Predicting ICU transfers using text messages between nurses and doctors

1 Introduction

- Failure to rescue can be caused by poor communication or lack of situational awareness in the care team (Brady and Goldenhar 2014).
- Real-time clinical information, especially communication between nurses and doctors, may be useful in improving the accuracy of detecting deteriorating patients (Rajkomar et al. 2018).
- Goal: Explore the use of text messages between nurses and doctors in predicting a patient’s transfer to the intensive care unit (ICU).

2 Methods

Data:
- 38k patients across 49k visits, between 2011 and 2017, divided into five different institutional codes.
- Treat each text message as a separate data point – text message occurs within the next 3 days of the message send date.
- Visit information: Patient’s age and gender, number of days in hospital, medication and diagnosis (encoded with TF-IDF).

Text messages:
- Consist of message headers (i.e., messages from nurses) and message replies (i.e., replies from doctors). We focus our analysis on message headers only.
- Challenging to analyze due to spelling mistakes, abbreviations specific to the medical domain, and missing punctuation.

Examples of message headers (mheader) and message replies (mreply)

  mreply: ‘ok
- mheader: ‘nurse calls to say pt. is intubated. Thnx.
  mreply: ‘ok

Text message representations:
- TF-IDF
- Word2vec with pre-trained PubMed embeddings (Moen and Annapoorna 2013)
- Word2vec (Mikolov et al. 2013) trained on text messages
- Linguistic features (e.g., polarity, POS tag counts)

3 Results

Total number of text messages (with % resulting in ICU transfer within 3 days of message send date) and model performance in baseline (i.e., visit information only), Word2vec (SMS) (i.e., Baseline + wordvec trained on text messages), and TF-IDF (i.e., Baseline + TF-IDF) features

<table>
<thead>
<tr>
<th>Group</th>
<th>Messages</th>
<th>Baseline</th>
<th>Word2vec (SMS)</th>
<th>TF-IDF</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>98,468</td>
<td>0.47 (0.01)</td>
<td>0.51 (0.02)</td>
<td>0.51 (0.01)</td>
</tr>
<tr>
<td>B</td>
<td>91,330</td>
<td>0.36 (0.01)</td>
<td>0.46 (0.07)</td>
<td>0.50 (0.01)</td>
</tr>
<tr>
<td>C</td>
<td>8,159</td>
<td>0.44 (0.02)</td>
<td>0.57 (0.05)</td>
<td>0.56 (0.04)</td>
</tr>
<tr>
<td>D</td>
<td>821</td>
<td>0.22 (0.12)</td>
<td>0.46 (0.07)</td>
<td>0.44 (0.04)</td>
</tr>
<tr>
<td>E</td>
<td>260</td>
<td>0.20 (0.28)</td>
<td>0.69 (0.28)</td>
<td>0.69 (0.28)</td>
</tr>
</tbody>
</table>

- Best performance in Group C: most ICU transfers, longest text messages and most text messages per visit and per patient.
- Word2vec word embeddings trained on our data performs better than the pre-trained ones, since they are able to capture different spellings and common misspellings.

4 Conclusion

- Identify key features of the text messages that are relevant in predicting ICU transfer.
- Investigate the utility of adding the message replies as features.
- Explore the added value of text messages in a more complex set of features (i.e., lab results and vitals).

Acknowledgements


References

