Knowledge graph representation of open-source homicide information

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Abstract

Homicide information is openly disseminated across various sources such as government websites, news portals, blogs, social media sites through which intelligence can be derived. However, conducting homicide investigations relying on open-source intelligence poses various challenges such as complexity, limited information and uncertainty. Ontology and knowledge graph have demonstrated some potential in mitigating complexity and uncertainty across various domains. However, their application in context to homicide investigations is still inadequate. This study addresses these problems and thus explores the potential of knowledge graph in representing open-source information to support homicide investigations. We demonstrate knowledge graph representation of criminological theories, uncertainty associated with open-source intelligence and the entire homicide case. The dataset used in the study consists of details regarding nine homicide cases in the Netherlands. Findings show the potential of knowledge graph in representing simpler criminological theories and uncertainty associated with open-source intelligence using probabilistic and visual attributes. However, the existing dataset lacked enough information to fully represent complex criminological theories. Additionally, the knowledge graph representation of the entire case lacked visual clarity. Overall, the findings signify the potential of knowledge graph to aid investigators in conducting effective homicide investigations.

Keywords

ontology, knowledge graph, open-source information, OSINT, homicide

1. Introduction

Homicide is defined as the act of killing a person intentionally (murder) or non-intentionally (manslaughter). In this digital era, information about homicide can be openly accessed from various sources such as government websites, news portals, blogs, social media sites. This openly available information is known as open-source information (OSINF) and the intelligence derived from OSINF is known as open-source intelligence (OSINT). Over the years, OSINT has shown its potential in policing and law enforcement, from identifying criminal behaviour to providing supporting evidence in court [1]. However, conducting OSINT based homicide investigations pose to be a challenging task.

First, homicide investigations are complex in nature as there are different elements associated with it such as suspect, victim, location, weapons. Second, open-sources mostly contain limited information about homicide. Third, OSINT possesses various epistemic issues such as unreliability, inconsistency and fuzziness [2]. Thus, relying on OSINT without evaluating the uncertainty associated with it may lead to wrong outcomes.

Ontology and knowledge graph (KG) have demonstrated some potential in mitigating complexity and uncertainty across various domains. Ontologies offer a potential solution to tackle this issue by providing a structure that enable investigators to acquire necessary information to get started with the investigation process [3]. Additionally, they help investigators understand the different elements associated with the case and thus make logical interpretations to conduct effective investigations [4]. Similarly, KGs have shown to be a powerful tool for organizing, storing and presenting complex data.

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A KG is a graph-structured knowledge base that enables the representation of knowledge in the form of entities and relationships between them [5]. However, the existing literature shows that the application of ontology and KG in the domain of homicide investigations is still lacking [5, 6, 7].

This study addresses the existing research gap and aims to explore the potential of KGs in representing open-source homicide to support homicide investigations using ontology-driven and knowledge graph-driven method. Thus, focusing on the KG representation in context to the following three aspects:

1. Criminological theories
2. Uncertainty associated with OSINT.
3. The entire homicide case

The paper is structured as follows. The existing literature of ontology and KG in the domain of homicide is described in section 2. Section 3 describes the data and methodology used in the study describing both ontology-driven and KG-driven approaches to visualise homicide OSINT using knowledge graphs. Section 4 presents the results and discussion. Lastly section 5, the presents the conclusion of the study and further highlights the contribution of this study across various domains.

2. Related Work

2.1. Homicide and Ontology

[8] introduced a conceptual model based on the ontological theory of roles to represent time dependent roles and it characteristics for various domains including homicides. Similarly, D2RCrime facilitates the the correspondence between the relational data and the classes and properties of a crime ontology for conceptual representation and reporting of crime including homicides [7] [9] developed an event top ontological approach based on the open standards of the semantic web to classify homicide and resolve situations during legal cases in Brazil. Similarly, [10] conceptualised a legal ontology for the unsolved homicide of Brazilian councilwoman Marielle Franco and developed a prototype to make inferences over criminal types and penalties based on the developed ontology. Additionally, [11] developed ontologies of motives and means as well as implemented link prediction based on KG-embedding techniques to conduct murder investigations of cases described on eight Sherlock Holmes mystery novels to identify the perpetrator with reasonable explanation. Lastly, [12] developed a system known as CRIMEO to automatically detect and identify different types of crimes including murders using an ontology-based approach.

2.2. Homicide and KG

The existing literature shows that KGs have been used to represent both fictional real homicides. [5] implemented KGs to study the television show about a private investigator Veronica Mars attempting to solve the murder of her best friend Lilly Kane. The study focused on the identification of relevant clues, topic extraction and link prediction to identify the perpetrator.

In context to the KG representation of real homicides, [6] developed KGs using criminological theory called Routine Activity Theory (RAT) to understand the interactions between the characteristics of evidence, and the investigative process of murders that occurred in Los Angeles, USA. [13] developed a KG structure for conducting murder investigations by using keyword extensions to identify and link different types of evidence and entities from crime reports. Similarly, [14] developed a homicide knowledge graph of Mexico City using a ontology driven method. This homicide dataset was further analysed by implementing a Louvain algorithm to study spatial relationships and communities in Mexico City [15].

3. Data and Methodology

3.1. Data

The dataset used in the study contains information about 9 homicide cases occurring in the Netherlands retrieved form 45 open-source articles. Each case consists of information from 3-5 articles. One common source for every case includes the De Rechtspraak (a Dutch government website that provides information about the proceedings in court cases, judgments and the organisation of the judiciary) whereas the remaining articles were sourced from various Dutch websites. For some cases, multiple articles from the same source are used as well. Table 1 shows the overview of the entities and the attributes retrieved from the homicide articles.

Table 1
Overview of homicide entities and attributes present in the dataset

Entity	Attributes
Source Article	Title, Summary, Article link
Homicide category	Murder or manslaughter
Location	Province, Type of Location
Perpetrator	Gender, Age, Murder weapon, Motivation
Victim	Gender, Age, Cause of death, Relationship to the perpetrator

3.2. Methodology

3.2.1. Experimental Setup

The existing dataset was provided to two group namely Group A and Group B in a excel data format (xlsx). Group A implemented an ontology-driven approach where as Group B implemented a KG-driven approach.

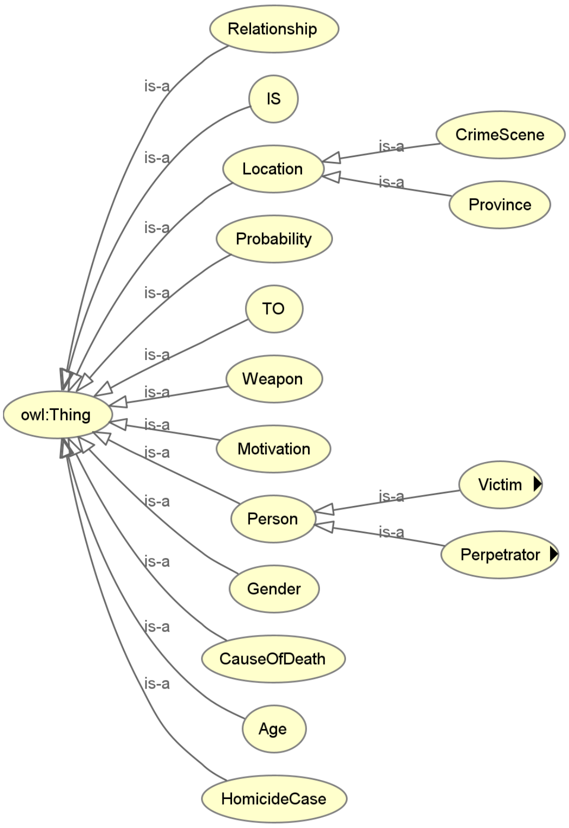
3.2.2. Group A: Ontology-driven approach

First, the pandas library was used to structure the dataset in the optimal format via transposition. The dataset had multiple rows that contained Dutch text which were translated into English using the EasyNMT module. There were also many empty values inside of the data, including both individually missing entries and completely empty columns. Though the dataset had missing information for different entities and their attributes, they were not handled using any approaches such as imputation techniques.

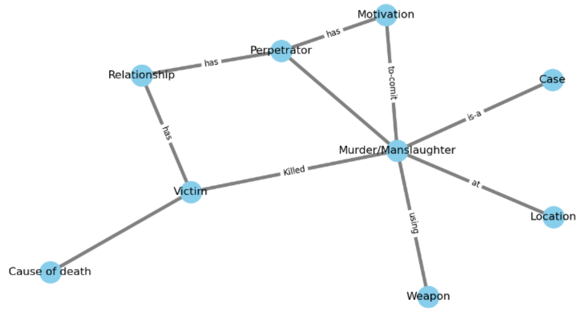
The next step involved developing an ontology to represent the available homicide information present in the existing dataset. The excel file was converted into Manchester syntax file format, which is a format for ontologies consisting of classes, instances and relationships. This file format was then imported into Protégé [16], which is a popular tool for managing ontologies.

The OWLviz plug-in was used to visualise the structure of the derived ontology as shown in Figure 1a. Thing is a superclass that represents all the different classes that describes the homicide case. Some classes in the ontology were further divided into sub classes such as the person class into the victim and perpetrator sub-classes and the location class into the crime scene and province sub classes. The ontology was designed to enable the representation of both uncertainty and criminological theories.

Each homicide case contained information originating from multiple sources. Thus a probability class was derived to represent the underlying uncertainty associated with open-source homicide information. For every uncertain piece of information, probabilities were computed. For instance, a perpetrator could have a deviating age due to conflicts in the sources. Assuming the most frequent age given is most likely to belong to a perpetrator, the number of times an age occurs is counted and divided by the total number of distinct age values to compute the probability of a given age.



(a) Ontology-driven approach



(b) KG-driven approach

Figure 1: Base structure for KG representation of open-source homicide information

Similarly, it was challenging to identify and represent the relationships between victims and perpetrators despite having a "relationship" property dedicated with each case. In the case of multiple perpetrators or victims, it was unclear which victim was associated with which perpetrator.

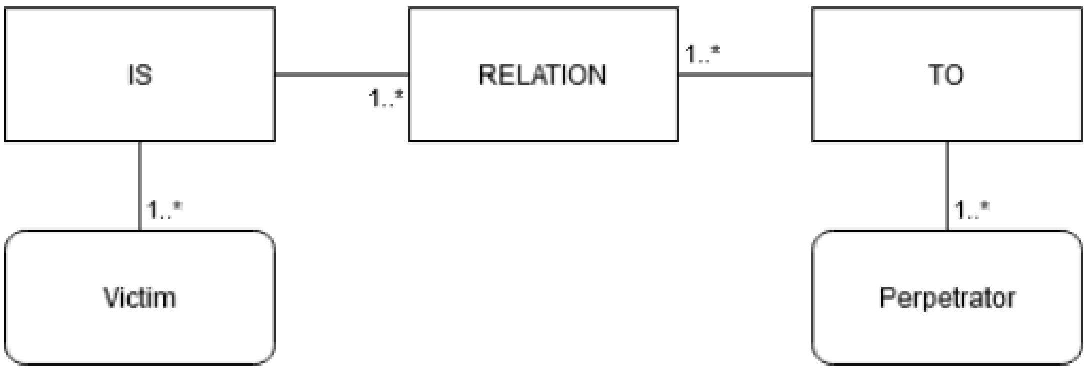


Figure 2: IS-TO connection added to enhance the relationship between victim and perpetrator

Thus an "IS" connection from the victims was added to the relationship attribute followed by the "TO" attribute connected to each perpetrator as shown in Figure 2. This relationship was particularly developed to enable the proper representation of criminological theories.

Lastly, the OntoGraf plug-in was used to to render the KGs to visualise different criminological theories, uncertainty associated with different sources and as well as the entire homicide case. The visualisation of criminological theories was implemented by displaying only the relevant nodes and edges associated with the relevant theory and hiding the rest of the elements from the from the entire case graph.

3.2.3. Group B: KG-driven approach

The data pre-processing step first involved removing unnecessary columns for each case for each case and then merging all cases into a single Data Frame. Then the confidence intervals was calculated using the Term Frequency (TF) by counting non-null values and dividing each value's occurrence count by the total count for each row [17]. If a row contained no non-null values, the confidence matrix assigns it a value of -1, indicating that no information is available for that specific variable, thereby excluding it from the final graph.

The next step included the development of the base structure of the knowledge graph comprising of the 4 elements namely source node, target node, weight and relations. All the columns present in the the excel file was then extracted and transferred into a designed structure. The networkX library [18] was then used to visualise the structure of the knowledge graph as shown in Figure 1b.

Article count was used as a primary metric to evaluate the uncertainty associated with open-source homicide information to enable decision makers to identify reliable information through corroboration. Similarly, visualisation aspects such as distance between nodes, width of edges, node colour were tested to visualise the knowledge graph. These visual aspects were selected based on Jacques Bertin's graphical representations of information [19]. Bertin asserts that size and position can be used for mapping continuous values whereas colour can used for mapping categorical values. Additionally, he emphasises that position provides greater accuracy than size when mapping a continuous value.

For distance-based visualisation, a squared mapping of the uncertainty values was implemented. This approach adjusted the "pull strength," or the metric governing node spacing, so that nodes with weaker correlations were positioned exponentially further apart as shown in Figure 4a. For edge thickness, uncertainties were normalized to values within the range of 1 to 2, ensuring line visibility across varying uncertainty levels by anchoring the minimum width at 1 as shown in Figure 4b. Finally, for colour-based visualization, values were categorized into three distinct colours: red, orange, and green as shown in Figure 4c. Based on defined threshold values, each data node was assigned a colour to signify the certainty level attributed to it within the dataset.

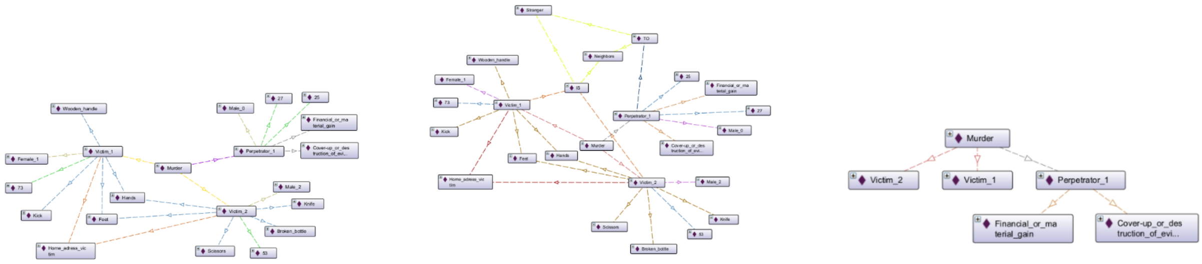
The next step involved populating the homicide case data into the designed structures and visualising the entire case data using knowledge graph. The visual clarity of the graphs was evaluated to identify the optimal approach to represent uncertainty based on visual clarity.

4. Results and Discussion

4.1. Representation of criminological theories

This section presents the KG representation of 3 criminological theories namely opportunity, RAT and strain theories as shown in Figure 3. We further explain how the power of KGs can be leveraged to derive hypothesis and scenarios that help investigators conduct homicide investigations.

The case which we will discuss primarily revolves around the murder of two victims Hennie N. and Hans T, both occurring in their own separate homes. A perpetrator, believed to be aged between 25-27, was convicted and sentenced to 24 years in prison for burgling and murdering two elderly victims aged 73 and 53. These murders occurred in February 2010, and the victims suffered severe injuries leading to their unfortunate demise. According to different sources, murders were committed using several weapons such as knives, scissors and broken bottles.



(a) Opportunity theory (b) RAT (c) Strain Theory

Figure 3: KG representation of criminological theories

4.1.1. Opportunity theory

According to opportunity theory, crime is the result of a rational choice made by the perpetrator, the facts relevant to us are limited to those that positively or negatively affect the individual for committing the crime . Additionally, the mental state of the perpetrator could influence the thought process and should be mentioned to get a more concrete view into the decision making [20].

The crime occurred at the victims' home address, which was selected due to the isolation of the area and lack of immediate witnesses. The perpetrator was motivated by financial gain, the positive factor to committing the crime. The victims were vulnerable due to their elderly age and being at home alone, creating an opportunity for the perpetrator to strike without resistance, adding an additional positive factor to performing the crime.

Figure 3a shows the KG visualisation of opportunity theory. The KG represents how situational conditions like mental state, victim vulnerability, location, presence of guardians and potential gains for the perpetrator—contribute to criminal actions. This perspective highlights the importance of addressing environmental factors and deterrence to reduce opportunities for crime or incentives to perform it.

4.1.2. Routine Activity Theory (RAT)

RAT is a sub-field of opportunity theory that explains that for a crime to a occur 3 conditions must be met namely a motivated perpetrator, a suitable target or victim, and the lack of any preventive measures [21].

Figure 3b shows the KG representation of RAT. Facts such as the age of the victims and the relationship to the perpetrator can improve the suitability of the target, increasing the viability of this person being picked over other possible victims due to fewer difficulties. The same applies to gender when the perpetrator happens to be male and the victim female, since the difference in physique can make a criminal act easier. This also applies to the presence of weapons, since a suitable target does not solely depend on the potential gain but also the ease of execution. The perpetrator was motivated by financial gain or covering up evidence of a previous criminal act. The victims happen to be suited for this as they both were of old age. Additionally, the relationships imply that for at least one of the victims, the perpetrator knew the victim. This provides details about potential wealth relevant to suitability of the victim.

4.1.3. Strain theory

From the perspective of strain theory, a person commits crime as an adverse reaction to being unable to conform to society's expectations, the facts relevant to us are the socio-economic situation of the criminal and their response to the strain created by not abiding by society's rules, e.g. poverty or failing to adhere to the expectations of others [22]. This leads to stress in an individual which can compel them to fix this dissonance, e.g. by fully rejecting society by acts such as vandalism (such acts referred to as rebellion) or by maintaining the goal while rejecting the use of lawful methods (referred to as innovation). These two terms, rebellion and innovation, are our focus as they lead to actions which can objectively be seen as anti-social and, or criminal. Though mostly for clarity, we will be using strain theory on a larger perspective as including each potential weapon and cause of death inflicted would draw attention away from the strain in question.

In context to the current case, the motivation of the perpetrator was financial or material gain, which according to strain theory can be caused by societal pressure and perpetrator's desire to illicitly attempt to abide by society's values of being wealthy. Applying strain theory to criminal cases, we can view correlations between societal factors and criminal behaviour as depicted in Figure 3c. Understanding the strains faced by individuals or communities can help identify underlying macro-level issues contributing to crime.

Overall the findings reveal that simpler theories such as strain and opportunity theories can be successfully represented using KGs whereas the available dataset lacked key features to fully represent complex criminological theories such as RAT.

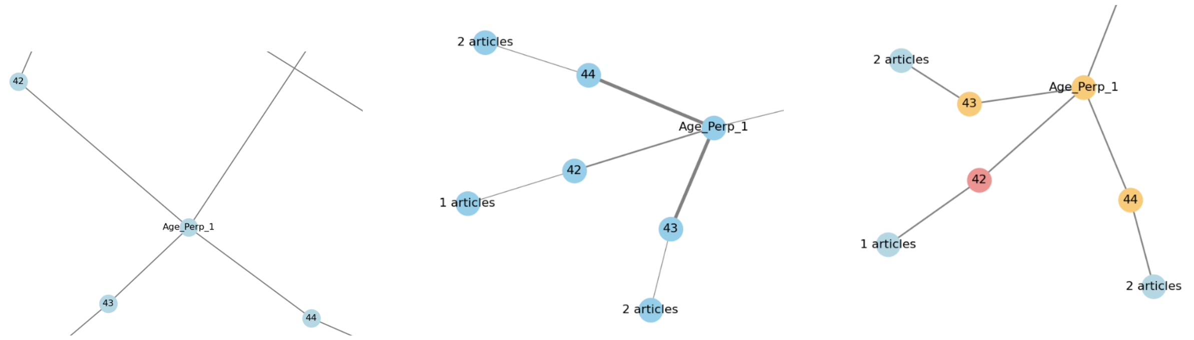
4.2. Uncertainty representation

4.2.1. Probabilistic approach

Figure 5a demonstrates how uncertainty is represented using a probabilistic approach in the knowledge graph. However, null values were not accounted for when computing the probabilities. For example, if only information from 3 sources out of a hundred sources was available, then, this approach would generate the probability of intelligence as 100% instead of 30 % thus misleading the decision makers. One possible solution could be inclusion of a threshold for each fact provided, for instance allowing certain facts to only be added when 30% or so of the articles present such a possibility.

4.2.2. Visual attributes approach

3 visual attributes namely distance, width, colour were tested during this study as shown in Figure 4. The initial testing involved varying the length of the connections of notes to portray the confidence in the data nodes, but this option proved to lack the clarity desired. Due to the scale of the knowledge graph, and how hard it is for users to detect variations in length according to (insert heuristic principle), the interpretability of this metric was lacking.



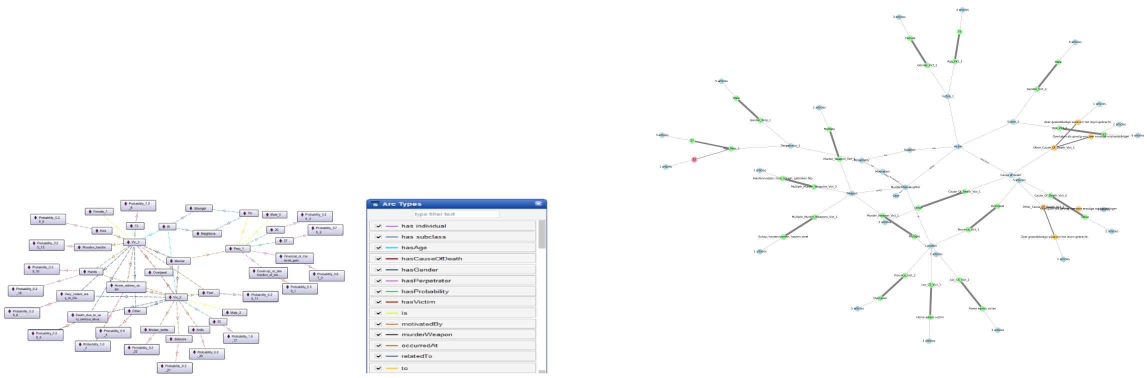
(a) Node distance variation (b) Edge width variation (c) Colour variation

Figure 4: Uncertainty representation using visual attributes

Similarly, varying the width of the edges stemming off of the skeleton to the data nodes was the second method of confidence visualization. This proved more successful, with users able to compare the widths of edges to those surrounding them, and the difference between high confidence, thick lines appearing far more clearly than the thin low confidence lines. That being said, the ability to actually gage how strong the confidence was was yet again lacking, as the relative difference only allowed for comparisons between edges, without a clear minimum and maximum being defined.

Variations in colour proved to be one of the most successful methods, allowing the user to easily identify low, medium, and high confidence values based off of a red, orange, green scale. By using thresholds rather than a sliding scale, nuance could be lost, but the fact that the number of articles supporting the data points as appended to the node allowed users to check how this value was attained. Data nodes were assigned a colour based off of the following thresholds: red < 0.3 tf, orange < 0.6 tf, else green. Along side assigning the data nodes colours, the source node would receive the same colour as the highest data value, showing how confident in general that aspect of the KG is. Thus the final selection among the 3 visual approaches includes the combination of edge width and colour variation.

4.3. Homicide case representation



(a) Ontology-driven approach

(b) KG-driven approach

Figure 5: KG visualisation of the homicide case of Hennie N. and Hans T

Using both ontology-driven and KG-driven approach the entire case has been visualised using KG as shown in Figure 5. In both cases, the visual clarity of the KG worsened with the increase in complexity of homicide information such as entities and data sources. However based on visual comparison, the KG generated using KG-driven approach looked better than the KG generated using ontology-driven approach.

5. Conclusion

In this study, we explored both ontology driven and KG-driven approach to represent open-source homicide information using KGs. Using ontology driven approach we represented opportunity, RAT and strain theory as well as represented uncertainty associated with OSINT through probabilistic approach. Similarly, KG-driven approach was explored to represent uncertainty associated with OSINT using visual attributes namely: node distance, edge width and colour. Lastly both approaches were explored the entire homicide case.

The overall findings demonstrates the potential of KG in representing open-source homicide information. KGs can indeed aid investigators in formulating criminological theories and evaluating uncertainty associated with OSINT. However, KG representation of an entire case did not generate optimal results due to the lack of visual clarity.

This research adds to the existing literature on OSINT by showcasing its application for homicide investigations. Second, it addresses the big research gap in the exploration of ontology and KGs in the domain of homicide investigations. Third, our research provides a contribution in addressing the problem of developing ontologies using limited and uncertain information.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

References

[1] F. Sampson, Intelligent evidence: Using open source intelligence (OSINT) in criminal proceedings, The Police Journal 90 (2017) 55–69. doi:10.1177/0032258X16671031, publisher: SAGE Publications Ltd.

[2] P. de Kock, Anticipating criminal behaviour: Using the narrative in crime-related data, Doctoral Thesis, Tilburg center for Cognition and Communication (TiCC), Tilburg, 2014. ISBN: 9789462401525.

[3] P. V. Srimukh, S. Shridevi, Development of Ontology on Crime Investigation process, J. Phys.: Conf. Ser. 1716 (2020) 012053. URL: https://iopscience.iop.org/article/10.1088/1742-6596/1716/1/012053. doi:10.1088/1742-6596/1716/1/012053.

[4] D. Dzemydiene, E. Kazemikaitiene, Ontology-Based Decision Support System for Crime Investigation Processes, in: O. Vasilecas, W. Wojtkowski, J. Zupančič, A. Caplinskas, W. G. Wojtkowski, S. Wrycza (Eds.), Information Systems Development, Springer-Verlag, New York, 2005, pp. 427–438. URL: http://link.springer.com/10.1007/0-387-28809-0_37. doi:10.1007/0-387-28809-0_37.

[5] M. Alaverdian, W. Gilroy, V. Kirgios, X. Li, C. Matuk, D. McKenzie, T. Ruangkriengsin, A. L. Bertozzi, P. Jeffrey Brantingham, Who killed Lilly Kane? A case study in applying knowledge graphs to crime fiction, in: 2020 IEEE International Conference on Big Data (Big Data), IEEE, Atlanta, GA, USA, 2020, pp. 2508–2512. URL: https://ieeexplore.ieee.org/document/9378079/. doi:10.1109/BigData50022.2020.9378079.

[6] R. Pandey, P. Brantingham, C. Uchida, G. Mohler, Building knowledge graphs of homicide investigation chronologies, volume 2020-November, 2020, pp. 790–798. doi:10.1109/ICDMW51313.2020.00115.

[7] J. Tavares, H. Santos, V. Furtado, E. Vasconcelos, D2RCrime: A Tool for Helping to Publish Crime Reports on the Web from Relational Data (2012).

[8] K. Kozaki, Y. Kitamura, R. Mizoguchi, A Model of Derived Roles, in: D. Hutchison, T. Kanade, J. Kittler, J. M. Kleinberg, F. Mattern, J. C. Mitchell, M. Naor, O. Nierstrasz, C. Pandu Rangan, B. Steffen, M. Sudan, D. Terzopoulos, D. Tygar, M. Y. Vardi, G. Weikum, A. Ten Teije, J. Völker, S. Handschuh, H. Stuckenschmidt, M. d'Acquin, A. Nikolov, N. Aussenac-Gilles, N. Hernandez (Eds.), Knowledge Engineering and Knowledge Management, volume 7603, Springer Berlin Heidelberg, Berlin, Heidelberg, 2012, pp. 227–236. URL: http://link.springer.com/10.1007/978-3-642-33876-2_21. doi:10.1007/978-3-642-33876-2_21, series Title: Lecture Notes in Computer Science.

[9] C. M. de Oliveira Rodrigues, F. L. Goncalves de Freitas, I. J. Da Silva Oliveira, An Ontological Approach to the Three-Phase Method of Imposing Penalties in the Brazilian Criminal Code, in: 2017 Brazilian Conference on Intelligent Systems (BRACIS), 2017, pp. 414–419. URL: https://ieeexplore.ieee.org/document/8247089/?arnumber=8247089. doi:10.1109/BRACIS.2017.21.

[10] C. M. de Oliveira Rodrigues, F. Luis Gonçalves de Freitas, I. J. Varzinczak, J. Fausto Lorenzato de Oliveira, Automated Reasoning with Legal Ontologies: A Case Study on Brazilian Councilwoman Marielle Franco's Murder, in: 2021 16th Iberian Conference on Information Systems and Technolo-

gies (CISTI), 2021, pp. 1–6. URL: https://ieeexplore.ieee.org/document/9476581/?arnumber=9476581. doi:10.23919/CISTI52073.2021.9476581, iSSN: 2166-0727.
[11] T. Ugai, Criminal Investigation with Augmented Ontology and Link Prediction, in: 2023 IEEE 17th International Conference on Semantic Computing (ICSC), 2023, pp. 288–289. URL: https://ieeexplore.ieee.org/document/10066762/?arnumber=10066762. doi:10.1109/ICSC56153.2023.00056, iSSN: 2325-6516.
[12] R. Abdallah, H. Harb, Y. Taher, S. Benbernou, R. Haque, CRIMEO: Criminal Behavioral Patterns Mining and Extraction from Video Contents, in: 2023 IEEE 10th International Conference on Data Science and Advanced Analytics (DSAA), 2023, pp. 1–8. URL: https://ieeexplore.ieee.org/document/10302629/?arnumber=10302629. doi:10.1109/DSAA60987.2023.10302629.
[13] S. Mazepa, V. Vysotska, D. Ivanchyshyn, L. Chyrun, V. Schuchmann, Y. Ryshkovets, Relationships Knowledge Graphs Construction Between Evidence Based on Crime Reports, in: 2022 IEEE 17th International Conference on Computer Sciences and Information Technologies (CSIT), 2022, pp. 165–171. URL: https://ieeexplore.ieee.org/document/10000587/?arnumber=10000587. doi:10.1109/CSIT56902.2022.10000587, iSSN: 2766-3639.
[14] J. A. de Koeijer, M. J. Sjerps, P. Vergeer, C. E. H. Berger, Combining evidence in complex cases - a practical approach to interdisciplinary casework, Science & Justice 60 (2020) 20–29. URL: https://www.sciencedirect.com/science/article/pii/S1355030619301170. doi:10.1016/j.scijus.2019.09.001.
[15] F. Carrillo-Brenes, L. M. Vilches-Blazquez, A Louvain-Based Approach to Discover Communities and Spatial Relations in a Homicide Knowledge Graph, in: H. Carlos-Martinez, R. Tapia-McClung, D. Moctezuma-Ochoa, A. Alegre-Mondragon (Eds.), RECENT DEVELOPMENTS IN GEOSPATIAL INFORMATION SCIENCES, IGISC 2023, Lecture Notes in Geoinformation and Cartography, Ctr Res Geospatial Informat Sci; Natl Geointelligence Lab, 2024, pp. 31–39. doi:10.1007/978-3-031-61440-8_3, iSSN: 1863-2246.
[16] M. A. Musen, The protégé project: a look back and a look forward, AI Matters 1 (2015) 4–12. URL: https://doi.org/10.1145/2757001.2757003. doi:10.1145/2757001.2757003.
[17] H.-J. Kim, J.-W. Baek, K. Chung, Optimization of Associative Knowledge Graph using TF-IDF based Ranking Score, Applied Sciences 10 (2020) 4590. URL: https://www.mdpi.com/2076-3417/10/13/4590. doi:10.3390/app10134590, number: 13 Publisher: Multidisciplinary Digital Publishing Institute.
[18] A. A. Hagberg, D. A. Schult, P. J. Swart, Exploring Network Structure, Dynamics, and Function using NetworkX, Pasadena, California, 2008, pp. 11–15. URL: https://doi.curvenote.com/10.25080/TCWV9851. doi:10.25080/TCWV9851.
[19] J. Bertin, W. J. Berg, Semiology of graphics: diagrams, networks, maps, 1st ed ed., ESRI Press : Distributed by Ingram Publisher Services, Redlands, Calif., 2011. OCLC: 656556106.
[20] P. Wilcox, F. T. Cullen, Situational Opportunity Theories of Crime, Annu. Rev. Criminol. 1 (2018) 123–148. URL: https://www.annualreviews.org/doi/10.1146/annurev-criminol-032317-092421. doi:10.1146/annurev-criminol-032317-092421.
[21] Cloward, Richard A., and Lloyd E. Ohlin: Delinquency and Opportunity, in: Encyclopedia of Criminological Theory, SAGE Publications, Inc., 2455 Teller Road, Thousand Oaks California 91320 United States, 2010. URL: https://sk.sagepub.com/reference/criminologicaltheory/n48.xml. doi:10.4135/9781412959193.n48.
[22] Strain theory | Social Control, Anomie & Deviance | Britannica, 2024. URL: https://www.britannica.com/topic/strain-theory-sociology.

6. Online Resources

The dataset and the code files for the project are available via

- GitHub