Knowledge Graph Representation of Open-source Homicide Information

Swikar Bhandari[1,*], Enrique Ramos[1], Ruud Rupert[1], Moamen Elkayal[1], Adham Elhabashy[1], Valeria María Serna Salazar[1], Christopher Nase[1], Justas Gvažiauskas[1] and Stef Wokke[1]

[1]*University of Twente, 7522 NB Enschede, Netherlands*

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, including complexity and epistemic uncertainty. Both ontology and knowledge graph have demonstrated some potential in mitigating complexity and uncertainty across various domains. However, their application in context to open-source intelligence and homicide investigations with respect to uncertainty representation is lacking. This study addresses the underlying research gaps and thus presents two different approaches to represent open-source information and the epistemic uncertainty associated with it using knowledge graphs to support homicide investigations. The dataset used in the study consists of details on nine homicide cases in the Netherlands. The first approach used web ontology language, whereas the second approach used graph-based modelling using the networkX library for ontological modelling. Similarly, probabilistic approach and visualisation attributes such as node distance, edge width and node colour were used to address the epistemic uncertainty associated with open-source homicide information in the first and second approach, respectively. The two knowledge graphs were visualised using an example of a homicide case and then evaluated on the basis of visual clarity. Both approaches demonstrated low visual clarity when visualising an entire homicide case. However, the knowledge graph developed using the second approach demonstrated better visual clarity. Overall, the findings signify the potential of knowledge graphs to support investigators in addressing the epistemic uncertainty associated with open sources for conducting effective homicide investigations.

Keywords

epistemic uncertainty, homicide, knowledge graph, ontology, OSINT

1. Introduction

Criminal investigations are very complex in nature. It involves deriving intelligence using information collected from a variety of sources. One such source that has gained significant popularity in recent years is open-source.

Information emerging from open-sources such as government websites, news portals, blogs and social media sites has been used by the police to derive intelligence to investigate various crimes. This intelligence derived from open-source information (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].

Among various crimes, homicides attract significantly more public attention. As a result, homicide information is widely disseminated across various open-sources. Therefore, open-source homicide information shows great potential in supporting police to investigate both active and unsolved homicides.

However, deriving OSINT from OSINF is a challenging task. This is because OSINT consists of various epistemic problems such as unreliability, inconsistency and fuzziness [2]. As such, relying on OSINT without evaluating the uncertainty associated with it can lead to wrong outcomes. Therefore,

Proceedings of the 18th International Workshop on Value Modelling and Business Ontologies (VMBO 2025), March 3–4, 2025, Enschede, The Netherlands

*Corresponding author.
s.b.bhandari@utwente.nl (S. Bhandari)
0009-0007-0824-5255 (S. Bhandari)

investigators must address the epistemic uncertainty associated with OSINT to use it for homicide investigations.

Ontology and knowledge graph (KG) have demonstrated significant potential in addressing both complexity and uncertainty across various domains. The existing literature shows that both ontology and KGs have been used in the homicide domain for a variety of applications [3, 4]. However, there is a lack of research focused on addressing the uncertainty associated with homicide investigations. In addition, only a few studies have explored ontology and KG-driven solutions to address the uncertainty associated with OSINT in critical domains. Therefore, this study aims to address the underlying research gaps and explores how KGs can be modelled to represent open-source homicide information and epistemic uncertainty associated with it to support homicide investigations?

In this study, two distinct approaches were used to develop KGs based on an existing homicide dataset consisting of information on 9 cases in the Netherlands; implementing the following five-step methodology: 1. Data exploration and tool selection; 2. Data processing; 3. Ontological modelling; 4. KG visualisation and 5. Evaluation. Lastly, the KGs developed using both approaches were visualised using an example of a homicide case and then evaluated on the basis of visual clarity.

The paper is structured as follows. The existing literature is described in section 2. Similarly section 3 describes the data and methodology used in the study. Section 4 contains the results and discussion. Lastly, section 5 concludes the study and further highlights the contribution of this study.

2. Related Work

2.1. Homicide

Many studies have used the concept of ontology and KG in the homicide domain. Ontologies have been used for conceptual representation and reporting of homicides as well as for legal resolution and penalty classification [5, 6, 7]. Similarly, KGs have been implemented mostly to support homicide investigation through approaches such as topic and evidence extraction, criminological theory representation; link identification and prediction across entities [8, 4, 9]. In addition, few studies have implemented both ontological modelling and KGs to map homicides and study spatial relationships across communities in Mexico City [10, 11]. However, the existing literature demonstrates a research gap on the application of ontology and KG to represent the uncertainty associated with homicide investigations.

2.2. Uncertainty Representation

In contrast, there are many studies that have implemented ontology and KG driven approach to represent uncertainty associated with different crimes, except homicide. Similarly, there are limited studies that have used ontology and KGs to address the uncertainty associated with OSINT in critical domains.

2.2.1. Ontology

The existing literature demonstrates two different ways of representing uncertainties using ontological modelling. Firstly, few studies have used built-in ontological frameworks or languages for uncertainty representation. For instance, Probabilistic Web Ontology Language (PR-OWL) was used in modelling probabilistic ontologies to represent the uncertainty associated with human intelligence (HUMINT) and OSINT reports for emergency services [12]. Similarly, the uncertainty associated with procurement fraud detection and prevention in Brazil was modelled using probabilistic ontology and PR-OWL, respectively [13, 14]. The Uncertainty Representation and Evaluation Framework (URREF) ontology was used to evaluate the uncertainty associated with game theory and null game models-based simulation platform for green security games by emulating realistic movement of rhinos, rangers and poachers in a park [15].

Alternatively, domain-based ontologies have been modelled using existing uncertainty representation approaches. Nick et al. developed a computational ontological framework based on OWL to identify the perpetrator in a crime-scene investigation [16]. Similarly, Mason et al. developed OWL ontologies to support the structure of evidence in a legal case to support identity judgments [17]. In both studies, the Dempster-Shafer theory was used to address the uncertainty associated with conflicting evidence. Similarly, a data quality aware ontology was conceptualised by Ferreira Saran and Castro Botega to represent situation awareness in risk management systems to solve theft-based crimes [18]. In addition, Zocholl et al. implemented an ontology-based approach to recognise illegal vessel activities such as human trafficking while addressing various uncertainties associated with the investigation. Aleatoric uncertainty, intent uncertainty as well as uncertainty about vague concepts and thresholds were addressed using probabilistic logic, description logic and fuzzy logic, respectively [19].

2.2.2. KG

The existing literature shows two different ways to represent uncertainty within a KG.

Probabilistic Approach

In this approach, the uncertainty is depicted using a numerical probability estimate in a KG [20]. Few studies have used this approach to represent the uncertainty associated with different crimes. In the maritime domain, Shiri et al. implemented probabilistic KGs to investigate the uncertainty associated with natural data for the investigation of piracy events [21]. Similarly, KG-based reasoning based on a belief function framework was used to represent and manage both aleatoric and epistemic uncertainty associated with mysterious crimes [22].

Visual Attributes Approach

This approach is widely used across many domains, including criminal investigations for sense-making and decision making purposes [23, 24, 25]. It involves evaluating uncertainty using different visual attributes present in a diagram. The existing literature shows many ways of representing uncertainty in knowledge graphs or network diagrams [20, 26] However, studies focused on representing uncertainty in knowledge graphs or network diagrams with respect to the criminal investigation domain are lacking.

3. Data and Methodology

3.1. Data

The dataset used in the study contains information about 9 homicide cases occurring in the Netherlands retrieved from 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 entities and 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

The study implemented the following five-step methodology through two distinct approaches:

3.2.1. Data Exploration and Tool Selection

In Approach 1, the Python programming language and its libraries were selected for data processing. Similarly, Protégé, a popular tool for managing ontologies, was chosen for both ontological modelling and KG visualisation using the OWLviz and OntoGraf plugins, respectively [27]. With respect to Approach 2, Python programming language and its libraries were selected for all tasks including data processing, ontological modelling and KG visualisation. Lastly, networkX, a popular library for graph visualisation was chosen for both modelling the ontology and visualising the KG [28].

In addition, the two different approaches were implemented to represent the uncertainty associated with the underlying data. A basic probabilistic approach was selected to represent the uncertainty associated with the underlying data in Approach 1. In context to Approach 2, networkX, a popular library for graph visualisation was chosen for both modelling the ontology and visualising the KG. Furthermore, Jacques Bertin's graphical representations of information was selected represent the uncertainty associated with open-source information [29].

3.2.2. Data Processing

In the second step, the data was processed using the insights developed during the previous step. It involved cleaning the data and processing existing columns; developing new columns, and then converting them into classes and instances.

Approach 1

First, the Dutch text was translated into English using the EasyNMT module. Then, the python data processing libraries such as pandas were used to further process the dataset by defining the instances of each case, attribute, entity and relationship. For every uncertain information, probabilities were computed by dividing the number of sources pointing to specific information by the total number of sources. Different sources presented conflicting information with respect to attributes such as the age of the perpetrator and murder weapon. However, the probabilities were only computed from sources that contained information and therefore rejecting sources with no information. For instance, if information was only available from 3 of 10 sources, then the probability is computed as 100% instead of 30%. Lastly, the processed excel file was converted into Manchester syntax, to develop ontologies based on OWL.

Approach 2

The unnecessary columns for each case were first removed and then case information in different data frames was all merged into a single data frame. The confidence intervals were then calculated using Term Frequency (TF) by counting non-null values and dividing the count of occurrence by the total count for each row [30]. 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.

To represent the underlying uncertainty, the source frequency for all uncertain information was first calculated. The data was then processed to facilitate the visualisation of uncertainty based on Jacques Bertin's approach through visualisation aspects such as distance between nodes, edge width and node colour variation [29]. For distance-based visualisation, a squared mapping of the confidence values was implemented. By adjusting the "pull strength" or the metric that governs the spacing of the nodes, the nodes with weaker correlations were positioned exponentially further apart. For edge thickness, confidence was normalised to values within the range of 1 to 2, ensuring line visibility across varying uncertainty levels by anchoring the minimum width at 1. Finally, for colour-based visualisation, the values were categorised into three distinct colours: red, orange, and green with green and red representing the highest and lowest certainty, respectively. Based on defined threshold values: red < 0.3 TF, orange < 0.6 TF and green > 0.6 TF; each data node was assigned a colour to signify the level of confidence attributed to it.

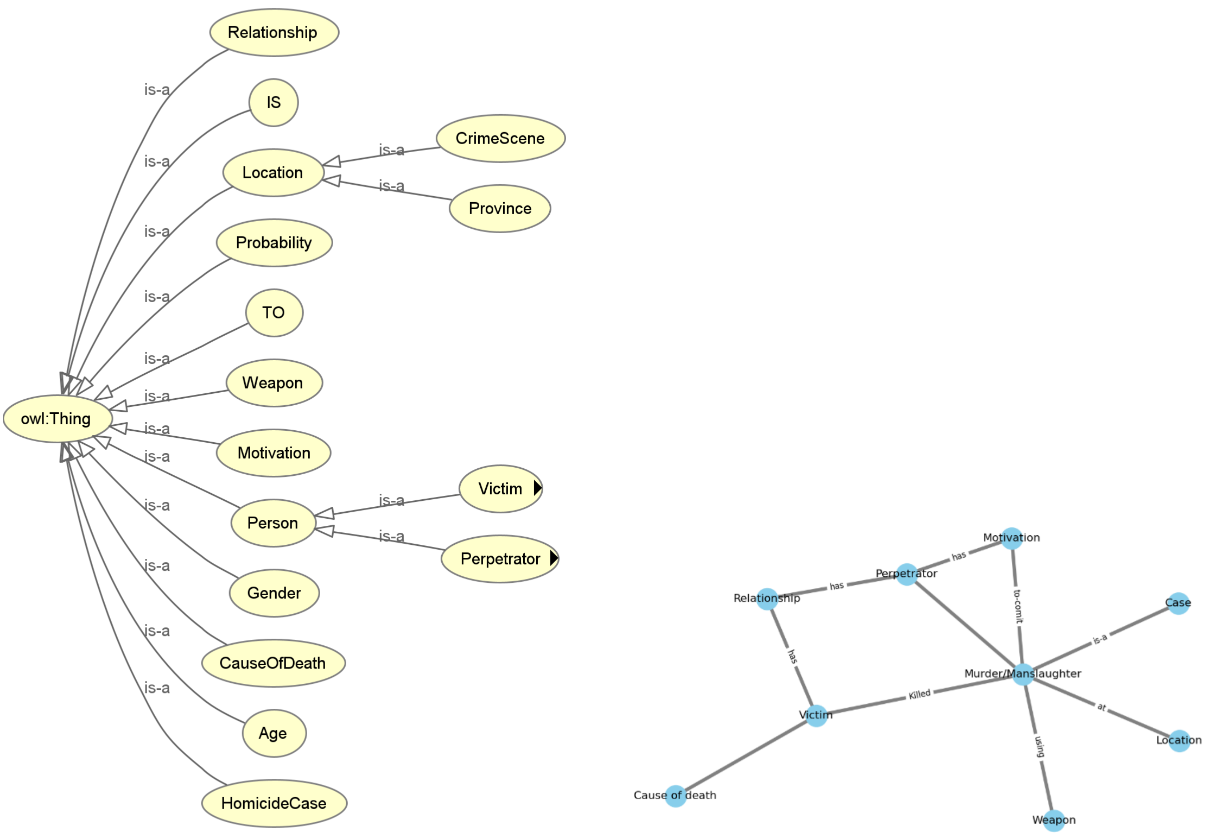
3.2.3. Ontological Modelling

This step consisted of developing the proposed ontological model containing the necessary entities, attributes and relationships for representing both the homicide information and uncertainty associated with it.

Approach 1

Among the two existing methods shown in the existing literature, we selected the domain-based ontological modelling approach instead of using an ontological framework to highlight the uncertainty associated with OSINT. The proposed ontological model is visualised using the Protégé OWLviz plugin as shown in Figure 1a.

Thing is a superclass that represents all the different classes that describe 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. Despite having a "relationship" entity dedicated to each case, it was difficult to properly represent the relationship between the victim and the perpetrator. In cases associated with multiple perpetrators or victims, it was unclear which victim was associated with which perpetrator. So, two classes named "IS" and "TO" were developed to clearly demonstrate the relationship between them. Similarly, each homicide case contained information originating from multiple sources. Therefore, a probability class was derived to represent the underlying uncertainty associated with open-source homicide information.



(a) Approach 1 (b) Approach 2

Figure 1: Ontological models for KG representation of open-source homicide information

Approach 2

The base structure of the ontological model comprising the 4 elements was developed including the source node, target node, weight, and relations. After that, all the columns present in the excel file were extracted and transferred to a designed structure. The networkX library was then used to visualise the ontological model as shown in Figure 1b.

The ontology depicts the inter-relationship across various entities across the homicide incident such as homicide type, cause of death, victim, perpetrator, weapon, motivation, location and relationship. Similarly, various relationships such as ”has”, ”killed”, ”to commit”, ”using”, ”is a” and ”at” were used to depict the relationship between entities. In particular, the victim-perpetrator relationship was depicted using the relationship node interconnected using the ”has” edge. Lastly, a source frequency node connected to each attribute of an entity is developed to represent the uncertainty associated with OSINF.

3.2.4. KG Visualisation

The penultimate step involves populating the processed data into the ontological models to generate KG visualisations. First, the uncertainty associated with the underlying data is visualised using KGs. Lastly, the entire homicide case information is visualised using both approaches.

3.2.5. Evaluation

The final step involves evaluating the KG visualisations developed in the previous step using the criteria of visual clarity.

4. Results and Discussion

The results achieved through both approaches are demonstrated using information about a homicide case. In February 2010, Hennie N. and Hans T., 73 and 53 years old, respectively, were both burgled and murdered in their own separate residences in Almelo. The perpetrator, Robert K. was convicted and sentenced to 24 years in prison.

4.1. Uncertainty Visualisation

To demonstrate how epistemic uncertainty is represented in KGs using both approaches, the perpetrator’s age is used as a reference. Among the 5 available sources, 3 sources indicated that the perpetrator was 27 years old. Among the remaining two sources, one source depicted the perpetrator’s age as 25 years, whereas the last source had no information regarding the perpetrator’s age. As null values are excluded, 4 sources are used for uncertainty representation.

4.1.1. Approach 1: Probabilistic Approach

The probabilities of age of the perpetrator based on 4 sources is calculated as 75% for 27 years and 25% for 25 years, respectively. Therefore, the underlying uncertainty is represented using the KG as shown in Figure 2.

4.1.2. Approach 2: Visual Attributes Approach

First, 3 attributes: node distance, edge width and node colour were initially tested to represent uncertainty based on the source frequency, as shown in Figure 3.

Among them, the node distance variation approach increased the size of the overall graph. Similarly, representing uncertainty using both node distance and edge width variation demonstrated low clarity. In contrast, the colour variation proved to be successful, allowing users to easily evaluate the uncertainty. Therefore, both the edge width and the node colour variation approaches were combined to further enhance visual clarity for the uncertainty evaluation, as shown in Figure 4.

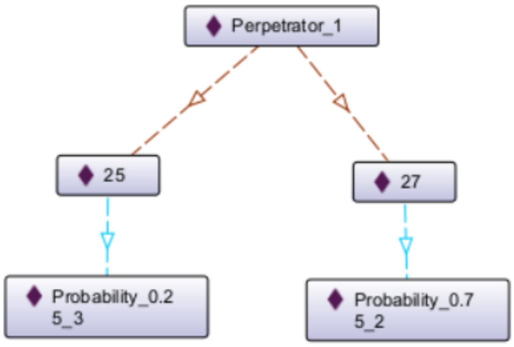
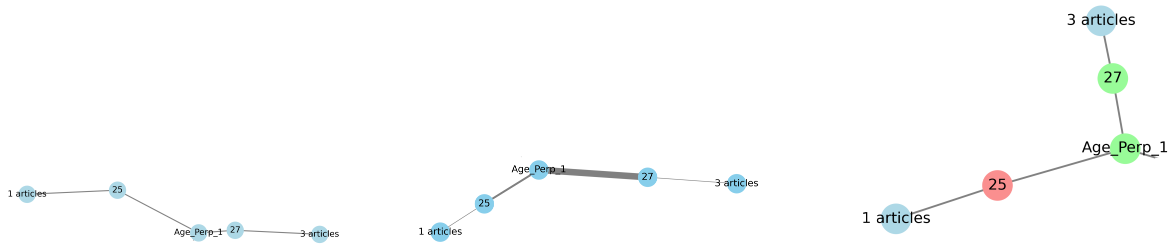


Figure 2: Uncertainty representation using probabilistic approach



(a) Node distance variation

(b) Edge width variation

(c) Colour variation

Figure 3: Initial uncertainty evaluation using 3 visual attributes

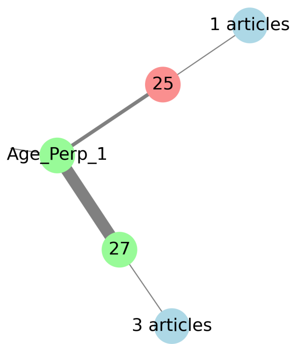


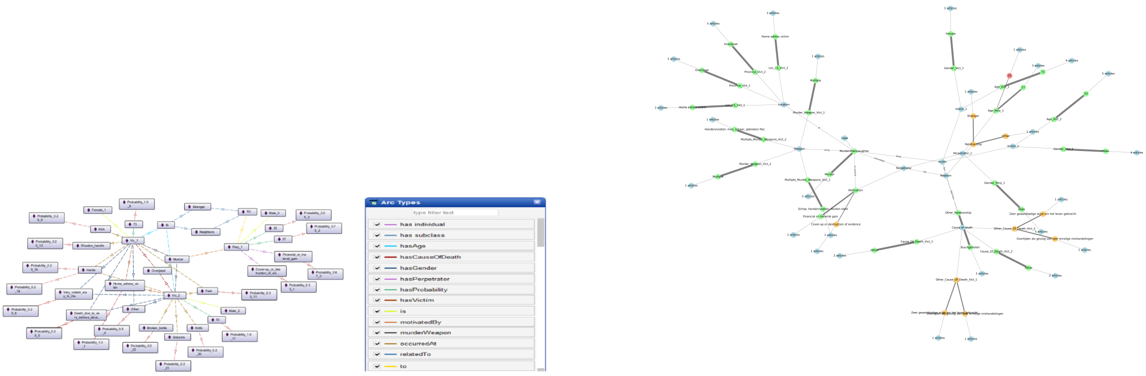
Figure 4: Uncertainty representation using the combination of edge width and node colour variation

4.2. Homicide Case Visualisation

The KG visualisation of the homicide case of Hennie N. and Hans T. using Approach 1 and Approach 2 is shown in Figure 5. The KGs depict how the probabilistic and visual attributes approach can help investigators evaluate the uncertainty associated with homicide information emerging from open sources.

In both approaches, the visual clarity of the KGs worsened due to the presence of overwhelming information emerging from different data sources. Based on the interpretation of the authors, the KG developed using Approach 2 (Figure5b) shows better visual clarity compared to Approach 1 (Figure5a).

This is primarily due to the presence of visual attributes such as edge width and node colours that enable investigators to easily depict uncertainty and identify the most reliable information. However, this interpretation cannot be fully validated. Previous studies have already shown that visualisation can be perceived differently by designers compared to practitioners [31, 26]. Thus, more research must



(a) Approach 1

(b) Approach 2

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

be done to evaluate the visual clarity of KGs from the perspective of homicide investigators.

It must be emphasised that KGs are not intended to only visualise all available information to deduce the relationship across different entities. Investigators use KGs mainly for reasoning purposes by developing scenarios, hypotheses or theories. Therefore, the visual clarity of the developed KGs will be less affected when visualising scenarios, hypotheses or theories when compared to the entire case.

Unfortunately, no suitable scenarios, hypotheses or theories could be developed and visualised using the existing dataset. This is because the dataset consisted of very limited information on already solved homicides. Therefore, future studies can be dedicated to the evaluation of existing methods on unsolved homicides.

5. Conclusion

This study explored two different approaches to represent open-source homicide information and the epistemic uncertainty associated with it using KGs. The first approach used OWL, whereas the second approach used graph-based modelling using the networkX library for modelling the ontologies of the KGs, respectively. Similarly, probabilistic approach and visualisation attributes such as node distance, edge width and node colour were used to address the epistemic uncertainty associated with open-source homicide information in the first and second approach, respectively. The findings showed that the second approach demonstrated better visual clarity compared to the first approach. Overall, this study contributes to the existing ontology and KG literature by addressing the research gap associated with uncertainty representation in the domains of OSINT and homicide investigations.

Acknowledgments

This research is funded by the Province of Gelderland and the Centre for Safety & Digitalisation. The authors are grateful for all the support provided by supervisors involved in this project from the University of Twente, Saxion University of Applied Sciences and the Police Academy of the Netherlands. Many thanks to Nico Stomp for providing the dataset used in the study.

Data Availability

The data used in this study originates from publicly available sources, including government websites and news articles. As a result, the data is subject to copyright restrictions. As such, the authors do not have the legal right to redistribute, publicly share or publish the dataset. However, information regarding all sources used to collect the data can be provided upon request. Please contact the corresponding author for any further inquiries.

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] 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.

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

[6] 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 Technologies (CISTI), 2021, pp. 1–6. URL: https://ieeexplore.ieee.org/document/9476581/?arnumber=9476581. doi:10.23919/CISTI52073.2021.9476581, iSSN: 2166-0727.

[7] 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.

[8] 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.

[9] 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.

[10] L. Carlson, J. Kennedy, K. A. Zeller, T. Busey, Describing communication during a forensic investigation using the Pebbles on a Scale metaphor, Forensic Science International: Synergy 4 (2022) 100199. URL: https://www.sciencedirect.com/science/article/pii/S2589871X21000693. doi:10.1016/j.fsisyn.2021.100199.

[11] 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 Geoinforma-

tion 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.
[12] D. Vincen, D. Stampouli, G. Powell, Foundations for system implementation for a centralised intelligence fusion framework for emergency services, in: 2009 12th International Conference on Information Fusion, 2009, pp. 1401–1408.
[13] R. N. Carvalho, S. Matsumoto, K. B. Laskey, P. C. G. Costa, M. Ladeira, L. L. Santos, Probabilistic Ontology and Knowledge Fusion for Procurement Fraud Detection in Brazil, 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, F. Bobillo, P. C. G. Costa, C. d'Amato, N. Fanizzi, K. B. Laskey, K. J. Laskey, T. Lukasiewicz, M. Nickles, M. Pool (Eds.), Uncertainty Reasoning for the Semantic Web II, volume 7123, Springer Berlin Heidelberg, Berlin, Heidelberg, 2013, pp. 19–40. doi:10.1007/978-3-642-35975-0_2.
[14] R. N. Carvalho, L. L. Dos Santos, M. Ladeira, H. A. Da Rocha, G. L. Mendes, UMP-ST Plug-in: Documenting, Maintaining and Evolving Probabilistic Ontologies Using UnBBayes Framework, in: F. Bobillo, R. N. Carvalho, P. C. Costa, C. d'Amato, N. Fanizzi, K. B. Laskey, K. J. Laskey, T. Lukasiewicz, M. Nickles, M. Pool (Eds.), Uncertainty Reasoning for the Semantic Web III, volume 8816, Springer International Publishing, Cham, 2014, pp. 1–20. doi:10.1007/978-3-319-13413-0_1.
[15] L. Kirkland, A. de Waal, J. de Villiers, Simulating Null Games for Uncertainty Evaluation in Green Security Games, 2019. doi:10.23919/FUSION43075.2019.9011280.
[16] W. Nick, E. Sloan, H. Foster, A. Esterline, A Computational Framework for Identity and Its Web-based Realization (2017).
[17] J. Mason, K. Kyei, H. Foster, A. Esterline, A Framework for Identity: Dempster-Shafer Theory the Flow and Combination of Evidence, 2018, pp. 1700–1706. doi:10.1109/SSCI.2018.8628738.
[18] J. Ferreira Saran, L. Castro Botega, Development of criminal ontologies to enhance situation assessment, 2019, pp. 669–674. doi:10.1109/BRACIS.2019.00122.
[19] M. Zocholl, C. Iphar, A.-L. Jousselme, C. Ray, Ontology-based approach for vessel activity recognition, in: Oceans Conference Record (IEEE), volume 2021-September, 2021. doi:10.23919/OCEANS44145.2021.9705824.
[20] C. Schulz, A. Nocaj, J. Goertler, O. Deussen, U. Brandes, D. Weiskopf, Probabilistic Graph Layout for Uncertain Network Visualization, IEEE Transactions on Visualization and Computer Graphics 23 (2017) 531–540. doi:10.1109/TVCG.2016.2598919.
[21] F. Shiri, T. Wang, S. Pan, X. Chang, Y.-F. Li, R. Haffari, V. Nguyen, S. Yu, Toward the Automated Construction of Probabilistic Knowledge Graphs for the Maritime Domain, 2021. doi:10.23919/FUSION49465.2021.9626935.
[22] L. Kunitomo-Jacquin, K. Fukuda, Towards reasoning over knowledge graphs under aleatoric and epistemic uncertainty, 2023, pp. 294–295. doi:10.1109/ICSC56153.2023.00059.
[23] J. Wood, A. Slingsby, N. Khalili-Shavarini, J. Dykes, D. Mountain, Visualization of uncertainty and analysis of geographical data, 2009, pp. 261–262. doi:10.1109/VAST.2009.5333965.
[24] S. Mohamad Asmara, Generating visualisation for crime scene investigation based on probability result of knowledge-based system, International Journal of Computer Applications in Technology 56 (2017) 18–26. doi:10.1504/IJCAT.2017.086556.
[25] M. J. Islam, K. Xu, B. L. W. Wong, Uncertainty of Visualizations for SenseMaking in Criminal Intelligence Analysis, 2018. doi:10.2312/EURORV3.20181145.
[26] M. Conroy, C. Gillmann, F. Harvey, T. Mchedlidze, S. I. Fabrikant, F. Windhager, G. Scheuermann, T. R. Tangherlini, C. N. Warren, S. B. Weingart, M. Rehbein, K. Börner, K. Elo, S. Jänicke, A. Kerren, M. Nöllenburg, T. Dwyer, Ø. Eide, S. Kobourov, G. Betz, Uncertainty in humanities network visualization, Frontiers in Communication 8 (2024). doi:10.3389/fcomm.2023.1305137.
[27] 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.
[28] 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.
[29] 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.
[30] 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.
[31] T. Munzner, Visualization Analysis and Design, A K Peters/CRC Press, New York, 2014. doi:10.1201/b17511.