

Despite being short and full of noise, **text messages sent between nurses and doctors** regarding patient conditions can augment other visit information to improve performance of **intensive care unit (ICU) transfer prediction**.

Predicting ICU transfers using text messages between nurses and doctors

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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 is determined to have the **outcome** if an **ICU transfer 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 TFIDF).

- 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)*
- | Examples |
|--|
| mheader: ‘hb=65, cr=123 & more lab res up from last nights bldwork. Ping if anything you want me to follow up.’ |
| mreply: ‘informed.’ |
| mheader: ‘dc hep drip on epr. Pls see chart order. Thnx.’ |
| mreply: ‘done thanks’ |
| mheader: ‘hey are icu recommends to be cosigned. thx.’ |
| mreply: ‘Ok. Pls run one l of ringers wide & then one more’ |

- Text message representations:**
- TF-IDF
 - Word2vec with **pre-trained PubMed embeddings (Moen and Ananiadou 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 + word2vec trained on text messages), and TF-IDF (i.e., Baseline + TF-IDF) features***
- | Group | Messages | Baseline | Word2vec (SMS) | TFIDF |
|-------|-----------------|-------------|--------------------|--------------------|
| A | 98,468 (16.75%) | 0.47 (0.01) | 0.51 (0.02) | 0.51 (0.01) |
| B | 91,330 (0.36%) | 0.48 (0.01) | 0.46 (0.07) | 0.50 (0.01) |
| C | 8,159 (35.85%) | 0.44 (0.02) | 0.57 (0.05) | 0.56 (0.04) |
| D | 821 (22.12%) | 0.44 (0.03) | 0.46 (0.07) | 0.44 (0.04) |
| E | 260 (2.01%) | 0.69 (0.28) | 0.69 (0.28) | 0.69 (0.28) |
- **Input:** Patient demographics, visit information, and text message representations.
 - **Model:** **Logistic regression** classifier.
 - **F1-macro** averages of 5-fold cross-validation.

Comparison of word embeddings - Top five similar words for common abbreviated medical terms

Word	w2v (SMS)	w2v (PubMed)
dr	dr., doctor, md, resident, oncologist	99:1, diastereoselectivities, ee, =98:2, 98:2
bld	blood, blood, blod, frozen, pt.iv	whi, bldB, EPS-deficient, transposon-generated, A-factor-deficient
med	medication, pill, lactulose, risperidone, hypoglycemics	Nicolae, Delores, Dres, habil., CSc.
bp	b/p, bp=, bp-, bpm, pulse	nt, bps, nts, bp-long, bp-long
icu	msicu, emerg, er, cvicu, gim	bag/mask, Patient-initiated, extrahospital, patient-cycled, airway-management

4 Conclusion

- 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**.
- Future work:**
 - **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).

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