

Natural Language Processing for Incident Learning in Radiotherapy

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Outline

Natural
Language
Processing for
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Learning in
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Hui Wang,
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Background

Incident
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Objectives

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1 Background

- Incident Learning
- Incident Reporting
- Incident Investigation
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Incident Learning

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- In radiotherapy, incident learning and reporting improve the quality of care by **reducing the recurrence** of unintended incidents and accidents.

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- During reporting, incidents are described in **free-form text**, which is difficult to analyze in large amounts.

Example

Noticed by nutritionist (pt had app. with support group) that patient needed to be evaluated for skin reaction. Patient noticed after her treatments were completed that her skin broke down, she tried to contact treatment unit and/or Rad Onc. on call with no success. Pt even presented herself x1 but left due to lengthy wait time.

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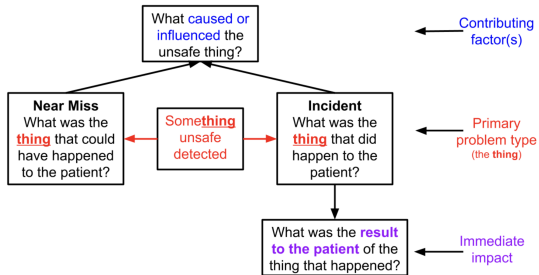
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Incident Investigation



- 9 process steps
- 25 problem types
- 21 contributing factors

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- People may rush through investigations.
 - "Other"
 - 20% of process step
 - 40% of problem type
 - 11% of contributing factors

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- This project aims to create a dropdown menu where the choices are ordered by decreasing likelihood with supervised learning.

(a)

Report an Incident

Incident: An incident is any unwanted or unexpected change from a normal system behaviour that causes, or has the potential to cause, an adverse effect to patients or residents. This includes reportable circumstances and near-misses.

Instructions: All of the fields on this entry report are mandatory for online submission. Please use the ID number provided to you upon successful submission of an online report. You may use this number to follow up on the incident during the investigation phase. Please note that an email will be sent to notify the associated physician for near-misses and actual incidents. For complete instructions on reporting incidents, please refer to the [reporting on Dapline](#).

Type of Report:

Event Type:

Functional Work Area:

How Incident was Detected:

Time Period Detected:

Incident Description: Briefly summarise the incident. Please avoid judgement, analysis, or speculation.

Incident Description: One sentence description of the incident.

Reported By:

Coordinator Comments: Additional coordinator comments (optional).

Staff Support Required?:

Investigation:

Username: Password:

(b)

Incident #999999 Investigation

Incident #99999

Incident Description: Description of a fake incident used for demonstration purposes. --Description Viewable for this Incident --Date Incident was Detected: Jan 1, 2017

Coordinator Comments: Comments added to incident description by senior therapist provided here.

Missing Information required to complete the investigation: Diagnostic Report, Labnor Medical History, Primary Problem Type, Contributing Factors, Radiation Treatment Techniques, Total Dose Prescribed (Gy), Number of Fractions Prescribed, Number of Fractions Delivered, Comments

Email Notifications: You are currently subscribed for email updates about this incident. [Click here to unsubscribe](#)

Instructions: Please refer to the [Incident on Dapline](#)

Patient Signature: The instructions on how patient disclosure should be carried out, please refer to the [RAH policy posted on Dapline](#)

Local Follow-up:

Reported Information:

HSIS-IT Section 1: Incident Impact:

HSIS-IT Section 2: Incident Classify:

HSIS-IT Section 3: Patient Characterisation:

HSIS-IT Section 4: Incident Details:

HSIS-IT Section 5: Treatment Delivery:

HSIS-IT Section 6: Incident Investigation:

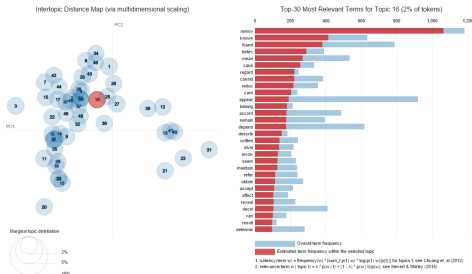
Patient and Staff Support:

Testable Actions:

Comments:

Objectives

- This project also aims to use unsupervised learning to cluster similar incident. This may enable the investigators to identify incidents that have recurred the most without classifying each incident.



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2 Preliminary Analysis

■ Datasets

■ Overview

Datasets

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- McGill University Health Centre (MUHC)
 - 734 incidents
 - NSIR-RT mapping
- Canadian Institute for Health Information (CIHI).
 - 2428 incidents
 - Translate

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2 Preliminary Analysis

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■ Overview

Overview

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■ Process Step

Treatment delivery	34.82
Other	20.05
Contouring and planning	18.12
Imaging for treatment planning	13.12
Patient medical consultation and physician assessment	6.55
Pre-treatment quality assurance	4.27
Radiation treatment prescription scheduling	1.42
On-treatment quality assurance	1.01
Interventional procedure for planning and/or delivery	0.38
Post-treatment completion	0.25

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■ Problem Type

Other	40.32
Wrong patient position, setup point, or shift	15.37
Radiation therapy scheduling error	10.56
Wrong, missing, mislabeled, or damaged treatment accessories	9.77
Excess imaging dose	3.35
Systematic hardware/software (including dose-volume) error	3.10
Wrong target or OAR contours or wrong planning (Retired Value)	2.47
Wrong prescription dose-fractionation or calculation error	1.83
Failure to perform on-treatment imaging as per instructions	1.61
Inadequate coordination of combined modality care	1.36
Wrong anatomical site (excluding laterality)	1.33
Wrong patient	1.27
Wrong side (laterality)	1.23
Fall or other patient injury or medical condition	1.20
Wrong target or OAR contours	0.95
Treatment plan acceptable but not physically deliverable	0.76
Untimely access to medical care or radiotherapy	0.76
Wrong plan dose (Retired value)	0.70
Interventional procedure error (Retired value)	0.57
Inappropriate or poorly informed decision to treat or plan	0.47
Treatment not delivered - personnel/hardware/software failure	0.38
Treatment plan (isodose distribution) unacceptable	0.32
Wrong planning margins	0.16
Infection	0.13
Allergic reaction	0.03

Overview

■ Contributing Factors

Distraction or diversions involving staff	0.23
Human resources inadequate	0.01
Other	0.12
Policies and/or procedures not followed	0.32
Staff behaviour	0.16
Communication or documentation inadequate (patient specific)	0.20
Failure to identify potential risks	0.06
Patient or family member medical condition preference or behaviour	0.00
Organizational and/or workspace resources inadequate (excluding human resources)	0.01
Staff education or training inadequate	0.02
Equipment software or hardware commissioning, calibration or acceptance testing inadequate	0.01
Expectation bias involving staff	0.22
External factors beyond programmatic control	0.01
Policies and/or procedures non-existent or inadequate	0.14
Change management	0.02
Equipment software or hardware design, including 'human factors' design, inadequate	0.07
Unfamiliar treatment approach or radiation treatment technique	0.01
Patient or family member medical condition, preference or behaviour	0.02
Equipment quality assurance and/or maintenance inadequate	0.01
Handoffs inadequate	0.01
Patient education inadequate	0.00

Roadmap

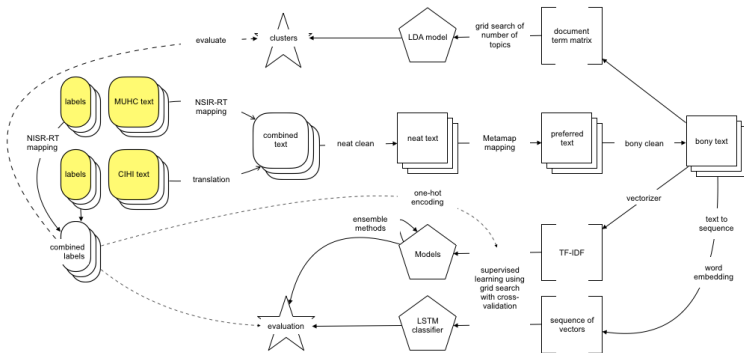
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3 Preprocessing

- Neat Clean
- Bony Clean
- Vectorization

Neat Clean

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- Remove line breaks
- Autocorrect
- Isolate punctuations
- Replace entities
 - Time
 - Date
 - Percent
 - Cardinal
 - Quantity
 - Ordinal
- Remove redundant spaces
- Lowercase

Neat Clean

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Before

Noticed by **nutistionist** (pt had app. with support **group**) that patient needed to be evaluated for skin reaction. Patient noticed after her treatments were completed that her skin broke down, she tried to contact trwatment unit and/or Rad Onc. on call with no success. Pt even presented herself **x1** but left due to **lenghty** wait time.

After

noticed by **nutritionist** (pt had app . with support **group**) that patient needed to be evaluated for skin reaction . patient noticed after her treatments were completed that her skin broke down , she tried to contact treatment unit and / or rad onc . on call with no success . pt even presented herself **x cardinal** but left due to **lengthy** wait time .

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- Remove stop words
- Lemmatize
- Remove punctuations
- Remove numerals

Bony Clean

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Before

noticed by nutritionist (pt had app . with support group) that patient needed to be evaluated for skin reaction . patient noticed after her treatments were completed that her skin broke down , she tried to contact treatment unit **and** / **or** rad onc . on call with no success . pt even presented herself x cardinal but left due to lengthy wait time .

After

notice nutritionist pt app support group patient need evaluate skin reaction pt assess rn date treatment patient notice treatment complete skin break try contact treatment unit rad onc success pt present x leave lengthy wait time

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3 Preprocessing

- Neat Clean
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- **Vectorization**

Roadmap

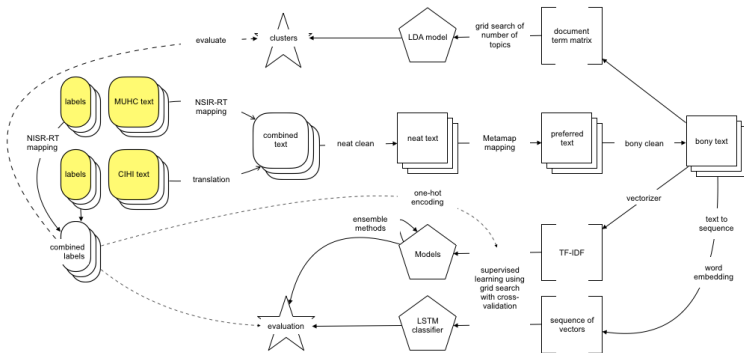
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Bag of Words

1. Bolus not done
2. CBCT not added to plan



	bolus	CBCT	not	done	added	to	plan
1	1	0	1	1	0	0	0
2	0	1	1	0	1	1	1

TF-IDF

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For a term i in document j :

$$tf_{i,j} \cdot \ln (N/df_i)$$

$tf_{i,j}$ = number of occurrences of i in j

df_i = number of documents containing i

N = total number of documents

TF-IDF

	bolus	CBCT	not	done	added	to	plan
1	1	0	1	1	0	0	0
2	0	1	1	0	1	1	1

↓

	bolus	CBCT	not	done	added	to	plan
1	0.63	0	0.44	0.63	0	0	0
2	0	0.47	0.34	0	0.47	0.47	0.47

↖ 1-3 grams

One-Hot Encoding

Process Step		Contouring and planning		Imaging for treatment planning	Treatment delivery
1	Contouring and planning	1	1	0	0
2	Imaging for treatment planning	2	0	1	0
3	Treatment delivery	3	0	0	1
4	Treatment delivery	4	0	0	1

Vectorized Data

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	bolus	CBCT	not	done	added	to	plan	Contouring and planning	Imaging for treatment planning	Treatment delivery
1	0.63	0	0.44	0.63	0	0	0	1	0	0
2	0	0.47	0.34	0	0.47	0.47	0.47	0	1	0

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4 Supervised Learning

■ Supervised Learning

■ Multi-Target Regression

■ Bagging

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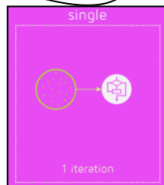
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	bolus	CBCT	not	done	added	to	plan	Contouring and planning
1	0.63	0	0.44	0.63	0	0	0	1
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Multi-Target Regression

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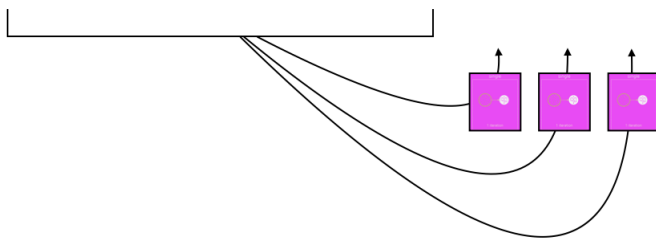
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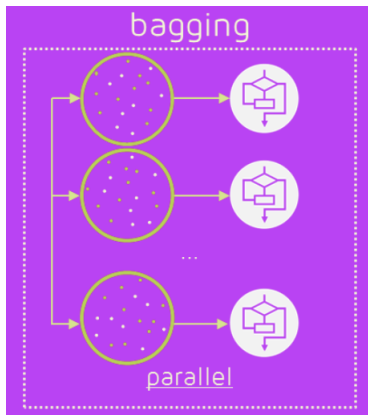
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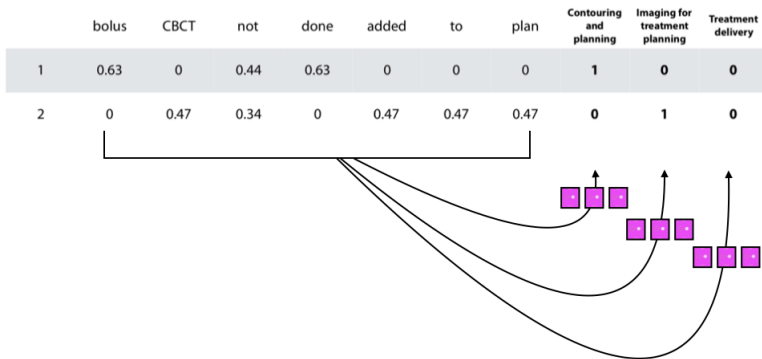
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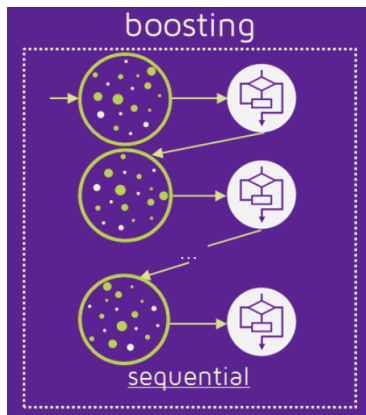
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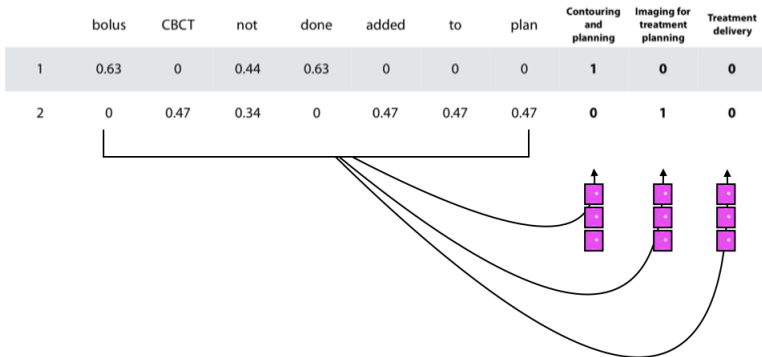
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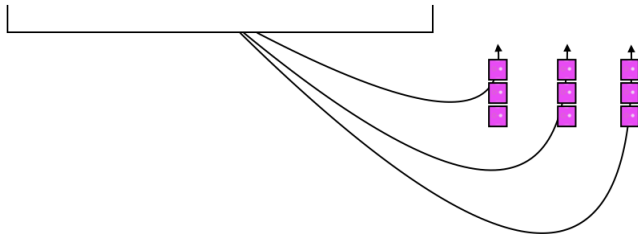
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1	0.63	0	0.44	0.63	0	0	0	1	0	0
2	0	0.47	0.34	0	0.47	0.47	0.47	0	1	0



- 52 base models
- 10 ensemble models

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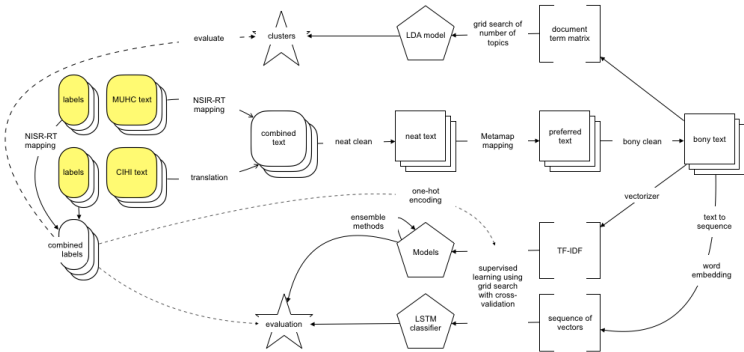
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- Process step
 - 1.69th position among 9 choices
- Problem type
 - 2.96th position among 24 choices
- Contributing factors
 - 5.17th position among 21 choices

Roadmap

Natural Language Processing for Incident Learning in Radiotherapy

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- 5 Unsupervised Learning**
 - **Unsupervised Learning**
 - Latent Dirichlet Allocation
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Unsupervised Learning

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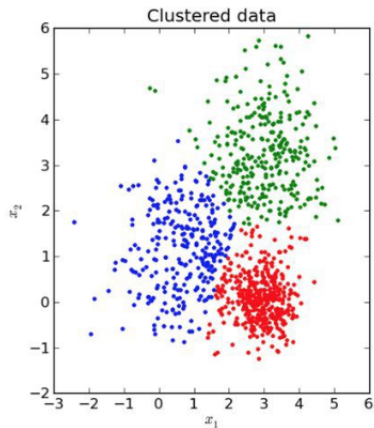
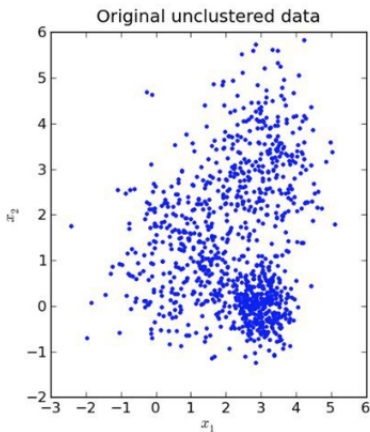
Supervised
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Unsupervised
Learning

Unsupervised
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- 5** Unsupervised Learning
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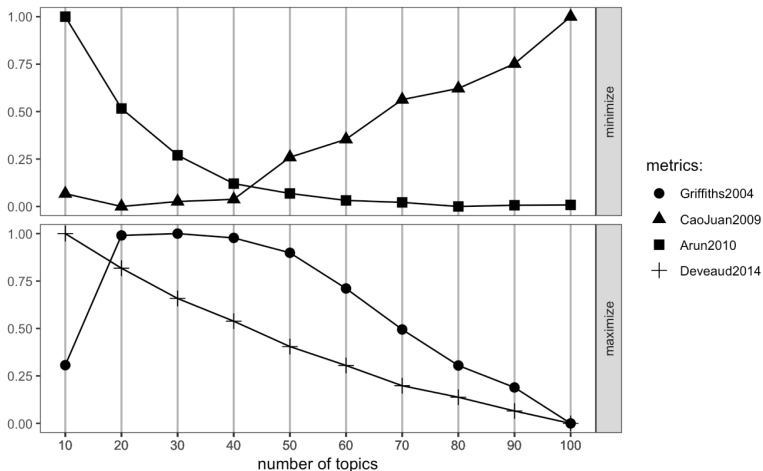
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- 195 incidents

- Take
- Extra
- Image
- Hold
- Breadth

- 185 incidents

- Take
- Image
- Select
- Anatomy
- Setting

- 121 incidents

- Catch
- Pre
- Tmt
- Incorrect
- Shift

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Visualization

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Unsupervised Learning

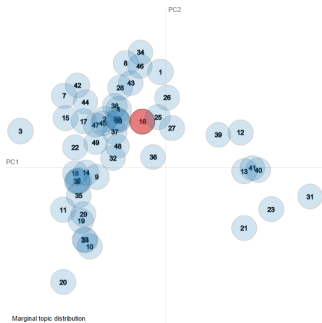
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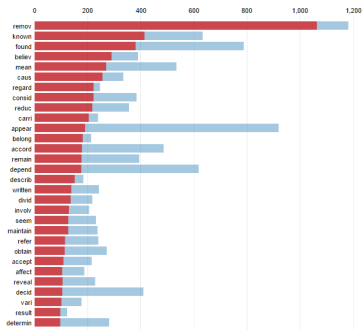
Intertopic Distance Map (via multidimensional scaling)



Marginal topic distribution



Top-30 Most Relevant Terms for Topic 16 (2% of tokens)



Overall term frequency

Estimated term frequency within the selected topic

1. $\text{saliency}(\text{term } w) = \text{frequency}(w) * \sum_j p(t_j | w) * \log(p(t_j | w) / p(t_j))$ for topics t ; see Chung et al. (2012)
2. $\text{relevance}(\text{term } w | \text{topic } t) = A * p(w | t) * (1 - A) * p(w | \cup p(w))$; see Sievert & Shirley (2014)

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- Supervised learning models cannot identify new problem types or contributing factors, while topic modelling can.
- Topic modelling may offer a patient-centric approach to incident learning.

Conclusion

- Natural language processing can facilitate the classification of incidents with good performance.
- Natural language processing may offer an alternative approach to analyze volumes of reports without investigating each incident.

Acknowledgement

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- John Kildea
- Logan Montgomery
- Erick Velazquez