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Text mining police narratives to identify types of abuse and victim injuries in family and domestic violence events

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Abstract | Police attend numerous family and domestic violence (FDV) related events each year and record details of these events as both structured data and unstructured free-text narratives. These descriptive narratives include information about the types of abuse (eg physical, emotional, financial) and the injuries sustained by victims. However, this information is not used in research. In this paper we demonstrate the application of an automated text mining method to identify abuse types and victim injuries in a large corpus of NSW Police Force FDV event narratives (492,393) recorded between January 2005 and December 2016. Specific types of abuse and victim injuries were identified in 71.3 percent and 35.9 percent of FDV event narratives respectively. The most commonly identified abuse types mentioned in the narratives were non-physical (55.4%). Our study supports the application of text mining for use in FDV research and monitoring.

Family and domestic violence (FDV) takes a range of forms including physical, sexual, psychological and economic (Coumarelos 2019) and has serious social and health consequences (Howard et al. 2010; Robinson & Spilsbury 2008; Trevillion et al. 2012). The consequences of FDV can depend on the characteristics of the individuals involved (eg age, gender, mental health) and the specific features of each FDV event (eg type of abuse, injury type; Capaldi et al. 2009; Cleak et al. 2018; Foshee 1996; Kelly & Johnson 2008). When the NSW Police Force (NSWPF) attends an event, they record a range of valuable information in the Web Computerised Operational Policing System (WebCOPS) about the characteristics of those involved in FDV and the specific features of each event, in both a structured format and an unstructured free-text narrative. While the WebCOPS structured data are readily accessible, the free-text narratives, on the other hand, contain a wealth of important descriptive information, including on the types of abuse and types of injuries sustained in FDV events, that remains untapped for research and reporting purposes.

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This information can potentially be used to examine the features of FDV events generally and to predict risks of escalation of FDV—for example, from verbal abuse to serious physical injuries or even murder.

In this paper we report on the applicability of a text-mining approach as a method of extracting detailed information from police event narratives about two aspects of FDV events:

- abuse types (eg intimidation, verbal abuse, financial control, physical assault) which may not be considered a criminal offence and not recorded in the fixed fields; and
- victim-sustained injuries for which medical attention may not have been sought and which therefore may not have been recorded in hospital, forensic or other medical databases.

Methods

Data

We used event narratives from 492,393 FDV events, provided by the NSWPF, occurring between January 2005 and December 2016. This dataset is described elsewhere (Karystianis et al. 2018, 2019). The FDV events were either flagged in WebCOPS as 'domestic violence related' or their violence description was coded as 'domestic', and the relationship between the victim and the person of interest (POI) included any of the following: 'spouse/partner' (including ex-spouse/ex-partner), 'boyfriend/girlfriend' (including ex-boyfriend/ex-girlfriend), 'parent/guardian' (including step/foster), 'child' (including step/foster), 'sibling', or 'other member of family' (including kin), or 'carer.'

In line with our agreement with the NSWPF, these FDV events covered the following incident categories in the structured data:

- types of physical assault;
- breach of apprehended domestic violence order;
- homicide;
- malicious damage to property; and
- other offence against another person—such as intimidation, kidnapping, abduction, and harassment.

Text mining the event narratives

Text mining has been used for more than 30 years to harvest information from unstructured text in many fields, particularly in biomedicine (Abbe et al. 2016; Friedman et al. 2004; Karystianis et al. 2015; Savova et al. 2010; Spasić et al. 2014; Wang et al. 2018). Recent efforts have sought to text-mine crime-related information from online media publications (Arulanandam, Savarimuthu & Purvis 2014; Matto & Mwangoka 2017; Nokhbeh, Manoharan & Barber 2017), with few attempts to process police reports (Ananyan 2004; Chau, Xu & Chen 2002; Iriberri & Leroy 2007; Karystianis et al. 2018; Ku, Iriberri & Leroy 2008; Poelmans et al. 2011). Recently, Karystianis et al. (2018) demonstrated the feasibility of text-mining a large corpus of police event narratives to identify mentions of mental illness among POIs and victims of FDV.

The implemented text-mining approach for this study used rule-based language expression patterns combined with dictionary terms to identify mentions of abuse types and victim injuries in the event narratives. It consisted of the following steps:

- creation of relevant dictionaries to identify mentions of a range of abuse types and victim injuries;
- design and implementation of rules to capture abuse types and victim injury mentions in context; and
- aggregation of multiple mentions in each narrative to reach FDV event–level annotation.

In total, 300 randomly selected narratives were used, with 200 for training and 100 for evaluation.

Dictionary creation

We manually compiled 22 dictionaries of terms for a range of abuse types and victim injuries by reviewing several sources to categorise abuse types (KPMG 2016; Mouzos & Makkai 2004; White Ribbon Australia 2018). We also reviewed the training set of 200 event narratives (the training data). For the recognition of all terms of interest, we included regular variations such as plurals, past and present tenses and misspellings (eg ‘harrassment’, ‘assalting’) that are frequently seen in the event narratives. Non-specific forms of violence (eg ‘bashing,’ ‘smack,’ ‘assaulted’ and ‘clipping’) were categorised as ‘assault (unspecified).’ The dictionaries contained nouns, verbs, phrases and sentences. A total of 44 abuse types and 17 common injury types were included in the dictionaries for identification in the event narratives.

Designing and implementing rules to capture mentions of abuse and injuries

The rules were based on syntactical patterns identified in the training data that indicated the presence of an abuse type or a victim’s injury, following the same methodology that was previously developed (Karystianis et al. 2018). The syntactical patterns included frozen syntactical expressions as anchors for certain elements—built through specific verbs, nouns, prepositions and phrases (eg ‘commenced to choke’)—and semantic placeholders which were identified using the manually compiled dictionaries, such as all possible synonyms describing a victim including ‘victim,’ ‘vic’ and ‘pinop’.

To create and apply the rules, we used the General Architecture for Text Engineering (GATE) software (Cunningham et al. 2013), a text mining framework for annotating and categorising text to enable information extraction. A total of 64 rules were created.

Elimination of multiple mentions

More than one syntactical pattern may be matched in a single event narrative and may refer to one or more varying mentions of abuse types or victim injuries, including semantic duplicates—for example, ‘punch’, ‘punched’ and ‘punching’ (same abuse type) and ‘bruised,’ ‘bruises,’ and ‘purple marks’ (same victim injury type). We eliminated any duplicate mentions by mapping all extracted ones to their ‘canonical’ representative, keeping only one instance for each abuse type or injury type mentioned in a single FDV event.

Evaluation

The text-mining methodology was evaluated using a set of 100 previously unseen, randomly chosen FDV event narratives. This dataset was manually inspected and annotated by the first and second authors (AA and GK), who identified the type(s) of abuse and victim injuries. Their inter-annotator agreement was calculated as the absolute agreement rate (Kim 2006). The metrics of precision (the number of correctly identified mentions by the methodology against the number of correctly and incorrectly identified mentions in total); recall (the number of correctly identified mentions against the number of correctly identified mentions and incorrectly unidentified mentions in total); and F-score (the harmonic mean between precision and recall) were calculated using their standard definitions (Ananiadou, Kell & Tsujii 2006).

Results

Validity and reliability

The inter-annotator agreement for the abuse types and victim injuries by GK and AA for the evaluation dataset (100 FDV events) was 91 percent, which suggests good inter-rater reliability. The calculated F1-scores for the automated identification of abuse and victim injury mentions were above 85 percent, indicating good results for the text-mining methodology. In particular, the precisions were high for abuse types and victim injuries (90.2% and 85.0% respectively), as were the recall values (89.6% for abuse types and 86.3% for victim injuries).

Sources of (limited) false positives after inspecting the evaluation set included: the misidentification of POI injuries as victim injuries (eg, 'minor grazing to the right shoulder of the POI' [false positive for victim injury]); the incorrect identification of victim injuries due to ambiguous words (eg 'injuries/medical treatment/damage to property: broken table leg' [false positive for victim injury]); actions conducted by the victim in self-defence being extracted as abuse types (eg 'admitted she physically pushed him [false positive for abuse type] back after he pushed [true positive for abuse type] into her'); and the recognition of abuse types with no FDV context (eg 'The accused was inside the caged area, where he began kicking [false positive for abuse type] at the door') or that were likely to happen in the future (eg 'if she stayed at the residence she would definitely have been bashed [false positive for abuse type] by the accused').

The sources of false negatives included a small number of injuries that were not explicitly stated as sustained by the victim (eg 'grazes [false negative for injury] sighted on back, dried blood [false negative for injury] on lips'), and abuse types that were implicit and required additional inference using some related terms (eg 'the POI placed his hand in the middle of the victim's sternum and applied force [false negative for injury] causing her pain'). These false negatives indicated that abuse types such as 'grabbing' and 'punching' can have quite a few lexical variations in the narratives.

Mentions of abuse types and victim injuries

Given the relatively accurate results of our method in identifying abuse types and victim injuries, we applied it to the corpus of 492,393 FDV events. At least one mention of an abuse type was identified in over two-thirds of FDV event narratives (351,178; 71.3%). One-third of these event narratives (177,607; 36.1%) had a mention of victim injuries. Of the 44 identified abuse types, 'emotional/verbal abuse' (117,488; 33.5%) was the most common, followed by 'punching' (86,322; 24.6%) and 'property damage' (78,203; 22.3%; Table 1).

Although the FDV cohort did not include events recorded as sexual assault as part of our agreement with the police, some events did identify sexual assault as a type of abuse (125; 0.04%). While more than half of the identified abuse types in the police narratives were non-physical (55.4%), these were reported in only 11.9 percent of the events in the WebCOPS structured format. In particular, 'intimidation' was reported in 11.9 percent of all events in the structured quantitative data and was identified in 21.6 percent of events in the free-text narratives.

A total of 35.5 percent (124,498 events) of FDV events contained only one identified abuse type, whereas 33.8 percent (118,819 events) of FDV events included three to five different abuse types (Table 2).

Table 1: Family and domestic violence events mentioning specific abuse types (*n*=351,178)

Abuse type	Events *n* (%)[a]
Assault (unspecified)	171,323 (48.8)
Emotional/verbal abuse	117,488 (33.5)
Punching	86,322 (24.6)
Property damage	78,203 (22.3)
Intimidation	75,662 (21.6)
Grabbing	66,728 (19.0)
Pushing	62,794 (17.9)
Scratching	20,493 (5.8)
Physical restraining	20,014 (5.7)
Kicking	19,435 (5.5)
Slapping	17,474 (5.0)
Apprehended domestic violence order breach	16,903 (4.8)
Attempting to hit with an object or weapon	13,592 (3.9)
Hair pulling/dragging by hair	13,048 (3.7)
Choking	11,325 (3.2)
Spitting	9,341 (2.7)
Hitting with an object or weapon	8,387 (2.4)
Pulling	6,373 (1.8)
Victim being thrown around	5,255 (1.5)
Lunging	4,685 (1.3)

Table 1: Family and domestic violence events mentioning specific abuse types (*n*=351,178) (cont.)

Abuse type	Events *n* (%)[a]
Possession of personal effects	3,265 (0.9)
Blocking	3,163 (0.9)
Harassment	3,100 (0.9)
Stalking	2,940 (0.8)
Self-harming	2,597 (0.7)
Biting	2,285 (0.7)
Dragging	2,216 (0.6)
Shaking	2,098 (0.6)
Stabbing	1,903 (0.5)
Forced entry	1,779 (0.5)
Headlock	1,482 (0.4)
Chasing	1,324 (0.4)
Kneeing	1,321 (0.4)
Gagging	1,161 (0.3)
Elbowing	225 (0.06)
Limb twisting	173 (0.05)
Headbutting	148 (0.04)
Sexual assault	125 (0.04)
Preventing child access	91 (0.03)
Social restriction	40 (0.01)
Financial control	29 (0.01)
Attempting to set fire to premises	28 (0.01)
Ordering dog attack	1 (<0.01)
Other	7,135 (2.0)

a: Percentages rounded to one decimal point. When percentage <0.1, two decimal points reported

Table 2: Family and domestic violence events according to the number of abuse types mentioned (*n*=351,178)

Number of abuse types mentioned	Events *n* (%)[a]
1	124,498 (35.5)
2	89,342 (25.4)
3–5	118,819 (33.8)
6–9	17,951 (5.1)
>10	568 (0.2)
Total	**351,178 (100.0)**

a: Percentages rounded to one decimal point. When percentage <0.1, two decimal points reported

The most frequent victim injury type identified in the narratives was ‘bruising’ (51,455; 29.0%), followed by ‘cut/abrasion’ (51,284; 28.9%) and ‘red marks/signs’ (42,038; 23.7%) (Table 3). A total of 105,812 FDV events (59.6%) had only one form of injury, and 24.4 percent (43,499) of FDV events had two forms of injury (Table 4).

Table 3: Family and domestic violence events mentioning specific injury types (*n*=177,607)[a]

Injury type	Events *n* (%)[a]
Bruising	51,455 (29.0)
Cut/abrasion	51,284 (28.9)
Red mark(s)	42,038 (23.7)
Swelling	32,581 (18.4)
Soreness	26,729 (15.1)
Bleeding	19,154 (10.8)
Fracture(s)	17,531 (9.9)
Lump	9482 (5.4)
Grazing	7305 (4.1)
Black eye(s)	2994 (1.7)
Scratching	2399 (1.4)
Bite mark(s)	2350 (1.3)
Stab wound(s)	2346 (1.3)
Burn mark(s)	1382 (0.8)
Broken tooth	620 (0.4)
Torn-off nail(s)	7 (<0.01)
Other	19,778 (11.2)

a: Percentages rounded to one decimal point. When percentage <0.1, two decimal points reported

Table 4: Family and domestic violence events according to the number of injury types mentioned (*n*=177,607)

Number of injury types mentioned	Events *n* (%)[a]
1	105,812 (59.6)
2	43,499 (24.4)
3–4	25,717 (14.5)
5–6	2490 (1.4)
≥7	89 (0.05)
Total	**177,607 (100.0)**

a: Percentage rounded to one decimal point. When percentage <0.1, two decimal points reported

Discussion

To our knowledge, this study is the first attempt to automatically capture various forms of abuse and victim injuries in a large corpus of police event narratives using text mining. We captured mentions of injuries for which the victims may have not sought medical attention. While fractures, bleeding and stab wounds may have resulted in admission to hospital or emergency room presentation, and a broken tooth may have required dental attention, most recorded injuries appeared to be less severe and may not have required medical attention and so would not have been identified in reporting mechanisms that rely on contact with the health system. Most of the injuries (eg 'red mark', 'soreness', 'grazing'; Table 1) are likely to have been self-treated and therefore undetected by the health system. Event narratives are therefore likely to represent the only readily available source of data for some types of abuse and injuries associated with FDV events. Thus, the police narratives may be an important source of information on victim injuries to complement FDV surveillance that relies on hospital-based reporting systems. Further work is required to determine the extent of untreated injuries arising from FDV events.

We acknowledge that many forms of abuse and victim injuries are frequently not reported to the police and that the capture of non-physical forms of abuse and injuries such as 'bruising' from the police narratives were mostly the by-product of investigating the FDV events with physical abuse in this study. Yet our findings showing high rates of non-physical forms of abuse—such as 'emotional/verbal abuse' (33.5%) and 'intimidation' (21.6%), and common types of victim injuries of a less severe nature such as 'bruising' (20.3%) and 'red marks' (23.7%)—are supported by previous studies (Muelleman, Lenaghan & Pakieser 1996; Outlaw 2009). Due to the frequency of violence against women in domestic situations, more attention has been given to investigating physical forms of abuse in intimate partner relationships (Outlaw 2009). However, other forms of violence (eg psychological or financial control) have important health and social consequences and may act as warning signs for future physical abuse including potentially serious bodily harm or even murder (Outlaw 2009).

The FDV risk assessment tool currently used in New South Wales, the Domestic Violence Safety Assessment Tool (DVSAT), has limited questions about the type of abuse and no questions about the victim's injuries. It is designed to be used in intimate partner violence (IPV) situations and not for other family relationships. Moreover, a recent evaluation has shown that the overall accuracy of DVSAT to predict the risk of repeat IPV within 12 months is low (Ringland 2018). A meta-analysis examined the validity of 39 FDV prediction tools, concluding that there is significant room to improve the predictive accuracy for the onset and recurrence of FDV (van Der Put, Gubbels & Assink 2019).

Text mining characteristics such as abuse type and victim injuries from police narratives can provide guidance for future data collection practices. This has the potential to enhance recording when officers attend FDV events—for example, by detailing the length and type of the abuse as well as the extent of any injuries. These records can be mined automatically at a later date to examine abuse types and sustained injuries in relation to other characteristics of victims and POIs (eg mental illness) in FDV situations. Further, text mining can be used as the first step in providing data for inclusion in predictive models to investigate the escalation of abuse types and sustained injuries in other FDV events.

Limitations

Our rules identified only the most common forms of injuries and abuse types, and some types of abuse and injuries were therefore not captured (eg acid thrown at a victim, poisoning, malnutrition). We designed our rules based on common syntactical patterns that would attribute abuse types/injury mentions to victims in order to avoid false positives. While the values of recall and precision for abuse types and injuries were high, enhancing the engineered rules will allow for the identification of a wider range of these characteristics. The addition of spellchecking algorithms would assist in identifying any misspelled abuse types or injuries and potentially further improve performance.

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