AI-Potential to Uncover Criminal Modus Operandi Features

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Abstract

Technological innovations such as digitalisation have an increasingly important role in our society. This development is also reflected in police work. In particular, the access to information on a global scale has increased the international character, adaptivity, and fluidity of criminal organisations. As such, there is a pressing need to better understand the evolving nature of these organisations and their associated modus operandi. While digitalisation enables access to lots of information and yields information overload challenges, developments in Artificial Intelligence (AI) offer new opportunities to tackle these challenges. In particular, they provide support in the automatic extraction and analysis of unstructured sources of information to efficiently make sense of large amounts of textual information sources. In this paper, we will explore the potential and challenges of various AI methods to extract criminal modus operandi from unstructured open text sources, like law court sentences. Such open text sources are reliable information sources that include detailed validated information on the criminal activities and the modus operandi evolution in a given country. The application of this approach offers an alternative to the examination of classified police information and it also facilitates cross-country comparisons. The inherent complexity of modus operandi and the unstructured character of law court sentences yield the need to align and structure the modus operandi question with particular text mining methods. Specifically, we propose a step-wise approach to analyse automatic extraction of modus operandi-related problems via exploration, detection, and categorisation analysis. This decomposition enables to align these problems to specific functions of text-mining or machine learning methods, such as similarity detection, clustering, or named entity recognition. Using practical examples we demonstrate how this approach enables to automatically extract relevant information from court cases sentences for analysing modus operandi evolution in time.

Keywords: Artificial Intelligence, Modus Operandi, Intelligence analysis

Introduction

Technological innovations have found their way into society. For instance, the incorporation of digital technologies into business and social processes (digitalisation) provides new possibilities for services and business and also easy access to information and new forms of communication. Criminal organisations also profit from these technological advances as they enable, among others, to enlarge the illicit market in an efficient and anonymous manner (Bird et al., 2020). Moreover, criminal organisations are also able to quickly adopt new technology (Allison, 2017) and adapt to change or counter strategies (Ayling, 2009: 182). For instance, digitalisation enables sharing information (how to avoid law enforcement efforts, to exploit the potential of new technology) and as such it accelerates this adaptation capability. These adaptations are reflected in the methods of operations taken by criminal organisations to achieve their criminal goal, the so-called Modus Operandi, MO. As the analysis of the MO supports the detection of criminal activities (Fosdick, 1915), it is important to develop a process to acquire more insight into MO features and their evolution in order to strengthen the police intelligence position.

Developments in Artificial Intelligence (AI) and particular text analytics and natural language processing (NLP) methods, provide support in this process as they enable automatic extraction and analysis of unstructured sources of textual information. For instance, Shabata, Omar, & Rahem (2014), have used AI to extract nationalities, weapons, and crime locations from online crime documents. Li & Qi (2019) have used a natural language processing method to extract the MO features from crime process information and Birks, Coleman, and Jackson (2020) introduce an Artificial Intelligence framework to identify different crime types in unstructured crime reports data, as these are often classified as a single crime category for administrative purposes.

In this paper, we will build on existing research in order to explore the potential and challenges of the application of AI methods to extract criminal modus operandi features from unstructured open text sources, like law court sentences. As often, these court sentences are available online and form an accessible and reliable information source that contains validated information on criminal activities. The exploration of these open sources offers an alternative to the examination of classified police information and it also facilitates cross-country comparisons.

The use of natural language processing (NLP) techniques for the analysis of court cases narrative texts enables the exploration of large volumes of these unstructured text documents, the extraction of relevant information, and the uncovering of patterns. For instance, the potential of these techniques to support sentencing is discussed by Stobbs, Hunter, & Bagaric (2017). Medvedeva, Vols & Wieling (2020) demonstrate the potential of NLP techniques to support the prediction of judicial decisions of the European Court of Human Rights. On the other hand, Wenger et al. (2021) have applied NLP for automated punishment extraction in sentencing decisions from criminal court cases sentences in Hebrew, which poses extra challenges due to the less availability of tooling for other languages. Das & Das (2017) proposed a two stage approach for the automated analysis of a large number of crime reports against women in India. The first phase focuses on the extraction from online newspaper articles of crime reports and its exploration in order to identify most frequent observed entities, like names of cities, etc. They also show that a second stage of processing is required in order to further categorise the identified basic entities in order to extract unique and relevant modus operandi features. This short literature overview shows the importance of the development of a framework with various AI approaches to extract modus operandi features from unstructured textual data. As such we propose a step-wise approach to analyse automatic extraction of modus operandi-related features via exploration, categorisation, and detection analysis. This decomposition enables to align these problems to specific functions of text-mining or machine learning methods, such as similarity detection, clustering, or named entity recognition. Using practical examples we demonstrate how this approach enables to automatically extract relevant information from court case sentences for analysing modus operandi evolution in time.

Methodology

Vijay Gaikwad, Chaugule & Patil (2014) underline the importance of articulating the goal of text analysis with the appropriate technique functionality. Moreover, Das & Das (2017) point out that modus operandi extraction is a challenging task specifically due to the complexity of organised crime. In order to create insights into the evolution of the synthetic drugs trade very specific details of the criminal process, like the precursors used to produce synthetic drugs (which will also influence the production process), need to be extracted and analysed. On the other hand, other types of crimes may require less specific information in order to reveal adaptation in the MO. For instance, focusing on the type of weapon used in murders can provide insight into the trends in murder MO. Therefore, different MO questions may require different text analysis technique functionalities given the available data at hand. As such we propose a step-wise text analytical approach for automated extraction of MO features from criminal court sentences. This approach uses different NLP methods to extract and understand information from textual data. Some of the methods in our approach are based on supervised machine learning, while others are based on unsupervised machine learning. An unsupervised learning approach uses machine learning algorithms to analyse and cluster unlabelled data sets. These algorithms discover hidden patterns in data without the need for human intervention, which yields the term "unsupervised". An example of an unsupervised learning method is topic modelling as it automatically analyses text data to determine cluster "topics" that occur in the set of documents. On the other hand, a supervised learning approach uses labelled datasets that have been designed to train or "supervise" algorithms into classifying data or predicting outcomes accurately. Using labelled inputs and outputs, the model can measure its accuracy and learn over time. As an example, a supervised method can be trained to perform Named Entity Recognition (NER). NER is the method of locating and categorizing important nouns and proper nouns in a text (like the name of a city or organisation) (Mohit, 2014).

Although supervised methods are prone to bias (due to the selection and labelling process), the analysis of large bodies of data without support is also prone to biases as one usually explores the data based on predefined keywords yielding a less objective analysis (Birks, Coleman and Jackson, 2020).

Our stepwise approach consists of three main steps that focus on different facets of MO extraction: *Exploration, Detection,* and *Categorisation*.

The *Exploration step* aims at getting a grip on the available data. In this step, broad MO questions can be addressed like what are the relevant terms in court sentences? Do these terms change over the years? Unsupervised methods are well suited for this step. Application of such methods is usually preceded by a process of tokenisation (separating a given text into smaller text pieces, tokens), sentence segmentation, parsing and other pre-processing tasks like lemmatization (a process that analyses words according to their root lexical components). Topic modelling techniques are often used to filter and identify the semantic structure (Landauer, Foltz, & Laham, 1998). Topic models are probabilistic methods that aim to discover latent themes that are the hidden structure that characterise the unstructured text. Depending on the parameter setting, which controls the number of categories, methods search for global themes or salient local themes. The Latent Dirichlet Allocation (LDA) method and Latent Semantic Analysis (LSA) method are conventional tools used to extract the various topics from the text (Blei, Ng & Jordan 2003). The LDA method applies a generative process in which the Dirichlet distribution is used to draw random samples from the data. With this procedure, a topic can be drawn from each word, and each word can be associated with a topic. By limiting the number of topics, each word is assigned to the most likely topic. Similarly, LSA provides contextual meaning to text (Landauer, Foltz, & Laham, 1998) as follows. First, a document-to-term matrix is generated, which is then used to decompose the text into different dimensions based on the parameter setting of the algorithm. In terms of modus operandi questions, unsupervised methods provide a general overview of available terms and a nonspecific overview of the underlying structure of the available information, in some sense, they offer the possibility of zooming out.

The results of the exploration step provide insight into the potential of the available data and also input for the Detection and Categorisation steps.

In the Detection step, a further deepening of the analysis of the available data takes place to identify specific MO features and possible links between these features. Supervised methods are particularly well suited to address these questions (Shabata, Omar, & Rahem, 2014). This is particularly of interest when quick and nuanced information is required of specific modus operandi types. Supervised methods usually require a pipeline of annotation (process of labelling text so that it can be used by a model), model training, and model evaluation. By training the model using the labelled examples, it can learn the capability to distinguish and classify specific information. Models that perform NER are very popular and efficient. In particular, the application of a supervised model that is trained to perform NER requires an existing pre-trained model (for example BERT; Devlin et al 2018) or self-trained models. However, due to the level of quality (these models are trained and require a large corpus of text) of the pre-trained models and the number of models that are publicly accessible on the internet, using a pre-trained model is usually more efficient to perform NER. Moreover, it is even possible to add your own entities to the pre-trained models which could tune the model to a specific domain. This is especially useful in order to extract relevant information about the modus operandi.

The identification process of entities enriches the analysis with additional information, such as the identification of persons, organisations, locations, or modus operandi specific information such as weapon and drug-related information. Therefore, validated supervised models performing NER are a powerful tool to quickly enable users to detect and extract specific information on modus operandi types and search for specific information in large data sets.

The *Categorisation step*, brings further deepening to the analysis by focusing on the detection of modus operandi features and their differences and types (for instance, which trends in the synthetic drugs modus operandi can be identified in a given period?). It can be executed when the dataset and more specifically the modus operandi question is sufficiently structured, and the necessary context (subject matter expertise) is available. In this step, a pipeline is formalised in which different types of methods are combined. This ranges from data transformation techniques like the Term Frequency-Inverse Document Frequency (TF-IDF), a numerical statistic that demonstrates how important a word is in the available data (Ramos, 2003), or the classic K-means clustering (unsupervised machine learning method that aims to derive a partition of the data occurrences into k clusters (Hartigan & Wong, 1979) and supervised machine learning which uses the labels identified by the K-means clustering.

Finally, and as a picture is worth a thousand words, several AI algorithms can be used to support the analysis and interpretation of the results of the above applications.

Results

In order to illustrate the potential of the proposed step-wise approach, we have conducted some experiments based on the published court case sentences on the website of the Dutch Judicial System (www.rechtspraak.nl). We focused on the sentence indictment component "Tenlastelegging", which summarises the reasoning behind the sentencing based on the evidence. As these open sources do not contain personal information (this data has been blurred) the data set does not pose ethical and/or privacy challenges. It should be noted that the data set is on itself biased as it focuses only on published court sentences and thus does not cover fully the reality of the criminality.

Exploration step

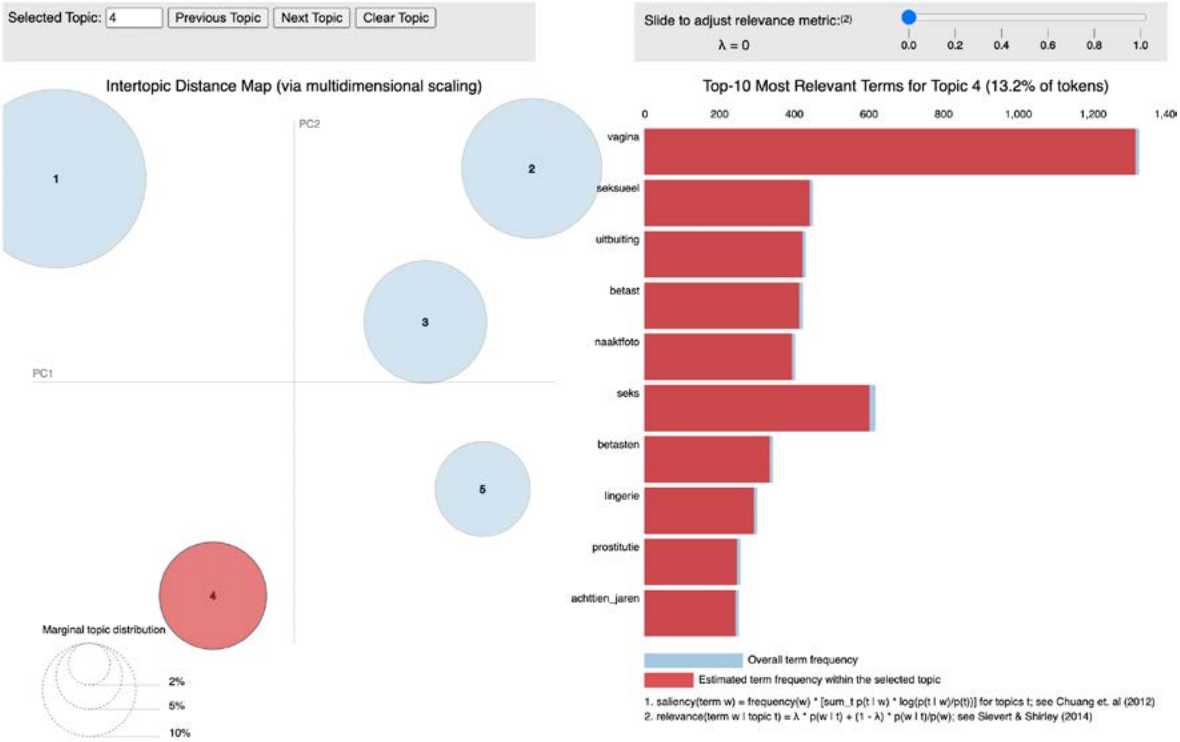
A first data set was extracted by considering available criminal law (in Dutch: strafrecht) verdicts between 2018 and 2021. This data set was further refined in order to include sentences that contained indictment or evidence, which resulted in 19.976 sentences (Jung et al., 2022).

In order to gain insight into this large data volume the exploration step was conducted. LDA (and a visualisation package pyLDAvis) was applied to uncover topics in the data set, see figure below.

In this figure, the identified topics for sexual offences are displayed on the left-hand side (topic modelling). This can be further analysed by clicking on the topic in the top-left corner. When selecting a topic, the ten most relevant terms of that topic are displayed on the right-hand side in decreasing importance order. As the above figure shows, the use of topic modelling supports the exploration of large sets in order to get an overview of the semantic structure in the textual information.

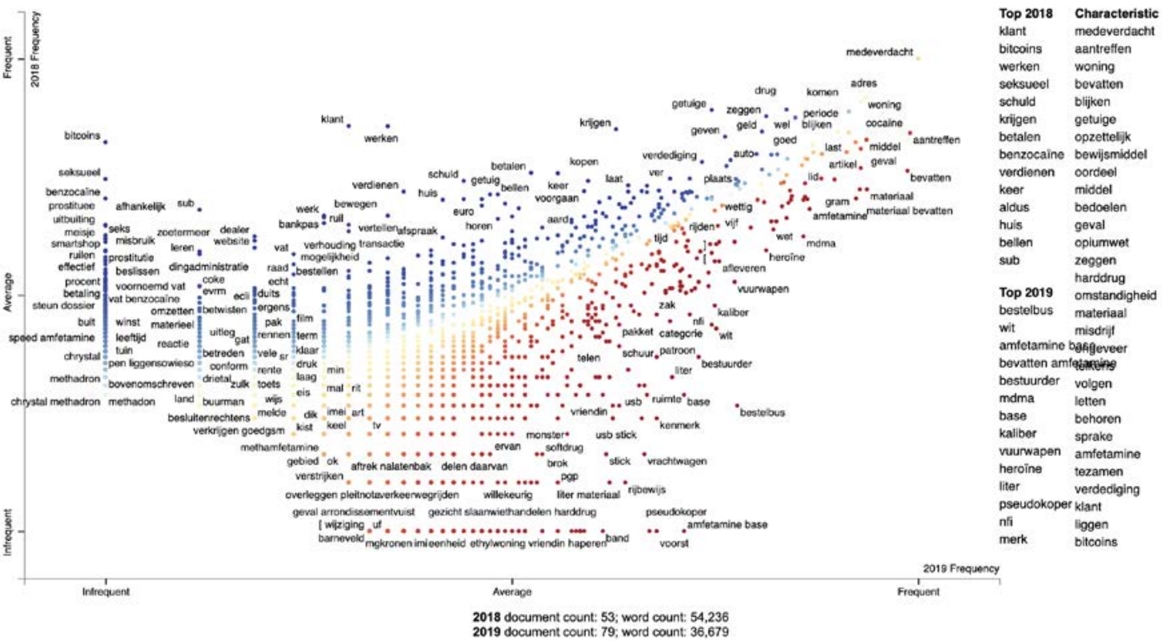
The potential of visualisation to aid the exploration is shown by the application of Scattertext (Python package to visualise the differences between two categories of text according to the term frequencies within each class), see Figure 2. This figure displays the comparison in frequency of all the words found in the used data set (available criminal law verdicts) between the years 2018 (X-axis) and 2019 (Y-axis). Each dot represents a word found in the data set court sentences of 2018 or 2019. A dot closer to the top of the plot indicates that this word occurred more frequently in 2018, while a dot

Figure 1: Example of topic modelling



further to the right of the plot shows that this word occurred more frequently in 2019. At the top-left corner "bitcoin" appears which indicates that Bitcoin occurred often in court sentences in 2018 but not in 2019. On the other hand, 'amphetamine' (bottom-right corner) occurred more often in 2019 and not in 2018

Figure 2: Example of data visualisation

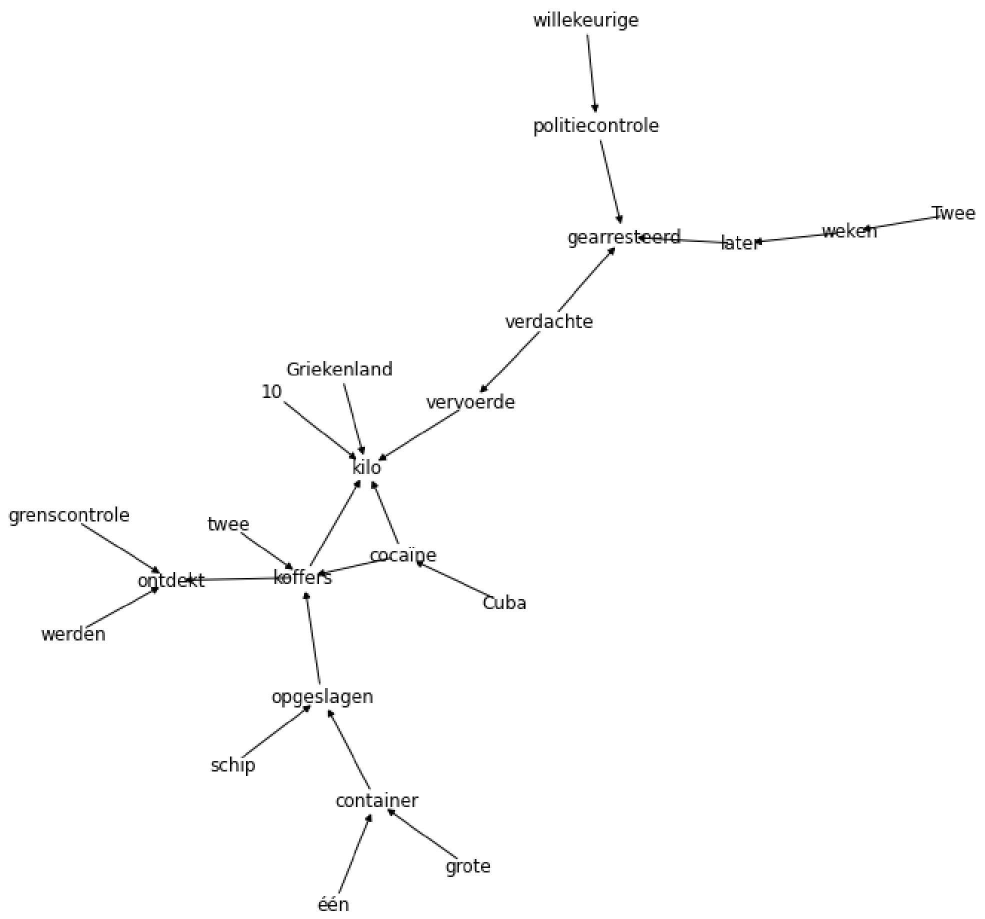


This exploration of the data using unsupervised methods quickly provides insight into the similarities and differences in the data and enables analysis across different time horizons, without requiring labelling of data. On the other hand, the topic clusters found might be too similar or too many.

Detection step

In order to illustrate this step, we will focus on court sentences related to a more complex type of crime, drugs trade, and in particular cocaine trade. As such the court sentences related to *Strafrecht* (Criminal Law) ranging from the 1930s to 2022 and containing the words cocaine and *tenlastelegging* (indictment) were selected (Dijkstra et al. 2022). In order to identify specific characteristics of modus operandi of cocaine trading in the court sentences and possible relations, NER was applied (from the open-source library SpaCy). Although the models available have been pre-trained for different languages including Dutch, the library model was not able to identify entities related to crime, like different types of drugs, weapons, and storage spaces. Therefore, it was necessary to retrain the model to identify these entities. The entities from the NER are used in *SpaCY displayCy dependency visualiser* to find relevant sentences and keywords, which are then exploited to create a graph, summarizing the relation between the MO cocaine features as shown in the figure below.

Figure 3: Possible relations between cocaine modus operandi features

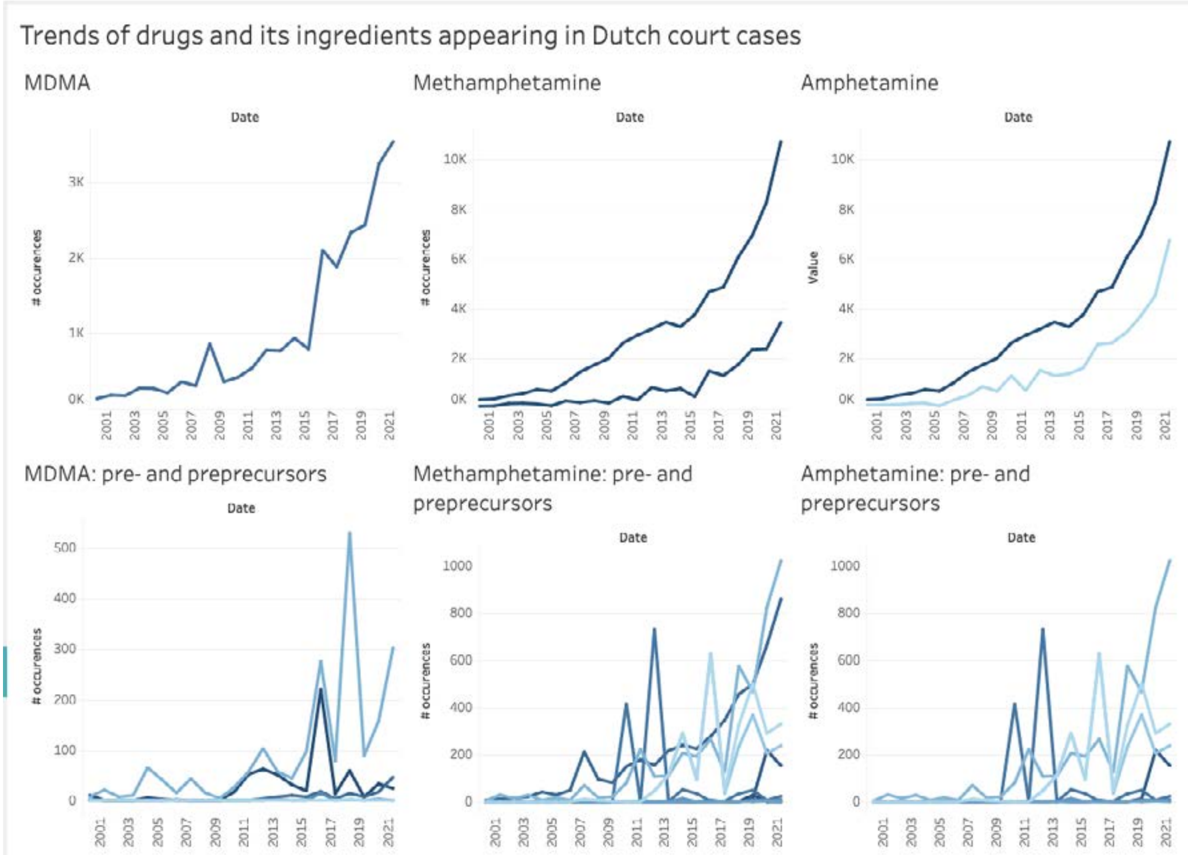


This experimental application of SpaCY NER was able to detect specific elements of modus operandi in the cocaine trade (means for transport, locations, etc). Moreover, the SpaCY displayCy dependency visualiser enables visualisation of these entities and their relationships creating extra insights. Nonetheless, the application of NER does require annotation of the data by experts in order to increase its performance, and also the development of dedicated training data sets as well as validation procedures.

Categorisation step

To illustrate this step court sentences related to synthetic drugs were considered as this has a rather intricate modus operandi. In order to address the research question regarding the evolution of synthetic drugs MO in the Netherlands, the court sentences related to *Strafrecht* (Criminal Law) up to 2022 and containing the words drugs and *tenlastelegging* (indictment) were selected which resulted in 17.714 drug-related court cases sentences (Bertrams et al, 2022). In this preliminary experiment, the textual data were transformed using the TF-IDF analysis. Using the TF-IDF on itself can already reveal interesting patterns. The figure below shows the trend of synthetic drugs and required precursors that appeared in Dutch court cases in the last years.

Figure 4: Synthetic drugs and required precursors trends in Dutch court cases

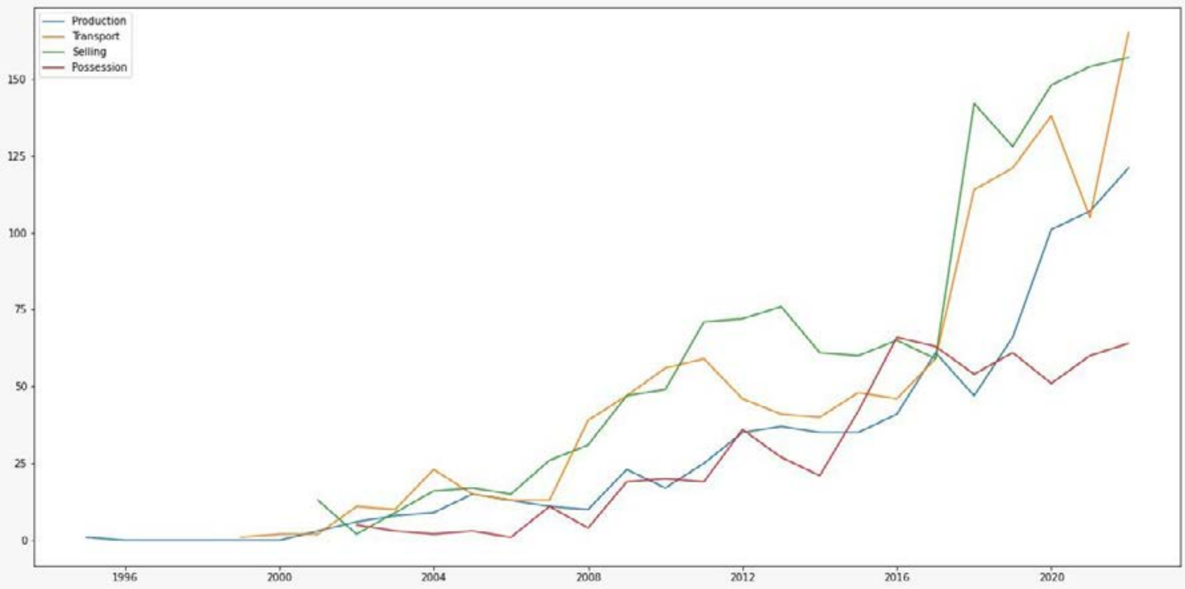


The first row of graphs shows the prevalence of the end product is mentioned over time in court cases. The second row shows the prevalence of synthetic drugs and the precursors and pre-precursors over time.

After the TF-IDF transformation, K-means clustering was used to generate several clusters. After examination of these clusters (and the words that were part of the cluster), 4 categories were identified (Production, Transport, Selling, and Possession). Using the court cases sentence dates the evolution over time of these categories can be observed, see figure below. In particular, an increased prevalence of court cases related to Production is visible around 2017.

These experiments show that the applications of categorisation methods does enable identifying differences and similarities between specific modus operandi characteristics. Moreover, they also support the analysis of the evolution of specific modus operandi features over time. However, the application of these methods require pre-identified specific modus operandi features that yield different modus operandi types. Such specific features need to be significant in order to be detected. Moreover, like other supervised methods it does require manual annotation and training process as well as validation.

Figure 5: Evolution over time of the occurrences of four synthetic drugs MO feature categories



Conclusions

The quick pace of technological innovations poses increasing challenges and opportunities to policing. As criminal organisations profit from these technological advances and quickly adopt new technology there is a pressing need to acquire insight into adaptations in the used criminal methods of operations, Modus Operandi (MO), and their evolution over time.

In this paper, we build on existing research in order to explore the potential and challenges of the application of AI methods to extract criminal modus operandi features from unstructured open text sources, like law court sentences. Court sentences provide an accessible (as they are often available online) and reliable information source that contains validated information on criminal activities, although not complete. Nonetheless, they form a solid basis for MO analysis and offer an alternative to the examination of classified police information. Moreover, the use of court case sentences also facilitates cross-country comparisons. The automatic analysis of court cases narrative texts using natural language processing (NLP) techniques enables the exploration of large volumes of court sentences, the extraction of relevant information and the uncovering of patterns. Consequently, it reduces the effort and time spent by crime analyst resources and it also supports an objective extraction process as the manual extraction of MO features by different crime analysts is more prone to errors and biases.

The inherent complexity of modus operandi and the unstructured character of law court sentences yield the need to align and structure the modus operandi questions with the appropriate methodologies. In fact, different MO features–related questions demand different approaches that vary from exploration, detection, and categorisation analysis. Therefore, the proposed stepwise approach offers support when tackling different MO features-related questions.

The preliminary experiments conducted show the potential but also highlight the caveats to its application in policing practice. In particular, they emphasise the need to consider the criminal context when applying AI and suggest the importance of establishing multi-disciplinary teams and stimulating a stronger cooperation between data scientists and IA specialists with crime analysts. Moreover, the experiments also reveal the importance of developing transparent data annotation schemes in order to support the development of unbiased supervised methods as well as creating training sets for the AI methods as also mentioned by Gumusel et al (2022).

Finally, more research is needed to further explore this initial effort in practice and to analyse its potential for cross-national comparisons.

References

- Allison, P. (1997) *Organised Crime Exploiting New Technology*. [online] ComputerWeekly.com. Available at: https://www.computerweekly.com/feature/Organised-crime-exploiting-new-technology [Accessed 24 June 2022]
- Ayling, J. (2009) Criminal Organizations and Resilience. *International Journal of Law, Crime and Justice*, *37*(4), pp.182-196.
- Bertrams, C., Hofstee, R., Malfa, I. & Miner, L. (2022) 'Mapping Synthetic Drug Production: Using Text Analysis to Track and Identify Precursor Prevalence'. *Data System Project 2021-2022 report*. University of Amsterdam. Amsterdam
- Bird, L., Hoang, T., Stanyard, J., Walker, S. & Haysom, S. (2020) *Transformative Technologies. How Digital is Changing the Landscape of Organized Crime*. 2020 Global Initiative Against Transnational Organized Crime, Switzerland.
- Birks, D., Coleman, A. & Jackson, D. (2020) Unsupervised Identification of Crime Problems from police free-text data. *Crime Science,* 9(1), pp.1–19.
- Blei, D. M., Ng, A. Y. & Jordan, M. I. (2003) Latent Dirichlet Allocation. *Journal of machine Learning research*, 3(Jan), pp.993-1022.
- Das, P. & Das, A.K. (2017) A Two-stage Approach of Named-entity Recognition for Crime analysis. In *2017 8th International Conference on Computing, Communications and Networking Technologies (ICCCNT)*, pp.1-5. IEEE.
- Devlin, J., Chang, M.-W., Lee, K., Google, K. & Language, A. (2018) BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. Available at: https://arxiv.org/pdf/1810.04805.pdf
- Dijkstra, S., Cheirmpos, G., Schipper, M. & Menarini, E. (2022) 'Graph Representation of Modus Operandi from Court Sentences'. Data System Project 2021-2022 report. University of Amsterdam. Amsterdam.
- Fosdick, R. (1915) The Modus Operandi System in the Detection of Criminals. *Journal of the American Institute of Criminal Law and Criminology*, 6(4), pp.560-570.
- Gumusel, E., Malic, V. Q., Donaldson, D. R., Ashley, K., & Liu, X. (2022) An Annotation Schema for the Detection of Social Bias in Legal Text Corpora. In International Conference on Information. pp.185-194. Springer, Cham.
- Hartigan, J.A. & Wong, M.A. (1979) Algorithm AS 136: A K-means Clustering Algorithm. *Journal of the royal statistical society* - series c (applied statistics), 28(1), pp.100-108.
- Jung, D., Kalff, E., da Rocha Bazilio, L., Rink L. & Mokkenstorm, M. (2020) 'Uncovering Modus Operandi: Using Unsupervised NLP algorithms to Identify Patterns in Unstructured Crime Data'. Data System Project 2021-2022 report. University of Amsterdam. Amsterdam
- Landauer, T. K., Foltz, P. W., & Laham, D. (1998) An introduction to latent semantic analysis. *Discourse processes*, 25(2-3), pp.259-284.
- Li, Y. S., & Qi, M. L (2019) An approach for understanding offender modus operandi to detect serial robbery crimes. *Journal of Computational Science*, 36, pp.101024.
- Medvedeva, M., Vols, M., & Wieling, M. (2020) Using Machine Learning to Predict Decisions of the European Court of Human Rights. *Artificial Intelligence and Law*, 28(2), pp 237-266.
- Mohit, B. (2014) Named Entity Recognition. In: Zitouni, I. (ed): Natural language processing of semitic languages, pp.221-245. Springer, Berlin, Heidelberg.
- Ramos, J. (2003) Using tf-idf to Determine Word relevance in document queries. In Proceedings of the first instructional conference on machine learning, 242(1), pp.29-48.
- Shabat, H., Omar, N., & Rahem, K. (2014) Named Entity Recognition in Crime using Machine Learning Approach. In Asia Information Retrieval Symposium (pp. 280-288). Springer, Cham.
- Stobbs, N., Hunter, D., & Bagaric, M. (2017) Can Sentencing be Enhanced by the Use of Artificial Intelligence? *Criminal Law Journal*, 41(5), pp.261-277.
- Vijay Gaikwad, S., Chaugule, A. & Patil, P. (2014) Text Mining Methods and Techniques. *International Journal of Computer Applications*, 85(17), pp.42-45.
- Wenger, M., Kalir, T., Berger, N., Chalamish, C., Keydar, R. & Stanovsky, G. (2021) Automated Extraction of Sentencing Decisions from Court Cases in the Hebrew Language. In Proceedings of the Natural Legal Language Processing Workshop 2021, pp.36-45.