Automated Validation of Patient Safety Clinical Incident Classification: Macro Analysis

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SEARCH
- For urgent & practical solutions to improve patient safety

WHY
- Alarming numbers one state alone over one million electronic text documents are available in IIMS

ISSUES
- Under 2 % scrutinized
- Labor intensive
- Poor classification models – No statistical validation
- No automation
- Text mining on large scale never used or attempted
Generic architecture of clinical incident report

Clinical Incident or Near Miss

- Respond
- Contributing Factors

Document Clinical Notes

Incident Data

Components

Terms (N = 20,000)

Incident Management System

SAC Matrix

Information Sources

Generic Reference Model

Healthcare Incident Types (HiTs):
Clinical HiTs
Non Clinical HiTs
Speciality HiTs

Free Text Data

Categorical Data

Clinical HiTs
1. Aggression Agressor
2. Aggression Victim
3. Behaviour Human Performance
4. Blood and Blood Product
5. Clinical Management
6. Documentation
7. Fall
8. Hospital Associated Infection
9. Medication
10. Nutrition
11. Pathology Lab
12. Primary Care
13. Pressure Ulcers
14. Oxygen/gases
15. Devices equipments

Non Clinical HiTs
1. Accident/OHS
2. Building/fittings
3. Organisational services
4. Security

Speciality HiTs
1. Anaesthesia
2. Complaints
3. Hyperbaric
4. Intensive care unit
5. Obstetric fetal
6. Obstetric maternal
Methodology

• Part 1
  • Determine content density in 73 fields per ETD
  • 1000 ETD 73,000 cells – Frequency analysis

• Part 2
  • 4 Statistical classifiers used J48, Naïve Bayes (NB), Naïve Bayes Multinominal (NBM) and Support Vector Machine using radial basis function (SVM_RBF) algorithms
  • 13 Classes validated – 5448 ETD classified.
Methodology (cont)

- General measures
  - % instances correctly classified,
  - kappa statistics,
  - mean absolute error weighted average

- Standard measure of accuracy
  - precision
  - Recall
  - F-measure
  - Area under curve (AUC) of receiver operating characteristics (ROC).
Methodology (cont.)

- Exp 1 - Categorical datasets
- Exp 2 - Free text datasets
- Exp 3 – Categorical + Free text datasets

- Tool – WEKA*
  - Waikato Environment for Knowledge Analysis

- Attribute evaluation was set to ICfsSubsetEval
- 10 fold cross validation process
Categorical datasets and illustration of data in the field used

<table>
<thead>
<tr>
<th>Fields</th>
<th>Pt 1</th>
<th>Pt 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Service type</td>
<td>Intensive care</td>
<td>Aged Care</td>
</tr>
<tr>
<td>Initial Consequences</td>
<td>Minor</td>
<td>Minor</td>
</tr>
<tr>
<td>Initial Likelihood</td>
<td>Frequent</td>
<td>Frequent</td>
</tr>
<tr>
<td>Initial SAC</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Actual Consequences</td>
<td>Minor</td>
<td>Minimum</td>
</tr>
<tr>
<td>Actual Likelihood</td>
<td>Likely</td>
<td>Likely</td>
</tr>
<tr>
<td>Actual SAC</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Time of incident</td>
<td>19:00</td>
<td>22:15</td>
</tr>
<tr>
<td>Title</td>
<td>Mr</td>
<td>Mr</td>
</tr>
<tr>
<td>Age</td>
<td>34</td>
<td>75</td>
</tr>
</tbody>
</table>
Example of fields and their content used for free text analysis

<table>
<thead>
<tr>
<th>Fields</th>
<th>Pt 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incident description</td>
<td>pt was found on floor of bathroom pt states she slipped whilst trying to put a socks on after having a shower pt states she slipped backwards and hit her head on toilet bowl.</td>
</tr>
<tr>
<td>Contributing factor</td>
<td>pt did not tell no nursing staff that she was going to have a shower. There is no nursing call bell in that bathroom, nursing staff heard pt calling out.</td>
</tr>
<tr>
<td>Initial Action taken</td>
<td>pt obs attended neuro obs attended medical officer called pt assited back to bed</td>
</tr>
<tr>
<td>Outcome</td>
<td>Nil</td>
</tr>
</tbody>
</table>
Results

- **Type of data** (73 fields, 1000 CI = 73,000 cells)
  - Categorical - date, multi class number, short multi class text
  - Free text - short text type.
- **74.6% of the cells had no data** (73 fields analysed)
- **58.7% of the cells had no data entered** (52 fields - required for less severe risk PIT)
- **23 of the 73 fields had data 70% and above**
- **100% data entry in 4.06% of the cells**
- **Exclusions** - Zero Content value, Confidential, redundant datasets
- **Inclusion** - 10 Categorical and 4 Free-text fields
Results

Percentage Correctly classified instances using 4 algorithms 3 experiments
(Exp1 Categorical data, Exp 2 Free text, 3 All data; Algorithm 1 =J8, 2 = NB, 3 = NBM, 4 = SVM_RBF)
Results

Kappa Statistics for 4 algorithms in 3 experiments
(Exp1 Categorical data, Exp2 Free text, 3 All data;)

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Exp1</th>
<th>Exp2</th>
<th>Exp3</th>
</tr>
</thead>
<tbody>
<tr>
<td>J48</td>
<td>0.44</td>
<td>0.62</td>
<td>0.74</td>
</tr>
<tr>
<td>NB</td>
<td>0.40</td>
<td>0.49</td>
<td>0.74</td>
</tr>
<tr>
<td>NBM</td>
<td>0.44</td>
<td>0.67</td>
<td>0.77</td>
</tr>
<tr>
<td>SVM_RBF</td>
<td>0.62</td>
<td>0.64</td>
<td>0.77</td>
</tr>
</tbody>
</table>
Results

F Measures for 4 algorithms in 3 experiments
(Exp1 Categorical data, Exp2 Free text, 3 All data)

J48  NB  NBM  SVM_RBF

Exp1 0.49  0.65  0.68  0.45  0.45  0.4
Exp2 0.74  0.7  0.78  0.76  0.67  0.67
Exp3 0.7  0.7  0.78  0.6  0.4  0.96
Conclusion

- Important to select certain fields
- Scope to explore 12-13 classes vs 2 done in the past
- Free text datasets perform better over categorical
- Combined data type perform the best as indicated by Kappa statistics
- J48 and multinominal Naïve Bayes used for the first time and multinominal performed better over Naïve Bayes and SVM.
- NBM fairly consistently showed better performance over J48 or NB or SVM_RBF
Next step & Implications

- A micro level analysis of each of the 13 classes using confusion matrix analysis.
- Most confused classes should be re-defined or better classification system be explored.

- Implications:
  - Help health sector to fill the current gap of reporting validated categories.
  - Improved statistically validated classification system
  - Automated classification will ease the pressure
  - Shorter turnover for accountability will improve patient safety and quality of service