Natural Language Processing for Incident Learning in Radiotherapy

Hui Wang[1] John Kildea[2]

[1]School of Computer Science
McGill University

[2]Medical Physics Unit
McGill University

August 24, 2018

Outline

Incident Learning

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

Outline

Reporting

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

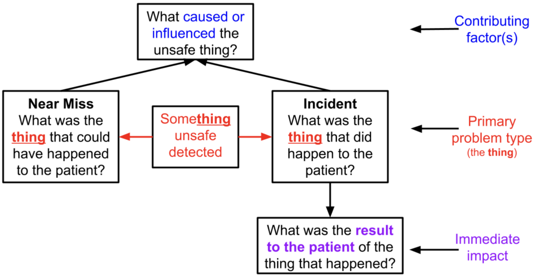
Example

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.

Outline

1 Background
- Incident Learning
- Incident Reporting
- Incident Investigation
- Challenge
- Objectives

Incident Investigation



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

Outline

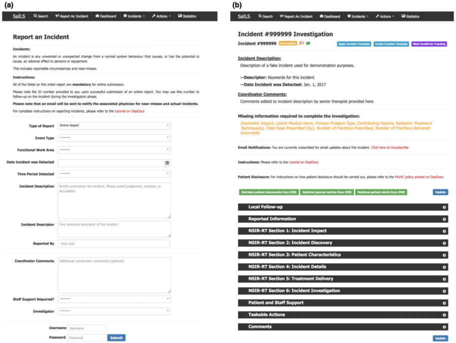
Challenge

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

Outline

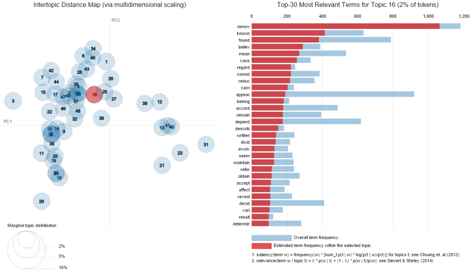
Objectives

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



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.



Outline

Datasets

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

Outline

Overview

- 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

Overview

Problem Type

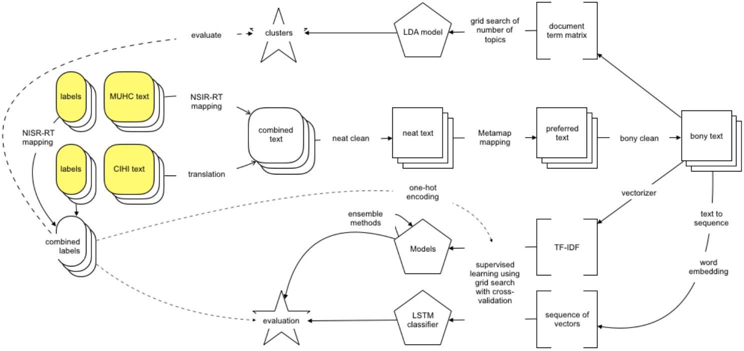
Other	40.32
Wrong patient position, setup point, or shift	15.37
Radiation therapy scheduling error	10.56
Wrong, missing, mislabeled, or damaged treatment accessories	9.77
Excess imaging dose	3.35
Systematic hardware/software (including dose-volume) error	3.10
Wrong target or OAR contours or wrong planning (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


evaluate
clusters
LDA model
grid search of number of topics
document term matrix
labels
MUHC text
NSIR-RT mapping
NISR-RT mapping
combined text
neat clean
neat text
Metamap mapping
preferred text
bony clean
bony text
labels
CIHI text
translation
one-hot encoding
vectorizer
ensemble methods
combined labels
Models
supervised learning using grid search with cross-validation
TF-IDF
text to sequence
word embedding
evaluation
LSTM classifier
sequence of vectors

Outline

Neat Clean

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

Neat Clean

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 .

Outline

Bony Clean

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

Bony Clean

Before

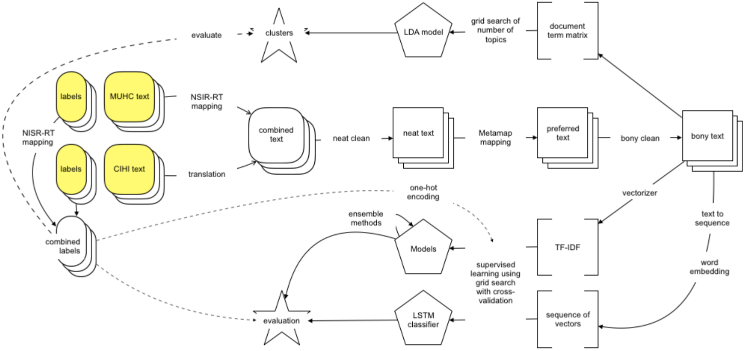
noticed by nutritionist (pt had app . with support group) that patient needed to be evaluated for skin reaction . patient noticed after her treatments were completed that her skin broke down , she tried to contact treatment unit and / or rad onc . on call with no success . pt even presented herself x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

Outline

Roadmap


evaluate
clusters
LDA model
grid search of number of topics
document term matrix
labels
MUHC text
NSIR-RT mapping
NSIR-RT mapping
combined text
neat clean
neat text
Metamap mapping
preferred text
bony clean
bony text
labels
CIHI text
translation
one-hot encoding
vectorizer
combined labels
ensemble methods
Models
supervised learning using grid search with cross-validation
TF-IDF
text to sequence
word embedding
evaluation
LSTM classifier
sequence of vectors

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

For a term *i* in document *j*:

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

$tf_{i,j}$ = 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

1-3 grams

	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

One-Hot Encoding

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

→

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

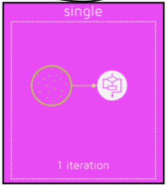
Vectorized Data

	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**

Outline

Supervised Learning

	bolus	CBCT	not	done	added	to	plan	**Contouring and planning**
1	0.63	0	0.44	0.63	0	0	0	**1**
2	0	0.47	0.34	0	0.47	0.47	0.47	**0**

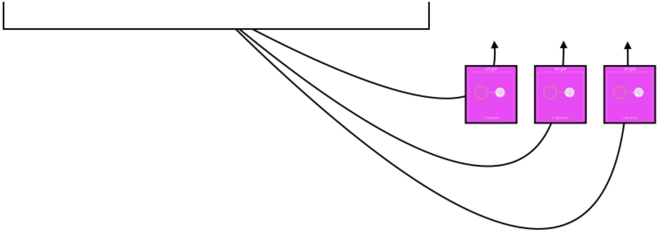


Outline

Multi-Target Regression

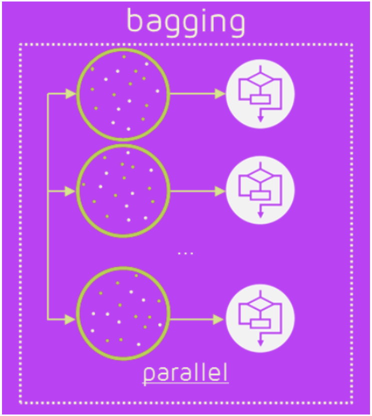
Hui Wang, John Kildea

	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**



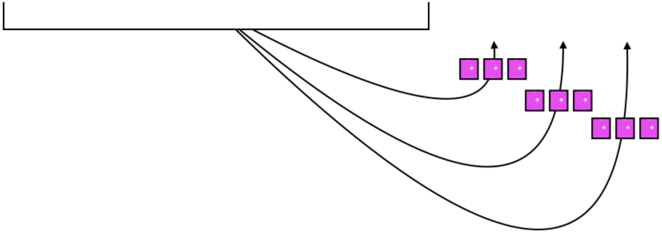
Outline

Bagging



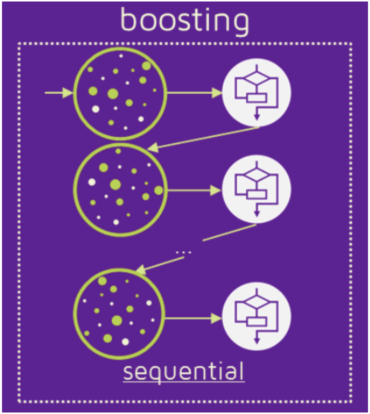
Bagging

	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**



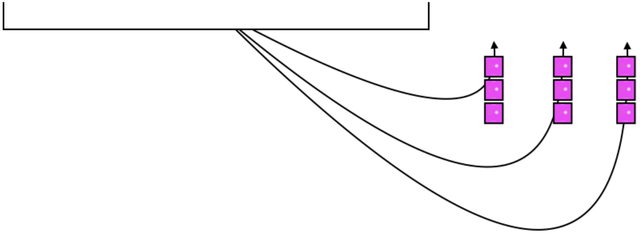
Outline

Boosting



Boosting

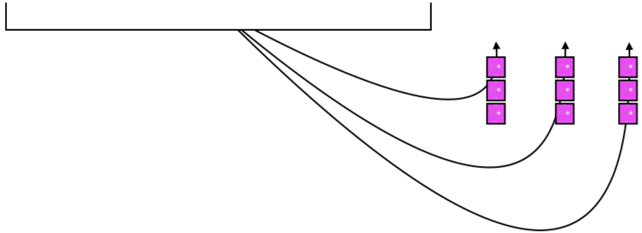
	bolus	CBCT	not	done	added	to	plan	Contouring and planning	Imaging for treatment planning	Treatment delivery
1	0.63	0	0.44	0.63	0	0	0	**1**	**0**	**0**
2	0	0.47	0.34	0	0.47	0.47	0.47	**0**	**1**	**0**



Outline

Multi-Target Ensemble Regression

	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**



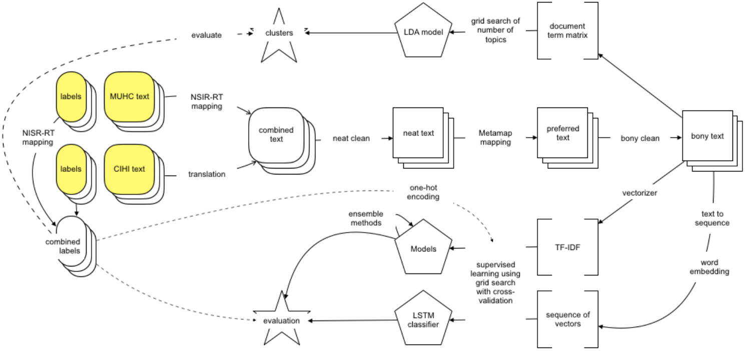
- 52 base models
- 10 ensemble models

Outline

Results

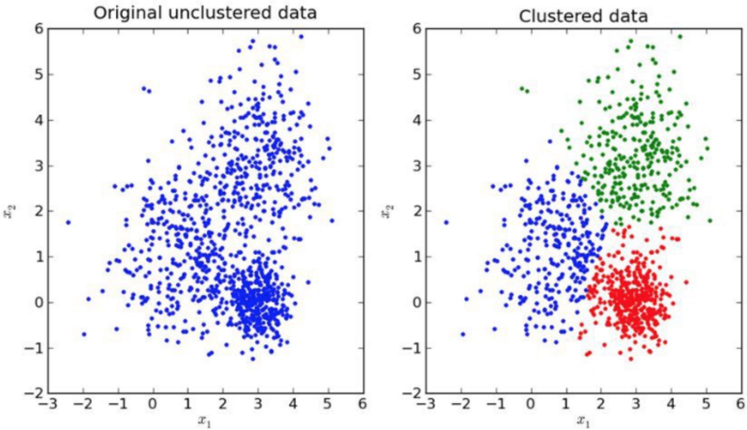
- Process step
  - 1.69th position among 9 choices
- Problem type
  - 2.96th position among 24 choices
- Contributing factors
  - 5.17th position among 21 choices

Roadmap


evaluate
clusters
LDA model
grid search of number of topics
document term matrix
labels
MUHC text
NSIR-RT mapping
NSIR-RT mapping
combined text
neat clean
neat text
Metamap mapping
preferred text
bony clean
bony text
labels
CIHI text
translation
one-hot encoding
vectorizer
ensemble methods
combined labels
Models
TF-IDF
text to sequence
supervised learning using grid search with cross-validation
word embedding
LSTM classifier
evaluation
sequence of vectors

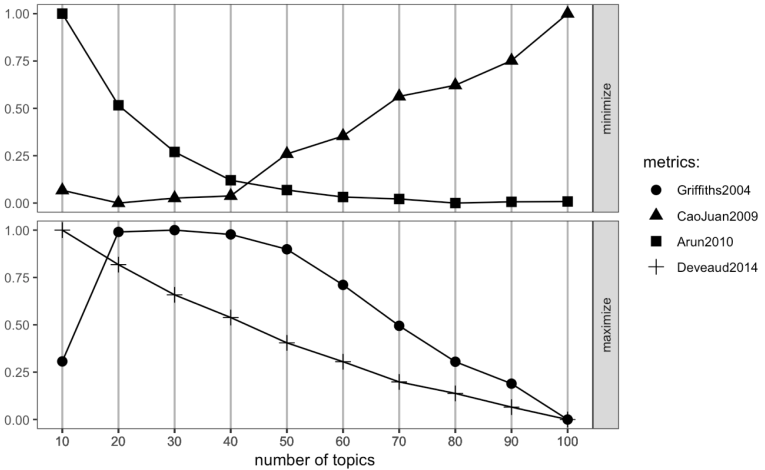
Outline

Unsupervised Learning



Outline

Latent Dirichlet Allocation



Outline

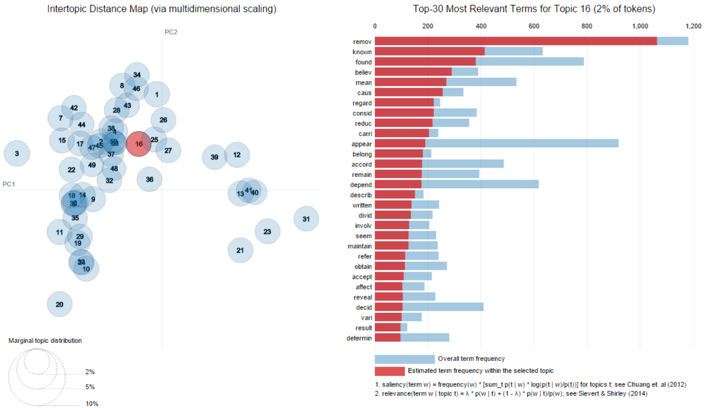
Results

- 195 incidents
  - Take
  - Extra
  - Image
  - Hold
  - Breadth
- 185 incidents
  - Take
  - Image
  - Select
  - Anatomy
  - Setting
- 121 incidents
  - Catch
  - Pre
  - Tmt
  - Incorrect
  - Shift

Outline

5 Unsupervised Learning
- Unsupervised Learning
- Latent Dirichlet Allocation
- Results
- Visualization

Visualization



Discussion

- 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

- John Kildea
- Logan Montgomery
- Erick Velazquez