Art Crime Does not pay: Multiplexed Social Network Analysis in Cultural Heritage Trafficking Forensics

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Abstract: Nowadays, crimes connected to cultural heritage can feature as a staple for organised crime networks and act as financial enablers for international conflicts, including terrorism organisations and even inter-state conflicts, in several ways. Goods of cultural significance include a range of valuable objects related to human cultures, like works of art, historical artefacts, and other antiques, but also forgeries based on such objects. These crimes are almost always transnational, for instance, involving theft or looting in one country and goods moved across borders to be sold. This article presents an intelligence methodology based on Social Network Analysis (SNA) techniques that can support law enforcement agencies (LEAs) in their daily struggle against criminals that also pose a threat to national security. The methodology proposed is based on the building of a blended, multiplexed social network graph, deriving from the fusion of a diverse set of data sources, both in the open-source domain (OSINT) and in the classified domain. We will present data collection methods, correlation between sources, possible ways to generate blended links between individuals that retain information from different sources, and SNA techniques applied to intelligence and investigations. The article provides an answer to the following research questions: how we can detect and identify criminal activities and networks related to cultural goods crimes, how we can assist LEAs in countering illicit trafficking, and how we can ensure that art crime does not pay.

Keywords: Cultural goods crime, Cybercrime, Open-source intelligence, Cybersecurity, Investigation

1. Introduction

There has been a considerable increase in organised looting, trafficking, and the illicit sale of cultural objects during the last decade (Interpol, 2021). The online art market reached 67,8 billion USD in 2022, with almost 38 million art transactions worldwide, while online sales accounted for roughly 16% of the total market value (Statista 2023). A Financial Action Task Force report also confirms that the cultural goods market attracts organised crime groups to fund their activities (FATF, 2023). These objects are expensive and difficult to trace in an opaque market that has moved mostly online. Given their complex nature, contrasting these networks is not easy. The online market enables better opportunities for the criminals through faster online sales, anonymity or falsified seller information, and even bank accounts not connected to the criminals. This makes it impossible for the authorities to detect illegal sales activities, stop monetary transactions, and seize the goods. Therefore, art crimes have an impact on national security since they can often be enablers for threats from terrorist groups, nation-state influence groups, or other forms of trafficking (weapons, drugs or human beings). We present a methodology to even the odds of authorities detecting the illicit trafficking of cultural goods in online marketplaces through approaches based on social network analysis (SNA) (Burcher, 2017). The technology is already in use, but our concept focuses more on the process perspective.

2. A Typical Cultural Heritage Trafficking Scenario

The looting and illicit trade of cultural items is a complex form of crime, transnational in nature, and involves a very diverse set of "stakeholders" (Interpol, 2023). Our scenario includes: i) looting groups close to heritage sites, often in developing countries; ii) figures taking advantage of or at some level abetting the looters, e.g., corrupt police officers, local authorities, heritage professionals; iii) transit professionals: shipping companies, border and customs agents, brokers; iv) art market professionals: legitimate actors like auction houses, dealers, collectors and museum employees; v) facilitators: for instance, restorers, authentication laboratories (who certify the provenance of items), and academics. These stakeholders are connected in a loose network of personal relations spanning over several countries and crossing the line between legal and illegal, licit and illicit activities. Looters in the origin country operate based on their local knowledge as well as on prompt advice from their supporting contacts; for instance, they might remove an ancient statue from an archaeological site. Supporting contacts are also a necessary part of the trade flow, collaborating, e.g., in moving the looted statue out of the country and into the destination market without interference from LEAs and authorities who, being unaware of the existence of the looted object, cannot investigate any crime in the original country before the statue is exported. The shipping phase might see the involvement of corrupt customs officers in the exporting countries and possibly in the transit and destination countries as well. Once it reaches the destination country, the statue could enter the

legitimate antiquities market with forged provenance and be put on sale by a legitimate auction house, where it is eventually acquired by a private collector, usually kept anonymous. Investigations of such cases involve crimes committed both in the original and destination countries and are often triggered by the claims of the original country government, which recognises the object as looted once it appears on the auction or gallery catalogue.

3. Background and Data Sources

In this section, we describe the possible data sources that can feed the blended social network graph (SNG). SANS (2023) defines open-source intelligence (OSINT) as "intelligence produced by collecting, evaluating, and analysing publicly available information with the purpose of answering a specific intelligence question". One of the most relevant OSINT techniques in our ongoing project is harvesting data from online sources such as websites, social media, and other online repositories/databases. They represent the most important sources for the creation of the SNG. Additional sources, such as call data records (CDRs) and geospatial intelligence (GEOINT) information, are also used to detect criminal activity, especially at cultural heritage sites. There is previous research on criminal investigation using CDR data (Khan et al., 2017) as well as on the use of CDR data in large-scale human and urban mobility (Thuillier et al., 2018). Data on cryptocurrency and other financial transactions can also be useful in criminal investigations, which has been studied among others by Nikkel (2020) and Kethineni and Cao (2020).

LEAs use many types of public records even outside of the ongoing criminal investigations, including court sentences, company registration records, tax records, etc. The challenge with these data sources is processing unstructured data into structured formats suitable for the building of an SNG layer. CDRs can be lawfully obtained by LEAs in most countries. CDRs contain sensitive information like phone numbers, terminal and account identifiers (IMEI, ICCID), and possibly IP addresses, and they may also provide link information and their significance (number of calls, texts between accounts, etc.). Existing digital evidence is extremely useful. For example, forensic images of seized phones or laptops yield treasure troves of information about the users and their contacts, providing ready-made correlations between call records, social media contacts, email messages, and more. Such sources, however, come with legal and ethical limitations to their use, even in the context of an existing criminal case.

4. Building the Multiplexed Social Network Graph

The SNG is the core data structure of the methodology. Nodes represent individuals (e.g., members of the looting criminal group, smugglers, art dealers) and their features (e.g., name, phone number) in the graphs. Links between individuals represent the strength of their relationship. In a SNG built using a corpus of email messages, the weights of the links are represented by the number of messages exchanged, and they can be either directional or not. Links are directional when it is important to consider the direction of the dependence between a node or individual and the others. For example, in the case of the members of a social network, a directional link represents the "follower to followed" relation. Our methodology aims at building a multiplexed SNG, which is the blend of the SNGs resulting from the processing of each data source. Of course, the graphs will not overlap precisely, so the challenge is to correlate the information pertaining to the same node (individual) across different data sources. To achieve this, AI-based techniques, manual input from expert operators, or a combination of the two can be used. Conflicts among sources should be solved, taking into consideration the reliability of each source that analysts evaluate. The result of the merging is a list of features associated with a single node. The individuated nodes could very well not present links from the entirety of the data sources, but that should not represent a problem. The actual challenge is to identify the relative weights to be assigned to each feature as well as their reliability. The intelligence tool implementing this methodology will be able to remove the SNG "layers" from one or more sources at any moment in time to accommodate the needs of the investigator or intelligence analyst. In our scenario, information about the individual looters may also come from CDRs (phone number, calls) and be correlated with social media posts or previous cases investigated by the LEAs.

5. Analysis of the Social Network Graph

A timely updated, content-rich SNG, timely updated with new information, is the object on which analysis tools can be brought to bear. We need to make a distinction between the use of our methodology by LEAs in the context of criminal investigations and its use as an intelligence tool by security agencies. In the first case, the SNA methodology is intended to support the intelligence-led policing paradigm explained in Burcher (2020). However, in this context, limitations in the collection and use of data imposed by privacy and data protection

laws, among others, could impact the insights that can be gained. Moreover, in this use case, the results of the analysis should be traceable and auditable to ensure a proper evidence chain of custody and the integrity of the potential digital evidence. In the second case, such limitations could, in many cases, be irrelevant.

Well-established measures and algorithms can be fruitfully employed to extract meaningful intelligence and investigative leads to efficiently target specific nodes. Of course, the first useful tool is the actual graphical visualisation of the network. Visual analysis is surprisingly helpful in the hands of a skilled operator. Centrality measures identify relevant nodes, albeit in different ways. The simplest kind (degree centrality) counts the number of links (degree) of a node. The most connected nodes could be, for instance, the leader of one organisation or part of it. In our scenario, for instance, the local leader of the looting group. Betweenness centrality measures an interesting aspect of complex networks as it has the power to identify "brokers", i.e., individuals that are not connected to many other nodes but lie between two distinct sections of the network that are internally highly connected. Mathematically, betweenness gauges (roughly defined) how nodes can reach out to the entirety of the network in an efficient way. The individuals identified by this measure could be, for instance, the "cut-off" between the criminal part of the whole network (looters, smugglers) and the legal one (art market, collectors), or the persons tasked with delivering messages and instructions from the leadership. In other words, intermediaries of information or power. Targeting these persons of interest could disrupt the whole network with a minimal use of resources. More complex algorithms can identify a consistent part of the whole network, for instance, because they are highly connected internally but weakly connected to the rest of the network. These are only a few examples of the potential analysis tools that, when employed on a nuanced, multi-layer SNG, can support investigations.

6. Discussion

The presented SNG methodology and especially the correlation engine, is currently still under development, and the final version will be ready early next year, after which it will be tested and evaluated by end-users. We have already identified a few challenges, one of which is the development of efficient AI-enabled algorithms for correlation definition. Another challenge is the lawful collection of massive amounts of data, which we are trying to overcome by producing artificial test data sets, which we aim to publish for future research and development needs.

7. Conclusion

We present ongoing research on SNA-based methodology to support criminal investigations on art crimes. The use of our methodology by LEAs will enable them to use their limited resources in the most efficient way and disrupt the criminal networks responsible for these kinds of crimes. The objective is to use OSINT techniques for harvesting data from online sources such as websites, social media, and other online repositories and using them to create a blended social network graph (SNG). Additional sources, such as call data records (CDR) and geospatial intelligence, can be used to enrich the graph, as well as data on cryptocurrency and other financial transactions. Nodes within the SNG represent individuals, such as the members of the criminal group; node features contain names, phone numbers and other relevant information; and the links and their weight represent the strength of the relationships between the nodes. With the use of our methodology, LEAs can enhance their investigations, discover criminal networks at a faster pace, and counter the illicit trafficking of cultural heritage goods, thus ensuring that art crime does not pay.

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