Leveraging Deep Learning and SNA approaches for Smart City Policing in the Developing World

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ABSTRACT

Is it possible to identify crime suspects by their mobile phone call records? Can the spatial-temporal movements of individuals linked to convicted criminals help to identify those who facilitate crime? Might we leverage the usage of mobile phones, such as incoming and outgoing call numbers, coordinates, call duration and frequency of calls, in a specific time window on either side of a crime to provide a focus for the location and period under investigation? Might the call data records of convicted criminals' social networks serve to distinguish criminals from non-criminals? To address these questions, we used heterogeneous call data records dataset by tapping into the power of social network analysis and the advancements in graph convolutional networks. In collaboration with the Punjab Police and Punjab Information Technology Board, these techniques were useful in identifying convicted individuals. The approaches employed are useful in identifying crime suspects and facilitators to support smart policing in the fight against the country's increasing crime rates. Last but not least, the applied methods are highly desirable to complement high-cost video-based smart city surveillance platforms in developing countries.

1. Introduction

The term ‘smart cities’ describes an instrumented, interconnected and intelligent metropolitan, equipped with various smart computing technologies to facilitate more efficient and sustainable governance (Yigitcanlar, 2009; Ismagilova, Hughes, Dwivedi, & Raman, 2019; Visvizi, Lytras, Damiani, & Mathkour, 2018). This critical infrastructure offers citizens a better quality of life by providing services including city administration, public safety, social welfare, transportation, real estate and healthcare and tourism (Park, Lee, Yoo, & Nam, 2016). Information and communication technologies (ICTs) are considered to be the key drivers of a ‘smart city’ (Eldrandaly, Abdel-Basset, & Abdel-Fatah, 2019; Hashem et al., 2016). Due to developments in communication technology and now-ubiquitous connectivity, millions of people now communicate through the mobile phone network, and this may be harnessed for smart policymaking to facilitate law enforcement (Ferrara, De Meo, Catanese, & Fiumara, 2014).

As part of ‘smart cities’, the use of ICT is expanding enormously and can be used for smart decision-making by the governments for the well-being of citizens (Lytras, Raghavan, & Damiani, 2017). According to a recent survey by the International Telecommunication Union,[1] the proportion of population of low-to-middle-income countries that uses the internet increased from 14 million to 30 million from 2010 to 2016. However, over this same period mobile phone subscriptions increased even more, from 99 million to a staggering 134 million, resulting in there being at least one mobile phone for every household. We argue that this immense network of mobile phone usage can be leveraged to detect anomalies in citizens’ communication patterns and thus to support law enforcement agencies.

In low to middle-income communities, defining and investigating ‘criminal activity’ are beset by challenges. These include the absence of not only accurate and reliable data but appropriate methodologies and effective police performance. Furthermore, such communities may not have the resources for high-cost, citizen-monitoring platforms such as video surveillance infrastructure, vital in the face of recent emerging needs in managing ‘smart cities’ (Visvizi & Lytras, 2018). Thus, developing such methods is the essential requirement to prevent crimes.

In this study, we propose to use the power of Social Network

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Analysis (SNA) techniques to investigate crime networks by using citizens' mobile phone call records. The SNA provides a rich set of measures for mining and analysing complex data. These can uncover the interactions between the actors in a social network – detecting subgroups or communities, discovering their interaction patterns, identifying the central individuals and revealing network structures and organization (Kim & Hastak, 2018; Xu & Chen, 2005). Further, the measures can describe a network's structure and an individual's role by means of indices such as clustering coefficients (Watts & Strogatz, 1998), betweenness centrality (De Meo et al., 2012) and modularity (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008).

Extensive work has been done on crime analytics in the past decade (Eck, Chainey, Cameron, & Wilson, 2005, Ratcliffe, 2016), however, these approaches employ the traditional data analytics and machine learning approaches and very few of them have explored the data in a network perspective. Networks or graphs is a natural way to represent complex data where pairs of actors may have a meaningful relation. Recent few years have seen a surge in approaches for exploring complex real-world data in the form of networks and have shown promising results. Motivated by these advancements in the field of network science, this study offers the following main contributions to design effective methodological approaches for crime analytics:

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  - We present a novel theoretical framework to discover a network of suspects potentially involved in criminal activities based on their communication records to mimic the social network of criminal groups. With a small set of seed nodes of convicted individuals (criminals), we grow this network using Control Data Records (CDRs) data.
  - We propose to use a clustering coefficient measure for the identification of criminals based on structural properties in their local neighbourhood. We use Blondel algorithm to detect communities of suspects in the network constructed in the first step (Blondel et al., 2008).
  - We leverage the power of deep learning by using a state-of-the-art Graph Convolutional Network (GCN) model to perform binary classification to distinguish criminals from rest of actors in the communication network.

This research paper proposes a theoretical framework for crime investigation using low-cost call data records. It establishes a connection of smart cities with recent advancements in social network analysis and deep learning and provides a generic framework to enhance crime investigation. The paper provides a detailed overview of the smart cities, social network analysis, and deep learning methods through recent and relevant approaches. It then discusses the proposed methodological approaches and elaborates on the applications of using the clustering coefficient, community detection, and GCNs methods. Further, it evaluates the methodological approaches using a case study and presents the results in Section 4. Finally, the paper provides a detailed discussion, implications for practice, limitations, future works and conclusions.

2. Related Work

In this Section, at first we present the preliminaries of the study to introduce notations. Then a brief review of SNA studies in relation to 'smart cities', criminal social networks and deep-learning models to mine graphs is presented to link the current study with the literature.

2.1. Preliminaries

In the following a communication network is modelled by a graph. A graph G is a collection (V, E) of vertices V, representing phone users in communication network, and edges E, representing a phone call between a pair of users. The graph G is undirected in the sense that a call from a user X to a user Y is indistinguishable from a call from user Y to user X. If there are n users in the network, then corresponding graph G is algebraically represented by an n x n adjacency matrix A where value of entry A_{ij} models whether there is a call placed between user I and user j. We denote by N_i the neighbourhood of a user i i.e. the users who have called I or who have received a call from the user i. The size of this neighbourhood called the degree of node i and is denoted by $\mathscr{d}_i$. The graph G is un-weighted in the sense that the exact number of calls between a pair of users does not play any role in the model as long as its nonzero i.e. entry A_{ij} is either zero or one. Another important notion that we will use is the number of edges between pairs of nodes in the neighbourhood N_i of user and is denoted by L_i. A diagonal matrix with entries $D_{ii} = \mathscr{d}_i$ is called the degree matrix of the graph; I denotes the identity matrix.

The users of our communication network or the nodes in the graph G have the following important subsets that we will repeatedly refer to in the following Sections: a) *criminals:* a set of users who have been found guilty by the courts of any relevant criminal behaviour, b) *suspects:* those who were near the crime location or were connected to identified criminals via their call records yet were never convicted, and c) *facilitators:* those who support criminals, such as by acting as a bridge between crime networks or individual criminals.

2.2. A brief review of 'smart cities'

'Smart cities' are conceptualised as urban areas that address the requirements of their institutions, their businesses and, especially, their citizens (Khatoun & Zeadally, 2016). In addition, they feature responsive and interactive administration, citizen protection and proper law and order (Visvizi, Mazzucelli, & Lytras, 2017). Research into 'smart cities' provides a framework for multidisciplinary debate on the valued added by cutting-edge technologies, wearable technology, web applications, cloud computing and internet technology (Lytras & Mathkour, 2017). Visvizi et al. (2018) examined state-of-the-art 'smart cities' research and presented an overview. They argue that sustainability and innovation are two aspects of social challenge in 'smart cities', and the advanced policies and sophisticated technological integration need a novel administrative paradigm at every level of decision-making, going beyond local boundaries.

Indeed, 'smart cities' play a vital role in the processes of information exchange and communication among the various members of a community (Zhuhadar, Thrasher, Marklin, & de Pablos, 2017). Though 'smart cities' encourage trade liberalization and mobility of labor and speed up transactions, simultaneously this increases both the challenges and risks exponentially (Kemeny & Cooke, 2017). Recently, Yigitcanlar (2009) introduce the citizen science and collaborative decision-making system that taps the power of a Web-based Geographic information system. The system helps the community to enhance the urban ecosystem and achieving sustainable development. Moreover, Visvizi and Lytras (2018) identify a normative bias in 'smart cities'. They allege that there is a gap in the research between what ICT allows us to envisage and what is technically attainable in the face of infrastructure limitations and socio-political constraints. According to them, what makes a city smart is the ability of its inhabitants to use smart facilities smartly. In another noticeable study by Yigitcanlar (2018), the author investigates the smart city phenomenon from an evolutionary perspective and defines smart and sustainable urbanism as "an urban development paradigm that is the antidote of current spatially, structurally, socially, ecologically imbalanced and vicious Anthropocentric urbanism practice." For more details, the readers are referred to recent works by Yigitcanlar (2018); Israilidis, Odusanya, and Mazhar, (2019) and Ismagiloiva, Hughes, Rana, and Dwivedi, (2019). Further, to evaluate sustainable outcomes of smart cities, Yigitcanlar, Kamruzzaman, Buys et al. (2018); Yigitcanlar, Kamruzzaman, Foth et al., 2018) investigate changes in carbon dioxide emission level of 15 cities in the UK. The

study reveals no positive correlation between sustainable outcomes and technology adoption and calls for further investigation.

Despite the great advancements in Artificial Intelligence (AI), still, the implementations of AI models in smart cities and urban areas beset by several challenges (Israilidis et al., 2019; Ismagiloiva et al., 2019). To link the AI-based systems with decision making, the authors in (Duan, Edwards, & Dwivedi, 2019) have proposed twelve research prepositions. Further, (Wu & Chen, 2019) introduced a structural method for policy selection in smart cities to provide a sustainable environment. Singh et al. (2019) suggested that more improvements in smart monitoring and controlling government policies can be achieved using public involvement. On the other hand, to ensure the vulnerability of these systems against intrusion and different attacks. Recently Li, Deng, Lee, and Wang, (2019) introduced an intrusion detection algorithm which helps to identify anomalies in the network and take the necessary countermeasure to ensure the reliability of the system. To ensure the usage of the Internet of Things (IoT) in smart cities architecture, the key challenges and the relationship between these challenges to support the development of smart cities has been highlighted in (Janssen, Luthra, Mangla, Rana, & Dwivedi, 2019).

Although smart cities provide various facilities to improve economy, environment and living standard, however, they beset several challenges in crime analytics. Generally, they use high-cost video surveillance systems which may require a lot of resources and extra intelligent systems to prevent crimes. On the other hand, very little efforts have been devoted to leverage recent scientific approaches to advance crime analytics with a low-cost data to achieve efficient algorithms and higher accuracy. In the following Section, we survey the relevant approaches introduced to advance crime analytics with low cost data.

2.3. A brief review of crime network analysis

Sparrow (1991) was a pioneer in analysing crime networks and their susceptibilities to intelligence gathering. He defined four features of crime networks: a) size – crime networks are often composed of, at most, a few thousand nodes; b) incompleteness – they are necessarily inadequate, due to fragmentary facts and invalid information; c) fuzzy boundaries – it is difficult to determine all the relations of any node; and d) dynamics – new connections indicate constant change in their structure (Sparrow, 1991). The author argued that these features are in fact quite typical to real-world networks and more challenging in terms of computational nightmare and algorithmic complexities. However, most advanced methods may be useful to address these challenges. A COPLINK system was developed with an associated suite of tools to help law enforcement officials to mine information from police case reports. The authors used data mining approaches to set up a concept space of entities and objects that can be explored to find relevant items (Xu & Chen, 2005). Further, a FinCEN system has been proposed to reveal links between criminals and crimes, and also to expose money-laundering networks by matching the financial transactions (Goldberg & Wong, 1998).

A toolkit has been developed to extract various attributes from police datasets in order to produce a digital profile of each criminal. This forms a cluster of certain features around an individual criminal against the profile, created from a distance matrix constructed of various attributes such as the frequency of crimes and the criminal's history (De Bruin, Cocx, Kosters, Laros, & Kok, 2006). Clustering techniques are widely used in law enforcement. For example, Adderley and Musgrove (2001) applied self-organizing maps and clustering techniques to identify the behavior of an individual who commits serious sexual assaults, and Cocx and Kosters (2006) applied clustering techniques in crime investigations to reveal those crimes committed by the same person.

More recently, network analysis has been used to mine the network diffusion of gun violence into the surrounding area (Loeffler & Flaxman, 2018); to investigate the short-term dynamics of peer influence (Weerman, Wilcox, & Sullivan, 2018); and to study the formation and evolution of a drug trafficking network (Gallupe, McLevey, & Brown, 2019). The analysis of networks has been widely adopted in various domains such as medicine, social networks and many others. The authors in (Said et al., 2019) studied the altmetrics' Twitter network and showed that analysing the altmetrics data in a network perspective reveals abundant hidden information such as interdisciplinary communication, influence of different types of entities and their underlying patterns. Overall, studies have shown the effectiveness of these methods in meeting the objectives of these cases.

2.4. A brief review of mining networks using deep learning

A lot of complex systems in the real world can be represented in the form of graphs, including the World Wide Web, social networks, biological networks and collaboration networks. Various attempts have been made in the last couple of years to exploit deep-learning techniques in the supervised classification of graph-structured data. A notable work in this direction uses a first-order approximation in the Fourier domain (Kipf & Welling, 2016). The main point of this model is that, for a given undirected and unweighted graph, the class of a node can be predicted by its local neighborhood. The authors propose a layer-wise propagation rule for semi-supervised classification. Additionally, they employ first-order approximation for spectral graph convolution. However, the proposed algorithm requires a full-graph Laplacian during the training phase. The model has achieved promising results with several benchmark datasets.

A formulation of Convolutional Neural Networks in the context of spectral graph theory has recently been suggested (Defferrard, Bresson, & Vandergheynst, 2016). Its main contributions include learning fast localized filters and graph coarsening of the graph signals. The authors approximated filters using the Chebyshev polynomial with free parameters and used graph coarsening to group together similar vertices. To learn the latent representation of the graph, Perozzi, Al-Rfou, and Skiena, (2014) presented an algorithm named DeepWalk. This learns the structural regularities in the graph on the basis of characteristics of community awareness and low dimensionality. Their work introduced deep learning as a tool to explore and analyse graph-structured data and has achieved a significant increase in classification accuracy. In this study, we employ an array of SNA techniques to identify potential suspects in a crime network. In addition, we modify and build upon the state-of-the-art GCN models and use it for the binary classification to distinguish criminals from non-criminals in a citizen's call data records.

3. Methodological Approaches

This Section presents methodological approaches, data, and case study on real-world data. At first, we discuss the approaches such as the community detection for identifying individuals of similar interests, clustering coefficient to find individuals' closed neighborhood and GCNs for distinguishing between criminals and non-criminals (see Sections 3.1–3.3). To evaluate the proposed approaches on real-world data, we designed a case study (see Section 4) in which we outlined the sources, properties, and pre-processing of the data. Then we investigate the community structure of the network and explore suspected individuals, and finally, we propose using GCNs for real-time criminal identification using CDRs data.

To investigate CDRs data using SNA and address the aforementioned problems, in the following Section, we present three approaches: identifying the community structure, suspects' identification and the real-time identification of criminals in a crime CDRs network. The community detection initially helps to identify the similar individuals of the seed nodes which is further explored by using the clustering coefficient to identify suspects. We further investigated the suspected users using their spatial temporal movements to verify their role within the network. Lastly, we employed GCNs to perform real-time criminal

identification.

3.1. Identifying individuals of similar interests

Having a set of seed nodes, it is a natural approach to identify and investigate other nodes having similar kind of interests and behaviours. In a network perspective, clustering such type of nodes is known community detection. Identifying community structure reveals a large amount of information hidden in the network and shows the subgroups of nodes with similar interests (Said, Abbasi, Maqbool, Daud, & Aljohani, 2018). In order to explore our CDR network and find phone users with similar interests, we applied a modularity-based community-detection algorithm (Blondel et al., 2008). This finds closely connected components by using the modularity function. Modularity is a well-known measure of the quality of the communities discovered in a network; it evaluates the extent of the network's division into modules. The denser the connections within the modules and the sparser the connections between them, the higher the modularity value. Thus, the goal of this exercise is to partition graph vertex set into a fixed number of clusters such that the *modularity score* given by the following equation is maximized:

$$Q = \sum_{c=1}^{n} \left[\frac{|E_c|}{|E|} - \left(\frac{k_c}{2|E|} \right)^2 \right] \tag{1}$$

Here, Q is the corresponding modularity value, n is the size of partition, $|E_c|$ represents the number of edges within a cluster c, $k_c = \sum_{i \in c} d_i$ (the total degree of all the nodes in the partition c), and $|E|$ is the total number of links in the graph. The value of modularity score lies within the ranges [-1, +1]. A higher value indicates good partitions while negative values indicates the absence of partitions within the network. In the case of assigning all nodes to the same community, the corresponding modularity value is zero and is negative if each node is assigned to a different community.

A subgroup of individuals made many calls to each other has a higher probability to have common interests (Gleich & Seshadhri, 2012). We are interested to explore the communication pattern of our network to understand the calling pattern and closely knit groups of the seed nodes. To this end, and by considering the above observation, Blondel algorithm (Blondel et al., 2008) is a suitable approach that helps us to identify groups of individuals having many intra-communication. This algorithm is quite popular because of showing promising results in such scenarios. Due to that, it is implemented in many network analysis tools like Gephi and iGraph.

3.2. Closed neighborhood identification

A node having dense neighbourhood is more likely to belong to its neighbors class. This heuristic has been explored in many previous studies (Gleich & Seshadhri, 2012) and has theoretically proved by (Sarkar & Chakrabarti, 2015) in context of clusters identification from the network Leveraging this heuristic, we use a clustering coefficient (Watts & Strogatz, 1998) to identify a criminals' closed neighborhood. A clustering coefficient measures connectedness among the neighbors of a node and can be computed as follows:

$$\mathbb{C}_v = \frac{L_v}{\binom{\mathscr{d}_v}{2}} \tag{2}$$

Where $\mathbb{C}_v$ represents the clustering coefficient value of node v. L_v is the number of links between pairs of nodes in the neighbourhood N_v, and $\binom{\mathscr{d}_v}{2}$ denotes the maximum number of possible links in such a neighborhood. Note that $\mathscr{d}_v$ denotes the degree of node v as mentioned in Section 1.2. The value of $\mathbb{C}_v$ always in the range of [0, 1]. A value of zero indicates that there is no edge in the neighbourhood N_v, and a value of oneindicates that all pairs of adjacent to each other making N_v a clique. Several other studies (Gleich & Seshadhri, 2012; Said et al., 2018) have used clustering coefficient for closed neighbourhood identification and community detection.

3.3. Criminal identification

The task of identifying a criminal in a list of individuals or checking whether an individual is criminal or not amounts to categorizing corresponding nodes in the communication graph. This is the classical graph classification problem. Unfortunately, due to high complexity and irregularity of neighbour structure in graph data, usual classification methods can't be affectively used for this task. Thus, we propose to use a specialized state-of-the-art GCN approach to perform a supervised binary classification (Kipf & Welling, 2016). The GCNs is a generalized neural network architecture for graph-structured data, that learns a node representation on the basis of first-order approximation in the Fourier domain. The overall problem can be formulated as follows. For more details, the reader is refer to (Kipf & Welling, 2016).

The input of this model is a simple undirected graph represented by the adjacency matrix A. As before, the vertices represent the phone users and the edges indicate call relationship between pairs of users. Output is a single binary for each node indicating whether the corresponding node is predicted to be a criminal or not. The model will also input labels of a small set of nodes as seed. To train the model, we use the same layer-wise propagation rules presented by Kipf and Welling (2016)), which can be formulated as shown in Equation (4):

$$H^{(l+1)} = \sigma(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}H^{(l)}W^{(l)}) \tag{3}$$

Here, $H^{(l)}$ is the activation at the l^{th} layer, σ is a non-linear activation function, $\tilde{A} = A + I_N$, is the adjacency matrix augmented with self-loops, $\tilde{D}$, is the degree matrix of the graph represented by $\tilde{A}$, and W are the learning parameters. We use the same model presented by Kipf & Welling, 2016 in our experimental setup which is shown in the following equation:

$$Z = sigmoid(\hat{A}ReLU(\hat{A}XW^{(0)})W^{(1)}) \tag{4}$$

Where $\hat{A} = \tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}$, which is computed in the pre-processing step and X is the matrix of node feature vectors (identity matrix in our case). This model learns node embedding in a given network by employing simple filters using 1-hope neighbourhood in a spatial domain. The multiplication of $\hat{A}$ sums the feature vectors of all the neighboring nodes (X) and can be seen as a node neighbourhood feature vectors aggregation function. To ensure the aggregation of feature vector with the node itself, an identity matrix is added to A and $\tilde{D}^{-1/2}$ is multiplied to scale the matrix forming normalized matrix $\hat{A}$. We use sigmoid activation function on the last layer to predict the binary class. The sigmoid function is also called the logistic function, and it is used to predict or classify the given instance as either 'yes' or 'no'. For the binary classification, we use binary cross-entropy to evaluate the predicted classes against the original labeled data with Adam optimizer.

4. Case Study: Suspects Identification and Criminal Prediction in Punjab

In this Section, we present a case study to leverage CDRs real-time data for the identification of suspects and criminals in Punjab province. Although, the identification of criminals and suspects from raw incomplete data is very challenging. However, the remarkable scientific advancements in the last few years provide us an adequate background to perform crime analytics on real-time data. Fig. 1 gives the overall framework of the processes of data input, methods and outcomes of this study.

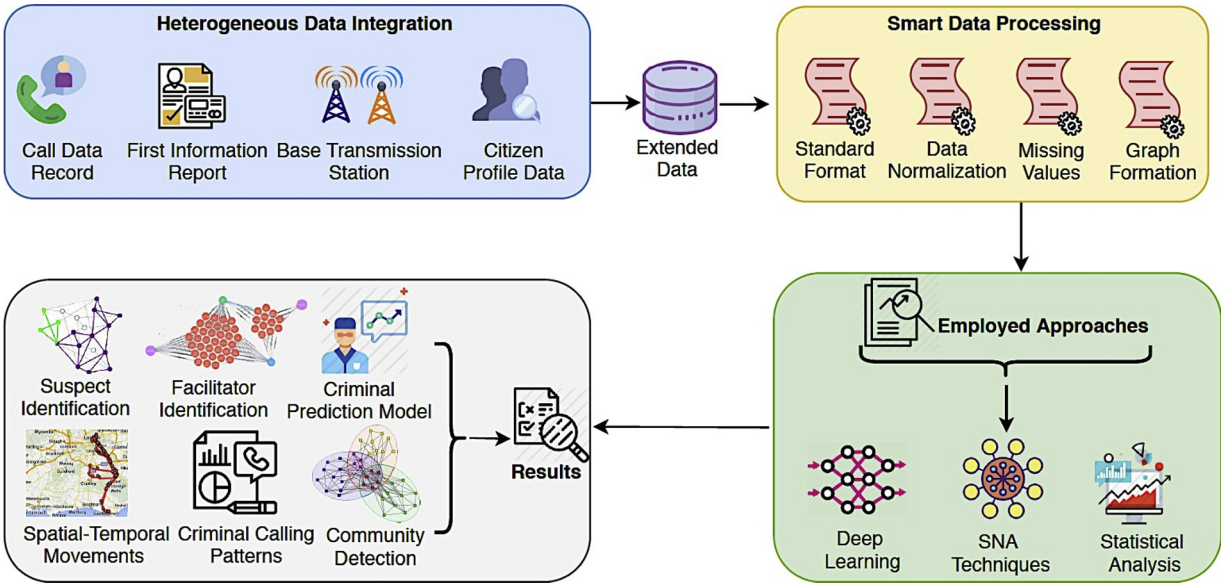

Fig. 1. Framework for crime and suspects identification.

4.1. Heterogeneous data integration

The first step in our framework was to integrate the data. We needed to combine the four diverse forms of our datasets, CDR, First Information Report (FIR), Base Transceiver Station (BTS) and Citizen Profile Database (CPD), in order to construct a single extended dataset for examination. Information about criminal users' log activities is in CDR, whereas BTS provides information on the geographical locations of the phones involved in a crime. The First Information Report (FIR) gives specific details about the committed crimes, while CPD provides facts to examine the history of individual criminals.

4.1.1. Call data record

The CDR is a huge repository of phone call information managed by the Punjab Information Technology Board (PITB) which contains metadata of telecommunication transactions, including calls and messages. Each user's log activities are stored on their phone and recorded by their mobile network operator. The CDR for a specific call contains both the caller's and the receiver's phone numbers, a time stamp (date and time), the duration of the call, the base transceiver station ID of the caller's location and other relevant details. Note that the research team was privileged to work in collaboration with Punjab Police for a period of 8 months in 2018, observing strict confidentiality, in a pilot project to explore the potential for applying mathematical techniques to CDR to delimit a crime's search locus

4.1.2. Base transceiver station

The BTS database comprises both phone logs and GPS coordinates, to pinpoint particular phone users within the area of the cell, and the geo-referenced locations of phones involved in crime events (Ferrara et al., 2014). It also has information about phone users' associations and service allocations. Fig. 2 depicts a cellular network consisting of base stations and the criminals connected to each. These base stations contain the log history of the associated phone users at each time stamp.

4.1.3. First information report

The FIR repository comprises information such as: the time of the FIR; the time of the crime; the location of the crime; the FIR number; the FIR year; the police station; the district; the section under which crime was committed; arrest details; and FIR data from closed cases. We used a subset of 161 FIRs from all over Pakistan in eight offense categories: Dacoity ('banditry', or violent robbery committed by an armed gang); burglary; kidnapping; motor vehicle theft; kidnapping for adultery; murder; rape; and miscellaneous (see Table 1). The total number of call logs in the database is 2.3 million, 317 of which have been identified by Punjab Police as those of convicted criminals. Note that a complete set of data is managed by Punjab Police, with technical assistance from PITB.

4.1.4. Citizen profile database

The Citizen Profile Database[2] holds data on all citizens, including their registered SIMs, vehicles, driving license, FIR witness, FIR complaints, FIR suspect and criminal record, against either their mobile phone number or their Computerized National Identity Card (CNIC) number. The CPD is maintained by Punjab Police in Punjab province, and is an extremely sensitive record against which we checked the history of each criminal, thus the highest levels of data security protocols were observed for the duration of the project to avoid any leaks, breaches of data protection, lapses of confidentiality or other offenses.

4.2. Smart data processing

The raw datasets provided by telecom companies are not always complete, correct or consistent, so they need to be processed before applying SNA and other statistical techniques. Pre-processing these large sets of raw data and representing them in the form of a network are vital but challenging tasks, as each telecom company uses its own format to store data. To convert these to a standard format, we merged the data from the providers and devised standard fields: caller number; receiver number; location; and case number. Next, we performed normalization on the data and mapped the records to the corresponding field. For those with missing values, the following heuristics were deployed: a) omit the incorrect field; b) omit the entire record containing incorrect field or value; c) enter the correct data with a default value; d) set both the missing and unknown data to zero.

We represent the pre-processed data in the form of a graph, $G = (V, E)$, where V denotes phone users and E represents the edges in the network. An edge is formed between two users who communicate by a mobile phone call. Of the total 2.3 million call records, we have 317

[2] https://citizenprofiling.punjabpolice.gov.pk/.

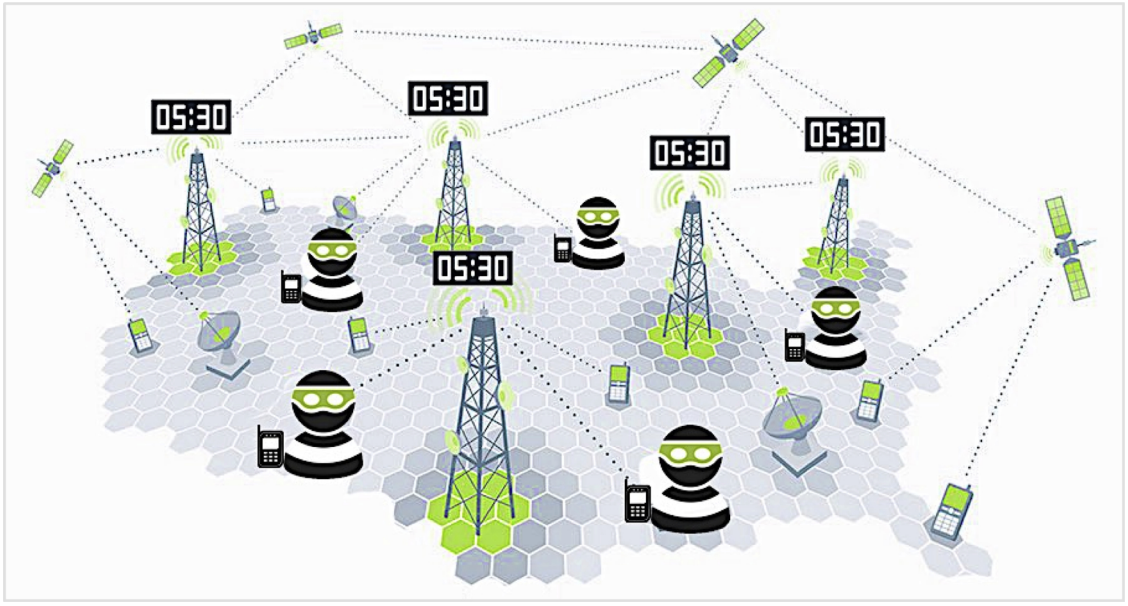

Fig. 2. Mobile cellular network.

Table 1
Dataset characteristics of FIRs.

Category	No. of call records	FIRs	No. of convicted individuals
Burglary	87,692	6	9
Dacoity	1,112,629	64	138
Kidnap of adult	57,247	8	23
Kidnapping	37,894	9	12
Motor vehicle theft	158,120	6	17
Murder	65,870	16	14
Rape	530,857	1	4
Miscellaneous	290,859	51	100
Total records	2,341,168	161	317

convicted individuals therefore, we choose a subset of call records regarding the local neighbourhood of labelled users. The main reason for choosing only the neighbourhood of convicted individuals was the unbalanced data in terms of labels. As we are mainly interested to explore and distinguish the criminal from normal users. This sampling strategy provides an adequate network on which supervised GCNs can be applied and validated accurately. Our sampled network has the following statistics: 46,499 nodes (unique phone users); 70,462 edges (unique call records); and 317 convicted individuals. The network statistics are as follows: average degree is 3.5; average path length is 7.84; and average clustering coefficient is 0.45. The best modularity value after clustering the network is reported as 0.967. Based on these statistics, we can certainly say that our extracted dataset is well structured and has a dense neighborhood and community structure.

We used Gephi, Tableau and Google Maps to visualize the crime networks. For statistical analysis, anomaly detection techniques were used in Python along with deep-learning models to predict the presence of a criminal in a given network. Our aim in these experiments was to identify the suspects, monitor criminals' spatial-temporal movements and check their call patterns. For each, we used a different case.

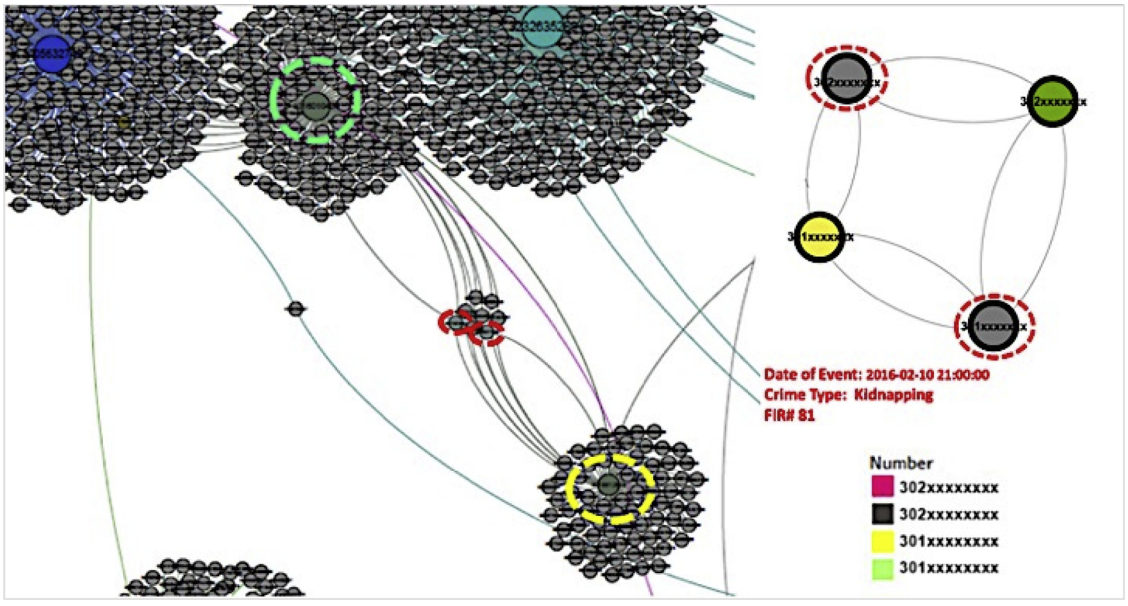

Fig. 3. Detection of CDR crime network community.

4.3. Exploring community structures

A key means of exploring complex networks is to detect their community structures. A community structure represents those individuals who have similar interests, forming a social network such as a friendship or family circle. Such a structure can be defined as the group of nodes that are densely intra-connected yet sparsely inter-connected to the rest of the network (Yang & Leskovec, 2015). Uncovering this structure reveals an abundant source of information that is hidden from simple monitoring. To detect the criminal communities in the network, we used the algorithm described in Section 3.4.1. Fig. 3 is a visualization of a sub-network that has closed-case data on a kidnapping-type crime in category FIR # X1. We can see that each crime shows up as a cluster in the network. Interestingly, the criminals identified in these cases performed a major role in the network, answering the hypothesis presented in Section 1. Another interesting finding is that, in some cases, there was a chain of communication between criminals and normal users. For the sake of simplicity, we have shown a small community consisting of just four phone users: two convicted individuals, represented in yellow and green; and two non-criminals, represented in grey. We can see that the non-criminals connected the two criminals. In such cases, we investigated these users through their spatial-temporal movements.

4.4. Suspects identification

Earlier, we defined a suspect as an individual who is believed to have been involved in a crime yet who has never been convicted of that crime. To identify suspects, we used the clustering coefficient measure described above. Here, we present data from an adult kidnapping closed case in the city of Multan under FIR #5063, involving eight identified criminals. After applying the community-detection algorithm, we ranked the phone users in each community based on their clustering coefficient values. In this case, we found three users with very high clustering coefficient values who were closely connected with the identified criminals. We further investigated these users through their spatial-temporal movements and marked them as suspects.

4.4.1. Spatial-temporal mining of criminals

The significance of spatial-temporal mining has been heightened by the increasing incidence and importance of enormous geo-spatial datasets, such as maps and databases of remote-sensing images. Spatial-temporal data include those from satellite images, mobile phones, sensor networks and GPS devices (Bogorny & Shekhar, 2010). To investigate further, we visualized the movements of criminals and facilitators using geographical points. Fig. 4 shows the spatial-temporal movements of identified criminals and facilitators. We found that before the event the known criminals were in various locations, yet the facilitators were already on the scene. On the day that the crime was committed, up to an hour beforehand both the criminals and supporters were present and made phone calls to each other from that location, yet immediately after the event the criminals moved away while the facilitators remained. It is interesting that both before and after the event the facilitators were at the crime scene and the criminals elsewhere. From this, we conclude that the facilitators lived in the area and supported the criminals to commit the crime. Note that these phone users had never been identified as involved in crime.

4.4.2. Criminal calling patterns

In early 2018, our data-driven techniques helped Punjab Police to delimit the search space for a serial killer who had raped more than nine girls aged between 6 and 11 years in the city of Kasur in Punjab province. Fig. 7 shows the locations of five crimes in which the DNA of perpetrator appeared to be the same. Of the total of 212,436 phone calls that were made near these five crime locations, 28 phone numbers were found to be common to at least four. These acted as a shortlist for conducting a DNA test of the phones' users and, by this test, the police were able to identify the guilty individual.

When we investigated the one-year CDR data of these shortlisted individuals in the Kasur case, we found that the serial killer had an abruptly altered call pattern near the time of each crime. Fig. 5 shows details of the calls to and from the guilty individual's phone number. For instance, Case 1 took place on 11 April 2017, and on that day, there were high rates of both incoming and outgoing calls compared to the previous and following days. Similarly, there were high rates of calls immediately after Case 2. In Case 3, there was a high level of call talk time near the date of the rape, 12 November 2017, and later on, on 25 November 2017, when the girl was rescued alive from an abandoned building. More recently, on 7 January 2018, a girl's body was found and, again, this date correlates to a peak in call talk time on this number. Overall, our methods have been effective in helping the police to delimit the scope of the search, which would otherwise be too extensive to investigate thoroughly.

4.5. Criminal classification with CDRs data

In this Section, we present the experimental setup and results for the GCN model that we used to distinguish criminals from non-criminal individuals. We trained a two-layer GCN model, as discussed in the framework Section, using 90:10 train-test split ratio to evaluate the accuracy of our results. We used a dropout rate of 0.5 for both layers and an L2 regularization factor for the first hidden layer. The model was trained for a maximum of 100 epochs with a learning rate of 0.01, using the Adam optimizer. Initialization of the weight matrix was undertaken using the *Glorot* (Xavier) initialization method. The accuracy of the model was evaluated using CDR dataset, as reported in Table 2. On the CDR network, the model achieved an encouraging 82% accuracy. Although we input identity matrix to GCNs because of not having the node features in our network, we have seen in Fig. 5 that the call pattern of suspect users is much different than the normal users. The corresponding criminal network also preserves such different patterns like it differs the local and global position of suspects and normal users within the network which leads GCNs to distinguish between them. The training and testing accuracy for the CDR dataset over 100 epochs is shown in Fig. 6.

5. Discussion

In this paper, we address a very important problem of crime prediction and analysis and propose an effective solution based on a user social network and interaction perspective. As shown in the results of the case study in Section 4, we use CDRs data to train our model for the identification of crime suspects with high accuracy. One of the most powerful features of this model is the straightforward network representation which leads to the extraction of a significant amount of information about relationships and connectivity among different suspects in the dataset. On the other hand, our proposed model is also capable to encode real-time individuals' activities which can be leveraged to improve security systems in the smart-cities context. In Section 2.1, we show how to map CDRs data into a network such that it preserves the overall properties and attributes of the data. Although, we did not exploit these attributes like geographic or metropolitan location, time or duration of a crime activity in our deep learning model, because the available information was not reliable enough to be used for training purposes. However, we build a case in Section 4.4.1 and 4.4.2 that this information can also be leveraged for spatial-temporal mining and finding calling patterns, which can further help identify suspect activities.

Understanding individuals' behaviors in complex systems where millions of competing entities are involved is a challenging task. However, as seen in the case study, a tiny set of seed nodes can, sometimes, help to filter out irrelevant actors and can thus drastically

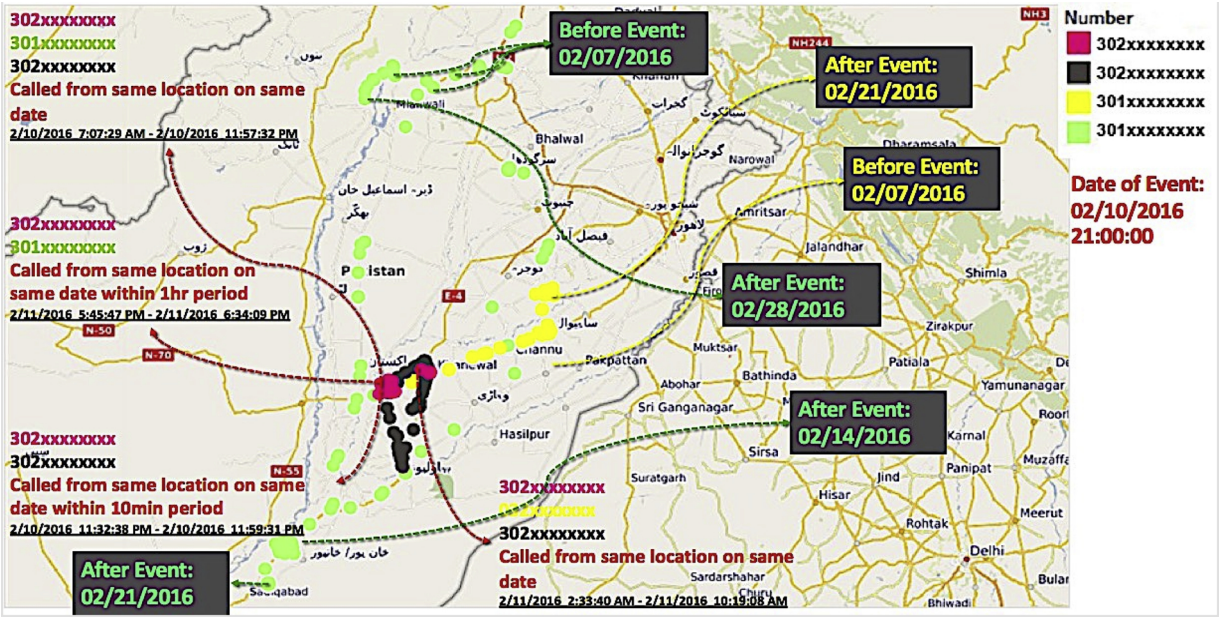

Fig. 4. Spatial-temporal movements of criminals and facilitators.

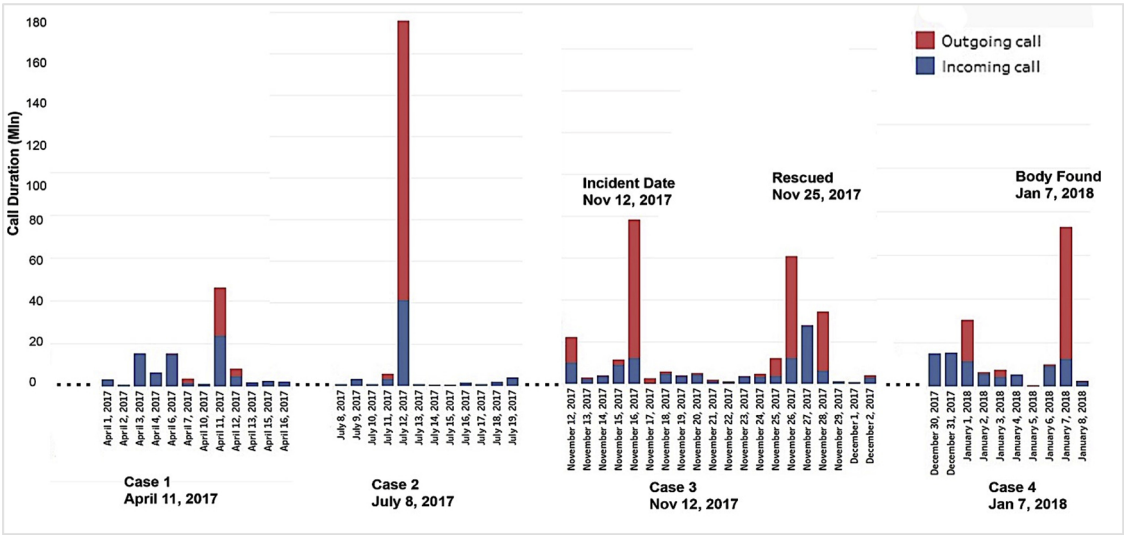

Fig. 5. Call pattern of the criminal's mobile phone in each Kasur case.

Table 2
Dataset details and classification accuracy.

Dataset	No. of nodes	No. of edges	Accuracy
CDRs	46,499	70,462	82%

reduce the size of a complex network. We leave the question of a practical lower bound on the size of the seed nodes set open for future studies. Once we have reliable information about the links between pairs of suspects, there is a rich body of literature on social network analysis that can be used to build tools for crime analysis. Significant amount of effort has been devoted in the last decade or so to mine the relevant information such as the identification of cohesive groups, predict network dynamics, apply sparsification techniques to bring large complex networks to manageable sizes, and ranking of nodes based on their influence or centrality measures in these networks (Kipf & Welling, 2016), (Yang & Leskovec, 2015), (Blondel et al., 2008), (Said et al., 2018)). One of the highly studied topics in this context is the

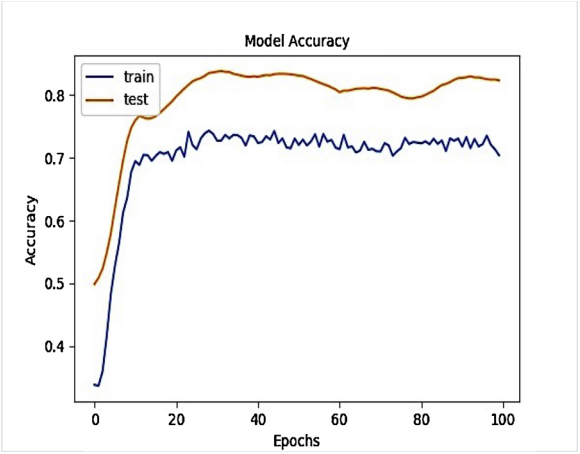

Fig. 6. Training and testing accuracy over 100 epochs.

identification of community structure which reveals abundant, otherwise often overlooked, information that is relevant in the context of crime analysis. This may help understand an individual's behavior in both local and global contexts for example as a family member, close friend, affiliate of a political or social group, or member of a religious organization. In the case study (Section 4.3), we demonstrate how community detection in crime networks can help to locate groups of interest starting for a small set of seed nodes and helps to identify and interpret the relationships among suspected users.

While community detection algorithms can identify groups of individuals with similar views, interests, or geographies, we still need to gauge the role of an individual within this group. For instance, a sleeper member of a group who is activated to perform certain duties on a rare seasonal basis is to be deemed different from an individual that is in relatively regular communication with other members of the group. Thus, it is necessary to study and rank individuals in a group context (nodes-level) based on their role. In Sections 3.2 and 4.4, we show that nodes-level properties and ranks can be identified using the clustering coefficient - which is a natural measure to quantify nodes' connectivity in a local neighborhood. As seen in the previous section, the clustering coefficient measure shows encouraging results in the identification of suspected users.

Lastly, for classification and prediction on crime networks, we exploit the current advances in deep learning approaches, especially in the computer vision field and now on learning with graphs structure data (Duan et al., 2019). We hope that our use of these advanced techniques and remarkable accuracies in prediction and analysis in crime networks will act as a motivating example to expedite the deployment of such systems in smart cities to not only prevent crimes and increase citizens' satisfaction but also to help engineer city-wide security policies. To this end, our framework also proposes a deep learning model to perform real-time crime identification. In the following, we discuss our theoretical contributions, followed by a discussion of practical implications and a summary of limitations of current work.

5.1. Theoretical Contributions

Our main contribution in this work to provide a network perspective to crime data which has only be treated as a relational database or a time-series data in previous works. We propose that a network or graph perspective is more natural and effective. Since graphs properties and algorithms have been actively studied for decades, this graph representation enables one to employ many readily available advanced graph-based approaches for crime investigation and suspect identification. We also show that this reduces the run-time complexity and deployment cost of the proposed framework. Secondly, we also propose to leverage efficient graph-based algorithms like the clustering coefficient and Blondel's community detection algorithm to detect groups of individuals that may share common ideology, political or social affiliation, and physical or virtual space, and to identify an individual's role in such a group. And lastly, we successfully demonstrate the use of advanced deep learning techniques like GCNs for the first time for criminal identification and prediction problem. We show that real-time criminal classification and predictions with high confidence can be achieved using GCNs.

GCNs naturally fit on many real-world networked systems having an inherent graph structure however it is known that the performance of GCNs largely effected by incorporating nodes' attributes. Despite not relying on nodes' attributes, our results highlight the significance of GCNs on CDRs data to make predictions based solely on the topology of the underlying network. Thus our results provide an encouraging demonstration to deploy GCNs on networks where either attributes or labels for nodes are not available or are unreliable. Based on the results of current study, we also propose to use GCNs to many other network-based problems in smart cities like the transportation network for congestion management or traffic flow, prediction and management of resources like water and energy, etc.

5.2. Implications for practice

The increasing ratio of crimes in urban settlement has caused a new set of challenges to reduce the quality of life. Nevertheless, the advances in ICT and data-driven policing can be instrumental in benefiting citizens through better policy-making, governance, and strategy is the essential component of any 'smart city' (Lytras & Visvizi, 2018; Visvizi et al., 2018; Wu & Chen, 2019; Yigitcanlar and Kamruzzaman, 2018). To reduce the crimes ratio, many smart cities adopt high-cost video surveillance systems. However, these systems may require expensive resources and additional layers of intelligent systems for data processing. There may not be sufficient resources to implement and manage all desired hardware and software systems simultaneously. Contrary to that, the proposed framework can be adapted to investigate crimes at relatively less cost.

The implications of this framework can be divided into two main categories (a). Data-driven policy formulation and (b) smart city governance.

5.3. Data-driven policy formulation

To tackle the challenges of prediction and prevention of criminal activities and ensure the safety of the citizens, the need for a government to make data-driven policies has been felt globally. Using the CDRs data and network analysis, better policies can be derived which helps to ensure the safety of the citizens. With these objectives in mind, one is required to stream the CDRs data to the centralized location, implement the systems to automatically preprocess this data and pass it through the deep learning model to train and make predictions. Further, for investigating a specific crime, the system needs to use the seed nodes and apply the proposed procedure to identify a shortlist of suspected individuals.

Many themes in smart cities like citizens' engagement, social interaction and communication, social media, smart collaboration, privacy, security and traffic management can be enhanced using the proposed framework. Social interactions and communication can be enhanced by mapping them to graph representation. On the other hand, citizen engagements and social interactions can be improved by GCNs to enhance smart city architecture. Traffic management is another main issue in urban areas due to the permanent growth in population and the number of vehicles and can be enhanced using GCNs.

5.4. Smart cities governance

Urban areas have been growing in terms of economy and population significantly as a trend over the last decade or so. To overcome challenges associated with increased population density, for example, environmental changes, individual safety and well-being, fair allocation of resources, the inclusion of fringe social groups, ethnicitites, etc., many governments and agencies and organization are seeking to design such long term data-driven policies, especially in smart cities. The framework proposed in this paper can be implemented to achieve some of these goals that related to safety and well-being of individuals. As compared to the video surveillance system, it helps to prevent and investigate crimes at a low cost. Further, it does not require the deployment of radically evasive technologies like face recognition, individual spying, and can be well-integrated with system already in place in almost every semi-modern metropolitan. The proposed framework has a lot of applications in many scenarios like the search space for criminals can be reduced by applying the proposed suspects' identification approaches. Our framework provides a structural way to assist the investigation team in evaluating crimes in urban areas. The results shown in the case study reveal that our proposed framework helps to identify

suspects with great confidence. On the other hand, the anomaly detection algorithm, as shown in Fig. 5, can identify the abrupt changes in the behavior of the individuals based on their phone record history. Deep learning methods running on top of these algorithms and datasets can make accurate predictions not only in the case of crime networks but also in the context of other networks like a network of traffic flow, a network of water quality sensors, or a network of public transportation entities. Thus proposed framework provides a low cost solution for smart-city governance as an alternative to other more expensive video-based solutions that may invade personal privacy at a much more direct level.

5.5. Limitations and future research direction

Though the proposed framework has shown encouraging results however, it suffers from certain limitations. Firstly, access to the CDR's data has a very sensitive nature and special mechanisms need to be put in-place to make sure that records are properly anonymized as a pre-requisite. All algorithms discussed in this work can be adapted to seamlessly for an anonymized dataset to respect individual privacy. Secondly, as the resultant network of CDRs data is quite sparse, therefore modeling the network in the context of seed nodes may also require some expertise. The size of the seed node set has a significant bearing on the accuracy of the results; that we propose should be a topic for a future study.

In other future studies, pertaining to the smart city research to facilitate law and order situation of the developing world, we are working to leverage textual features to combine data from news articles (Thompson, Nawaz, McNaught, & Ananiadou, 2017), blogs, social media networks to build predictive models (Ananiadou, Thompson, & Nawaz, 2013; Nawaz, Thompson, & Ananiadou, 2012) for proactive crime investigations by using natural language processing techniques (Batista-Navarro et al., 2013; Shardlow et al., 2018) and advance deep learning models (Jahangir, Afzal, Ahmed, Khurshid, & Nawaz, 2017). Last but not least, the potential for the application of these techniques is huge. However, like all surveillance, its value depends on the strict observation of data protection and civil rights be enforced by the authorities responsible.

6. Concluding Remarks

The advancements in technology are growing at a rapid pace. Various organizations and governments are proactive to adopt the new technology to enhance the quality of life and provide a sustainable environment to their citizens. To this end, one of the most important issues to handle is prediction and control of the crime rates. Various efforts have been devoted to enhance the crime prevention and investigation strategies (Eck et al., 2005; Yigitcanlar, 2009; Ismagilova et al., 2019), using video surveillance system and data which is quite computationally costly in most of the cases. In addition to computational cost, the availability, operability and maintenance of such video surveillance system and data processing platform is alos quite expensive task. Our proposed solution proposes a low cost theoretical framework to investigate CDRs data by leveraging SNA and deep learning approaches. It starts by taking the CDRs data as input and evaluate the data in different aspects to provide accurate recommendations. As shown earlier, the CDRs data encapsulates various pieces of information about individuals and thus is a good indicator to mine individuals' behaviors. The abrupt changes in behaviors also enable the machine learning model to distinguish suspects and criminal from common citizens. We validate our proposed methodology by presenting a case study to show the efficacy of our proposed approach. The encouraging results of our case study indicate the applicability of the proposed framework to equip the law enforcement agencies with a data driven crime prevention and analysis approach. In future, we plan to add more data source and exploit the impact of a lager set of attributes over our network.

CRediT authorship contribution statement

Saeed-Ul Hassan: Supervision, Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing. **Mudassir Shabbir:** Validation, Writing - original draft. **Sehrish Iqbal:** Investigation, Writing - review & editing. **Anwar Said:** Investigation, Software. **Faisal Kamiran:** Supervision, Writing - original draft, Writing - review & editing. **Raheel Nawaz:** Investigation, Writing - original draft, Writing - review & editing. **Umar Saif:** Supervision.

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References

Adderley, R., & Musgrove, P. B. (2001). Data mining case study: Modeling the behavior of offenders who commit serious sexual assaults. *Proceedings of the Seventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 215–220).

Ananiadou, S., Thompson, P., & Nawaz, R. (2013). Enhancing search: Events and their discourse context. March *International Conference on Intelligent Text Processing and Computational Linguistics* (pp. 318–334).

Batista-Navarro, R. T., Kontonatsios, G., Mihăilă, C., Thompson, P., Rak, R., Nawaz, R., et al. (2013). Facilitating the analysis of discourse phenomena in an interoperable NLP platform. March *International Conference on Intelligent Text Processing and Computational Linguistics* (pp. 559–571).

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *J. Stat. Mech. Theory Exp. 2008*, 10008.

Bogorny, V., & Shekhar, S. (2010). Spatial and spatio-temporal data mining. *Data Mining (ICDM), 2010 IEEE 10th International Conference on IEEE* 1217–1217.

Cocx, T. K., & Kosters, W. A. (2006). A distance measure for determining similarity between criminal investigations. *Industrial Conference on Data Mining* (pp. 511–525).

De Bruin, J. S., Cocx, T. K., Kosters, W. A., Laros, J. F., & Kok, J. N. (2006). Data mining approaches to criminal career analysis. *Data Mining, 2006. ICDM'06. Sixth International Conference on. IEEE,* 171–177.

Defferrard, M., Bresson, X., & Vandergheynst, P. (2016). Convolutional neural networks on graphs with fast localized spectral filtering. *Advances in Neural Information Processing Systems,* 3844–3852.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63–71.

Eck, J., Chainey, S., Cameron, J., & Wilson, R. (2005). *Mapping crime: Understanding hotspots*.

Eldrandaly, K. A., Abdel-Basset, M., & Abdel-Fatah, L. (2019). PTZ-Surveillance coverage based on artificial intelligence for smart cities. *International Journal of Information Management*. in press http://10.1016/j.ijinfomgt.2019.04.017.

Ferrara, E., De Meo, P., Catanese, S., & Fiumara, G. (2014). Detecting criminal organizations in mobile phone networks. *Expert Syst. Appl. 41*, 5733–5750.

Gallupe, O., McLevey, J., & Brown, S. (2019). Selection and influence: A meta-analysis of the association between peer and personal offending. *Journal of Quantitative Criminology, 35*(2), 313–335 Ratcliffe, J. H. (2016). Intelligence-led policing. Routledge.

Gleich, D. F., & Seshadhri, C. (2012). Vertex neighborhoods, low conductance cuts, and good seeds for local community methods. August *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 597–605).

Goldberg, H. G., & Wong, R. W. (1998). *Restructuring transactional data for link analysis in the FinCEN AI system. AAAI Fall Symposium*38–46.

Hashem, I. A. T., Chang, V., Anuar, N. B., Adewole, K., Yaqoob, I., Gani, A., et al. (2016). The role of big data in smart city. *Int. J. Inf. Manag. 36*, 748–758.

Ismagilova, E., Hughes, L., Dwivedi, Y. K., & Raman, K. R. (2019). Smart cities: Advances in research—An information systems perspective. *Int. J. Inf. Manag. 47*, 88–100.

Israilidis, J., Odusanya, K., & Mazhar, M. U. (2019). Exploring knowledge management perspectives in smart city research: A review and future research agenda. *International Journal of Information Management*.

Ismagiloiva, E., Hughes, L., Rana, N., & Dwivedi, Y. (2019). *Role of Smart Cities in Creating Sustainable Cities and Communities: A Systematic Literature Review.* June*International Working Conference on Transfer and Diffusion of IT*. Cham: Springer311–324.

Jahangir, M., Afzal, H., Ahmed, M., Khurshid, K., & Nawaz, R. (2017). An expert system

for diabetes prediction using auto tuned multi-layer perceptron. September *2017 Intelligent Systems Conference (IntelliSys)* (pp. 722–728).
Janssen, M., Luthra, S., Mangla, S., Rana, N. P., & Dwivedi, Y. K. (2019). Challenges for adopting and implementing IoT in smart cities. *Internet Research*.
Kemeny, T., & Cooke, A. (2017). Spillovers from immigrant diversity in cities. *J. Econ. Geogr, 18*, 213–245.
Khatoun, R., & Zeadally, S. (2016). Smart cities: concepts, architectures, research opportunities. *Commun. ACM, 59*, 46–57.
Kim, J., & Hastak, M. (2018). Social network analysis: Characteristics of online social networks after a disaster. *Int. J. Inf. Manag. 38*, 86–96.
Kipf, T. N., & Welling, M. (2016). *Semi-supervised classification with graph convolutional networks.* ArXiv Prepr. ArXiv160902907.
Li, D., Deng, L., Lee, M., & Wang, H. (2019). IoT data feature extraction and intrusion detection system for smart cities based on deep migration learning. *International Journal of Information Management*.
Loeffler, C., & Flaxman, S. (2018). Is gun violence contagious? A spatiotemporal test. *J. Quant. Criminol. 34*, 999–1017.
Lytras, M., & Visvizi, A. (2018). Who uses smart city services and what to make of it: Toward interdisciplinary smart cities research. *Sustainability, 10*, 1998.
Lytras, M. D., & Mathkour, H. (2017). Advances in research in social networking for open and distributed learning. *Int. Rev. Res. Open Distrib. Learn. 18*, 1–4.
Lytras, M. D., Raghavan, V., & Damiani, E. (2017). Big data and data analytics research: From metaphors to value space for collective wisdom in human decision making and smart machines. *Int. J. Semantic Web Inf. Syst. IJSWIS, 13*, 1–10.
Nawaz, R., Thompson, P., & Ananiadou, S. (2012). *Identification of Manner in Bio-Events.* May*LREC*3505–3510.
Park, J. H., Lee, C., Yoo, C., & Nam, Y. (2016). An analysis of the utilization of Facebook by local Korean governments for tourism development and the network of smart tourism ecosystem. *International Journal of Information Management, 36*(6), 1320–1327.
Perozzi, B., Al-Rfou, R., & Skiena, S. (2014). Deepwalk: Online learning of social representations. *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 701–710).
Said, A., Abbasi, R. A., Maqbool, O., Daud, A., & Aljohani, N. R. (2018). CC-GA: A clustering coefficient based genetic algorithm for detecting communities in social networks. *Applied Soft Computing, 63*, 59–70.
Said, A., Bowman, T. D., Abbasi, R. A., Aljohani, N. R., Hassan, S. U., & Nawaz, R. (2019). Mining network-level properties of Twitter altmetrics data. *Scientometrics, 120*(1), 217–235.
Sarkar, P., & Chakrabarti, D. (2015). *The consistency of common neighbors for link prediction in stochastic blockmodels. Advances in Neural Information Processing Systems*3016–3024.
Shardlow, M., Batista-Navarro, R., Thompson, P., Nawaz, R., McNaught, J., & Ananiadou, S. (2018). Identification of research hypotheses and new knowledge from scientific literature. *BMC medical informatics and decision making, 18*(1), 46.
Singh, P., Dwivedi, Y. K., Kahlon, K. S., Sawhney, R. S., Alalwan, A. A., & Rana, N. P. (2019). Smart Monitoring and Controlling of Government Policies Using Social Media and Cloud Computing. *Information Systems Frontiers,* 1–23.
Sparrow, M. K. (1991). The application of network analysis to criminal intelligence: An assessment of the prospects. *Soc. Netw. 13*, 251–274.
Thompson, P., Nawaz, R., McNaught, J., & Ananiadou, S. (2017). Enriching news events with meta-knowledge information. *Language Resources and Evaluation, 51*(2), 409–438.
Visvizi, A., & Lytras, M. D. (2018). Rescaling and refocusing smart cities research: From mega cities to smart villages. *J. Sci. Technol. Policy Manag, 9*, 134–145.
Visvizi, A., Lytras, M. D., Damiani, E., & Mathkour, H. (2018). Policy making for smart cities: Innovation and social inclusive economic growth for sustainability. *J. Sci. Technol. Policy Manag, 9*, 126–133.
Visvizi, A., Mazzucelli, C., & Lytras, M. (2017). Irregular migratory flows: Towards an ICTs' enabled integrated framework for resilient urban systems. *J. Sci. Technol. Policy Manag. 8*, 227–242.
Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world'networks. *Nature, 393*, 440.
Weerman, F. M., Wilcox, P., & Sullivan, C. J. (2018). The short-term dynamics of peers and delinquent behavior: an analysis of bi-weekly changes within a high school student network. *J. Quant. Criminol, 34*, 431–463.
Wu, Y. J., & Chen, J. C. (2019). A structured method for smart city project selection. *International Journal of Information Management*.
Xu, J., & Chen, H. (2005). Criminal network analysis and visualization. *Commun. ACM, 48*, 100–107.
Yang, J., & Leskovec, J. (2015). Defining and evaluating network communities based on ground-truth. *Knowl. Inf. Syst. 42*, 181–213.
Yigitcanlar, T. (2009). Planning for smart urban ecosystems: information technology applications for capacity building in environmental decision making. *Theoretical and Empirical Researches in Urban Management, 4*(12), 5–21 3.
Yigitcanlar, T., & Kamruzzaman, M. (2018). Does smart city policy lead to sustainability of cities? *Land Use Policy, 73*, 49–58.
Yigitcanlar, T. (2018). Smart city policies revisited: Considerations for a truly smart and sustainable urbanism practice. *World Technopolis Rev, 7*, 97–112.
Yigitcanlar, T., Kamruzzaman, M., Buys, L., Ioppolo, G., Sabatini-Marques, J., da Costa, E. M., et al. (2018). Understanding 'smart cities': Intertwining development drivers with desired outcomes in a multidimensional framework. *Cities, 81*, 145–160.
Yigitcanlar, T., Kamruzzaman, M., Foth, M., Sabatini, J., da Costa, E., & Ioppolo, G. (2018). Can cities become smart without being sustainable? A systematic review of the literature. *Sustainable cities and society*.
Zhuhadar, L., Thrasher, E., Marklin, S., & de Pablos, P. O. (2017). The next wave of innovation—Review of smart cities intelligent operation systems. *Comput. Hum. Behav, 66*, 273–281.