Building knowledge graphs of homicide investigation chronologies

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***Abstract*—Homicide investigations generate large and diverse data in the form of witness interview transcripts, physical evidence, photographs, DNA, etc. Homicide case chronologies are summaries of these data created by investigators that consist of short text-based entries documenting specific steps taken in the investigation. A chronology tracks the evolution of an investigation, including when and how persons involved and items of evidence became part of a case. In this article we discuss a framework for creating knowledge graphs of case chronologies that may aid investigators in analyzing homicide case data and also allow for *post hoc* analysis of the key features that determine whether a homicide is ultimately solved. Our method consists of 1) performing named entity recognition to determine witnesses, suspects, and detectives from chronology entries 2) using keyword expansion to identify documentary, physical, and forensic evidence in each entry and 3) linking entities and evidence to construct a homicide investigation knowledge graph. We compare the performance of several choices of methodologies for these sub-tasks using homicide investigation chronologies from Los Angeles, California. We then analyze the association between network statistics of the knowledge graphs and homicide solvability.**

***Index Terms*—knowledge graph, named entity recognition, homicide investigation**

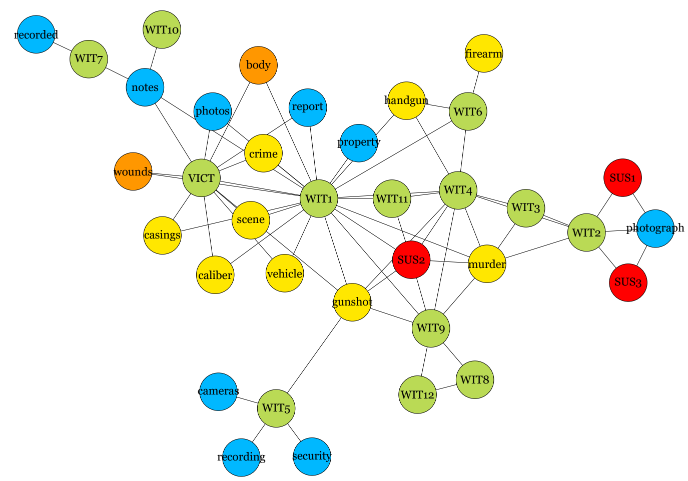


Fig. 1: Example knowledge graph of a homicide investigation chronology. Entities include witnesses, suspects and detectives as well as physical, documentary and forensic type evidences.

I. Introduction

A large amount of text-based data is produced during a homicide investigation including basic descriptions of the event, evidence logs, forensic reports, maps and annotated photographs, and transcripts of investigator's notes and witness interviews. These data are compiled into a so-called "Murder Book" that summarizes the paper trail from the time the incident was reported to the time a case is closed.

In the United States nationally, around 60% of homicides are solved or cleared via arrest or other exceptional means such as death of the offender [1]. Several factors appear to play an important role in homicide solvability [2]. Some crimes are inherently more difficult to solve than others; clearance rates generally are lower for homicides that involve guns, are perpetrated by strangers, lack witnesses, or occur in neighborhoods where cooperation with police is strained [3]–[5]. The quality of police investigations also appears to matter [6]. High volumes of casework, lack of investigative resources, investigator inexperience, and variability in investigator motivation (e.g., bias) can all drive down homicide clearance rates [7], [8].

Our primary interest in this work is to understand the interactions between the characteristics of a crime, as represented by collected evidence, and the investigative process. We hypothesize that some of these interactions are non-obvious and therefore difficult to leverage using traditional methods designed to improve homicide solvability. We explore methods to construct "knowledge graphs" from text-based investigative information contained within Murder Books and evaluate the association between structural features of the resulting graphs and solvability of the cases. We see this as a precursor to methods that can be used actively during investigations to improve clearance rates for homicides that would typically go unsolved.

In Figure 1 we show an example knowledge graph constructed from a homicide chronology using the methods detailed in this paper. In the graph there are 3 suspect nodes, 12 witness nodes and a single node for the victim. There are 3 types of evidence nodes connected to these 16 individuals, including physical evidence nodes (yellow), documentary evidence nodes (cyan), and forensic evidence nodes (orange). Our ultimate goal is to correlate features of the network with the outcome of the investigation (whether or not it is solved).

The remainder of this paper proceeds as follows. In Section II we outline at a conceptual level an ontology for homicide knowledge graphs. In Section III we describe the data used in our study. In Section IV we compare four deep learning approaches for named entity recognition in homicide investigation chronologies. We also introduce a keyword expansion methodology for extracting evidence from chronology entries. In Section V we consider two approaches for constructing knowledge graphs of homicide investigations using the entity extraction techniques introduced earlier in the paper and in Section VI we analyze statistics of the constructed knowledge graphs as they relate to solvability outcomes. We discuss the implications of our findings and directions for future work in Section VII.

II. Homicide Graph Ontologies

Our approach to knowledge graph construction starts with the routine activities theory of crime [9]. RAT outlines a core ontological framework for any potential threat that arises from the normal activities that people engage in on a day-to-day basis. For crime such as homicide, RAT helps delineate the key elements and contexts that must underlie the crime. It is this underlying structure that detectives seek to capture in their investigation and that we seek to represent in a knowledge graph. The minimal elements necessary for a homicide consist of an offender (node) killing (edge) a victim (node). The homicide takes place in a setting (node), which can act upon both the offender and victim. By virtue of the fact that an offender and victim must converge in a setting for a homicide to occur, these core elements necessarily form a complete graph. The core graph can be further refined and extended based on other specific knowledge about an event. For example, the act of killing may be mediated by a weapon (node) and offenders, victims and settings each may be conditioned by other characteristics such as motives (nodes), such as jealousy, and contexts (nodes), such as alcohol and witnesses. Note that the hypothetical graph for the crime itself must have elements such as an offender (node) that exist with certainty. A corresponding investigative knowledge graph may have elements such as a suspect (node) or evidence (node) labeled to reflect uncertainty.

There have been a few attempts to map out the ontology of graphs related to various threats [10], [11], but these remain relatively simple at present. Homicide investigations can easily generate tens-of-thousands of unique data points, suggesting that homicide knowledge graphs will include a proportional number of graphical elements. We expect the core ontology suggested above to quickly become challenging to understand and difficult to analyze for plausible causal pathways (e.g., attribution of guilt). We therefore require methods that can easily extract and accurately label investigative elements and their relationships according to a specified ontology and then use the resulting graphical structure for various investigative tasks.

III. Data Description

A so-called "Murder Book" is a case file management structure developed to ensure organization and standardization in homicide investigations. The Los Angeles Police Department (LAPD) has been successfully using Murder Books for nearly four decades [12]. It allows anyone involved in the investigation to find investigative reports, crime scene reports, witness list, interview transcripts, photos and other material. Every Murder Book contains a case chronology which consists of a time-ordered list of steps taken by the investigators over the entire history of the case. The chronology typically starts with an entry describing which detectives are assigned to the case and how they were notified, followed by a separate entry describing arrival at the scene and general scene description (e.g., state of the victim and initial evidence collected). A chronology typically ends with an entry describing how a case was closed (e.g., suspect arrested) or, if the case remains open, the date and time of the last case review. Hundreds of entries in between cover investigative events such as the date, time and location of witness interviews, date of receipt of forensic reports, and date of warrant requests. Each entry in the chronology is typically a compact, text-based statement totalling no more than 120-150 words. The purpose is to provide a quick reference for the state of the investigation, rather than a sounding-board for a theory of the crime.

The dataset we analyze at present consists of the case chronologies for 24 randomly-sampled Murder Books for homicides that occurred in LAPD's South Bureau between 1990 to 2010. The data were provided by the LAPD and are analyzed under UCLA IRB Protocol 19-000588. The 24 cases generated 2482 unique chronological entries.

For the purpose of named entity recognition (detailed explanation in the next section), we first hand labeled 610 narrative reports from the total of 2482 reports and split them into a training set (348 reports) and validation set (162 reports). Each word in a sentence was tagged as detective (*Det*), witness (*Wit*), suspect (*Sus*) or other (*O*). All of the detectives, investigators, coroner and supervisors involved in the case were tagged as *Det*. People who were interviewed or provided information related to the case were assigned to the *Wit* label. People were tagged as *Sus* if they were under investigation at any point during the chronology (for example if a warrant was issued or they were arrested).

IV. Identifying named entities and evidence

Named entity recognition (NER) is a framework for identifying named entities from text and classifying them into pre-

TABLE I: NER model comparison for homicide investigation chronologies.

Model		Overall			Detective			Witness			Suspect		
		Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
spaCy	train	0.86	0.91	0.88	0.90	0.94	0.92	0.79	0.93	0.86	0.88	0.77	0.82
	valid	0.36	0.26	0.30	0.28	0.17	0.21	0.39	0.53	0.45	0.39	0.06	0.11
BiLSTM-CRF	train	0.95	0.96	0.96	0.96	0.97	0.97	0.98	0.92	0.95	0.91	**0.99**	0.95
	valid	**0.74**	**0.83**	**0.78**	**0.82**	**0.82**	**0.82**	**0.84**	0.83	0.84	0.17	**0.91**	0.29
BiLSTM-BiLSTM-CRF	train	0.98	**0.97**	0.97	**0.99**	**0.98**	0.98	**0.99**	0.94	**0.97**	0.96	**0.99**	**0.97**
	valid	0.67	**0.83**	0.74	0.64	0.70	0.67	**0.84**	**0.92**	**0.88**	0.12	0.88	0.21
BiLSTM-CNN-CRF	train	**0.99**	0.96	**0.98**	0.99	**0.98**	**0.99**	0.98	**0.96**	**0.97**	**0.99**	0.94	**0.97**
	valid	0.72	0.79	0.76	0.70	0.65	0.68	0.82	**0.92**	0.87	**0.43**	0.76	**0.55**

defined categories. Deep learning based approaches for NER are currently state of the art and we compare four deep learning models for the task of identifying detectives, witnesses, and suspects from homicide chronologies. For a review of deep learning based NER see [13].

A. *spaCy*

The first deep learning based approach we evaluate is the NER method implemented in spaCy[1], a Python based open source library that provides tools for natural language processing [14], [15]. The default NER model in spaCy utilizes subword features and bloom embeddings [16], along with a convolution neural network with residual connections.

B. *Bidirectional LSTM-CRF*

We also apply a bidirectional LSTM-CRF (conditional random field) model for NER [17] and compared it with two other alternative architectures. The models makes use of both past and future input features and sequence level tagging information and use pre-trained GloVe [18] embeddings.

For the implementation of bi-LSTM and CRF, we input pre-trained GloVe [18] embeddings into the neural network, apply a dropout to the word representation in order to prevent over-fitting [19], and then train the Bi-LSTM to get a contextual representation. The final step in the model includes applying CRF to decode the sentence [19]. We refer to this model as BiLSTM-CRF.

In the first alternative [20], we concatenate with character level word embeddings from a bi-LSTM model. The character level model uses a forward and backward LSTM to obtain a representation of the suffix and prefix of a word [20]. After obtaining the word representation, we apply a bi-LSTM to get another sequence of vectors providing contextual representations. Again, at the end we use a CRF to decode sentence level tag information. We refer to this model as BiLSTM-BiLSTM-CRF.

In the third LSTM-CRF variant, we consider uses a CNN layer instead of Bi-LSTM to derive character embeddings. We train a 1-D Convolutional Neural Network (CNN) followed by a max pooling layer to get the character level embeddings and concatenate the layer with pre-trained GloVe embeddings. The CNN is an effective architecture for extracting morphological information from characters of a word [21]–[23]. This word representation is then fed to a bi-directional LSTM network in order to extract a contextual word representation which is then fed to the CRF model to decode the sequence tags for the sentence. We refer to this model as BiLSTM-CNN-CRF.

C. *Application of NER to homicide investigation chronologies*

We compare the above four NER models to the LAPD homicide investigation dataset. We first hand labeled 610 narrative reports from the total of 2482 reports and split them into a training set (348 reports) and validation set (162 reports). Each word in a sentence was tagged as detective (*Det*), witness (*Wit*), suspect (*Sus*) or other (*O*). All of the detectives, investigators, coroner and supervisors involved in the case were tagged as *Det*. People who were interviewed or provided information related to the case were assigned to the *Wit* label. People were tagged as *Sus* if they were under investigation at any point during the chronology (for example if a warrant was issued or they were arrested).

In Table I we show the performance of the four NER models on our dataset. We evaluate the models in terms of precision, recall and f1-score. We find that overall, the BiLSTM-CRF model has the best precision (.74), recall (.83) and f1-score (.78) on the validation data. We therefore use the BiLSTM-CRF in constructing knowledge graphs in the following sections. Due to the small dataset, it is likely that the NER models may be overfitting the data. An example of the NER extraction is shown in Figure 2a.

D. *Identifying evidence using keyword expansion*

While NER can be used to extract named entities, we use domain expertise coupled with a key word expansion to extract evidence from each sentence. We first start with a key word list of evidence classified into three types: physical, documentary and forensic evidence. The list is shown in Table II. Physical evidence includes tangible objects such as gun, knife, bullet, etc. Documentary evidence includes tapes, photos, video, etc. containing pertinent information to the case. Forensic evidence, on the other hand, includes DNA, blood, fingerprints, autopsy information, etc.

Next we used a keyword expansion [24] to extract additional keywords related to evidence from the text. In particular, we

[1] https://spacy.io/

TABLE II: Initial List for Identifying Types of Evidence in Text

Evidence Type	Keywords
Documentary Evidence	tapes, recording, surveillance, photo, video, camera, photograph
Physical Evidence	weapon, gun, knife, gunshot, caliber, casing
Forensic Evidence	dna, blood, fingerprint, autopsy

TABLE III: Evidence List after applying Keyword Expansion

Evidence Type	Keywords
Documentary Evidence	tapes, recording, surveillance, photo, video, camera, photograph, print, letter, security, camera, printout, record, recording, report, notes, document, monitor, footage, warrant, property, picture, chronology, log
Physical Evidence	weapon, gun, knife, gunshot, caliber, casing, handgun, firearm, item, shooting, bullet, murder, crime, scene, crimescene, shot, kill, stab, revolver, fire, discovery, criminal, kick, vehicle, veh
Forensic Evidence	wound, body, polygraph, exam, examination, test, hair, impression

preprocessed the data by removing stopwords and eliminating any word with length less than 3 and frequency less than 5. We used Gensim Word2Vec [2] to embed each word in the remaining text and computed the similarity (distance) of each word to those in the defined list in Table II. We then thresholded the similarity scores and again used domain expertise to select and prune the resulting expanded keyword list. We applied this process iteratively three times, the result of which is shown in Table III. An example sentence with NER and evidence detection is shown in Figure 2a.

V. Building a Knowledge Graph of Homicide Investigation Chronologies

A knowledge graph (KG) is a representation of structured information in the form of entities and relations (links) between them. Here we describe our approach to constructing knowledge graphs of homicide investigation chronologies. We utilize an end-to-end text to knowledge graph framework, t2kg, [25] to construct the knowledge graph in four stages:

1) Entity Mapping
2) Coreference Resolution
3) Entity Extraction
4) Entity Disambiguation

During the first stage an entity is mapped to a uniform resource identifier (URI). In the context of a homicide investigation, entity mapping can be viewed as identifying law enforcement detectives, witnesses, suspects and evidences from text performed using named entity recognition and keyword expansion.

In the next stage, we perform coreference resolution which is the task of finding mentions in text that refer to the same underlying entity. This is done in order to capture different expressions of identical entities [26], [27]. For this purpose we use neuralcoref[3] to resolve coreference clusters. In the third stage we perform entity extraction, for which we considered the following two approaches:

1) **Triple Extraction Approach** Subject-object-relation triples are extracted using the Open Information Extraction technique implemented in the Stanford CoreNLP library. In Figure 2b we show an example of a sub-graph created from the paragraph in Figure 2a using the triple extraction approach. For example, *vehicle* keys are provided to a *witness* leading to an edge between vehicle and witness being added to the knowledge graph.
2) **Domain Knowledge** The triple extraction approach uses grammatical structure to add edges, without regard to domain knowledge or the fact that all sentences in a chronology are related. Therefore we consider an alternative approach, that we refer to as “domain knowledge,” where we add a complete (fully-connected) sub-graph of all extracted entities detected in the chronology entry. We show an example of this approach in Figure 2c.

Coreference resolution using neuralcoref in stage 2 above is only able to resolve high level coreference clusters in the text. We therefore add an entity disambiguation stage, where identical entities are grouped together and duplicates are eliminated. In the entity disambiguation phase, multiple versions of the same entity are mapped to a unique entity identifier. For instance, entity John Middle Doe may be referenced in the text with variations such as John, John M Doe, Doe, J. Doe etc. To merge these variations we employed partial string matching. We then merged redundant entities that are identified in the triple extraction approach. For example, the triple (DET, interviewed, WIT) is merged with the triple (DET, interviewed with, WIT) into the single entity-relation tuple (DET, interviewed with, WIT). They are then matched with their uniform resource identifier(URI).

Extracted entities and evidence using NER and keyword expansion play a vital role in knowledge graph generation both for the domain knowledge graph and triple extraction approach. In triple extraction approach, triples are mapped to their URI (extracted in entity mapping stage). The subjects and object from the triples are then connected for knowledge graph generation. In domain knowledge approach, extracted entities in each chronology from stage 1 are fully connected in order to generate a knowledge graph. Furthermore, each nodes in a knowledge graph is colored according to different entity and evidence type.

In Figure 5 and 6 we present example knowledge graphs for the domain knowledge approach and triple extraction approach

[2]https://radimrehurek.com/gensim/
[3]https://spacy.io/universe/project/neuralcoref

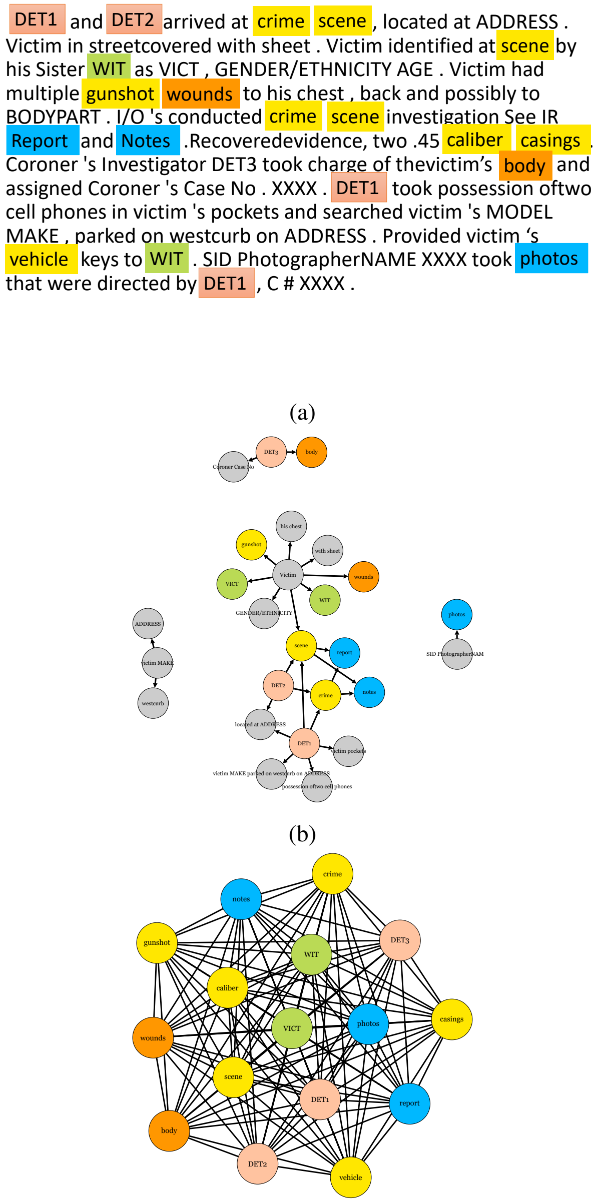


Fig. 2: Building knowledge sub-graphs using Named Entity Recognition and Keyword Expansion. (a) Entity extraction using Named entity recognition and Keyword Expansion. Some text is redacted such as detective names (replaced with DET), witness names (replaced with WIT), suspect names (replaced with SUS), etc. (b) Extracted knowledge sub-graph using Stanford OpenIE Triple Extraction approach. (c) Extracted knowledge sub-graph using Domain Knowledge Approach. Text and nodes are colored by its entity type (Detective- pink, Witness- green, Suspect- red, Physical evidence- yellow, Documentary evidence- cyan, Forensic evidence- orange, Other- gray)

respectively. In general we find that the domain knowledge graphs are more connected, given the fully connected subgraph used for each chronology entry. This can be seen in the degree distributions corresponding to each method in Figure 3. We also note that much of the information contained in the knowledge graphs is already present after the first week of the homicide investigation (see Figure 4).

VI. Association between Knowledge Graph Features and Homicide Solvability

To evaluate the quality of the knowledge graphs we construct, we investigate the extent to which knowledge graph features (statistics) are asssociated with solvability. The methods we introduce here may be stepping stones towards AI-assisted homicide investigation, where key elements of the graph may be identified as playing a role in whether the case is ultimately solved (a suspect is charged for the crime). We are cautious in avoiding the term *prediction*, given the small dataset size and our inability to disentangle causality from correlation.

First, we create knowledge graphs for each of the 24 cases provided by the LAPD using the triple extraction and domain knowledge approaches. After the creation of the knowledge graphs, we compute network statistics for each KG, e.g., number of nodes, number of edges, network density.

In Figure 7, we display the 15 network statistics we compute for each network along with the AUC of the statistic as it relates to solvability of the homicide investigation. Here we find that the number of evidence nodes, suspect nodes and average degree of detective nodes yield the highest AUC.

For each approach (domain knowledge and triple extraction), we consider networks where detective nodes are included and networks where they are removed. While detective node based features have a high AUC score, causality may be in the wrong direction. On the one hand, an increase in the number of detective nodes may be due to the case being solvable. On the other, cases with more dedicated resources may be more likely to be solved. We show results for both types of networks.

We next evaluate a simple generalized linear model (GLM) with binary response for determining solvability:

$$\log(p(y=1)/(1-p(y=1))) = c_0 + c_1 s + c_2 e + c_3 s \cdot e \quad (1)$$

where s is the number of suspect nodes, e is the number of evidence nodes, and y indicates whether the homicide is solved. The features were selected based on their individual AUC scores in Figure 7 and limited to the top-two (averaged across network types) to prevent over-fitting.

Due to the small dataset size we use leave-one-out cross validation (LOOCV). In Figure 8 we show the AUC scores of the GLM model for each network type (domain knowledge vs. tripe extraction, with and without detective nodes) constructed using data up to a given week past the start of the investigation. Here we generally find that the domain knowledge approach outperforms the triple extraction approach. We also do not find much improvement in the association between the model scores and solvability past 1-3 weeks in the investigation. In the case of the triple extraction networks without detective

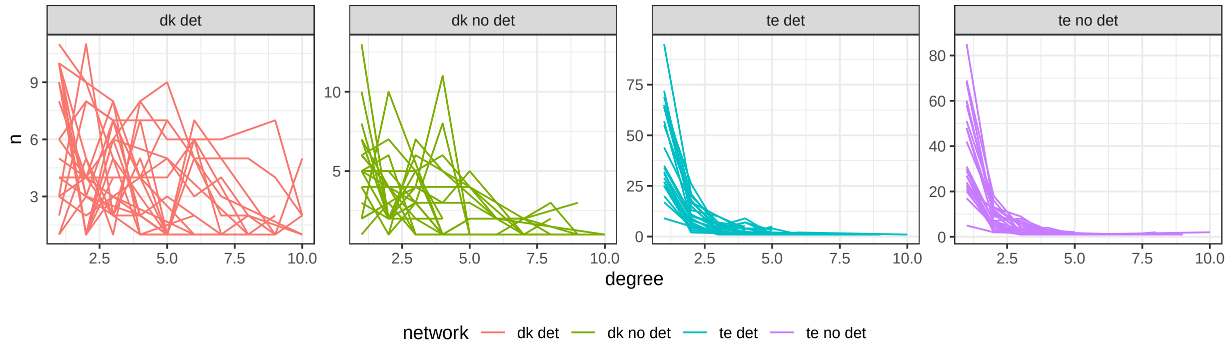


Fig. 3: Degree distributions of the 24 homicide investigation knowledge graphs of domain knowledge type (with and without detective nodes) and triple extraction type (with and without detective nodes).

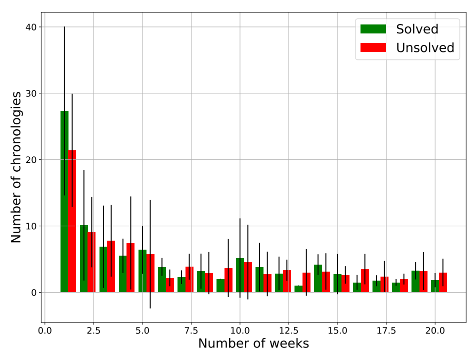


Fig. 4: Average number of chronology entries over first 20 weeks into the investigation.

nodes, we find that the GLM model yields AUC scores at or below .5 (using LOOCV), indicating that the GLM model is over-fitting for that type of network.

VII. Discussion

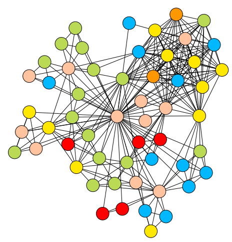
We show that it is possible to construct knowledge graphs representing homicide investigations from text-based case file information. The topological features of these knowledge graphs offers some traction in classifying whether or not homicides are solvable. Features that prove to be important in classifying homicide solvability (e.g., evidence nodes, suspect nodes) are consistent with analysis of investigative process using other methods [8]. Importantly, the results also suggest that the most significant topological structure are established early in an investigation, reinforcing the common view that cases can be divided into “self-solvers” that produce sufficient evidence at the scene and “whodunits” that do not [28].

That knowledge graph topological structures appear to provide useful information suggests that AI could eventually be used to improve solvability. It is too early to know exactly what to expect. However, we hypothesize that there will be regular structural and relational features of solved homicides that will distinguish them from unsolved ones. When comparing graphs, we may be able to identify gaps or holes in graphical structures that, if closed, could improve the chances of a case being solved. To the extent that such graph-based insights go beyond what common investigative practice would yield, AI-assisted homicide investigation may be valuable.

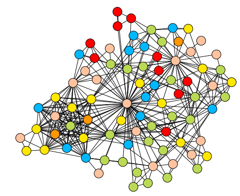
A common expressed view is that solving homicides helps build community trust in police, while failure to do so erodes that trust and creates a sense of impunity among offenders [4], [5]. If AI can help improve homicide solvability, then it can also be seen to contribute to building community trust. However, the question is not simply whether such methods augment the process of homicide investigation. Rather, since homicide investigations must adhere to the policy requirements of the organization and the procedural requirements of the law, so must AI used within those investigations. For example, if we consider a hypothetical knoweldge graph-based recommender system that suggests investigative steps, then those recommendations cannot violate policy or the law.

AI-assisted homicide investigation would also need to be evaluated in terms of fairness. The evidence is mixed on whether homicide clearance rates are mediated by race and gender [2], [5], [8], [29], though many expect that clearances rates are lower when the victim is a person of color [4]. In any case, AI should not introduce or amplify any clearance rate imbalances. We should also consider the possibility that AI-assisted investigation might ease clearance rate imbalances. Such imbalances may originate with the event itself if, for instance, so-called “whodunit” cases arise more often in association with certain demographic characteristics [30]. They might also appear if there is “victim devaluing” based on demographic characteristics [4], [5]. Identifying such biases in investigative knowledge graphs is a necessary and important step towards correcting for them.

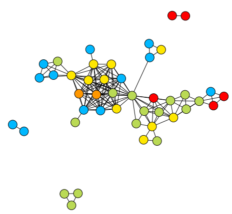
Finally, we must also be aware of the potential for the miscarriage of justice. Recent evidence suggests that wrongful convictions may occur in $< 5\%$ of capital cases such as murder [31]. That wrongful convictions may also differ by race [32], demands that the contributing factors be taken into consideration in AI-assisted homicide investigations. While careful adherence to rules of evidence and procedure may offer



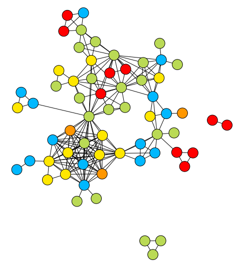
(a) Domain Knowledge Approach (including detective nodes- Week 1



(b) Domain Knowledge Approach (including detective nodes- Week 10



(c) Domain Knowledge Approach (not including detective nodes- Week 1



(d) Domain Knowledge Approach (not including detective nodes- Week 10

Fig. 5: Knowledge graph using Domain Knowledge Approach with and without detective nodes. Each node is colored by its entity type (Detective- pink, Witness- green, Suspect- red, Physical evidence- yellow, Documentary evidence- cyan, Forensic evidence- orange).

some protection, it does not provide a guarantee. Wrongful convictions can sometimes be linked back to false witness statements, forensic error, or police misconduct [33]. Eventually, whether there are recognizable differences between knowledge graphs that include corrupted information and those that do not needs to be investigated.

Ultimately, considerations of fairness, accountability, and transparency need to be central to the development of machine learning methods for homicide investigations.

VIII. Acknowledgments

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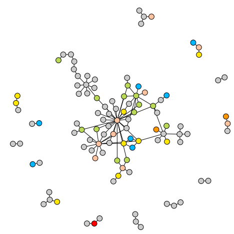
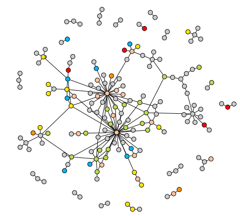
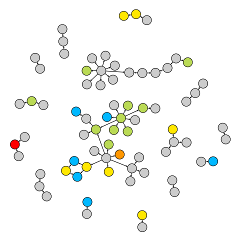


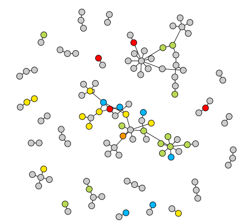
(a) Triple Extraction (including detective nodes- Week 1



(b) Triple Extraction (including detective nodes- Week 10



(c) Triple Extraction (after removing detective nodes- Week 1



(d) Triple Extraction (after removing detective nodes- Week 10

Fig. 6: Knowledge graph using Triple extraction approach with and without detective nodes. Each node is colored by its entity type (Detective- pink, Witness- green, Suspect- red, Physical evidence- yellow, Documentary evidence- cyan, Forensic evidence- orange, Other- gray).

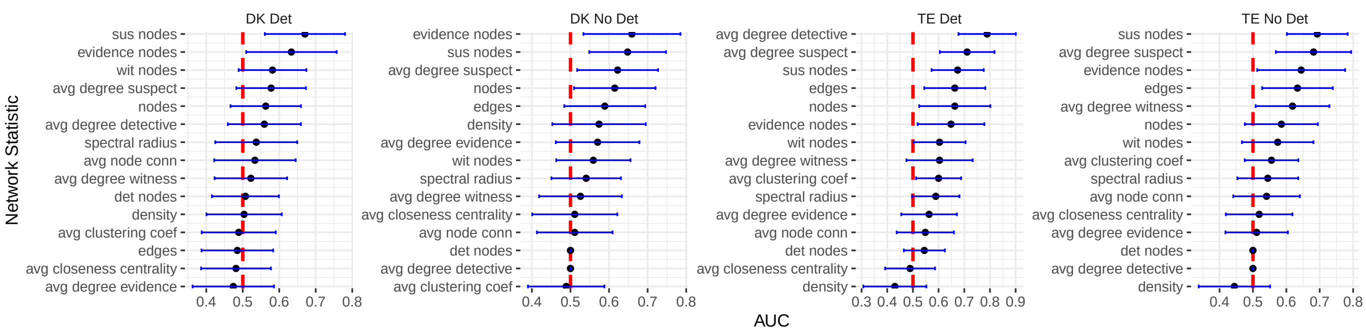


Fig. 7: AUC and standard error for each network statistic in week 1 of the investigation.

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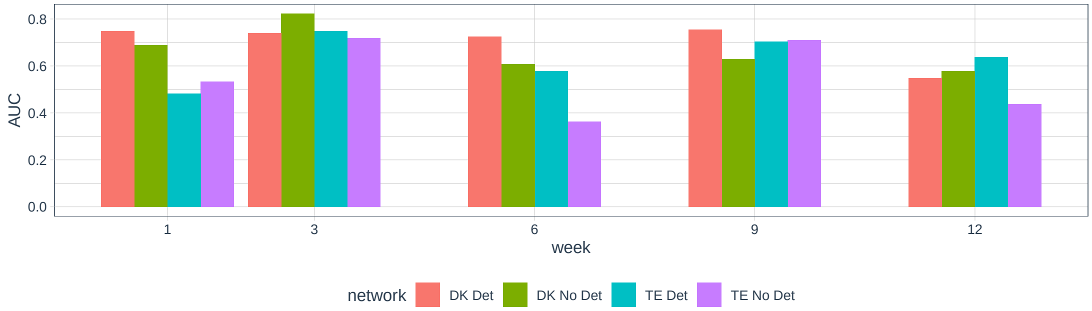

Fig. 8: AUC of GLM model (computed uses leeave one out cross-validation) vs. number of weeks into the investigation.

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