

Fall Detection in EHR using Word Embeddings and Deep Learning

Henrique Santos - PUCRS - Brazil 19th IEEE International Conference on Bioinformatics and Bioengineering

Brief context ...



Multidisciplinary Group and ...

PUCRS

Pontifical Catholic University - Rio Grande do Sul

PPGCC and PPGGB

Graduate program in Computer Science Graduate program in Biomedical Gerontology



... and Multicentric Group

















Scope of this Research

Fall

This adverse event is very common in the hospital environment. The Morse Fall Scale measure the risk of patient fall.

There is a underreport number of fall event notifications.



Report System





Underreported Events

Events are notified voluntarily in the system

Source of useful information to improve care and subsidize continuing education!

Due to lack of knowledge, forgetfulness or lack of time, it is underreported. Only 10-20% of these events are reported.



IHI Global Trigger Tool

Institute for Healthcare Improvement

"This tool includes a list of known AE triggers as well as **instructions for selecting records**, training information, and appendices with references and common questions."



Problems and Objectives



Detect falls incidents in Progress Notes

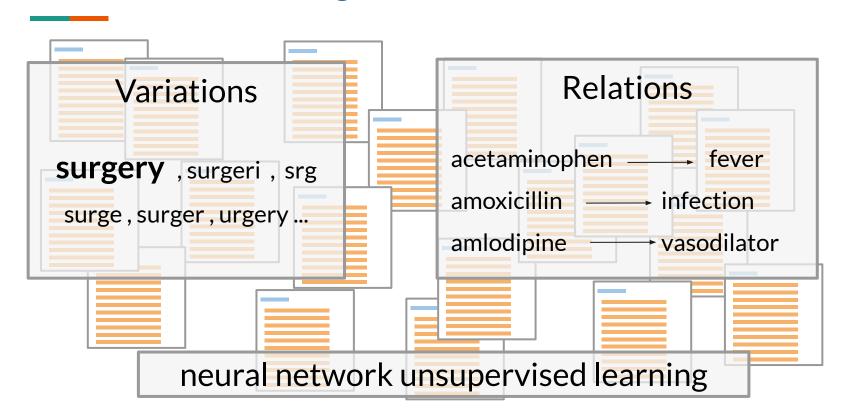


Evaluate language models performance using LSTM in this task

Methods and Materials

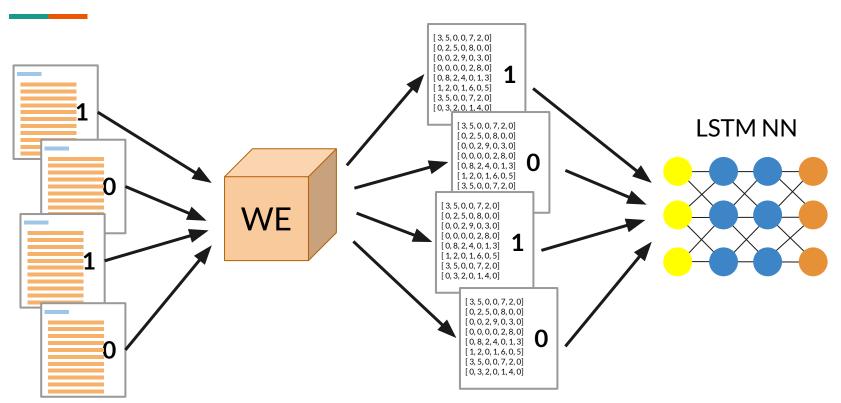


Word Embeddings



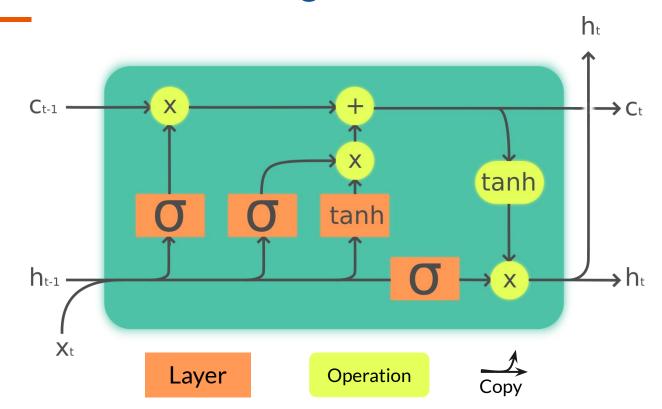


Word Embeddings Encoding





LSTM Neuron (Long Short-Term Memory)

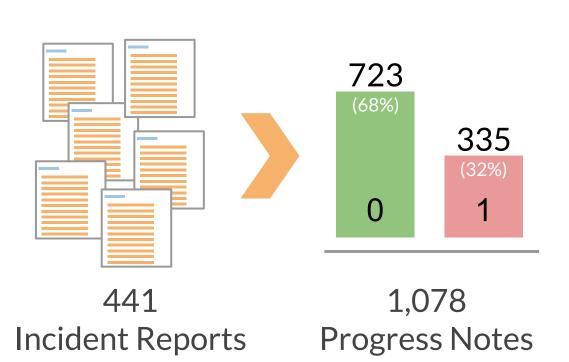




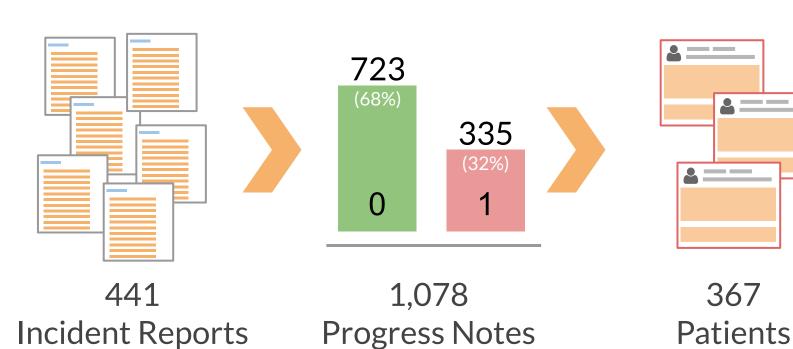


441 Incident Reports











Fall per Patient in Annotated Dataset

# of Patients	% of Total	# of Falls
316	87.0 %	1 fall
36	10.0%	2 falls
11	3.0 %	3 falls
1	0.3 %	4 falls
•••	•••	•••



Language Models

Wikipedia-PT

- Wikipedia dump of May 2019
- 250 million tokens

NILC (broad-domain)

- Wikipedia + 20 sources (News and Researches)
- 1.3 billion tokens

EHR-Notes (biomedical-domain)

- 24 million sentences from Progress Notes
- 603 million tokens



Fall Detection - Experiments

Annotation of 1,078 Progress Notes

Evaluation of three Word Embedding Models

- Wikipedia-PT
- NILC (Wikipedia + 20 sources)
- EHR-Notes (Progress Notes)

State-of-the-art NLP Neural Network (LSTM)

Baseline: SVM and Random Forest

Results ...



Fall Detection - Results

Embeddings 5-Fold Cross Validation: F-Measure

	Word2Vec	FastText
Wikipedia	0.88 ± 0.14	0.87 ± 0.11
NILC (broad-domain)	0.77 ± 0.06	0.89 ± 0.13
EHR (biomedical-domain)	0.88 ± 0.14	0.90 ± 0.13



Fall Detection - Results

Embeddings 5-Fold Cross Validation: F-Measure

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Random Forest SVM	0.73 ± 0.03 0.60 ± 0.05	



Conclusion

Better with biomedical-domain Language Model

LSTM prove to be best than Random Forest



Research Limitations

- Progress Notes Sampling (natural distribution)
- Self-Attention Neural Network
- BERT, GPT-2, XLNet Embeddings
- Quality Evaluation (why right, why wrong)



Source Code

- Experiments scripts
- Annotated Dataset (1,078 records)
- Pre-trained Word Embeddings

https://github.com/nlp-pucrs/fall-detection

Further Work ...



Further Work

Sequence Tagging Task: F-Measure

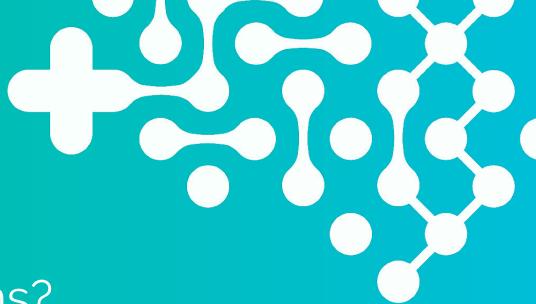
	LSTM + CRF
Wikipedia	0.55
NILC (broad-domain)	0.67
EHR (specific-domain)	0.80



Further Work

Quality Embeddings - Analogies Task

	Specific	Broad
Wikipedia	1.38 %	79.00 %
NILC (broad-domain)	2.61%	82.38 %
EHR (specific-domain)	2.85 %	0.00 %



Thanks! Questions?

http://www.inf.pucrs.br/ia-saude/

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Annotation Process - WebAnno

