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Automated identification of wound information in clinical notes of patients with heart diseases: Developing and validating a natural language processing application

Maxim Topaz[a,b,*], Kenneth Lai[a], Dawn Dowding[c,d], Victor J. Lei[a], Anna Zisberg[e], Kathryn H. Bowles[c,f], Li Zhou[a,b]

[a] Brigham and Women's Hospital, Boston, MA, USA
[b] Harvard Medical School, Boston, MA, USA
[c] Visiting Nurse Service of New York, NY, USA
[d] School of Nursing, Columbia University, NY, USA
[e] The Cheryl Spencer Department of Nursing, Haifa University, Israel
[f] School of Nursing, University of Pennsylvania, PA, USA

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ABSTRACT

Background: Electronic health records are being increasingly used by nurses with up to 80% of the health data recorded as free text. However, only a few studies have developed nursing-relevant tools that help busy clinicians to identify information they need at the point of care.
Objective: This study developed and validated one of the first automated natural language processing applications to extract wound information (wound type, pressure ulcer stage, wound size, anatomic location, and wound treatment) from free text clinical notes.
Methods and design: First, two human annotators manually reviewed a purposeful training sample (n = 360) and random test sample (n = 1100) of clinical notes (including 50% discharge summaries and 50% outpatient notes), identified wound cases, and created a gold standard dataset. We then trained and tested our natural language processing system (known as MTERMS) to process the wound information. Finally, we assessed our automated approach by comparing system-generated findings against the gold standard. We also compared the prevalence of wound cases identified from free-text data with coded diagnoses in the structured data.
Results: The testing dataset included 101 notes (9.2%) with wound information. The overall system performance was good (F-measure is a compiled measure of system's accuracy = 92.7%), with best results for wound treatment (F-measure = 95.7%) and poorest results for wound size (F-measure = 81.9%). Only 46.5% of wound notes had a structured code for a wound diagnosis.
Conclusions: The natural language processing system achieved good performance on a subset of randomly selected discharge summaries and outpatient notes. In more than half of the wound notes, there were no coded wound diagnoses, which highlight the significance of using natural language processing to enrich clinical decision making. Our future steps will include expansion of the application's information coverage to other relevant wound factors and validation of the model with external data.

What is already known about the topic

- There were significant advances in the field of medical natural language processing (or automated information extraction from narrative clinical notes) over the past two decades.
- To date, no studies have explicitly focused on the feasibility of using natural language processing methods to process wound information.

What this paper adds

- We developed and validated one of the first automated natural language processing applications to extract wound information (wound type, pressure ulcer stage, wound size, anatomic location, and wound treatment) from free text clinical notes.

* Corresponding author at: 93 Worcester St., Wellesley Gateway, Suite 2030I, Wellesley, MA, 02481 USA.
E-mail address: mtopaz80@gmail.com (M. Topaz).

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- In more than half of the wound notes, there were no coded wound diagnoses, which highlight the significance of using natural language processing to enrich clinical decision making.

1. Introduction and background

Wounds, defined as injuries to soft tissues that can vary from minor tears to severe crushing wounds, and can be acute or chronic in nature (O'Connell Smeltzer et al., 2010). In general, acute wounds (e.g., skin graft donor sites, partial thickness burns, and posttraumatic or surgical wounds) heal in an orderly and timely fashion. On the other hand, chronic wounds (e.g., leg ulcers, pressure ulcers and diabetic foot ulcers) take longer to heal as a result of impaired tissue repair due to malnutrition, infection, or poor oxygenation (Chaby et al., 2007). Wounds are a key issue in terms of morbidity and quality of life. It has been estimated that in the United States, Medicare spent $2.4 billion on hospital stays for infections of surgical and traumatic wounds and disruption of surgical wounds in 2005 (Schwien and Lang, 2008), and that the cost of treating chronic wounds exceeds $50 billion per year (Fife et al., 2012). International studies support the high prevalence and increasing costs of wound treatments (Hurd and Posnett, 2009; Posnett and Franks, 2016; Vanderwee et al., 2007). Wounds are more common among several clinical populations, such as patients with cardiac diseases (this study's patient population) (Sen et al., 2009). A significant proportion of wound patients require hospitalization or emergent care within 30 days of their hospital admission; in a recent study, having a skin ulcer or wound was the largest predictor of a patient being re-hospitalized (Westra et al., 2013). With the increase in age of the world's population, together with a rise in comorbidities (e.g., obesity, diabetes and venous insufficiency), the number of individuals with chronic wounds is estimated to rise in the near future (Werdin et al., 2009). Thus, identifying patients with wounds to ensure timely interventions and appropriate management is of key importance in health care settings.

In general, health practitioners tend to record up to 80% of health information as free text (Murdoch and Detsky, 2013). Free text documentation is very common in nursing, in part, due to poor usability and lack of standards in electronic health record systems and also because it is hard to capture all the nursing-sensitive information as structured data (Cho et al., 2016; Farber et al., 2007). Although large databases of health and wound specific information exist on local and national levels, only a fraction of this data is captured in a standardized structured format (Ross et al., 2014; Roth et al., 2009). Free-text narratives can help clinicians make a better sense of the patient's wound status (Rosenbloom et al., 2011), using unstructured data may limit the quality and safety of care by increasing the time required to find the relevant data or reducing the ability to use computer-aided applications, such as clinical decision support. Also, our ability to conduct much-needed wound research (i.e. identifying optimal treatments for different types of wounds) with free-text data is limited.

Recently, novel informatics methods have been increasingly applied to large health data sources for data standardization and extraction (Ross et al., 2014). One promising technique- an automated natural language processing (NLP)- can potentially assist in processing free-text wound information in clinical notes. In previous studies, NLP has been successfully used to extract family history data (Zhou et al., 2014), medication information (Zhou et al., 2011), radiology findings (Pham et al., 2014), and other health information from different types of clinical notes (Demner-Fushman et al., 2009; Meystre et al., 2008). To our knowledge, no studies have explicitly focused on the feasibility of using natural language processing methods to process nursing-sensitive data, such as wound information in clinical notes.

The goal of this study was to develop and validate an NLP-based approach to automatically extract wound information (including wound type, pressure ulcer stage if applicable, wound size, anatomic location, and wound treatment) from free-text clinical narratives. We also assessed the performance of the NLP application designed to summarize wound-related information on a corpus of discharge summaries and outpatient notes.

2. Methods

For the purposes of this study, a wound was defined as any skin lesion, regardless of external (e.g., trauma) or internal (e.g., venous hypertension with its secondary consequences to skin integrity) etiology. Several preparatory steps for this study included data collection and building a wound minimum-dataset information model. Our NLP system development and testing methods are summarized in Fig. 1. We first manually reviewed a purposeful training sample and random test sample of clinical notes (including discharge summaries and outpatient notes), identified wound cases, and created a gold standard dataset with the help of domain experts (Steps 1–2). We then trained our NLP system (known as MTERMS) (Zhou et al., 2015, 2014, 2011) to process the wound information and applied our system on a randomly selected sample of clinical notes (Steps 3–4). Finally, we assessed our automated approach by comparing system-generated findings against the gold standard (Step 5). We also identified coded wound diagnoses and compared wound cases identified from free-text data with coded diagnoses in the structured data (Steps 6–7).

2.1. Natural language processing engine description

In this study, we utilized our natural language processing system called Medical Text Extraction, Reasoning and Mapping System (MTERMS). MTERMS applies advanced methodologies and technologies in computer science, artificial intelligence, computational linguistics, and biomedical informatics to conduct text analytics. MTERMS' natural language processing engine consists of both computational and knowledge components. It uses a modular, pipeline approach to conducting linguistic analyses at different linguistic structure levels (i.e., words, phrases, paragraphs, sections and whole notes) while handling abbreviations and lexical variations. MTERMS' engine generates structured output in a standard, interoperable documentation format that can be used for subsequent applications. The system was previously validated for identifying clinical terms within narrative health records in order to extract medications, clinical problems (e.g., presence of depression), family history, and so forth, with high accuracy metrics (Zhou et al., 2015, 2014, 2011).

2.2. Preparatory steps

2.2.1. Data collection

We used a retrospective cohort of patients from an ongoing study focusing on identifying factors associated with readmissions. Patients in this cohort had a history of ischemic heart disease and were hospitalized between 01/01/2011 and 12/31/2013 at different hospitals in Partners Healthcare System, a large integrated healthcare network in Boston, Massachusetts, United States. The database included about 120,000 distinct patients and 3 million notes generated over 2 years of the study period. This study was approved by Partners Institutional Review Board (IRB) at Partners Healthcare System.

Because of a relatively low general distribution of wound information in clinical notes (about 10% of patients), we first