Text Mining Patient Safety Data

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Overview

My PhD work focused on modelling incident reporting in the NHS.

Webinar will cover:

- What is 'patient safety' and 'incident reporting'?
- Overview of text mining
- Introduce the `tidytext` package and approach
- Introduce topic models
- Show how this has been applied to incident reporting to:
  - Visualise preparation
  - Visualise terms in reports
  - Model topics
  - Use topics to predict harm-level of incident report

Using Julia Silge's excellent Sherlock Holmes tutorial as examples: https://github.com/juliasilge/sherlock-holmes

Material: https://github.com/chrismainey/Text_Mining_NHS_Incident_Reports

Sponsorship and supervision

- Supervised by:
  - Prof. Nick Freemantle - UCL
  - Dr Milena Falcaro - UCL / King's
- Sponsored by UHB
- UHB input:
  - Prof. Daniel Ray
  - Prof. Simon Ball
  - Dr David McNulty
- Data and insight from NHS Improvement
  - Dr Frances Healy
  - Dr Julia Abernathy
  - Ms Noreen Gul

Patient Safety and Incident Reporting

- Prevention of errors and adverse effects to patients associated with health care - *World Health Organisation*
- Increasingly prominent in NHS, after 'An Organisation with memory' ***(Donaldson, 2000)***
- Incident reporting is seen as a pillar of this:
  - Based on other industries
  - Not implemented in same way ***(Macrae, 2015)***
  - Should be a cue for further investigation
  - 'Tip of the iceberg'
  - Incidents represent multiple failures of systems

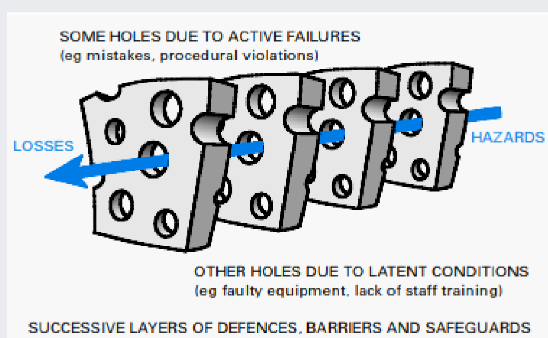


Figure from ***Donaldson (2002)***, based on ***Reason (1990)***. Defensive systems as solid parts of each slice, holes are vulnerabilities. Adverse events often result of alignment of several system weaknesses, represented by blue arrow.

The National Reporting and Learning System (NRLS)

Incidents:

"Any unintended event caused by the health care that either did or could have led to patient harm" ***(Sari et al., 2007)***

- Local incident reporting systems, e.g. Datix
- Mapped and submitted to national system (NRLS)
- Examples of learning:
  - Risks in airway management between critical care and other settings ***(McGrath and Thomas, 2011)***
  - Drug-related errors are commonly about wrong administration ***(Cousins et al., 2012) (Franklin et al., 2014))***
  - Risks of shock and death using bone cement for fractured neck of femur surgery ***(Rutter et al., 2014)***
- Major problems with data, including completeness, anonymisation, quality of reports etc.

How is it used?

- Quarterly and monthly figures
  - Counts
  - Is high number of reports good or bad?
  - Different size organisations?
  - Major part of my work was developing risk-adjustment methods to improve this

- Manual reading of incident reports:
  - Trained clinical reviewers
  - Qualitative methods
  - NRLS cannot be an exhaustive source
  - Specific targets, or random samples?

See the problem?

- Real signal is in free-text
- Regulator is only able to review 0.5%, representing severe harm or death

“The number of reports received is … huge, so that raises the question of how can we analyse them all properly. Decisions therefore need to be made as to whether we need tighter rules on incident reporting, and the distinction between local and national level reporting and follow-through’

Prof. Sir Liam Donaldson, (Francis, 2013).

What if we can use text mining methods to help?

Previous work

- PhD project on text mining ***(Bentham, 2010)***
    - Rendered as high-dimensional matrix then PCA to reduce dimensionality
    - Anomaly detection based on proximity of clusters in feature space
- Commercial partnerships
    - Text mining using LDA and word-clouds on local data ***(Mastodon C, 2019)***
- Local hospital data in graph model based on paragraph embeddings ***(Altuncu et al., 2019)***
    - Technically challenging, but corresponds well with 'hand-coding'
- Primary care application ***(Evans et al., 2019)***
    - Words transformed as inputs for regression trees, SVM and Naive Bayes.

My work

Used the `tidytext` package, as easy entry point ***(Silge & Robinson, 2016)***

Used the 'bag-of-words' approach:

- No semantics
- Order not important, just presence
- No negation

Spelling, and jargon!

- Jargon is a major part of clinical noting
- No validation!
  - Some reports single letters (despite not being allowed) ***(Bentham, 2010)***
  - Application errors, including code fragments ***(Bentham, 2010)***
  - One team found 371 ways of spelling "clostridium difficile" ***(Mayer et al., 2017)***

Example 1:

Processing Sherlock Holmes data

Processes

The text was imported from SQL database in a single column, several million rows, each representing a unique incident report. The preparation steps were:

- Import to R (watch out for ODBC and varchar(max))!
- Convert to lower case
- Tokenise (split into words, n-grams, or "skip-grams")
- Remove stop words
- Remove additional known 'noise' including possessive endings and non-alpha numeric characters
- Remove dominant word 'patient' and abbreviation 'pt'
- Stemming - reducing variant endings on words (using `SnowballC` stemmer)

- Visualise: plots, word-clouds etc.
- TF-IDF? Didn't really help, too many documents and rare words
- Topic models
- Use topics as predictors of harm

Preparation

```
tidy_dt <- mydataframe %>%
  unnest_tokens(word, Descrip, token = "words") %>%
  as.data.frame() %>%
  anti_join(get_stopwords()) %>%
  mutate(word = ifelse(word=="pt", "patient", word)) %>%
  filter(!str_detect(word, "patient")) %>%
  mutate(word_clean = str_replace_all(word,"\u2019s|'s","")) %>%
  mutate(word_clean = ifelse(str_detect(word_clean,"[^[:alpha:]]"),NA,word_cl
  filter(!is.na(word_clean)) %>%
  add_count(word_clean)


#### Stem ####
library(SnowballC)

tidy_dt2<-tidy_dt %>%
  mutate(word_stem = wordStem(word_clean, language="english"))
```

Visualise

Whichever method you like!

You could use "word-clouds":

```
library(wordcloud)
library(RColorBrewer)

# Set up a palette
pal2 <- brewer.pal(8,"Dark2")

tidy_dt2 %>%
  count(word_stem) %>%
  with(wordcloud(word_stem, n, max.words = 100#, color="#E76BF3"
                 , random.order = FALSE, colors=pal2, rot.per = 0, fixed.asp
```

Can be a bit tricky with window size etc.

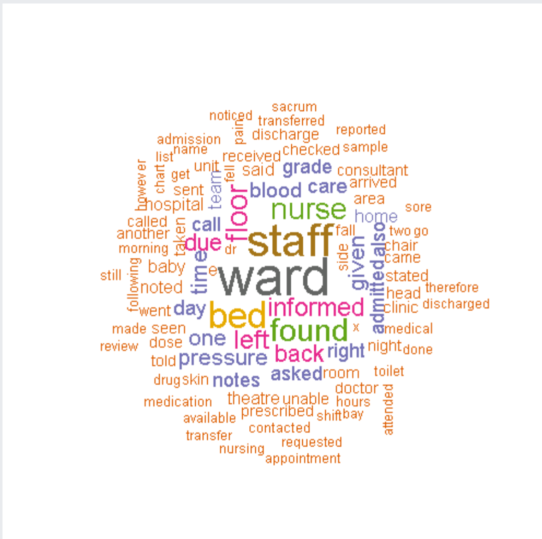
Processing word-clouds (1)

Simply Tokenised

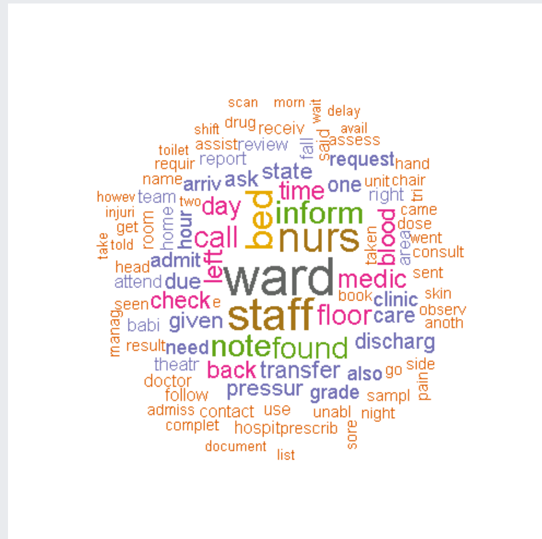
Cleaned

Processing word-clouds (2)

Cleaned, and stop-words removed

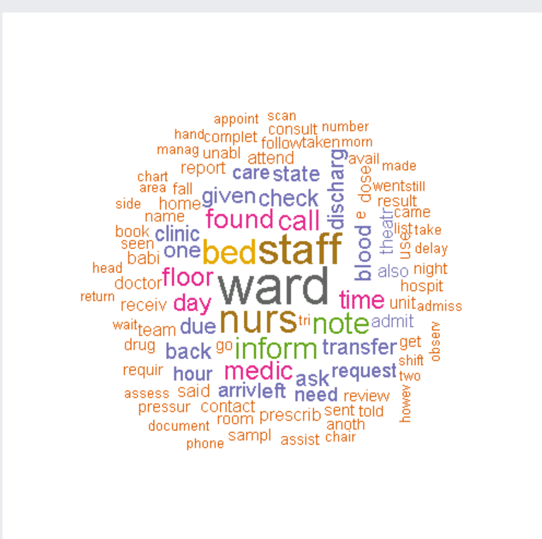


Cleaned, stop-words removed, and stemmed

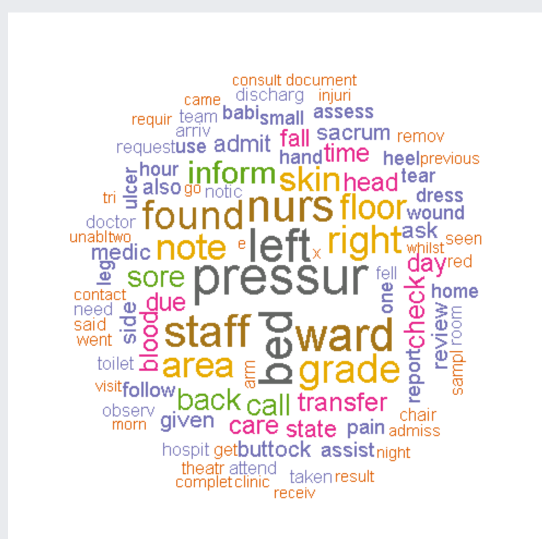


Words by Harm-level (1)

No Harm

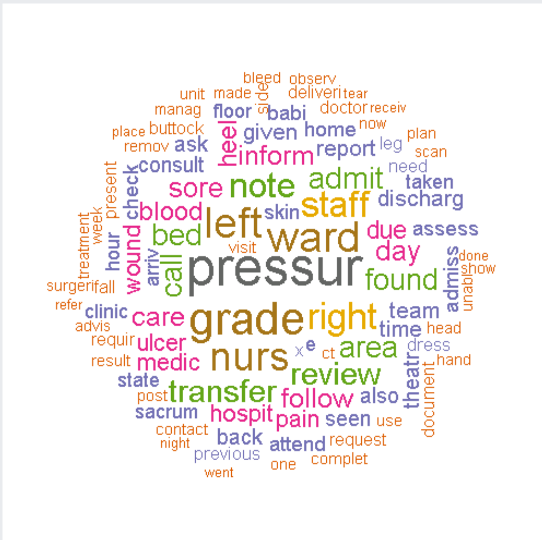


Low Harm



Words by Harm-level (2)

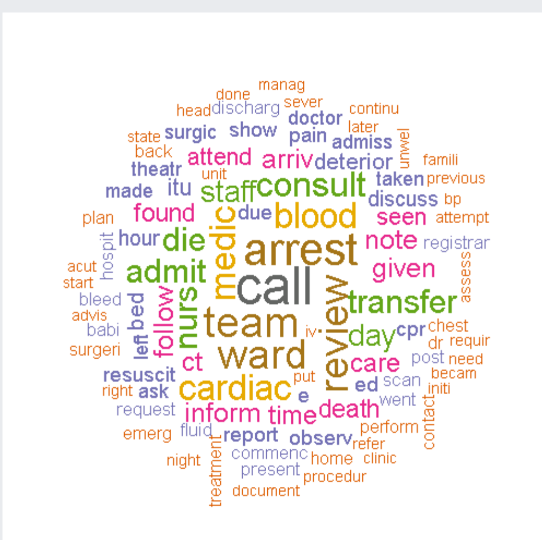
Moderate Harm



Severe Harm

Words by Harm-level (3)

Death



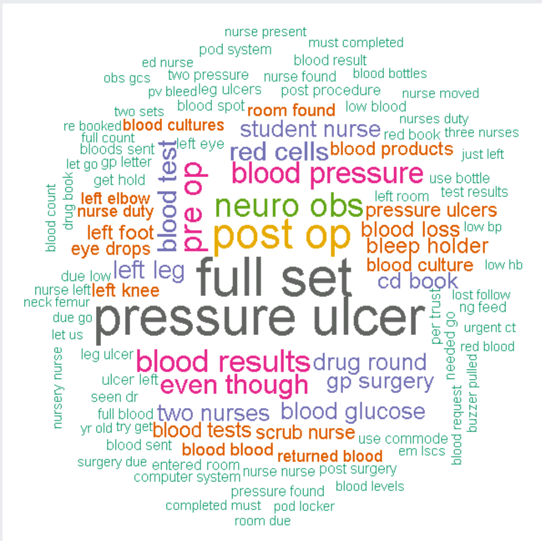
- "patient" dominated, removed in cleaning and "PT" mapped to "patient"
- "pressur" prevalent in lower harm incidents
- "cardiac" prevalent in severe and death incidents

- words associated with beds, staffing and transfer were common in most levels of harm.

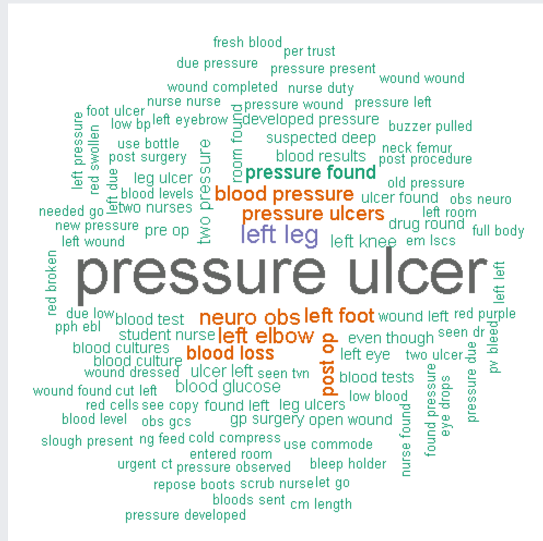
- Size of groups varies hugely

Skip-grams by Harm-level (1)

No Harm

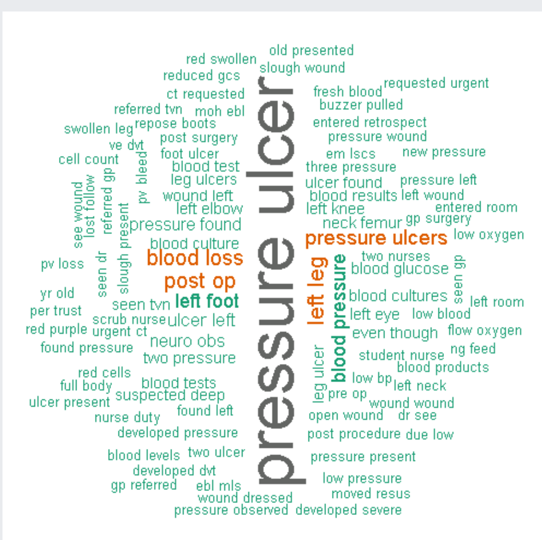


Low Harm

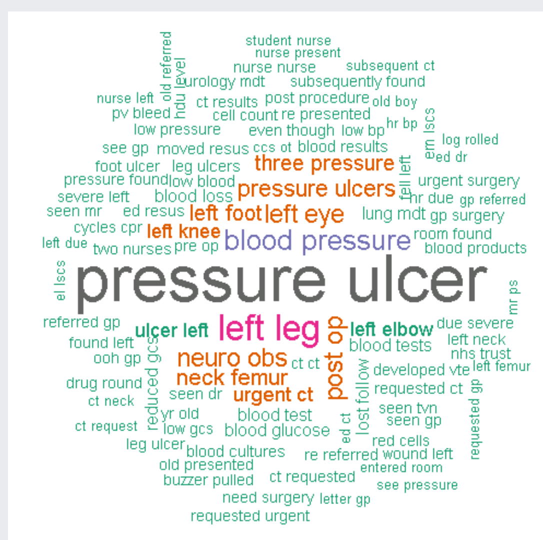


Skip-grams by Harm-level (2)

Moderate Harm

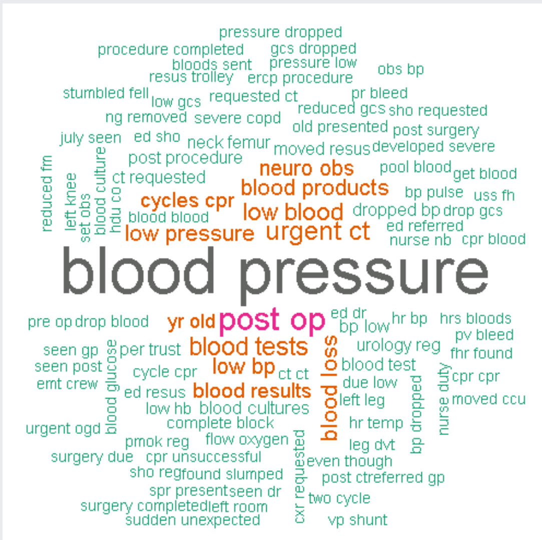


Severe Harm



Skip-grams by Harm-level (3)

Death



- removed single letters
- "blood pressure" and "pressure ulcer" differentiated
- "neuro obs" common in most levels of harm
- "left" side incidents surprisingly common

- skip-grams, even naively constructed, can differentiate between terms that share words

Topic Modelling

- Various methods, commonly: Latent Dirichlet Allocation (LDA) *(Blei, 2003)*
- Unsupervised model:
  - Generative probabilistic model
  - Three-level structure of terms/words, topics and documents
  - Words distributed across topics, topics distributed across documents
  - Probability of topic, not classification.

- How many topics?
  - Can model as many as you like
  - Various metrics, cross-validation
  - `ldatuning` package is a good option *(Murzintcev, 2019)*

- Can then be use to predict:
  - probability topic represents document (γ)
  - probability word represents a topic (β)

Example 2:

Topic model for Sherlock Holmes

LDA

Applying this to the NRLS data:

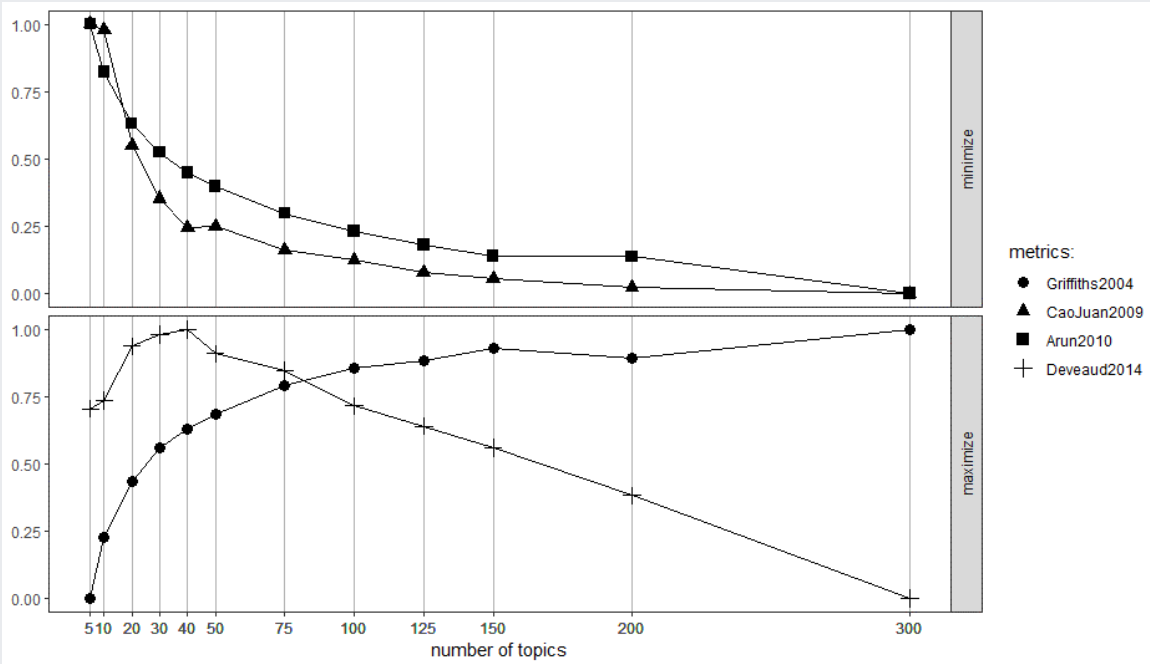
```
library(topicmodels)
library(ldatuning)

dtm<- tidy_dt %>% count(ID, word, sort = TRUE) %>% cast_dtm(ID, word, n)

lda40 <- LDA(dtm, k = 40, method="Gibbs",control=list(seed=123, verbose=1))

LDAtopics <-
  FindTopicsNumber(
    dtm,
    topics = c(5, seq(10, 50, 10), seq(75, 150, 25), 200,300)
    metrics = c("Griffiths2004",
                "CaoJuan2009", "Arun2010", "Deveaud2014"),
    method = "Gibbs",
    control = list(seed = 77, verbose=1),
    mc.cores = 3L,
    verbose = TRUE
  )
```

Topics



LDA models:

- Words: 40, 100 & 150
- Skip-grams: 20, 30, 40 & 50

Used γ predictions in multiclass classification model for harm level:

- **Naive Bayes** - essentially conditional mean predictors, using `naiveBayes` from `e1071`
- **Multinomial regression** - using `multinom` from `nnet`
- **LASSO regression** - penalized regression that shrinks non-predictive inputs to avoid over-fitting, using `cv.glmnet` from `glmnet` (beware, this requires a model matrix input, not a formula interface)
- **Random Forest** - boostrapped regression trees (and resampled predictors) using `randomForest`, `h2o`, and `caret`
- **Gradient Boosting** - boostrapped regression trees re-weighted on residuals, using `gbm`, `h2o`, and `caret`
- **Neural network** - using various multi-layer perceptrons, build using using `keras`

LDA Words results:

	Naïve Bayes			Multinomial Regression			Lasso			Random Forest			Gradient Boosting		
Topics	40	100	150	40	100	150	40	100	150	40	100	150	40	100	150
Accuracy															
Total	55.34%	48.08%	44.11%	77.23%	77.52%	77.72%	77.23%	77.52%	77.71%	82.66%	81.40%	80.80%	81.43%	79.61%	79.65%
True Positive Rate (Sensitivity)															
No Harm	55.10%	47.06%	42.19%	95.92%	95.90%	95.93%	95.92%	95.90%	95.94%	96.20%	96.29%	96.91%	96.34%	94.25%	94.71%
Low Harm	62.37%	55.41%	53.66%	24.23%	25.65%	26.37%	24.21%	25.63%	26.34%	46.01%	41.43%	36.94%	41.40%	40.43%	38.84%
Moderate	14.22%	22.21%	24.01%	1.05%	1.04%	1.41%	1.06%	1.01%	1.39%	14.02%	4.74%	2.53%	4.79%	3.37%	4.41%
Severe	9.46%	16.88%	19.85%	0.03%	0.23%	0.25%	0.03%	0.20%	0.23%	25.17%	10.07%	5.24%	10.19%	9.41%	10.22%
Death	56.39%	72.38%	75.44%	1.36%	2.93%	3.33%	1.36%	2.24%	2.93%	39.46%	20.75%	17.21%	21.09%	23.67%	25.85%
True Negative Rate (Specificity)															
No Harm	77.55%	82.65%	84.73%	24.20%	25.46%	26.13%	24.18%	25.44%	82.16%	45.23%	39.81%	35.22%	39.79%	39.61%	38.23%
Low Harm	67.03%	69.89%	70.49%	95.23%	95.22%	95.28%	95.24%	95.22%	63.47%	95.33%	95.45%	96.15%	95.49%	93.32%	93.83%
Moderate	95.29%	93.01%	91.75%	99.91%	99.91%	99.88%	99.90%	99.91%	61.98%	100.00%	100.00%	100.00%	100.00%	99.94%	99.92%
Severe	97.28%	96.38%	95.09%	100.00%	100.00%	100.00%	100.00%	100.00%	83.92%	100.00%	100.00%	100.00%	100.00%	99.99%	99.99%
Death	94.06%	86.39%	83.93%	99.99%	99.98%	99.98%	99.99%	99.98%	88.58%	100.00%	100.00%	100.00%	100.00%	99.99%	100.00%

- Naive Bayes performed worst, but was conservative due to imbalance
- Random Forest showed best performance

LDA skip-gram results:

	Technique							
	Random Forest				Gradient Boosting			
Topics	20	30	40	50	20	30	40	50
Accuracy								
Total	74.21%	74.04%	74.01%	73.97%	73.48%	73.49%	73.52%	73.54%
True Positive Rate (Sensitivity)								
No Harm	99.03%	99.20%	99.26%	99.41%	98.79%	98.94%	98.94%	99.04%
Low Harm	7.20%	6.08%	5.85%	5.21%	5.32%	4.88%	5.01%	4.75%
Moderate	3.12%	2.26%	1.87%	1.57%	0.23%	0.26%	0.36%	0.42%
Severe	5.11%	3.73%	3.26%	2.70%	1.12%	1.20%	1.12%	1.20%
Death	9.72%	7.15%	5.70%	4.58%	3.46%	3.13%	2.68%	3.24%
True Negative Rate (Specificity)								
No Harm	7.54%	6.33%	6.03%	5.35%	5.59%	5.13%	5.24%	5.00%
Low Harm	98.77%	98.97%	99.04%	99.21%	98.50%	98.68%	98.68%	98.79%
Moderate	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Severe	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Death	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

- Skip-gram models performed poorer than words
- Random Forest still best performing model

Conclusions

Incident reporting is big target for text mining!

- Word-based models are easy to implement, `tidytext` is a great way to access it if you know `tidyverse`
- Skip-grams and words together allow differentiation in terms
- Dictionaries of medical/patient safety terms would aid these techniques
- Better validation from submitting Trusts would aid models

- LDA models were helpful for predicting harm level to 82.7%
- Class imbalance is an impediment to many methods, including predicting harm
- More complicated models have also been demonstrated, but topic modelling performed as well as,or better, than other methods.

Where to next?

- Compare topics to clinical review/hand-coding
- Word/paragraph embeddings / Fast-text are next steps
- Identify clusters in feature-space:
  - Targets for review
  - Validate models
- Identify similar/related incidents
- Improve searches for incidents in data

Thank you for your time!

I hope this encourages you to try and apply these methods for yourself!

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