top). The dense cloud between these two hubs reveals the complex flow of these specific amounts of money through various organizations in different locations. This suggests that the objective was to make the source untraceable. In fact, it was not detected by previous financial investigations. The specific amounts of money act as hubs for locations, organizations, and even other resources, which enables inferences to be drawn about the money flow. The amount of "8,550,000" and the amount of "10,000,000" have a number of ties to companies and, to a limited degree, this also holds for the amount of "15,000". Moreover, hubs for certain amounts of money ("währung 1,500,000" and "währung 15,000") have direct ties to other concrete amounts of money. This indicates a differentiation between different individual amounts of money. Some seem to play a central role, giving rise to other financial transactions. Again, these specific amounts of money have been transferred through the organizations with which they are related. This indicates an attempt to obscure the source of the money, which suggests that these financial transactions are part of the layering in the money laundering activity.

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Figure 5 investigates the details of this activity, and is a network of resources and agents. The resources are currencies ("währung"), or money. This network shows how specific financial resources are tied to specific agents. In particular, we wish to draw attention to the relationship between agent 2 and the amount of 15,000. As we know from Figure 1, agent 2 is one of the central actors in the network. From reading the text in a qualitative way, it became apparent that the amount of 15,000 was related to a number of interrogations of a person who was paid 15,000 per month in return for personal consultancy services in relation to financial issues for one of the criminals. Neither the concrete business field of the company in which this individual worked, nor his official profession, were uncovered in the data. However, presumably he worked as something like a tax consultant. In the interviews, it was clear that he did not regard himself as a criminal. In fact, his activities did not violate any law. Several times he insisted that this extra money – paid in addition to the usual payments from his employer – was not something unusual. Thus, this person was a perfectly law-abiding businessman. Nevertheless, the huge cluster of other amounts of money related to the hub of "currency 15,000" (i.e. his monthly payment) indicates that he nevertheless played a central role in the money laundering. These other values refer to the financial transactions that he organized. Apparently, the service provided in return for the monthly payments was the organization of the money flow in the laundering activities. Note that, once the transactions had been undertaken by a legal businessman working for a reputable and legal company, the money became integrated into the legal economy, which is a prime goal of money laundering.

Here, we find a case in which illegal money permeated the legal economy through a legal businessman, and thereby corrupted the legal economy, at least to a certain degree. While the financial activities were not illegal, it remains questionable whether the individual should have accepted a significant payment in return for this professional service without further consideration. It could be said that he was paid for "not asking questions". Obviously, the financial transactions are suspicious by FATF standards (Turner, 2015). These standards have been in existence since 1989 and their aim is to combat money laundering. However, they have been implemented as soft law, and do not have the same legal authority as international treaties. While it was a clear violation of the informal conventions of FATF that agent 2 did not report these activities, it was not a violation of any legal obligation. Moreover, the case of agent 2 reveals the central role of *human capital* in the professional performance of the financial transactions. Specialized competencies are needed that enable the execution of specialized tasks. These activities require skills that can only be obtained through a specialized education.

Apart from agents 344 and 346, most agents in Figure 5 are not central hubs in Figure 1; thus, they play a different role from that of agent 2. This sheds light on the exploitation of *social* capital. These agents are also related to specific amounts of money: a number of agents are related to "währung 10,000,000" and two agents (346 and 321) are related to "währung 1,500,000". While agent 344 was one of the

key agents controlling the overall company structure, the other agents might have been some kind of straw men, holding, for instance, positions in letterbox companies in offshore locations. This indicates a considerable degree of specialization of tasks in performing the overall activity of money laundering, involving various forms of human and social capital. For instance, qualitative analysis revealed that the straw men often had intimate personal relationships with the central agents, being their brothers or girlfriends. These were actors who were highly trusted by the central agents because of their personal ties. Nevertheless, they remained distant from the central hubs in the professional money-laundering network, with only a few ties to the professional network. This feature made these people appear innocent, hiding their involvement in the activities of the core network that carried on professional money laundering in the background.

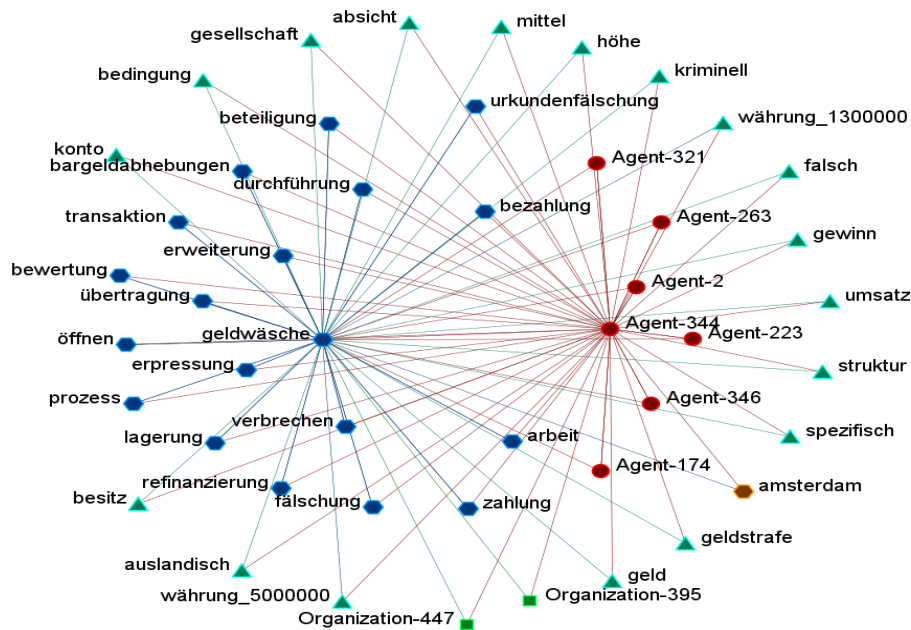**Figure 6. Ego network of money laundering and agent 344**

Figure 6 is a conjoint representation of the ego networks of the concepts agent 344 and money laundering ("geldwäsche"). As we know, agent 344 was one of the central actors controlling the company structure. While the ego network of an agent corresponds to the analytical concept of classical SNA, the ego network of a semantic concept such as money laundering can be regarded as a disentangling of the semantic field relating to a particular social activity. This is an attempt to examine issues relating to the topic of money laundering ("geldwäsche") in greater detail. In terms of ANT, it can be described as the actor network of money laundering in which human and non-human elements interact. Disentangling this semantic field reveals that the ego networks relating to the task of money laundering

refer mainly to the resources and organizations involved in this activity. Only one location appears in this network. Compared with the huge number of companies in the overall company structure (as shown in Figure 3), it is rather surprising that only two organizations, organizations 447 and 395, have direct ties to both agent 344 and the concept of money laundering. This suggests that the company structure displayed in Figure 3 also had a legal business aspect into which money laundering activities had been inserted. However, as we know from Figure 2, organization 447 is one of the central organizations in the overall network, and the number of other people in the network is relatively small. All have direct ties to agent 344, as well as to the concept of money laundering; they are clustered around these two concepts. It is striking that the resources are less often the concrete currency values seen in the earlier networks. Only one currency value appears in this network, "währung 1,300,000". Instead, the resources describe the attributes and properties needed to undertake the activity of money laundering, such as criminal ("kriminell"), false ("falsch"), volume of sales ("umsatz"), and asset ("gewinn"). Similarly, the tasks include activities that are typical of classical economic activities such as cash withdrawal ("bargeldabhebung", a task that is also typical of illegal financial activities), assessment ("bewertung"), transaction ("transaktion"), equity holding ("beteiligung") and refinancing ("refinanzierung"). However, the tasks also include crime ("verbrechen"), blackmail ("erpressung") and forgery ("fälschung"), which are clearly concepts from the criminal field. This feature makes money laundering a double-faced activity.

Figure 7 shows the ego network of Curacao, one of the most prominent offshore centres. The concept is shown in relation to actors, locations, tasks and resources. Remarkably, the concept "bank", which, according to Figure 4, is one of the most important organizations in the overall network, is intimately related to "Curacao". The two other most central organizations detected in Figure 2, namely organizations 31 and 447, also appear in relation to the concept "Curacao". It is also interesting to look at other locations, including Panama, another offshore location, and also European centres such as Rotterdam and the Swiss cities of Zurich ("zürich") and Geneva ("genf"). This seems to confirm the traditional assumption that the money will ultimately end up in a Swiss bank account. Again, the central agents 2 and 344 can be found. Note that agent 2 is the professional businessman discussed in Figure 5. This is a hint that Curacao played a central role in the professional management of the financial transactions. However, the other actors do not belong to the central hub shown in Figure 1. The fact that these actors appear to be linked to the concept of an offshore centre such as Curacao is a further indicator of the existence of straw men, as already suggested by Figure 5. The tasks confirm the assumption that activities related to the concept of Curacao are related to money laundering. Activities related to services in the financial economy are even more dominant than in Figure 6. The only criminal task is blackmail ("erpressung"). The other tasks include, for instance, payment ("zahlung"), sale ("verkauf"), venture ("unternehmen") and investment ("investition").

Figure 7. Ego network of Curacao
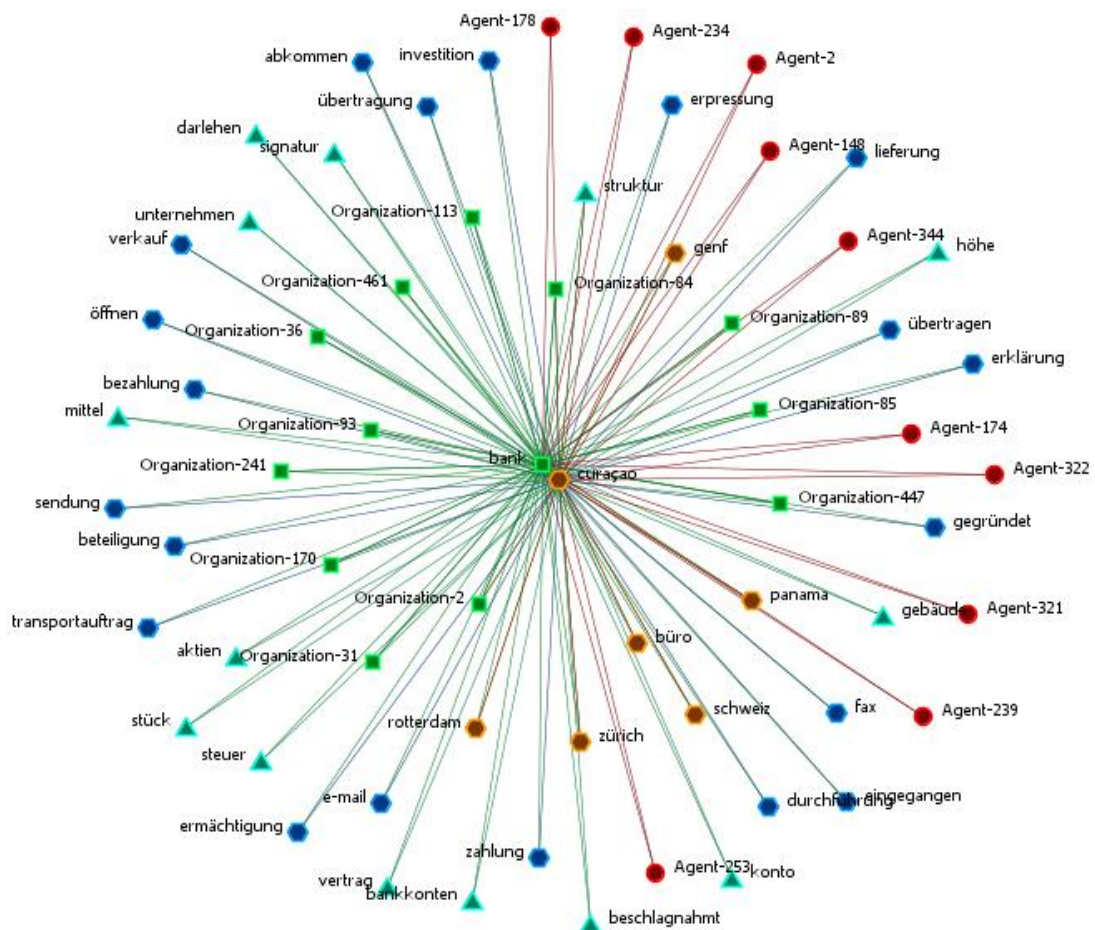
Finally, a clique analysis was undertaken to identify patterns of related concepts. Using the Newman algorithm, cliques with at least 15 members were extracted. Cliques are patterns of concepts that have a high number of internal, but only a small number of external links. Thus, they are cohesive subgroups of the overall network with a certain degree of closure. It can therefore be assumed that they belong together (Wassermann & Faust, 1994). In contrast to classical SNA, these cliques involve all the kinds of concepts that can be found in the text. So a clique can be regarded as a semantic field associated with the task of money laundering: 31 cliques with at least 15 elements were identified. For instance, clique 1 consists of 17 companies and a specific amount of money "Waehrung 1,600,000", which is an indicator of a flow of this amount of money through these organizations. It has to be noted that the cliques are not fully closed – ties exist between cliques, and the cliques are not mutually exclusive – so concepts may be part of several cliques. Organizations 57, 84, 256 and 442 appear, for instance, in 30 of the 31 cliques identified. The same holds for "£_9000" and "€_1728.06". It is striking that the latter is a very specific amount of money that is part of many cliques. Again, this suggests that this sum had been the subject of multiple transactions. These are indicators of an intention to conceal the source of the money. Finally, since the concepts of "buying" and "selling" are obviously central to financial transactions, the relationships of these concepts will be described: "buying" is related in the data

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to 22 places, 36 persons and 76 organizations, and "selling" is related to 71 places, 58 persons and 101 organizations. Interestingly, "buying" only has links to 38 different sums of money, and "selling" refers to only 61 different sums of money. Thus, both concepts are related to far fewer concrete values than organizations. This does not prove anything: it might have multiple causes. However, it might well be the case, if more organizations than concrete values are at play, that one and the same amount of money was transferred through various organizations. This is a classical pattern of layering in the process of money laundering in order to conceal the source of the money.

CONCLUSION

In this investigation, a semantic network was constructed from unstructured textual data. A central difference between classical SNA and semantic networks is that concepts are not restricted to actors. The ontology is far bigger and enables more detailed and differentiated insights into the field of investigation. One can simply examine what turns out to be relevant. In the police interrogations, all words that might be related to money laundering were selected and classified according to a meta-ontology for network construction. Investigation of the relationships between semantic concepts grants an insight into how entities with different ontological statuses are related in the semantic field of money laundering. This approach is similar to ANT, insofar as it describes networks between heterogeneous concepts. Human and non-human, as well as material and non-material concepts are treated equally as they constitute concepts in the field of money laundering.

As a result, a complex structure of companies involved in highly professional financial transactions was uncovered. The relationships between actors and resources enabled us to describe the human capital invested in these activities. The example of the professional businessman (agent 2) shows how legal business became corrupted by criminal enterprise. With regard to the money-laundering cycle of placement, layering and integration, the focus of the data was on layering, namely obscuring the source of assets. This is indicated by the huge number of complex financial transactions. The organization of a complex company structure, as outlined in Figure 3, indicates a high degree of professionalism. This is further substantiated by the involvement of professional consultants in financial issues, as revealed in Figure 5. The data show that, for this purpose, the same offshore centres were used as in the official financial economy. This shows that the FATF regulations have not been effective in preventing money laundering.

Indeed, this corresponds closely with the threat scenario outlined at the beginning of this paper: the threat of professional and transnational criminal activities undermining the legal economy and society. Since this is a case study, it does not allow for any generalizations. It is likely that most money-laundering activities do not follow this scheme, simply because it requires more skill and resources than could be supplied by petty criminals. Professionalism is costly. On a small scale, a

business such as selling used cars might be a more realistic option. From the statistics, non-professional and rather local activities are more likely to prevail, as the data from Spain indicate. However, public opinion is particularly occupied by the impact on society. The case investigated here is indeed a case of the illegal economy undermining legal business. This brings into question whether statistical and causal relevance should be differentiated: a small number of extreme cases might have a bigger impact than many cases of petty crime. The case demonstrates that, in principle, professional money laundering is a challenge for regulations aimed at preventing it.

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