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Near-miss narratives from the fire service: A Bayesian analysis☆

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ABSTRACT

Background: In occupational safety research, narrative text analysis has been combined with coded surveillance, data to improve identification and understanding of injuries and their circumstances. Injury data give, information about incidence and the direct cause of an injury, while near-miss data enable the, identification of various hazards within an organization or industry. Further, near-miss data provide an, opportunity for surveillance and risk reduction. The National Firefighter Near-Miss Reporting System, (NFFNMRS) is a voluntary reporting system that collects narrative text data on near-miss and injurious, events within the fire and emergency services industry. In recent research, autocoding techniques, using Bayesian models have been used to categorize/code injury narratives with up to 90% accuracy, thereby reducing the amount of human effort required to manually code large datasets. Autocoding, techniques have not yet been applied to near-miss narrative data.
Methods: We manually assigned mechanism of injury codes to previously un-coded narratives from the, NFFNMRS and used this as a training set to develop two Bayesian autocoding models, Fuzzy and Naïve. We calculated sensitivity, specificity and positive predictive value for both models. We also evaluated, the effect of training set size on prediction sensitivity and compared the models' predictive ability as, related to injury outcome. We cross-validated a subset of the prediction set for accuracy of the model, predictions.
Results: Overall, the Fuzzy model performed better than Naïve, with a sensitivity of 0.74 compared to 0.678., Where Fuzzy and Naïve shared the same prediction, the cross-validation showed a sensitivity of 0.602., As the number of records in the training set increased, the models performed at a higher sensitivity, suggesting that both the Fuzzy and Naïve models were essentially "learning". Injury records were, predicted with greater sensitivity than near-miss records.
Conclusion: We conclude that the application of Bayesian autocoding methods can successfully code both near misses, and injuries in longer-than-average narratives with non-specific prompts regarding injury. Such, coding allowed for the creation of two new quantitative data elements for injury outcome and injury, mechanism.

1. Introduction

1.1. Collection and analysis of narrative text

In occupational safety research, narrative text analysis has been combined with coded surveillance data to improve identification and understanding of injuries and their circumstances. Narrative text analysis identifies more target events than can be found using injury codes alone, thus reducing the problem of undercounting—a critical concern in injury surveillance. Further, narrative text analysis provides a means to check coding accuracy, and provides important information on circumstances surrounding injuries and unknown risk factors (Lipscomb et al., 2004; Bondy et al., 2005;

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Smith et al., 2006; Bunn et al., 2008). New risk factors identified through narrative text analysis are an important source of variables to be added to administrative coding systems (Bunn et al., 2008). Narrative data analysis can also be a basis for comparing data among systems and countries that use different coding schemes, or to study historical data that include narrative text (Stout, 1998).

The large-scale study of narrative text has only recently been made possible by advances in computerized information retrieval techniques. This is particularly important for large, growing datasets which adds to increased time, cost and labor, in order to code these narratives. Computerized coding algorithms have enabled large-scale analysis of narrative text, presenting an efficient and plausible way for individuals to code large narrative datasets. Although computer coding is a cost-efficient alternative to manual coding with an accuracy of up to 90%, it does not eliminate the need for human review entirely (Lehto and Sorock, 1996; Wellman et al., 2004; Lehto et al., 2009; Bertke et al., 2012; Patel et al., 2012).

The most critical bottle-neck is that computer coding methods require a learning set of previously coded cases. The accuracy of computer coding also tends to improve when larger training sets are used to develop the algorithms. The latter issue is especially important when the coded categories differ greatly in frequency, as it may become difficult to obtain enough training cases for the small, rarely occurring codes. For this and other reasons, computer coding algorithms tend to predict some codes much more accurately than others. One solution strategy is for the coding algorithm to assign the “easy” cases and flag the remaining potentially ambiguous cases for human review (Lehto et al., 2009). This approach allows computer coding errors to be efficiently identified and corrected during use. The results of the human review can also be fed back into the system, allowing the model to learn over time after implementation.

1.2. The importance of near-miss data

A near-miss is an incident that had the capacity to cause injury but did not, due to either intervention or chance (Aspden et al., 2004). Both injury and near-miss data are important to collect in surveillance systems. While injury data give information about incidence and the direct cause of an injury, near-miss data enable the identification of various hazards within an organization or industry while providing an opportunity for surveillance and risk reduction. Near-miss narratives in particular provide insight to the upstream causes of injury (Rivard et al., 2006). Near-miss reporting can capture the successful recovery from potentially harmful incidents. In the field of healthcare, research has found that even a few reports can be sufficient to detect and communicate a hazard that is actionable for prevention (Leape, 2002) and prompt an organizational response. Importantly, near-misses occur more frequently than adverse events (Barach and Small, 2000), and can be combined with injuries to increase statistical power for analysis as supported by the common cause hypothesis (Alamgir et al., 2009).

1.3. Purpose of this study

Injury narratives are frequently coded for mechanism of injury (using ICD-9-CM or ICECI codes), but there is an absence of literature that addresses application of mechanism-of-injury coding to near-miss narratives. In theory, assigning a mechanism-of-injury code to a near-miss narrative should be straight forward—the reporter explains briefly the circumstances, what led to the event, and why it was a near-miss. Coding of near-misses will help to construct hazard scenarios, and inform development of appropriate interventions to prevent future injury and harm (Lincoln et al., 2004).

Our objective was to manually code narratives from the National Firefighter Near Miss Reporting System (NFFNMRS) and use this coded set to train a computer algorithm to assign mechanism of injury codes to un-coded narratives. Since no variable currently exists on the NFFNMRS reporting form to capture the presence or absence of an injury, the study also sought to create a quantitative variable to identify injury and near-miss events.

2. Method

2.1. Data source

In order to improve understanding of the circumstances leading to firefighter injuries, the International Association of Fire Chiefs (IAFC) (with funding from the Assistance to Firefighters Grant Program of the U.S. Department of Homeland Security) launched the NFFNMRS in 2005. Reporting to the system is voluntary and non-punitive. The NFFNMRS defines a near-miss as “an unintentional, unsafe occurrence that could have resulted in an injury, fatality, or property damage” (www.firefighternearmiss.com). Despite this definition, the NFFNMRS captures a number of actual injuries, including fractures, back injuries, hypothermia, burns, and cyanide poisoning, as well as melted equipment and destroyed engines.

The reporting form consists of 22 fields. Two of these fields are narrative sections, asking the reporter to “Describe the event”, and to share “Lessons Learned”. Within these fields, reporters can submit as much text as they wish.

2.2. Selection of narratives for manual coding

The quantitative component of the near-miss forms contains a field called “Event Type” in which the reporter selects whether the incident occurred during a fire emergency event, a vehicle event, a training activity, etc. (the form can be viewed at http://www.firefighternearmiss.com/Resources/NMRS-Mail.pdf). In order to reduce cognitive shifts required for coding of different event types (hazards described in vehicle event narratives are different than those in fire event narratives), we limited our analysis to only include those indicated as fire emergency events, as identified by the reporter. This data set contained 2285 narratives. Of these “Fire Emergency Events”, we manually coded 1000 narratives, which resulted in 764 fire-related events considered suitable as training narratives for the algorithm. The 236 narratives discarded from the training set were not “Fire” related cases (e.g., neither the precipitating nor proximal cause was a fire event), or they were fire-related but lacked specific information for sub-categorization (e.g., fire-burn, fire-struck-by/against), or they fell into a category that ended up having fewer than five narratives (e.g., motor vehicle-rollover, hot substance or object, caustic or corrosive material, and steam). Fig. 1 shows the case inclusion criteria for our analysis.

2.3. Manual coding rubric

The initial rubric was a set of mechanism of injury codes from the International Classification of Disease 9 Clinical Modification Manual (ICD-9-CM), selected by the Principal Investigator (JAT) as codes that were possible within the fire-fighting/EMS occupational field. The rubric was modified over time in an iterative, consensus-driven process. Whenever a change was made the Project Manager (AVL) went back over the previously coded narratives and amended the code in accordance with the revised rule when necessary. A precipitating mechanism (what set the injury chain of events in motion) and a proximal mechanism (what caused the injury or near-miss) were assigned to each narrative.