

Text mining electronic health records to identify hospital adverse events

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Conclusions and perspectives

- It is possible to use text mining to identify common adverse events, and in particular to develop algorithms which exclude health records of patients without problems.
- Developing good algorithms takes time, and requires both understanding of complex clinical texts and use of advanced text analytics.
- Extraction of key information from narrative texts in electronic health records can be used for monitoring patient safety, but also has wider perspectives.

Background

Using the IHI *Global Trigger Tool* (GTT) to conduct structured reviews of health records to identify adverse events consumes costly human resources.

We are developing an IT-tool based on natural language processing (NLP) of the unstructured and semi-structured narrative texts in electronic health records to identify common triggers as well as some adverse events.

Methods

Data

About 500 randomly selected health records had been manually analysed from April 2010 through May 2012 as part of a routine use of GTT to monitor patient safety in a 450-bed acute care hospital.

All narrative texts in these records were extracted to a corpus of XML-files.

Software

- We use the SAS® *Text Miner* and the SAS® *Enterprise Content Categorization* to build algorithms.
- We build module-based algorithms with clinically specific word lists, and Boolean operators.
- The algorithms typically read 500 records in about 15 seconds.



Results

We are working with the 12 most common triggers and adverse events found in the records using GTT, including use of anti-emetic medications, pressure ulcers, hospital-acquired infections and patient falls.

Example: Pressure ulcers

GTT	Text mining		Total
	Yes	No	
Yes	28	12	40
No	22	436	458
Total	50	448	498

Assuming that the GTT gives the truth, the positive predictive value of finding a pressure ulcer using text mining is only 56% (95-Cl: 42% to 69%), but the negative predictive value is high: 97% (95-Cl: 95% to 99%), i.e. the probability of a patient having a pressure ulcer is low if the text mining algorithm scores negative.

When we manually *re-reviewed* the medical records used in the study, the original GTT-results were frequently questionable, and the text mining algorithms are often doing better in 'approaching the truth' about adverse events; e.g. many of the 12 'false negative' and 22 'false positive' findings in the table above were true.

The algorithms have been tested with about 250 new health records and perform well when compared to findings by humans.

Challenges

- *The narrative texts.* Writings by physicians and nurses in health records are often informed telegram style notes with many acronyms and context-dependent abbreviations, and with spelling errors.
- *Time.* Developing good algorithms requires repetitive cycles of modifying word lists etc., running the algorithms and manually controlling the findings.
- *Brought in or acquired?* It is difficult, for humans as well as for computer algorithms, to distinguish between conditions present on admission and problems acquired during a hospital stay.

See more information about this study —



:: link to a website::