UniMHe: Unified Multi Hyperedge Prediction A Case Study on Crime Dataset

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***Abstract*—Edge prediction is a fundamental challenge in network science, with broad applications, notably in social networks. It plays a crucial role in unveiling complex system dynamics by forecasting connections between entities. Our paper introduces UniMHe (Unified Multi Hyperedge Prediction), a novel framework for predicting multiple hyperedges associated with each node using hypergraph representations. We present a case study focused on crime network analysis, where UniMHe reveals intricate patterns in criminal activities, including crime types, locations, and seasonal variations. Our research leverages extensive historical crime data encompassing geographical information, timestamps, points of interest, and crime categories. In an extensive evaluation, we benchmark UniMHe against state-of-the-art hypergraph deep learning techniques, highlighting its superior performance. These findings underscore the significance of UniMHe across various domains and problem-solving scenarios.**

***Index Terms*—hypergraph, hyperedge prediction, predictive modeling, crime networks**

I. Introduction

Crime prediction is a multifaceted challenge that has garnered significant attention from law enforcement agencies, researchers, and technologists alike. Historically, policing strategies were largely reactive, responding to crimes after they occurred. However, with the advent of advanced data analytics and machine learning, there has been a paradigm shift towards proactive policing. By analyzing historical crime data, patterns and trends can be identified, enabling law enforcement to anticipate where and when crimes are likely to occur. Crime prediction models often operate by identifying links between various crimes and the factors that influence them. For instance, certain socioeconomic conditions, temporal patterns, and geographical locations might be correlated with higher crime rates. By understanding these relationships, predictive models can provide insights into potential future hotspots or periods of increased criminal activity. This predictive approach aims to allocate resources more efficiently and deter potential criminal activities, ultimately creating safer communities.

Existing research on crime prediction has increasingly explored graph-based methods to model the intricate relationships between various crime-related factors[1], [2], [3]. These studies often represent crime data as nodes and edges in a graph, capturing spatial and temporal dependencies between criminal events. By leveraging graph algorithms and deep learning techniques, such as Graph Neural Networks (GNNs)[4], researchers have been able to uncover hidden patterns and predict future criminal activities with enhanced accuracy. Some of these methods treated the task as a link prediction problem. Notably, Berlusconi et al. [5] adopted an approach centered on the scrutiny of judicial source documents, while Lim et al. [6] leveraged a diverse array of data sources, including corrupted criminal network data, arrest warrants, and the proximity of police stations. These efforts, though commendable, primarily employ traditional graph structures [6] or bipartite networks [7] to model crime relationships. These methods suffer from a few limitations: (1) limited relationship representation since they only capture pairwise relationships, (2) information loss due to aggregation to fit pairwise relationships, and (3) lack of flexibility in modeling different types of relationships.

Recognizing that crime-related networks exhibit complex and multifaceted relationships that may not be fully captured by standard graph models or bipartite networks and in an effort to address the limitations mentioned above, we propose using hypergraphs to model crime data to capture the high-order relations, allowing complex relationship representations, and modeling different types of relationships.

In this paper, we introduce a novel framework called UniMHe, which stands for Unified Multi Hyperedge Prediction. In contrast to graph models, our proposed approach leverages a diverse set of features, including crime type, points of interest, and date-related information, for multiple learning objectives. We construct three distinct types of hyperedges within our framework:

Location Hyperedges: These hyperedges are designed to capture spatial-based interactions among criminal incidents.

Crime Type Hyperedges: Crime type hyperedges provide insights into the distribution of different types of crimes within the network.

Season Hyperedges: These hyperedges focus on learning temporal-based relationships among crimes, particularly with regard to seasonal variations.

Our contributions can be summarized as follows:

- **Development of a hypergraph framework for crime prediction**: We introduce a novel hypergraph framework

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that allows us to effectively model and analyze three types of hyperedges, providing a comprehensive view of the complex relationships within crime networks leading to improved crime prediction.

- **Design a multitask modeling algorithm for multi-hyperedge prediction**: We propose an efficient multitask modeling algorithm tailored for the prediction of multiple hyperedges, enhancing our ability to capture various aspects of crime-related interactions in terms of location, crime type, and season.
- **We perform extensive experiments to measure the capabilities of hypergraph-based models in comparison to traditional graph neural network models, especially for multi-hyperedge prediction tasks**: Our hypergraph-based approach surpasses conventional graph models in this context. The experimental results demonstrate the enhanced performance gained from the proposed hypergraph method.

II. Related Work

In this part, we focus on crime prediction and hyperedge prediction articles.

A. Crime Prediction

Crime prediction involves analyzing diverse factors such as geographic, spatial, and temporal patterns, socio-economic indicators, demographic traits, and contextual variables. This complexity is underscored in the research by Yin [8]. A significant strand of the literature is dedicated to hotspot analysis, leveraging spatial analysis and Geographic Information Systems (GIS) to map crime patterns. This approach has been championed by researchers like Hajela et al. [9], Borges et al. [10], and Hajela [11], with Zhang and Cheng [12] even introducing a deep learning framework for predictive hotspot mapping.

Another focal point is the prediction of crime occurrences, where time series analysis stands out, analyzing historical crime data to discern patterns [13], trends, and seasonality [14], [15]. This domain has seen the application of supervised machine learning algorithms [16], [17] and advanced deep learning techniques [18], [19]. Particularly, graph and hypergraph-based predictions have been pivotal in extracting spatial-temporal and external features, with works like [20], [21], [22], [1], [23], [24] emphasizing their efficacy. Lastly, the realm of crime classification seeks to discern causal relationships and pinpoint anomalies, with methodologies ranging from deep neural networks [25] to graph-based ensemble classification [26] and pigeonhole multiclass algorithms [27].

B. Hyperedge Prediction

Hypergraphs have emerged as a versatile tool for representing intricate relationships, proving invaluable across a myriad of real-life problem domains. Their ability to depict connections between nodes that extend beyond mere pairwise interactions allows for a richer and more realistic representation. This has found applications in diverse areas such as social networks, where they've been instrumental in predicting dynamics [28], mining sparse hypergraphs [29], and enhancing location-based networks [30]. In recommendation systems, hypergraphs have been harnessed for anomaly detection [31], hyperbolic embeddings [32], and knowledge graph leveraging [33]. Furthermore, the pharmacy and life sciences sectors have benefited from hypergraph-driven advancements in drug discovery [34], sparse learning [35], and neural network applications [36]. A detailed survey by Chen et al. [37] categorizes hyperedge prediction techniques, emphasizing the significance of Deep Learning-Based Methods. This study particularly underscores the profound impact of neural network techniques in navigating the intricate prediction challenges posed by hypergraph structures.

III. Proposed Method

In this section, we define our problem and explain our proposed method, UniMHe, including the hypergraph construction, hypergraph neural network application, and hyperedge prediction task. Figure 1 shows our proposed framework.

A. Problem Definition

Let $G = (H, X)$ be a hypergraph, where $H = (\mathcal{N}, E)$ represents the hypergraph structure of committed crimes and X encapsulates the node attributes: location $l \in \mathcal{L}$, crime type $c \in \mathcal{C}$, and season $s_l \in \mathcal{S}$. In this work, we propose a method for hyperedge prediction that leverages the hypergraph G to capture intricate relationships between committed crimes based on their associated attributes. The goal is to predict the hyperedge H that connects a subset of crime nodes in $\mathcal{N}$ based on their associated location l, crime type c, and season s_l.

B. Framework Overview

We introduce UniMHe (Unified Multi-Hyperedge) as a solution for predicting multi-hyperedges for each node, as illustrated in Figure 1 and in Algorithm 1. Our framework begins with the collection of datasets comprising crime and points of interest data. Subsequently, we extract various attributes, including crime types, months, years, latitude, longitude, and region. We proceed to construct a hypergraph in which nodes represent committed crimes, and the edge types encompass location edges, crime type edges, and season edges. The hypergraph neural network is then applied in Shared Layer. After that, we implement linear layers in Seperated Layers shown in in Figure 1 to get results for multi-hyperedge prediction. We describe the details of our framework below:

C. Hypergraph Construction

In our proposed method, a hypergraph $H = (\mathcal{N}, H)$ is constructed. The set $\mathcal{N}$ denotes the collection of crime nodes, where each individual node encapsulates information about a specific crime event, characterized by its location l, crime type c, and season s_l. Conversely, H represents the set of hyperedges. Each hyperedge within the set H is a specific subset of $\mathcal{N}$ and symbolizes a potential connection or relationship amongst the crime events based on their shared attributes or patterns.

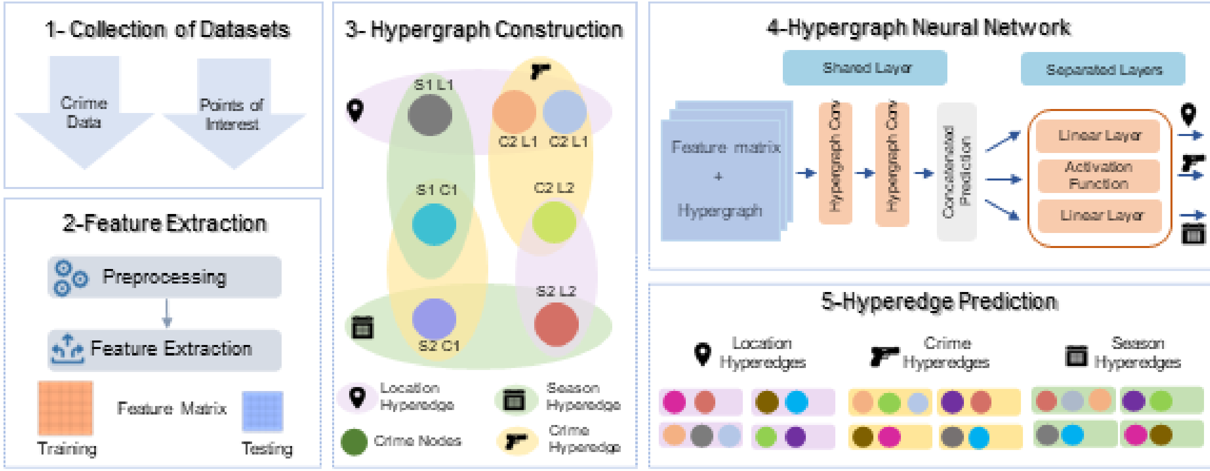

Fig. 1. Proposed Framework

In our hypergraph construction, we introduce three distinct types of hyperedges: location hyperedges, crime type hyperedges, and season hyperedges.

1. Location Hyperedges: For each unique location l_i in the dataset, we define a location hyperedge E_{l_i} such that:

$$E_{l_i} = \{n \in \mathcal{N} \mid n \text{ is associated with location } l_i\} \tag{1}$$

This hyperedge groups all crime nodes that occur in the same location l_i.

2. Crime Type Hyperedges: Similarly, for each unique crime type c_j, we define a crime type hyperedge E_{c_j} as:

$$E_{c_j} = \{n \in \mathcal{N} \mid n \text{ is of crime type } c_j\} \tag{2}$$

This hyperedge groups all crime nodes that are of the same crime type c_j.

3. Season Hyperedges: For each unique season s_k, we define a season hyperedge E_{s_k} such that:

$$E_{s_k} = \{n \in \mathcal{N} \mid n \text{ occurred in season } s_k\} \tag{3}$$

This hyperedge groups all crime nodes that took place in the same season s_k.

These hyperedges allow us to capture relationships and patterns among crime nodes based on their shared attributes, facilitating more nuanced and detailed analyses.

D. Model Description:

Our proposed model operates on a hypergraph $H = (\mathcal{N}, H)$ where nodes $\mathcal{N}$ represent individual crime events and hyperedges H capture relationships based on location, crime type, and season. The model aims to learn a comprehensive representation of each crime node by aggregating information from its neighboring nodes and the hyperedges it is associated with.

Feature Aggregation: The primary step in the model is the aggregation of features from neighboring nodes. For a given node n, its updated feature $\tilde{x}_n$ is computed by aggregating information from all hyperedges it is part of. Specifically, for each type of hyperedge E_t (where $t \in \{l, c, s\}$ corresponds to location, crime type, and season, respectively), the aggregation is defined as:

$$\hat{x}_{n,E_t} = \frac{1}{\sqrt{d_{n,E_t}}} \sum_{e \in E_t} \frac{1}{\sqrt{d_e}} h_e \tag{4}$$

Here, d_{n,E_t} represents the degree of node n concerning hyperedge type E_t, and d_e is the degree of hyperedge e. The aggregated feature $\hat{x}_{n,E_t}$ captures the essence of node n with respect to the hyperedge type E_t.

Feature Transformation: After aggregating features for each hyperedge type, the model applies a transformation to combine these features and refine the node representation. This transformation is formulated as:

$$\tilde{x}_n = ((1-\beta)I + \beta W) \left((1-\alpha) \sum_{t \in \{l,c,s\}} \hat{x}_{n,E_t} + \alpha x_n^0 \right) \tag{5}$$

In this equation, x_n^0 is the initial feature of node n, while α and β are hyperparameters that control the balance between the aggregated features and the original node features. The matrix W is a learnable weight matrix that adjusts the importance of different hyperedge types in the final node representation.

Through this methodology, the model effectively integrates information from all three hyperedge types, yielding a robust representation of crime nodes that encompasses their location, crime type, and season.

E. Hyperedge Prediction:

Once the model has learned a comprehensive representation for each crime node, the next step is to predict the presence or absence of hyperedges in the hypergraph. This prediction process aims to determine potential relationships or connections between crime nodes based on their refined representations.

For a potential hyperedge E_p consisting of a subset of nodes $\mathcal{N}_p \subseteq \mathcal{N}$, the prediction score $S(E_p)$ is computed as a function of the aggregated node representations within that subset:

$$S(E_p) = f\left(\sum_{n \in \mathcal{N}_p} \tilde{x}_n \right) \tag{6}$$

TABLE I
DATASET DESCRIPTION

Node Features	Types
Crime category	Robbery, Burglary, Felony Assault and Dangerous Drugs
Months	From January to December
Location	77 disjointed police districts
POI	Arts - Entertainment, Automotive - Vehicles etc.

Here, f is a nonlinear function that maps the aggregated node representations to a score indicating the likelihood of the hyperedge's existence. The model is then trained to optimize this score using a cross-entropy for classification tasks.

Thresholding and Decision Making: After computing the prediction scores for all potential hyperedges, a threshold T is set to decide the presence or absence of each hyperedge. If $S(E_p) > T$, the hyperedge E_p is predicted to be present; otherwise, it is predicted to be absent. The choice of T is based on the trade-off between precision and recall.

IV. EXPERIMENTS

To assess the performance of our proposed model, UniMHe, we conducted extensive experiments to validate its effectiveness.

A. Dataset

We combined crime data [38] and points of interest [39] dataset collected from the New York City (NYC) Open-Data portal. In points of interest dataset, there are information including education, cultural, and recreational facilities. The crime dataset includes all the crimes committed from Jan 1, 2018, to Dec 31, 2022. Each crime record has crime category, latitude, longitude, and timestamp information. We focus on four crime categories in the top 10. We propose to examine the inherent correlations between regions, crime categories, and seasons. New York City is divided into 77 disjointed police districts. We defined these districts using latitude and longitude. The node features for our model are shown in Table I. For each hyperedge, all crimes corresponding to the characteristics of that hyperedge were collected, and the ground truth values were labeled accordingly. The hypergraph includes 124,967 nodes for training and 31,276 nodes for testing. Test nodes are selected randomly from all data with a 20/80 split.

B. Baselines

We compared our proposed method with seven baselines that can be categorized into two groups: graph-based methods and deep hypergraph methods. For the graph-based methods, we converted our constructed hypergraph to a bipartite graph, which ensures a fair comparison. In the bipartite graph, hyperedges are transformed into node types.

Graph-based methods:

- GNN [4]: Predicts crime occurrences by learning node representations based on the underlying graph structure and historical crime data.

Algorithm 1 Unified Multi-Hyperedge Prediction (UniMHe)

Require: Crime dataset with attributes: location l, crime type c, season s_l
Ensure: Predicted hyperedges for each node
Construct hypergraph $H = (\mathcal{N}, H)$
for l_i in unique locations **do**
  Define location hyperedge E_{l_i} ▷ Create hyperedges based on locations
for c_j in unique crime types **do**
  Define crime type hyperedge E_{c_j} ▷ Create hyperedges based on crime types
for s_k in unique seasons **do**
  Define season hyperedge E_{s_k} ▷ Create hyperedges based on seasons
for node n **do**
  for hyperedge type E_t **do**
    Compute aggregated feature $\hat{x}_{n,E_t}$ ▷ Aggregate features from hyperedges
  Update node feature $\tilde{x}_n$ ▷ Update node feature based on aggregated hyperedge features
for potential hyperedge E_p **do**
  Compute score $S(E_p)$ ▷ Compute prediction score for potential hyperedges
  if $S(E_p) > T$ **then**
    Mark hyperedge E_p as present ▷ Threshold-based decision for hyperedge presence
  else
    Mark hyperedge E_p as absent
  return Predicted hyperedges ▷ Final set of predicted hyperedges

- GCN [40]: Classifies crime nodes by leveraging their spatial and temporal features along with the features of their neighboring nodes.
- GAT [41]: Predicts crime events by assigning different importance to different nodes in a neighborhood, allowing for a more flexible representation.

Deep hypergraph methods:

- UniSAGE [42]: Predicts crime occurrences by aggregating features from a node's local neighborhood using sampling-based methods.
- UniGCN [42]: Classifies crime nodes by leveraging their inherent features and the features of their neighboring nodes in a unified manner.
- UniGAT [42]: Enhances crime prediction by assigning varying importance to different neighboring nodes using an attention mechanism.
- UniGIN [42]: Predicts crime events by employing a graph isomorphism network that captures structural equivalence among nodes.

C. Evaluation Metrics

The prediction of hyperedges for each node is a classification problem. F1-score and accuracy are computed to

TABLE II
MULTI HYPEREDGE PREDICTION PERFORMANCE

	Overall Accuracy	F1 Score	Location Edge Accuracy	Crime Edge Accuracy	Season Edge Accuracy
GNN	31%	5%	2%	37%	56%
GAT	35%	6%	2%	51%	52%
GCN	25%	1%	3%	37%	34%
UniSAGE	63%	47%	36%	57%	97%
UniGCN	50%	11%	10%	58%	82%
UniGAT	54%	45%	50%	54%	57%
UniGIN	64%	62%	55%	59%	79%
UniMHe	**83%**	**96%**	**97%**	**51%**	**99%**

evaluate the performance. We calculated the overall F1-score and accuracy for each model.

TABLE III
ABLATION STUDY

	Location	Crime	Season	Overall Accuracy	F1 Score
First Task	+	+		73%	92%
Second Task	+		+	94%	90%
Third Task		+	+	76%	76%
Forth Task	+			98%	98%
Fifth Task		+		51%	50%
Sixth Task			+	99%	99%

V. RESULTS AND DISCUSSION

A. Multi Hyperedge Prediction Performance

As shown in Table II, our proposed methodology demonstrates notable superiority when compared to existing graph and hypergraph neural network models. Although the overall accuracy and location edge accuracy of GNN, GAT, and GCN exhibit similar performance levels, each of these models excels in specific hyperedges. Specifically, GNN achieves better results in season edge accuracy compared to other edge types. On the other hand, GAT demonstrates nearly equal performance in season and crime edge accuracy results. In contrast, GCN yields the least favorable outcomes. Comparing between our model and UniGNN approaches, our model exhibits superior performance across various metrics. Particularly, it outperforms all models in terms of overall accuracy, location edge prediction, and season edge prediction. Notably, the accuracy in crime edge prediction is quite similar among the models, with negligible variations.

The success of the UniMHe framework heavily relies on the quality and completeness of the crime and points of interest data. Incomplete or inaccurate data may lead to biased hypergraph construction and impact the overall predictive performance of the model.

B. Ablation Study

We conducted an ablation study to systematically investigate the impact of different types of hyperedges on the performance of our model. The results of this study are presented in Table III, showcasing the model's performance under various combinations of hyperedges. In cases of season and location hyperedge types, the model is overfit. This insight emphasizes the need for a balanced and diverse set of hyperedges to prevent overfitting issues. Conversely, when using only crime hyperedges, the model does not learn enough to predict correctly. This emphasizes the complementary nature of the information encoded in different hyperedge types. The inclusion of diverse hyperedge types enriches the learning process, enabling the model to capture intricate relationships within the hypergraph.

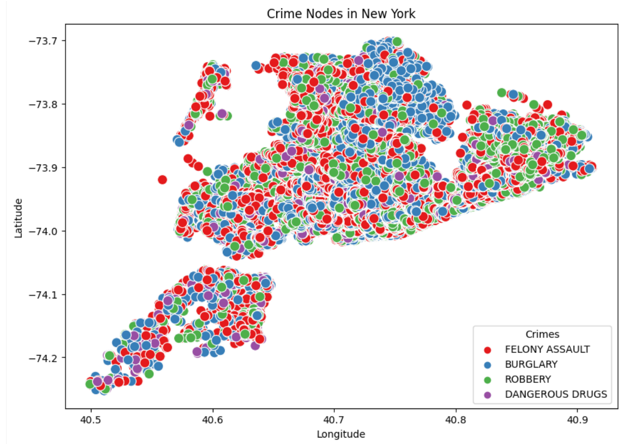

Fig. 2. Crime in Newyork

VI. CASE STUDY

In the city of New York, a multitude of criminal activities takes place on a regular basis. The visualization presented in Figure 2 provides an overview of the incidents of crime that occurred in the year 2022, categorized by their types. Within the context of our model, each recorded criminal occurrence is represented as a node. The attributes associated with these nodes encompass critical information such as location, latitude, longitude, time, season, and points of interest linked to their geographical coordinates. For the purpose of our analysis, we have identified four distinct crime types, each of which can be conceptualized as a hyperedge within the hypergraph model. The primary objective of this paper is to predict the edges of each crime, determining the location, the crime type, and the season in which it is likely to transpire.

VII. CONCLUSION

In conclusion, this paper introduces UniMHe, a novel framework for Unified Multi Hyperedge Prediction, addressing challenges in hypergraph-based crime network analysis. We tackle feature extraction and multi-class hyperedge prediction complexities, advancing predictive models in this domain. Our innovative framework incorporates crime type, points of interest, and temporal information, facilitating the construction of various hyperedge types. Through extensive experiments and comparisons, UniMHe outperforms traditional graph models and hypergraph neural networks, particularly in overall accuracy.

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REFERENCES

[1] S. F. Tekin, S. S. Kozat, Crime prediction with graph neural networks and multivariate normal distributions, Signal, Image and Video Processing 17 (4) (2023) 1053–1059.

[2] T. Almanie, R. Mirza, E. Lor, Crime prediction based on crime types and using spatial and temporal criminal hotspots, arXiv preprint arXiv:1508.02050 (2015).

[3] Y. Qian, L. Pan, P. Wu, Z. Xia, Gest: A grid embedding based spatio-temporal correlation model for crime prediction, in: 2020 IEEE Fifth International Conference on Data Science in Cyberspace (DSC), IEEE, 2020, pp. 1–7.

[4] F. Scarselli, M. Gori, A. C. Tsoi, M. Hagenbuchner, G. Monfardini, The graph neural network model, IEEE transactions on neural networks 20 (1) (2008) 61–80.

[5] G. Berlusconi, F. Calderoni, N. Parolini, M. Verani, C. Piccardi, Link prediction in criminal networks: A tool for criminal intelligence analysis, PloS one 11 (4) (2016) e0154244.

[6] M. Lim, A. Abdullah, N. Jhanjhi, M. Supramaniam, Hidden link prediction in criminal networks using the deep reinforcement learning technique, Computers 8 (1) (2019) 8.

[7] N. Assouli, K. Benahmed, B. Gasbaoui, How to predict crime—informatics-inspired approach from link prediction, Physica A: Statistical Mechanics and its Applications 570 (2021) 125795.

[8] J. Yin, Crime prediction methods based on machine learning: A survey., Computers, Materials & Continua 74 (2) (2023).

[9] G. Hajela, M. Chawla, A. Rasool, A multi-dimensional crime spatial pattern analysis and prediction model based on classification, ETRI Journal 43 (2) (2021) 272–287.

[10] J. Borges, D. Ziehr, M. Beigl, N. Cacho, A. Martins, S. Sudrich, S. Abt, P. Frey, T. Knapp, M. Etter, et al., Feature engineering for crime hotspot detection, in: 2017 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computed, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), IEEE, 2017, pp. 1–8.

[11] G. Hajela, M. Chawla, A. Rasool, A clustering based hotspot identification approach for crime prediction, Procedia Computer Science 167 (2020) 1462–1470.

[12] Y. Zhang, T. Cheng, Graph deep learning model for network-based predictive hotspot mapping of sparse spatio-temporal events, Computers, Environment and Urban Systems 79 (2020) 101403.

[13] S. Yadav, M. Timbadia, A. Yadav, R. Vishwakarma, N. Yadav, Crime pattern detection, analysis & prediction, in: 2017 International conference of Electronics, Communication and Aerospace Technology (ICECA), Vol. 1, IEEE, 2017, pp. 225–230.

[14] S. J. Linning, M. A. Andresen, P. J. Brantingham, Crime seasonality: Examining the temporal fluctuations of property crime in cities with varying climates, International journal of offender therapy and comparative criminology 61 (16) (2017) 1866–1891.

[15] N. Aldossari, A. Algefes, F. Masmoudi, E. Kariri, Data science approach for crime analysis and prediction: Saudi arabia use-case, in: 2022 Fifth International Conference of Women in Data Science at Prince Sultan University (WiDS PSU), IEEE, 2022, pp. 20–25.

[16] S. Kim, P. Joshi, P. S. Kalsi, P. Taheri, Crime analysis through machine learning, in: 2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), IEEE, 2018, pp. 415–420.

[17] Y.-L. Lin, M.-F. Yen, L.-C. Yu, Grid-based crime prediction using geographical features, ISPRS International Journal of Geo-Information 7 (8) (2018) 298.

[18] C. Huang, J. Zhang, Y. Zheng, N. V. Chawla, Deepcrime: Attentive hierarchical recurrent networks for crime prediction, in: Proceedings of the 27th ACM international conference on information and knowledge management, 2018, pp. 1423–1432.

[19] N. Tasnim, I. T. Imam, M. Hashem, A novel multi-module approach to predict crime based on multivariate spatio-temporal data using attention and sequential fusion model, IEEE Access 10 (2022) 48009–48030.

[20] M. Hou, X. Hu, J. Cai, X. Han, S. Yuan, An integrated graph model for spatial–temporal urban crime prediction based on attention mechanism, ISPRS International Journal of Geo-Information 11 (5) (2022) 294.

[21] M. Sun, P. Zhou, H. Tian, Y. Liao, H. Xie, Spatial-temporal attention network for crime prediction with adaptive graph learning, in: International Conference on Artificial Neural Networks, Springer, 2022, pp. 656–669.

[22] Y. Wang, L. Ge, S. Li, F. Chang, Deep temporal multi-graph convolutional network for crime prediction, in: Conceptual Modeling: 39th International Conference, ER 2020, Vienna, Austria, November 3–6, 2020, Proceedings 39, Springer, 2020, pp. 525–538.

[23] Z. Li, C. Huang, L. Xia, Y. Xu, J. Pei, Spatial-temporal hypergraph self-supervised learning for crime prediction, in: 2022 IEEE 38th International Conference on Data Engineering (ICDE), IEEE, 2022, pp. 2984–2996.

[24] L. Xia, C. Huang, Y. Xu, P. Dai, L. Bo, X. Zhang, T. Chen, Spatial-temporal sequential hypergraph network for crime prediction with dynamic multiplex relation learning, arXiv preprint arXiv:2201.02435 (2022).

[25] S. Sandagiri, Deep neural network-based approach to classification the crime related news posts (2021).

[26] A. K. Das, P. Das, Graph based ensemble classification for crime report prediction, Applied Soft Computing 125 (2022) 109215.

[27] I. Pradhan, K. Potika, M. Eirinaki, P. Potikas, Exploratory data analysis and crime prediction for smart cities, in: Proceedings of the 23rd international database applications & engineering symposium, 2019, pp. 1–9.

[28] Y.-J. He, X.-K. Xu, J. Xiao, Predicting higher order links in social interaction networks, IEEE Transactions on Computational Social Systems (2023).

[29] Y. Guan, X. Sun, Y. Sun, Sparse relation prediction based on hypergraph neural networks in online social networks, World Wide Web 26 (1) (2023) 7–31.

[30] D. Yang, B. Qu, J. Yang, P. Cudré-Mauroux, Lbsn2vec++: Heterogeneous hypergraph embedding for location-based social networks, IEEE Transactions on Knowledge and Data Engineering 34 (4) (2020) 1843–1855.

[31] Y. Su, Y. Zhao, S. Erfani, J. Gan, R. Zhang, Detecting arbitrary order beneficial feature interactions for recommender systems, in: Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, 2022, pp. 1676–1686.

[32] Y. Li, H. Chen, X. Sun, Z. Sun, L. Li, L. Cui, P. S. Yu, G. Xu, Hyperbolic hypergraphs for sequential recommendation, in: Proceedings of the 30th ACM international conference on information & knowledge management, 2021, pp. 988–997.

[33] B. Liu, P. Zhao, F. Zhuang, X. Xian, Y. Liu, V. S. Sheng, Knowledge-aware hypergraph neural network for recommender systems, in: Database Systems for Advanced Applications: 26th International Conference, DASFAA 2021, Taipei, Taiwan, April 11–14, 2021, Proceedings, Part III 26, Springer, 2021, pp. 132–147.

[34] M. Vaida, K. Purcell, Hypergraph link prediction: learning drug interaction networks embeddings, in: 2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA), IEEE, 2019, pp. 1860–1865.

[35] D. A. Nguyen, C. H. Nguyen, P. Petschner, H. Mamitsuka, Sparse: a sparse hypergraph neural network for learning multiple types of latent combinations to accurately predict drug–drug interactions, Bioinformatics 38 (Supplement_1) (2022) i333–i341.

[36] K. M. Saifuddin, B. Bumgardner, F. Tanvir, E. Akbas, Hygnn: Drug-drug interaction prediction via hypergraph neural network, in: 2023 IEEE 39th International Conference on Data Engineering (ICDE), IEEE, 2023, pp. 1503–1516.

[37] C. Chen, Y.-Y. Liu, A survey on hyperlink prediction, IEEE Transactions on Neural Networks and Learning Systems (2023).

[38] P. D. (NYPD), Nyc crime (2023).
URL `http://data.cityofnewyork.us/Public-Safety`

[39] O. of Technology, I. (OTI), Points of interest (2023).
URL `http://data.cityofnewyork.us/City-Government`

[40] T. N. Kipf, M. Welling, Semi-supervised classification with graph convolutional networks, arXiv preprint arXiv:1609.02907 (2016).

[41] P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Lio, Y. Bengio, Graph attention networks, arXiv preprint arXiv:1710.10903 (2017).

[42] J. Huang, J. Yang, Unignn: a unified framework for graph and hypergraph neural networks, arXiv preprint arXiv:2105.00956 (2021).